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ORIGINAL ARTICLE

Assessing the efficacy of a sequential general variational mode decomposition-based combination model for United States wind power forecasting

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Abstract

Accurate forecasting of wind energy is essential for maintaining grid stability and ensuring efficient energy management. Hybrid modeling approaches offer enhanced predictive accuracy and reliability, supporting wind farm performance, seamless grid integration, and informed market operations. This study presents an adaptive forecasting system that compares hybrid and standalone models using a univariate framework to preserve simplicity and reduce computational overhead. Historical U.S. wind energy data spanning 2001–2025 were utilized, with optimal lag selection based on correlation coefficients exceeding 0.899. The dataset was partitioned into training and testing subsets in a 70:30 ratio. Two hybrid frameworks were implemented: one combining Convolutional Neural Networks with Long Short-Term Memory (CNN-LSTM), and another integrating Artificial Neural Networks with Sequential Variable Mode Decomposition (SVMD-ANN). Two standalone models were implemented: Support Vector Regression (SVR) and ANN. The Combination Model Based on Sequential General Variational Mode Decomposition is important for wind power prediction because it significantly enhances the accuracy and robustness of forecasting wind power output by effectively decomposing complex, non-stationary wind power time series into intrinsic mode components. This decomposition allows more accurate modeling of different wind power signal characteristics and improved handling of fluctuations and abrupt changes commonly seen in wind power data. Performance was assessed using graphical visualizations and quantitative metrics, including Root Mean Square Error (RMSE), Coefficient of Determination (R^2), symmetric Mean Absolute Percentage Error (sMAPE), and Mean Absolute Percentage Error (MAPE). The SVMD-ANN model achieved the highest accuracy, with a total error of 4.16×10^5 MWh, R^2 of 0.964, sMAPE of 10.43%, and MAPE of 20.12%. CNN-LSTM showed competitive results (RMSE: 5.75×10^5 MWh, R^2: 0.952, sMAPE:16.26%, MAPE: 31.34%), outperforming ANN (RMSE: 5.79×10^5 MWh, R^2: 0.949, sMAPE:16.67%, MAPE: 34.76%) and SVR (RMSE: 5.91×10^5 MWh, R^2: 0.947, sMAPE:18.43%, MAPE: 45.44%). These findings validate the robustness of the proposed SVMD-ANN model and highlight its potential for modeling monthly wind energy production.

Keywords Wind energy prediction · Hybrid model · Renewable energy integration · Data-driven modeling

Introduction

Renewable energy plays a pivotal role in shaping a sustainable future by substantially lowering greenhouse gas emissions and minimizing air pollution, thereby aiding efforts to mitigate climate change and safeguard natural ecosystems. It also drives economic development through job creation and reduced energy expenses, while bolstering energy independence by decreasing reliance on fossil fuels. Technological advancements in renewables offer communities access to cleaner and more dependable energy sources, contributing to improved public health and enhanced social resilience (Bashiru et al. 2024; Naveed et al. 2025). In essence, the shift toward renewable energy is fundamental to achieving

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Extended author information available on the last page of the article environmental preservation, economic robustness, and global prosperity. Wind energy, in particular, stands out as a key renewable resource due to its ability to generate electricity with negligible greenhouse gas emissions during operation. This significantly curtails the release of carbon dioxide and other pollutants associated with climate change and poor air quality. Wind turbines occupy relatively little land and do not require water for cooling, making them less environmentally taxing than traditional power facilities. From an economic perspective, wind power contributes to local development through employment opportunities and financial incentives such as land-lease agreements and tax revenues. It is also among the most cost-effective energy options currently available (Saidur et al. 2011). While there are some localized environmental challenges—such as risks to avian species, noise disturbances, and visual impacts—these can be addressed through strategic planning and thoughtful design. Overall, wind energy is an essential element in the transition to a low-carbon energy system, offering wide-ranging benefits across environmental, economic, and societal dimensions.

Wind power has become a crucial energy source in shaping the United States' energy future, playing a vital role in environmental protection, economic advancement, and enhancing energy independence (McKenna et al. 2025). The U.S. Department of Energy highlights that this renewable source can markedly lessen the nation's reliance on fossil fuels, fostering a more sustainable and eco-conscious energy framework. Utilizing wind as a resource allows the U.S. to combat climate-related impacts and move toward a greener, more robust energy system. As of 2025, wind power accounts for over 12% of U.S. electricity generation, with states like Texas leading production and numerous others rapidly expanding their wind capacity (Fuchs et al. 2024). Supported by federal policies such as the Inflation Reduction Act, the wind industry has attracted billions in investments and created over 125,000 jobs nationwide. The sector continues to grow robustly, with both onshore and offshore projects under development, driving economic growth, enhancing energy security, and helping the U.S. meet its climate goals. By harnessing abundant and renewable wind resources, the country is advancing toward a cleaner, more sustainable energy system that benefits the environment, economy, and communities alike. Sun et al. (2024) introduced a machine learning-based framework to predict land suitability for large-scale wind energy development by integrating national wind farm inventories with diverse spatial criteria. Focusing on China, the USA, and the EU, the framework utilizes four advanced algorithms—Deep Neural Network (DNN), Random Forest (RF), XGBoost, and LightGBM—alongside 30 biophysical, geographical, and socio-economic variables. Bhavsar et al. (2024) presented a K-means clustering-based machine learning framework for improving stochastic economic dispatch under wind uncertainty. By extracting physically meaningful analog scenarios and applying extreme-sample selection, the approach enhanced the representation of wind variability. The methodology is tested on a synthetic 200-bus system across seasonal WIND Toolkit data over Illinois. Other research, Liu et al. (2025) reviewed the challenges and prospects of urban wind resource development as a complementary solution to global energy and climate issues. Key topics included urban airflow dynamics, wind resource assessment strategies, and turbine technologies. Findings highlight the benefits of exploiting airflow around buildings and favor vertical-axis wind turbines (VAWTs) for urban settings.

Wind energy prediction plays a crucial role in integrating wind power into modern energy systems by addressing the inherent variability and intermittency of wind. Accurate forecasting enables grid operators to balance supply and demand, ensuring grid stability and reliability while reducing the need for costly backup power. It also supports economic efficiency by optimizing turbine operations, maintenance scheduling, and market participation, ultimately facilitating better investment decisions and cost savings. Advances in machine learning and hybrid models have significantly improved prediction accuracy by analyzing complex patterns in large datasets, overcoming limitations of traditional physical and statistical methods, and providing more reliable short, medium, and long-term forecasts.

The importance of wind energy prediction extends beyond operational benefits, as it is vital for the global transition to renewable energy and the reduction of greenhouse gas emissions. Enhanced forecasting supports the development of smart grids and sustainable energy markets by enabling more effective grid management and economic transactions. Recent research highlights innovative models that reduce forecasting errors by leveraging spatial and temporal correlations among wind farms, improving uncertainty quantification, and enabling better planning and allocation of wind resources. These advancements underscore the critical role of accurate wind power forecasting in achieving a greener, more resilient energy future. Tawinprai et al. (2023) explored wind energy potential in Thailand's upper northeast region, emphasizing its role in mitigating climate change. Using MC2 and Ms-Micro atmospheric models alongside a decade of climate data from NCEP/FNL, researchers simulated wind flow to identify optimal sites for wind power projects. The analysis included energy output, turbine selection, and cost assessments. Results showed that mountainous areas, particularly Kalasin, offer the highest wind energy potential. Milla-Val et al. (2024) introduced a machine learning-based method for predicting high-resolution wind patterns using coarse mesoscale weather data, offering a cost-effective alternative to computational fluid dynamics (CFD). Four supervised learning models, linear regression (SGD), support vector machine (SVM), k-nearest neighbors (KNN), and random forest (RFR), were evaluated. SVM achieved the lowest error in wind speed prediction (1.81 m/s), while KNn excelled in wind direction accuracy. The proposed approach delivers wind predictions with a speedup factor of approximately 290 compared to CFD, making it suitable for applications in energy, urban planning, environmental health, and drone navigation. Buestán-Andrade et al. (2024) evaluated deep learning models, including CNN, FC, GRU, and transformer architectures, for wind power forecasting, with a focus on deployability across diverse computing platforms. The research benchmarks model was performed in terms of accuracy, speed, and energy efficiency on both standard systems and low-cost hardware such as the Raspberry Pi 3. Results highlight the feasibility of real-time, accurate forecasting on affordable platforms, advancing the accessibility and decentralized management of wind energy—a pivotal step toward clean energy democratization. Galarza-Chavez et al. (2025) presented a comprehensive methodology for forecasting wind farm energy generation in the Isthmus region, incorporating data exploration, preprocessing, and multi-step prediction by five regression algorithms—Linear Regression (LR), Support Vector Regression (SVR), Multiple-SVR (M-SVR), General Regression Neural Network (GRNN), and Long Short-Term Memory (LSTM)—which were evaluated using recursive and Multi-Input Multi-Output (MIMO) forecasting strategies. Wang et al. (2025) proposed a two-phase framework for wind farm planning and development, using the NREL 5 MW baseline turbine as a case study. This integrated framework enhances the speed and precision of design evaluations, ultimately supporting downstream tasks like layout optimization and wake steering. Ogunjo (2025) investigated wind speed dynamics at a coastal tropical site using multifractal detrended fluctuation and cross-correlation analyses at two altitudes (50 m and 100 m). Wind data collected at 30-minute intervals throughout 2008 revealed monthly variations ranging from 1.57 to 2.71 m/s at 50 m and 2.25–4.17 m/s at 100 m. The Weibull distribution provided a better statistical fit than the Gamma distribution. Multifractal analysis highlighted the influence of land and sea breezes, with multifractal strength ranging from 0.07 to 0.27 (50 m) and 0.72–2.11 (100 m).

Hybrid models for wind energy prediction combine multiple techniques, often integrating machine learning algorithms with data preprocessing methods or physics-based models, to significantly enhance forecasting accuracy and reliability. These models excel at capturing the complex, nonlinear, and nonstationary characteristics of wind power data by decomposing it into more manageable components or by blending complementary algorithms. The impact of these hybrid models is profound in both operational and strategic contexts. By delivering more precise and reliable wind power forecasts, they enable grid operators to better balance supply and demand, optimize turbine performance, and reduce reliance on costly backup power, thereby enhancing grid stability and reducing operational costs (Li et al. 2024). Furthermore, hybrid models that combine physics-based insights with data-driven residual learning improve interpretability and uncertainty quantification, aiding maintenance and fault detection efforts. However, challenges such as boundary effects and data leakage in preprocessing require careful methodological design to ensure realistic forecasting performance. Alhussan et al. (2023) presented an optimized ensemble model integrating LSTM, GRU, and bidirectional LSTM regressors. Model outputs are weighted and combined through a novel hybrid optimization algorithm derived from the whale and dipper-throated optimization techniques. The algorithm is further adapted to a binary form for feature selection, enhancing predictive accuracy. Zhang et al. (2023) introduced a variational modal decomposition, a Sparrow Search Algorithm, and a temporal-convolutional-network-based bi-directional gated recurrent unit (VMD-SSA-TCN-BiGRU) hybrid model for short-term wind power prediction in a Chinese wind farm, aiming to improve prediction accuracy for safer power system operation. The framework integrates VMD to decompose raw data, followed by individual predictions via SSA-optimized TCN-BiGRU models for each component. Beyond their value in wind energy forecasting, hybrid models are equally impactful in enhancing solar energy predictions (Naveed et al. 2024; Hanif et al. 2025). Hybrid models are critical for unlocking the full potential of renewable energy by making it more dependable, eco-friendly, and economically viable, thereby accelerating the transition to sustainable energy systems.

While the U.S. wind energy sector is rapidly expanding—with installed capacity projected to reach over 150 GW by 2025 and continued growth fueled by federal incentives such as the Inflation Reduction Act—comprehensive, U.S.-wide comparative assessments of hybrid wind forecasting models remain relatively sparse. Existing studies often focus on regional case studies or specific wind farms, lacking coverage across diverse geographic and climatic zones within the country. This study develops a dynamic system for monthly wind energy prediction across the United States, leveraging SVMD-ANN, CNN-LSTM, ANN, and SVR models. It evaluates both independent and combined modeling architectures to assess predictive performance. The comparative analysis provides insights into the benefits and limitations of ensemble versus standalone predicting approaches for large-scale wind energy prediction. Also, by using available data and univariate modeling, an attempt has been made to avoid excessive modeling complexity and increase performance. It is worth noting that no study has been conducted to compare the independent model with the advanced SVMD-ANN hybrid model for predicting and modeling wind energy generation in the United States. This work represents one of the few efforts to systematically benchmark hybrid machine learning and signal decomposition approaches at a national scale, providing insights into their generalizability and robustness across varied environments. Therefore, while acknowledging the growing body of work on hybrid models targeting wind speed and power prediction, our contribution lies in the comprehensive U.S.-wide scope of evaluation combined with a novel hybrid modeling framework that demonstrably improves forecasting accuracy and interpretability.

Materials and methods

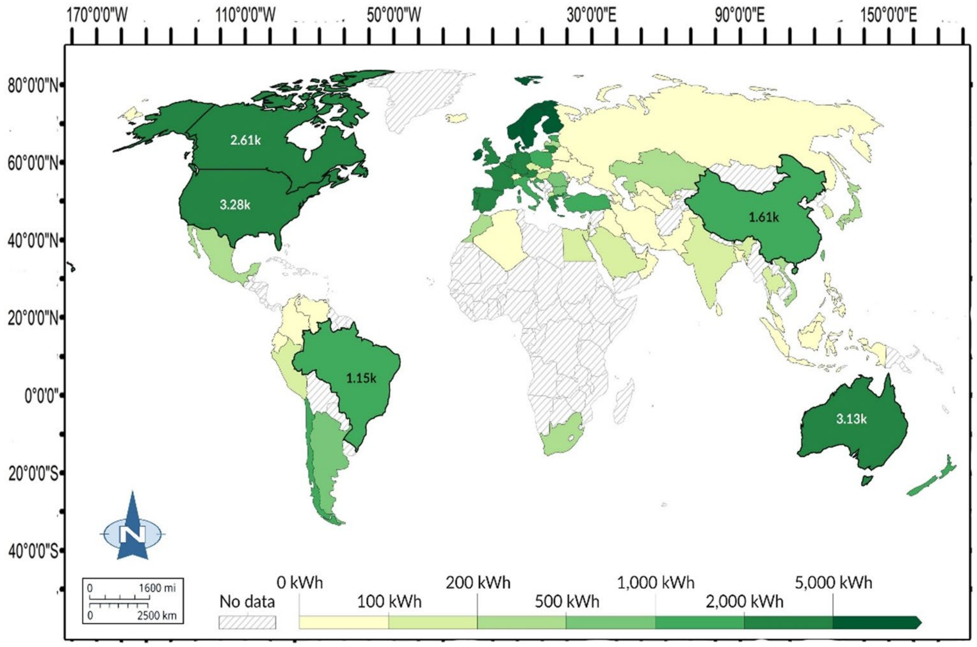
Overview of wind power generation in the United States

Wind power generation in the United States has experienced significant growth and is now a major component of the country's energy mix. As of 2024, wind power generated approximately 453.5 terawatt-hours (TWh), accounting for 10.54% of the total U.S. electricity production, making it the largest source of renewable energy in the nation, surpassing hydroelectric power since 2019 (Cook et al. 2024). By the close of 2023, the United States had reached an installed wind power capacity of approximately 147,500 megawatts (MW), ranking second globally after China and the European Union. Texas held the top spot among U.S. states, with an installed capacity nearing 39,450 MW, accounting for roughly 25% of its electricity generation from wind in 2024. Iowa stood out for deriving more than 57% of its electricity from wind, the highest share nationwide, while North Dakota led in wind generation on a per capita basis (Campbell et al. 2024). Significant progress in technology, along with supportive policies such as renewable portfolio standards and tax incentives, has fueled the swift growth of wind energy. On average, a modern wind turbine can produce sufficient electricity in just 46 min to meet a typical American household's monthly energy needs. Wind power's growth reflects a broader trend toward renewable energy, driven by declining costs, technological advancements, and strong public support. The U.S. Energy Information Administration (EIA) forecasts that most new energy capacity additions will come from renewables like wind and solar, helping reduce carbon emissions from the energy sector. Figure 1 shows the per capita wind energy consumption for 2023. According to this figure, the United States, with the highest per capita consumption of wind energy, has the largest share among the major countries in the world.

Dataset and modeling preprocessing

Univariate modeling focuses on analyzing a single variable in isolation to understand its fundamental characteristics, such as distribution, central tendency (mean, median, mode), and variability (range, variance, standard deviation). This type of analysis is purely descriptive and does not consider relationships with other variables. It serves as a crucial

Fig. 1 Per capita energy consumption from wind, 2023 (Hannah et al. 2023)



first step in data exploration, helping to identify patterns, detect outliers, and assess data quality before moving on to more complex analyses like multivariate modeling.

Moreover, univariate modeling offers a simpler yet effective framework for wind power prediction, especially when multivariate data (such as weather parameters) are limited or unavailable. It helps energy producers and grid operators anticipate fluctuations in wind generation, optimize resource allocation, and reduce reliance on fossil fuels. Although advanced machine learning models often incorporate multiple variables, univariate models remain valuable for their computational efficiency and interpretability. Studies show that univariate models can achieve competitive accuracy in short-term wind energy forecasting, making them practical tools for decision-makers to improve wind farm performance and integrate renewable energy more reliably into the power grid (Azmi et al. 2022; Ban et al. 2024).

Data preprocessing is the essential process of cleaning, transforming, and organizing raw data into a structured and usable format for analysis, machine learning (ML), and artificial intelligence (AI) applications. The importance of data preprocessing lies in its ability to enhance data quality and model outcomes by eliminating noise, correcting inconsistencies, and standardizing features. It reduces computational complexity and prevents biased or inaccurate predictions caused by poor-quality data. Techniques like sampling, imputation, normalization, and feature extraction are commonly used to refine datasets. Additionally, data validation through splitting into training and testing sets helps assess model accuracy and guides further refinement of preprocessing steps. Proper preprocessing is foundational to successful data science workflows and scalable production pipelines.

Table 1 Statistical characteristics of wind energy generation for the united States

Statistical	Wind energy generation (MWh)
Max	9,721,128
Mean	2,484,664
Min	6806
Median	1,983,625
Number zero	0
Number of observations	292

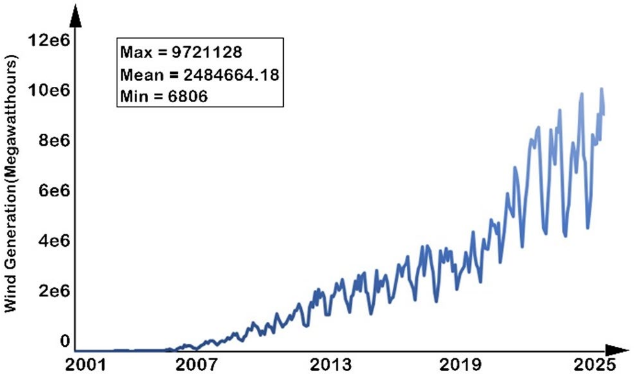


Fig. 2 Time series of wind energy generation for the United States from 2001 to 2025

Data points exhibiting substantial deviation from the general distribution were either excluded or adjusted. Missing entries were imputed using the arithmetic average to preserve consistency across the dataset. Subsequently, all features underwent Z-score normalization, ensuring a mean of zero and a standard deviation of one. Approximately 2% of the data was modified due to irregularities or incomplete information. To prevent information bleed between training and test datasets during model development, normalization of features was strictly performed using parameters computed exclusively from the training data within each fold of evaluation. Specifically, for each training window, the mean and standard deviation required for Z-score normalization were calculated only from the training subset. These statistics were then applied to normalize both the training data and the succeeding test set. Data sourced from the U.S. Energy Information Administration (EIA) platform (https://www.eia.gov/). The U.S. Energy Information Administration (EIA) is a comprehensive federal agency that collects, analyzes, and disseminates energy data at the national and state levels, serving as an authoritative source for energy statistics in the United States. Its data coverage spans a wide range of energy sources, including petroleum, natural gas, coal, nuclear, renewable sources (hydropower, solar, wind, geothermal, biomass), as well as electricity generation, consumption, and prices. The EIA aggregates data from thousands of power plants, energy producers, and consumers through mandatory monthly and annual surveys such as Form EIA-923 and others, ensuring high data fidelity and continuity from historical to current records. The extensive scale and granularity of EIA's energy data, combined with its rigorous collection methodologies and public accessibility, make it a trusted resource for large-scale analyses like multi-state wind energy forecasting, enabling accurate model training and validation across diverse U.S. geographic and climatic regions. Table 1 summarizes the descriptive statistics of these input variables. Figure 2 shows the time series of wind energy generation for the United States from 2001 to 2025. The maximum and minimum amounts of energy produced in megawatt hours (MWh) are 9,721,128 and 6806, respectively.

After data collection and preprocessing, monthly lags were used to perform univariate modeling. To increase the efficiency of the models and provide greater confidence, the most appropriate lag was selected up to a correlation of 0.899. Also, in this study, we replaced the initial random 70:30 data split with a rolling-origin cross-validation (also known as walk-forward validation) approach, which respects the temporal order inherent in time series data. This method involves iteratively expanding (or sliding) the training window forward through time and generating forecasts for subsequent data points without future information leakage. In this way, 70% of the data was used for training the SVMD-ANN, CNN-LSTM, ANN, and SVR models, and the remaining 30% was used for testing. To avoid information leakage when selecting the optimal lag for model inputs, lag selection was strictly performed within the training window of each rolling-origin iteration. At each retraining step, the correlation coefficients between the target variable and its lagged values were calculated using only the training data available up to that point. The lag choice was thereby dynamically adapted to the training set characteristics, ensuring that future data did not inform input feature selection. This approach generates multiple out-of-sample forecast sets across the evaluation period, providing a realistic and robust assessment of model generalization. After modeling and predicting the energy generated by wind monthly, the results were compared with graphical indicators and evaluation criteria. All experiments were conducted using Python 3.13.3 (released April 2025) on a Windows 11 operating system with 16 GB of RAM. Key Python packages employed include NumPy 1.25.0, Pandas 2.0.1, Scikit-learn 1.3.0, TensorFlow 2.13.0, and Matplotlib 3.8.0. The use of recently updated libraries ensures compatibility and leverages performance optimizations introduced in 2024–2025. The flow chart of the steps taken to model monthly wind generation using machine-learning models is shown in Fig. 3.

In this research, hyperparameter selection was carried out using the Random Search optimization technique. Unlike Grid Search, which exhaustively evaluates all possible parameter combinations, Random Search stochastically samples from a defined parameter space, enabling more efficient exploration, particularly in high-dimensional scenarios where exhaustive methods are computationally intensive. To enhance the reliability of the results, 10 independent training iterations were executed. Model complexity denotes a model's ability to represent diverse functions; although highly intricate models like deep neural networks offer substantial expressive capacity, they are also susceptible to overfitting by fitting to noise rather than genuine patterns. By systematically varying model architecture, size, and parameter count, this study achieved a compromise between underfitting and overfitting. For each machine learning model, we performed 50 random-search iterations to explore the hyperparameter space while maintaining computational feasibility. To ensure reproducibility, a fixed random seed was set before the start of each random search process and for each model training iteration. During model training, early stopping was applied based on validation loss to prevent overfitting. Training was halted if no improvement was observed over 10 consecutive epochs, thereby reducing unnecessary computation and enhancing generalization. The hyperparameters used for ANN, CNN-LSTM, and SVMD-ANN models are outlined in Table 2.

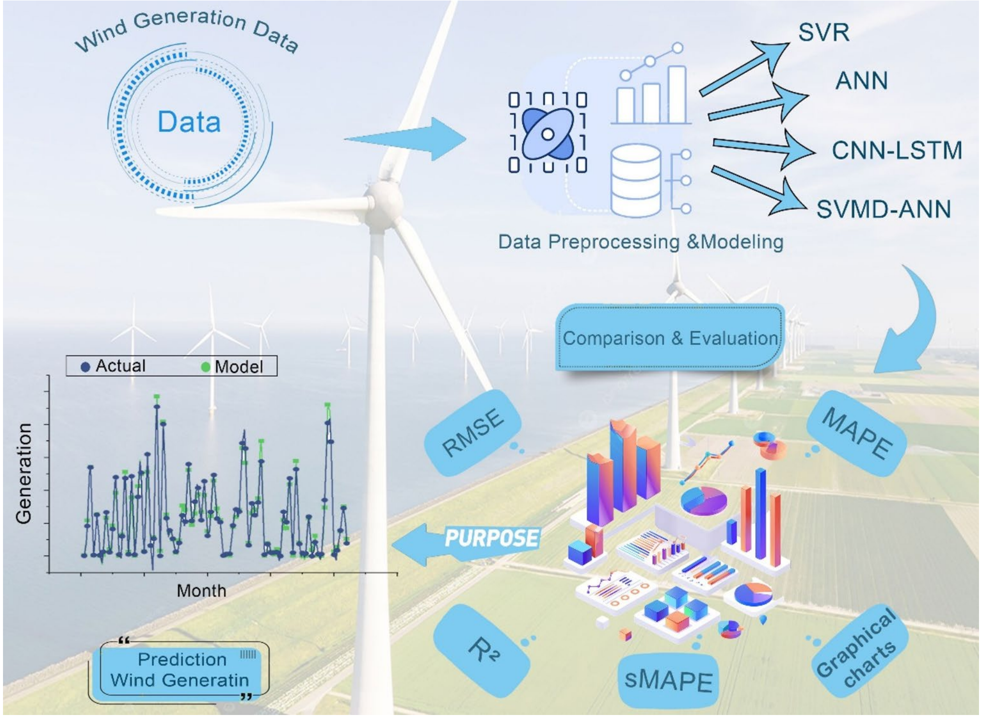


Fig. 3 Flow chart of the steps taken to model monthly wind generation using machine learning models

Table 2 Hyperparameters are used to model CNN-LSTM, ANN, and SVMD-ANN models

Type of parameters	Values/Layer
Network type	Feed-forward propagation
Data division	Training (70%) Test (30%)
Number of hidden layers (Neurons)	10–55
Batch size	5–210
learning function	0.01–0.086
Activation function	Ramp, Tanh
Normalization function	Batch normalization
Training function	Adam

Components of predictive models

An overview of the SVR model

Support Vector Regression (SVR) is an extension of the Support Vector Machine (SVM) algorithm tailored for regression tasks, where the goal is to predict continuous values rather than classify data. SVR works by finding a function—often represented as a hyperplane—that approximates the relationship between input features and target values while maintaining a margin of tolerance (($\in$)) within which errors are ignored (Awad et al. 2015). This margin defines a “tube” around the function, and the algorithm aims to fit as many data points as possible within this tube, balancing model flatness (complexity) and prediction accuracy. The key parameters include the regularization term (C), which controls the trade-off between fitting the training data and keeping the model simple, and the epsilon margin, which sets the allowable error threshold without penalty (Zhang and Donnell 2020). Given training data (x_i, y_i) for $i = 1, \ldots, n$, where $x_i \in \mathbb{R}^p$ are predictors and $y_i \in \mathbb{R}$ are target values, SVR seeks a function:

$$f(x) = w^T \varphi(x) + b \tag{1}$$

Where w is the weight vector, $\varphi(x)$ is a (possibly non-linear) mapping of the input features into a higher-dimensional space, b is the bias term. The coefficients *w* and *b* are estimated by minimizing a risk function that balances the model’s complexity and the degree to which predictions deviate from the true values by more than $\in$.

Formally, SVR minimizes

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

subject to

$$\begin{cases} y_i - w^T x_i - b \le \epsilon + \xi_i \\ w^T x_i + b - y_i \le \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{3}$$

where ϵ is the margin of tolerance (epsilon-insensitive zone), ξ_i, ξ_i^* are slack variables for errors outside the margin, C controls the trade-off between model flatness and tolerance of deviations.

Using kernels $K(x_i, x_j)$, the prediction becomes

$$f(x) = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) K(x_i, x) + b \tag{4}$$

where α_i, α_i^* are Lagrange multipliers learned during training.

This simple form captures the core idea: fit a function as flat as possible while ignoring small errors within ϵ, and penalizing larger deviations linearly.

Unlike many regression models that focus on minimizing overall error, SVR emphasizes fitting the data within this epsilon-insensitive zone, making it robust to noise and outliers. Support vectors—the data points closest to the margin boundaries—play a crucial role in defining the regression function (Zhang and Donnell 2020). SVR can handle both linear and non-linear relationships through kernel functions, which map data into higher-dimensional spaces to capture complex patterns. This makes SVR a powerful and flexible tool for various applications, including time series forecasting and financial predictions, where balancing accuracy and generalization is critical.

In this study, employed SVR with a radial basis function (RBF) kernel was employed to model the relationship between input features and continuous target variables. The SVR model is initialized with the following key hyperparameters: a regularization parameter C=800, kernel coefficient γ =scale, and an epsilon-insensitive margin $\in$=0.01. The RBF kernel enables the model to capture complex, non-linear patterns in the data by implicitly mapping inputs into a higher-dimensional feature space. C controls the balance between minimizing training error and maintaining model simplicity, with a relatively high value of 800 emphasizing a closer fit to the training data. The gamma parameter set to ‘scale’, automatically adjusts based on the number of features and their variance, optimizing the kernel’s flexibility. The epsilon parameter defines a margin of tolerance within which prediction errors are not penalized, set here to a small value of 0.01 to allow precise fitting while ignoring minor noise.

An overview of the CNN-LSTM hybrid model

A CNN-LSTM model is a powerful hybrid neural network architecture designed to handle time series data by combining the strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. In this setup, the CNN layers act as feature extractors, identifying local patterns and trends within the time series, such as spikes, cycles, or anomalies (Huang et al. 2025). These extracted features are then passed on to the LSTM layers, which are adept at learning long-term dependencies and temporal relationships within sequential data. This architecture is particularly useful for complex time series forecasting and classification tasks where both short-term fluctuations and long-term trends are important (Ali et al. 2025). For example, in energy demand forecasting, the CNN layers can detect recurring daily or weekly patterns, while the LSTM layers model how these patterns evolve over months or years.

For time series data, a 1D CNN is used first to extract local spatial features and patterns from the input sequence, such as trends or fluctuations over short time windows. These convolutional layers often include convolution filters followed by pooling layers to reduce dimensionality and highlight important features. The output of the CNN is a sequence of feature vectors representing the input data at each time step. Next, the extracted features are fed into one or more LSTM layers, which model the temporal dependencies and long-term relationships across the sequence. The LSTM acts as a decoder that learns how these features evolve and generates predictions, such as multi-step forecasts or classifications. Finally, dense (fully connected) layers are applied to the LSTM output to produce the final prediction (Kim and Cho 2019). This encoder-decoder architecture has been demonstrated for tasks like multi-step energy usage forecasting, where the CNN encodes the input sequence and the LSTM predicts future values step-by-step, achieving strong performance with lower error rates. Figure 4 shows the structure of the CNN-LSTM model for predicting the energy generated by wind.

The proposed CNN-LSTM model integrates convolutional and recurrent layers to effectively capture both spatial and temporal features in sequential data. The model begins with a TimeDistributed Conv1D layer with 64 filters and a kernel size of 2, which applies convolutional operations independently to each subsequence of the input, extracting local temporal patterns within each segment. This is followed by a TimeDistributed MaxPooling1D layer that reduces the dimensionality and highlights the most salient features. The output is then flattened within each time step using a TimeDistributed Flatten layer, preparing the data for sequential modeling. Next, the flattened feature sequences are fed into an LSTM layer with 50 units and a tanh activation function, which learns long-term dependencies and temporal dynamics across the subsequences. Finally, a Dense

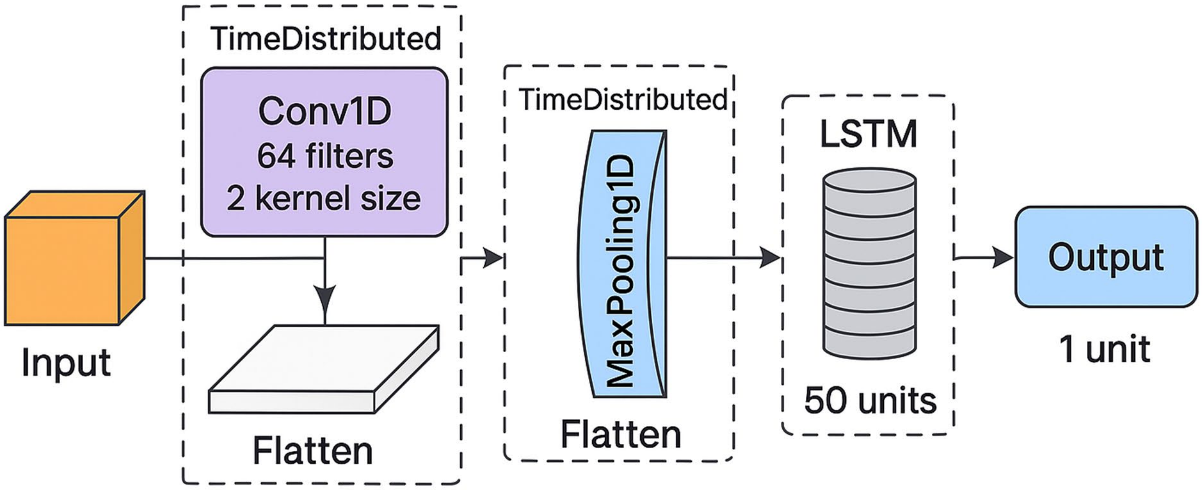


Fig. 4 The structure of the CNN-LSTM model used in this study

layer with a single neuron produces the output prediction, suitable for regression tasks such as time series forecasting. The model is compiled using the Adam optimizer and mean squared error loss function to optimize prediction accuracy. This architecture effectively combines CNN's local feature extraction with LSTM's sequence modeling capabilities, making it well-suited for complex time series data with hierarchical temporal structures.

The model is trained for 50 epochs with a batch size of 32. This training setup allows the model to learn robust representations while monitoring performance on unseen data to prevent overfitting. The use of TimeDistributed wrappers ensures that convolution and pooling operations are applied consistently across all subsequences, preserving the temporal order for the LSTM to process. This structured approach enables the CNN-LSTM model to capture both fine-grained and long-range temporal patterns, resulting in improved forecasting performance.

An overview of the SVMD-ANN hybrid model

The SVMD-ANN hybrid model is an advanced forecasting technique that combines Successive Variational Mode Decomposition (SVMD) with an Artificial Neural Network (ANN) to improve the accuracy of time series predictions.

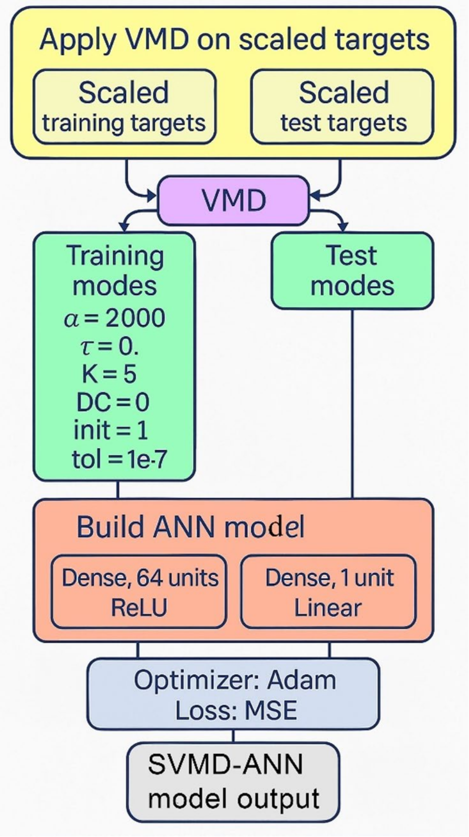


Fig. 5 The structure of the SVMD-ANN model used in this study

SVMD decomposes complex data into intrinsic modes sequentially, which helps in extracting hidden features and reducing noise. These decomposed components are then used as inputs to the ANN, which captures nonlinear relationships to forecast future values (Guo et al. 2022). This two-step approach—careful preprocessing with SVMD followed by ANN modeling—enhances the model's ability to handle complex and non-stationary data, especially for long-term prediction. SVMD generalizes variational mode decomposition by iteratively decomposing a signal $x\,(t)$ into K modes $\{u_k(\,t)\}_{k=1}^{K}$ by solving (Gao et al. 2025):

$$\min_{u_k,\omega_k} \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta\,(t) + \frac{j}{\pi\,t} \right) * u_k\,(t) \right] e^{-j\omega_k t} \right\|_2^2 \tag{5}$$

subject to:

$$\sum_{k=1}^{K} u_k\,(t) = x\,(t) \tag{6}$$

Where ω_k is the center frequency of mode k, ∂_t denotes time derivative, $*$ denotes convolution, $j = \sqrt{-1}$.

This optimization extracts modes that have compact frequency support and reconstructs $x\,(t)$ without overlap.

Modeling and predicting univariate wind energy production using the SVMD-ANN hybrid model is important because it addresses the inherent complexity, nonlinearity, and non-stationarity of energy data. By first decomposing the wind energy time series into intrinsic modes through Successive Variational Mode Decomposition (SVMD), the model isolates meaningful components and reduces noise, which enhances the quality of the input data. The subsequent ANN then effectively captures nonlinear relationships and temporal dependencies to produce accurate forecasts. This combination improves prediction accuracy, which is crucial for managing the variability and intermittency of wind energy, enabling better grid integration, scheduling, and energy management. The structure of the SVMD-ANN model used to model the energy generated by wind is shown in Fig. 5.

The SVMD-ANN hybrid model integrates SVMD with an ANN to enhance the prediction of wind energy production. Initially, the scaled target wind energy data is decomposed into multiple intrinsic mode functions using VMD, which isolates distinct oscillatory components and reduces noise. To ensure consistency, the decomposed modes and original input features are truncated to matching lengths and then combined to form an enriched feature set. This preprocessing step allows the model to capture both the original data characteristics and the underlying signal patterns more effectively.

The SVMD-ANN hybrid model for wind energy prediction utilizes SVMD to decompose the scaled wind power time series into five intrinsic mode functions (IMFs), with parameters set as alpha = 2000, tau = 0, and tolerance = 1e-7, thereby ensuring the precise extraction of signal components. After decomposition, the modes and original input features are truncated to the minimum matching length to maintain data alignment. These modes are then concatenated with the original feature set, effectively expanding the input dimension and enriching the data representation for the ANN. The ANN architecture consists of two hidden layers with 64 and 32 neurons, respectively, using ReLU activation, and a linear output layer, optimized with the Adam algorithm and trained over 100 epochs with a batch size of 16. A summary of the structure and key parameters of the SVMD-ANN model is given in Table 3.

Model evaluation metrics

A key rationale for the use of evaluation criteria in comparative modeling lies in their role in establishing a standardized framework for assessing alternative approaches. In the absence of defined benchmarks, objective comparison and informed decision-making become difficult. By offering a structured method for analyzing models against specific parameters, evaluation criteria facilitate a more systematic, consistent, and transparent assessment process.

Table 3 Summary of the structure and key parameters of the SVMD-ANN hybrid model

Step	Description	Parameters/Details
1. Data scaling	Scale the target wind energy data and input features for normalization	–
2. Variational Mode Decomposition (VMD)	Decompose scaled target series into intrinsic modes to extract signal components	Alpha (α) = 2000 Tau (τ) = 0 K (modes) = 5 DC = 0 Init = 1 (random) Tolerance = 1e-7
3. Data alignment and truncation	Truncate input features and VMD modes to minimum matching length for consistency	–
4. Feature augmentation	Concatenate truncated VMD modes with original scaled features to form extended feature vectors	–
5. ANN architecture	Build feedforward neural network with two hidden layers and one output layer	Input dimension = (original features + 5 modes) Hidden layers: 64 neurons (ReLU), 32 neurons (ReLU) Output layer: 1 neuron (linear)
6. Training	Train the ANN model on extended features	Optimizer: Adam Loss: Mean Squared Error (MSE) Epochs: 100 Batch size: 16

Root Mean Square Error (RMSE) serves as a fundamental metric in both statistics and machine learning for quantifying the predictive accuracy of models. It calculates the average magnitude of deviation between forecasted and actual values within a dataset. Widely adopted for performance assessment, RMSE enables objective model comparisons by identifying those with superior predictive reliability (Chicco et al. 2021). Lower RMSE values typically reflect consistent and precise predictions, whereas higher values may indicate reduced reliability and signal the need for model refinement.

In statistical modeling and data analysis, the coefficient of determination (R^2) plays a critical role in evaluating the predictive strength and validity of regression models. It quantifies the proportion of variability in the dependent variable that is accounted for by the independent variables, effectively measuring model fit (Saunders et al. 2012). This metric serves as a benchmark for assessing explanatory power, where higher R^2 values denote strong alignment between predicted and observed outcomes. Conversely, a low R^2 implies that the model fails to capture the underlying patterns adequately, indicating the need for refinement or alternative approaches.

Mean Absolute Percentage Error (MAPE) is widely recognized as a key performance indicator for evaluating the precision and dependability of forecasting models. It assesses predictive accuracy by quantifying the average percentage deviation between estimated and observed values (Chicco et al. 2021). By offering a consistent and interpretable error metric, MAPE supports robust model evaluation and enables practitioners to compare the relative effectiveness of different forecasting techniques, facilitating data-driven selection based on accuracy and efficiency.

Symmetric Mean Absolute Percentage Error (SMAPE) is a metric used to measure the accuracy of predictive models, especially in forecasting, by calculating the average absolute percentage difference between predicted and actual values while treating overestimation and underestimation symmetrically. It divides the absolute error by the average of the absolute actual and predicted values, which makes it more stable and balanced compared to traditional MAPE, especially when actual values are near zero (Maiseli 2019). The SMAPE value ranges from 0% (perfect prediction) to 200%, with lower values indicating better accuracy. This symmetric property helps avoid issues like undefined or excessively large errors when the actual values are near zero.

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}\left(X_{pi} - X_{oi}\right)^2} \tag{7}$$

$$R^2 = \frac{\sum_{i=1}^{N}\left(X_{oi}-\bar{X}_o\right)\left(X_{pi}-\bar{X}_p\right)}{\sum_{i=1}^{N}\left(X_{oi}-\bar{X}_o\right)^2 \cdot \sum_{i=1}^{N}\left(X_{pi}-\bar{X}_p\right)^2} \tag{8}$$

$$MAPE = 100 \times \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_{oi}-X_{pi}}{X_{oi}}\right| \tag{9}$$

$$\text{sMAPE} = \frac{100}{n}\sum_{i=1}^{N}\frac{\left|X_{pi}-X_{oi}\right|}{\frac{\left|X_{oi}\right|+\left|X_{pi}\right|}{2}} \tag{10}$$

where X_{pi} and X_{oi} are the predicted and observed values, $\bar{X}_o$ and $\bar{X}_p$ are the mean observed and predicted values, respectively, and N is the total number of data points.

Experimental results

Since this study focuses on optimizing univariate modeling performance, the selection of suitable time lags was guided by the correlation coefficient metric. To enhance model reliability and performance, time lags were selected based on correlation coefficients approaching 0.899. As illustrated in Fig. 6—depicting the correlation values across varying lag intervals—the fourth lag, exhibiting a coefficient of 0.899, was deemed suitable. Consequently, four-month lag was incorporated as input for this study.

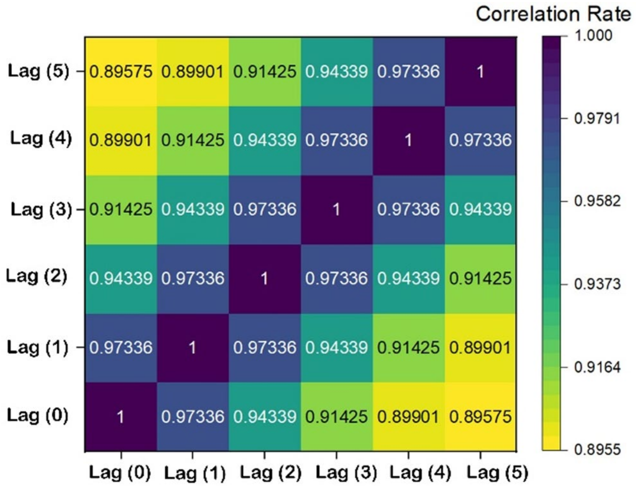


Fig. 6 Correlation coefficient chart of different lags to determine model inputs

Table 4 presents the performance metrics RMSE, R², sMAPE, and MAPE for the three prediction models: SVMD-ANN, CNN-LSTM, ANN, and SVR. Among them, the SVMD-ANN hybrid model demonstrated the highest predictive accuracy during the test phase, yielding an RMSE of 4.16×10^5 MWh, R² of 0.966, sMAPE of 10.43%, and MAPE of 20.12%. In comparison, the CNN-LSTM framework achieved respectable performance with RMSE of 5.75×10^5 MWh, R² of 0.952, sMAPE of 16.26%, and MAPE of 31.44%, outperforming the standalone SVR model, which registered RMSE of 5.91×10^5 MWh, R² of 0.947, sMAPE of 18.43%, and MAPE of 45.44%, and the ANN model, which registered RMSE of 5.79×10^5 MWh, R² of 0.949, sMAPE of 16.67%, and MAPE of 34.76%. The application of the hybrid SVMD-ANN model significantly contributes to improving wind energy prediction results by effectively combining signal decomposition and neural network learning. The SVMD component decomposes the original wind speed time series into intrinsic mode functions, which separate complex, nonlinear patterns and multi-scale temporal variations inherent in wind data. This decomposition reduces noise and reveals more meaningful patterns for subsequent modeling.

The sMAPE results demonstrate that the SVMD-ANN model achieved the best performance with the lowest values during both the testing (10.43%) and training (9.06%) phases. This indicates that the SVMD-ANN model produces more accurate wind energy predictions compared to the other models, with less relative error between predicted and actual values. The smaller sMAPE values reflect greater robustness and reliability of this hybrid model in capturing the variations in wind energy generation. In contrast, the CNN-LSTM and ANN models achieved moderate sMAPE values around 16% during both testing and training, suggesting reasonable but less accurate forecasts. The SVR model obtained the highest sMAPE values—18.43% in testing and 17.75% in training—indicating lower prediction precision. Overall, the sMAPE results underscore the superior capability of the SVMD-ANN hybrid model to minimize symmetric percentage errors and deliver enhanced prediction accuracy for wind energy generation. The SVMD-ANN hybrid algorithm has significantly improved the accuracy of the plain ANN model in wind energy prediction, as evidenced by the evaluation metrics in the uploaded

Table 4 Evaluation criteria for three SVR, ANN, CNN-LSTM, and SVMD-ANN models

	Testing				Training			
Model	RMSE (MWh)	R^2	MAPE (%)	sMAPE (%)	RMSE (MWh)	R^2	MAPE (%)	sMAPE (%)
SVR	591415.53	0.947	45.44	18.43	580237.05	0.959	43.87	17.75
ANN	579408.35	0.949	34.76	16.67	579043.21	0.960	32.46	16.22
CNN-LSTM	575545.16	0.952	31.34	16.26	556102.76	0.961	29.07	15.78
SVMD-ANN	416972.27	0.966	20.12	10.43	386015.43	0.973	19.36	9.06

table. This improvement can also be seen in other metrics: SVMD-ANN has lower RMSE and higher R^2 scores than ANN during both phases, confirming its gains in both precision and explained variance. By decomposing input signals and separating informative modes before feeding them into the ANN, the SVMD-ANN model reduces noise and boosts overall model learning efficiency. Ultimately, the SVMD algorithm helps the ANN overcome limitations related to scale and variability in wind energy datasets, leading to more robust and accurate predictions, which are crucial for operational efficiency and practical deployment in energy prediction scenarios.

Table 5 reports the statistical characteristics of both the actual values and the outputs from the SVMD-ANN, CNN-LSTM, and SVR models. The SVMD-ANN framework demonstrated superior performance, with a maximum output of 9.09×10^6 MWh, a mean of 2.28×10^6, a minimum of 1.21×10^3, and a standard deviation of 2.27×10^6. In contrast, the actual data exhibited a maximum of 9.72×10^6, mean of 2.27×10^6, minimum of 1.43×10^4, and standard deviation of 2.28×10^6. These comparisons highlight the SVMD-ANN model's closer alignment with observed data and its reduced error margins relative to the CNN-LSTM, ANN, and SVR alternatives. It is important to note that the SVR model occasionally produces predicted maximum values that slightly exceed the actual observed maximum values. Inspection of the raw scaled predictions revealed that extrapolation beyond the training data range can occur when the input features in the test set fall outside the distribution seen during training. This phenomenon is intrinsic to the SVR modeling approach and reflects its predictive flexibility.

Figure 7 displays both time series and scatter plots comparing wind energy forecasts across three models—SVMD-ANN, CNN-LSTM, and SVR—for the United States. The SVMD-ANN hybrid model shows a strong correspondence with actual generation data, deviating only slightly at certain peak intervals. Its scatter plot reveals a compact distribution, marked by a dispersion value of 0.966. In contrast, the CNN-LSTM model tends to produce more frequent errors at high-output points, with its scatter plot showing a broader spread (0.952) than SVMD-ANN. The SVR model, meanwhile, struggles with accuracy at extreme values and presents the most dispersed scatter plot (0.947), indicating lower consistency in its predictions.

Table 5 Statistical characteristics of the parameters used for the actual value and the four models

Model	Maximum (MWh)	Average (MWh)	Minimum (MWh)	Standard deviation (MWh)
Actual	9,721,128	2,278,436	14352.00	2,281,103
SVMD-ANN	9,092,941	2,289,876	1217.672	2,276,280
CNN-LSTM	8,033,859	2,657,913	59113.97	2,432,364
ANN	10,305,333	2,703,168	13307.45	2,768,792
SVR	10,558,988	2,700,375	70902.67	2,626,409

Among these models, SVMD-ANN performs best at capturing both peaks and valleys. Its predicted curve closely tracks the actual values, accurately reflecting the sharp rises and drops in energy generation. This suggests that the SVMD decomposition effectively extracts meaningful temporal features and reduces noise, enabling the ANN to model complex variations in wind energy output. CNN-LSTM and ANN models perform moderately well, generally following the trend but with less precision around sharp peaks and troughs. They frequently show larger deviations from actual values during these critical extremes, indicating a less robust ability to capture sudden changes. The SVR model performs the poorest at these peaks and valleys. Its predictions often smooth over or miss sharp rises and drops, resulting in a flatter curve with wider gaps from actual generation values. This poorer responsiveness to dynamic changes limits SVR's accuracy, especially during periods of high and low energy production. Overall, the time series graph clearly evidences that SVMD-ANN's hybrid approach substantially improves the model's ability to represent real fluctuations, especially around critical peak and valley periods, which is vital for reliable wind energy forecasting and effective grid management.

Figure 8 displays the SVMD-ANN model's prediction plot, which reveals a strong resemblance between forecasted and actual wind energy generation values. This close alignment suggests the model effectively captures nonlinear dynamics and temporal patterns. The SVMD preprocessing step plays a crucial role by breaking down the original time series into more manageable subcomponents, thereby enhancing the ANN's capacity to model intricate variations. As a result, the predicted outputs are tightly grouped around the observed data, reflecting high precision and minimal error dispersion. Although other models also approximate the actual values, their predictions tend to exhibit slightly greater variability than SVMD-ANN. Notably, the SVR model shows broader prediction spread and weaker alignment with the true values, indicating reduced reliability. While SVR is capable of modeling nonlinearities, its limitations in handling complex temporal structures make it less accurate than SVMD-ANN and CNN-LSTM for forecasting time series with nuanced patterns.

Figure 9 showcases boxplot comparisons for the SVMD-ANN, CNN-LSTM, and SVR models alongside actual wind energy generation data. The comparative assessment reveals distinct variations in predictive accuracy and distributional consistency among the models. SVMD-ANN exhibits the closest match to real-world data, with tight alignment across median values, interquartile ranges, and outlier

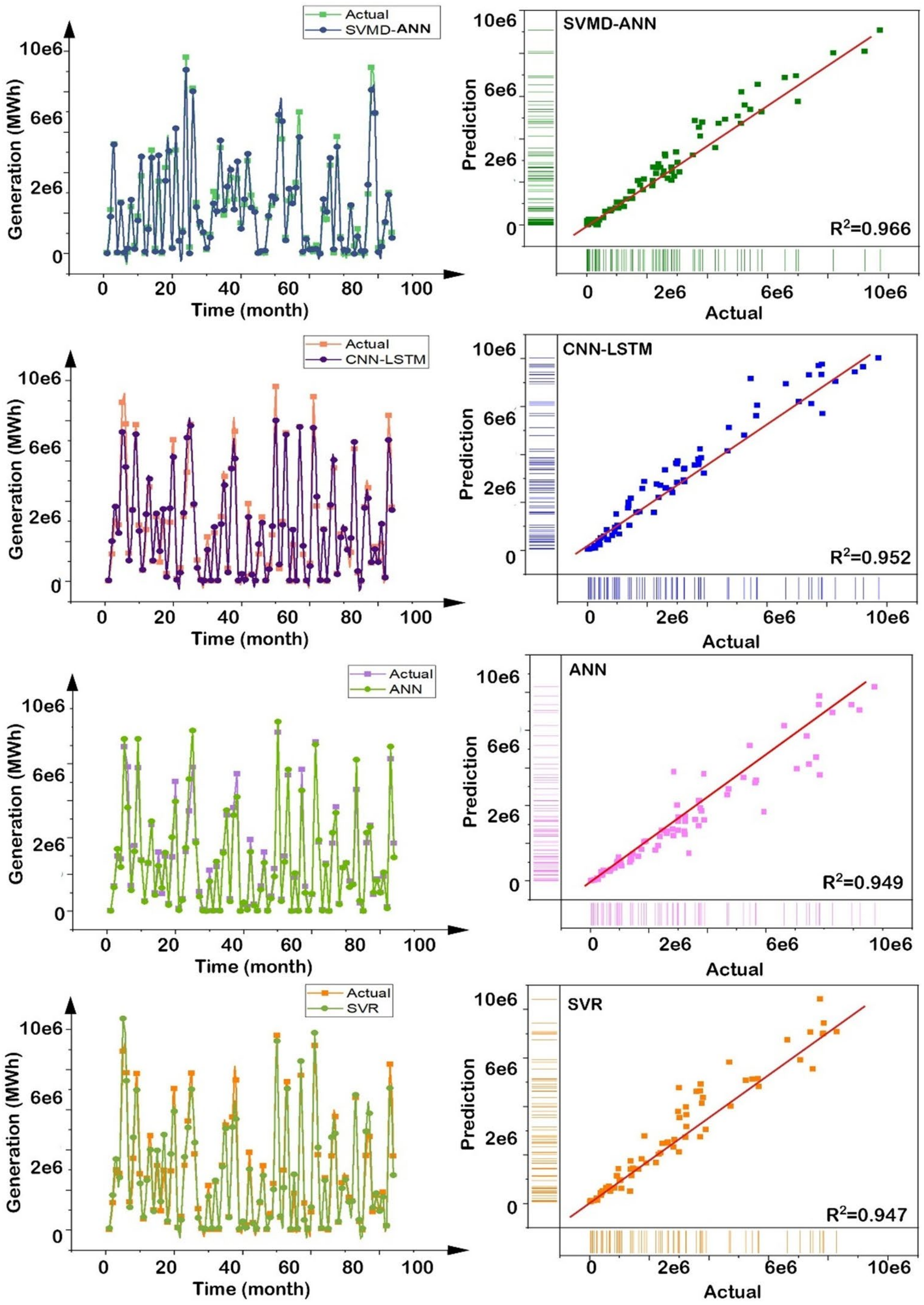


Fig. 7 Time series and scatter plots for comparing observed and predicted wind energy production using three models: SVMD-ANN, CNN-LSTM, ANN, and SVR

boundaries—signifying strong precision in both central tendency and variability. CNN-LSTM also performs well compared to SVR, effectively mirroring the overall data distribution and staying relatively close to actual values, albeit with slight discrepancies in outlier representation. Conversely, the SVR model displays a wider spread and less accurate median alignment, suggesting diminished reliability, especially in modeling extreme generation values.

The error diagrams illustrate the prediction errors of the four models—SVMD-ANN, ANN, CNN-LSTM, and SVR—over time for wind energy generation in Fig. 10. The error is defined as the difference between the predicted and actual energy production values in megawatt-hours (MWh). The SVMD-ANN error plot shows that the majority of errors fluctuate within a narrower range around zero, with fewer and smaller deviations compared to the other models. This indicates that SVMD-ANN consistently provides more accurate predictions and fewer extreme errors throughout the time series. By contrast, the ANN, CNN-LSTM, and SVR show larger spikes and more frequent high errors,

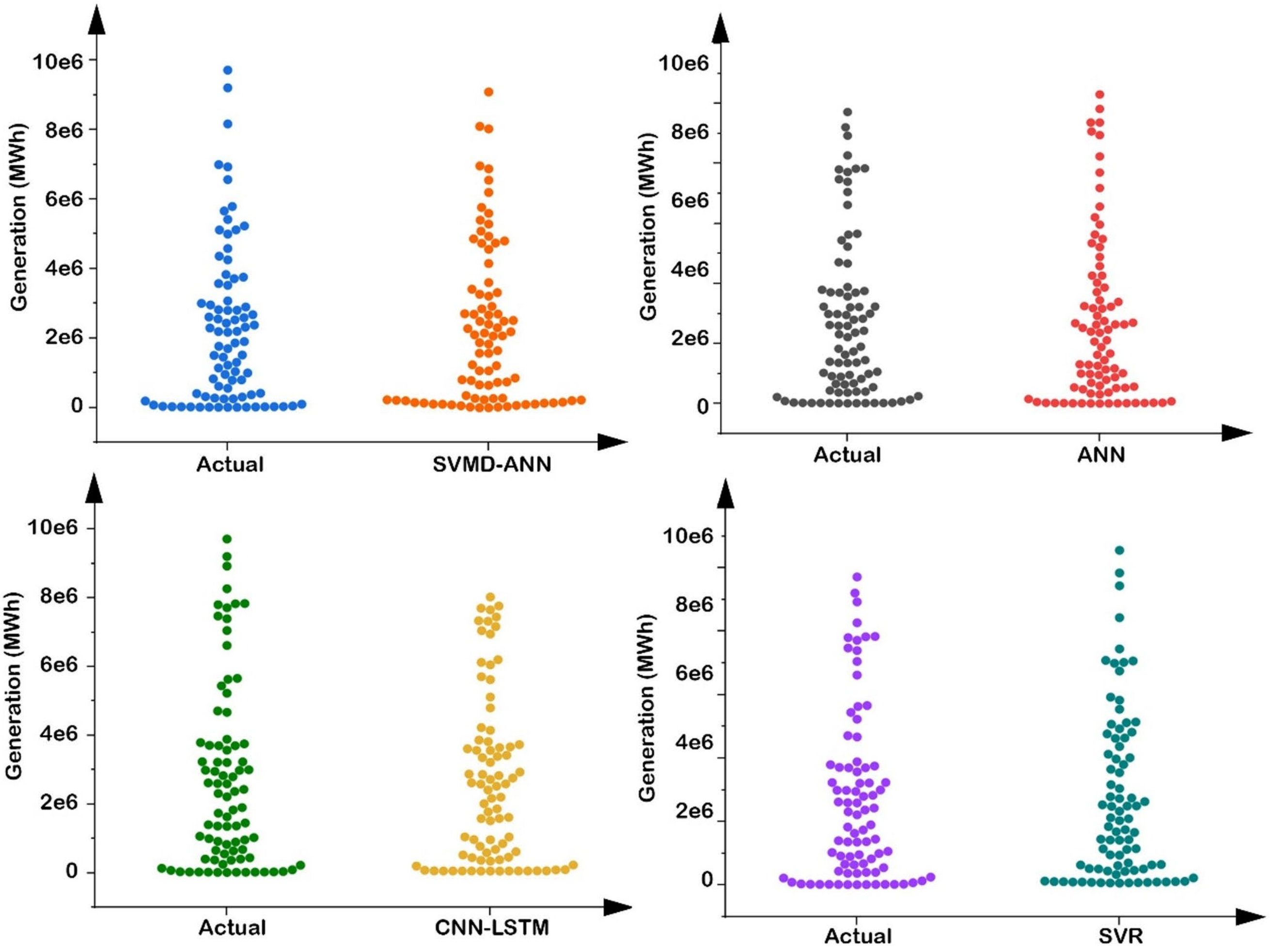


Fig. 8 Bee swarm plots for comparing observed and predicted wind energy production using three models: SVMD-ANN, CNN-LSTM, ANN, and SVR

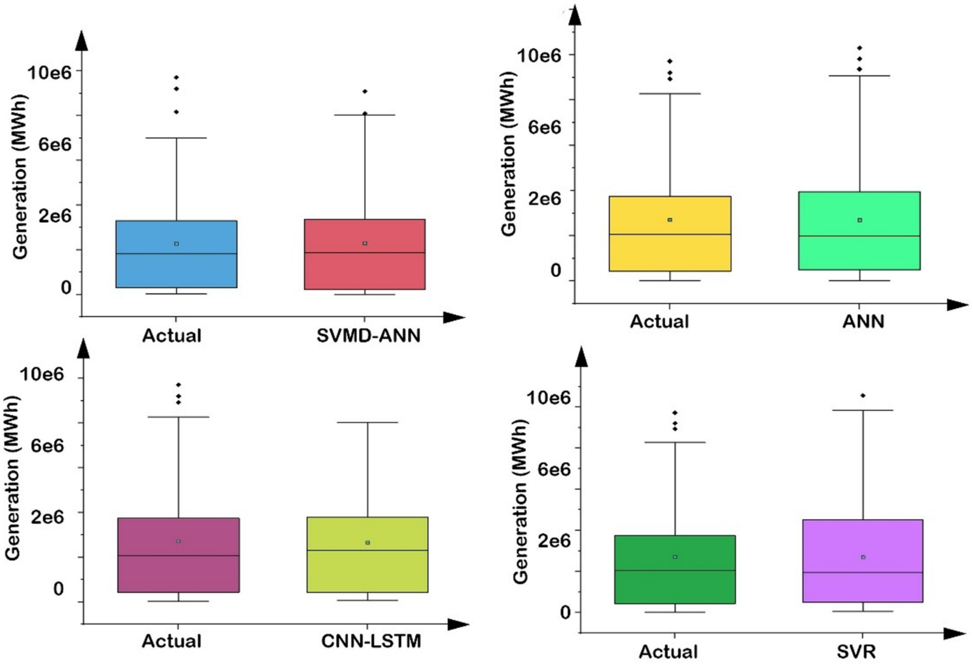


Fig. 9 Box plots for comparing observed and predicted wind energy production using three models: SVMD-ANN, CNN-LSTM, ANN, and SVR

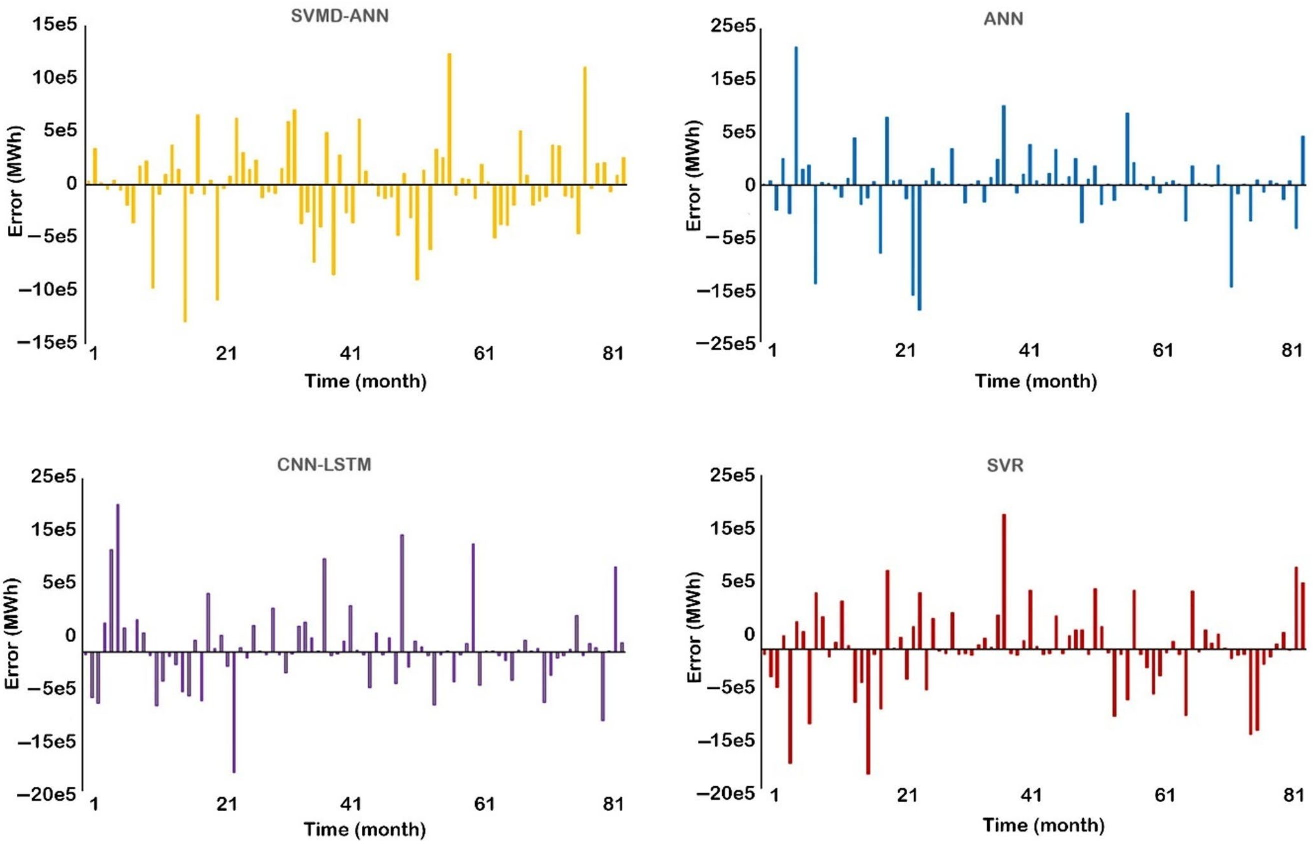


Fig. 10 Error plots for comparing observed and predicted wind energy production using three models: SVMD-ANN, CNN-LSTM, ANN, and SVR

ranging widely and deviating substantially from zero. These bigger fluctuations reveal less reliable performance in certain months, with significant under- or over-prediction events occurring more often than in the SVMD-ANN model. Overall, the error diagrams confirm the quantitative results by illustrating lower volatility and reduced magnitude of prediction errors in the SVMD-ANN model. This visual evidence supports the claim that integrating SVMD decomposition effectively reduces noise and improves the ANN's predictive stability and accuracy in wind energy forecasting.

Discussion

SVMD-ANN, CNN-LSTM, and SVR models are chosen for wind energy prediction due to their ability to handle the complex, nonlinear, and volatile nature of wind power data. SVMD-ANN combines Variational Mode Decomposition to break down wind data into simpler components with Artificial Neural Networks to capture nonlinear relationships, improving prediction accuracy and reducing noise. CNN-LSTM models utilize convolutional layers to automatically extract key features and LSTM layers to capture long-term temporal dependencies, rendering them highly effective for modeling the intermittent and sequential patterns of wind energy time series. On the other hand, SVR offers a robust and computationally efficient approach that performs well even with limited data, using kernel functions to map nonlinear relationships. While deep learning models like CNN-LSTM and SVMD-ANN provide higher flexibility and accuracy, SVR is valuable for faster training and simpler tuning. Together, these models provide complementary strengths, enabling more reliable and accurate short-term wind energy forecasting depending on data availability, computational resources, and specific prediction needs. Compared to other models, such as traditional statistical approaches (e.g., SARIMA) or popular deep learning methods (e.g., CNN-LSTM), SVMD-ANN offers greater robustness across different sites and climates by better handling nonstationary and nonlinear wind patterns (Ruan et al. 2022; Islam et al. 2023). Its decomposition-based feature extraction also enhances interpretability relative to black-box neural networks. Overall, SVMD-ANN's integration of advanced signal processing with flexible neural models positions it as a powerful and interpretable tool for improving wind power forecast accuracy and reliability over a wide range of operating conditions.

Numerous research efforts in this domain have yielded significant outcomes by employing hybrid modeling techniques. Zhang et al. (2020) presented an enhanced short-term wind speed prediction model that integrates Variational Mode Decomposition (VMD) with a Genetic Algorithm-optimized Artificial Neural Network (GA-ANN). Historical data similar to the target day is selected via a hierarchical clustering method, then decomposed using VMD based on sample entropy to reveal underlying patterns. Each decomposed sequence is modeled using a GA-optimized ANN, and the outputs are combined for the final prediction. The approach significantly improves forecasting accuracy over traditional BP neural networks and captures multi-scale wind speed fluctuations. Qin et al. (2022) introduced a hybrid model, variational mode decomposition, a simulated annealing algorithm, and a deep belief network (VMD-SA-DBN) for short-term prediction of building energy consumption by integrating Variational Mode Decomposition, Simulated Annealing, and Deep Belief Networks. The VMD component helps reduce data fluctuations by breaking the time series into distinct modes. Each mode is then individually forecasted using a DBN optimized via SA. The aggregated outputs improve prediction accuracy and stability, outperforming seven established models, including LSTM and GRU, with up to 65.5% lower mean absolute percent error. Momeneh and Nourani (2023) tackled streamflow forecasting—especially vital in arid and semi-arid regions prone to water shortages and floods—by combining advanced data preprocessing methods with ANN. It tests five preprocessing techniques: discrete wavelet transforms (DWT), empirical mode decomposition (EMD), complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), successive variational mode decomposition (SVMD), and multi-filter of the smoothing (MFS), each designed to reveal hidden features in time-series stream data. These techniques are paired with ANN to create hybrid models, and results show that forecasting accuracy depends heavily on both input selection and preprocessing choice. Among all tested combinations, MFS-ANN excels in short-term predictions, while SVMD-ANN proves superior for long-term forecasting, providing valuable insights for water resource management. Parri Teeparthi (2024) introduced a cutting-edge hybrid model—SVMD-TF-QS—for accurate wind speed prediction (WSP). It fuses Successive Variational Mode Decomposition (SVMD) with a Transformer-based (TF) architecture enhanced by a Query Selection (QS) mechanism. SVMD adaptively and efficiently decomposes wind speed data into meaningful components, which are then processed by TF-QS. The QS mechanism uses a deterministic algorithm to sparsely approximate the Transformer's attention matrix, boosting prediction accuracy while reducing computational demands. Agarwal et al. (2025) proposed a hybrid model—SVMD-LSTM—that combines Successive Variational Mode Decomposition (SVMD) with Long Short-Term Memory (LSTM) networks to improve forecasting accuracy for complex, nonlinear financial time series. SVMD effectively breaks down nonstationary signals into intrinsic mode functions (IMFs), simplifying the input data for the LSTM, which then captures historical patterns and temporal dependencies for each decomposed signal. Performance metrics reveal notable reductions—down to 52.2799, 41.8430, and 0.1620—with further decreases of 10.3%, 8.5%, and 6% respectively, highlighting the model's superior accuracy over both standalone LSTM to VMD-LSTM and then to SVMD-LSTM.

Hybrid models in wind energy forecasting are extensively applied to enhance the accuracy and reliability of wind power predictions, which are critical for efficient grid operations and renewable energy integration. They support short-term forecasting for real-time grid balancing and long-term planning for maintenance and energy trading. By combining various machine learning and deep learning techniques, these models enable wind farm operators to optimize turbine performance, schedule maintenance during periods of low wind, and adapt dynamically to changing weather conditions. This leads to improved operational efficiency and reduced downtime.

In electricity markets, hybrid models play a vital role in day-ahead and intraday bidding strategies by minimizing forecast errors and helping producers avoid financial penalties. They also integrate diverse data sources, such as weather forecasts and terrain information, to enhance prediction robustness. Their scalability and adaptability make them suitable for both individual wind farms and regional forecasting, supporting large-scale renewable energy deployment. Overall, hybrid models are key enablers for reliable, cost-effective, and sustainable wind power integration into modern power systems.

Conclusion

Wind energy forecasting is vital in the U.S. for maximizing the benefits of wind power, ensuring grid reliability, enhancing safety, reducing costs, and supporting the transition to a cleaner energy portfolio. Prediction with hybrid models in wind power forecasting involves combining multiple machine learning or deep learning techniques to improve accuracy and robustness in predicting wind power generation. These models leverage the strengths of different algorithms and optimization methods to handle the intermittent and complex nature of wind energy. This research employed two hybrid models—SVMD-ANN and CNN-LSTM—alongside two standalone ANN, and SVR model to evaluate their effectiveness in predicting wind energy generation across the United States over 24 years. Findings revealed that the SVMD-ANN model demonstrated superior accuracy and dependability, exhibiting an error margin of 4.1×10^5 MWh, an R^2 value of 0.966, sMAPE of 10.43%, and a MAPE of 20.12%. These metrics highlight its enhanced performance relative to the CNN-LSTM and SVR models. This decomposition significantly improves the ANN's ability to capture nonlinear relationships and temporal dependencies in wind energy data, resulting in more robust and accurate predictions. As evidenced by evaluation metrics (such as reduced RMSE and sMAPE, and increased R^2), the SVMD-ANN hybrid outperforms the standalone ANN model in both training and testing phases. In summary, SVMD's preprocessing step transforms complex raw data into a set of more informative features, enabling the ANN to deliver superior forecasting performance in real-world environmental and hydrological modeling tasks.

Wind energy prediction using hybrid models has made significant strides by combining advanced machine learning techniques to improve prediction accuracy and reliability. However, these models face several limitations, including challenges with adaptability to different geographic regions and varying meteorological conditions. Data quality issues, such as missing or noisy sensor data, especially in complex terrains, further complicate accurate forecasting. Additionally, the high computational demands of sophisticated hybrid models can limit their scalability and real-time applicability, posing practical constraints for widespread deployment. Moreover, forecasting accuracy still suffers from relatively high error rates and a lack of robust uncertainty quantification, which is critical for effective grid management and risk assessment. Hybrid models also risk overfitting and often lack interpretability, making it difficult for stakeholders to fully trust and understand their predictions. Integration of wind forecasts into grid operations remains complex due to variability in wind power and regulatory challenges. Addressing these limitations is essential to enhance the operational value of wind energy forecasting and support the growing penetration of renewable energy in power systems.

Future work in wind energy prediction with hybrid models focuses on improving model efficiency, accuracy, and practical applicability. One key direction is developing lightweight networks that reduce computational complexity and training time while maintaining high prediction accuracy, addressing current models' large parameter sizes and heavy resource demands. Additionally, enhancing temporal feature extraction methods is critical to better capture multi-scale time dependencies in wind power data, which can further improve forecasting performance, especially for short-term predictions. Balancing the trade-off between convergence speed and accuracy remains a significant challenge that future research aims to optimize. Moreover, integrating long-sequence input capabilities with advanced architectures like convolutional neural networks combined with transformer-based models (e.g., Informer) shows promise in improving long-term wind power forecasts. Future studies also plan to incorporate more diverse data sources, including numerical weather predictions and multimodal environmental data, to enhance robustness and reduce uncertainty. Overall, the goal is to create hybrid forecasting models that are not only more accurate but also computationally efficient and adaptable for real-time grid operations and large-scale integration of wind power. Furthermore, an optional extension involves adding tree-based machine learning baselines, such as gradient boosting methods (e.g., XGBoost or LightGBM), which will be tuned under the same hyperparameter search budget and early stopping criteria as the primary models. These efforts will ensure a fair and comprehensive comparison across diverse modeling approaches, strengthening the robustness and interpretability of prediction performance evaluations.

Also, future research should focus on rigorously quantifying prediction uncertainty in wind energy forecasting models using advanced statistical techniques such as bootstrap confidence intervals and repeated train-test split variability for metrics like RMSE. R^2, and MAPE. Such uncertainty quantification will provide more robust and transparent assessments of model reliability, critical for practical applications in grid management and energy trading. Additionally, deeper residual diagnostic analyses are needed to identify specific conditions under which models underperform, such as during sharp wind ramps or peak events, which currently remain challenging to forecast accurately. Addressing these aspects will guide the development of more resilient hybrid models, improving their robustness and usefulness for operational decision-making in renewable energy integration.

Author contributions M.S. Writing – review and editing, Writing – original draft, Visualization, Validation. R.S. Software, Methodology, Investigation, Formal analysis, Conceptualization. S.A. Writing – review and editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. O.RI. Writing – review and editing. E.A. Supervision, Resources, Data curation. H.A.N. Methodology, Writing – review and editing. E.X. Investigation, Writing – review and editing. All authors reviewed the manuscript.

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Data availability Data and codes used for the case study are available on request.

Declarations

Conflict of interest The authors declare no competing interests. The authors declare they have no financial interests.

Ethical approval All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

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