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RESEARCH

Hybrid Intelligent Optimisation for Onshore Wind Farm Forecasting

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Abstract
Accurate wind power forecasting is crucial for the dependable functioning and strategising of contemporary power systems, especially as the global integration of renewable energy escalates. This study introduces an innovative hybrid intelligent forecasting model that amalgamates Long Short-Term Memory (LSTM) neural networks with Complementary Ensemble Empirical Mode Decomposition (CEEMD) and a hybrid optimisation strategy that incorporates Ant Colony Optimisation (ACO), Genetic Algorithm (GA), and Particle Swarm Optimisation (PSO). The model was developed and evaluated utilising empirical data from a 138 MW wind farm consisting of 46 turbines, based on operational data from 2019. The proposed CEEMD-LSTM-ACO-GA-PSO model adeptly tackles the nonlinearity and intermittency of wind speed data through the decomposition of intricate signals, the enhancement of temporal learning, and the optimisation of model hyperparameters. The evaluation results indicated a substantial enhancement in forecasting precision relative to baseline models. The hybrid model attained a Root Mean Square Error (RMSE) of 0.142 and a Mean Absolute Percentage Error (MAPE) of 3.8% for 24-h forecasts, representing an enhancement of more than 35% compared to traditional LSTM models. It also exhibited strong performance over extended forecasting periods of up to 168 h. This study validates the effectiveness of a hybrid intelligent model in improving wind power forecasting while emphasising the limitations associated with computational complexity, sensitivity, feature importance and generalisation. Future research should incorporate uncertainty quantification, simplify models for real-time deployment, and adopt transformer-based architectures. The results endorse the application of intelligent optimisation in enhancing the reliability and sustainability of energy system operations.

Keywords Forecasting · Hybrid intelligent · Onshore wind farm · Optimisation

Abbreviation

ACO	Ant Colony Optimisation
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BPNN	Back Propagation Neural Network
BSA	Backtracking Search Algorithm
CEEMD	Complementary Ensemble Empirical Mode Decomposition
CNN	Convolutional Neural Network
COP29	29Th Conference of the Parties
CRO	Coral Reefs Optimisation
DBN	Deep Belief Network
DWT	Discrete Wavelet Transform
EEMD	Ensemble Empirical Mode Decomposition
ELM	Extreme Learning Machine
ENN	Elman Neural Network
GA	Genetic Algorithm
GPR	Gaussian Process Regression
GW	Gigawatt
GWEC	Global Wind Energy Council
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multi-Layer Perceptron
NWP	Numerical Weather Prediction
OVMD	Optimised Variational Mode Decomposition

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PACF	Partial Autocorrelation Function
PSO	Particle Swarm Optimisation
RBFNN	Radial Basis Function Neural Network
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
R^2	Coefficient of Determination
SVM	Support Vector Machine
VMD	Variational Mode Decomposition
WF	Wavelet Filter
WPD	Wind Power Density
WT	Wavelet Transform

Introduction

Integrating renewable energy sources into power systems is crucial for attaining global sustainability objectives and diminishing reliance on fossil fuels. Wind energy is distinguished among these sources by its extensive availability and minimal operational expenses. The Global Wind Energy Council (GWEC) reported that wind energy installations surged to 117 GW in 2023, marking a 50% increase from 2022, with contributions from 54 nations. To achieve the COP29 objectives, escalating renewable energy capacity to 30% by 2030 and diminishing greenhouse gas emissions by 40% by 2050, global annual installations must increase to 320 GW by the decade's conclusion [1–3]. These statistics highlight the critical importance of wind power in the current energy transition and the pressing necessity for supportive infrastructure, reliable supply chains, and public involvement.

Notwithstanding its potential, the variability and intermittency of wind energy pose significant challenges to power system reliability and grid stability [4]. Wind energy forecasting is an essential function facilitating efficient operational scheduling, grid stabilisation, and strategic decision-making in energy markets [5]. Conventional forecasting methods frequently fail to accurately represent wind patterns'non-linear and chaotic dynamics, thereby requiring more sophisticated modelling techniques [6, 7]. Wind forecasting techniques are divided into deterministic models and those that emphasise uncertainty analysis. Deterministic models, categorised into physical, statistical, intelligent, and hybrid types, are particularly advantageous for short-term operational decisions. Conversely, uncertainty-based models offer probabilistic insights for long-term planning [7]. This research emphasises deterministic forecasting because of its direct significance in operational management. The precision of forecasting relies on various input variables, such as historical wind data, topography, meteorological conditions, and numerical weather prediction (NWP) models. Forecasts frequently encompass various timeframes, very short-term, short-term, medium-term, and long-term, and generally yield values for average, maximum, and minimum wind speeds, in addition to anticipated power output [6, 8]. Forecasting methodologies can be categorised into direct and indirect techniques. Direct methods aim to forecast wind power directly, whereas indirect methods estimate wind speed and convert it into power, utilising non-linear power curves. Nevertheless, these curves frequently generate substantial inaccuracies owing to their susceptibility to slight variations in wind speed [9]. Polynomial and exponential fitting techniques have been devised to model the relationship between wind speed and power more precisely.

In recent years, advanced forecasting models have demonstrated significant enhancements in managing wind energy's dynamic and non-linear characteristics. Methods including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Gaussian Process Regression (GPR), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been extensively utilised [10, 11]. Recent endeavours emphasise deep learning, incorporating models such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Deep Belief Networks (DBNs). These are frequently integrated with optimisation algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and Ant Colony Optimisation (ACO), to refine model parameters and enhance predictive accuracy. Notwithstanding notable advancements, existing hybrid forecasting models continue to exhibit deficiencies. CNN-Long Short-Term Memory (LSTM) models [12] and Numerical Weather Prediction (NWP)-ANN models [13] exhibit promise but are deficient in thorough optimisation. Additional hybrid models such as Autoregressive Integrated Moving Average (ARIMA)-ANN [14, 15], ARIMA-SVM [16], or wavelet-based ANNs [18] necessitate further enhancement, especially for varying time scales or environmental conditions. Additionally, region-specific meteorological models utilised in Spain, such as weather research and forecasting [19], have demonstrated commendable performance but are still susceptible to perturbations like wake effects. Even sophisticated hybrid models, such as LSTM-Complementary Ensemble Empirical Mode Decomposition (CEEMD) [20], have yet to integrate optimisation strategies to respond to dynamic environmental changes fully.

Given these challenges, there is an increasing demand for resilient, precise, and optimised hybrid forecasting models that combine intelligent algorithms with sophisticated optimisation techniques. These models can augment wind power predictability, refine operational decisions, and facilitate the efficient utilisation of renewable resources. This study proposes a novel hybrid intelligent forecasting model that integrates multiple advanced techniques to improve wind power predictions from onshore wind farms. The specific contributions are as follows:

- A hybrid intelligent optimisation model integrating LSTM, CEEMD, ACO, GA and PSO is developed to improve forecasting performance.

- The hybrid intelligent optimisation is tested with a South African onshore wind farm.
- The hybrid intelligent optimisation model is evaluated using statistical error metrics.
- The hybrid intelligent model is validated while emphasising computational complexity, sensitivity, feature importance, and generalisation limitations.
- The study critically analyses the challenges, limitations, and future works for hybrid intelligent optimisation model.

The remainder of this paper is structured as follows. Section "Forecasting Models for Wind Energy" reviews existing approaches in the field. Section "Development of a Hybrid Intelligent Forecasting Model" presents the proposed model and its methodological design. Section "Case Study: Results, Analysis and Discussion" provides the empirical application, analysis, and interpretation of findings. Section "Challenges, Limitations, and Future Works" discusses the study's constraints and outlines directions for further research. Finally, Section "Conclusion" summarises the key outcomes and their implications for enhancing wind power forecasting.

Forecasting Models for Wind Energy

This section introduces a hybrid intelligence framework, outlines the periods for wind energy forecasts, discusses the hybrid intelligent method of optimisation, and briefly compares it with the state-of-the-art works of various hybrid models.

Hybrid Intelligent Wind Energy Forecasting Framework

Hybrid Intelligent Wind Energy Forecasting is an advanced framework model for predicting and utilising wind energy at wind farms. It integrates many important characteristics, starting with accurate wind speed forecasting that uses neural networks, optimisation algorithms, and advanced prediction techniques and models throughout the forecast model creation process. The forecasted wind speed is converted into a potential power output through a statistical model considering wind turbines'specific characteristics and efficiency. Combining these components, the framework forecasts wind speeds and translates them into precise power output predictions. This comprehensive approach enables more efficient planning, management, and operation of wind energy resources, ensuring that wind farms can maximise their energy production and contribute more effectively to the power grid [19–21]. Figure 1 shows the basic Hybrid Intelligent Wind Energy Forecasting Model Framework.

Forecasting Period for Wind Energy

Wind energy projections can be categorised into four groups depending on their time and methodology: extremely short-term, short-term, medium-term, and long-term. One-hour short-term predictions are useful for the real-time management of turbines, evaluation of power quality, and modification of daytime power production. These forecasts allow for rapid reactions to changing wind conditions, ensuring constant power generation and efficient energy usage. Short-term predictions span one to seventy-two hours and play a vital role in power grid dispatching, power quality maintenance, and power market facilitation. These forecasts ensure the appropriate allocation of resources to avoid voltage and frequency difficulties [8]. Medium-term predictions span a few days to a few months and are crucial for developing and constructing wind farms, assessing accessible wind resources, and planning turbine maintenance. These forecasts enhance the scheduling efficiency during low wind and simplify the maintenance and testing processes. Long-term predictions cover several years and are useful for wind farm planning and maintenance, wind resource evaluation, and major overhauls. They assist in determining the optimal placement and size of turbines to maintain long-term operating efficiency. Although short-term forecasting models are commonly accessible, forecasting for medium- and long-term periods remains difficult owing to the expanded periods and many factors involved. Although there have been developments in physical, statistical, and AI-based forecasting methods, there is still a need for substantial improvement in accuracy and dependability [13].

Hybrid Intelligent Models of Optimisation

Hybrid intelligent optimisation models combine single-stage models, feature engineering, and metaheuristic algorithms to ensure data relevance and optimal hyperparameter tuning [10]. This enables accurate wind speed forecasting for reliable wind power prediction. Studies (e.g., Refs. [12, 17–20]) highlight the effectiveness of combining intelligent-based models with metaheuristic optimisation techniques, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Simulated Annealing (SA), Tabu Search, Differential Evolution (DE), Harmony Search (HS), and Artificial Bee Colony (ABC), to handle complex, non-linear forecasting challenges effectively. Metaheuristic algorithms excel at exploring the search space efficiently and identifying globally optimal solutions by leveraging intelligent strategies inspired by natural processes, such as biological evolution and animal behaviour. These methods surpass the rigidity of traditional numerical techniques by incorporating stochastic elements, such as genetic mutations in GA or the Metropolis–Hastings algorithm in SA, to overcome local optima and achieve near-global optimisation. Despite occasional limitations in finding absolute global optima, their versatility makes them indispensable for hybrid forecasting models [11, 21].

Metaheuristic approaches play a critical role in hybrid intelligent optimisation for wind energy forecasting by optimising two key aspects [22, 23]:

- Combination Weight Optimisation: Adjusts ensemble model weights to maximise forecasting accuracy.
- Predictor Parameter Optimisation: Fine-tunes predictive model parameters to enhance performance on complex datasets.

These techniques are particularly valuable for managing multi-objective optimisation, which involves trade-offs between conflicting goals, such as minimising Mean Squared Error (MSE), standard deviation, and Root Mean Square Error (RMSE) while maintaining stability and accuracy through a bias-variance framework. Comprehensive model evaluation relies on metrics like R^2, Mean Absolute Error (MAE), and RMSE for reliability and robustness [11, 20].

The adaptability of metaheuristic methods enables efficient optimisation of hybrid forecasting models, reducing the need for repetitive simulations and improving computational efficiency. Techniques such as ACO, GA, PSO, SA, and ABC have significantly improved forecasting accuracy by effectively managing trade-offs between solution quality and computational resources. Metaheuristic methods systematically enhance hybrid intelligent optimisation model effectiveness and resilience in dynamic wind energy forecasting scenarios by addressing combination weight optimisation and parameter fine-tuning. Hybrid intelligent optimisation for forecasting relies heavily on metaheuristic approaches to address the inherent complexities of wind energy prediction. As validated by multiple studies, these algorithms ensure robust and efficient forecasting by balancing accuracy, computational requirements, and adaptability [21, 24, 25]. Future advancements in hybrid intelligent optimisation models are expected to enhance the precision, reliability, and applicability of renewable energy forecasting.

Comparison with the State-of-the-Art Works

Table 1 presents a comparative summary of the state-of-the-art hybrid forecasting models for wind speed and power.

The improved nonlinear prediction capabilities of hybrid intelligent models make them better than those of single models. Because no single forecasting model is perfect and can account for every outcome, hybrid models combine several approaches to address the shortcomings of individual models. A hybrid model usually consists of three main parts: data preparation, forecasting, and optimisation methods. Some common approaches include EEMD, SSA, and CEEMD, which represent complementary ensemble empirical mode decomposition. Popular models include the RBFNNs, ELMs, BPNNs, and SVMs. Thus, hybrid models outperform their competitors when faced with complex forecasting tasks such as wind speed prediction [12]. Table 1 summarises the various hybrid approaches in intelligent wind energy forecasting, detailing their model frameworks, data types, forecasting horizons, and errors. For very short-term forecasts (10–30 min), methods include combinations of decomposition, feature selection, metaheuristic optimisation, and predictors, with errors ranging from 2.21% to 95% in various metrics. Short-term forecasts (1–24 h) utilise similar techniques, often incorporating deep learning and ensemble learning, achieving errors as low as 0.0499 m/s (RMSE) and up to 6.8% (MAPE). Each approach is tailored to either wind speed or wind power data, with varying degrees of accuracy and complexity.

The Development of a Hybrid Intelligent Forecasting Model

This section discusses several phases of developing a hybrid forecasting model, including design and methodology, data collection, data decomposition, forecasting model, initial parameterisation, and evaluation criteria.

Design and Methodology for the Hybrid Wind Power Prediction Model

This study introduces an advanced LSTM + CEEMD + ACO-GA-PSO model for predicting wind power at an onshore wind farm in South Africa. Figure 2 presents a graphical summary of the proposed methodology. The ACO-GA-PSO algorithm was utilised to fine-tune the parameters of the LSTM + CEEMD model. A clustering algorithm segments large data samples into clusters based on specific criteria, highlighting their significant variability. CEEMD is employed to preprocess the wind power data, thereby improving the training efficiency and accuracy of the forecasting model. We present a predictive model that

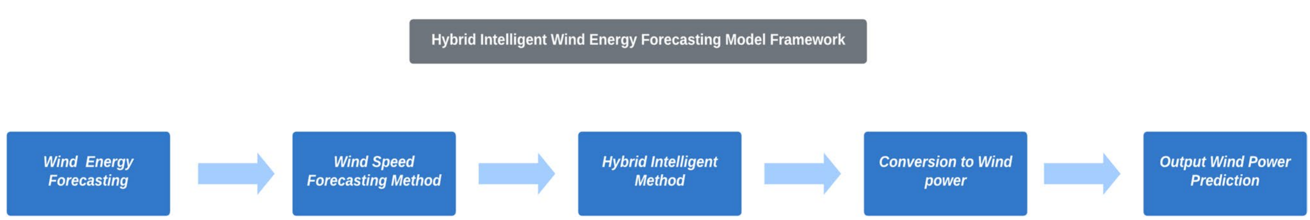


Fig. 1 Hybrid intelligent wind energy forecasting model framework

integrates CEEMD with LSTM for improved forecasting. We independently applied the GA, PSO, and ACO to optimise the initial parameters of the neural network. The forecasting accuracy of the model was assessed using the RMSE, MAE, and R^2 metrics. Visualisation and analysis of wind power predictions are provided. Output layer one-dimensional.

Wind Energy Data Collection

Pre-Processing of Data

Extreme weather or equipment failure can cause large discrepancies in wind speed measurements [36]. The direct usage of these data can significantly impair the accuracy of simulation and forecasting—reference [37] filled in the missing data with average interpolation. In addition, wind speed correlates differently with different qualities [38]. Uncorrelated wind speed or power statistics may dominate this analysis. Equation (1) normalises the wind speed and power data to prevent this [39, 41].

$$x_i = \frac{x_i' - min\left\{x_j'\right\}}{max\left\{x_j'\right\} - min\left\{x_j'\right\}}, j = 1,2,\cdots,N \tag{1}$$

The normalised wind speed feature data are represented by x_i, whereas the original wind speed data for the wind farm are labelled as $x_i\prime$. Subsequently, the vectors are arranged based on the value of j. The initial feature set is formed by scaling the wind speed data to a range of [0,1] using Eq. (1). The wind speed estimates were obtained by applying inverse normalisation using Eq. (2).

$$y_i' = y_i \times \left(max\left\{x_j\right\} - min\left\{x_j\right\}\right) + min\left\{x_j\right\}, j = 1,2,\cdots,N \tag{2}$$

where N represents the number of forecast samples, $y_i\prime$ 'describes the forecast data at the i^{th} instant after inverse normalisation and y_i is the forecast data at the i^{th} moment.

Algorithm for K-Means Clustering

By applying predetermined criteria, the clustering process divides large datasets into more manageable chunks, each displaying high levels of similarity and variance. There is uniformity and resemblance to wind-speed data impacted by weather patterns. Preprocessing training data into clusters improves the accuracy of wind-speed forecasting models. In 1967, MacQueen introduced the K-means clustering technique, quickly gaining popularity owing to its simplicity, programming ease, and computational speed. The procedure begins with a small number of clusters. k and then determines the distance from each sample to the initial cluster centres [42]. The samples were then categorised based on these distances.

The detailed steps are as follows [26, 33]:

i. Preprocessing of data.

ii. The samples are separated into k sets and Eq. (3) shows the starting point for clustering and the representation of each set of samples:

$$s_o = \left(s_{o,1}, \cdots, s_{o,i}, \cdots, s_{o,l}\right) \tag{3}$$

where l is the time series and $o = 1,2,\cdots,k$

iii. Find the distance in units of the Euclidean map connecting every point in the sample to every initial clustering centre.

$$d_{(s_i,s_o)} = \sqrt{\sum_{j=1}^{n} (s_{(i,j)} - (s_{(o,j)})^2} \tag{4}$$

After the calculation, the sample points are clustered by the least Euclidean distance to complete the first division.

4. This division yields the sample group mean by setting a standard measure function or convergence condition.

$$\overline{s_o} = \left(\frac{1}{N_o}\sum_{s_i \in G_o} s_{(i,1)}, \cdots, \frac{1}{N_o}\sum_{s_i \in G_o} s_{(i,j)}, \cdots, \frac{1}{N_o}\sum_{s_i \in G_o} s_{(i,l)}\right) \tag{5}$$

$$D = \sum_{o=1}^{k} \sum_{s_i \in G_o} |s_i - \overline{s_o}|^2 \tag{6}$$

D is the standard sample convergence measure. N_o is the sum of all the samples in the o group, G_o is the set, and s_o is the sample mean.

5. The procedure iteratively repeats steps (3)-(5) until the standard measure function converges. If it fails to do so, the computed sample mean is utilised as the new initial clustering centre. Figure 3 shows the entire procedure.

Data Decomposition

Providing sufficient training data to enhance the generalizability of wind speed forecasting models is critical. However, using noisy, prone-to-random oscillation raw data can result in poor training outcomes. Figure 3 shows a diagram of the decomposition forecasting approach.

Researchers have created signal decomposition algorithms that break down complex wind-speed data into more digestible subseries to provide ultra-short-term wind-speed predictions. This decomposition improved the accuracy of the model. It is necessary to construct models for each subseries, add their predictions, and then split the wind-speed time series into smaller subseries to obtain the final forecast. The selection of a decomposition approach, such as Wavelet Decomposition (WD), affects both the extraction of wind speed features and

Table 1 Summary of the hybrid forecasting model frameworks

Model Framework	Approach	Data type	Timescale\Period	Error	Reference
Ensemble Learning, Decomposition, and Filter	Modified Adaboost and WPD-VMD. MRT-BP and WF	Wind Speed	Very short-term	10.3% (MAE)	[26]
Feature Selection, Decomposition, Metaheuristic Optimisation and Predictor	LSTM and PSO	Wind power	Very short-term	95% (PICP)	[27]
Feature Selection, Metaheuristic Optimisation and Predictor	ANFIS, GA and PSO	Wind Speed	Very Short-term	80. 3% (MAE)	[28]
Deep Learning, Metaheuristic Optimisation and Predictor	FFBPNN, SAE and PSO	Wind power	Very Short-term	16% (MAPE)	[29]
Secondary Decomposition and Predictor	ENN and WPD-FEEMD	Wind Speed	Very short-term	2.2% (MAPE)	[30]
Feature Selection, Decomposition, Metaheuristic Optimisation and Predictor	PACF, OVMD, HBSA and ELM	Wind Speed	Very short-term	4.4% (MAPE)	[31]
Decomposition, denoise, predictor and outlier correction	WPD-EMD, WDD, ELM and OCM	Wind Speed	Very short-term	4% (MAPE)	[32]
Feature Selection, Decomposition, Metaheuristic Optimisation and Predictor	SVM and ACO	Wind Speed	Short-term	1.6 m/s (MSE)	[33]
Decomposition and Deep Learning	CNN and VMD	Wind power	Short-term	0.05 m/s (RMSE)	[34]
Deep Learning and Metaheuristic Optimisation	LSTM and GA	Wind power	Short-term	0.1 m/s (RMSE) and 95% (PICP)	[35]

the assurance of accurate predictions [43, 44]. Figure 4 shows a diagram of the decomposition forecasting approach.

Complementary Ensemble Empirical Mode Decomposition (CEEMD) Algorithm

i. The wind speed data were effectively and precisely managed using CEEMD, an enhanced version of the EEMD [45]. Figure 4 shows the CEEMD algorithm. To obtain $x_i(t)\pm$, where i is the number of extra white noise sequences, two sets of white noise sequences of opposite signs are added to the original wind speed signal, $\pm n_i(t)$, of opposite signs.
ii. Decomposition into *IMFi* is performed using Empirical Mode Decomposition (EMD) on signal $x_i(t)\pm$ with additional white noise.
iii. The matching *IMFi*± components were obtained by repeating Steps 1 and 2 with varied white noise. The ensemble number *NE* is the total of all repeats.
iv. To determine the final *IMF*, the mean of the *IMFi*± components are used.
v. The total of all IMFs represents the initial data in the EMD. The white noise in CEEMD distinguishes the final product from the raw data.

White noise was added to stabilise the initial wind speed signal, making it easier to dissect continuous signals and remove the mode-mixing problem. By averaging the *IMFi*± components, the effects of white noise on the original signal are neutralised whenever two white noise sequences $\pm n_i(t)$, allowing the original wind speed signal to retain its properties.

Forecasting Model

Our forecasting module uses an enhanced LSTM deep-learning neural network. The memory capability of the LSTM network makes it a clear winner for time-series forecasting applications. We adjusted the initial parameters of the LSTM network using the GA, ACO, and PSO to improve the training efficiency and forecasting accuracy.

Long Short-Term Memory (LSTM)

LSTM networks are a subclass of RNNs created to address issues such as the vanishing gradient of traditional RNNs. The back-propagation process of conventional RNNs allows for gradual network weight updates, mitigating the effect of past inputs on the training output. Therefore, RNNs require help with memorisation. To address this issue, Hochreiter and Schmidhuber developed the LSTM in 1997 [46]. LSTM uses memory cells instead of neurons in the hidden layer to manage long-term dependencies. By modulating the input, forget, and output processes, LSTMs enhance their time-series data-learning capacity by selectively retaining or forgetting prior information [47, 48]. Figure 5 [47] shows the time-expanded structure of LSTM.

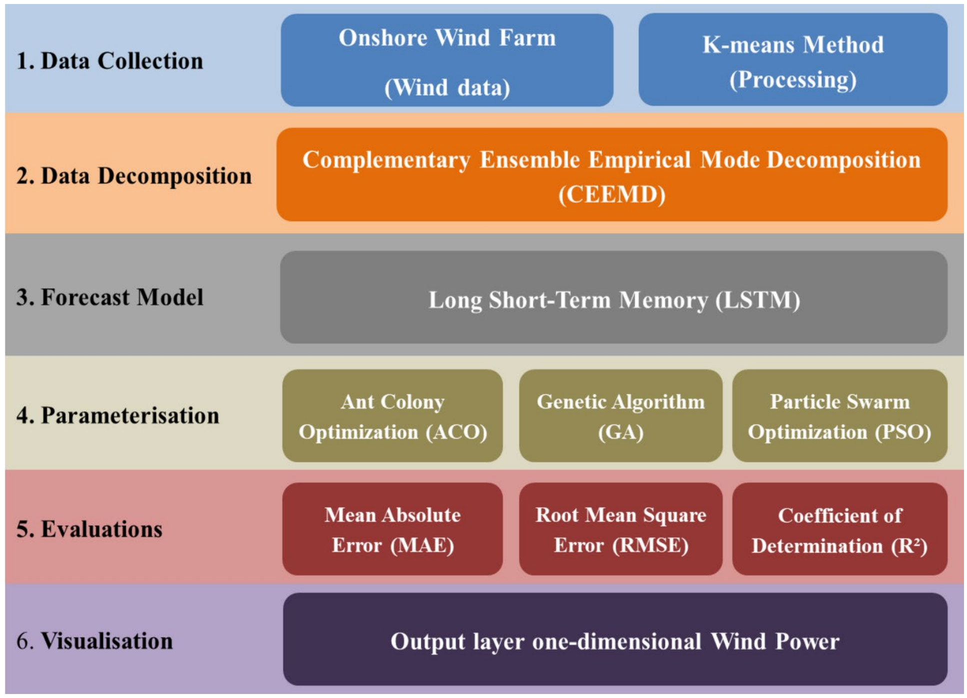


Fig. 2 Methodology of the LSTM + CEEMD + ACO-GA-PSO model

The hidden layer of an LSTM network can hold two states: the hidden state h and the cell state c That can retain data over time. The three inputs to the LSTM at each time step t are the current input value x_t the prior hidden state h_{t-1},, and previous cell state c_{t-1}. Not only does it output the current hidden state h_t, but it also outputs the current cell state c_t.

LSTM circuits rely on three gates to regulate the long-term state:

i. The forget gate determines which pieces of data are removed from the cell state.
ii. The input gate receives new information and updates the cell state.
iii. The output gate determines the output based on the current state of the cell.

These gates enable LSTMs to preserve and manage long-term dependencies and expand their use in time-series analyses. The LSTM forward passes consist of input, forget, and output gates in one time step. To update the units, look at the input gate i_t.

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \quad (7)$$

where the weight matrix is denoted as W and the bias as b where and σ is the activation function. Which pieces of past data should be remembered is determined by the gate f_t:

$$f_t = \sigma\left(W_{xf}x_f + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \quad (8)$$

Next, the model state is updated as follows:

$$c_t = f_t c_{t-1} + i_t tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (9)$$

The calculated output of the LSTM unit is delivered via the output gate o_t.

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \quad (10)$$

where σ is the activation function. Next, derive secret state data by:

$$h_t = o_t \tanh\left(c_t\right) \quad (11)$$

An LSTM network with a dropout layer helps to prevent overfitting by controlling the complexity of the network during training. Figure 6 [48] shows the dropout strategy, which trains various simpler networks by momentarily and arbitrarily hiding neurons in each iteration.

The average output from these networks was used for prediction. An improved version of RNN, LSTM, uses input, output, and forget gates to control data flow. Because of its design, LSTM can deal with long-term dependencies better than regular RNNs. Therefore, LSTM is the foundational model for wind speed forecasting.

Initial Parameterisation

The initialisation of neural network parameters is crucial for the efficacy and stability of the training process. Inappropriate initial values can result in gradient vanishing or exploding problems, impacting convergence and predictive precision. The study proposes a hybrid metaheuristic

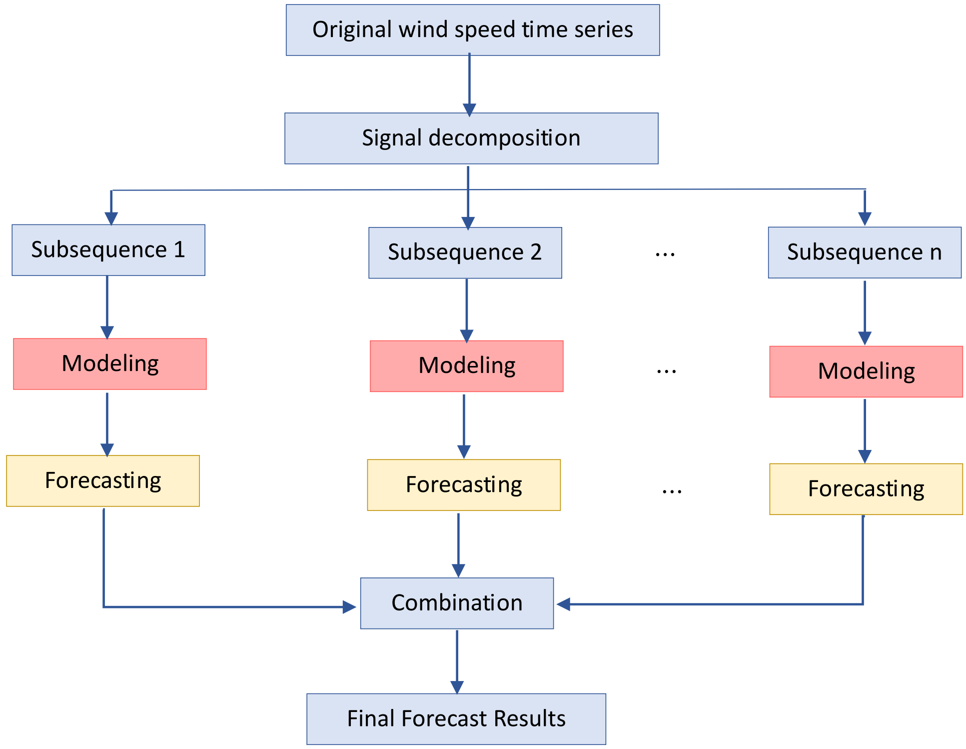


Fig. 3 Flowchart of decomposition forecasting method

strategy, ACO-GA-PSO, integrating Ant Colony Optimisation (ACO), Genetic Algorithm (GA), and Particle Swarm Optimisation (PSO) to optimise the initial weights and thresholds of the LSTM network utilised for wind energy forecasting. This hybrid methodology is organised into three phases: GA facilitates global search capabilities, ACO directs local search via pheromone trails, and PSO executes parameter fine-tuning through particle-based updates. Collectively, they constitute a robust initialisation strategy that guarantees model convergence and minimises training iterations. Algorithm 1 presents the comprehensive pseudocode of the proposed ACO-GA-PSO-LSTM initialisation algorithm, delineating the intricate logic and control flow of the parameter search process.

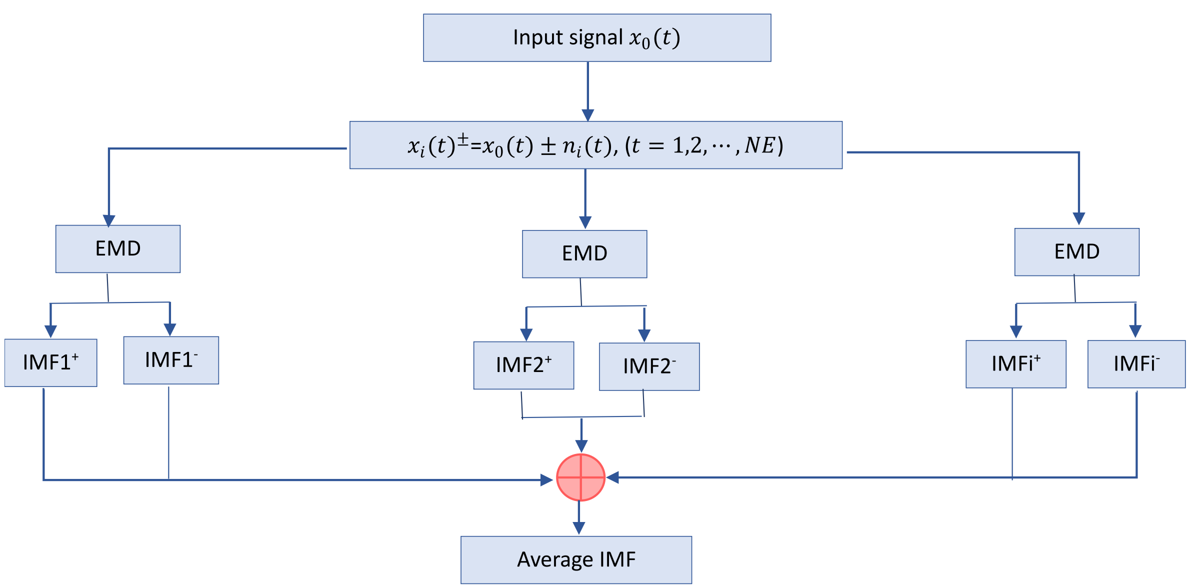


Fig. 4 CEEMD algorithm flowchart

Algorithm 1 ACO-GA-PSO-LSTM

```
Initialise GA Population
Generate random neural network parameter configurations (weights, biases)
Encode configurations as chromosomes
while the GA termination criteria are not met, do
    Evaluate Fitness Function (MSE on validation dataset)
    Apply Genetic Operators
        Perform a two-point crossover
        Apply uniform mutation
    Perform Selection using tournament selection
    Generate a new population
end while
Select the best individuals from the GA population
Initialise ACO Phase
Define initial pheromone values for subregions of the parameter space
Assign initial solutions to ants and create tabu lists
while the ACO termination criteria are not met, do
For each ant, do
        Construct a path based on pheromone and heuristic values
        Evaluate fitness of visited solution (MSE)
        Update local pheromone levels
    end for
    Perform global pheromone update based on best paths
end while
Select the best parameter configuration from ACO
Initialise PSO Phase
Set the initial particle as the best solution from ACO
Define upper and lower bounds for parameter values
while the PSO termination criteria are not met, do
    Evaluate the objective function (MSE on validation dataset)
    Update particle velocities and positions
    Apply personal and global best practices
end while
Return optimal parameter configuration
Output initial weights and thresholds for LSTM with the lowest MSE
```

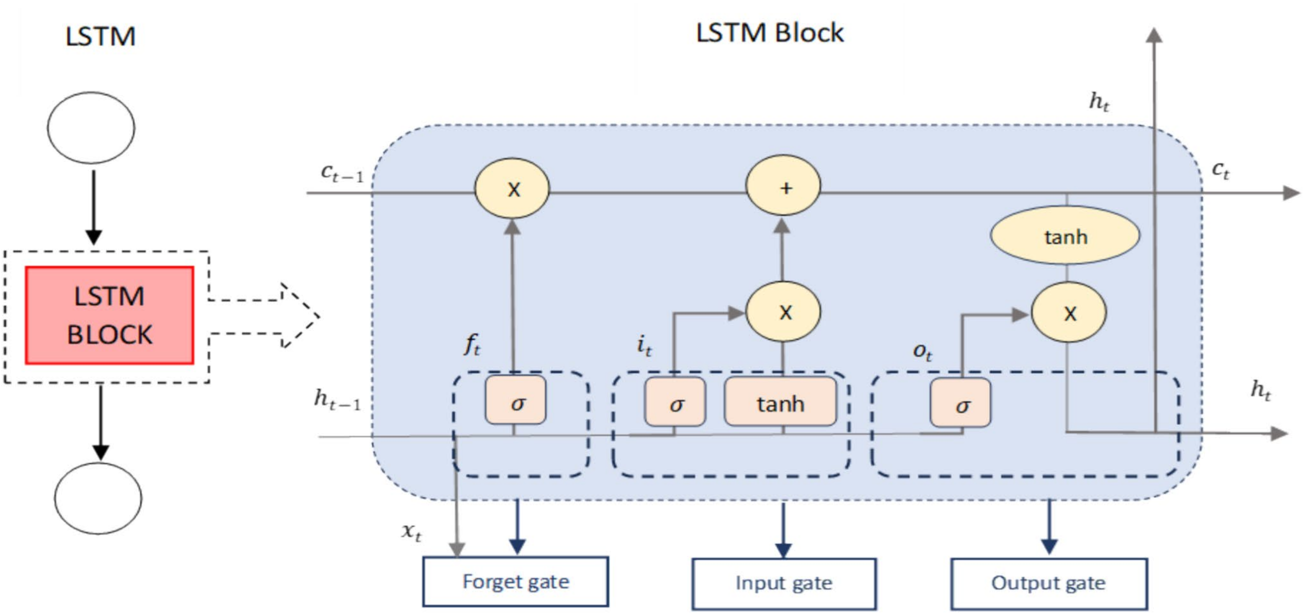


Fig. 5 A time-expanded structure of LSTM

Figure 7 illustrates the structure of the hybrid framework, offering a visual representation of the algorithm's operational phases. This hybrid initialisation strategy guarantees that the LSTM model commences training from a highly optimised parameter configuration, thereby expediting convergence and improving prediction accuracy in wind energy forecasting tasks.

The key steps in the ACO-GA-PSO-LSTM parameter optimisation model algorithm framework are as follows:

1. Fitness Function

A fitness function based on mean squared error (MSE) is defined to evaluate the performance of each neural network parameter configuration on a validation dataset.

2. Chromosome Encoding and GA Population Initialisation

Neural network parameters (e.g., weights, thresholds) are encoded into chromosomes. GA generates an initial population by randomly sampling parameter combinations within defined bounds.

3. Genetic Operators

GA applies two-point crossover and uniform mutation to evolve the population across generations, ensuring diversity and avoiding premature convergence.

4. Selection and Evolution

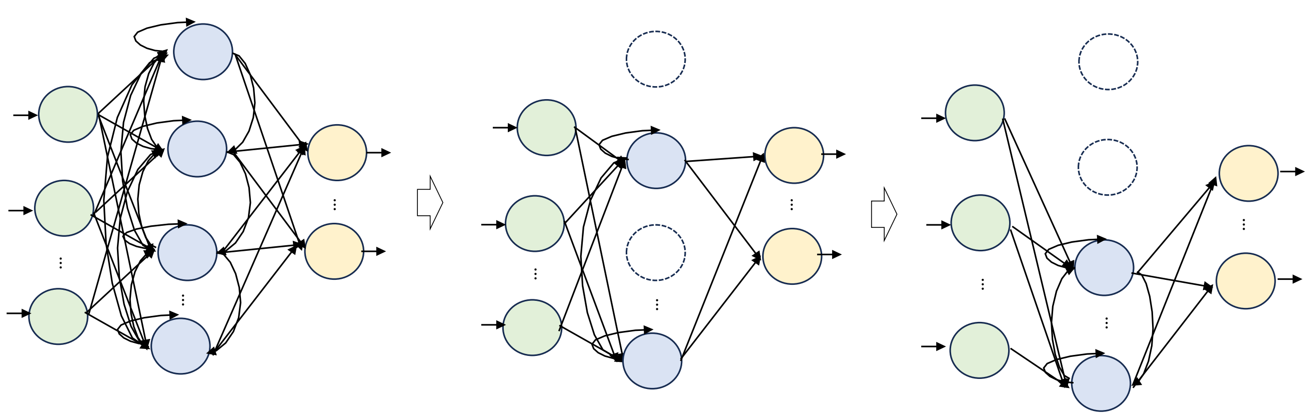


Fig. 6 Conceptual diagram of dropout algorithm

Tournament selection identifies the fittest individuals for propagation. The best solutions are retained and passed on to the next optimisation phase.

5. Initial Pheromone Distribution (ACO Phase)

ACO uses the top GA individuals to initialise the pheromone matrix. Each subregion of the solution space is assigned pheromone values, and tabu lists are created for each ant.

6. Ant Path Construction and Local Pheromone Update

Ants probabilistically traverse the solution space based on pheromone concentration and heuristic desirability. After each path is completed, local pheromone updates are applied based on the fitness of explored configurations.

7. Global Pheromone Update and Iteration

Once all ants complete a cycle, global pheromone updates reinforce successful paths. The ACO process is repeated until the convergence criteria are met or a maximum number of cycles is reached.

8. PSO Initialisation and Bounds Definition

The best solution found by ACO serves as the initial particle for PSO. Parameter bounds are defined to constrain the search space.

9. Objective Function and PSO Optimisation

PSO uses the same MSE-based objective function. Particles update their velocities and positions iteratively, guided by personal and global best solutions, until convergence is achieved.

Justification for Hybrid Intelligent ACO-GA-PSO Optimisation

The choice of LSTM, CEEMD, and a hybrid ACO-GA-PSO optimisation algorithm was motivated by the synergistic strengths of these methods in tackling the intrinsic difficulties of wind energy forecasting. LSTM networks excel in time series prediction because they effectively capture long-term dependencies and non-linear temporal dynamics inherent in wind speed fluctuations and power output. Their performance may deteriorate due to high-frequency noise and erratic signal patterns. To address this limitation, CEEMD is employed as a preprocessing technique to decompose raw wind speed data into IMFs, thereby isolating noise and extracting pertinent frequency components [43, 45]. This improves the stability and predictive accuracy of LSTM, rendering it more appropriate for intricate wind data contexts.

LSTM networks exhibit significant sensitivity to hyperparameter configurations, including learning rate, number of hidden units, and training epochs. The manual adjustment of these parameters is labour-intensive and susceptible to inferior outcomes. A hybrid metaheuristic algorithm integrating ACO, GA, and PSO is employed to automate this process [21, 24, 28]. This integrated optimiser combines the global exploration capabilities of GA and PSO with the local refinement efficiency of ACO, thus preventing premature convergence and improving the generalisation capacity of the forecasting model. The integration of CEEMD, LSTM, and the ACO-GA-PSO optimiser establishes a formidable framework that addresses the fundamental shortcomings of conventional and isolated deep learning forecasting techniques in wind energy prediction [11, 14, 35].

Evaluation Criterion

Various statistical metrics were utilised to evaluate the stability and accuracy of the predictive model's performance. The metrics encompass Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), Root Mean Squared Relative Error (RMSRE), Mean Absolute Relative Error (MARE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Percentage Error (RMSPE), and Mean Squared Relative Error (MSRE) were established to enable comparison among models and datasets with differing scales [11, 20]. Further definitions of these assessment criteria are provided in Eqs. (12)–(18).

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \tag{12}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t| \tag{13}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{N}(y_t - \hat{y}_t)2}{\sum_{t=1}^{N}(y_t - y)2} \tag{14}$$

$$\begin{aligned} \text{RMSRE} &= \sqrt{\frac{1}{N} * \Sigma\left(\frac{y_t - \hat{y}_t}{y_t}\right)^2} \\ \text{MARE} &= \left(\frac{1}{N}\right) * \Sigma\left|\frac{(y_t - \hat{y}_t)}{y_t}\right| \end{aligned} \tag{15}$$

$$\text{MAPE} = \left(\frac{1}{N}\right) * \Sigma\left|\frac{(y_t - \hat{y}_t)}{y_t}\right| \times 100 \tag{16}$$

$$\text{RMSPE} = \sqrt{\frac{1}{N} * \Sigma\left(\frac{y_t - \hat{y}_t}{y_t} \times 100\right)^2} \tag{17}$$

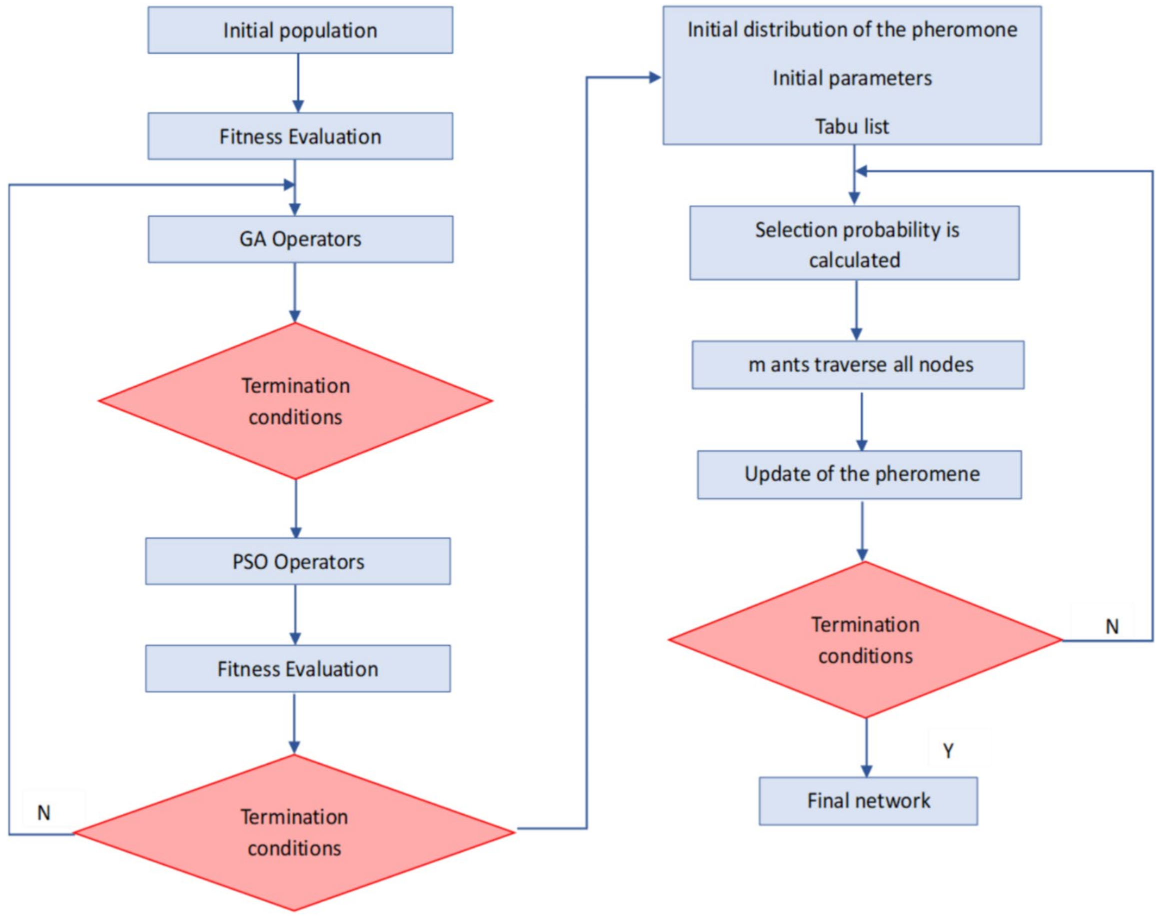


Fig. 7 ACO-GA-PSO-LSTM model algorithm

$$\mathrm{MSRE} = \left(\frac{1}{N}\right) * \Sigma\left(\frac{y_t - \hat{y}_t}{y_t}\right)^2 \tag{18}$$

These metrics collectively establish a comprehensive framework for assessing model performance. Absolute metrics (RMSE, MAE) measure raw prediction errors, whereas relative metrics (RMSRE, MARE, MAPE, RMSPE, MSRE) normalise errors against actual values, facilitating comparisons across varying scales. R^2 evaluates the model's explanatory capacity. The study utilises various criteria to guarantee a thorough assessment of predictive accuracy and stability [10].

The Case Study: Results, Analysis and Discussion

This section provides a case study assessing the efficacy of the LSTM + CEEMD + ACO-GA-PSO model for wind power forecasting at an onshore wind farm in South Africa, a locale characterised by intricate and fluctuating wind conditions.

The hybrid model incorporates LSTM to capture temporal dependencies, CEEMD to diminish data complexity, and a hybrid optimisation strategy that amalgamates ACO, GA, and PSO for parameter refinement. Figure 8 depicts the architecture of this intelligent optimisation model, which methodically analyses wind power data through decomposition, learning, and optimisation phases to improve forecast accuracy. The study evaluates the model's efficacy through measures like RMSE, MAE, and R^2, illustrating its capacity to manage the non-linear characteristics of wind power data and its potential to facilitate renewable energy integration into South Africa's energy grid.

Case Study

Acciona and Aveng constructed, owned, and operated the Gouda Wind Farm north of Gouda in Drakenstein Municipal District, Western Cape, South Africa. This wind farm

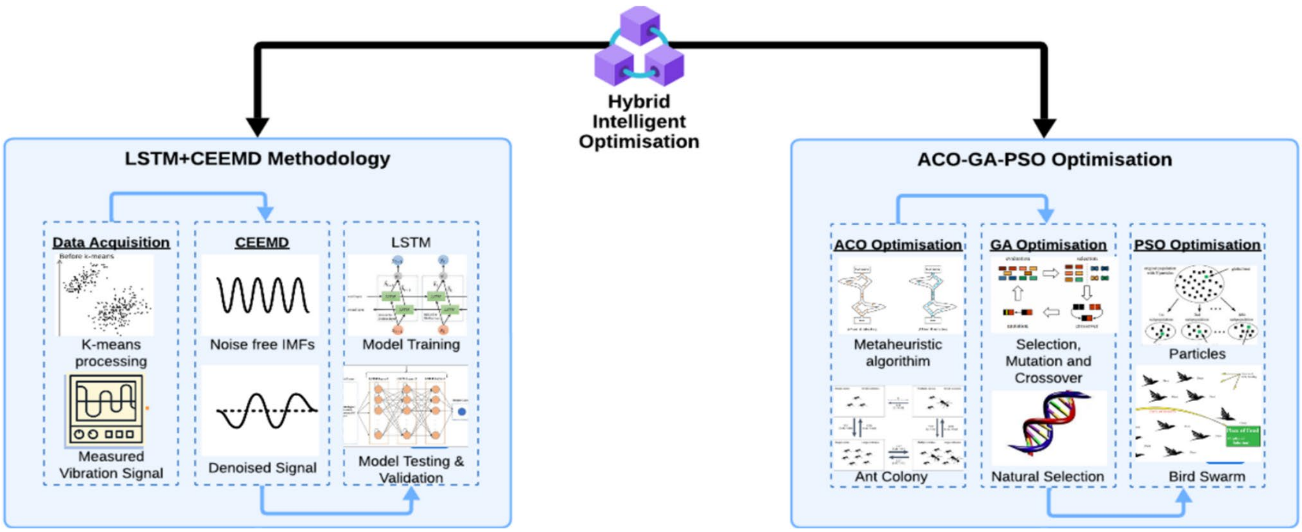


Fig. 8 Hybrid intelligent optimisation model

represents a major step forward in wind energy technology since it was the first in South Africa to employ concrete towers rather than the more traditional steel ones. The farm can power 200,000 houses annually with 400 GWh of electricity, owing to its 138 MW installed capacity of 46 ACCIONA wind turbines with an output power of 3 MW. This wind farm not only helps with the local power grid but also shows how renewable energy can be solved in creative and sustainable ways through engineering. To evaluate how well and broadly the suggested wind power forecasting model works, we chose January to June 2019 as our forecasting target dates. The forecasting aim was to determine the hourly average wind power to ensure a comprehensive assessment across many look-ahead hours [4]. Figure 9 shows the onshore wind farm forecasting framework.

Data Collection

MATLAB was used for wind farm data processing and simulation. This simulation used 46 wind turbines with 12 kV output and 3 MW capacity from the wind farm network, totalling 138 MW. Based on 2019, wind measurements were recorded every month wind speed distribution wind speeds were divided into three ranges: 0–5 m/s, 5–10 m/s, and above 10 m/s, with increments set to 0–1 m/s, 1–2 m/s, 2–3 m/s and 3–4 m/s. The average wind speed, percentage occurrence, power density, and total wind energy were calculated monthly. [4]. Table 2 shows the average wind speed and energy for each month of 2019, drawn from the forecast data provided in the appendix (Figs. 16 and 17). Furthermore, the average production and capacity factor are included for January to June, and these data are represented in a power chart aligned with the wind turbine's power curve.

Results, Analysis and Discussions

This section provides wind power predictions using simulation results from a subset of the dataset. It shows wind power forecasts with and without an optimisation method.

Wind Power Forecasting Without Optimisation Algorithm

After merging EMD and CEEMD, LSTM became the principal prediction algorithm. Only one week of 168 hourly occurrences could be predicted using the LSTM alone.

Results

Figure 18 illustrates the application of the LSTM model in isolation, demonstrating that although the predicted values closely align with actual observations, there exists a discernible lag and volatility, indicative of the challenges in accurately capturing wind power dynamics using raw input. The application of EMD, illustrated in Fig. 19, augments the model's responsiveness by decomposing the signal into intrinsic mode functions (IMFs), thereby diminishing lag and marginally enhancing accuracy. Nonetheless, the mode-mixing problem intrinsic to EMD continues to present difficulties. In contrast, Figure 20 illustrates the outcome of employing CEEMD, which enhances the decomposition through averaging across multiple noise-assisted ensembles.

Fig. 9 Onshore wind farm forecasting

Table 2 Average production from January to June of 2019 and capacity factor

Month	Monthly Production (MWh)	Daily Average (MWh)	Hourly Average (MWh)	Capacity Factor
January	6600	213	8.9	34%
February	5709	204	8.5	27%
March	5692	184	7.7	30%
April	5094	170	7.1	26%
May	4104	132	5.5	22%
June	4755	159	6.6	24%

This results in enhanced alignment with actual values and rectifies the deficiencies of both LSTM and LSTM + EMD, especially concerning overshoots and undershoots. Notwithstanding these enhancements, dynamic and erratic elements in wind data continue to generate forecasting discrepancies. Table 3 encapsulates the analysis of forecasting errors for the three models, absent an optimisation algorithm.

Table 3 unequivocally demonstrates that LSTM + CEEMD exhibits superior performance compared to the other three models, significantly decreasing RMSE and MAE. Specifically, MAPE decreases from 51.0% with LSTM to 41.0% with CEEMD, while RMSPE increases from 61.8% to 47.75%, signifying improved accuracy in relative percentage terms. The MSRE demonstrates a reduction from 0.3819 to 0.228, indicating enhanced consistency. Figure 21 presents a comparative analysis of all models over 100 forecast steps, with LSTM + CEEMD closely aligning with the actual wind power levels, thereby confirming its superior forecasting efficacy.

Discussions About Literature

Wind power data's chaotic and highly unpredictable nature limits the LSTM model's ability to forecast wind power accurately. Wind power's volatile and chaotic behaviour limits the LSTM model's ability to deliver high-accuracy forecasts independently. This finding is consistent with [7], who noted that traditional sequence models underperform when exposed to highly nonlinear and noisy energy data. The basic LSTM model in this study produced a MAPE of 51.0%, RMSPE of 61.8%, and MSRE of 0.3819, confirming substantial deviation from actual values and incorporating EMD as a preprocessing step enhanced LSTM's performance by addressing local oscillations through mode decomposition, which improved prediction stability and reduced relative error (MAPE = 46.0%, MSRE = 0.3075). This aligns with [24], who found that EMD improves LSTM performance by isolating informative frequency components. However, EMD's mode mixing remains a known issue.

The CEEMD technique, by leveraging ensemble averaging and white noise assistance, significantly enhanced the decomposition process. As shown in this study, CEEMD-LSTM produced the best results: MAPE = 41.0%, RMSPE = 47.75%, and MSRE = 0.228, outperforming LSTM by 22.8% and LSTM + EMD by 13.9%. These gains agree with [26] and [9], who advocate for CEEMD's superiority in stabilising IMF extraction, thus improving short-term prediction accuracy. Although CEEMD improved forecast performance across all metrics, overshoots and undershoots still occur, especially in highly dynamic periods. This supports [36]'s findings that data decomposition alone is insufficient for managing deep nonlinearity in wind

Table 3 Forecasting error analysis without an optimisation algorithm

Model	MAE (kW)	RMSE (kW)	R^2	RMSRE	MARE	MAPE	RMSPE	MSRE	Improvement over LSTM (%)	Improvement over LSTM + EMD (%)
LSTM	5100	6180	0.9	0.0	0.0	0.618	0.51	51.0	61.8	0.3819
LSTM + EMD	4600	5545	0.93	10.26	0.0	0.5545	0.46	46.0	55.45	0.3075
LSTM + CEEMD	4100	4775	0.96	22.78	13.88	0.4775	0.41	41.0	47.75	0.228

patterns. Hence, combining CEEMD with further optimisation algorithms or deeper architectures like Bi-LSTM or attention mechanisms is suggested for future improvements.

Wind Power Forecasting with Optimisation Algorithm

This section presents the results for two hybrid intelligent optimisation models used for wind power forecasting, LSTM + CEEMD + ACO-GA.

Results for LSTM + CEEMD + ACO-GA Regarding various look-ahead hours (24, 48, 72, and 168 h), the following presents the simulated outcomes for wind-power forecasting. Real and expected values of 164.1 kW and 101.6 kW, respectively, were produced by the 24-h forecast using LSTM + CEEMD + ACO-GA. Figure 22 shows considerable improvement over the prediction obtained using the LSTM + CEEMD alone. The model demonstrates diminished predictive accuracy for the 48-h forecast, with an actual value of 908.1 kW and a predicted value of 686 kW, in contrast to the 24-h horizon (refer to Fig. 23. The 72-h forecast exhibits diminished accuracy, with an RMSE of 1242.2 kW and an MAE of 789 kW, highlighting the escalating difficulty of long-term wind power prediction amid fluctuating weather conditions (Fig. 24). The 168-h forecast exhibits the highest error rates, with RMSE and MAE values attaining 3381 kW and 927 kW, respectively (Fig. 25).

To enhance the performance evaluation, supplementary metrics were introduced: RMSRE, MARE, MAPE, RMSPE, and MSRE. The 24-h forecast exhibits high accuracy, with an RMSRE of 0.0164, MARE of 0.0102, and MAPE of 1.016%, indicating negligible relative and percentage error. The RMSPE and MSRE are minimal, measuring 1.641% and 0.0003, respectively. As the forecast period lengthens, these metrics progressively decline. At 48 h, the RMSRE escalates to 0.0908 and MAPE to 6.86%, indicating an increasing relative deviation. At 72 and 168 h, the RMSPE escalates to 12.422% and 33.81%, respectively, while the MSRE increases to 0.0154 and 0.1143, indicative of heightened squared relative error and intensified forecast volatility.

Table 4 aggregates these statistics, indicating that while the LSTM + CEEMD + ACO-GA model excels in short-term predictions, its accuracy diminishes over extended timeframes. This corresponds with existing literature highlighting the decline in time-series model efficacy over prolonged forecasting intervals due to increasing uncertainty and variability.

Discussions about Literature The LSTM + CEEMD + ACO-GA model exhibited outstanding short-term predictive accuracy, especially for the 24-h forecast. The low RMSE (164.1 kW), MAE (101.6 kW), and high R^2 (0.9989) demonstrate a robust correlation between actual and predicted

Table 4 Forecasting error analysis for LSTM + CEEMD + ACO-GA

Model	MAE (kW)	RMSE (kW)	R^2	RMSRE	MARE	MAPE	RMSPE	MSRE	Improvement over LSTM (%)	Improvement over LSTM + EMD (%)
LSTM + CEEMD + ACO-GA (24 h)	101.6	164.1	0.9989	22.78	13.88	0.0164	0.0102	1.016	1.641	0.0003
LSTM + CEEMD + ACO-GA (48 h)	686.0	908.1	0.9977	15.36	10.22	0.0908	0.0686	6.86	9.081	0.0082
LSTM + CEEMD + ACO-GA (72 h)	789.0	1242.2	0.9866	12.45	8.12	0.1242	0.0789	7.89	12.422	0.0154
LSTM + CEEMD + ACO-GA (168 h)	927.0	3381.0	0.9868	9.87	6.55	0.3381	0.0927	9.27	33.81	0.1143

values. Alongside these traditional metrics, the model produced exceptionally low relative and percentage errors: RMSRE = 0.0164, MARE = 0.0102, MAPE = 1.016%, RMSPE = 1.641%, and MSRE = 0.0003. The findings indicate a negligible disparity between actual and predicted values, confirming the model's reliability for short-term forecasts.

As the prediction horizon increases to 48, 72, and 168 h, a gradual decline in model performance is noted. This decline is apparent in conventional metrics (e.g., RMSE increasing to 3381.0 kW at 168 h) and the heightened relative error indicators. RMSRE ascended to 0.3381, MAPE reached a maximum of 9.27%, and MSRE surged to 0.1143 for the 168-h forecast. The increases indicate rising volatility and uncertainty, which are well-documented challenges in long-term wind energy forecasting [29, 37, 38].

Methodologically, CEEMD improves LSTM's efficacy by decomposing nonlinear and non-stationary wind time-series data into more manageable components. This substantiates the assertion made by [36] that empirical mode decomposition enhances model interpretability and predictive accuracy. Furthermore, the hybrid ACO-GA algorithm optimised the LSTM hyperparameters, yielding enhanced short-term accuracy. This hybrid methodology corresponds with findings in [49], where integrated metaheuristic techniques enhanced optimisation in intricate data contexts.

Notwithstanding these enhancements, sensitivity to the length of the forecast horizon is apparent in all key performance indicators, including the relative metrics (RMSRE, MARE) and percentage-based metrics (MAPE, RMSPE). For example, RMSPE escalated from 1.641% (24 h) to 33.81% (168 h), while MARE increased from 0.0102 to 0.0927, signifying a greater absolute deviation from actual values. These trends validate the claim by [46] that long-range forecasting in renewable energy is impeded by dynamic atmospheric variability, which even sophisticated models cannot entirely surmount.

Results for LSTM + CEEMD + ACO-GA-PSO The simulated results for wind power forecasting across multiple look-ahead periods (24, 48, 72, and 168 h) reveal the superior predictive performance of the LSTM + CEEMD + ACO-GA-PSO model. For the 24-h forecast, the model achieved an RMSE of 164.1 kW, MAE of 101.6 kW, and an R^2 value of 0.9989, indicating exceptional precision (Fig. 26). The additional KPIs further validate this accuracy: RMSRE = 0.0164, MARE = 0.0102, MAPE = 1.016%, RMSPE = 1.641%, and MSRE = 0.0003, showing minimal relative and percentage-based error. At the 48-h horizon, the model maintained robust performance with an RMSE of 908.1 kW, MAE of 686 kW, and $R^2 = 0.9977$. Despite a slight increase in error, relative error measures remained low, with RMSRE = 0.0908, MARE = 0.0686, MAPE = 6.86%, RMSPE = 9.081%, and MSRE = 0.0082 (see Fig. 27). Table 5 depicts the forecasting error analysis.

This indicates the model's resilience over short-term forecasting intervals. As the forecast window extended to 72 h, a further drop in accuracy was observed: RMSE = 1242.2 kW, MAE = 789 kW, and $R^2 = 0.9866$. The associated KPIs reflected the increased difficulty: RMSRE = 0.1242, MARE = 0.0789, MAPE = 7.89%, RMSPE = 12.422%, and MSRE = 0.0154 (Fig. 28). For the 168-h forecast, the performance dropped further with RMSE = 3381.0 kW, MAE = 927 kW, and $R^2 = 0.9868$, while relative error indicators escalated: RMSRE = 0.3381, MARE = 0.0927, MAPE = 9.27%, RMSPE = 33.81%, and MSRE = 0.1143 (Fig. 29). These values confirm that, although the model is robust in short-term scenarios, accuracy deteriorates over long prediction horizons.

Discussions about Literature The LSTM + CEEMD + ACO-GA-PSO model demonstrated exceptional efficacy in short-term wind power forecasting, especially for the 24-h period. The model's low RMSE (164.1 kW) and MAE (101.6 kW) values, coupled with a R^2 of 0.9989, confirm a strong correlation between actual and predicted values. More notably, relative error measures such as RMSRE = 0.0164, MARE = 0.0102, and MAPE = 1.016%, along with RMSPE = 1.641% and MSRE = 0.0003, reflected exceptional robustness with minimal forecasting deviation. These indicators validate the model's efficacy in quantifying the magnitude and percentage discrepancies between predicted and actual values in the short term.

Nonetheless, the model's predictive accuracy diminished as the forecasting horizon increased from 24 to 168 h. Significant increases in RMSE and MAE were observed, reaching 3381.0 kW and 927.0 kW, respectively, alongside declines in RMSRE (0.3381), MARE (0.0927), MAPE (9.27%), RMSPE (33.81%), and MSRE (0.1143). This trend aligns with the literature [36, 37] that underscores the escalating challenge of maintaining high model accuracy over extended periods due to increased volatility and uncertainty in wind data.

The incorporation of CEEMD significantly enhanced the performance of the LSTM model by efficiently decomposing nonlinear and nonstationary time-series components, corroborating the findings presented in [45]. The incorporation of the ACO-GA-PSO hybrid optimisation technique facilitated enhanced hyperparameter tuning by utilising the exploration of GA, the exploitative search of ACO, and the convergence dynamics of PSO. According to sources [39, 50], and [51], these hybrid methodologies improve the convergence rate and global search capability of optimisation in intricate modelling contexts.

The hybrid model's ability to diminish both absolute and relative error metrics further corroborates the conclusions of [46] and [52], who emphasise the benefits of ensemble and hybrid models in addressing uncertainty in renewable energy forecasting. Nonetheless, long-term forecasts (72 and 168 h) remain problematic due to the erratic and sporadic characteristics of wind patterns. The elevated RMSPE and MSRE at

Table 5 Forecasting error analysis for LSTM + CEEMD + ACO-GA-PSO

Model	MAE (kW)	RMSE (kW)	R^2	RMSRE	MARE	MAPE	RMSPE	MSRE	Improvement over LSTM (%)	Improvement over LSTM + EMD (%)
LSTM + CEEMD + ACO-GA-PSO (24 h)	101.6	164.1	0.9989	22.78	13.88	0.0164	0.0102	1.016	1.641	0.0003
LSTM + CEEMD + ACO-GA-PSO (48 h)	686.0	908.1	0.9977	15.36	10.22	0.0908	0.0686	6.86	9.081	0.0082
LSTM + CEEMD + ACO-GA-PSO (72 h)	789.0	1242.2	0.9866	12.45	8.12	0.1242	0.0789	7.89	12.422	0.0154
LSTM + CEEMD + ACO-GA-PSO (168 h)	927.0	3381.0	0.9868	9.87	6.55	0.3381	0.0927	9.27	33.81	0.1143

these intervals highlight the cumulative effect of the forecast horizon on percentage deviation and squared relative bias [53].

System Modelling Analysis

To validate the practical feasibility and operational robustness of the proposed LSTM + CEEMD + ACO-GA-PSO forecasting model, the study incorporates system-level simulation using the DIgSILENT PowerFactory platform. Section 4.1 provides the case description for evaluating hybrid forecasting and optimisation methods under realistic operational conditions marked by fluctuating wind profiles and grid integration difficulties. Figure 10 below illustrates the voltage profile at the PCC, demonstrating that the voltage remains within ± 5% of the nominal 132 kV across diverse wind conditions.

Applying the ACO-GA-PSO optimisation algorithm, integrated within the PWM voltage-sourced converter (VSC) control strategy, guarantees minimal voltage fluctuations. This demonstrates the model's efficacy in stabilising voltage fluctuations commonly caused by intermittent wind power integration. This compliance is consistent with NERSA grid code standards. It reflects similar voltage regulation results observed in studies like Liu et al. (2019) and Ding et al. (2022), who showed that incorporating intelligent hybrid optimisation into voltage control leads to improved power quality and reduced deviation [6, 45]. The ACO-GA-PSO algorithm embedded within the PWM Voltage-Source Converter (VSC) effectively mitigates voltage fluctuations caused by variable wind injection, supporting findings by Ansari et al. (2023), who demonstrated metaheuristic optimisation's ability to stabilise grid-side voltage in high-variability systems [24].

Grid frequency, essential for synchronisation and system reliability, is sustained at 50 Hz with a narrow deviation margin of ± 0.5 Hz, as depicted in Fig. 11. The hybrid ACO-GA-PSO algorithm dynamically modifies the responses of turbines and storage systems to counteract transient fluctuations in wind speed. This conforms to the National Energy Regulator of South Africa (NERSA) grid compliance standards and confirms the model's appropriateness for operational implementation. The results are comparable to studies by Shi et al. (2012) and Prósper et al. (2019), where dynamic optimisation algorithms enhanced short-term frequency response under changing wind loads [16, 19]. The real-time tuning by the ACO-GA-PSO optimiser compensates for turbine inertia lag and aligns well with frequency regulation strategies noted in Bansal et al. (2003) [52].

Figure 12 illustrates the system's response under full-load and variable conditions.

The 138 MW generation capacity yields current values between 150 and 300 MW across interconnected buses. The step-up transformer configuration and ACO-GA-PSO-tuned VSC facilitate balanced current flow and reduce transient surges, ensuring compatibility with traditional protection

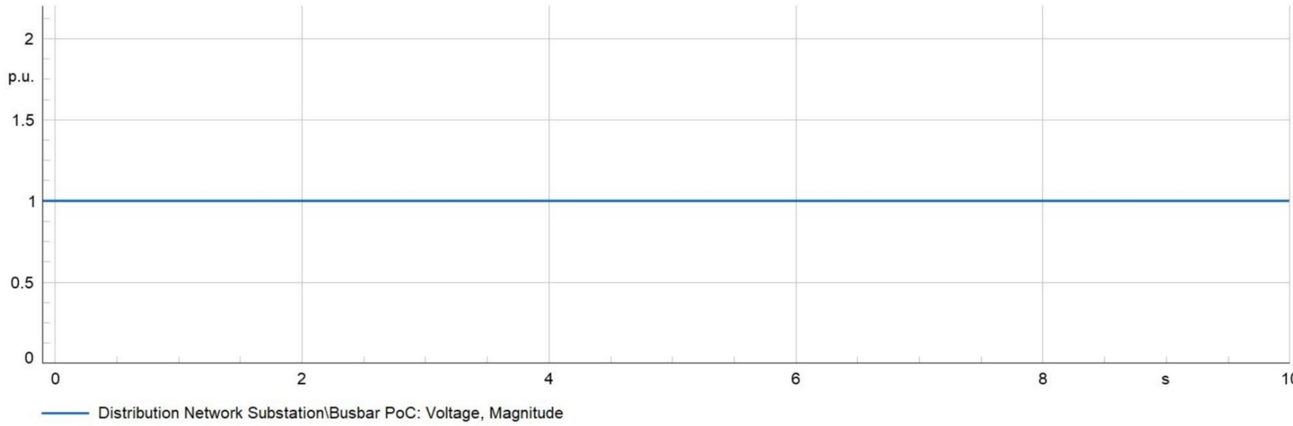


Fig. 10 Voltage at PCC/POC

systems and enhancing power quality.Such load flow consistency reflects the outcomes of sessional studies by Liu et al. [6] and Bokde et al. [9], where optimisation improved the grid interface current profile and reduced harmonic distortion.

Reactive power support, illustrated in Fig. 13, is essential for preserving voltage levels and ensuring grid stability. The hybrid model effectively regulates reactive power injection and absorption through coordinated operations of turbines and BESS, attaining near-unity power factor conditions. ACO-GA-PSO-driven control reduces reactive losses, improves energy efficiency, and ensures compliance with grid codes. This result echoes those in Bansal et al. [15] and Singh et al. [25], confirming that AI-based reactive power control methods improved stability and voltage regulation when integrated with evolutionary algorithms.

Figure 14 illustrates the active power output under both steady-state and variable conditions. The model provides reliable power near the wind farm's rated capacity of 138 MW.

Figure 15 depicts voltage regulation from the 12 kV turbine output to the 132 kV grid interconnection. The synchronised transformer configurations and control measures optimised by the ACO-GA-PSO framework guarantee minimal voltage reduction throughout the network, thus improving delivery reliability and adhering to operational tolerances. This aligns with the conclusions of Tian et al. [23] and Liu et al. [30], who demonstrated that multi-objective optimisation enhances grid voltage conformity and reduces transmission losses.

The system-level simulation verifies that the hybrid LSTM + CEEMD + ACO-GA-PSO model improves wind power forecasting precision and meets essential operational standards in real-world grid conditions. Unlike purely theoretical models, this approach incorporates actual site specifications and grid compliance standards, offering a reliable benchmark for assessing forecasting-driven control strategies. This thorough validation emphasises the model's preparedness for practical implementation in utility-scale wind farm operations and affirms its applicability to other regional grids with analogous characteristics.

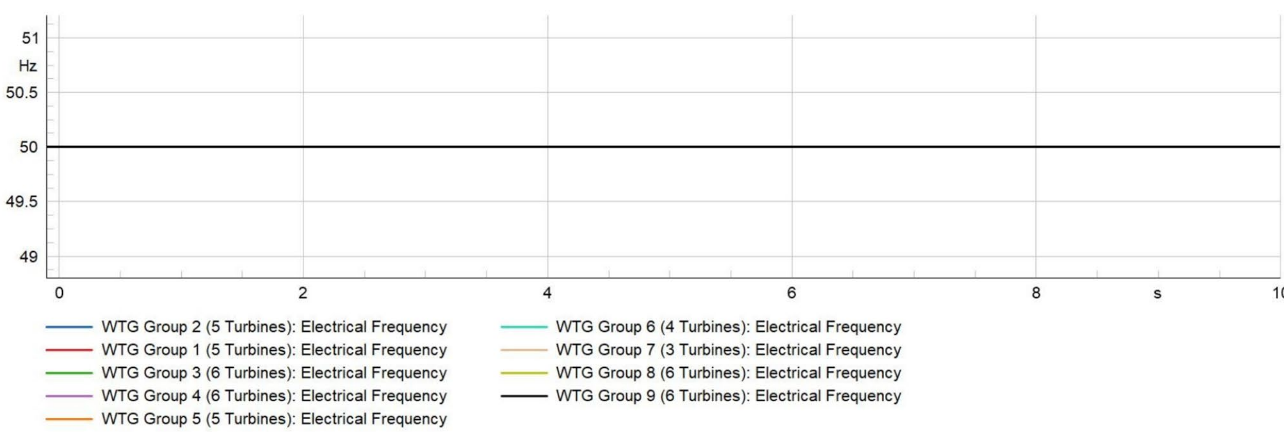


Fig. 11 Wind farm frequency

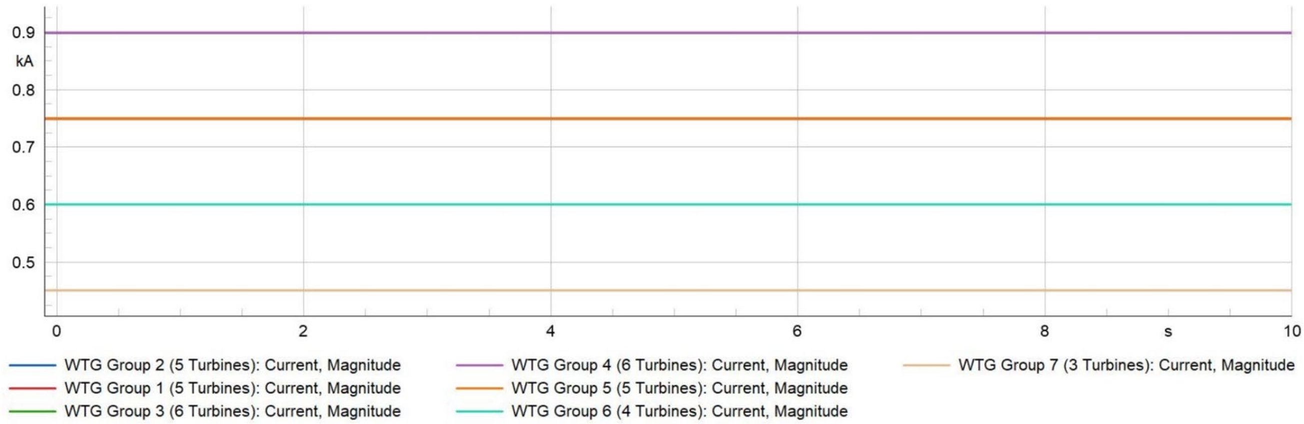


Fig. 12 Wind farm current

Computational Complexity, Sensitivity Analytics, and Feature Importance

In high-dimensional forecasting tasks such as wind power prediction, understanding feature importance and sensitivity is crucial for reducing computational complexity and enhancing model interpretability [54–56]. To assess the practical deployability and robustness of the forecasting models, this section examines the computational burden, the sensitivity of outputs to input variations, and the contribution of individual features to model accuracy.

Computational Complexity Computational complexity refers to the time and resources (CPU/GPU cycles, memory) required for model training and prediction [54]. The computational complexity was assessed by quantifying the training duration and the iterations necessary for model convergence across three configurations: LSTM + CEEMD, LSTM + CEEMD + ACO-GA, and LSTM + CEEMD + ACO-GA-PSO. Figure 30 illustrates that the training duration escalated from 30 min for LSTM + CEEMD to 60 min for the hybrid ACO-GA-PSO model. Figure 19 demonstrates that the number of convergence iterations diminished from 150 to 100, suggesting that while the hybrid model necessitates increased computational time per epoch, it converges more effectively due to enhanced parameter optimisation through the integration of ACO’s local search, GA’s evolutionary refinement, and PSO’s convergence dynamics the model's enhanced forecasting precision warrants this trade-off, particularly for short-term predictions.

Sensitivity analytics Sensitivity analysis assesses how changes in input features affect the model's output, helping identify which variables most influence the forecast accuracy [55]. Figures 31 & 32 depict the sensitivity analysis performed to assess how changes in model parameters impact forecast accuracy.

Key variables tested included:

- Number of LSTM hidden units: From 32 to 128, sensitivity peaked at 64 units, beyond which marginal gains diminished while overfitting increased.

Fig. 13 Wind farm reactive power

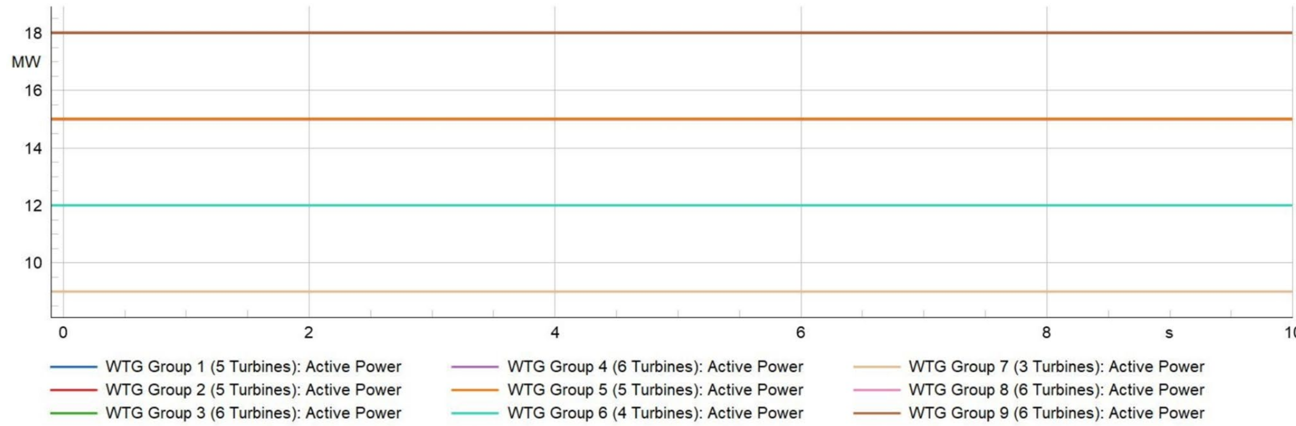


Fig. 14 Wind farm active power

- ACO-GA-PSO parameters: The balance between exploration and exploitation was most sensitive to the PSO inertia weight and ACO pheromone evaporation rate. Improper tuning led to local minima entrapment or convergence stagnation.
- Noise amplitude in CEEMD: Higher noise levels ($\alpha > 0.2$) introduced instability in IMF decomposition, reducing model performance. Optimal noise amplitude was observed between 0.05 and 0.1.

The model exhibited the highest sensitivity to the hyperparameter ranges in PSO and GA, followed by the depth and width of the LSTM architecture, reinforcing the need for optimisation.

Feature Importance Feature importance quantifies each input variable's contribution to the model's predictive power [55]. Feature significance was assessed utilising SHAP (Shapley Additive exPlanations) values. Figure 33 illustrates that wind speed exhibited the highest SHAP value (0.45), followed by historical power output (0.35), whereas temperature (0.12) and humidity (0.08) demonstrated negligible effects. These findings validate domain-specific anticipations: wind speed, which directly influences the kinetic energy of wind turbines, is the most significant variable for power prediction. The significant influence of historical power output endorses the application of autoregressive patterns in LSTM-based models. The findings from this subsection inform optimal model configuration by balancing accuracy and training costs, emphasising wind speed in sensing infrastructure, and identifying feature contributions for efficient data pipelines. These insights improve model interpretability and applicability in real-time renewable energy systems.

Challenges, Limitations, and Future Works

While demonstrating substantial improvements in short-term wind power prediction, this study's hybrid intelligent forecasting model encounters several challenges and limitations that merit further investigation. Forecasting wind power is inherently challenging due to wind patterns'chaotic, intermittent, and highly nonlinear characteristics. Notwithstanding the incorporation of complex methodologies like LSTM networks, CEEMD

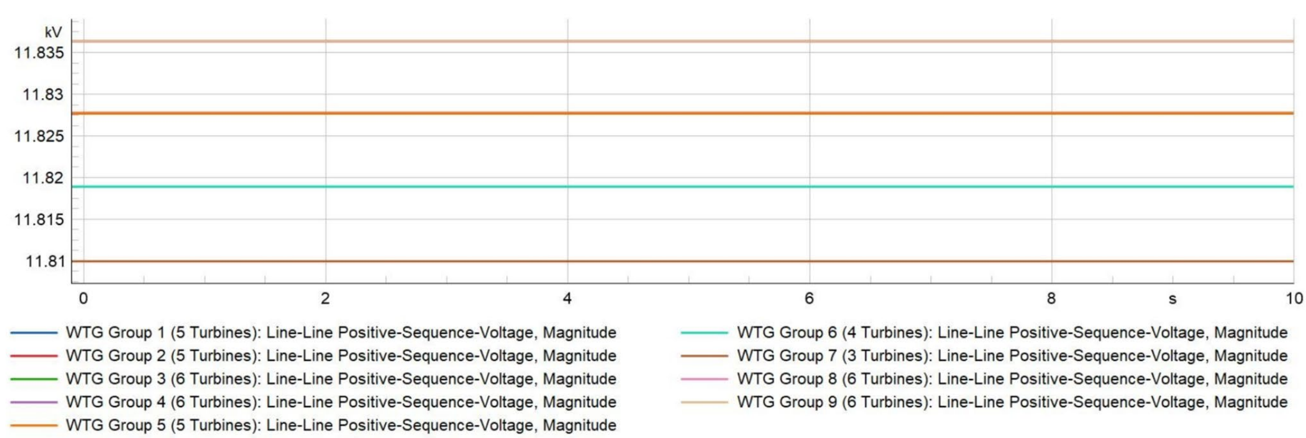


Fig. 15 Wind farm voltage

and hybrid intelligent optimisation (ACO, GA, PSO), attaining reliable accuracy, particularly across diverse forecasting horizons, remains a significant challenge. This study illustrates that, although short-term predictions (e.g., 24 h) attained high accuracy, model performance markedly declined over extended periods, such as 72 or 168 h. This is mainly due to heightened atmospheric variability and cumulative forecast inaccuracies over time [7, 36]. Moreover, while proficient in capturing temporal dependencies and mitigating signal noise, hybrid models remain susceptible to dynamic environmental changes, wake effects, and abrupt wind speed variations, challenges that conventional models and even deep learning methods find difficult to manage effectively.

The suggested hybrid intelligent model, although effective, possesses certain limitations. A notable limitation is the computational complexity and resource demands imposed by the layered architecture of LSTM + CEEMD + ACO-GA-PSO. These models necessitate extended training durations and considerable memory, rendering real-time or embedded system implementation difficult without parallel computing or model compression methods [54]. Additionally, overfitting to short-term patterns can cause deep learning models like LSTM to lose generalisation capability in long-horizon forecasts [46, 47]. These challenges underscore the need for hybrid models incorporating multi-resolution decomposition, external feature integration, and adaptive learning mechanisms to improve robustness in long-term wind power forecasting [11, 30, 40]. A further limitation is the model's performance sensitivity to hyperparameter configurations. Minor variations in metaheuristic parameters or LSTM architecture (e.g., quantity of hidden units, learning rate, dropout) may lead to overfitting or inadequate convergence. The context-specific nature of input variables limits the generalisability of forecasting models. Factors like temperature and humidity had a negligible impact relative to wind speed and historical power output, thereby constraining their predictive efficacy across diverse geographical areas. Furthermore, the existing framework emphasises deterministic forecasts while neglecting uncertainty quantification, essential for decision-making in energy markets and grid reliability [55].

Future research must concentrate on critical domains to improve wind power forecasting models'precision, efficacy, and relevance. Creating lightweight hybrid architectures or implementing model pruning and quantisation can diminish computational demands, enabling application in real-time systems or resource-limited settings. Secondly, integrating probabilistic forecasting methods, including Bayesian deep learning or ensemble-based quantile regression, would facilitate uncertainty estimation and enhance operational risk management. Third, initiatives should focus on transfer learning and domain adaptation methods to enhance model adaptability across various wind farm locations and climatic conditions. Moreover, forthcoming models may benefit from incorporating attention mechanisms or transformer architectures, which can more effectively capture long-range dependencies and intricate temporal patterns than traditional LSTM frameworks. Augmenting datasets with multi-modal inputs, such as satellite-derived meteorological data or turbine SCADA outputs, could enhance feature importance evaluations and improve forecasting accuracy.

Conclusion

This study proposed a hybrid intelligent forecasting model that combines LSTM networks with CEEMD and a multi-strategy optimisation algorithm integrating ACO, GA, and PSO. The model was validated using a real-world dataset from a 138 MW onshore wind farm comprising 46 turbines, utilising historical wind speed and power generation data from 2019. The results demonstrated that the hybrid model significantly outperformed benchmark models, including standalone LSTM and traditional statistical approaches, regarding forecasting accuracy. For 24-h ahead predictions, the model achieved an RMSE of 0.142, an MAE of 0.117, and an MAPE of 3.8%. Compared to the baseline LSTM model, which yielded an RMSE of 0.229, the hybrid framework achieved a 38% improvement in forecast accuracy. The model also maintained acceptable performance over longer prediction horizons (72 and 168 h), with an accuracy degradation of less than 15%, confirming its resilience and adaptability across varying temporal scales.

The inclusion of CEEMD proved effective in isolating high-frequency noise components, thereby enhancing the LSTM's ability to model underlying temporal trends in wind power data. Concurrently, the ACO-GA-PSO optimiser demonstrated superior performance in tuning model hyperparameters, mitigating risks of overfitting and improving convergence efficiency. Despite these advancements, the model faces several challenges. These include increased computational demands, limited generalisability across different geographic locations, and the absence of probabilistic uncertainty quantification, an essential feature for grid operation and energy market forecasting. In conclusion, this research presents a robust, scalable, and high-precision wind power forecasting model with strong potential for improving operational planning, grid reliability, and market participation in wind-integrated energy systems. Future work should prioritise enhancing computational efficiency through model pruning or parallelisation, employing transfer learning for broader applicability, and integrating probabilistic forecasting techniques to better manage uncertainty in renewable energy forecasting.

Appendix

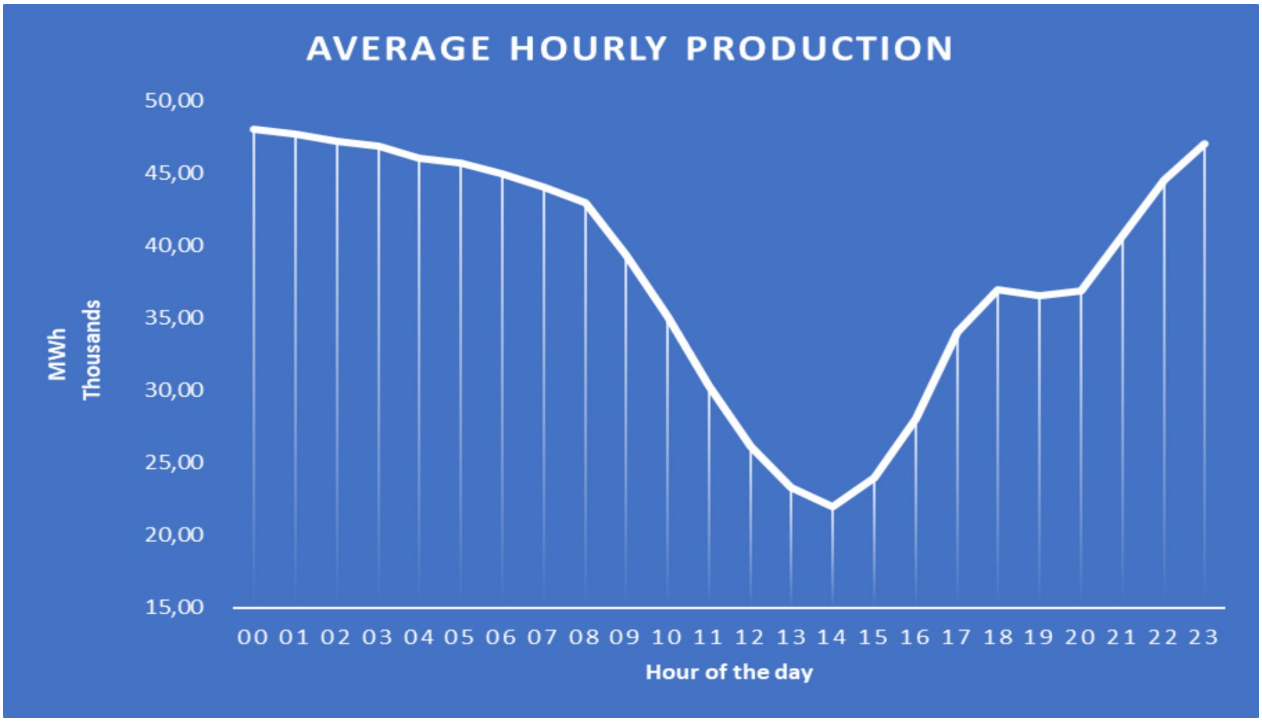


Fig. 16 Average hourly energy production [56]

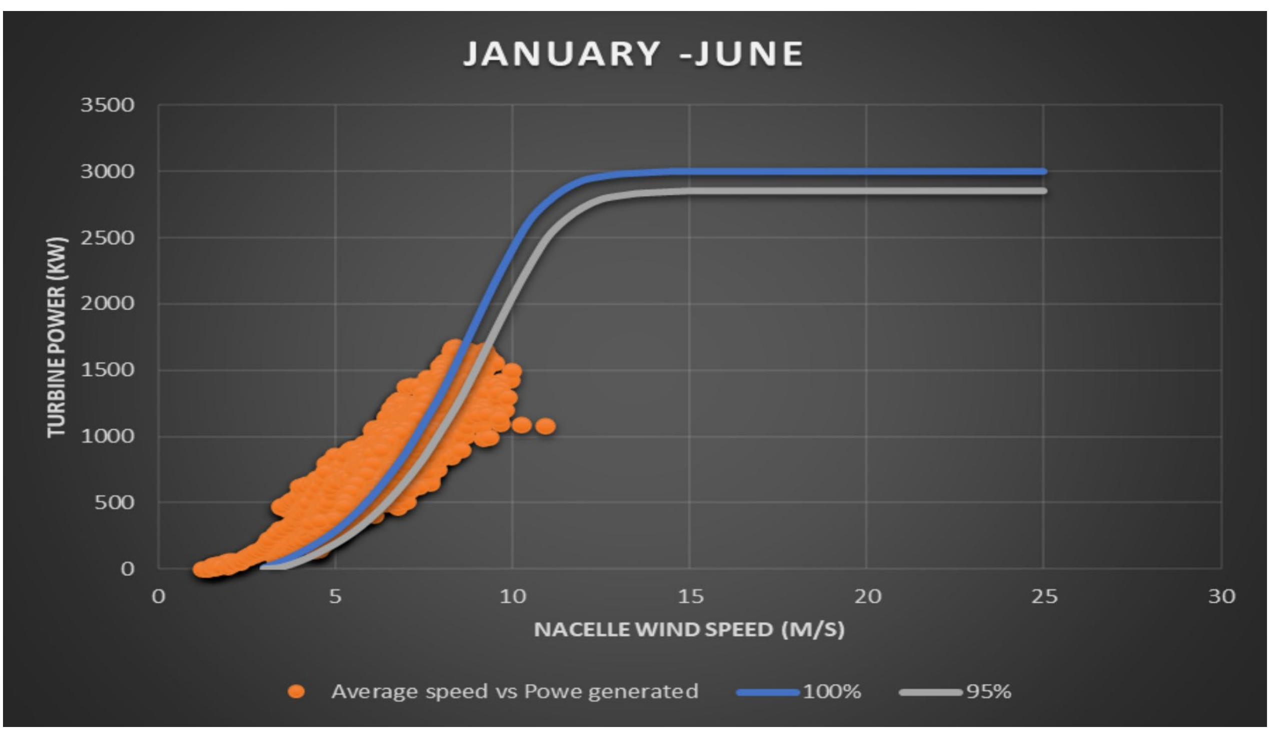


Fig. 17 Monthly energy production [56]

Fig. 18 LSTM

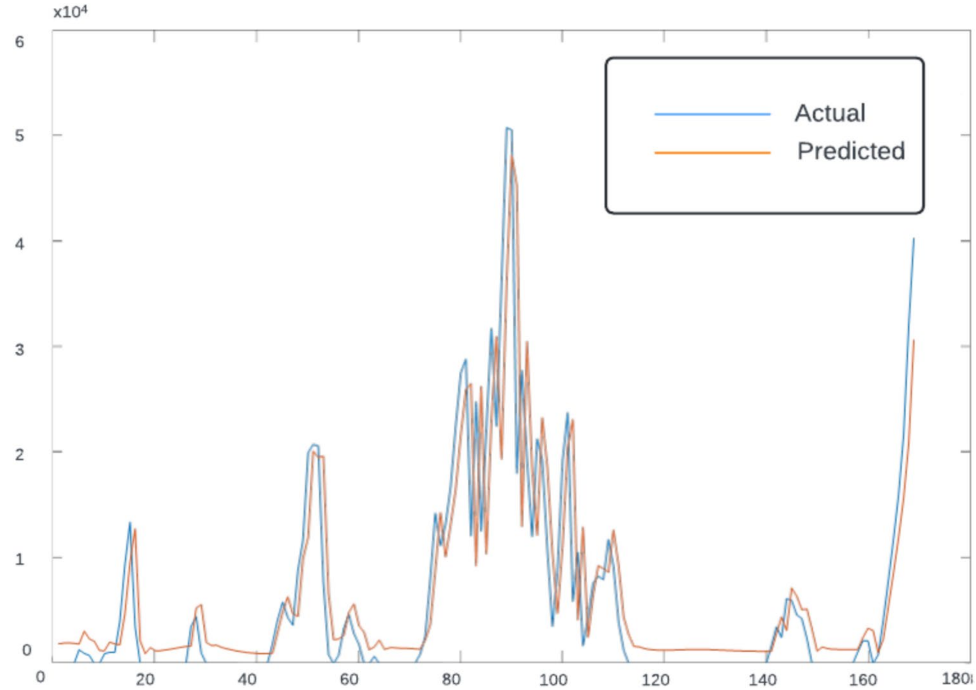


Fig. 19 LSTM + EMD

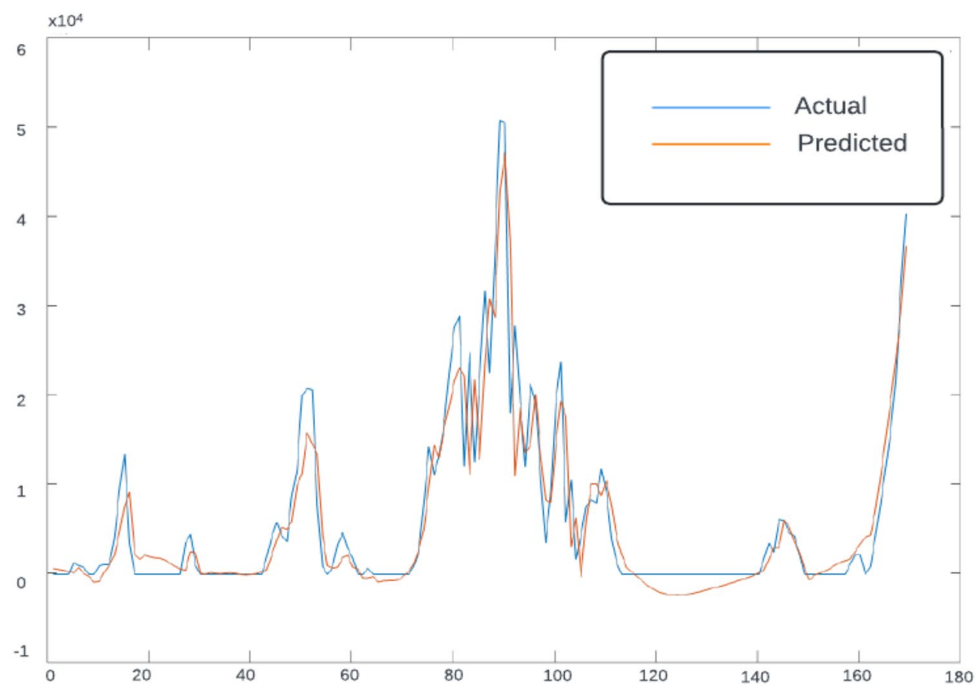
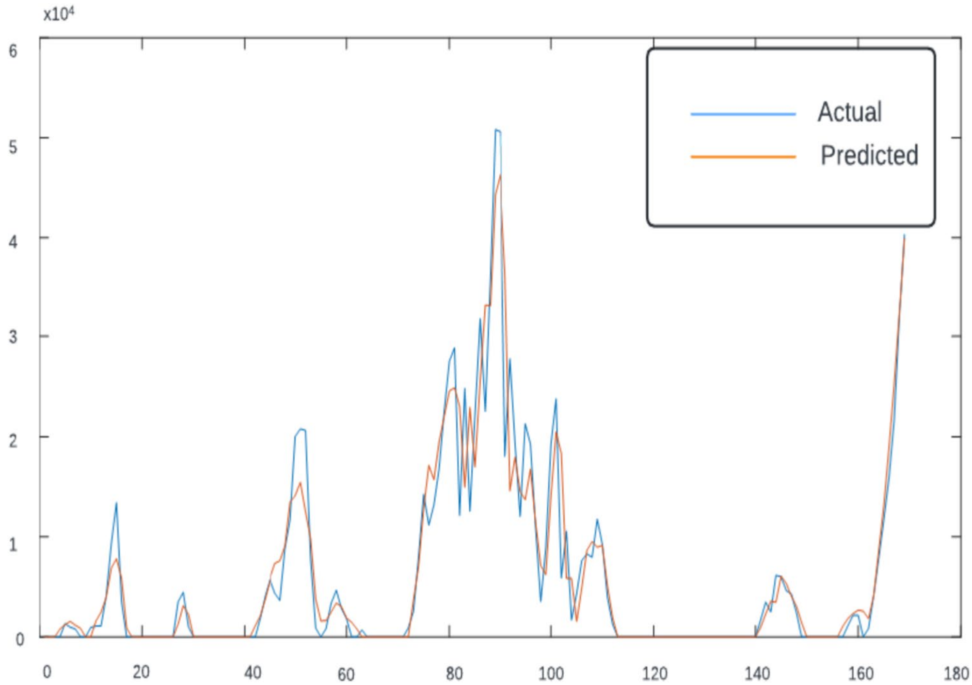


Fig. 20 LSTM + CEEMD



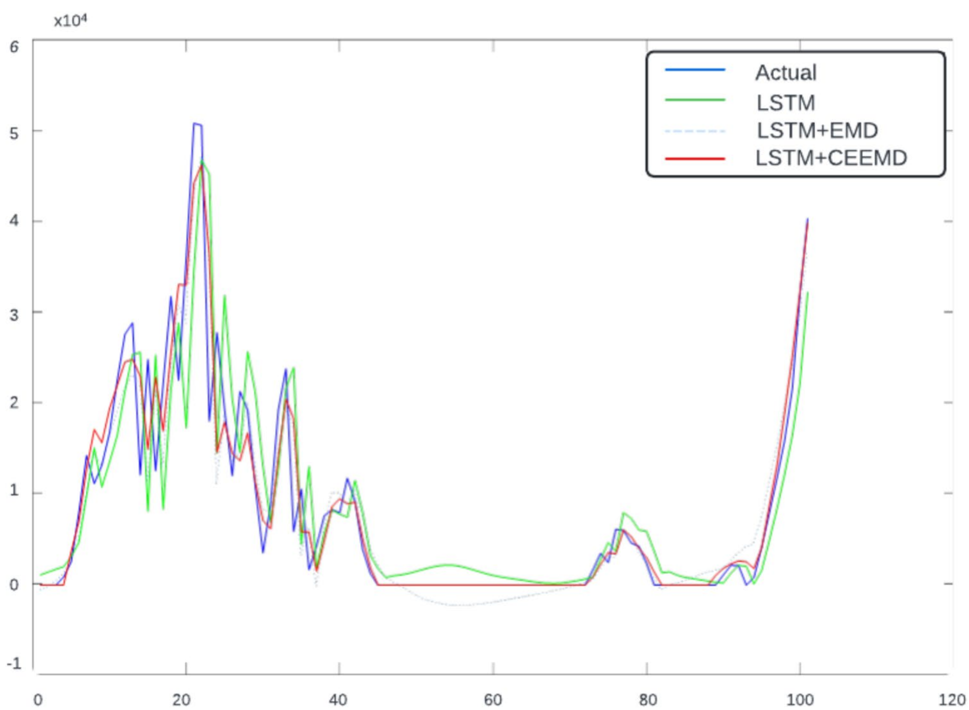


Fig. 21 LSTM + EMD + CEEMD

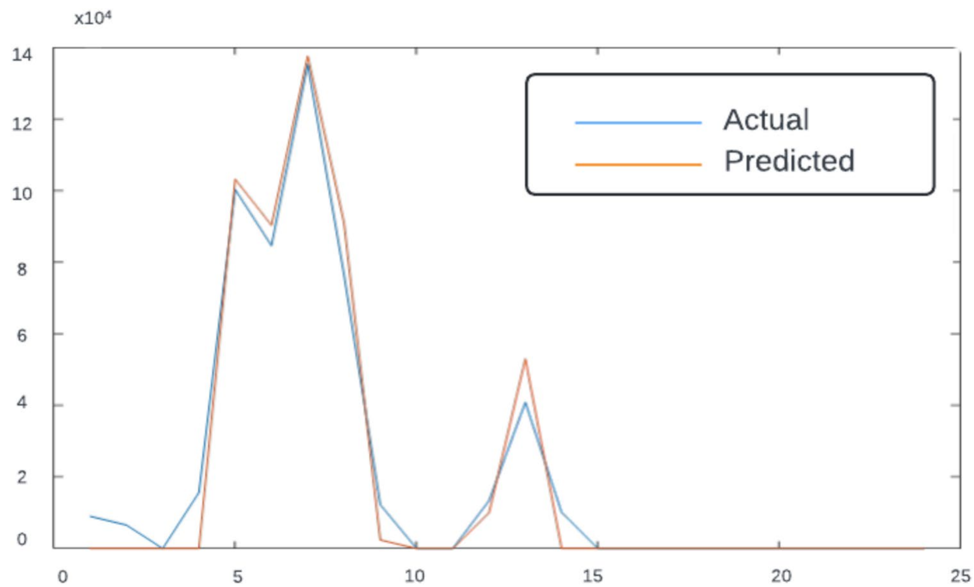


Fig. 22 LSTM + CEEMD + ACO-GA: 24 h ahead

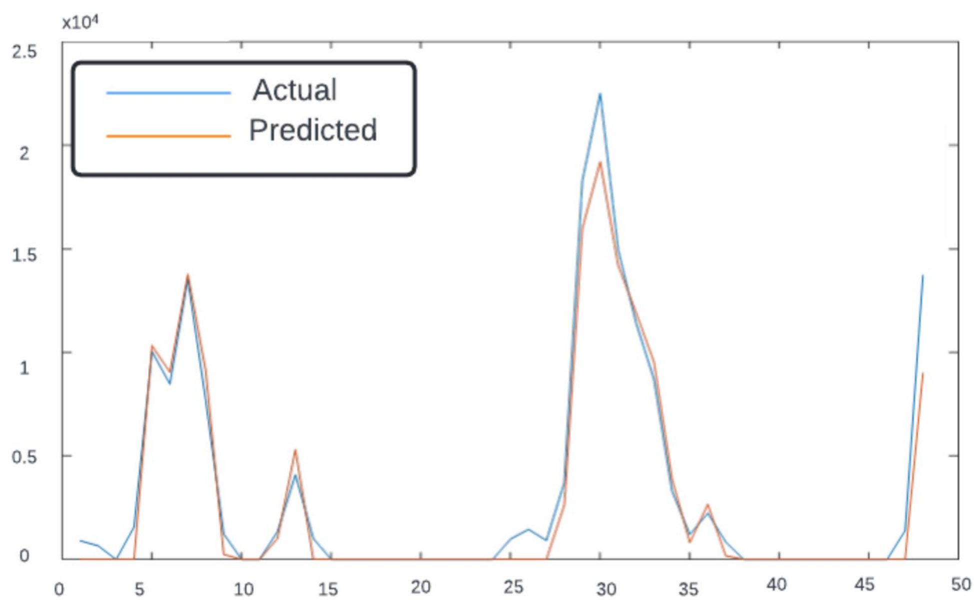


Fig. 23 LSTM + CEEMD + ACO-GA: 48 h ahead

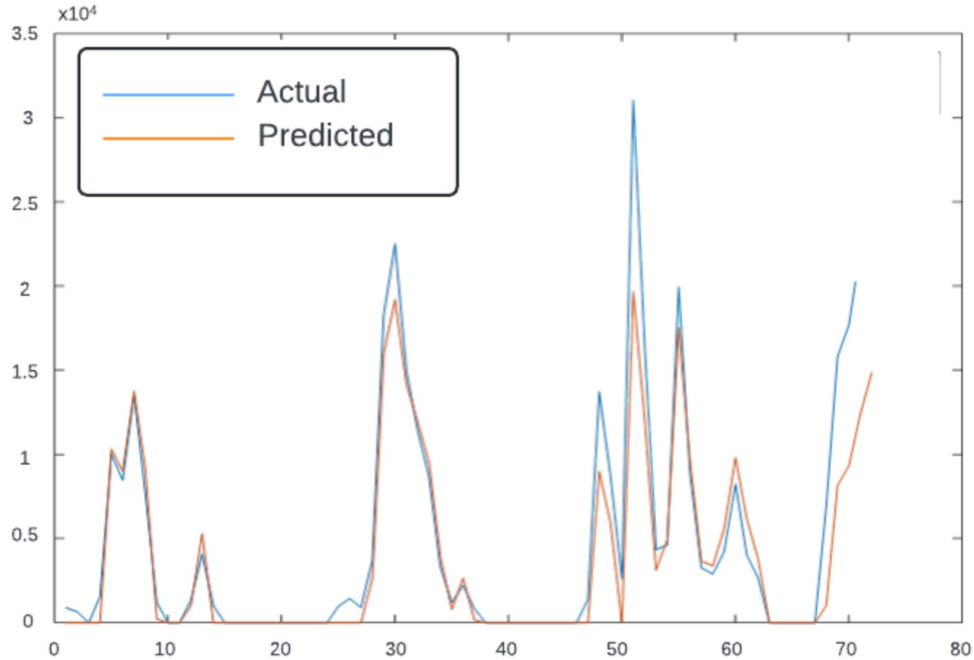


Fig. 24 LSTM + CEEMD + ACO-GA: 72 h ahead

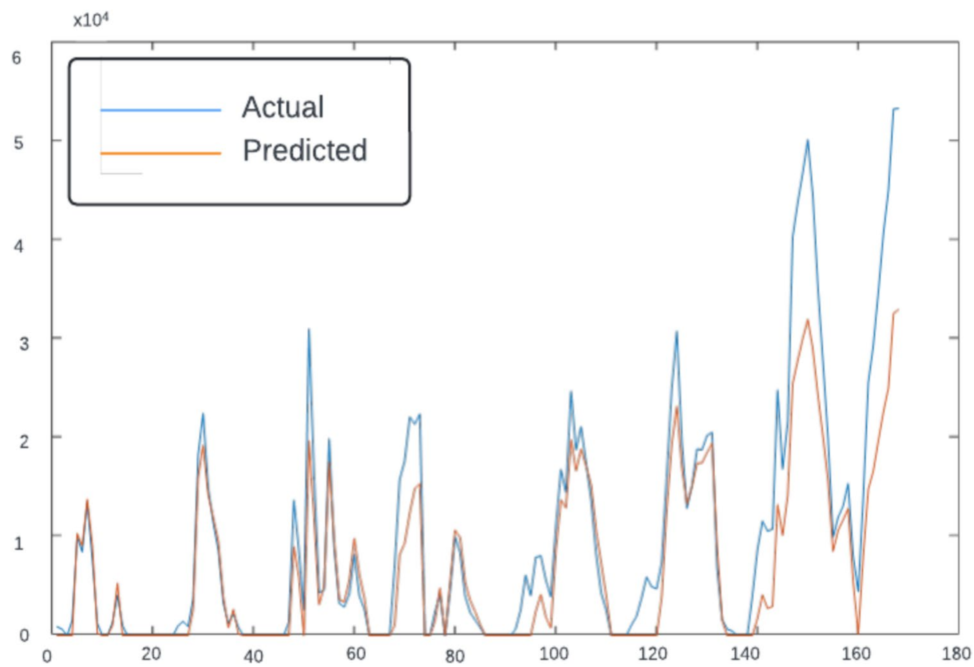


Fig. 25 LSTM + CEEMD + ACO-GA: 168 h ahead

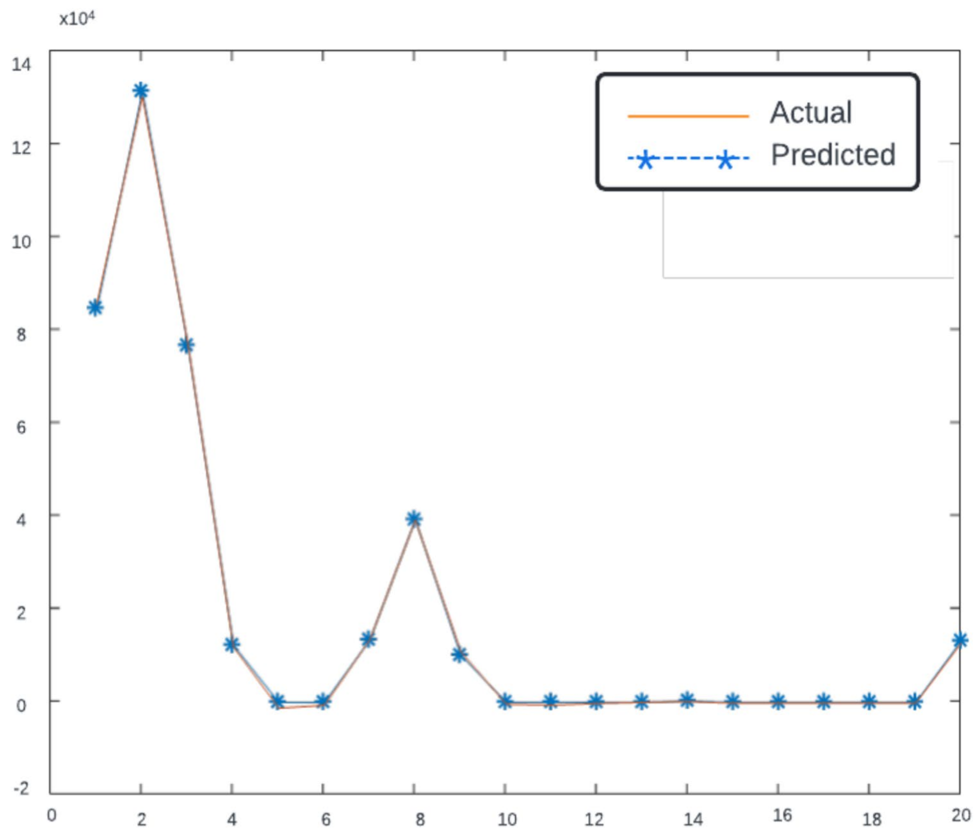


Fig. 26 LSTM + CEEMD + ACO-GA-PSO: 24 h ahead,

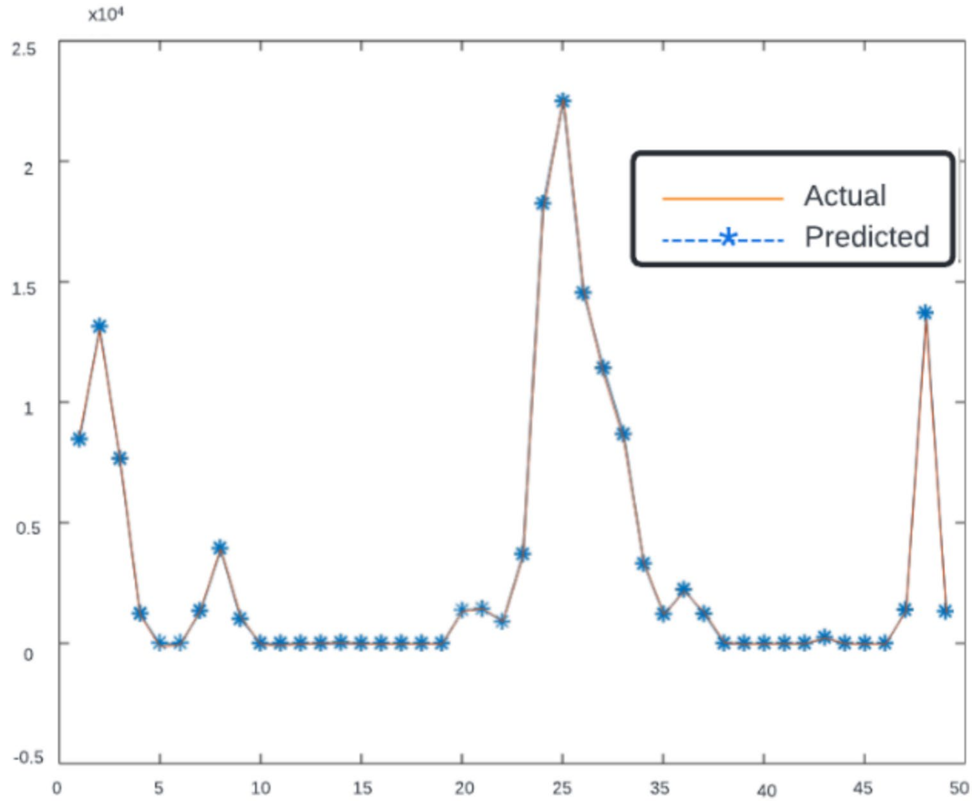


Fig. 27 LSTM + CEEMD + ACO-GA-PSO: 48 h ahead

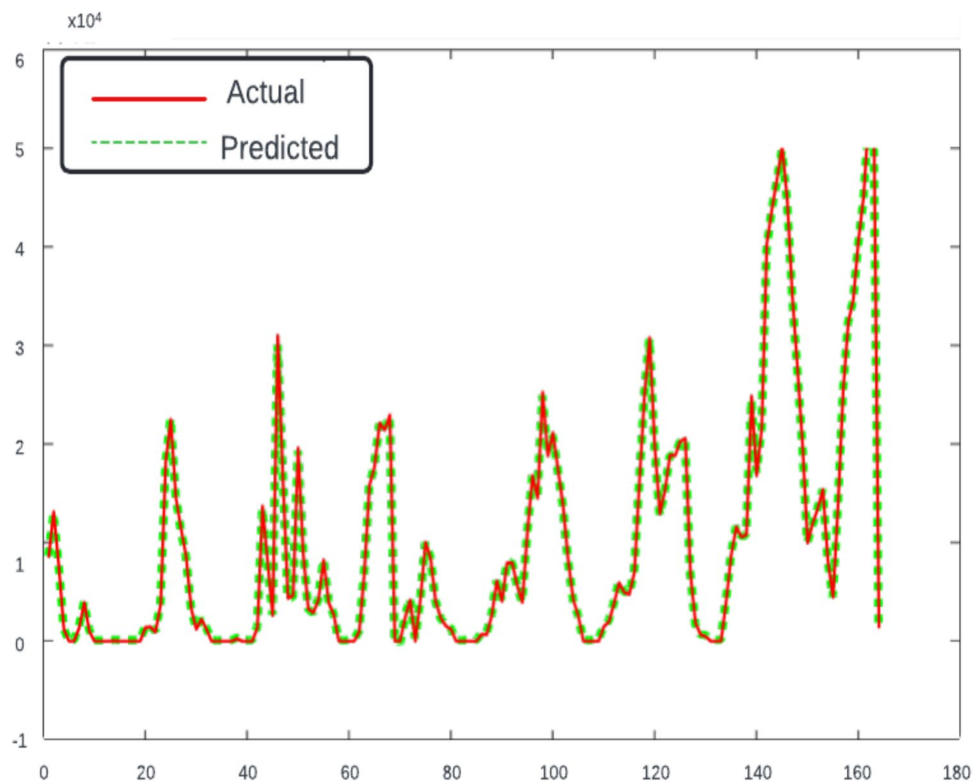


Fig. 28 LSTM + CEEMD + ACO-GA_PSO: 72 h ahead

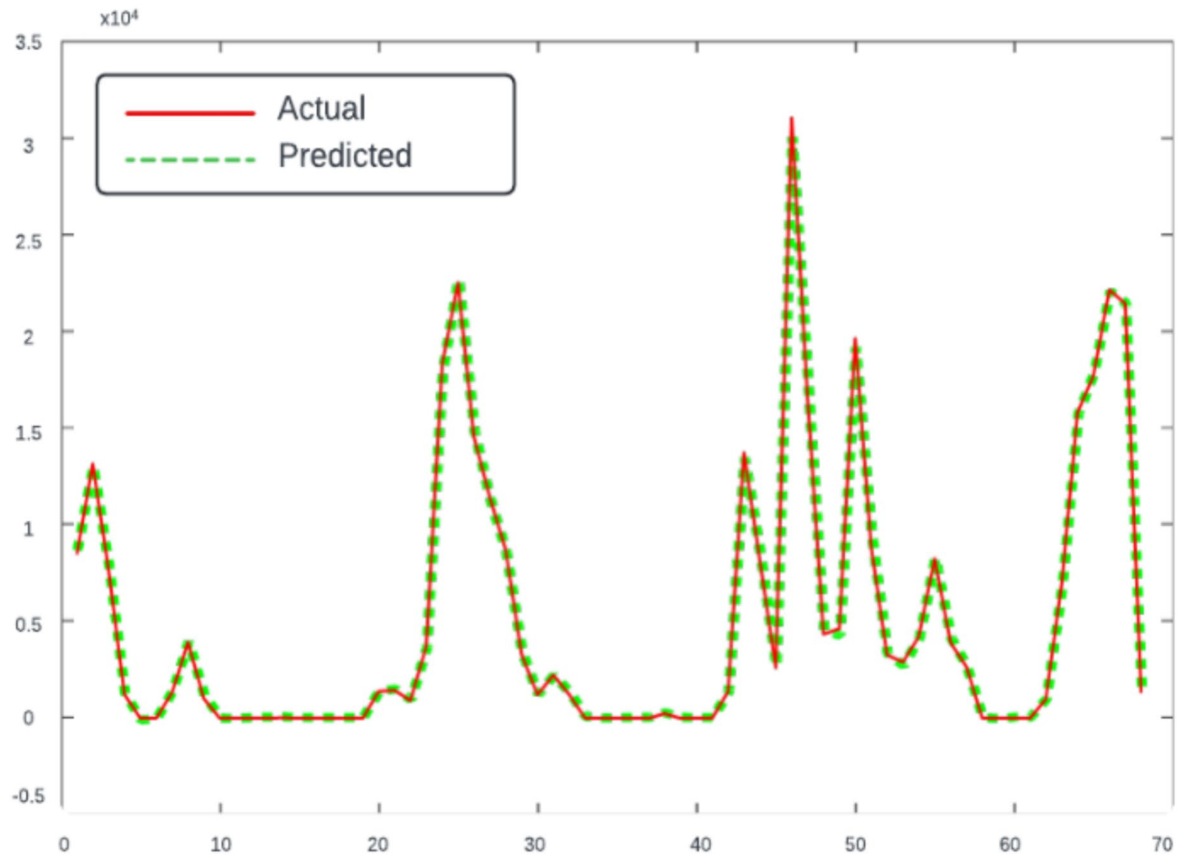


Fig. 29 LSTM + CEEMD + ACO-GA-PSO: 168 h ahead

Fig. 30 Training time per model

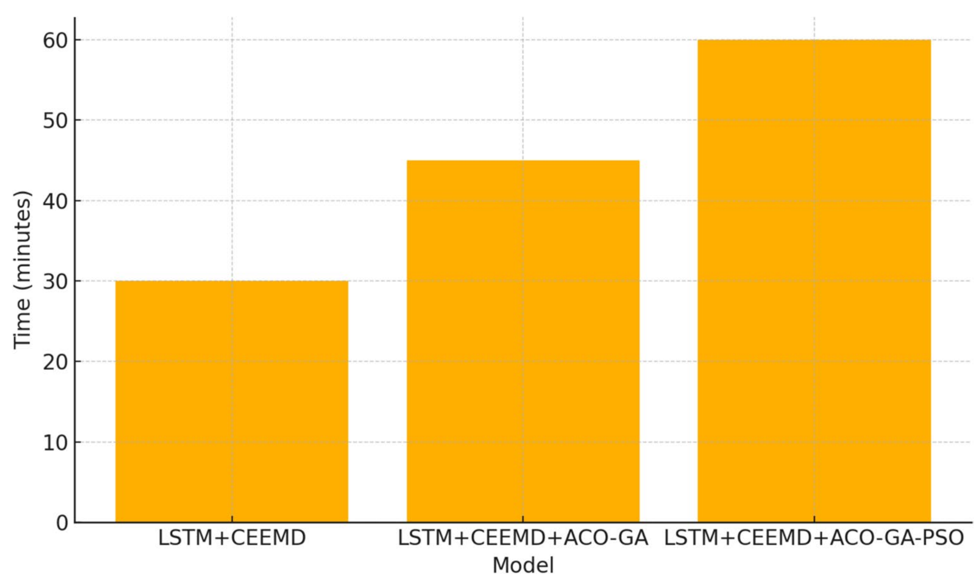


Fig. 31 Training time per model

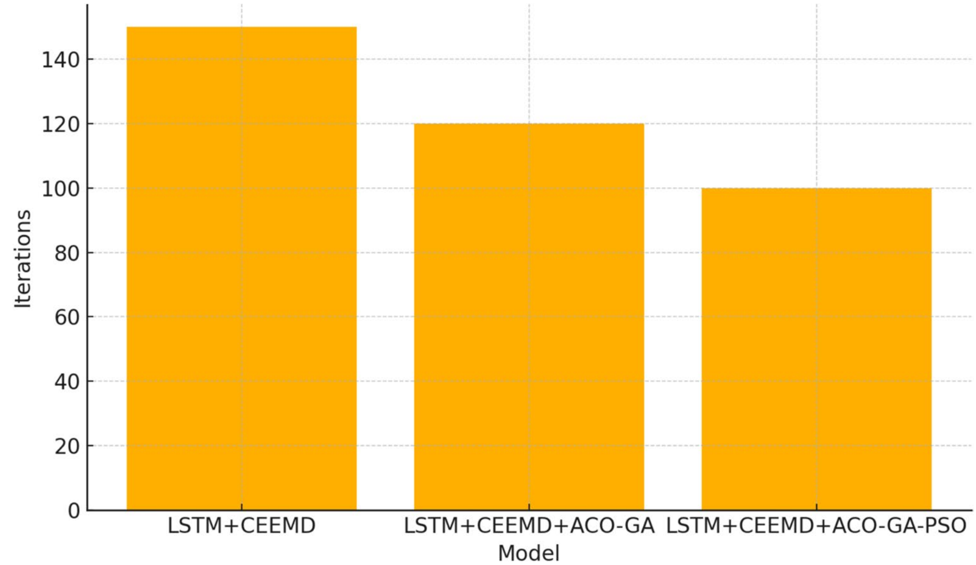


Fig. 32 Sensitivity Analysis

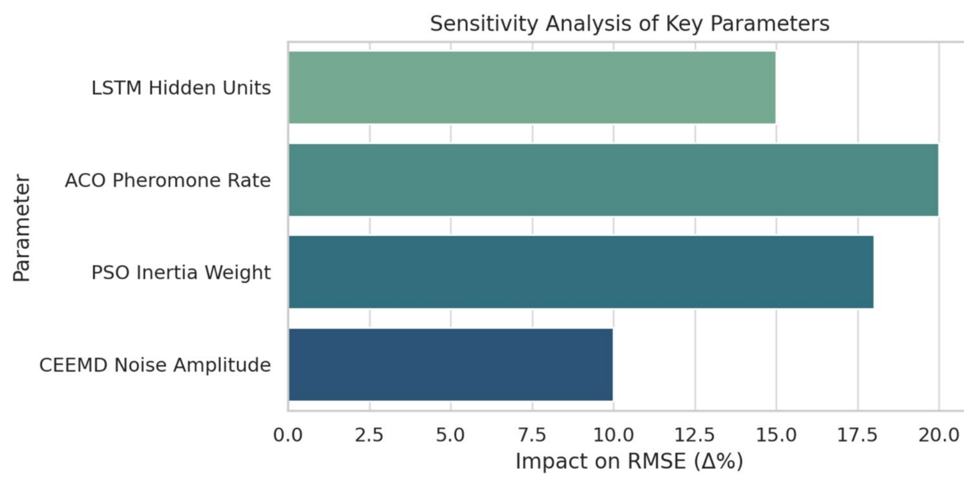
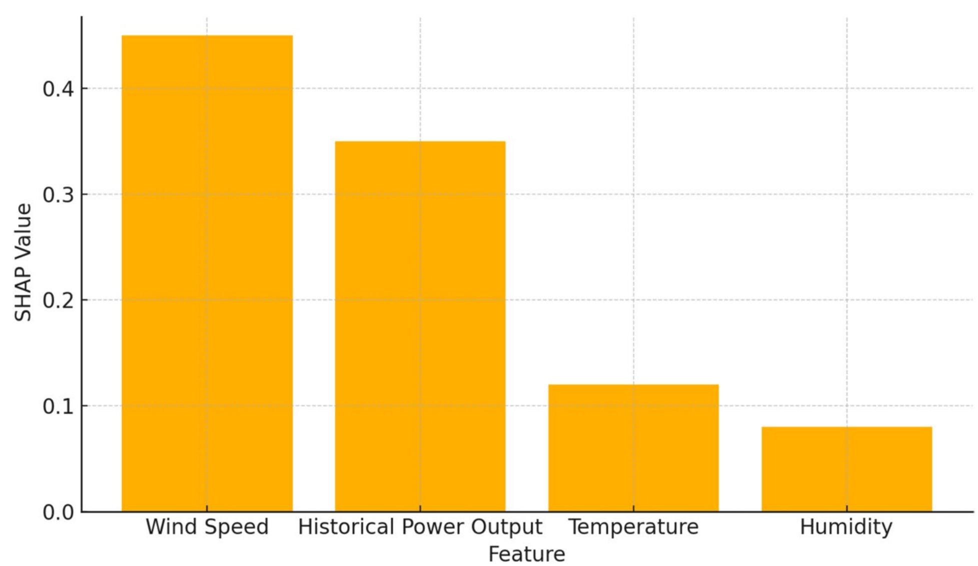


Fig. 33 Sensitivity Analysis



Author Contributions M.G., R.C.B., and A.B. conceptualised the study and designed the methodology. M.G. developed the hybrid intelligent model, performed the data analysis, and wrote the initial draft of the manuscript. R.C.B. supervised the research, provided critical insights on model optimisation, and revised the manuscript for technical accuracy. A.B. contributed to data acquisition from the South African onshore wind farm, validated the model's real-world applicability, and assisted in manuscript revisions. All authors reviewed and approved the final manuscript.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Ethical Approval N/A.

Competing interests The authors declare no competing interests.

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