

National Roundtable-cum-Knowledge Exchange Workshop on Scaling Renewables without breaking the GRID

Importance of Forecasting in RE Sector: Wind Speed Forecasting Using Deep Learning Models

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HRED: Academic Programmes

a) Undergraduate – B.Tech program in Energy Engineering from July 2024 onwards with annual intake of 20 students through JEE advance

b) Post Graduate

- Minor degree specialization in Renewable Energy Technology (5-6 courses)
- 06 Elective Courses per year

Area	Intake
M.Tech (Renewable and Hydro Energy) (since 1997)	15 Regular (GATE Qualified) 05 Sponsored – Govt. nominees 05 GATE Qualified (MNRE fellowship) 15 Sponsored – through ITEC of MEA
M.Tech (Environmental Management of Rivers and Lakes) (Since 2004)	15 Regular GATE qualified 05 (Sponsored by Ministry of Jal Shakti) 05 (Sponsored by others) 10 Sponsored – through ITEC of MEA

c) Ph.D.

100+ scholars Awarded, 70+ currently working

HRED: Research Domains



Research Areas of Department of Hydro and Renewable Energy (HRED)

Renewable Energy

Hydro Power



Designs, Economic and Financial Analysis
Policy, Cost Optimization, Tariff analysis

Solar Energy



Solar photovoltaics,
Solar thermal energy
Storage & utilization
Inverters and protection from overvoltage in PV

Grid Integration



Grid reliability and resilience under very – high variable renewable energy penetration

Energy Storage, EV and other area



Energy storage, charging, solar assisted EV, V2G, G2V

Bio Energy



Biomass Conversion processes such as torrefaction, gasification, pyrolysis

Waste to Energy Green Hydrogen and Fuel Cells



PEM Fuel Cells, Electrolysers, Stack Development

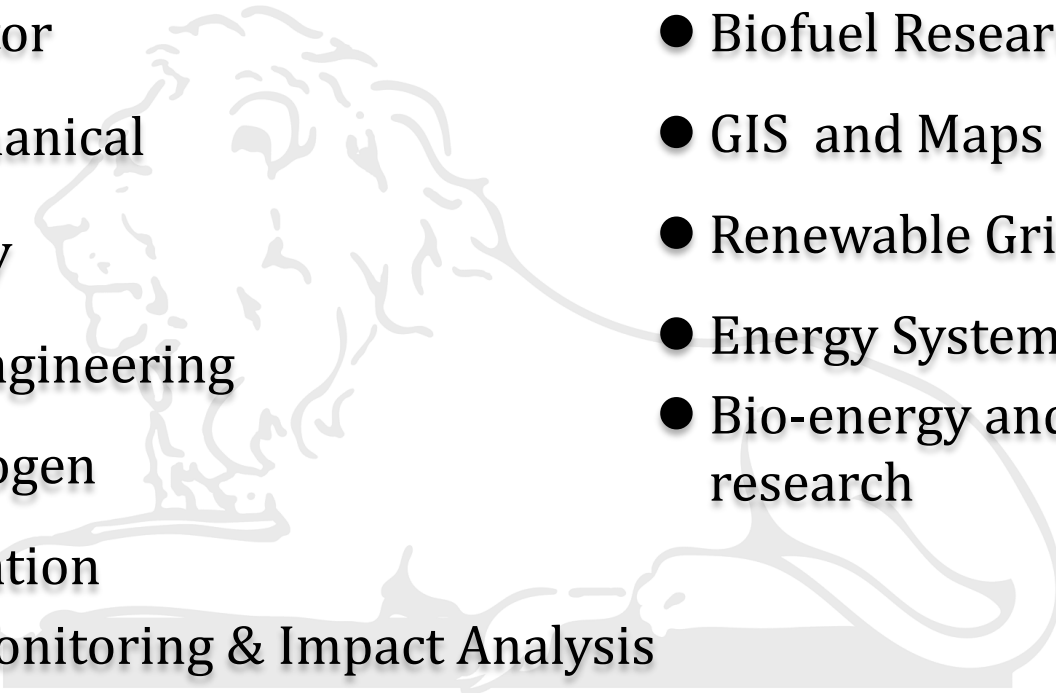
Environmental Management

Environmental Management of Water Bodies



- Cumulative EIA
- GHG Emission from Hydropower Reservoir, MSW Dump Sites / Landfill gas sites,
- River Water Quality Mapping
- Ecological Health & Carrying Capacity of Rivers
- Wastewater Treatment

HRED: Laboratories

- 
- A faint, light-colored background image of a statue, likely a historical figure, is visible behind the text.
- Hydraulic turbine R&D
 - SHP Simulator
 - Hydro-mechanical
 - Solar Energy
 - Electrical Engineering
 - Green Hydrogen
 - Instrumentation
 - Sediment Monitoring & Impact Analysis
 - Environmental
 - Biofuel Research
 - GIS and Maps
 - Renewable Grid Integration
 - Energy Systems Modelling
 - Bio-energy and water research

Introduction

- India has committed to achieve 50% of its installed electricity capacity from non-fossil fuels, by 2030.
- AI, data centres, and advance manufacturing collectively account for $\approx 20\%$ of global electricity consumption [1].
- To account for intermittency, a long-duration storage solution is needed.



$\approx 20\%$
Global demand

Global electricity demand growth due to advance economics



500 GW

Non-fossil capacity target by 2030



India, 2030 target



Peak

Midnight

Midnight

Intermittent solar output

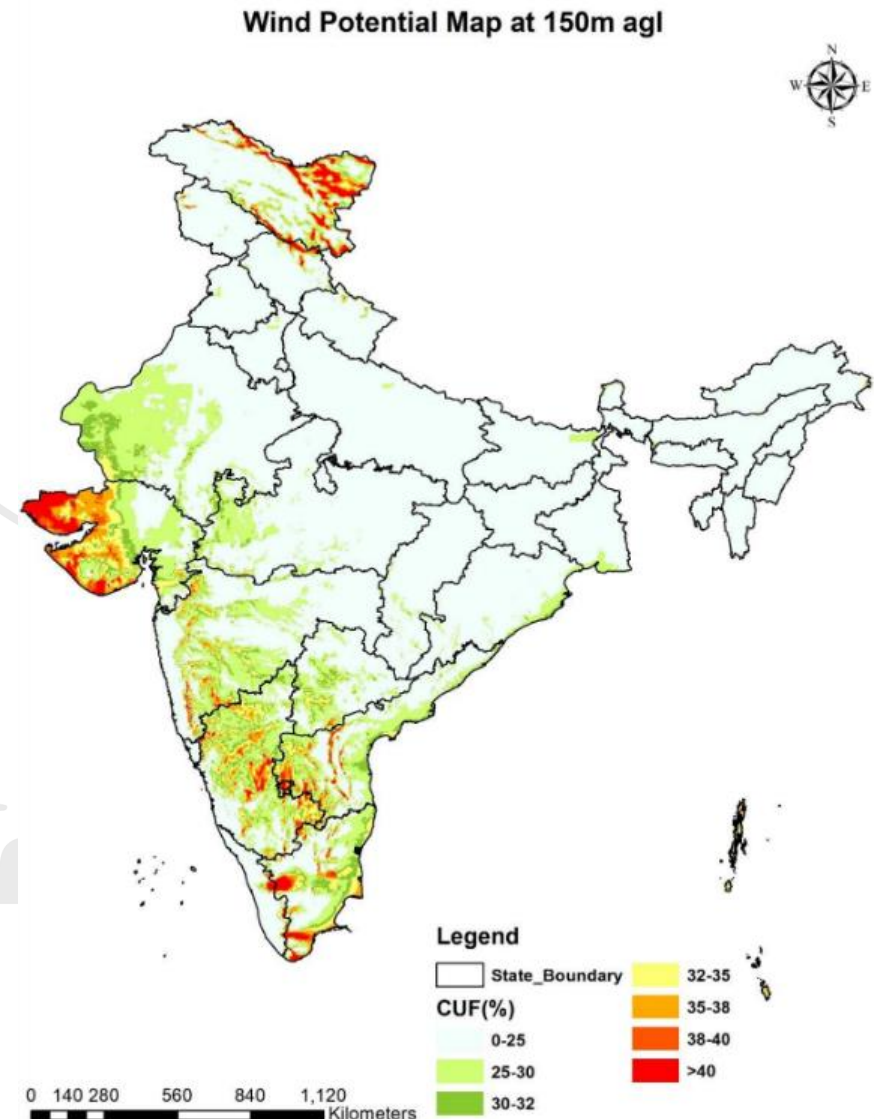
Long-duration storage



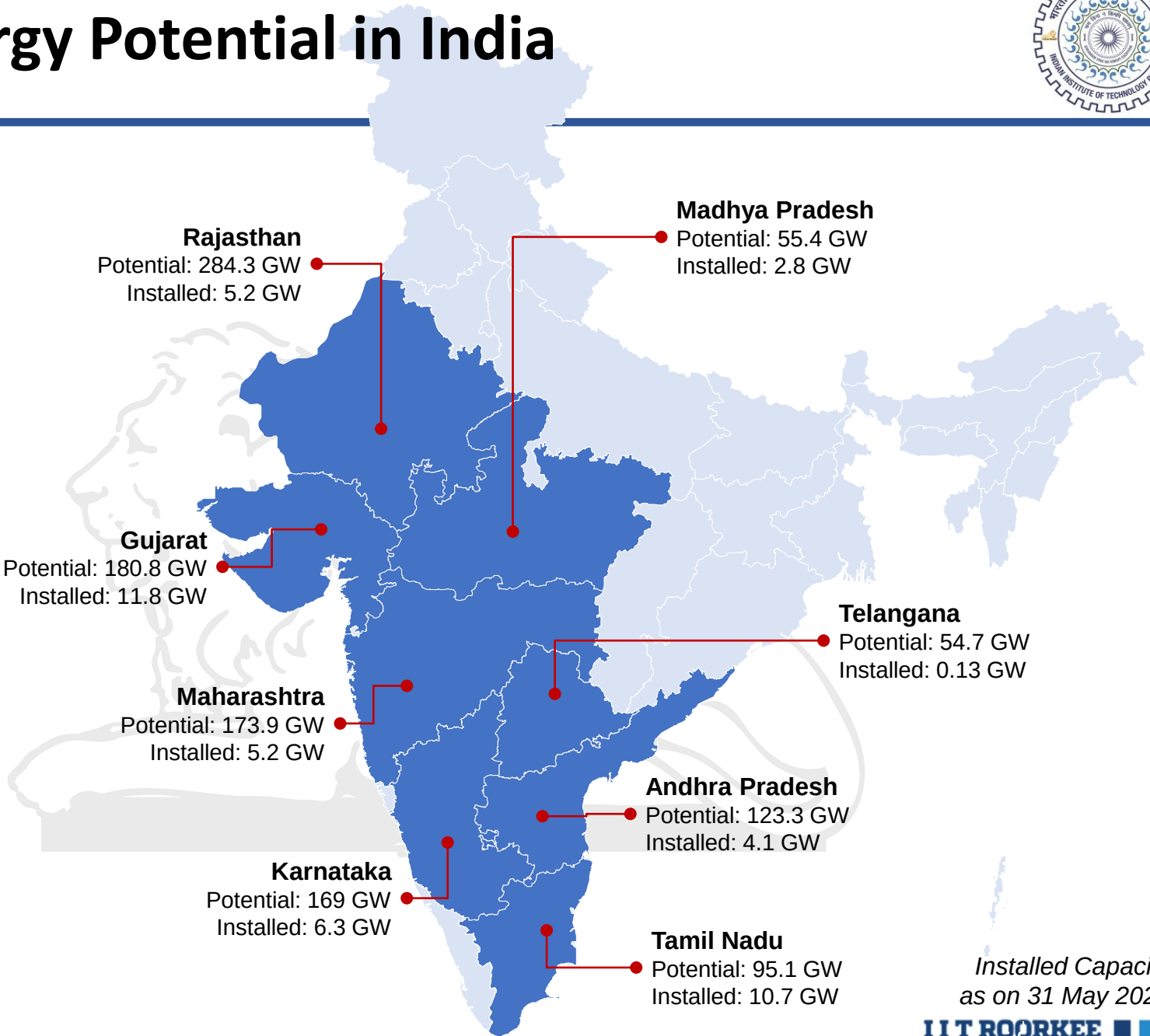
Needed storage for evening and overnight

Wind Energy Potential in India

- The WRA programme in India was initiated in 1986, and the programme currently has nearly 3,000 wind monitoring stations for data collection
- Data from the met masts are coupled with the wind resource assessments generated through meso-micro coupled WRF modelling techniques
- Over the years, the National Wind Resource Assessment Program of NIWE has carried out potential estimation at various heights – 50 m, 80 m, 100 m, 120 m and 150m



Wind Energy Potential in India



Estimated by
NIWE at 150 m
agl

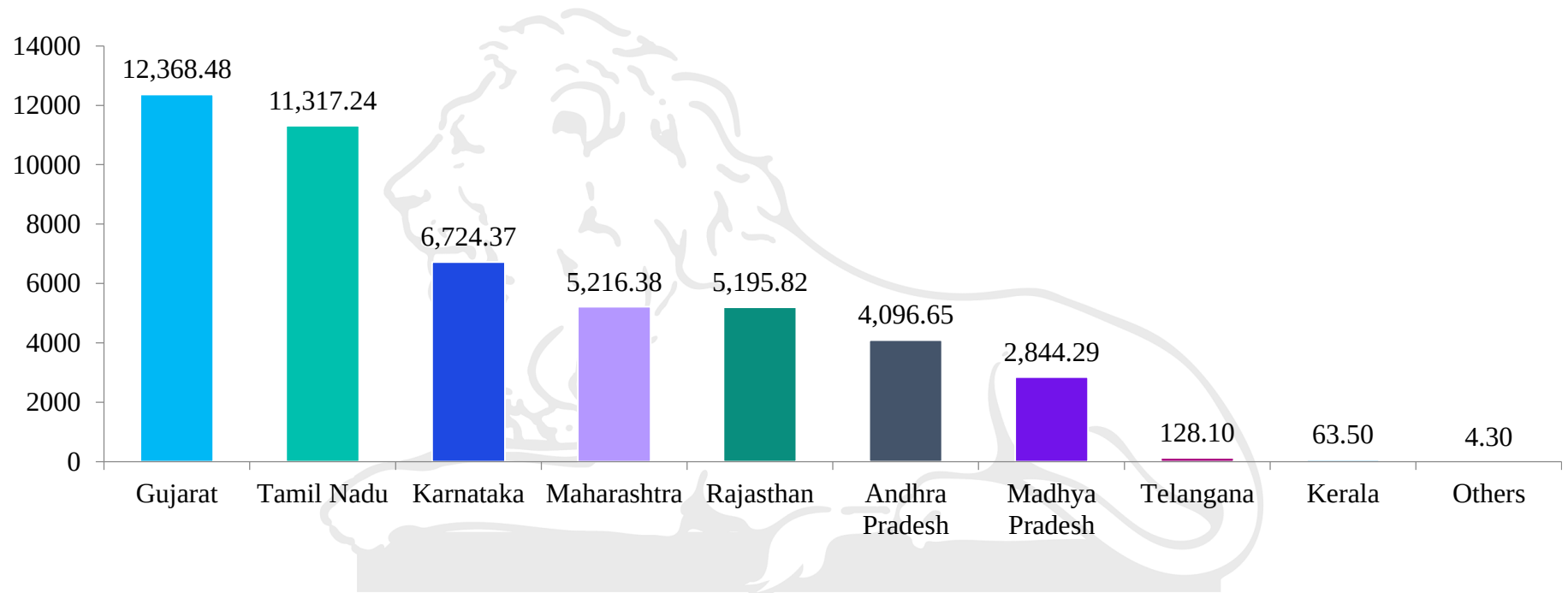
Total (8 windy
states) = 1,136
GW

Total (All India)
= 1,164 GW

Installed Capacity
as on 31 May 2024

Major States of Wind Power Capacity in India

- Gujarat Leads India's Wind Power Capacity
- Top 3 states holds ~63% share



Opportunities, Challenges and Solutions

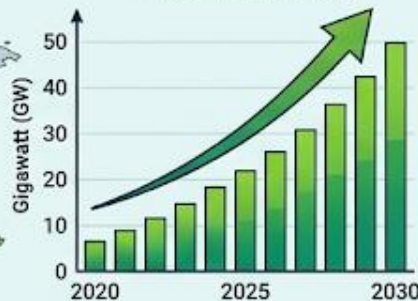
WIND POWER: OPPORTUNITIES AND CHALLENGES IN GRID INTEGRATION

THE OPPORTUNITIES & GROWTH OF WIND POWER

Wind power has become an important part of smart grids, smart microgrids, and plays an important role in power supply.



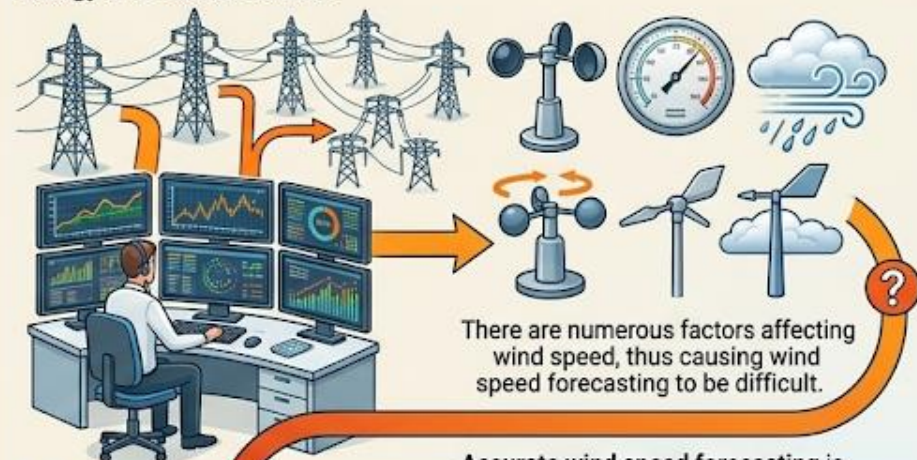
Nations with wind power growth = Total Wind Capacity



■ Nations with wind power growth
■ High potential regions

THE INTEGRATION CHALLENGES & SOLUTION

Besides, uncontrollable and fluctuating wind speeds can significantly affect the stability exhibited by the power system, limiting the full utilization of wind energy to a certain extent.



There are numerous factors affecting wind speed, thus causing wind speed forecasting to be difficult.

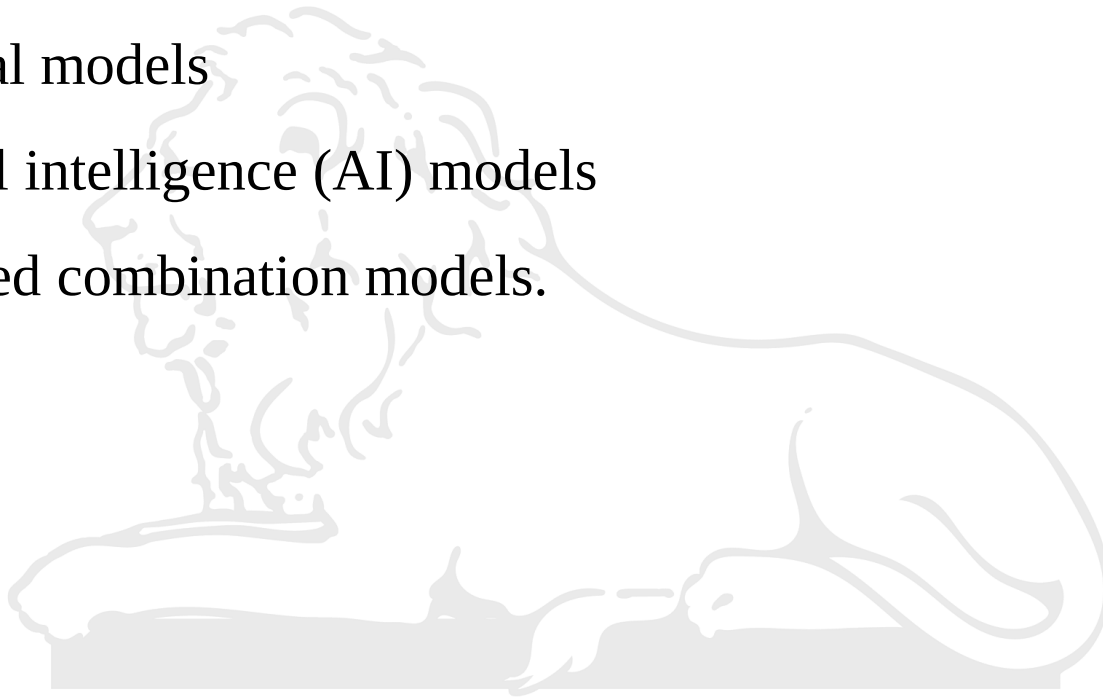
Accurate wind speed forecasting is capable of increasing the stability of wind power systems.



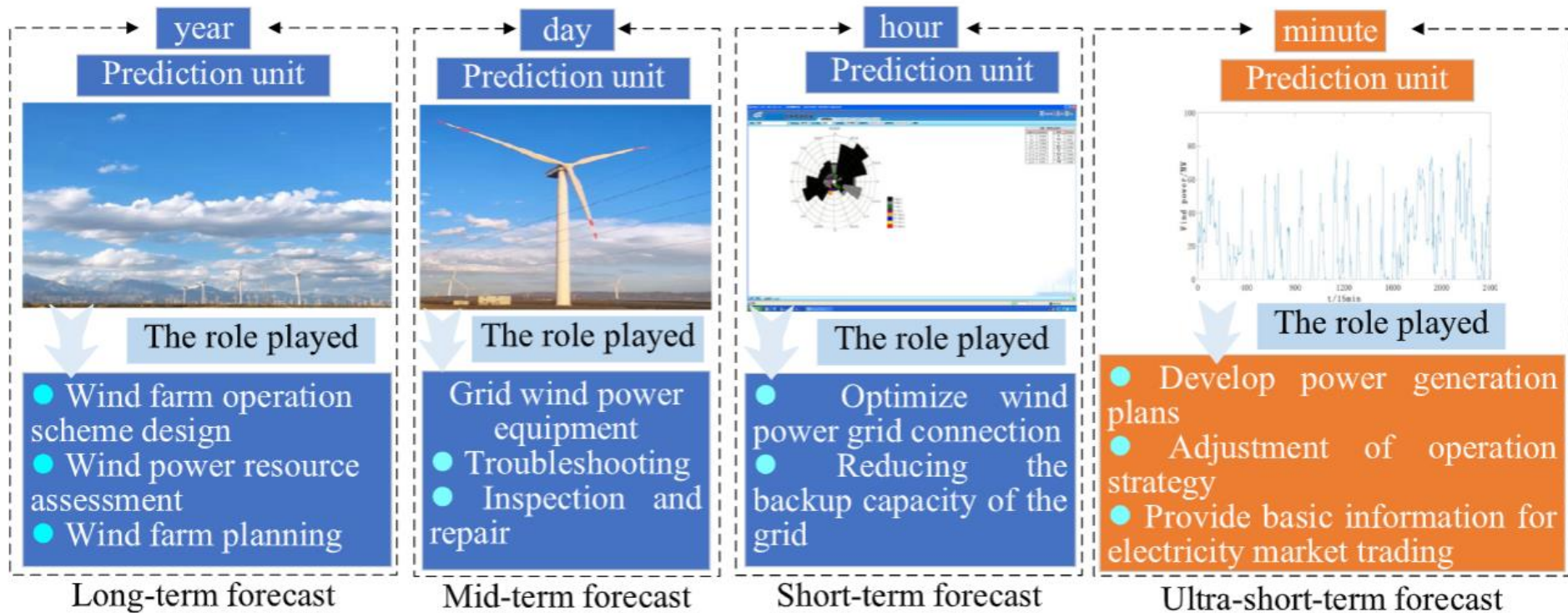
ADVANCING POWER SYSTEM STABILITY THROUGH PREDICTION

Classification of Wind Speed Forecasting

- Wind speed forecasting models are divided into four categories:
 - ☐ Physical models
 - ☐ Statistical models
 - ☐ Artificial intelligence (AI) models
 - ☐ Optimized combination models.



Classification of forecasting methods



- ☐ Ultra-short-term wind forecasting (few minutes to 30 min)
- ☐ Short-term wind forecasting (30 min to 6 h)
- ☐ Medium-term wind forecasting (6 h to a day)
- ☐ Long-term forecasting (more than a day)

Importance of Forecasting in the RE Sector

• GRID STABILITY



Supply must equal demand in real-time; unpredictable wind generation can cause frequency drops or blackouts without accurate advanced planning.

• ECONOMIC OPTIMIZATION



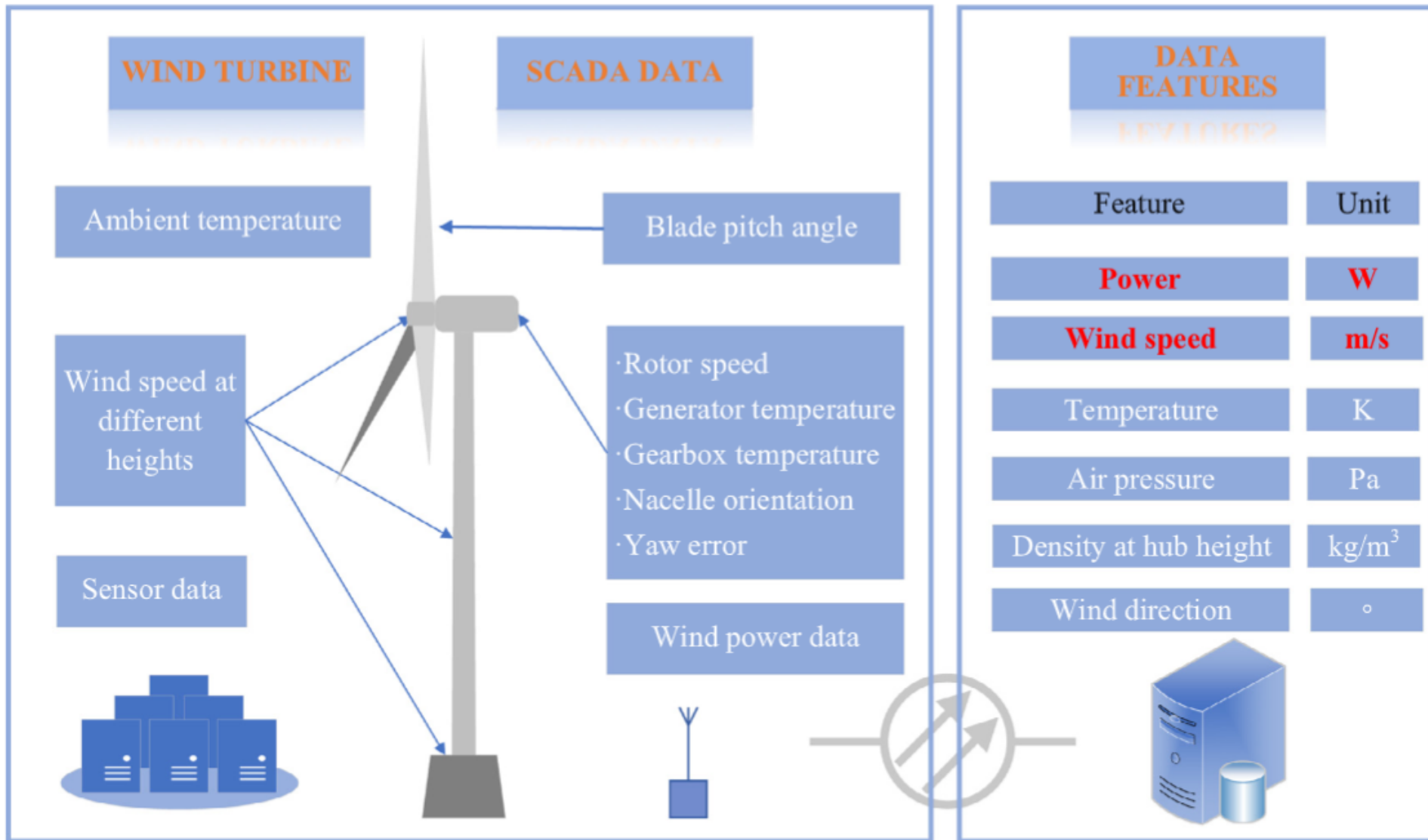
Precise forecasts improve market trading strategies, unit commitment, and economic dispatching while avoiding severe penalties on balancing markets.

• WASTE REDUCTION



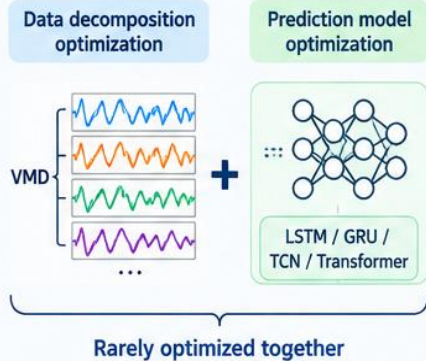
Reliable predictions prevent unnecessary power-limiting or curtailment policies that waste clean energy and lower plant profits.

Wind Turbines Data Characteristics



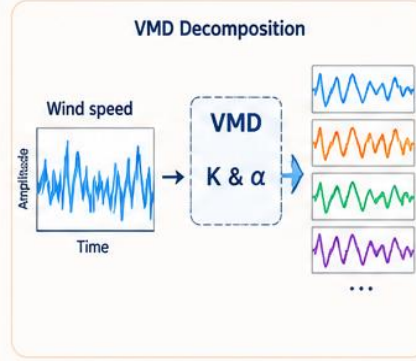
Critical Gaps in Wind Speed Forecasting

1 Limited optimization of the hybrid model



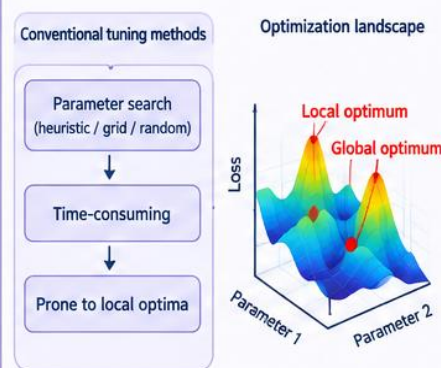
The existing hybrid wind speed forecasting models focus on optimizing either the data decomposition stage or the prediction model, but rarely both simultaneously.

2 Empirical selection of VMD parameters



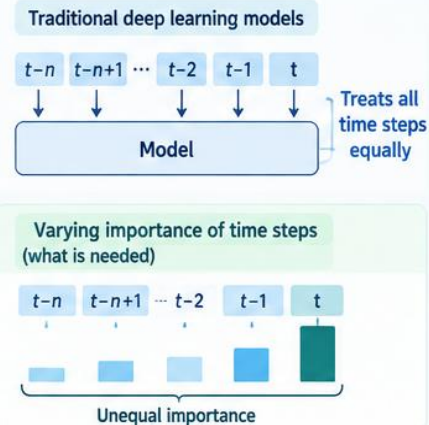
In many studies, the key parameters of VMD – K & α , are selected empirically or by trial-and-error, resulting in incomplete decomposition.

3 Time-consuming tuning and local optima



Conventional tuning methods are time-consuming and prone to local optima, negatively affecting forecasting stability.

4 Equal treatment of historical inputs



Many deep learning forecasting models treat all historical inputs equally, ignoring the varying importance of different time steps, which reduces their ability to capture complex wind speed dynamics.

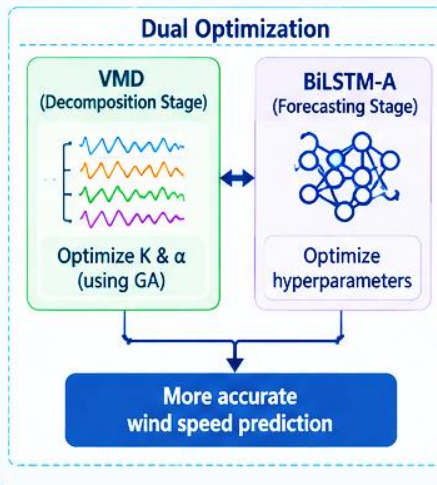


Addressing these gaps is essential for developing more accurate, stable and reliable wind speed forecasting models.

Optimized Hybrid Framework Development

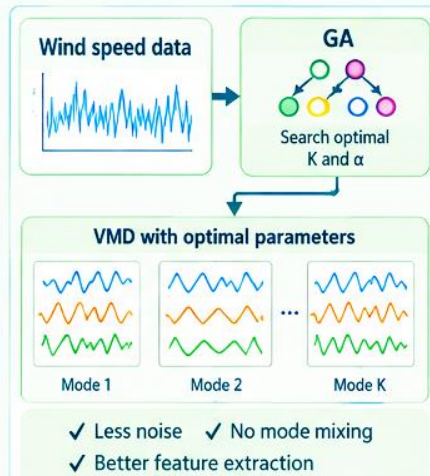
1 Dual-optimization framework

To develop a dual-optimization wind speed forecasting framework by integrating parameter optimization at both the data decomposition stage (VMD) and the forecasting stage (BiLSTM-A) to enhance overall prediction accuracy.



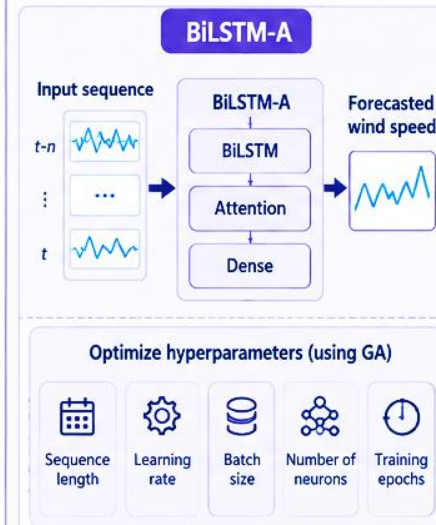
2 GA-based VMD parameter optimization

To optimize VMD parameters by employing GA to automatically determine optimal VMD parameters (K and α), thereby reducing noise, avoiding mode mixing, and improving feature extraction from wind speed data.



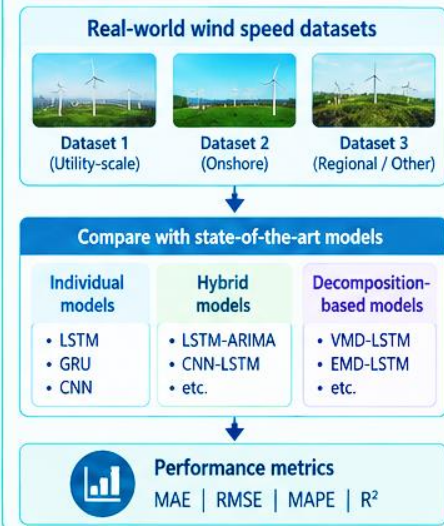
3 BiLSTM-A hyperparameter optimization

To optimize BiLSTM-A hyperparameters including sequence length, learning rate, batch size, number of neurons, and training epochs.



4 Comprehensive evaluation and comparison

To evaluate forecasting performance using multiple real-world wind speed datasets and compare results against several state-of-the-art individual, hybrid, and decomposition-based models.

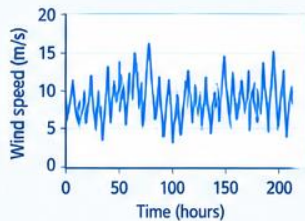


Outcome: An optimized hybrid wind speed forecasting framework for higher accuracy, stability and reliability.

GA-VMD-IDBO-BiLSTM – A Hybrid Framework

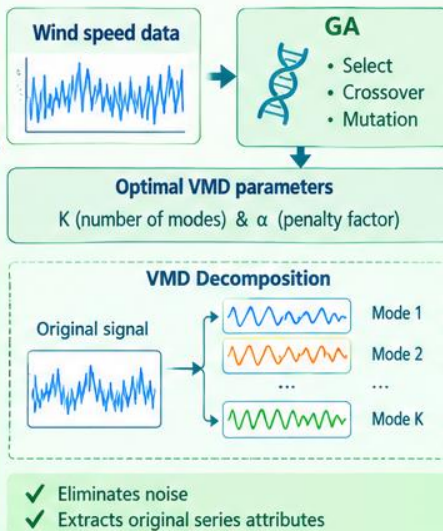
1 Input Data

Historical wind speed data



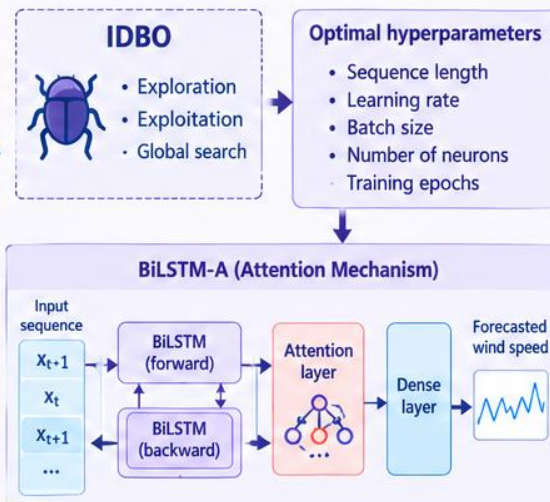
2 GA Optimized VMD

Genetic Algorithm (GA) optimizes VMD parameters (K and α).



3 IDBO Optimized BiLSTM-A

Improved Dung Beetle Optimization (IDBO) selects optimal hyperparameters for BiLSTM-A.



4 Model Evaluation

The proposed GA-VMD-IDBO-BiLSTM-A is compared with existing models to verify its forecasting performance.

Compared models

- Individual models (e.g., LSTM, GRU, CNN)
- Hybrid models (e.g., LSTM-ARIMA, CNN-LSTM)
- Decomposition-based models (e.g., VMD-LSTM, EMD-LSTM)

Evaluation metrics

MAE | RMSE | MAPE | R^2



Key Contributions

- 1 GA optimizes VMD for better decomposition and feature extraction.
- 2 IDBO optimizes BiLSTM-A hyperparameters for improved learning.
- 3 Integrated GA-VMD-IDBO-BiLSTM-A hybrid model for accurate forecasting.
- 4 Validated on real-world data from two locations: Stratford, California (USA) and Mumbai (India).
- 5 Outperforms existing state-of-the-art individual, hybrid and decomposition-based models.



More accurate wind speed forecasting for a sustainable and reliable energy future.



Mathematical Modeling

1. Variational Mode Decomposition:

VMD is used for decomposing the wind speed and the variational model is:

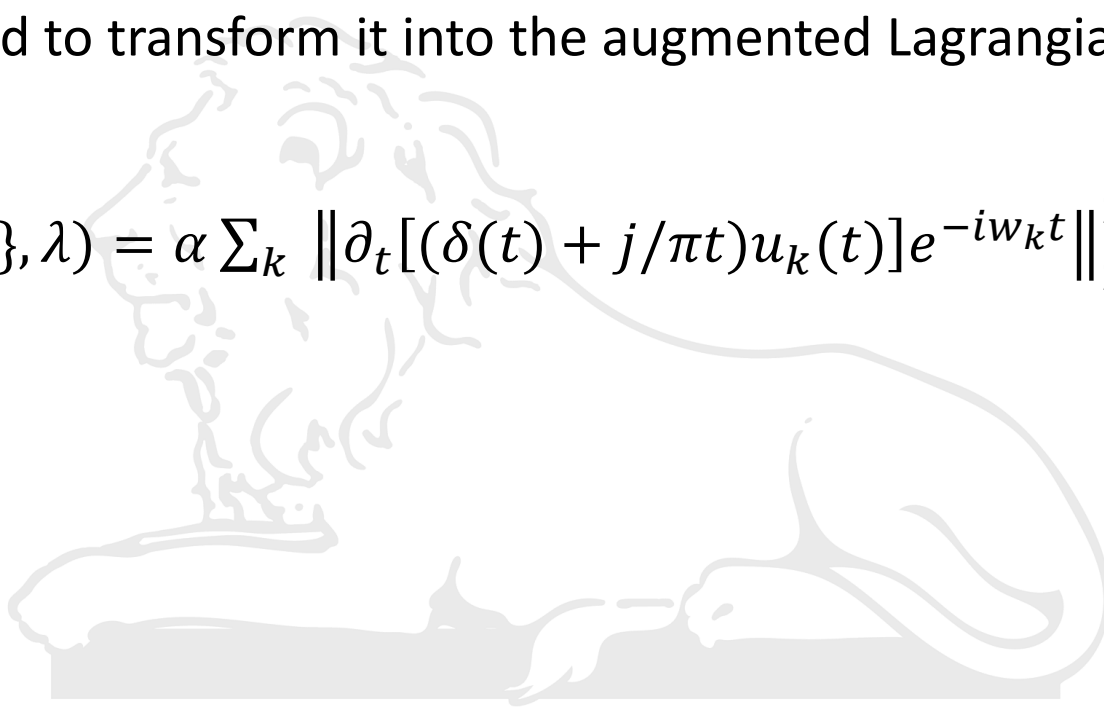
$$\min_{\{u_k\}, \{w_k\}} \left\{ \sum_k \left\| \partial_t [(\delta(t) + j/\pi t) u_k(t)] e^{-i w_k t} \right\|_2^2 \right\} \text{ s.t. } \sum_k u_k = f$$

- Where $\{u\} = \{u_1, u_2, \dots, u_k\}$ represent the decomposed K IMFs
- $\{w\} = \{w_1, w_2, \dots, w_k\}$ are the central frequencies of each component
($k = 1, 2, \dots, K$)
- $\delta(t)$ and $\partial(t)$ are the unit impulse function and the partial derivative

Mathematical Modeling Contd...

- Since direct solution of the constrained optimization problem is computationally difficult, the penalty factor (α) and Lagrange multiplier (λ) are introduced to transform it into the augmented Lagrangian form :

$$L(\{u_k\}, \{w_k\}, \lambda) = \alpha \sum_k \left\| \partial_t [(\delta(t) + j/\pi t) u_k(t)] e^{-i w_k t} \right\|_2^2 + \|f(t) -$$



Mathematical Modeling Contd...

2. Dung Beetle Optimization (DBO) Algorithm

- Consists of 4-optimization processes including the **rolling balls, breeding, foraging, and stealing.**
- Unobstructed and obstructed are the two modes of ball rolling dung beetle. The ball-rolling dung beetle position for Unobstructed mode:

$$P_i^{t+1} = P_i^t + \lambda k P_i^{t-1} + b |P_i^t - P_{\text{worst}}^t|$$

where λ –for control direction (1 or -1), k –deflection coefficient (0 to 0.2), b –constant for scale movement (0 to 1)

- In the obstacle mode, It continuously rolls the dung ball in the new direction and its position is given as:

$$P_i^{t+1} = P_i^t + \tan \theta |P_i^t - P_i^{t-1}|$$

Mathematical Modeling Contd...

- In the breeding optimization processes, beetles roll the balls to a safer place that is ideal to lay their eggs.

- The brood balls position boundary is defined as:

$$L_b^* = \max\{P_{gbest}^t \times (1 - R), L_b\}$$

$$U_b^* = \min\{P_{gbest}^t \times (1 + R), U_b\}$$

- $R = (i - t)/Tmax$ at i -th position and t -th iteration
- $Tmax$ is the maximum iteration number
- The female dung beetle lays only one egg in the respective iteration. B_i^t is i -th brood ball position at t -th iteration.

$$B_i^{t+1} = P_{gbest}^t + b_1 \times (B_i^t - L_b^*) + b_2 \times (B_i^t - U_b^*)$$

Mathematical Modeling Contd...

- In the foraging optimization processes, the small dung beetles come out of the ground for food search, after becoming adults.
- The foraging area is continuously updated as:

$$L_f^b = \max\{P_{lbest}^t \times (1 - R), L_f\}$$

$$U_f^b = \min\{P_{lbest}^t \times (1 + R), U_f\}$$

- P_{lbest}^t is the global best position.
 - L_f & U_f are the foraging area lower and upper bounds for small dung beetles
- The location updating equation as follows:
$$P_i^{t+1} = P_i^t + C_1 \times (P_i^t - L_f^b) + C_2 \times (P_i^t - U_f^b)$$
$$C_1 \text{ \& } C_2 \text{ are random number with normal distribution and a random vector in interval } (0, 1) \text{ respectively.}$$

Mathematical Modeling Contd...

- In the stealing optimization processes, a few of dung beetles in the population called thieves, steal dung balls from other dung beetles. The position of these thieves is update as:

$$P_i^{t+1} = P_{lbest}^t + S \cdot g \cdot (|P_i^t - P_{gbest}^t| + |P_i^t - P_{lbest}^t|)$$

S is a constant value and g is a D-dimensional random vector having normal distribution

2. Improved DBO Phase

- Chaos and reverse learning strategies have been combined for population initialization: The initial population is generated using the Fuch map given as:

$$P(t+1) = \cos \left[\frac{1}{P(t)^2} \right]$$

- $P(t)$ is chaotic variable with Fuch mapping, $P \in Z^+$, $t = 1, 2, \dots, T$ and $P(t) \neq 0$

Mathematical Modeling Contd...

- Using Fuch maping and reverse learning, the dung beetle search space is expanded and improving the initial population solutions quality.
- The reverse learning strategy is defined as:
$$OP_i = K(P_{\min} + P_{\max}) - P_i$$
 - K is the random value (0,1)
 - $P_{\max}$ and $P_{\min}$ are the maximum and minimum values in the initial solution, and OP_i is the reverse solution corresponding to each initial solution P_i
- The target position update the strategies of the convex lens inverse imaging and the adaptive step size under a given probability:

$$\text{Adaptive step factor: } \alpha_0 = \cos \left(\frac{\pi}{3} \times \left(1 + \frac{t}{T} \right) \right)$$

Mathematical Modeling Contd...

Convex lens imaging:
$$P_j^* = \frac{a_j + b_j}{2} + \frac{a_j + b_j}{2k} - \frac{P_j}{k}$$

where P_j^* is the convex lens inverse solution of P_j , P_j is j -th dimensional current individual component. a_j & b_j are min and max values of j -th dimension, k scaling factor.

- Dynamic update strategy using selection probability, P_s :

$$P_s = -\exp\left(1 - \frac{t}{T}\right)^{10}$$

- The position update uses either random step or convex lens reverse learning strategy depending on P_s value ($t \approx 0$, P_s is large favour wider exploration and when $t \rightarrow T$, $P_s \rightarrow 0$ favor adaptive step).

Mathematical Modeling Contd...

Three common error evaluation metrics

- **Mean Absolute Error:**

$$MAE = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i|$$

- **Root Mean Squared Error:**

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2}$$

- **Mean Absolute Percentage Error:**

$$MAPE = \frac{100\%}{N} \sum_{i=1}^N \left| \frac{\hat{y}_i - y_i}{y_i} \right|$$

Methodology

Improved Dung Beetle Optimization (IDBO)

1. Population Initialization
2. Fitness Evaluation
3. Rolling Behaviour
4. Foraging Behaviour
5. Reproduction Behaviour
6. Stealing Behaviour
7. Global Best Update
8. Optimal Solution Search

Objective Function

$$\theta^* = \arg \min_{\theta} \text{RMSE}(\theta)$$

where
 $\theta = \{U_1, U_2, LR, p, L\}$

Search Space (Hyperparameters)

U_1 : Units in BiLSTM-1
 U_2 : Units in BiLSTM-2
 LR : Learning Rate
 p : Dropout Rate
 L : Sequence Length

Optimization Vector

$$\theta = \{U_1, U_2, LR, p, L\}$$

Optimal Hyperparameters

Raw Wind Speed Data (ERA5)

Wind Speed (m/s)
 (Hourly Resolution)

VMD-Reconstructed Signal

$$IMF_1 + IMF_2 + IMF_3 + IMF_4$$

Reconstructed Wind Speed Signal

(VMD Parameters: $K = 4$, $\alpha = 2000$, $\tau = 0$, $DC = 0$, $\text{init} = 1$, $\text{tol} = 1e-7$)

Input Sequence

$$X = \{x(t-11), x(t-10), \dots, x(t)\}$$

Tensor Shape: (12×1)

BiLSTM Layer 1

Units = 32

$$h_{\text{forward}}(t) = \text{LSTM}_{\text{forward}}(x(t))$$

$$h_{\text{backward}}(t) = \text{LSTM}_{\text{backward}}(x(t))$$

$$H(t) = [h_{\text{forward}}(t), h_{\text{backward}}(t)]$$

Output Tensor: (12×64)

BiLSTM Layer 2

Units = 16

Temporal Feature Matrix:

$$H = \{h_1, h_2, h_3, \dots, h_n\}$$

Output Tensor: (12×32)

Temporal Attention Module

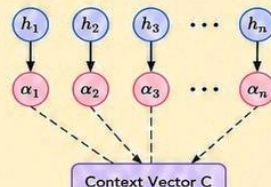
Score Calculation:
 $\text{score} = \tanh(XW + b)$

Attention Weight:
 $\alpha(i) = \frac{\exp(\text{score}(i))}{\sum_{j=1}^n \exp(\text{score}(j))}$

Context Vector:
 $C = \sum_{i=1}^n \alpha(i) h(i)$

Feature Importance Learning

Output Tensor: (32)



Dense Layer

Dense(16)

Activation Function:

$$f(x) = \max(0, x)$$

Output Tensor: (16)

Temporal Attention Module

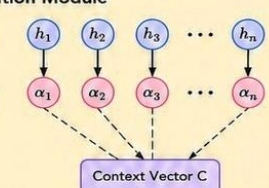
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Context Vector:
 $C = \sum_{i=1}^n \alpha(i) h(i)$

Feature Importance Learning

Output Tensor: (32)



Dense Layer

Dense(16)

Activation Function:

$$f(x) = \max(0, x)$$

Output Tensor: (16)

Regularization

Dropout Rate: $p = 0.1$

Purpose: Overfitting Reduction

Output Layer

Dense(1)

Prediction Equation:

$$\hat{y} = W \cdot C + b$$

Output Tensor: (1)

Forecasted Wind Speed

$$\hat{y}(t+1)$$

Master Prediction Equation:

$$\hat{y}(t+1) = F(X(t))$$

F = optimized IDBO-BiLSTM-Attention model

Forecast Output

Objective Metrics

RMSE

MAE

MAPE

R

Mathematical Summary

$$\theta^* = \arg \min_{\theta} \text{RMSE}(\theta)$$

$$\hat{y}(t+1) = F_{\text{IDBO-BiLSTM-Attention}}(X(t))$$

where:

$F_{\text{IDBO-BiLSTM-Attention}}$ represents the optimized forecasting framework

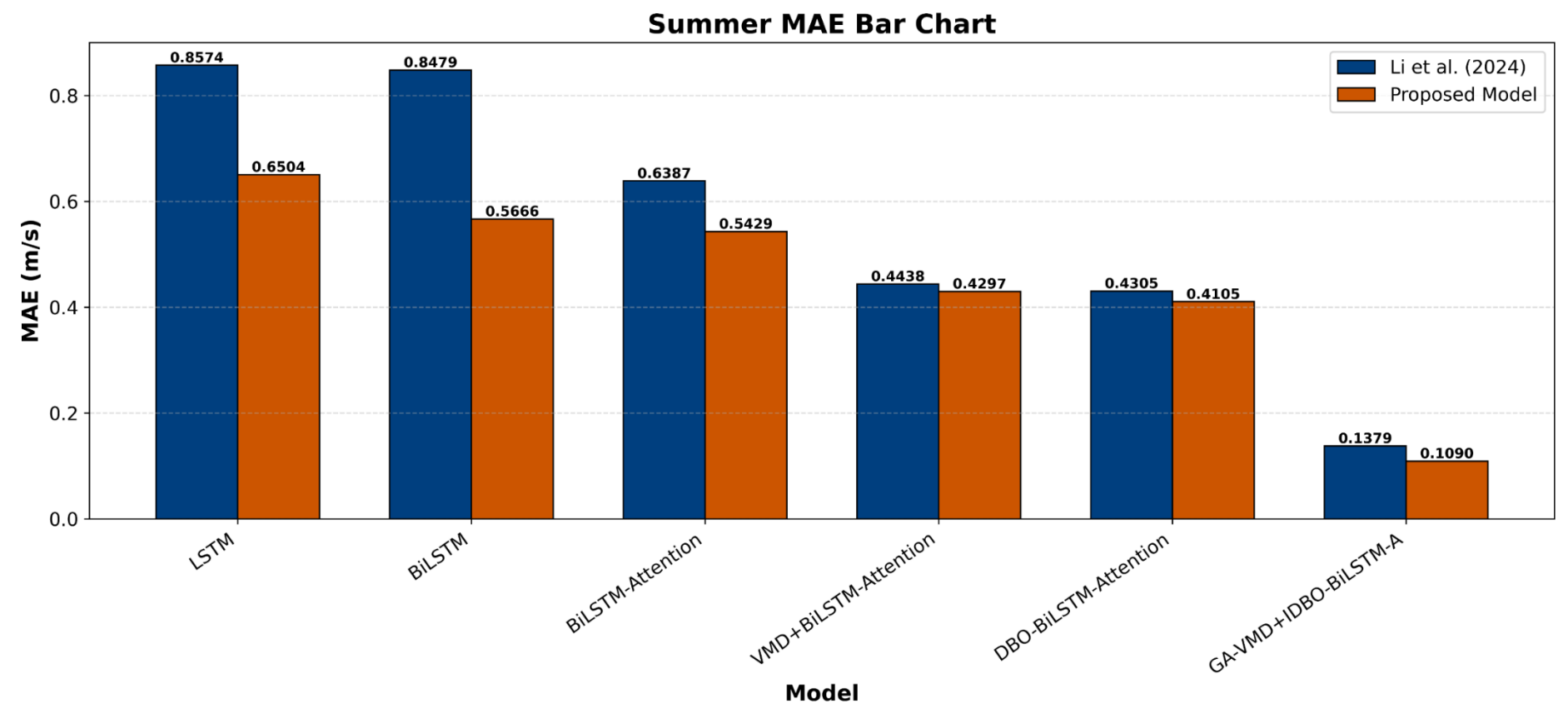
θ^* denotes the optimal hyperparameter set obtained through IDBO

Feedback to IDBO

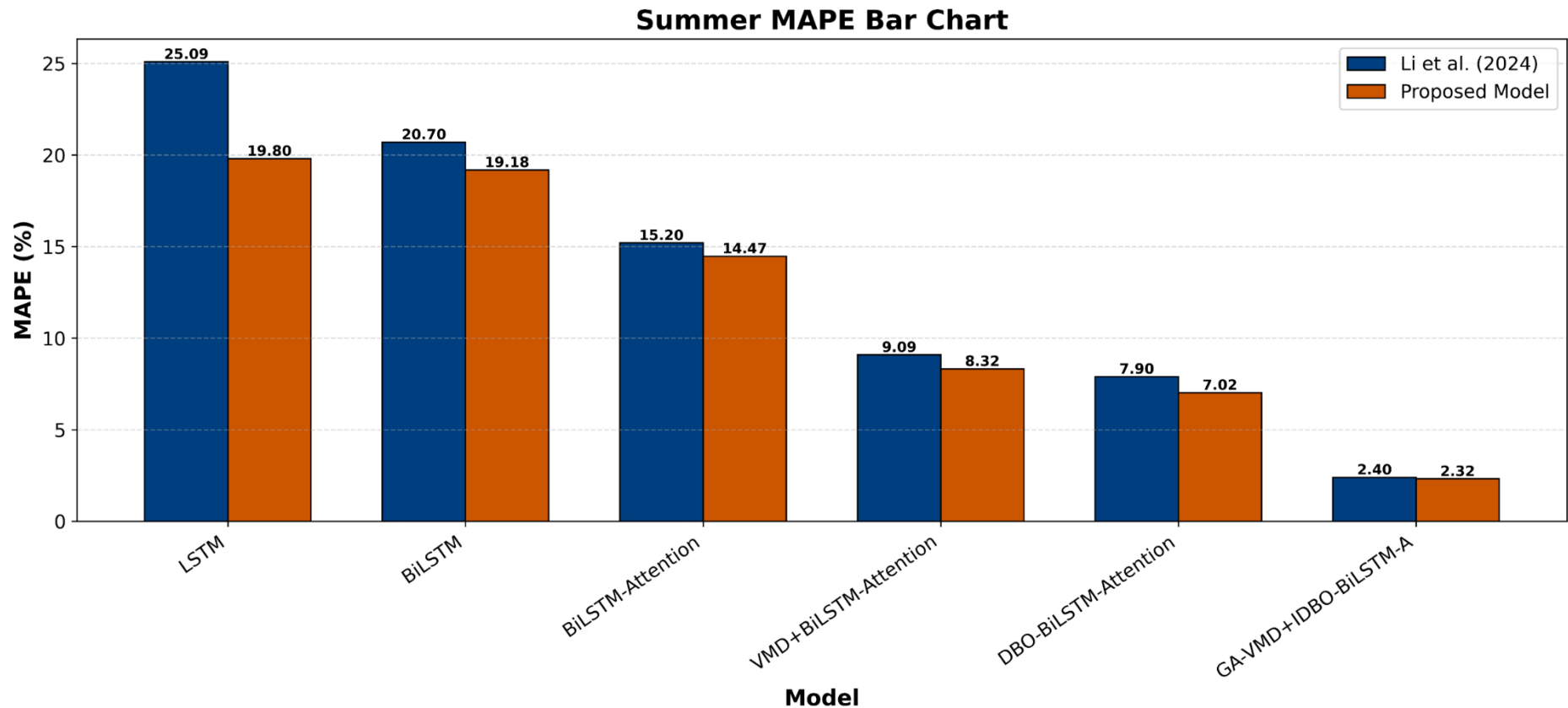
Parameters Setting

- The maximum number of iterations of the GA is 10.
- The initial population is set to 15.
- The total number of modal decompositions K is searched between [10, 40]
- The penalty term coefficient α is searched between [500, 3000].
- The optimal parameter combinations for VMD for the four datasets are [1775, 28], [585, 33], [1872, 33] and [1005, 28] separately.
- In this study, IDBO was used to find the optimal parameters of the wind speed forecasting model BiLSTM-A, the time steps of the BiLSTMA is within [1, 24], the maximum number of training epochs, [1, 200], number of neurons in the hidden layer, [1, 128], number of batch sizes, [1, 120], learning rate, [0.001, 0.5].

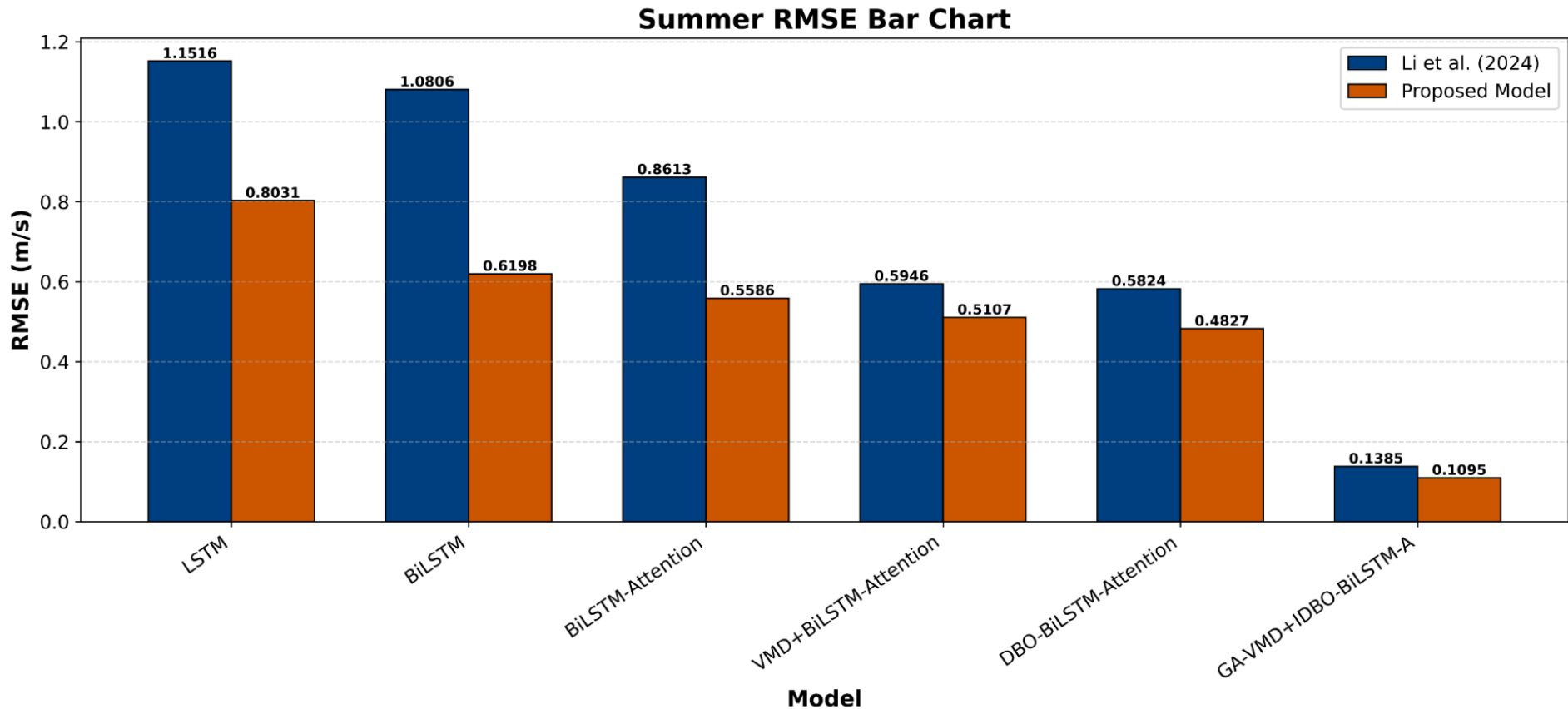
Results: Summer (MAE)



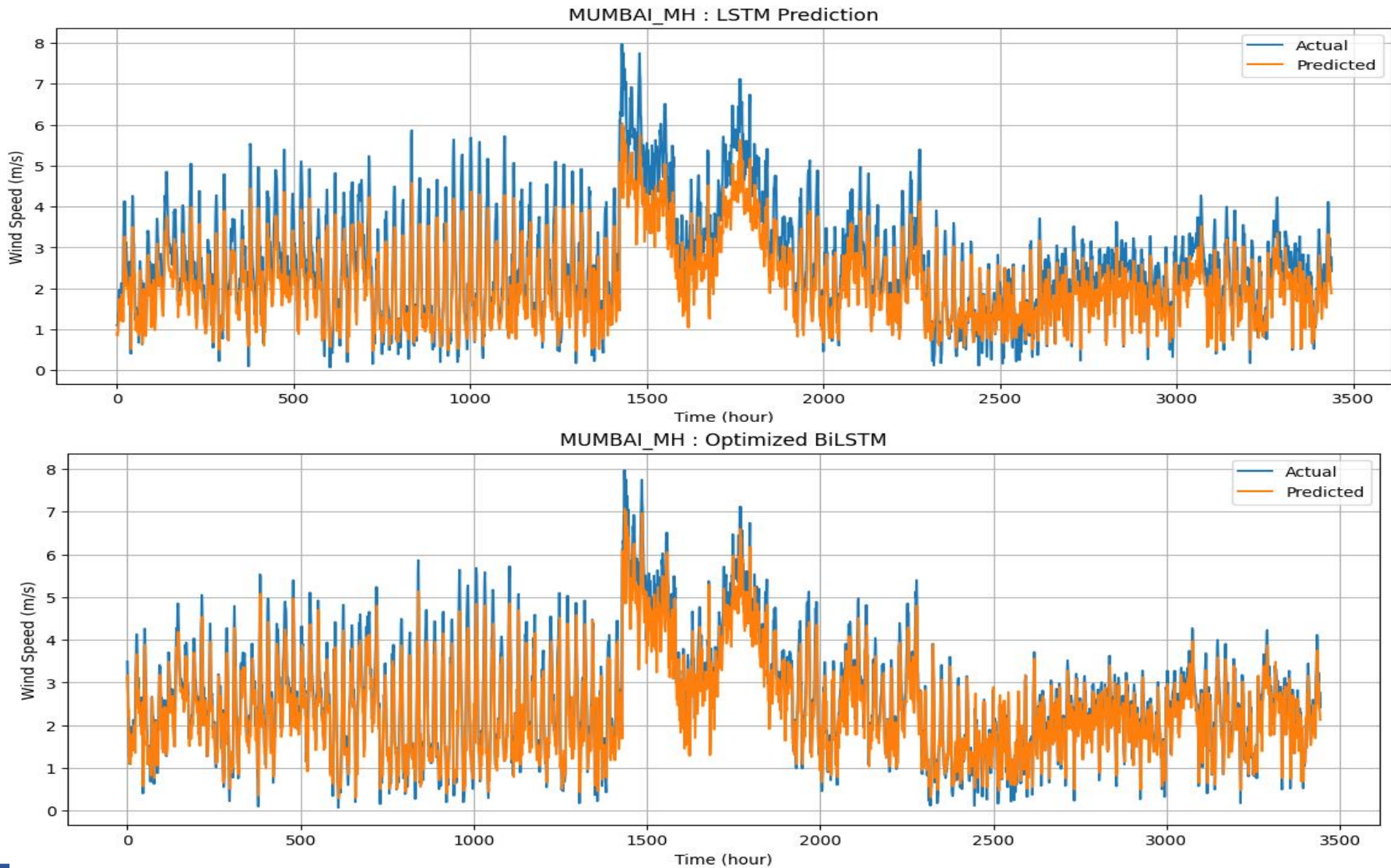
Results: Summer (MAPE)



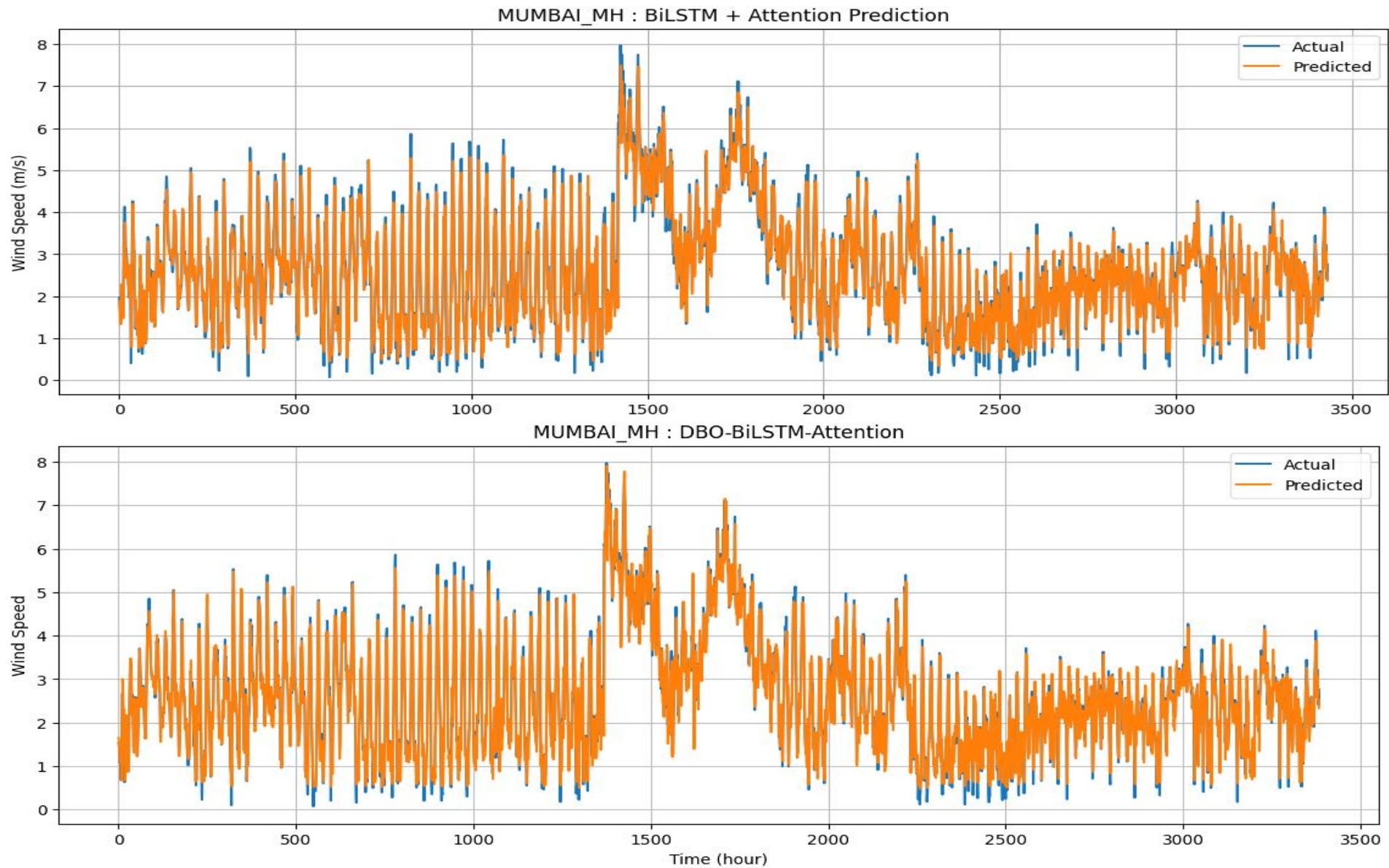
Results: Summer (RMSE)



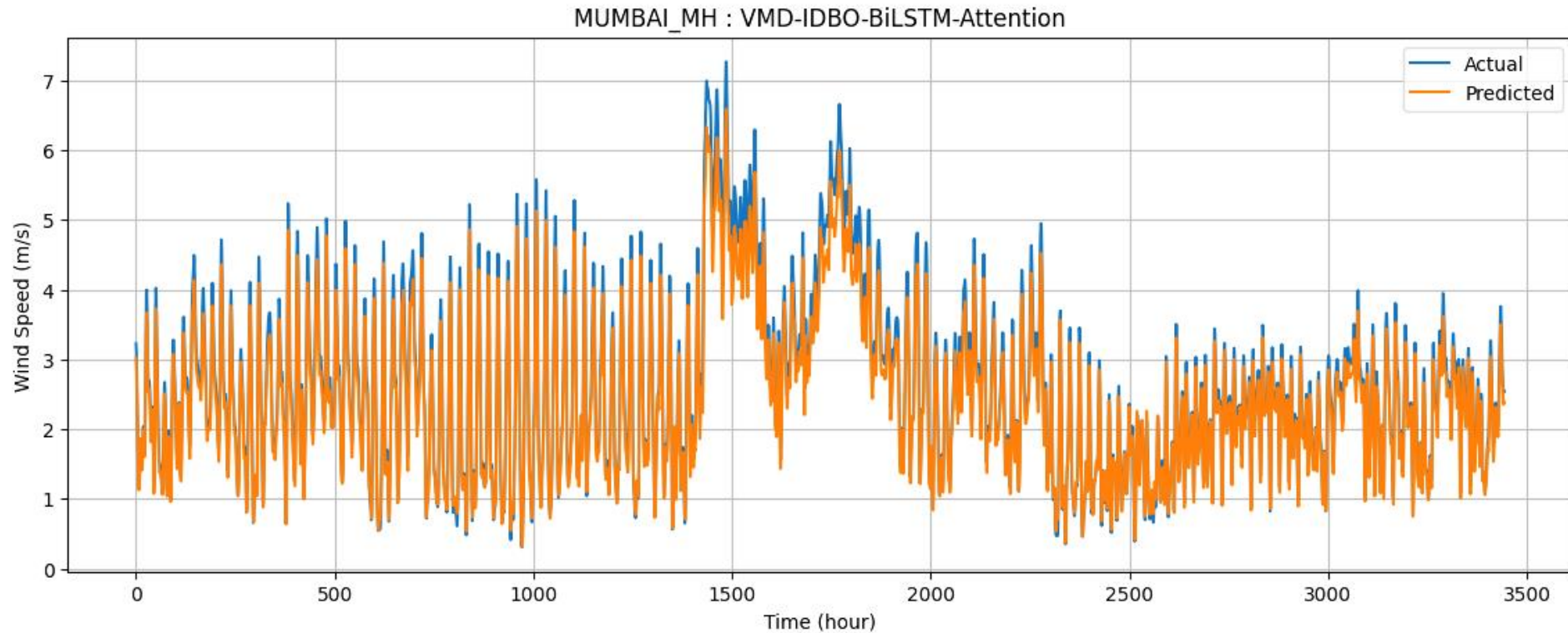
Results: Mumbai (LSTM & BiLSTM)



Results: Mumbai (BiLSTM-A and DBO-BiLSTM-A)

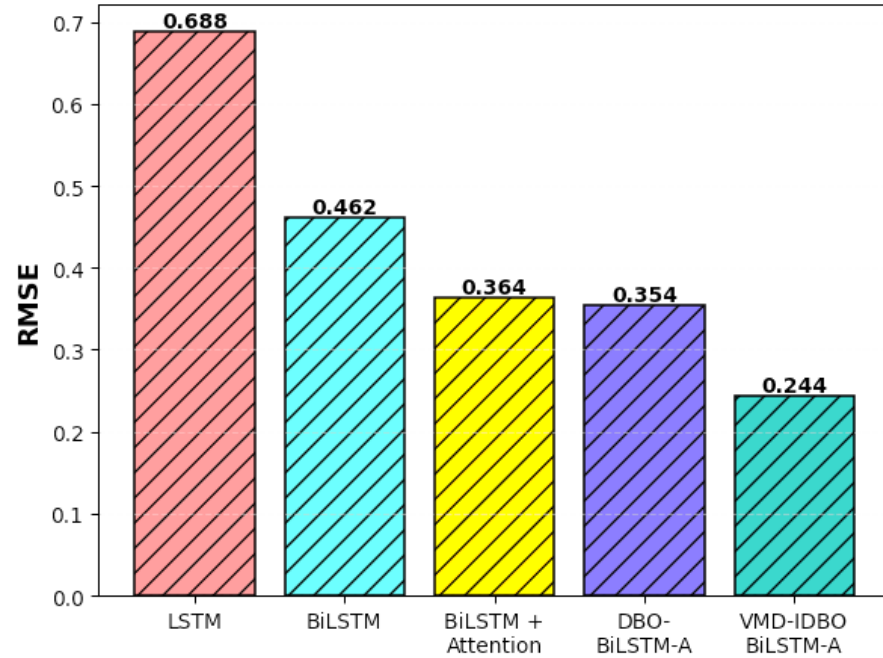


Results: Mumbai (VMD-DBO-BiLSTM-Attention)

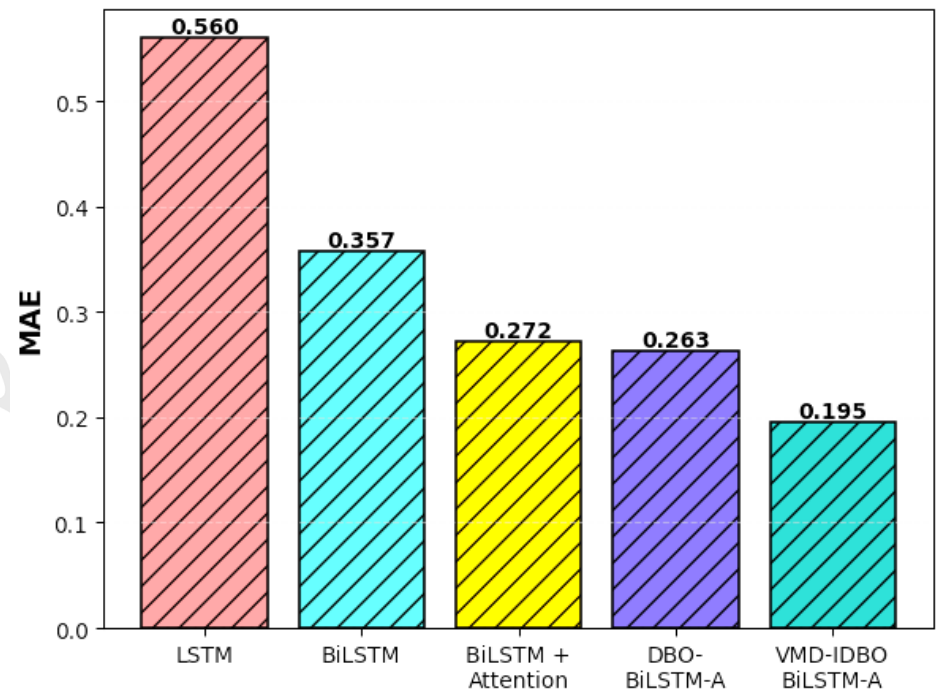


Results: Mumbai (RMSE & MAE)

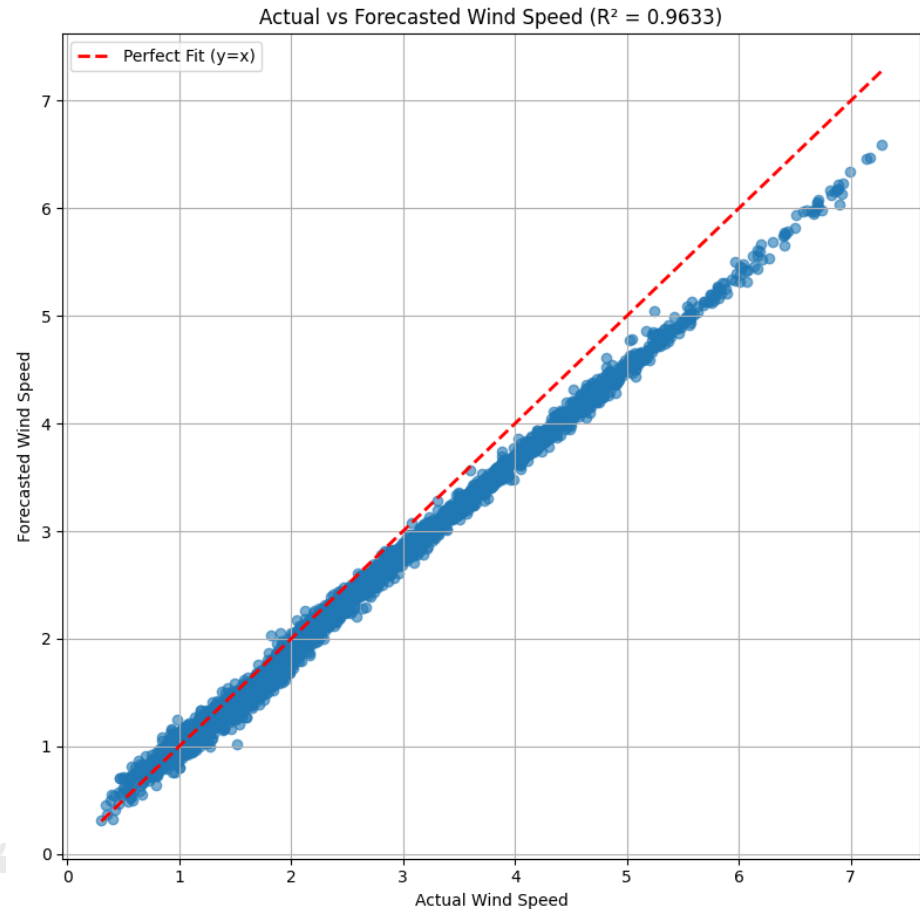
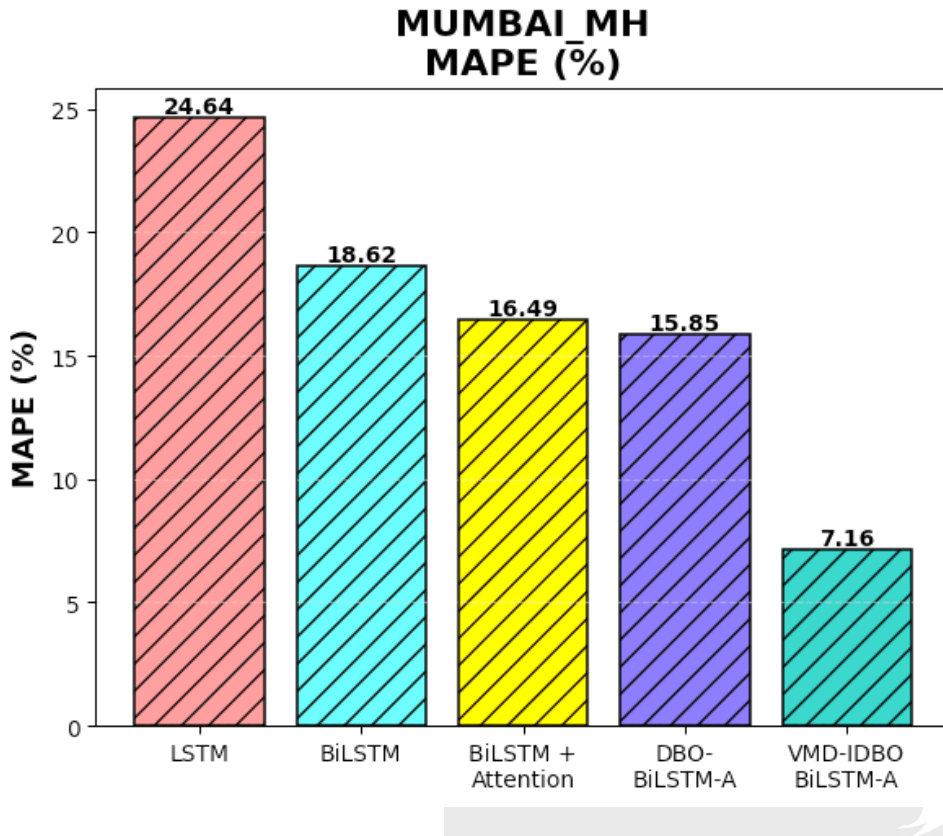
MUMBAI_MH
RMSE



MUMBAI_MH
MAE



Results: Mumbai (MAPE)



Conclusion and Future Scope

- The dual-optimization model for short-term WSF, optimized both VMD decomposition parameters and BiLSTM-A forecasting parameters simultaneously and obtained substantially lower RMSE, MAE, and MAPE values compared to single-optimization and traditional hybrid models.
- Provides accurate & reliable forecasts, with the GA-based model demonstrating slightly improved prediction capability and the IDBO algorithm demonstrates stronger global search capability, faster convergence, and better avoidance of local optima than standard DBO and other metaheuristic optimizers
- Highly suitable for WSF applications and improved wind power prediction, renewable energy integration, and power system operational planning.
- May further improve the forecasting accuracy, especially under highly volatile weather conditions. Additionally, the generalization capability of the model can be extended across multiple wind farms, diverse terrains, and different climatic regions, including offshore wind farms.

A faint, light gray line drawing of a lioness sculpture is positioned in the background, behind the "Thank You" text. The lioness is depicted in a resting pose, facing left, with its front paws extended forward and its tail curled behind it. The drawing is minimalist, using only outlines to define the form.

Thank You