machine learning in climate science

A Combined Model Based on CEEMDAN, Permutation Entropy, Gated Recurrent Unit Network, and an Improved Bat Algorithm for Wind Speed Forecasting

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Journal Club

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- Goal and Challenges
- Model overview

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- CEEMDAN, Permutation entropy, Gated recurrent unit
- RBFNN, Improved bat algorithm

Combined Model

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- Step 1: Data preprocessing
- Step 2: PE-IMFS
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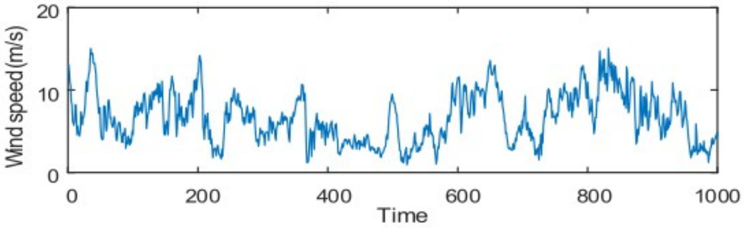
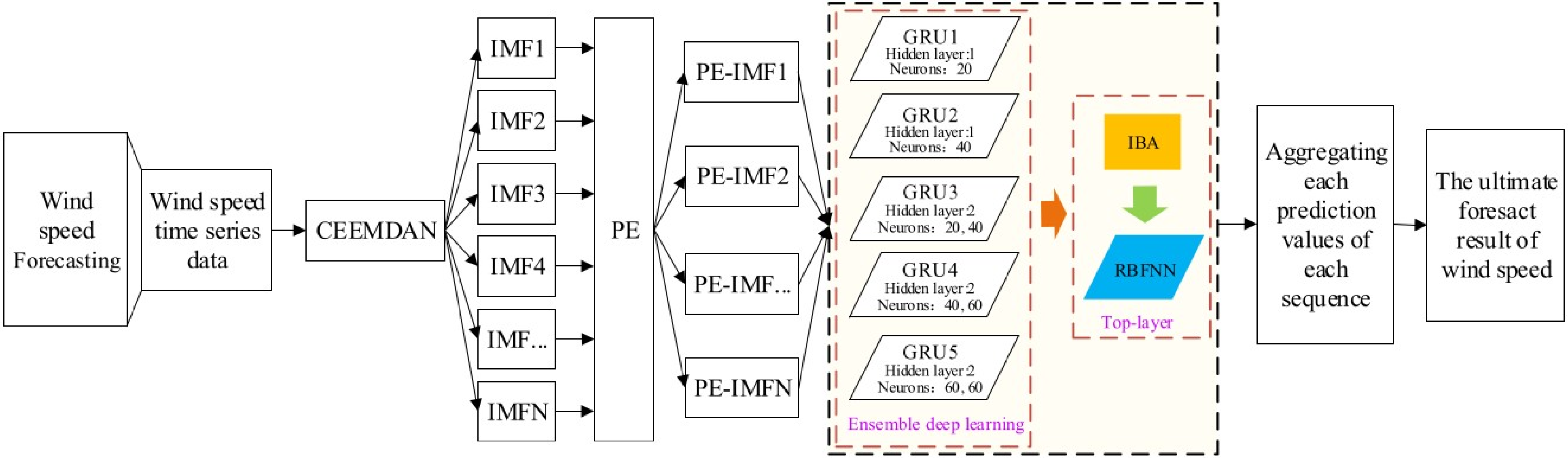
- Goal: centralized wind speed monitoring center
- Challenge: scale, geographic location, climate conditions and wind turbine models of each wind farm are different
- Original wind speed time series is noisy and unstable

Photo by Waldemar Brandt on Unsplash



Original wind speed data from Zhangjiakou wind farm.



Structure of proposed combined model

CEEMDAN: complete ensemble empirical mode decomposition adaptive noise
IMF: intrinsic mode functions
PE: permutation entropy
GRU: gated recurrent unit networks
IBA: improved bat algorithm
RBFNN: radial basis function neural network

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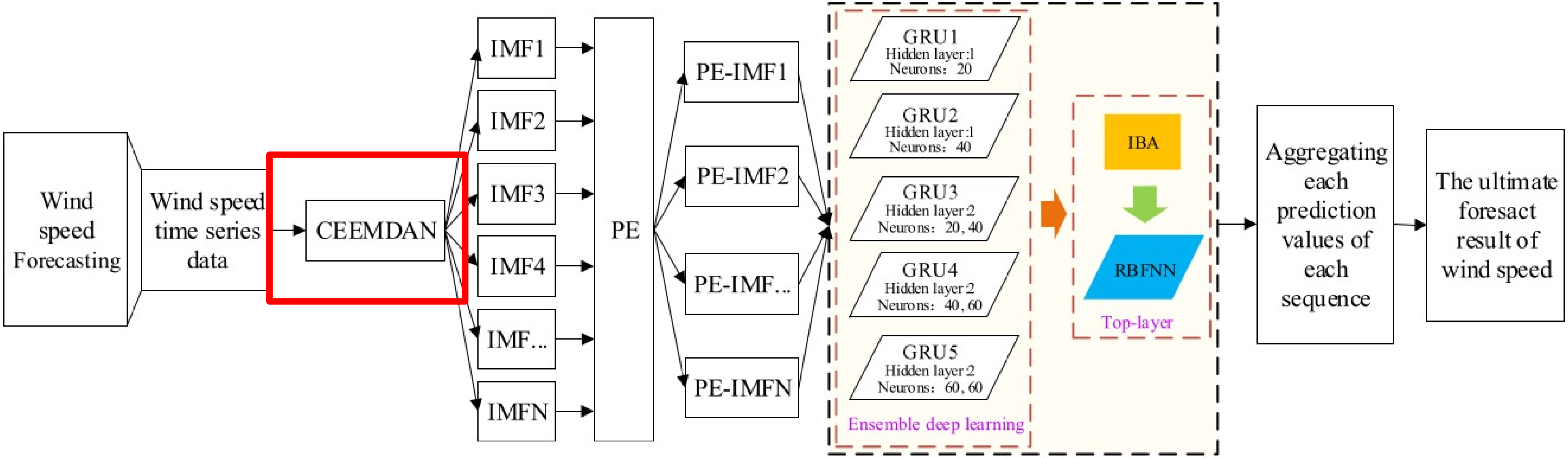


Structure of proposed combined model

EMD: empirical mode decomposition

→ an adaptive signal processing method that decomposes time series into intrinsic mode functions (IMFs) and a residue

But: EMD comes with some problems, e.g. related to boundary error, to the presence of spikes or jumps in the signal and the decomposition of highly-stochastic signals.

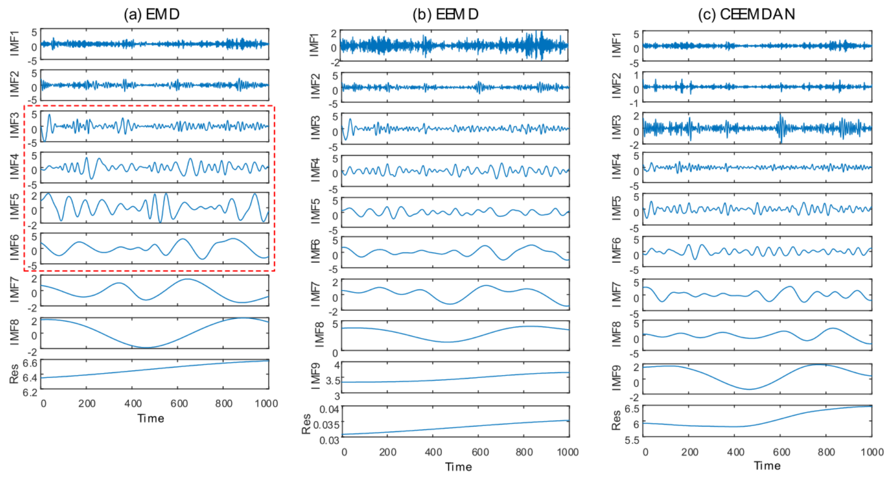
EEMD: combined empirical mode decomposition with an Elman neural network

→ adds different white Gaussian noise multiple times, then separately performs EMD decomposition, and finally obtain the final result by the average of the obtained IMF components

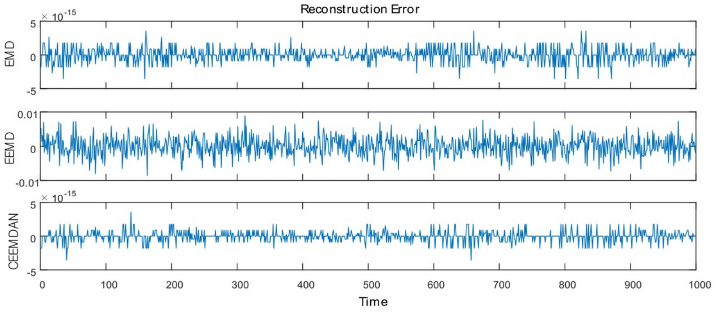
But: in practice white noise added by the EEMD method does not be canceled completely

CEEMDAN based on EEMD

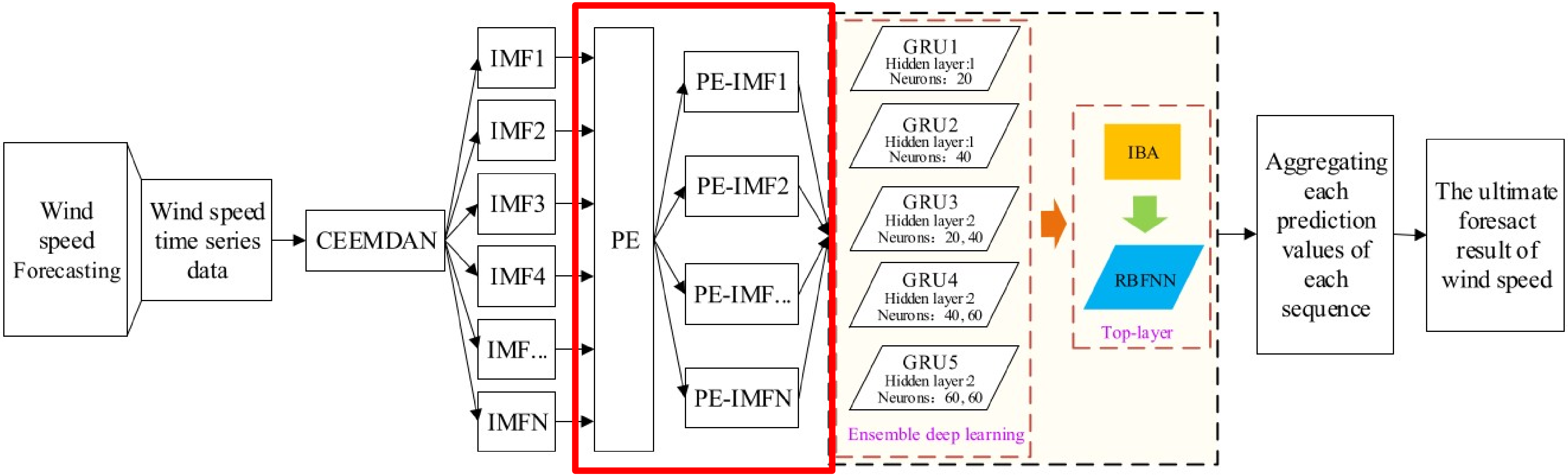
Obtains the IMF by adding adaptive white noise and calculating the unique margin signal



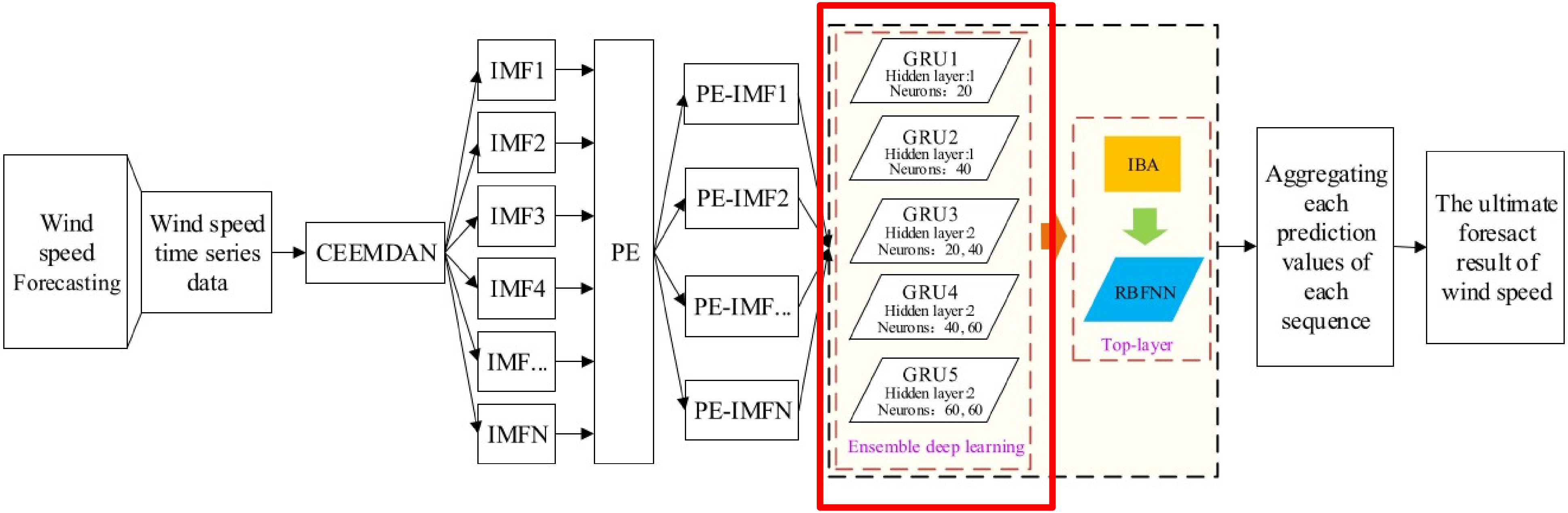
Decomposition results of wind speed by EMD, EEMD and CEEMDAN.



Error of reconstruction using EMD, EEMD and CEEMDAN algorithms for wind speed decomposition.



Structure of proposed combined model



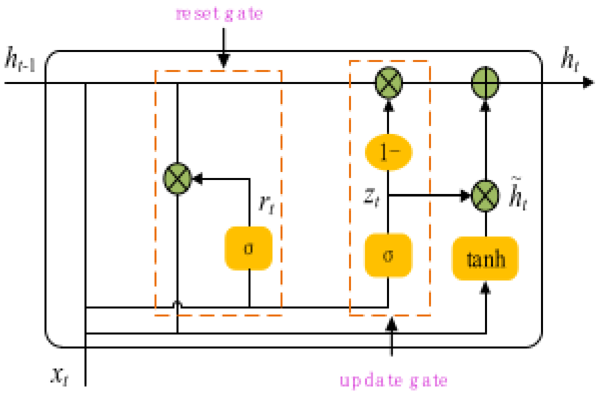
Structure of proposed combined model

Gated recurrent structure

Based on recurrent neural networks

GRUs deals with the RNN problem of gradient disappearance and gradient explosion in actual training

→ similar to LSTM, authors claim that GRUs are faster and have better accuracy



Gated recurrent unit structure

(1) Reset Gate (r):

$$r_t = \sigma\left(\omega_r \cdot [h_{t-1}, x_t]\right)$$

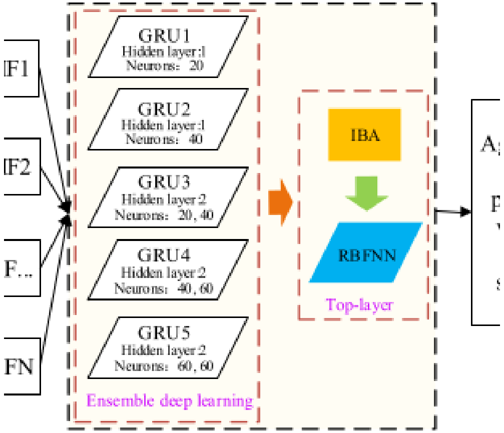
(2) Update Gate (z):

$$\begin{aligned} z_t &= \sigma\left(\omega_z \cdot [h_{t-1}, x_t]\right) \\ \tilde{h}_t &= \tanh\left(\omega \cdot [r_t \cdot h_{t-1}, x_t]\right) \\ h_t &= (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \end{aligned}$$

(3) Output:

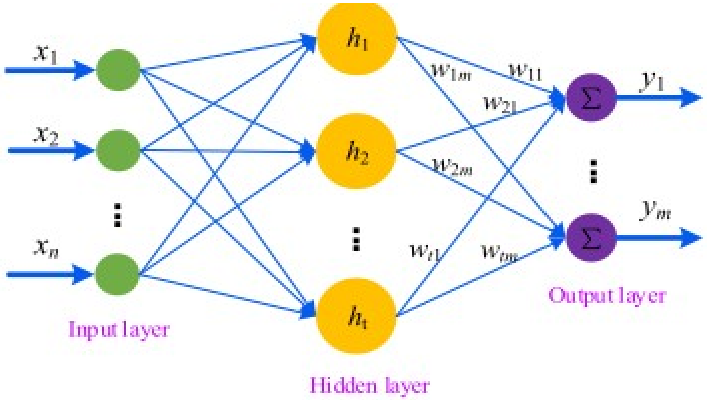
$$y_t = \sigma\left(\omega_o \cdot h_t\right)$$

Nonlinear learning ensemble of GRU time series prediction

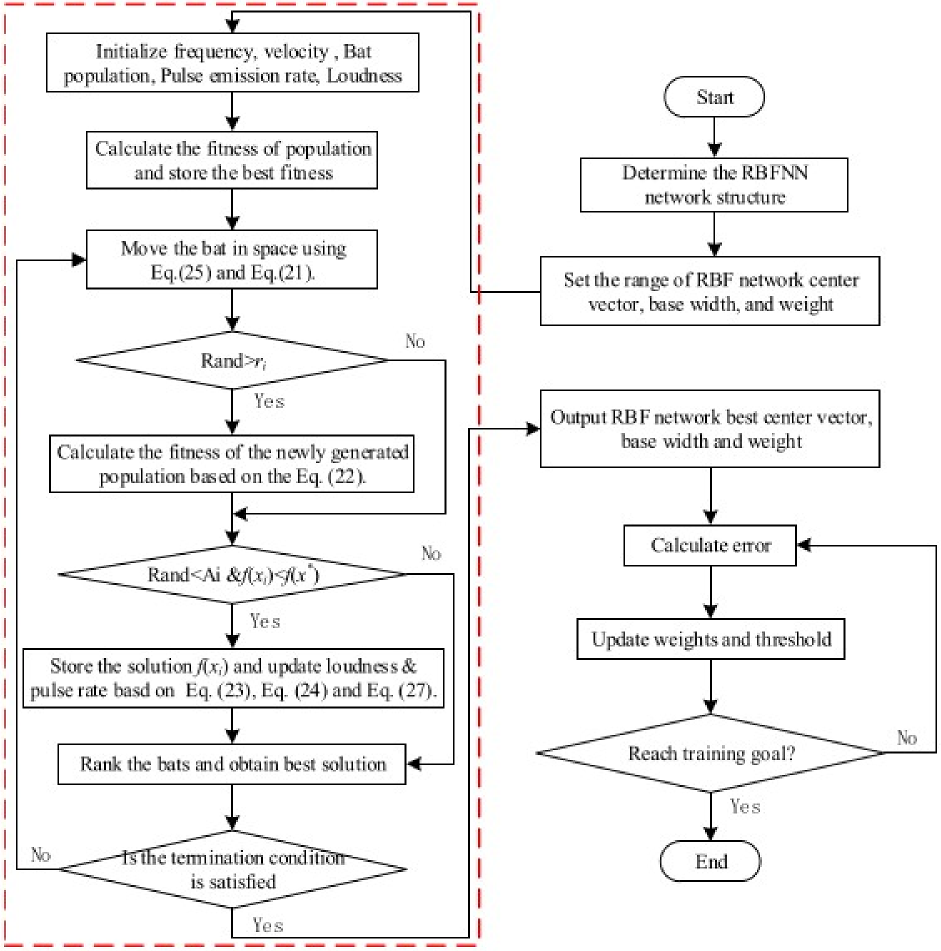


- GRUs are aggregated into a radial basis function neural network (RBFNN)
- Improved bat algorithm (IBA) is used to optimize the parameters of the RMFNN

RBFNN: neural network that uses radial basis functions as activation functions (e.g. Gaussian function)



Structure of a RBF neural network



$$x_{new} = x_{old} + \varepsilon A^t \tag{22}$$

$$A_i^{t+1} = \beta A_i^t \tag{23}$$

$$r_i^t = r_i^0[1 - \exp(-\gamma t)] \tag{24}$$

$$v_i^{t+1} = \omega_i(t) v_i^t + (x_i^t - x^*).f_i \tag{25}$$

$$\omega_i(t+1) = \omega_i(t) + N(0,1) \tag{26}$$

$$\beta^{new} = (\frac{1}{2t})^{1/2t} \beta^{old} \tag{27}$$

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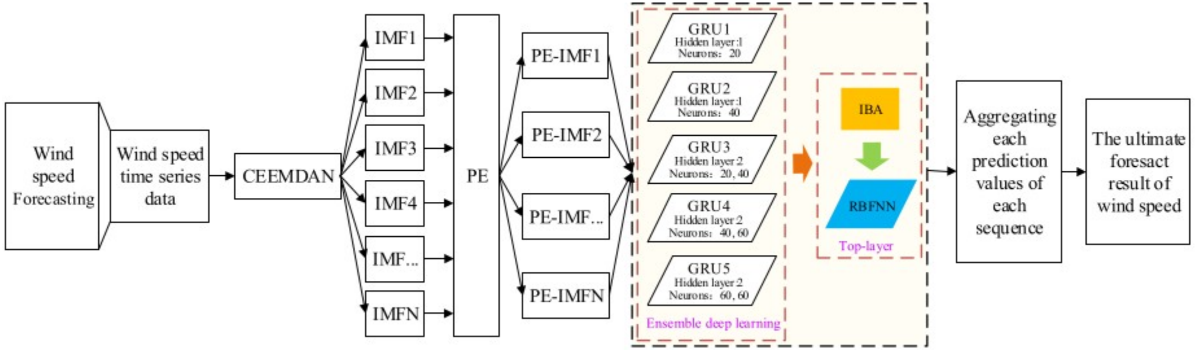
Step 2: Nonlinear learning ensemble of deep learning time series prediction for PE-IMFs

Step 3: Assemble forecasting results



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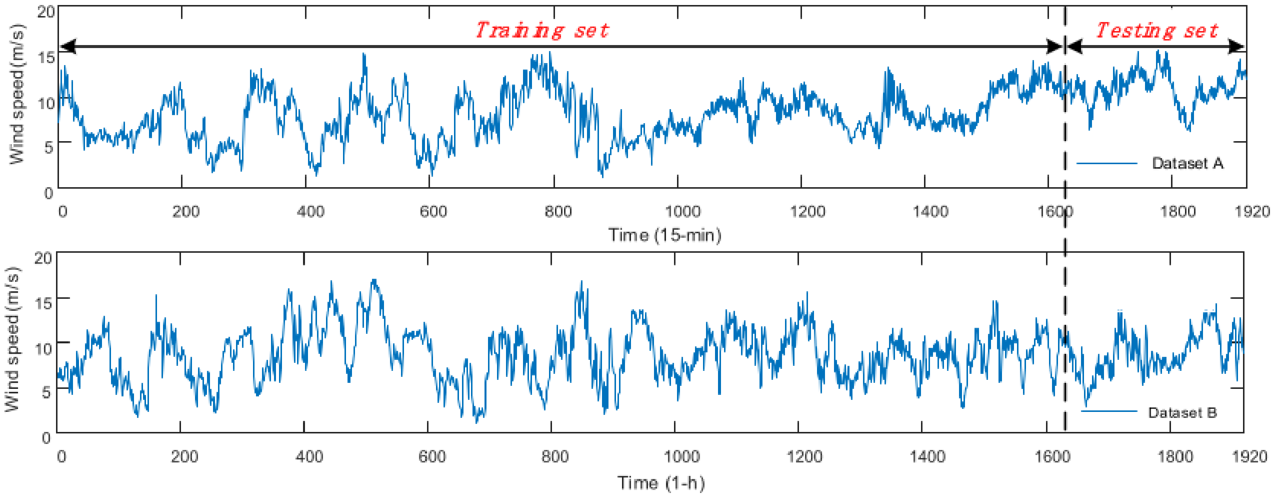


The original wind speed time series from Zhangjiakou wind farm.

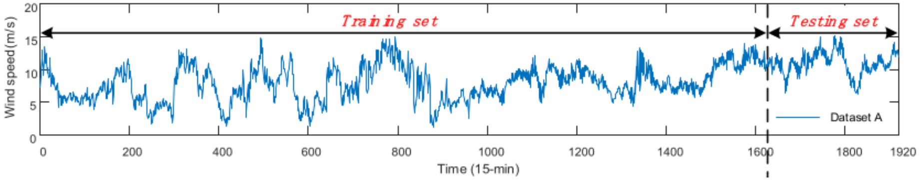
Metric	Equation	Definition
MAE	$MAE = \frac{1}{N}\sum_{n=1}^{N}\lvert y_n - \hat{y}_n \rvert$	Mean absolute error of N forecasting results
RMSE	$RMSE = (\frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n)^2)^{1/2}$	Square root of average of error squares
MAPE	$MAPE = \frac{1}{N}\sum_{n=1}^{N}\lvert \frac{y_n - \hat{y}_n}{y_n} \rvert \times 100\%$	Average of N absolute percentage error
SSE	$SSE = \sum_{n=1}^{N}(y_n - \hat{y}_n)^2$	The square sum of the error

Evaluation criteria for forecasting performance

Experimental setup

- Data decomposition with CEEMDAN-PE
- Case study 1: 15-min time-scale wind speed forecasting
- Case study 2: 1 h time scale wind speed forecasting
- In both case studies:
  - Experiment 1: Comparison with models using different data decomposition techniques
  - Experiment 2: Comparison with models using same data decomposition technique
  - Experiment 3: Comparison with models using different nonlinear-learning top-layer

Data decomposition with CEEMDAN-PE



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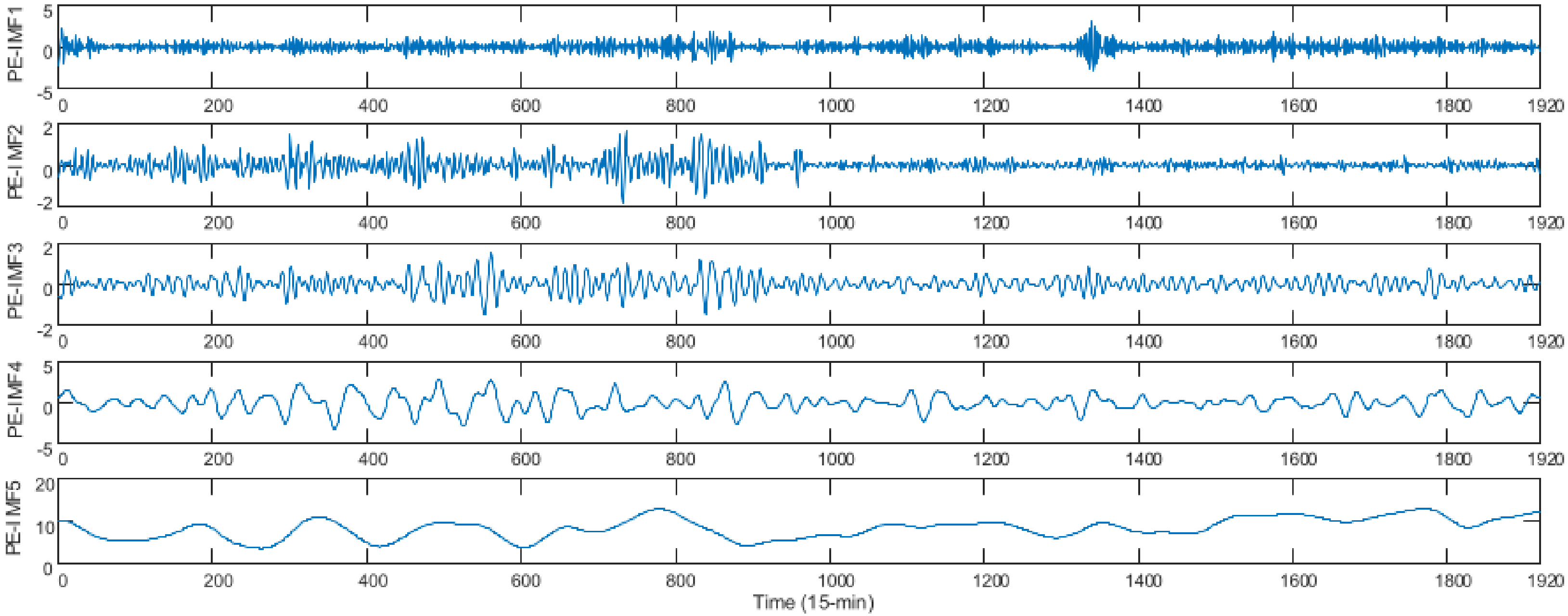
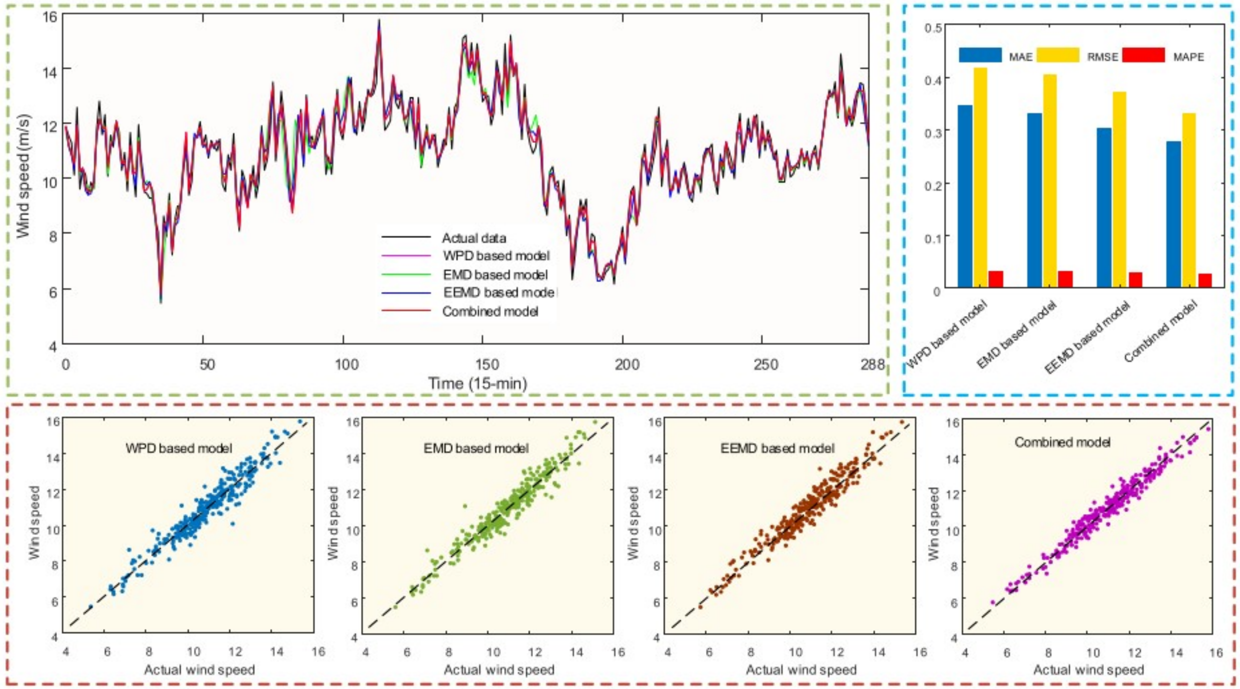


Recombination results for the dataset A (15 minutes) decomposed using CEEMDAN-PE.

Case study 1: 15-min time-scale wind speed forecasting

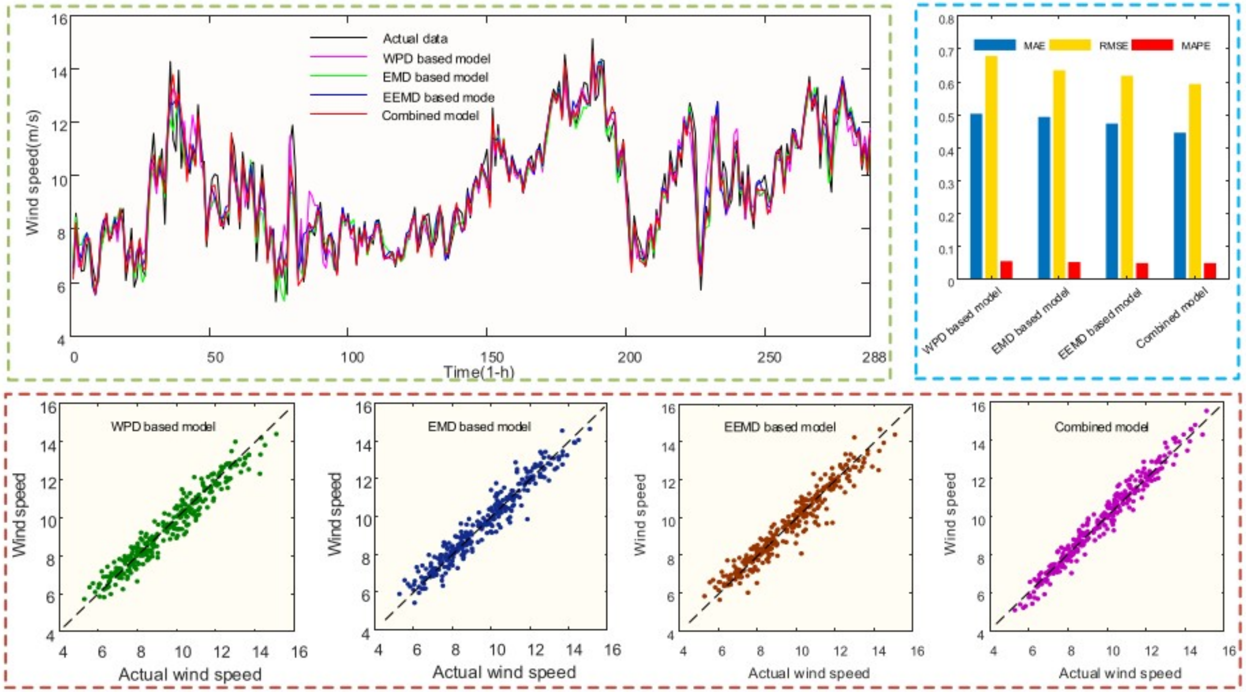
- Experiment 1: Comparison with models using different data decomposition techniques



Forecasting results of combined model and models employing diverse data decomposition techniques in case study 1.

Case study 2: 1 h time-scale wind speed forecasting

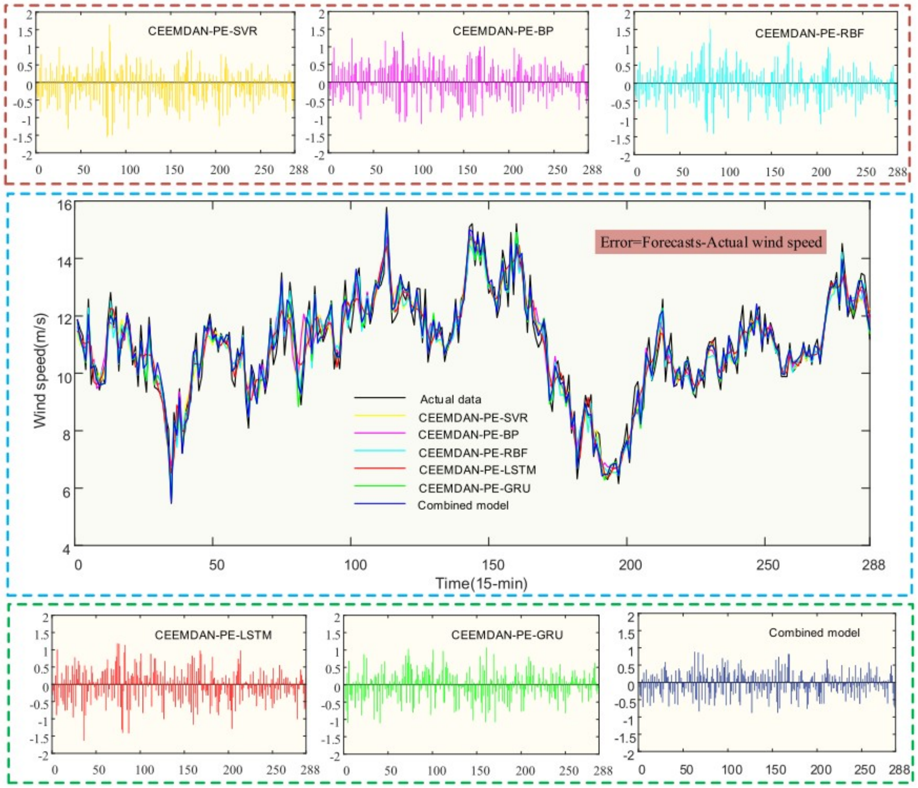
- Experiment 1: Comparison with models using different data decomposition techniques



Forecasting results of combined model and models employing diverse data decomposition techniques in case study 2.

Case study 1: 15-min time-scale wind speed forecasting

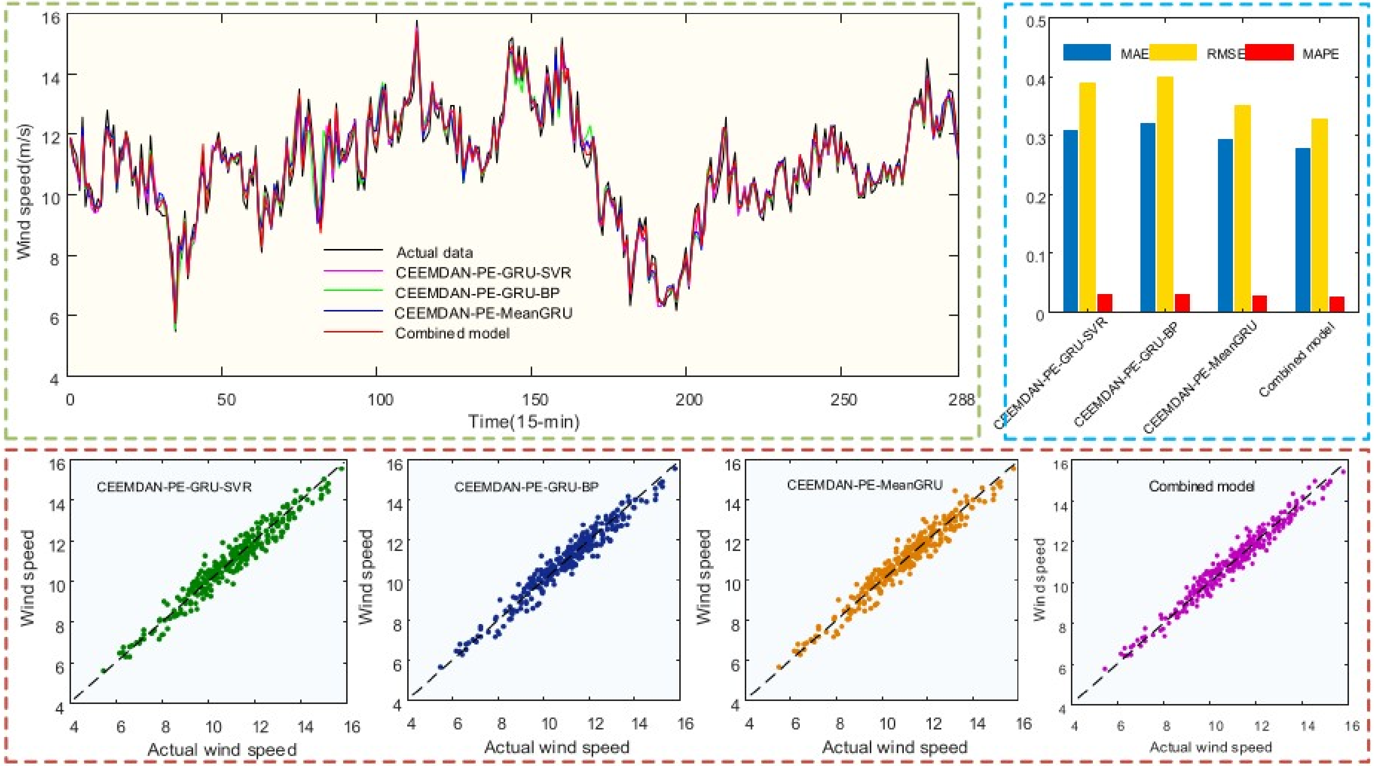
- Experiment 2: Comparison with models using same data decomposition technique



Forecasting results of combined model and models using same data decomposition technique in case study 1.

Case study 1: 15-min time-scale wind speed forecasting

– Experiment 3: Comparison with models using different nonlinear-learning top-layer



Forecasting results of combined model and models employing different nonlinear-learning top-layer in case study 1.

Summary and conclusion

- Introduction to complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) and permutation entropy (PE) to split original time-series into sub-series
- cluster of gated recurrent unit networks (GRUs) with different hidden layers and neurons are applied to capture the unsteady characteristics and implicit information of each sub-series
- predictions of the GRUs of each sub-series are aggregated into a nonlinear-learning regression top-layer with radial basis function neural network (RBFNN), and improved bat algorithm (IBA) for parameter optimization
- These values are now superimposed to get final results.
- Combined model for decomposition and forecasting with CEEMDAN-PE and GRUs with RBFNN top layer with IBA
- Good results for short time wind forecasting, but already worse results from case study 1 to case study 2

Sources

- Liang, T., Xie, G., Fan, S., & Meng, Z. (2020). A Combined Model Based on CEEMDAN, Permutation Entropy, Gated Recurrent Unit Network, and an Improved Bat Algorithm for Wind Speed Forecasting. IEEE Access, 8, 165612-165630.
- Stallone, A., Cicone, A., & Materassi, M. (2020). New insights and best practices for the successful use of Empirical Mode Decomposition, Iterative Filtering and derived algorithms. Scientific reports, 10(1), 1-15.