Multi-step wind variability prediction based on deep learning neural network

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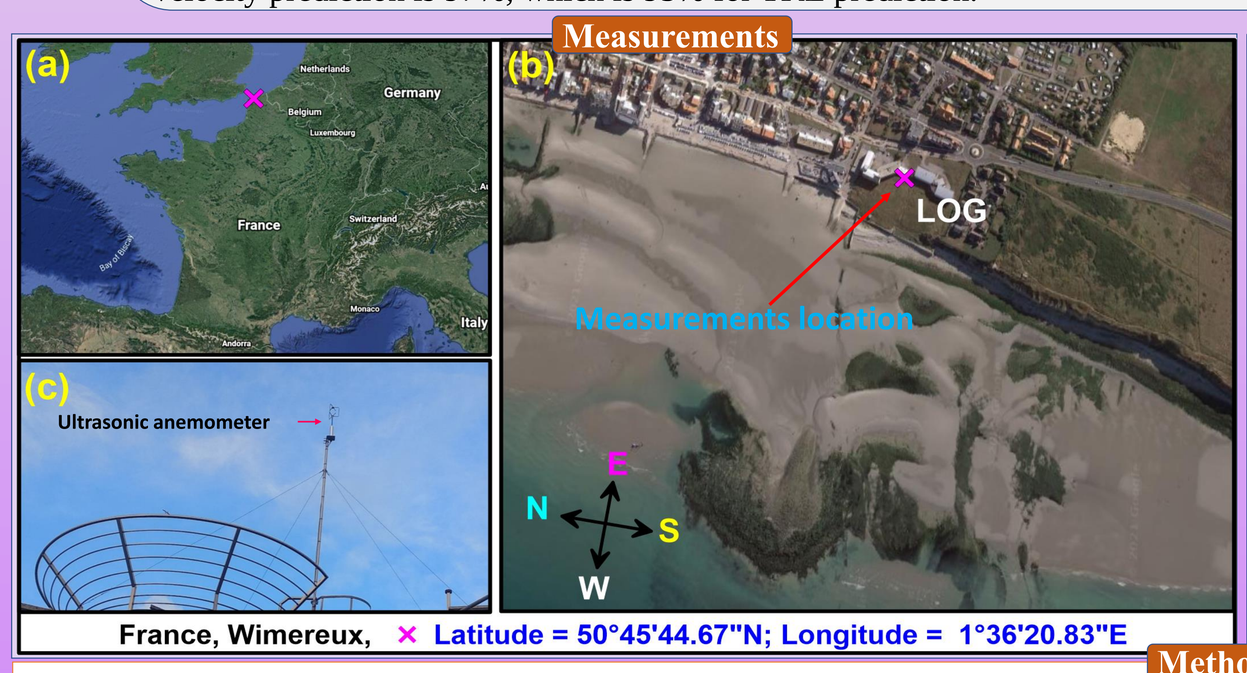
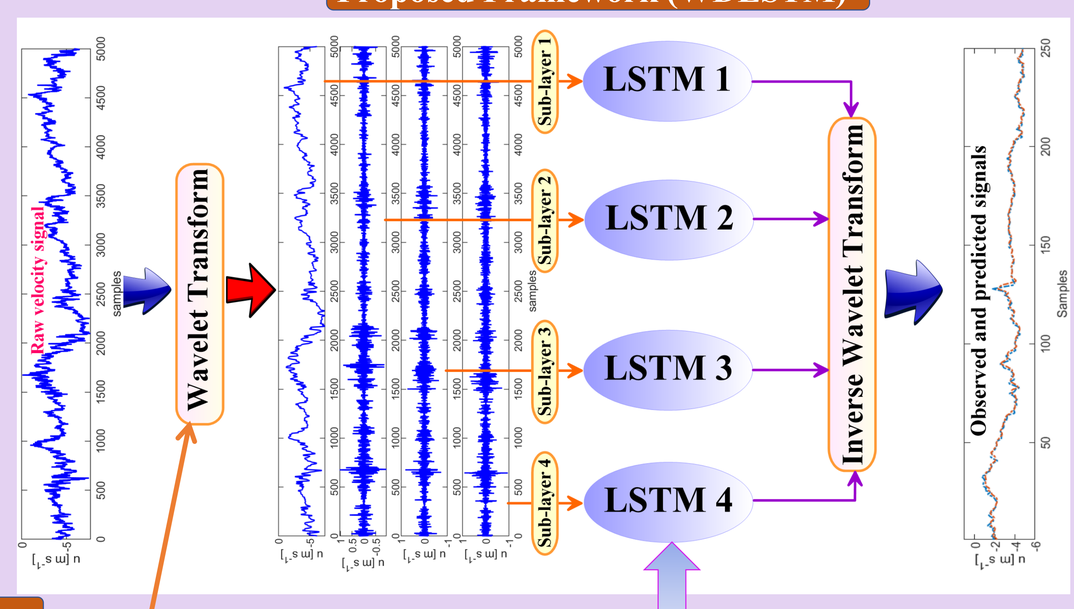
Abstract

Wind energy is widely used for power production by wind turbines but the randomness and the intermittence of the wind make its accurate prediction difficult. This study develops an advanced and reliable model for multi-step wind variability prediction using wavelet decomposed long short-term memory (WDLSTM) network based on deep learning neural network (DLNN). A 20 Hz Ultrasonic anemometer was deployed for one-year long period on the seashore of northern France at the site of Laboratoire d'Océanologie et de Géosciences (LOG) to measure the random wind variability for the duration of thirty-four days. Real-time turbulence kinetic energy (TKE) is computed from the measured wind velocity components, and multi-resolution features of wind velocity and TKE are used as input for the prediction model. These multi-resolution features of wind variability are extracted using one-dimensional discrete wavelet transformation. The proposed DLNN is framed to implement multi-step prediction ranging from 10 min to 48 h. We found that the coefficient of determination for 1-64h feature-space velocity prediction is 97%, which is 95% for TKE prediction.

Measurements



Proposed Framework (WDLSTM)



Methodology

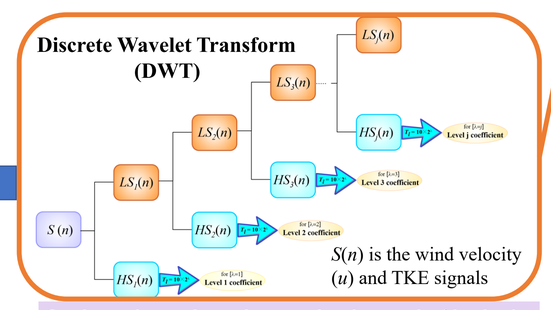
The velocity components u, v, and w of the turbulent wind flow are decomposed into a mean part and fluctuating part as:

$$u = \overline{u} + u', v = \overline{v} + v', w = \overline{w} + w'$$

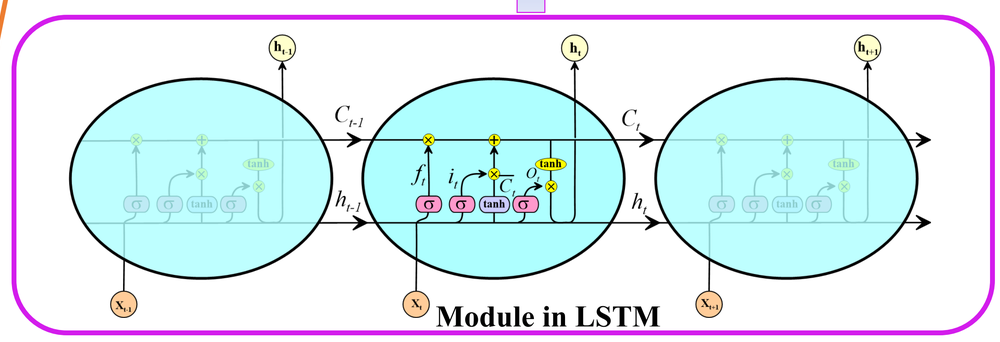
The Turbulence Kinetic Energy (*TKE*) can be written as:

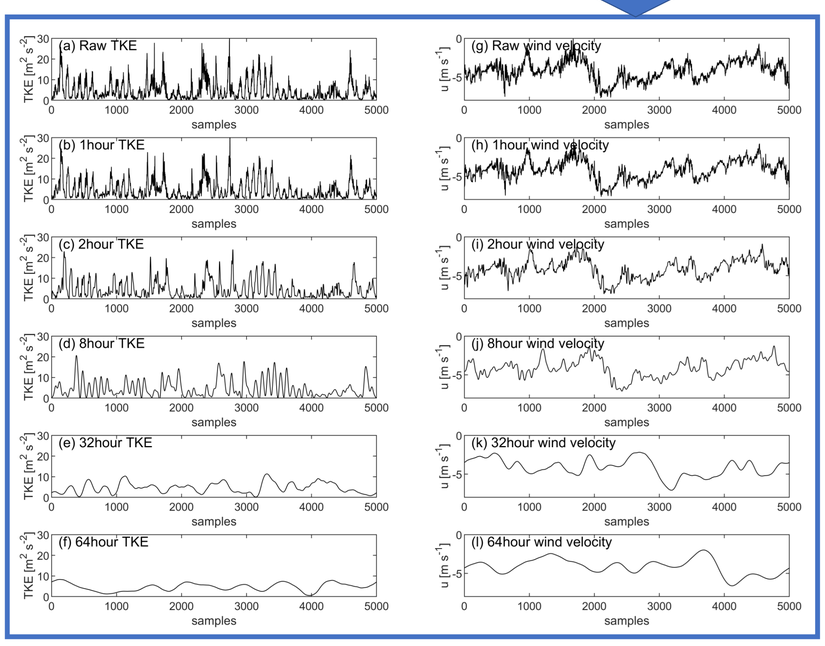
$$TKE = \frac{1}{2}\left(\overline{u'^2} + \overline{v'^2} + \overline{w'^2}\right)$$

Using DWT



Symlets orthogonal wavelet is used in the wavelet filter bank.





Multi resolution (1-64 hours) feature space on wind velocity and TKE

The cell state in one LSTM block is updated by four interacting layers demonstrated as: (1) forgetting gate, (2) input gate, (3) cell state updating (4) output gate.

Here W_f, W_i, W_C, W_o symbolize the weight matrix for each component, δ_f, δ_i, δ_C, δ_o symbolize the bias term for each component, x_t is the current input data, h_{t-1} is the output of the previous LSTM block

Layers used herein

Input layer	[numFeatures = 1]
LSTM layer	[numHiddenUnits = 400]
Fully connected layer	[numResponses = 1]
Regression layer	

$$f_t = \sigma(W_f(x_t, h_{t-1}) + \delta_f)$$

Forgetting gate: amount of old information should be remained in cell state.

$$i_t = \sigma(W_i(x_t, h_{t-1}) + \delta_i)$$

Input gate: any new information should add to the cell state

$$C_t = f_i \times C_{t-1} + i_t \times \overline{C_t}$$

Where

$$\overline{C_t} = \tanh(W_c(x_t, h_{t-1}) + \delta_C)$$

Cell state updating: used to update the current cell state C_t

$$h_t = o_t \times \tanh(C_t)$$

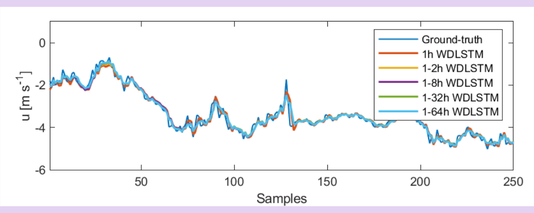
Where

$$o_t = \sigma(W_o(x_t, h_{t-1}) + \delta_o)$$

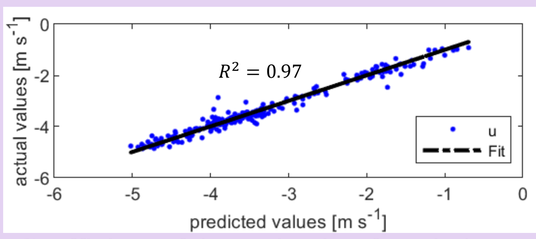
output gate: the integrated input information h_t in the next unit

Activation functions: $\sigma(x) = \frac{1}{1+e^{-x}}$; $tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

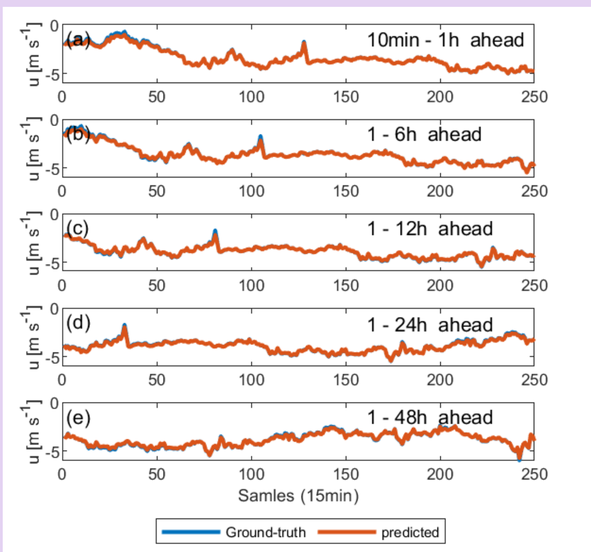
Results



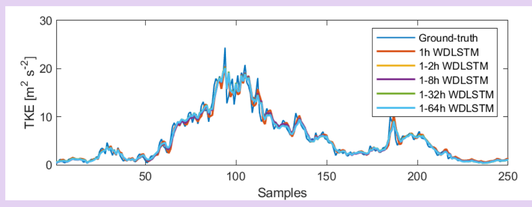
Comparisons of observed (ground-truth) and multi-resolution predicted wind velocity.



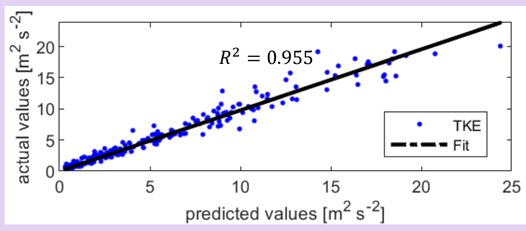
Coefficient of determination for wind velocity.



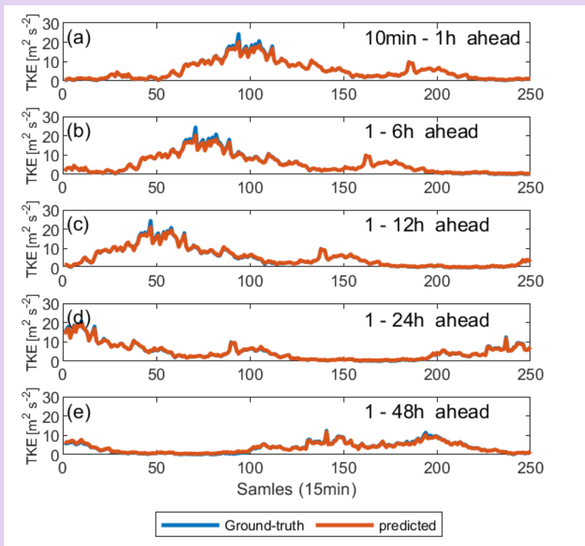
Multi-step ahead prediction



Comparisons of observed (ground-truth) and multi-resolution predicted TKE.



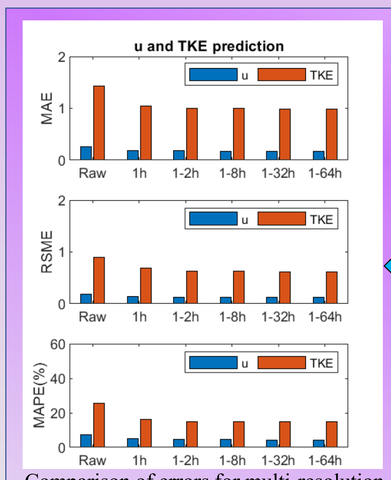
Coefficient of determination for TKE.



Multi-step ahead prediction

Conclusions

- For 1-64h feature-space velocity prediction, the root mean square error (RSME), mean absolute error (MAE) and mean absolute percentage error (MAPE) are 0.047 m/s, 0.19 m/s, and 11.3% respectively, which depicts the reliability of the proposed WDLSTM model. However the discrepancy is larger for the TKE prediction.
- We found that the present model performs well for mid-long-term (6-48h ahead) wind velocity prediction. While this model is good for the long-term (24-48h ahead) turbulence kinetic energy prediction.
- The coefficient of determination for velocity prediction is 2% higher than TKE prediction.
- The intermittent behavior of the TKE signal is one of the main reasons for the weak prediction.



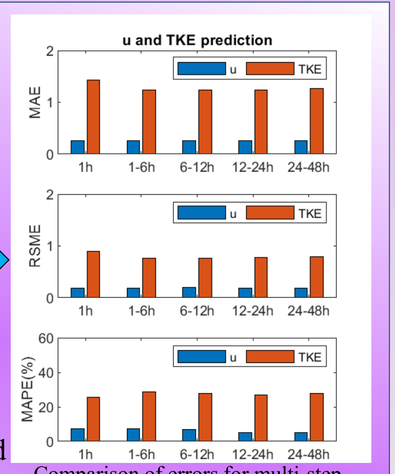
Comparison of errors for multi-resolution predicted Wind velocity and TKE

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |S_{act} - S_{pred}|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (S_{act} - S_{pred})^2}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \frac{|S_{act} - S_{pred}|}{S_{act}} \times 100$$

S_{act} and S_{pred} is the observed and predicted signals



Comparison of errors for multi-step predicted Wind velocity and TKE

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