The 12th Annual Workshop:
Low Carbon Technologies and Resilience for Long-Lasting Infrastructure

Typhoon wind speed prediction model for cross-sea bridge based on deep learning improved by VMD

Zihao Song, Hebei University of Technology, 202031604011@stu.hebut.edu.cn
Jiale Li, Hebei University of Technology, jiale.li@hebut.edu.cn

Introduction and abstract

The top 10 cross-sea bridges in the world in total length

Name	Length (km)	Completed	Country
Hong Kong-Zhuhai-Macao Bridge	55.0	2018	China
Seto Ohashi	37.3	1988	Japanese
Chesapeake Bay Bridge	37.0	1964	United States
Jiaozhou Bay Bridge	36.5	2011	China
Hangzhou Bay Bridge	35.7	2010	China
East Sea Bridge	32.5	2016	China
Jintang Bridge	26.5	2009	China
King Fahd Causeway	25.0	2005	Saudi Arabia
Great Belt Bridge	17.5	1998	Denmark
Oresund Strait Bridge	16.0	2000	Denmark

Table.1 List of longest cross-sea bridges

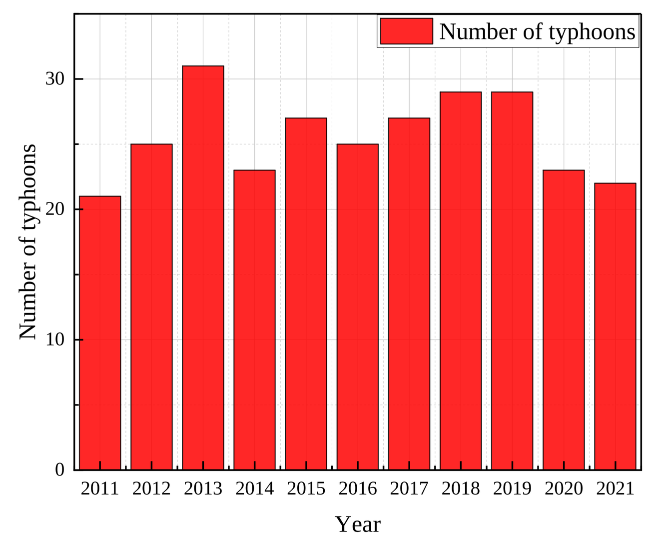
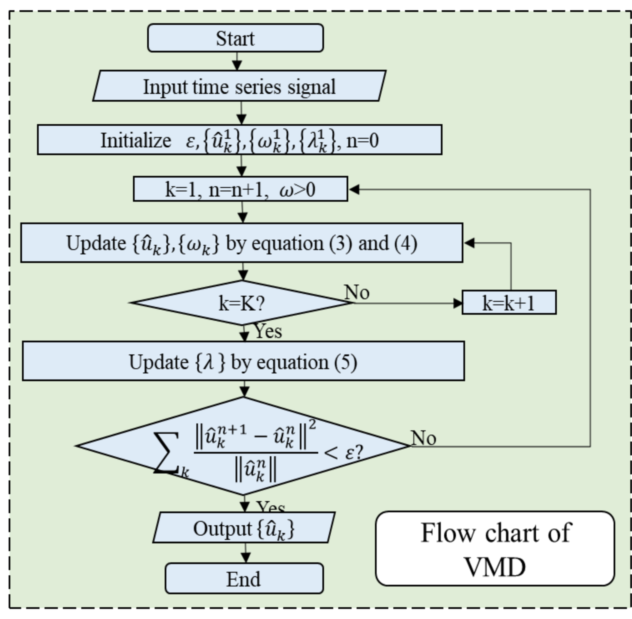


Fig.1 Annual typhoon numbers

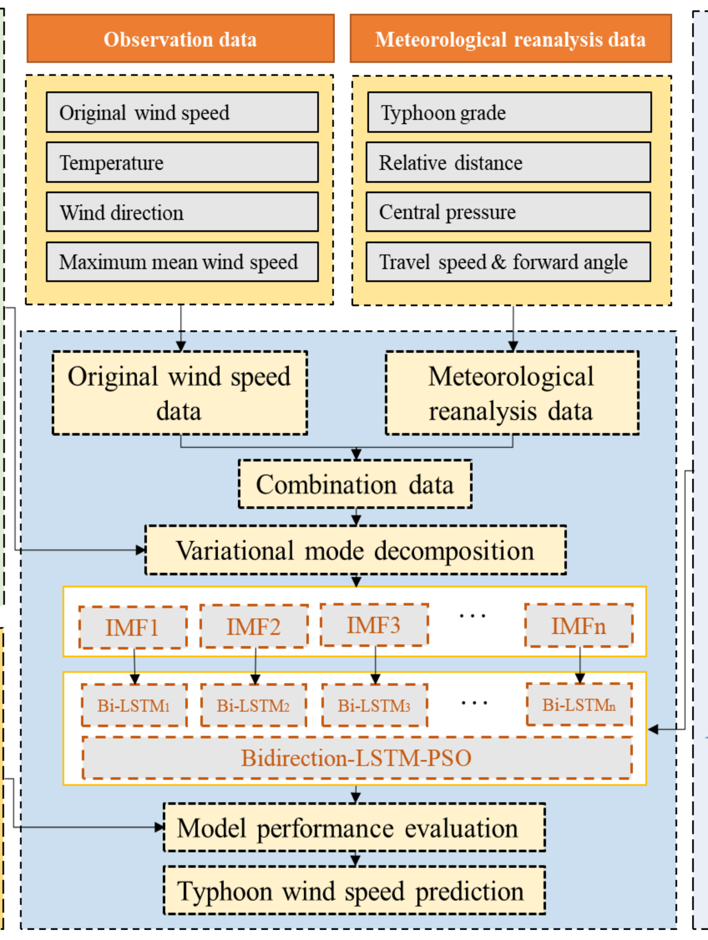
- China accounts for 7 of the world's top 10 cross-sea bridges in total length. Lots of bridges are located along the east coast of China.
- China's southeast coast suffers from lots of typhoons every year.
- Accurate typhoon wind speed prediction is significant for transportation infrastructures to protect the infrastructures from damage and avoid casualties.

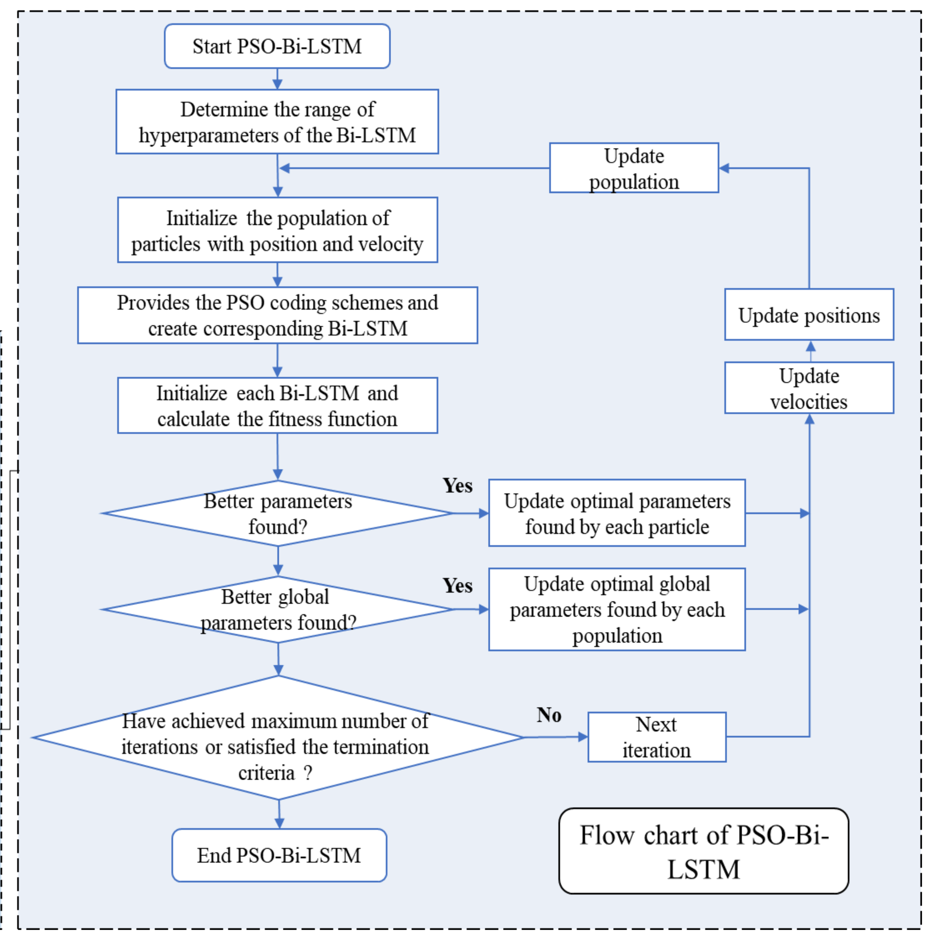
Flow Chart of proposed hybrid model



$$MAPE = \frac{100\%}{\bar{n}}\sum_{i=1}^{a}\left|\frac{z_i - y_i}{y_i}\right| \qquad MAE = \frac{1}{\bar{n}}\sum_{i=1}^{a}|z_i - y_i|$$

$$MSE = \frac{1}{a}\sum_{i=1}^{a}(y_i - z_i)^2 \qquad R^2 = \frac{\sum_{i=1}^{a}(z_i - y_i)^2}{\frac{1}{a}\sum_{i=1}^{a}(y_i - \bar{y})^2}$$





Data description and model introduction

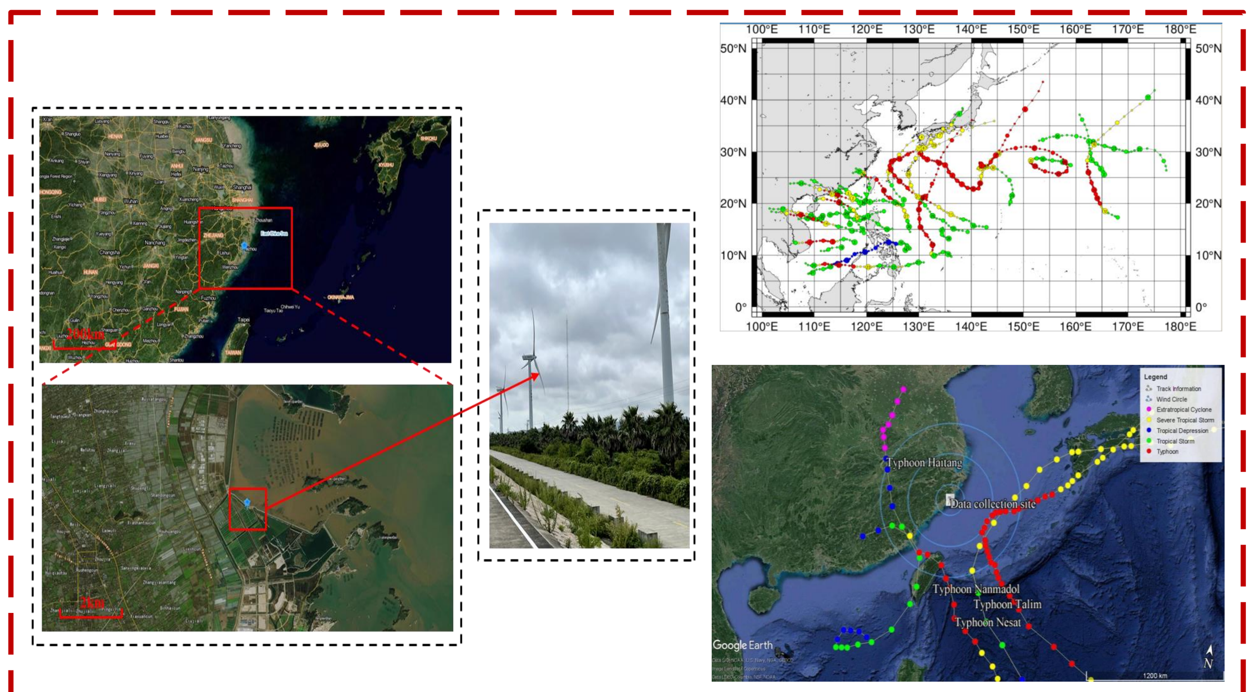
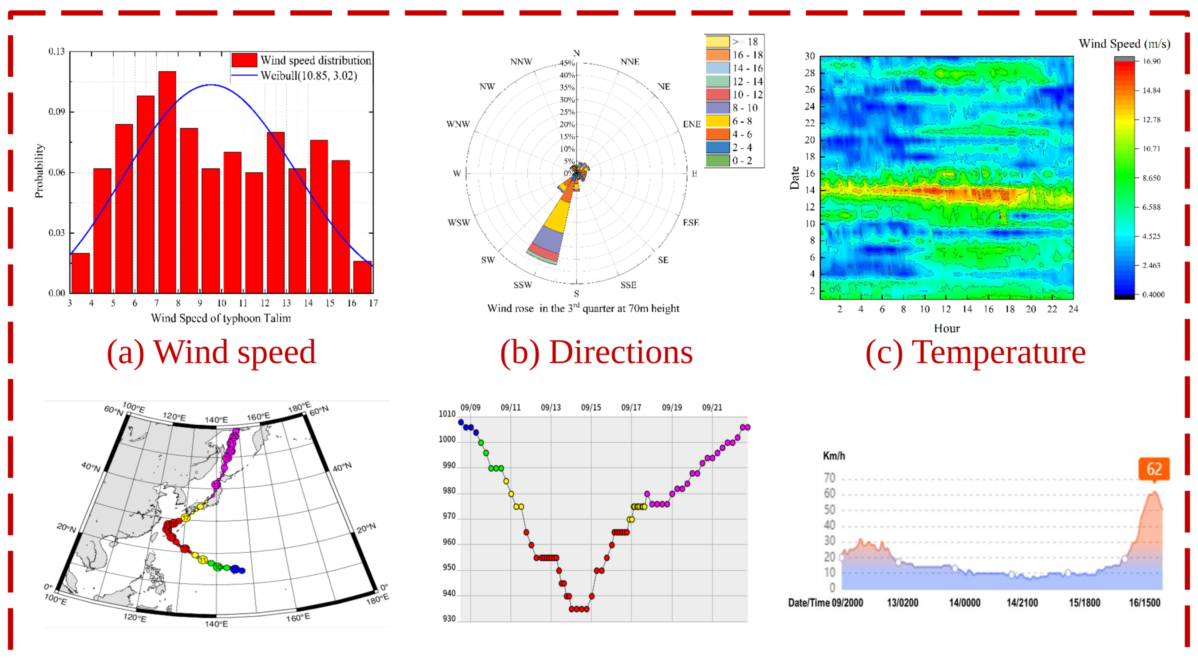
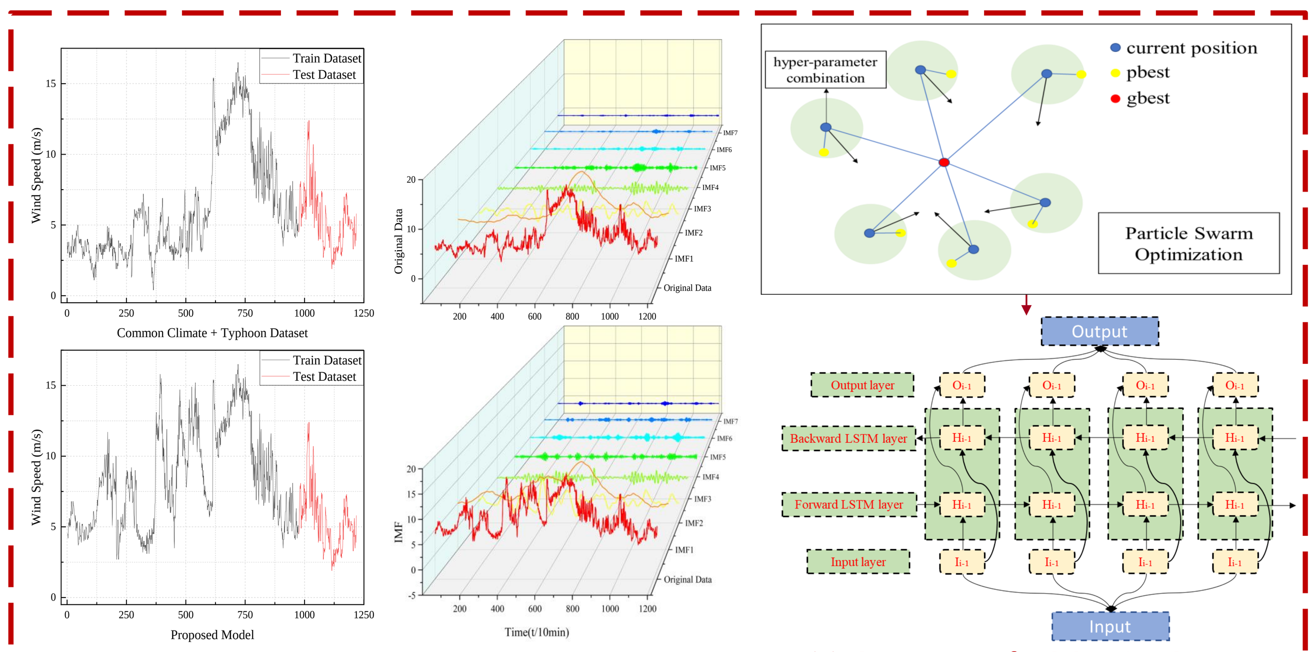


Fig.2 Observation site and selected typhoons

- Observation data comes from a wind farm in **Taizhou, Zhejiang.**
- Data of entire year of **2017** used to study.
- According to the average typhoon annual extreme wind speed return period curve, four typhoons approach in **500km wind circle** of observation site to study, such as the **'Haitang'**, **'Nanmadol'**, **'Talim'** and **'Nesat'** in year 2017 as the research objects.


(a) Wind speed (b) Directions (c) Temperature
(d) Typhoon tracks (e) Central pressure (f) Travel speed
Fig.3 State information of typhoon 'Talim'

- The **characteristics of a typhoon** are clearly different from those of ordinary weather, whether it is wind speed, temperature, wind direction or pressure.
- Therefore, this article collects **meteorological reanalysis data** such as central air pressure, moving speed, relative distance, and typhoon level.



(a) Comparative data (b) Decompose data (c) Structure of PSO-Bi-LSTM
Fig.4 Two different data set decomposed by VMD and model Bi-LSTM

- **Two groups of data** composed of pure typhoon data and combination data composed of both normal data and typhoon data are compared.
- **VMD** (Variational mode decomposition**)** is adopted to decompose the wind speed sequence into 7 modes according to center frequency ratio.
- **Bi-LSTM** (Bi-directional Long-short term neural network) is chosen as the model to make the prediction.

Result

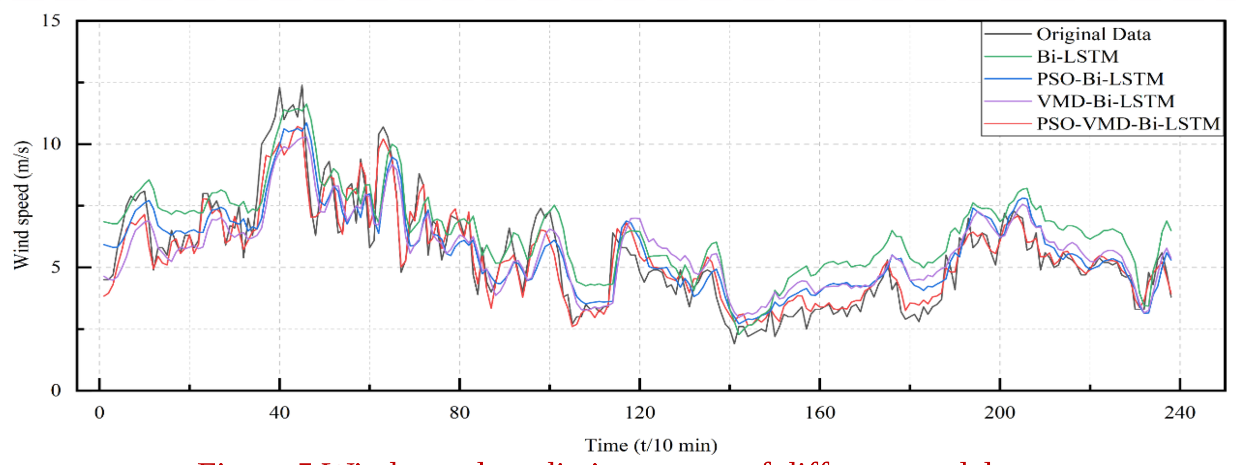
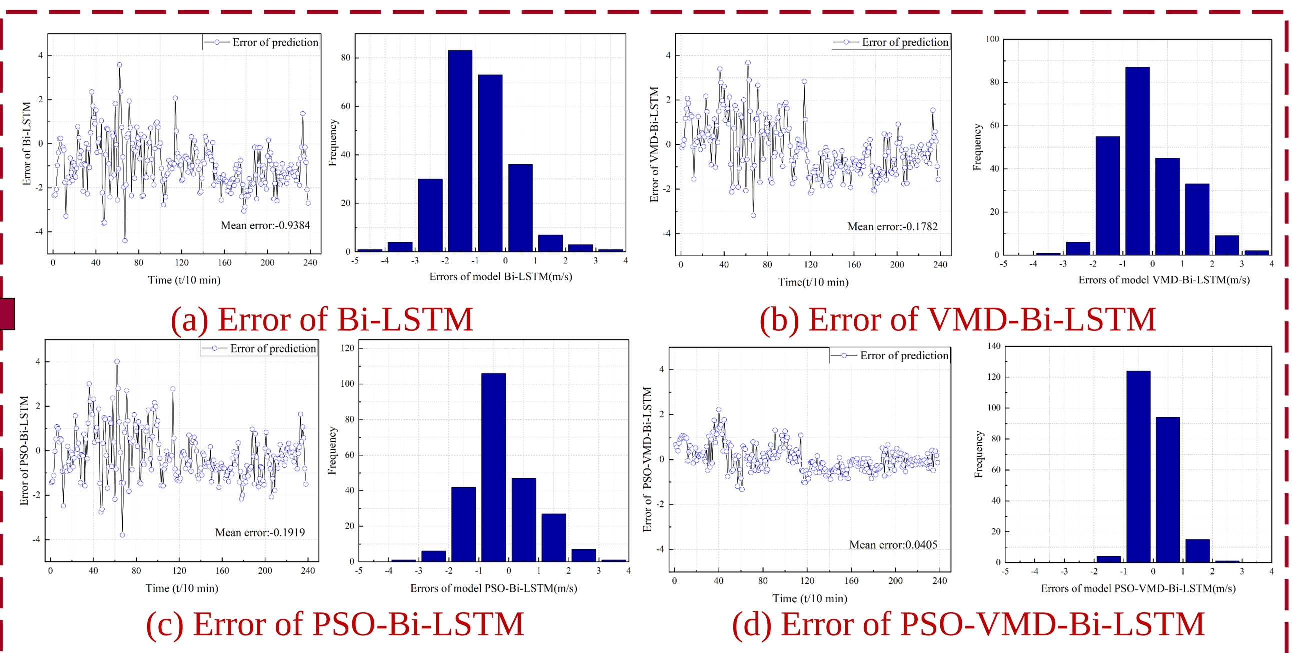
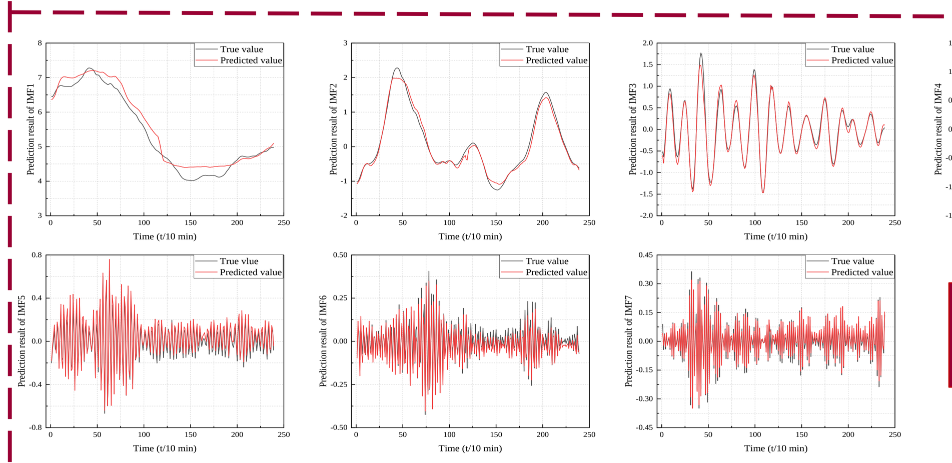


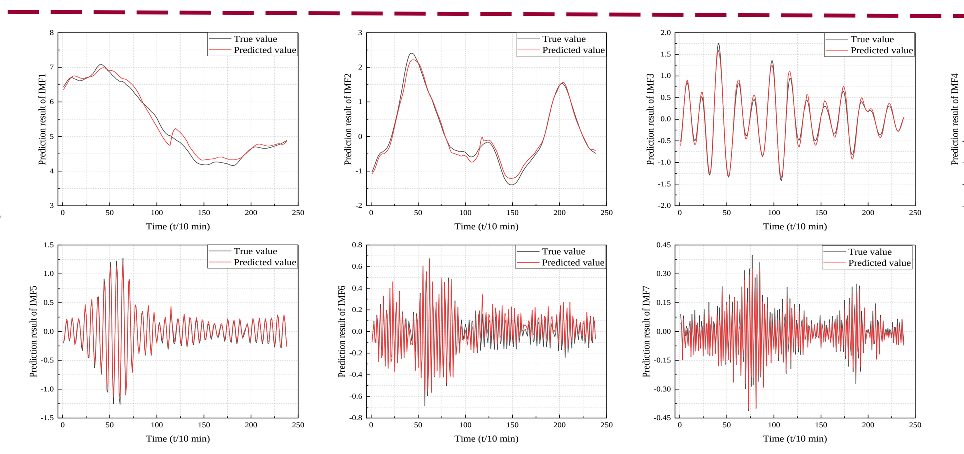
Figure.5 Wind speed prediction curves of different models

Prediction model	MAPE (%)	MSE	MAE	R2
	Evaluating indicator			
Bi-LSTM	0.2011	1.4819	0.9797	0.6716
VMD-Bi-LSTM	0.1771	1.089	0.8746	0.7233
PSO-Bi-LSTM	0.1424	1.0523	0.7583	0.7668
PSO-VMD-Bi-LSTM	0.0673	0.0027	0.0677	0.9753

Table.2 Evaluating indicator of the prediction model


(a) Error of Bi-LSTM (b) Error of VMD-Bi-LSTM
(c) Error of PSO-Bi-LSTM (d) Error of PSO-VMD-Bi-LSTM
Figure.6 Wind speed prediction error and error distribution of different models


Combinated typhoon data
Figure.7 Prediction of each IMF component of pure typhoon data


Pure typhoon data
Figure.8 Prediction of each IMF component of pure typhoon data

Evaluating indicator	IMF 1	2	3	4	5	6	7	PSO-VMD-Bi-LSTM
MAPE (%)	0.0282	0.1096	0.1298	0.1477	0.5498	0.3997	0.0311	0.1994
MSE	0.0374	0.0243	0.0045	0.0038	0.0021	0.0028	0.0003	0.0107
MAE	0.1552	0.1216	0.0533	0.0462	0.5498	0.3998	0.0311	0.1939
R2	0.9703	0.9706	0.9879	0.9651	0.9424	0.8897	0.9779	0.9577

Table.3 Evaluating indicator of each IMF in pure typhoon data

Evaluating indicator	IMF 1	2	3	4	5	6	7	PSO-VMD-Bi-LSTM
MAPE (%)	0.0124	0.0263	0.036	0.2834	0.0457	0.0512	0.0165	0.0673
MSE	0.0067	0.003	0.0038	0.0009	0.0009	0.0036	0.0006	0.0027
MAE	0.0124	0.0263	0.036	0.2834	0.0457	0.0512	0.0191	0.0677
R2	0.9934	0.9968	0.9891	0.9911	0.9928	0.9021	0.9622	0.9753

Table.4 Evaluating indicator of each IMF in pure typhoon data

- **Pure typhoon data** has better prediction performance based on the proposed model.
- **PSO** (Particle swarm optimization) has a good ability of model optimization and can improve the accuracy of prediction.
- **VMD** has a good ability of data process and can deeply mine the internal laws of data.
- **PSO-VMD-Bi-LSTM** model has the best performance in describing the dynamic change of the original wind speed sequence.

Conclusion

- **PSO-VMD-Bi-LSTM** model has the good performance in predicting the complex typhoon wind speed sequence.
- The **data selection method** by considering the typhoon characterizes is feasible to predict the wind speed during typhoons.
- This study is the first of its kind **combining both physical model and ANN model** in predicting typhoon wind speed.

Acknowledgement

The funding supports from the National Natural Science Foundation of China (No. 51908185, No.51508419), Natural Science Foundation of Hebei Province (No. E2019202072), Zhejiang Natural Science Foundation Project (LY19E080022) and Innovation Center for Wind Engineering and Wind Energy Technology of Hebei Province (ICWEHB202002) are gratefully acknowledged.