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Hierarchical learning method for array flow field prediction integrated with a deep neural network

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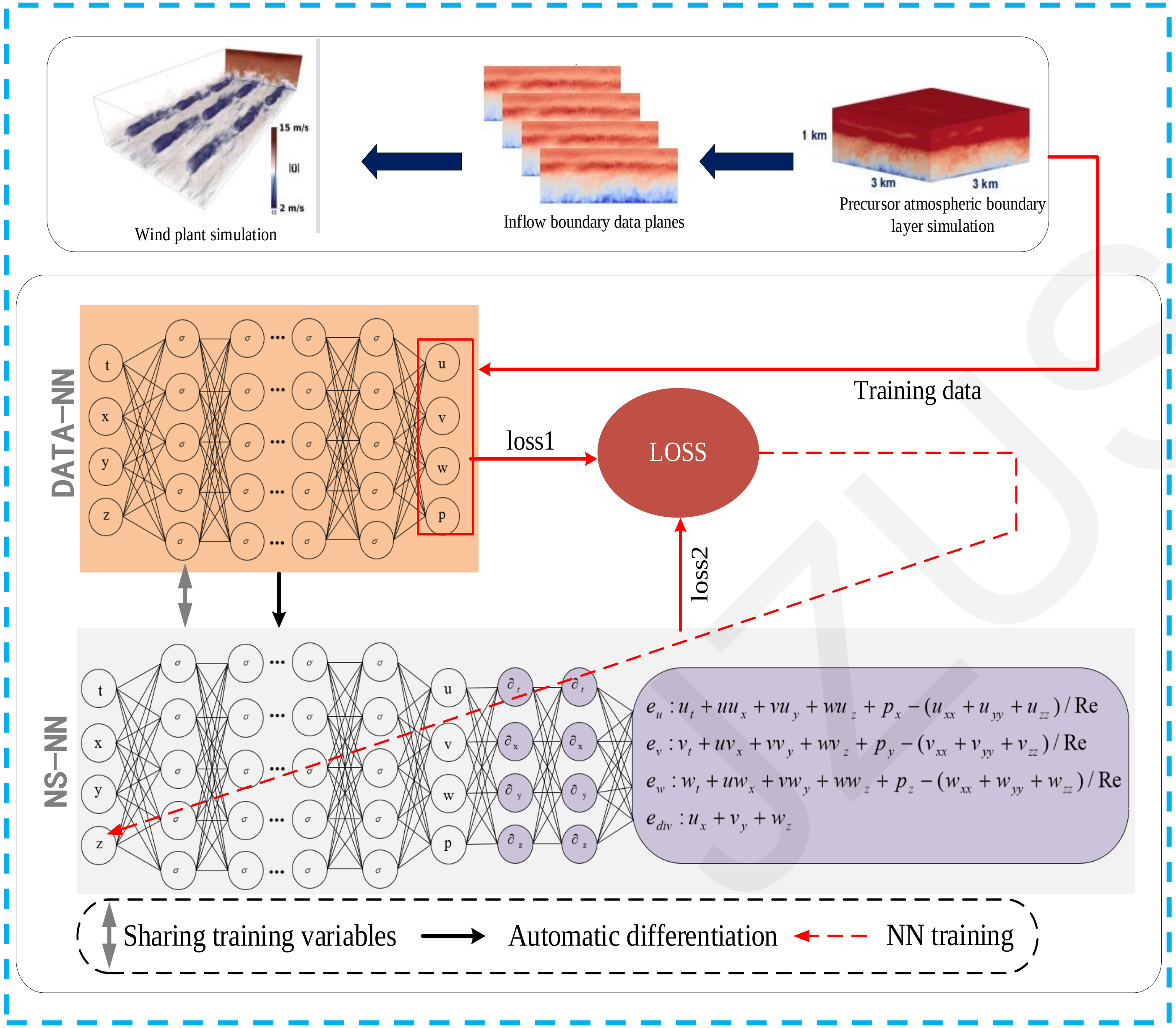
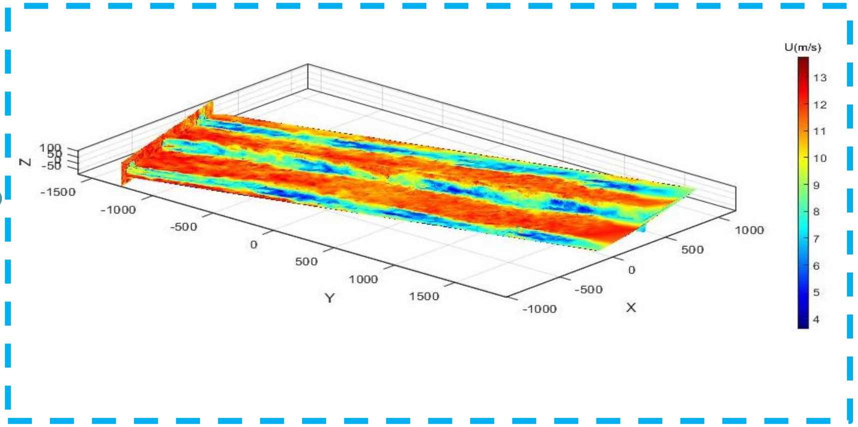
Technical route



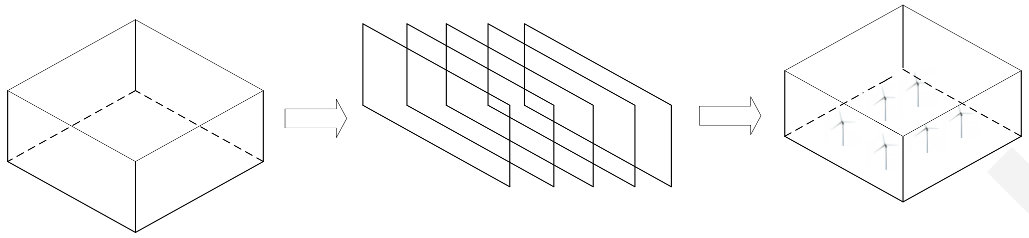
The technical roadmap of the proposed method is shown in the figure. First, high-precision training data are obtained through numerical simulation. Subsequently, the data are screened based on the principle of hierarchical learning. Finally, the final prediction results are output after model training.

Predicted



Wind turbine array simulation setup

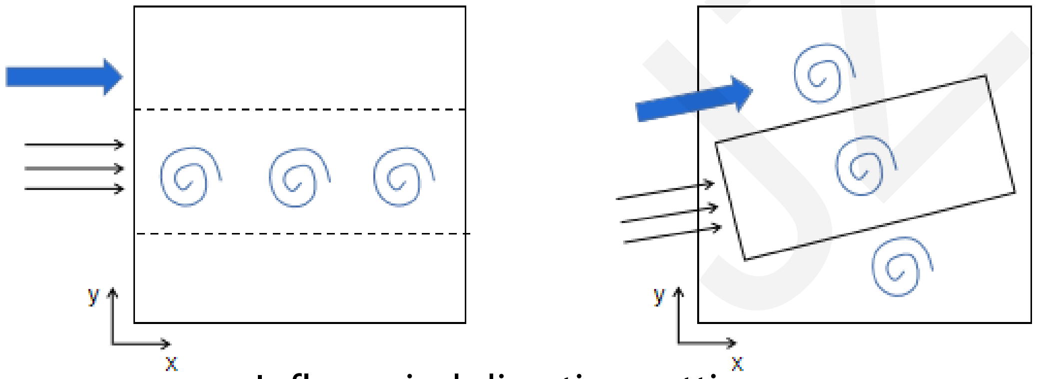
The numerical simulation adopts the precursor-main simulation method, with the wind turbine layout based on the Vested experimental study. Twelve orderly arranged wind turbines are placed in the wind farm to calculate the wake and obtain high-precision simulation data.



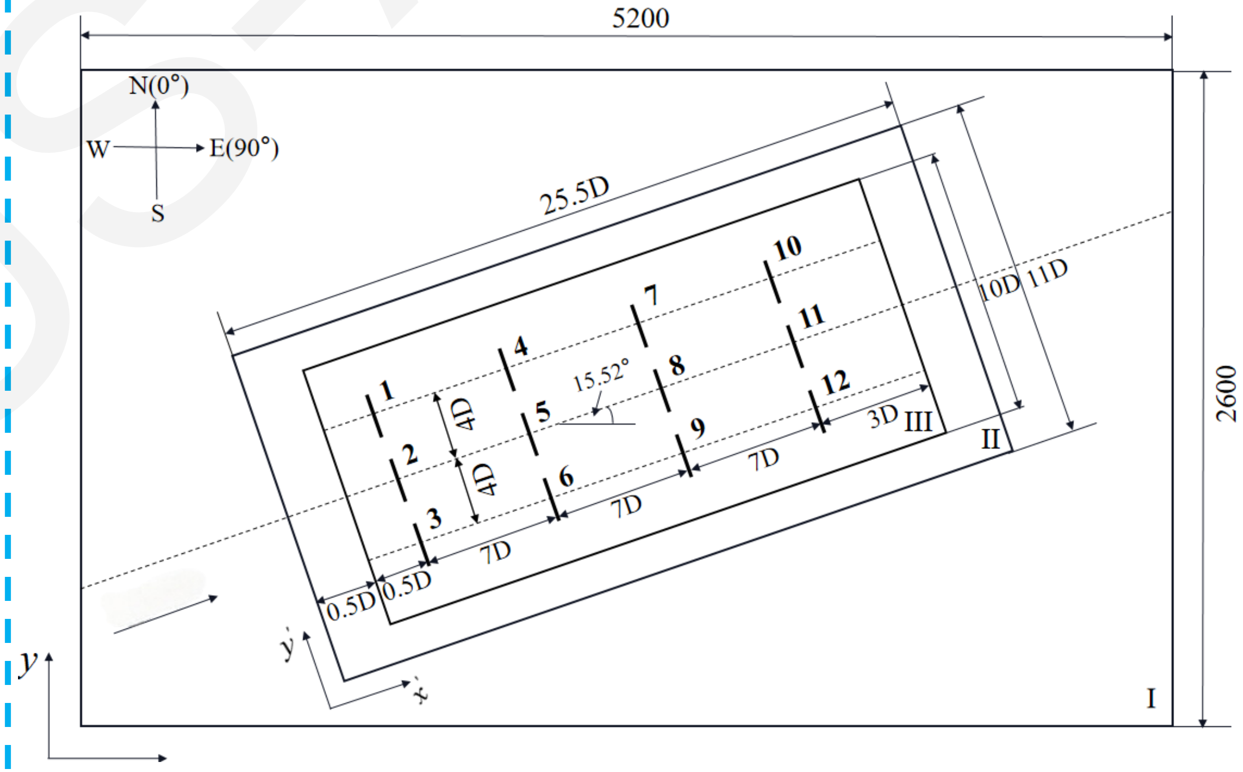
Precursor atmospheric boundary layer simulation

Save the wind farm inflow data

Wind farm main simulation

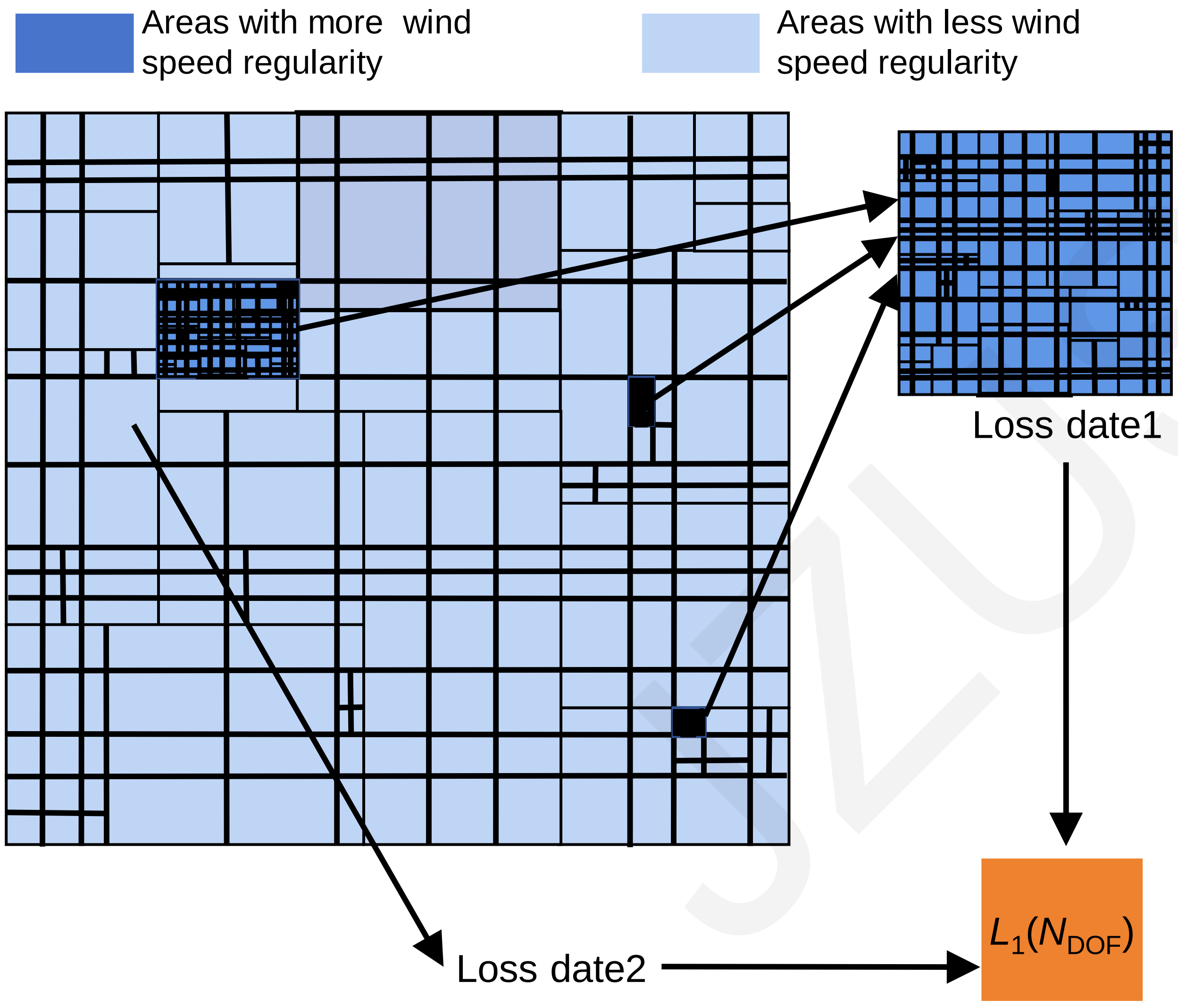


Inflow wind direction setting



Computational domain layout and grid size

Principle of Hierarchical Learning



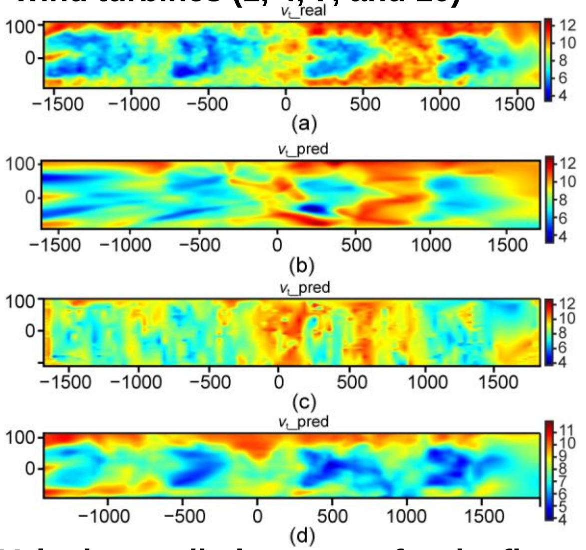
The core principle of the hierarchical learning model is to screen the data in the wind farm database based on the wind speed variations induced by the wake

The navy blue regions with significant wind speed variations are used as training data to minimize Loss data1, while for the light blue regions with minor wind speed variations, 1/10 of the data is randomly selected as training data to minimize Loss data2. Loss data1 and Loss data2 together constitute the data loss function $L_1(N_{DOF})$ of the entire model.

Results and comparison of the wake field predictions

To demonstrate the superior wake prediction of our method, we plotted vertical resultant velocity contours at each turbine location (three rows of four) and compared them with MLP and CNN results.(a) numerically simulated result; (b) predicted by MLP; (c) predicted by CNN; (d) predicted by the proposed method.Here, vt1 represents the resultant velocity predicted by the proposed method, while vt2 and vt3 represent the resultant velocity predicted by the MLP and CNN, respectively.

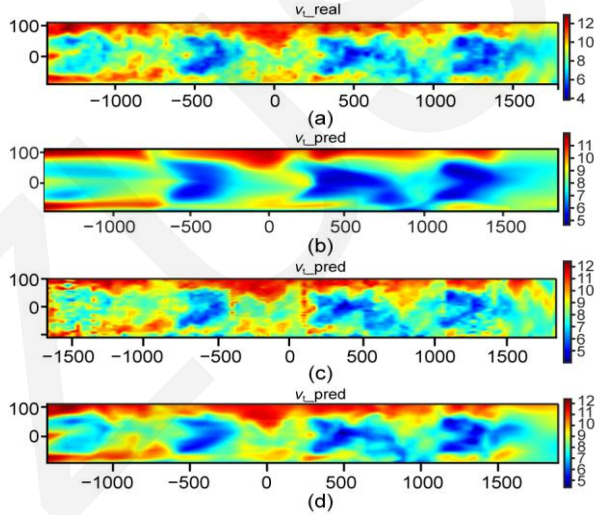
Velocity contour maps of the first row of wind turbines (1, 4, 7, and 10)



Velocity prediction errors for the first row

	ME	me	MAE	MRE	RMSE
v_{t1}	−0.301	0.410	0.311	0.0345	0.396
v_{t2}	0.346	−0.820	0.663	0.0771	0.887
v_{t3}	1.420	−1.584	0.637	0.0786	0.702

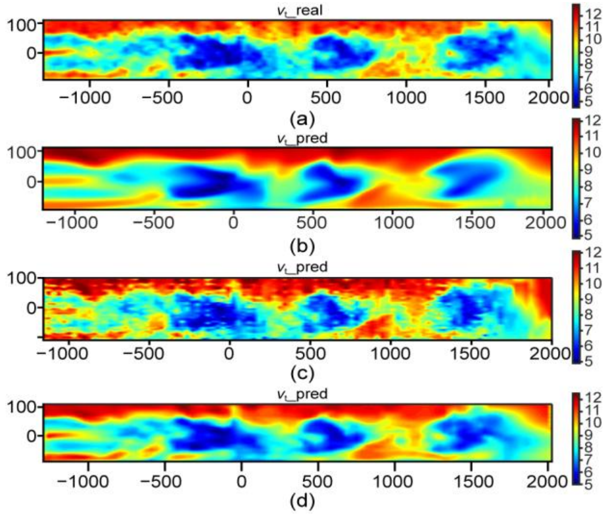
Velocity contour maps of the second row of wind turbines (2, 5, 8, and 11)



Velocity prediction errors for the second row

	ME	me	MAE	MRE	RMSE
v_{t1}	−0.433	0.390	0.297	0.0401	0.397
v_{t2}	−1.110	0.843	0.689	0.0821	0.855
v_{t3}	1.707	−1.579	0.447	0.0534	0.535

Velocity contour maps of the third row of wind turbines (3, 6, 9, and 12)

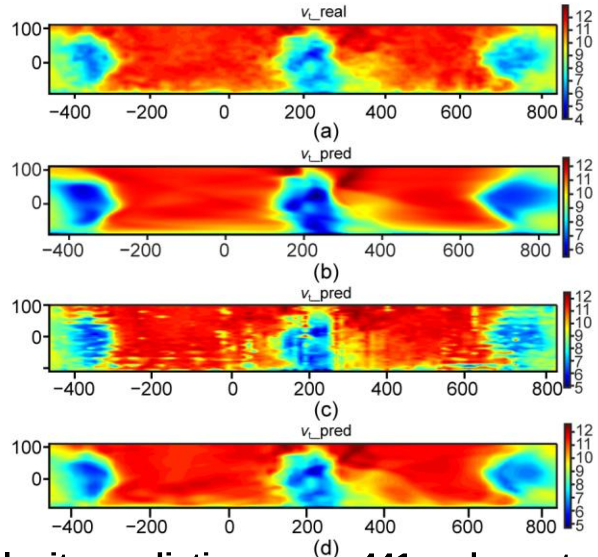


Velocity prediction errors for the third row

	ME	me	MAE	MRE	RMSE
v_{t1}	−0.252	0.360	0.207	0.0251	0.452
v_{t2}	−0.861	0.478	0.263	0.0538	0.616
v_{t3}	1.506	−1.848	0.337	0.0404	0.439

To further evaluate the superiority of the hierarchical learning model in wind farm prediction, based on the overall observation of the predicted three-dimensional flow field, cross-sections with richer wake dynamics and a larger amount of data, as well as those with fewer wake dynamics and a smaller amount of data, were selected for visualization after data processing.

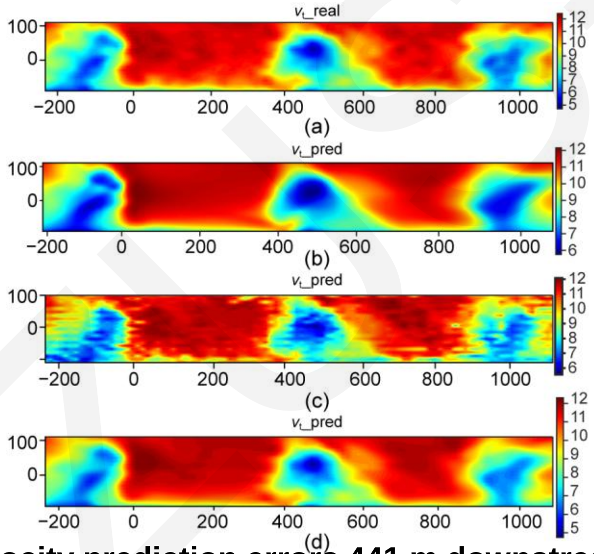
Cross-sections of the flow field 441 m downstream of the third column (7, 8, and 9) of wind turbines



Velocity prediction errors 441 m downstream of the third column of wind turbines

	ME	me	MAE	MRE	RMSE
v_{t1}	−0.241	0.512	0.210	0.0218	0.288
v_{t2}	−0.342	1.465	0.316	0.0312	0.437
v_{t3}	1.552	−1.744	0.288	0.0324	0.401

Cross-sections of the flow field 441 m downstream of the fourth column (10, 11, and 12) of wind turbines



Velocity prediction errors 441 m downstream of the third column of wind turbines

	ME	me	MAE	MRE	RMSE
v_{t1}	−0.065	0.070	0.154	0.0155	0.209
v_{t2}	−0.161	0.827	0.255	0.0257	0.334
v_{t3}	1.497	−1.362	0.326	0.0357	0.432

The cross-section 441 m behind the third column of wind turbines contains richer wake dynamics and a larger amount of data, while the cross-section 441 m behind the fourth column of wind turbines exhibits fewer wake dynamics and a smaller amount of data. Comparative analysis reveals that the overall flow structure and wind shear of the wind farm are well predicted, and the predicted results closely match the actual wind farm conditions, indicating that the proposed method successfully captures the three-dimensional spatial variations and temporal evolution of the incoming turbulent wind, demonstrating excellent spatiotemporal prediction performance.

Conclusions

To achieve accurate prediction of wind turbine wake fields, we applied a hierarchical learning approach within an integrated neural network framework, proposing a real-time dynamic wind field prediction method that balances both global and local aspects. By incorporating hierarchical learning and partial differential equations, the method reconstructs dynamic wake fields at any spatiotemporal coordinates using sparse data. Simulation results showed that the proposed method has a lower algorithmic complexity, which achieves reliable prediction accuracy while reducing data requirements, effectively capturing the correlations and dependencies among wind speeds in various dimensions of the wind farm.