Evaluating the impact of Numerical Weather Prediction variables on wind power forecasting: A case study of the Alpha Ventus offshore wind farm

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Offshore wind power forecasting

- Demand for sustainable and renewable energy sources increases.
- Offshore wind power generation has emerged as a critical contributor.
- Wind variability complicates accurate short-term forecasting of power generation.

Short-term forecasting is critical to:

- integrating wind power into the energy grid,
- reducing the reliance on additional power sources
- ensuring stability and efficiency

We have quantified the impact on short-term forecasting of:

- Numerical Weather Prediction
- Different Machine Learning models, including LSTM
- Lagged explanatory variables

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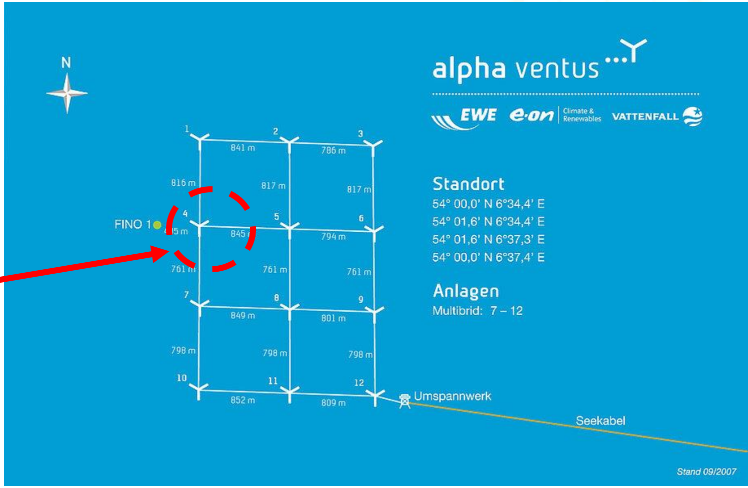
1. Alpha Ventus

- North Sea, 60 km from the coast
- 12 turbines – 60 MW

Attribute	Senvion 5M	Adwen AD-5116
Rated Power (MW)	5.075	5
Foundation	Jacket	Tripod
Hub Height (m)	92	90
Rotor Diameter (m)	126	116

- Data sources:
  Wind turbine sensors
  FINO1 research platform
- Data platform:
  RAVE (Research at Alpha VEntus)
- Senvion 5M turbine AV04 studied

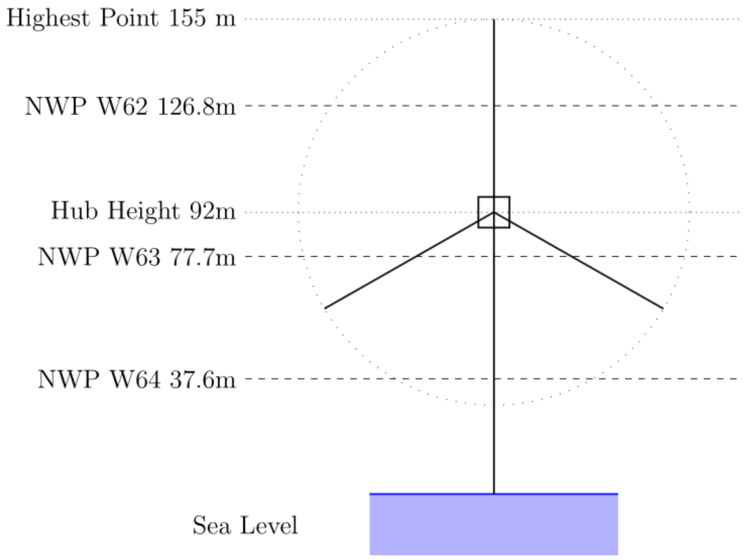


Source: https://www.alpha-ventus.de/

2. Numerical Weather Prediction (NWP)

Mathematical models based on physical principles to predict the weather.

- German Weather Service (Deutscher Wetterdienst, DWD) regional model, ICON-D2
  - Short-range forecasting up to 48h
  - 2.2 km horizontal resolution
- Data platform: Pamore



- We have tested wind speed at layers 62, 63 and 64

3. Machine Learning Models Tested

Decision Tree Models

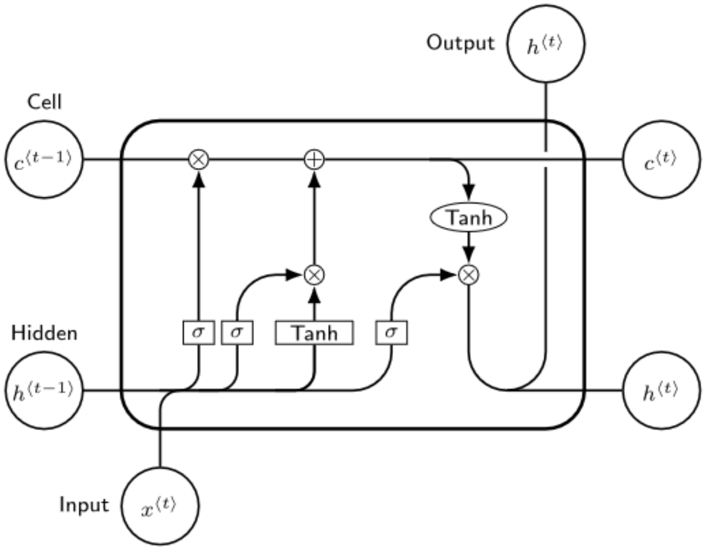
- Random Forest
- XGBoost
- LightGBM

Neural Network Models

- MLP
- LSTM

3.1 Long Short-Term Memory (LSTM)

- Specialized form of recurrent neural networks (RNNs)
- Incorporates memory cells and gating mechanisms that regulate the flow of information
- Effective in capturing long-term dependencies



4. Data Preprocessing

FINO1 variables:

- Wind Speed
- Atmospheric Pressure

	Variable	Units	Source
AP	Active Power	kW	RAVE
WS	Wind speed at the nacelle	m/s	RAVE
APr	Atmospheric pressure at the nacelle	hPa	RAVE
GS	Generator speed	rpm	RAVE
W62	Wind speed at 126.8 m	m/s	NWP
W63	Wind speed at 77.7 m	m/s	NWP
W64	Wind speed at 37.6 m	m/s	NWP

FINO1 data recovery
- meteostat Python package

Wind sensor data recovery
- XGBoost models trained on FINO1 data

Active Power data recovery
- Theoretical wind power equation
- Cp (power coefficient) minimizing MSE

Outlier detection
- Filter negative wind power values
- Isolation Forest

Data normalization
- **Scaling individual samples to have unit norm**

Data split
- 80 % training
- 10 % tuning, 10 % validation

5. Experiments Configuration

We have tested a comprehensive combination of

- Measured explanatory variables
  - Wind Speed, Atmospheric Pressure, Generator Speed
- One of the NWP variables at a time or none
  - W62, W63, W64
- Lagged explanatory & objective variables
  - 0, 1, 2, 3, 4, 6, 12
- Machine Learning models
  - Random Forest, XGBoost, LightGBM, MLP, LSTM

Metric	MAE
Hyperparams tuning	Optuna
Significance test	Diebold-Mariano

6. NWP Impact

☂ Among the NWP variables tested, statistical significance

- W62 in 4/7 configurations
- **W63 in 5/7 configurations**
- W64 in 3/7 configurations

MAE values (kW) for the LSTM model with and without NWP. The values marked with * indicate a significant difference (p-value<0.05) between the models. The p-values are calculated using the Diebold–Mariano test. The best result is in bold. While W63 shows the most consistent improvements, the best model combines W62 with Wind Speed, Active Power and Air Pressure.

Explanatory variables	No NWP	W62	W63	W64
AP, APr	234.63	229.49 *	236.27	245.94
AP	235.79	250.05	232.68 *	233.72
WS, AP, APr	243.11	**228.93** *	231.10 *	239.25 *
WS, AP	246.73	234.67 *	239.11 *	241.89 *
WS, APr, GS, AP	236.91	239.21	239.19	242.40
WS, APr, GS	260.13	263.09	243.21 *	260.88
WS	265.54	245.78 *	246.71 *	259.83 *

7. Lagged Variables Impact

- Adding a single lag tends to improve performance in most cases.
- Further increasing the lags does not result in additional benefits.
- Combining of NWP variable with lagged variables improves results.

Significant improvement	
*	NWP
†	Lags

Explanatory variables	NWP	0	1	2	3	4	6	12
AP, APr	No NWP	234.63	239.46	251.42	249.16	246.40	254.27	319.58
AP, APr	W62	229.49	231.13	241.47 *	247.58 *	895.69	247.45 *	902.51
AP, APr	W63	236.27	226.82 *	236.72	258.13	242.07	251.84 *	243.01
AP, APr	W64	245.94	231.10 †	240.92	245.60 *	249.56	258.56	901.46
AP	No NWP	235.79	237.44	239.21	239.83	245.71	251.42	249.94
AP	W62	250.05	228.81 * †	243.64	250.03	249.05	244.19	318.84
AP	W63	232.68 *	230.20 * †	242.23	245.85	243.60 *	251.07 *	902.91
AP	W64	233.72 *	234.77 *	241.35	252.38	252.53	288.89	267.74
WS, AP, APr	No NWP	243.11	233.28 †	248.52	250.13	241.59	253.03	902.78
WS, AP, APr	W62	228.93 *	226.75 * †	241.10 *	252.02	243.29	251.06 *	253.05 *
WS, AP, APr	W63	231.10 *	**224.22** * †	238.37 *	252.89	251.78	901.70	902.27 *
WS, AP, APr	W64	239.25 *	234.92 †	240.06 *	248.29 *	246.38	897.17	257.50 *
WS, AP	No NWP	246.73	235.13 †	239.31	246.86	242.83	262.25	249.90
WS, AP	W62	234.67 *	225.38 * †	234.04 *	241.26 *	248.85	247.05	261.79
WS, AP	W63	239.11 *	230.26 * †	244.67	247.76	254.53	244.16 *	246.86 *
WS, AP	W64	241.89 *	230.63 * †	245.72	250.40	243.31	251.94 *	254.66
WS	No NWP	265.54	267.33	275.15	281.74	276.92	897.99	902.61
WS	W62	245.78 *	256.14 *	262.23 *	263.72 *	274.60 *	901.39	272.35 *
WS	W63	246.71 *	256.02 *	257.01 *	267.17 *	271.84 *	257.96 *	344.45
WS	W64	259.83 *	255.95 *	254.78 *	259.83 *	261.49 *	273.24 *	285.14 *

8. NWP, Lagged Variables & Different Models

Results are consistent across models

- Adding a single lag tends to improve performance in most cases.
- Further increasing the lags does not result in additional benefits.
- Combining the NWP variable with lagged variables improves results.

Proportion of Diebold–Mariano tests that resulted in statistically significant improvements (p-value <0.05) when increasing the number of lags used as input features for each model. The table shows how including 1-h lagged variables yields improvements in the majority of cases, while more lagged variables do not seem relevant, except for the MLP algorithm.

	LSTM	MLP	Random forest	XGBoost	LightGBM
1 lags	0.55	0.75	0.61	0.57	0.46
2 lags	0.00	0.18	0.00	0.07	0.14
3 lags	0.00	0.21	0.07	0.00	0.04
4 lags	0.00	0.18	0.04	0.00	0.07
6 lags	0.00	0.21	0.00	0.07	0.00
12 lags	0.00	0.11	0.00	0.00	0.00

Proportion of Diebold–Mariano tests that resulted in statistically significant improvements (p-value <0.05) when including NWP wind speed as an input feature for each model. The inclusion of NWP variables yield to significant improvements in most of cases.

NWP	Lags	LSTM	MLP	Random forest	XGBoost	LightGBM
W62	0 lag	0.60	0.43	0.71	0.86	0.86
	1 lag	0.80	0.57	1.00	1.00	0.86
W63	0 lag	0.80	0.43	1.00	0.86	0.86
	1 lag	1.00	0.57	0.71	1.00	0.86
W64	0 lag	0.80	0.29	0.86	0.86	0.71
	1 lag	0.60	0.71	1.00	1.00	1.00

9. Models Comparison

- Leading model is LSTM
- Follows MLP, LightGBM, XGBoost and Random Forest
  - Interesting options when computational resources are limited

- Best performing models include
  - NWP & 1h lagged vars
  - Active Power (and generally Wind Speed)

MAE results (kW) for the top 5 performing configurations by model type. LSTM stands out with the best results, followed by the MLP. All models use NWP variables and most include 1-h lagged explanatory variables.

	LSTM				MLP			
	MAE	Vars	NWP	Lags	MAE	Vars	NWP	Lags
1	224.22	WS, AP, APr	W63	1	232.56	WS, APr, GS, AP	W63	1
2	225.38	WS, AP	W62	1	235.32	AP	W62	1
3	226.75	WS, AP, APr	W62	1	236.48	AP, APr	W64	3
4	226.82	AP, APr	W63	1	238.45	AP, APr	W63	4
5	228.81	AP	W62	1	238.45	WS, APr, GS, AP	W62	2
	Random Forest				XGBoost			
	MAE	Vars	NWP	Lags	MAE	Vars	NWP	Lags
1	243.63	AP, APr	W62	0	242.11	AP, APr	W63	0
2	243.82	WS, AP, APr	W63	0	242.97	WS, APr, GS, AP	W62	1
3	245.94	AP, APr	W63	0	244.11	AP, APr	W62	1
4	246.35	WS, AP, APr	W63	1	244.51	AP	W62	2
5	246.95	AP, APr	W62	1	244.55	AP	W62	1
	LightGBM							
	MAE	Vars	NWP	Lags				
1	236.25	AP, APr	W63	1				
2	236.32	AP, APr	W62	1				
3	240.98	WS, APr, GS, AP	W63	1				
4	241.10	WS, APr, GS, AP	W63	0				
5	241.97	WS, AP, APr	W64	0				

10. Conclusions and Future Works

Elements leading to best performance

- LSTM
  - Alternative ML models were also competitive and demand less computational resources
- 1 hour lagged variables (no more lags)
- NWP variables
- Lagged objective variable (Active Power)
- Wind Speed as explanatory variable

Future works

- Reproducing results on other offshore wind farms
- Incorporating other NWP systems
- Testing other deep-learning architectures

Thank you!

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