Severe Wind Event Prediction with Multivariate Physics-Informed Deep Learning

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Introduction

Wind turbines play a crucial role in combating climate change by harnessing the force of the wind to generate clean and renewable energy.

Predicting weather events, such as severe wind, can support clean and renewable energy via wind turbines by:

- Reducing maintenance costs due to damage from wind events.
- Mitigating lost production time from unnecessary or premature shutdowns due to uncertainty in wind event timing.
- Extending the longevity of turbine equipment with proactive shutdowns.
- Mitigating turbine operation cost to maintain wind power as a financially attractive clean energy source.

Prior work is limited by the following factors, among others:

- Forecasting methods generally struggle to model high frequency data, such as on the scale of seconds, with rapid fluctuations and short-lived patterns, resulting in increased prediction errors.
- Temporal Classification methods can be influenced by label imbalances due to the scarcity of severe weather events in limited historical data.
- Survival Analysis methods adhere to assumptions, such as the independence of survival times and censoring mechanisms, which might be violated by the complex interactions and dependencies inherent in weather patterns.

To address these challenges we propose:

1. A preliminary physics-informed deep learning model to improve predictions of severe wind events.
2. A multivariate time series extension for this work.

Data

Data Specifications:

- **Target:** Severe wind events (wind speed >20 m/s)
- **Features:** Wind speed, wind direction, ambient temperature, distance (m) and angle (degrees) between turbines
- **Duration:** 30 days of data for each turbine
- **Frequency:** Data was downsampled to 0.1 Hz (10 seconds)
- **Total number of events:** 179

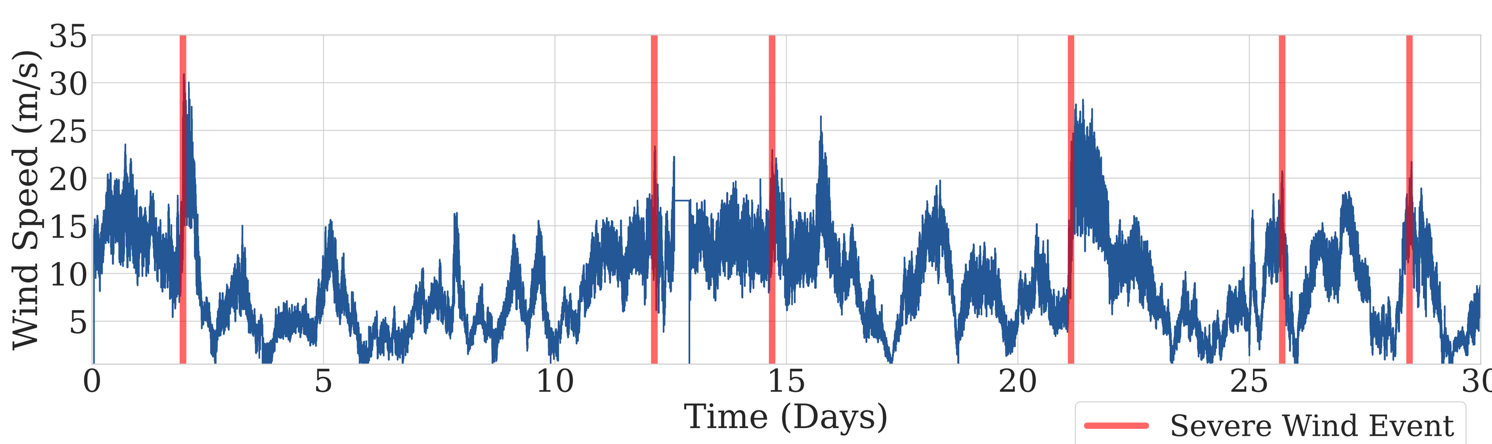

Fig. 1: Multiple wind events were observed for each turbine within a 1-month period.

Data from 3 wind events prior to day 22 were used to train the model and the wind event on day 22 was used for the final evaluation to maintain temporal ordering and prevent data leakage.

Methods

Wind speed recorded at the turbine with the first registered wind event may vary for subsequent turbines due to wind direction and terrain, among other factors. To account for discrepancies in velocity, we incorporate a velocity scaling factor, s, that is learned using a multilayer perceptron (MLP) [1, 2].

ML Physics Hybrid Model:

$$\hat{t} = \frac{d}{v \cdot s}$$

$$s = f_\theta(x)$$

$$x \in \mathbb{R}^{N \times C}$$

Where N is the number of turbines and C is the number of features in x.

Training:

$$MSE(\hat{t}) = \frac{1}{N}\sum(\hat{t} - t)^2$$

Evaluation:

$$MAE(\hat{t}) = \frac{1}{N}\sum|(\hat{t} - t)|$$

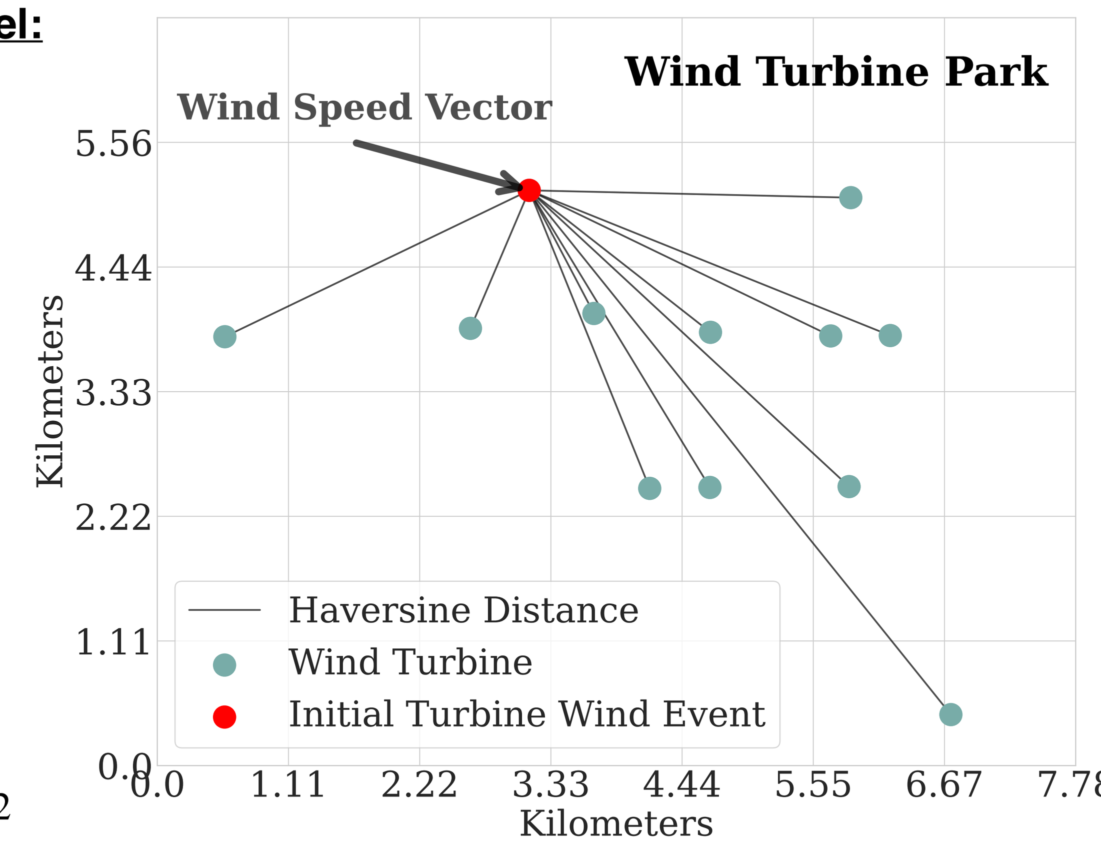

Fig. 2: Wind speed, wind direction, and distance between turbines can inform wind event predictions for subsequent turbines.

Results

The **proposed hybrid model** demonstrates improved performance over both purely physics and ML baselines.

Additionally, the hybrid model only leverages aggregate information 1-minute prior to the first turbine wind event yet **outperforms the best physics baseline that updates predictions at new events.**

Model		Equation	MAE (standard deviation)
Baselines	Average	$\hat{t} = \bar{t}$	45.57 (7.03)
	Physics	$\hat{t} = \frac{d}{v}$	6.79 (6.19)
		$\hat{t} = \frac{d_t}{v_t}$	5.03 (4.45)
	ML	$\hat{t} = MLP(x)$	12.72 (6.94)
		$\hat{t} = DSM(x)$ [3]	6.62 (5.43)
Proposed	ML Physics Hybrid	$\hat{t} = \frac{d}{v \cdot s}$	**2.61 (4.02)**

Table. 1: MAE computed across turbine wind event predictions in the test set.

Results

The ML Physics Hybrid model can more accurately predict wind events (red) with longer lead times between model inference (yellow) and predicted event (teal) compared to the best physics baseline model.

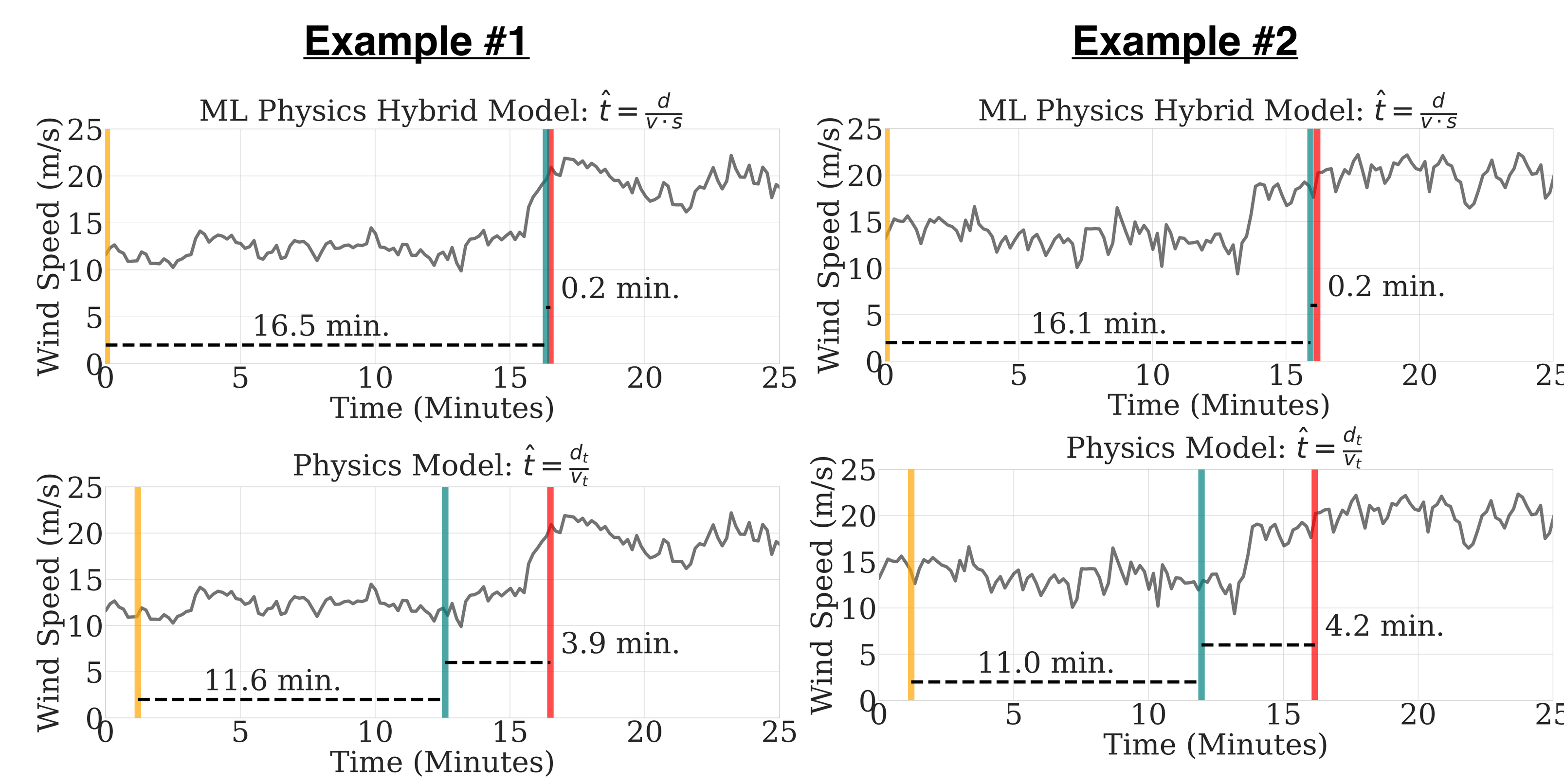

Fig. 3: Two turbine example cases that compare the ML Physics Hybrid model (top) to the best physics baseline model (bottom).

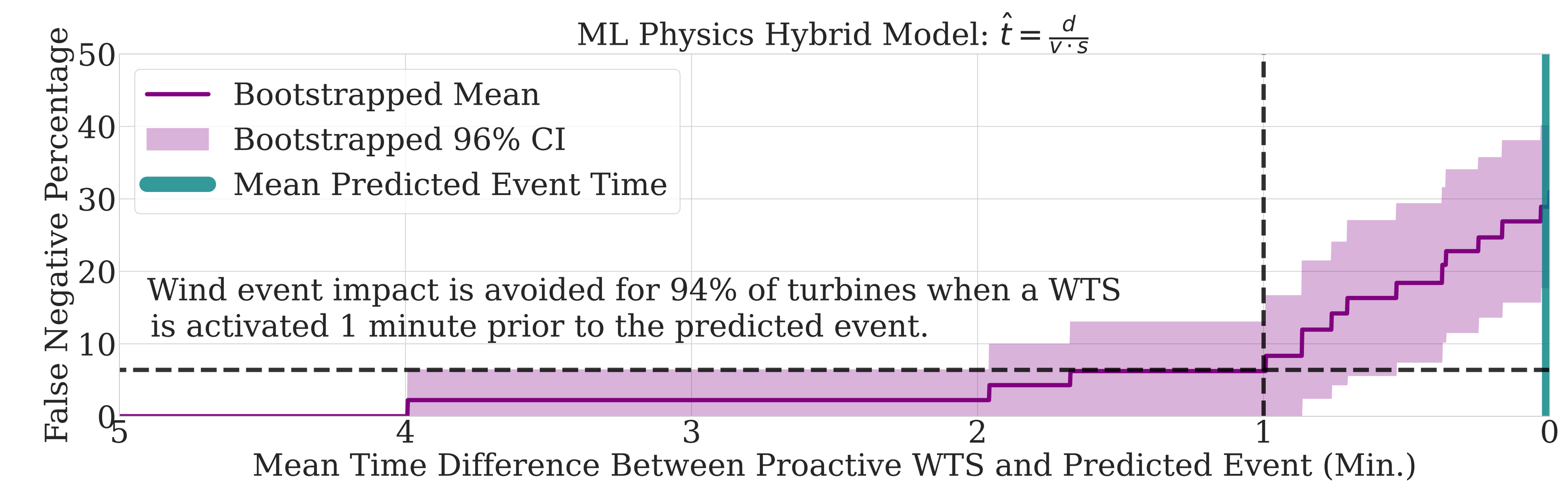

Fig. 4: Trade off in false negatives (late predicted events) for larger proactive WTS lead times.

Proposed Model Extensions

We propose to extend our preliminary ML Physics Hybrid model to:

- Leverage time series data across multiple turbines to infer a time-dependent velocity representation or scaling factors.
- Leverage attention mechanisms to weight importance of neighboring turbine time series such as with Graph Attention Networks (GATs) [4].

Conclusions

The proposed hybrid model demonstrates improved performance over both purely physics and ML baselines. Implementing such a model in practice could mitigate economic losses due to maintenance and thus, enhance the cost-effectiveness of wind turbines for clean and renewable energy.

References

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2. Frank Rosenblatt. The perceptron: A probabilistic model for information storage and organization in the brain. Psychological Review, 65(6):386—408, 1958.
3. Chirag Nagpal, Xinyu Li, and Artur Dubrawski. Deep survival machines: Fully parametric survival regression and representation learning for censored data with competing risks. IEEE Journal of Biomedical and health Informatics, 25 (8):3163-3175, 2021.
4. Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio. Graph attention networks, 2018.