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.

Introduction (cont.)

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

A key factor in ensuring the long-term effectiveness of wind turbines is the reduction of costly wind turbine shutdowns (WTS) due to maintenance for weather impacts, such as severe wind events.

Introduction (cont.)

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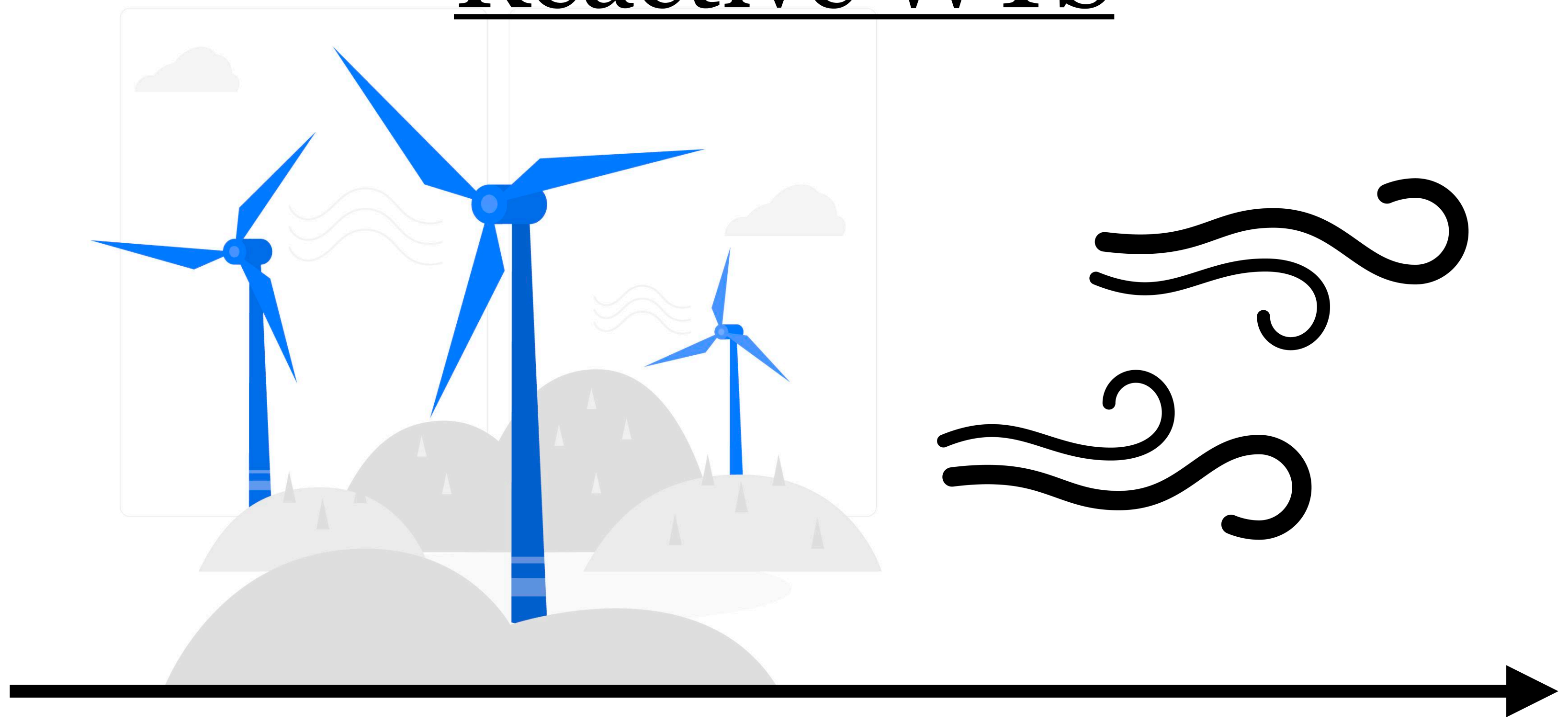
Reactive WTS



Time *Shutdown Alarm

Image: Image by storyset on Freepik

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By leveraging historic weather data, machine learning (ML) can enable more precise predictions of wind events allowing for a **proactive WTS** prior to wind event impact.

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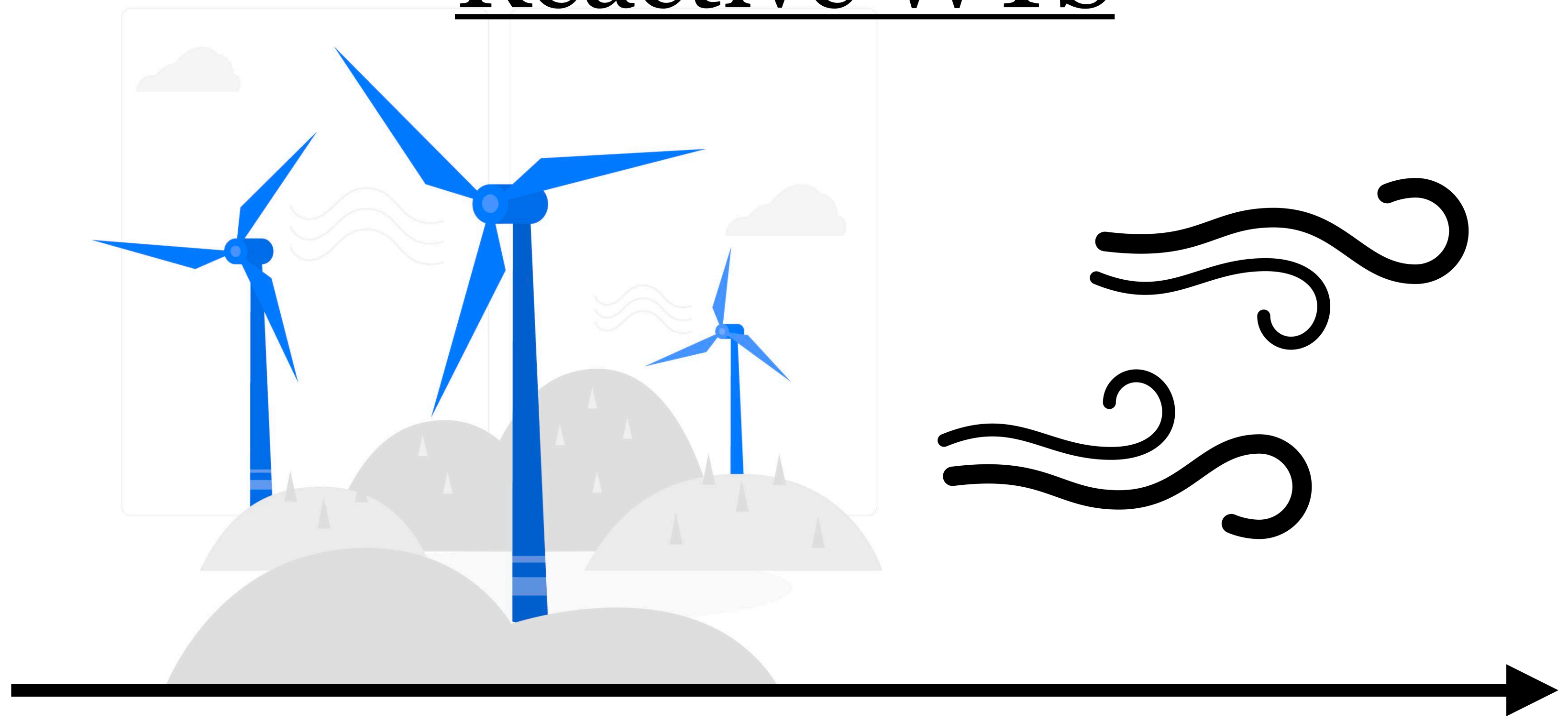

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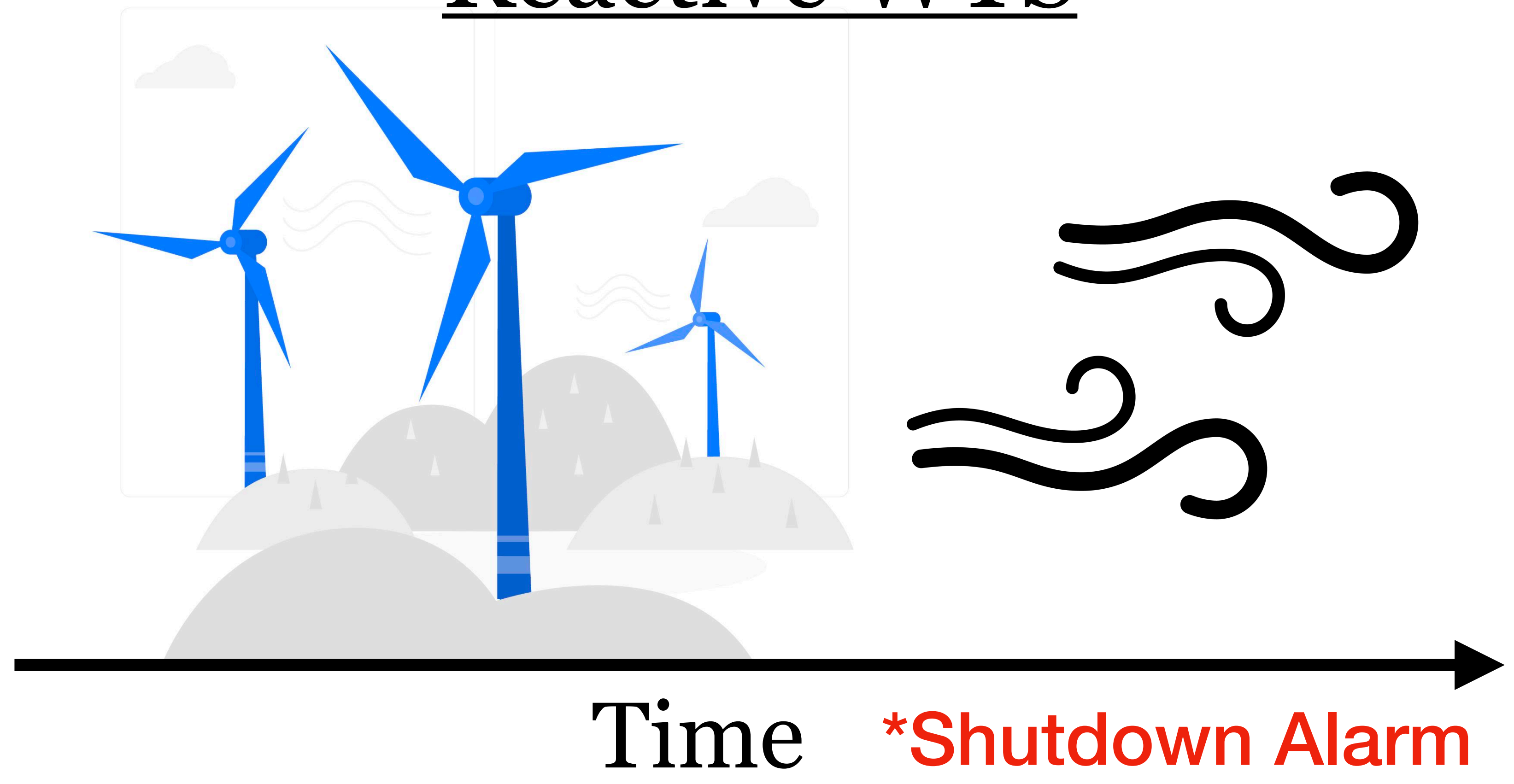
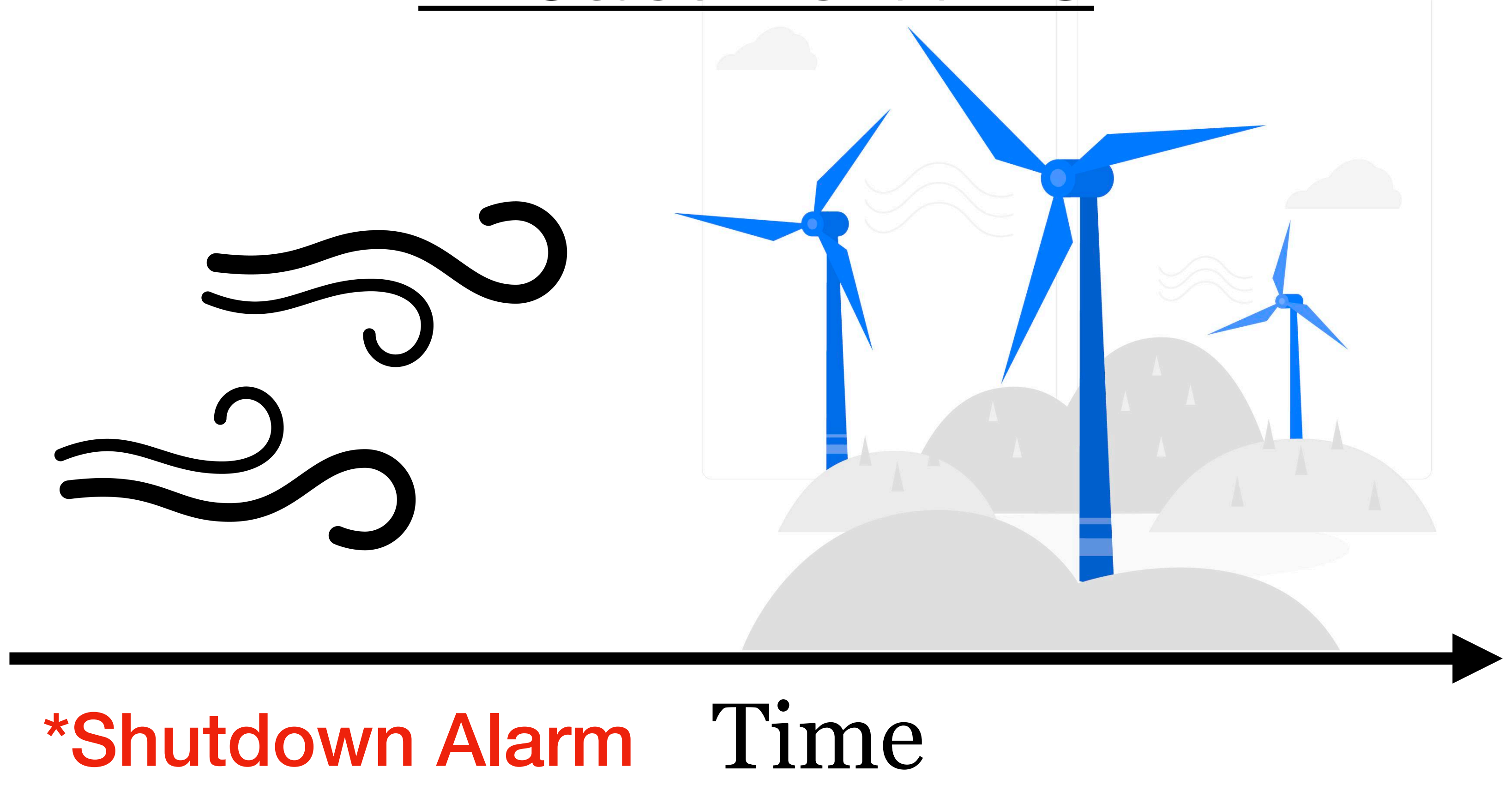


Proactive WTS



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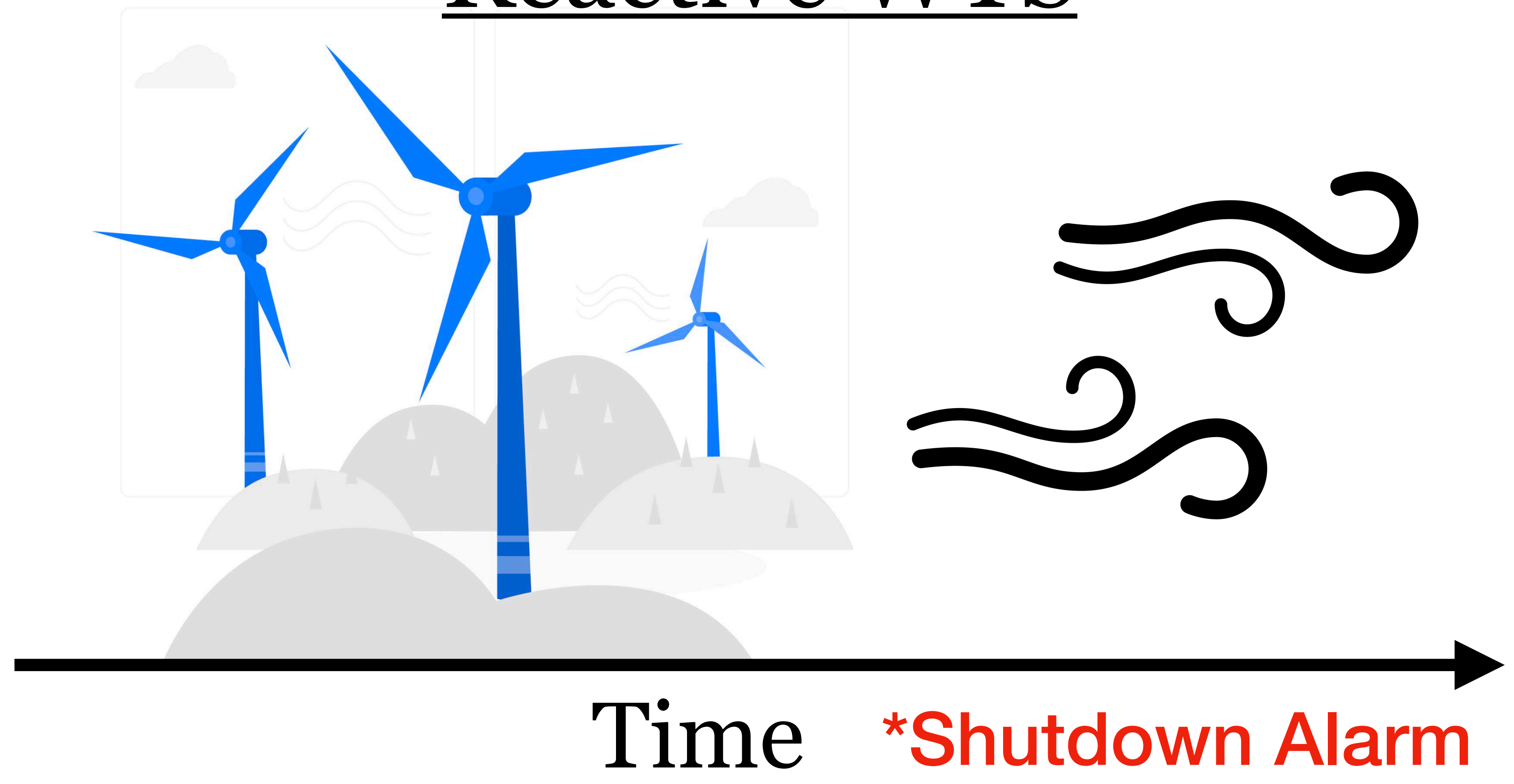
A proactive WTS can help safeguard turbines against costly damage and extend the longevity of the equipment, thereby helping to maintain wind power as a financially attractive clean energy source.

Reactive WTS



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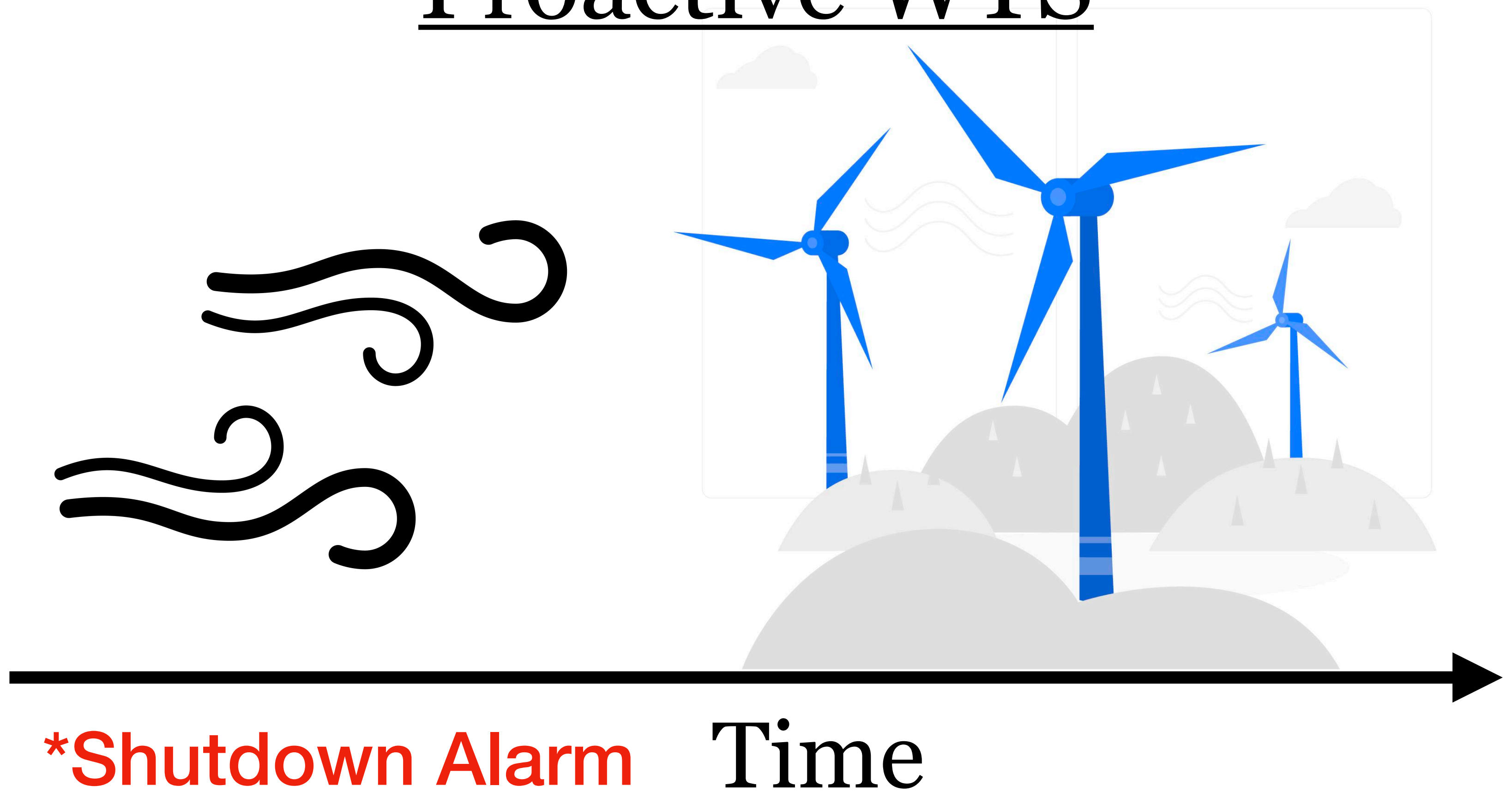

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Prior work is limited by the following factors, among others:

- 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.

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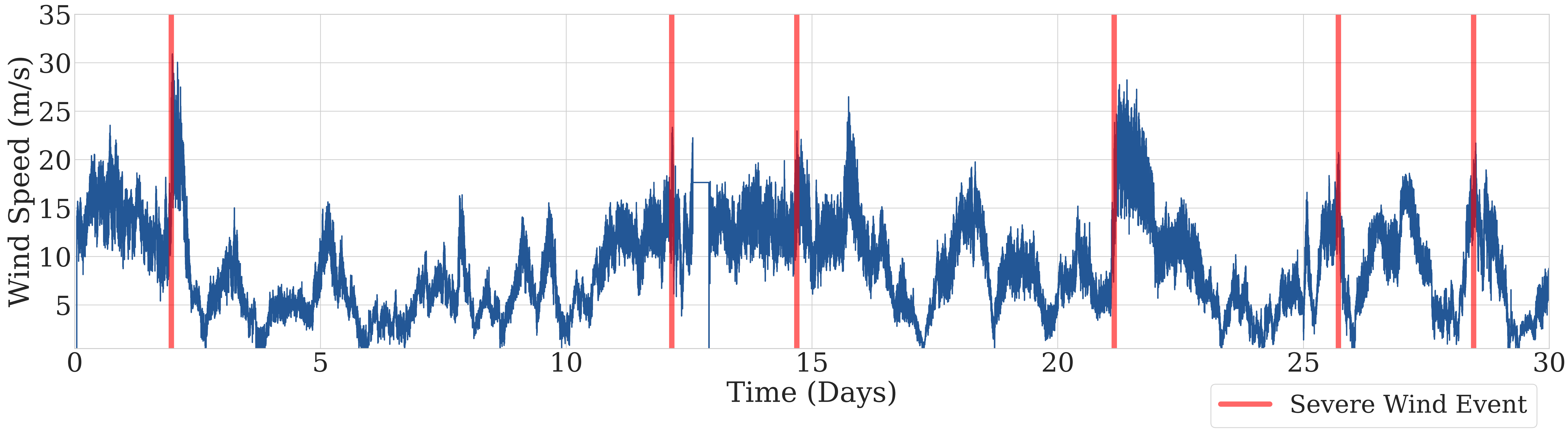
To address these challenges we propose:

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

- **Target:** Wind gust events (wind speed >20 meters/second)
- **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



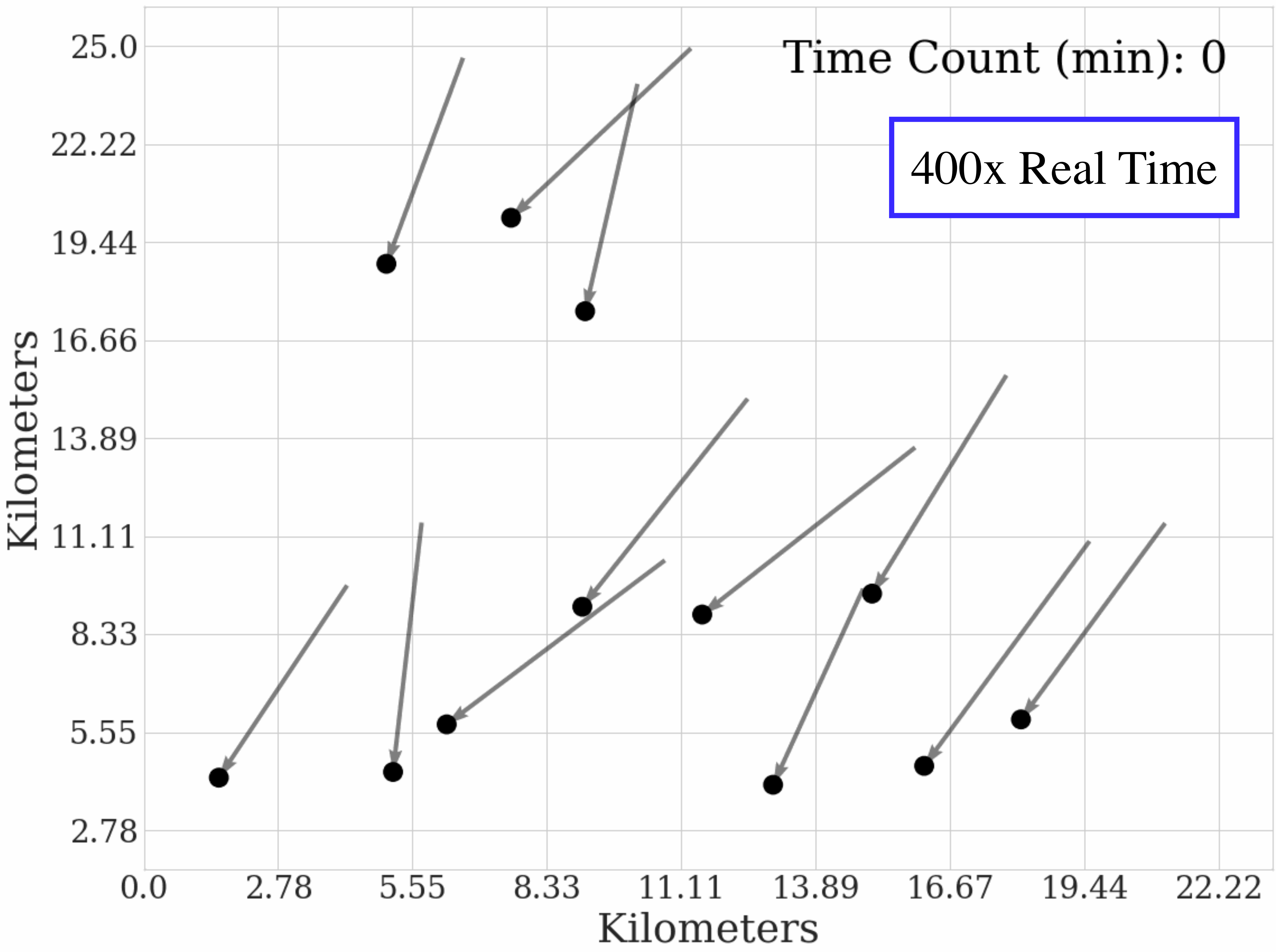
Method

We observe that a wind event traverses wind turbines from north to south as anticipated by the wind direction of the first recorded event.

Research Questions:

1. Can we apply physics-based mathematical functions that relate distance, velocity, and time to predict severe wind events?

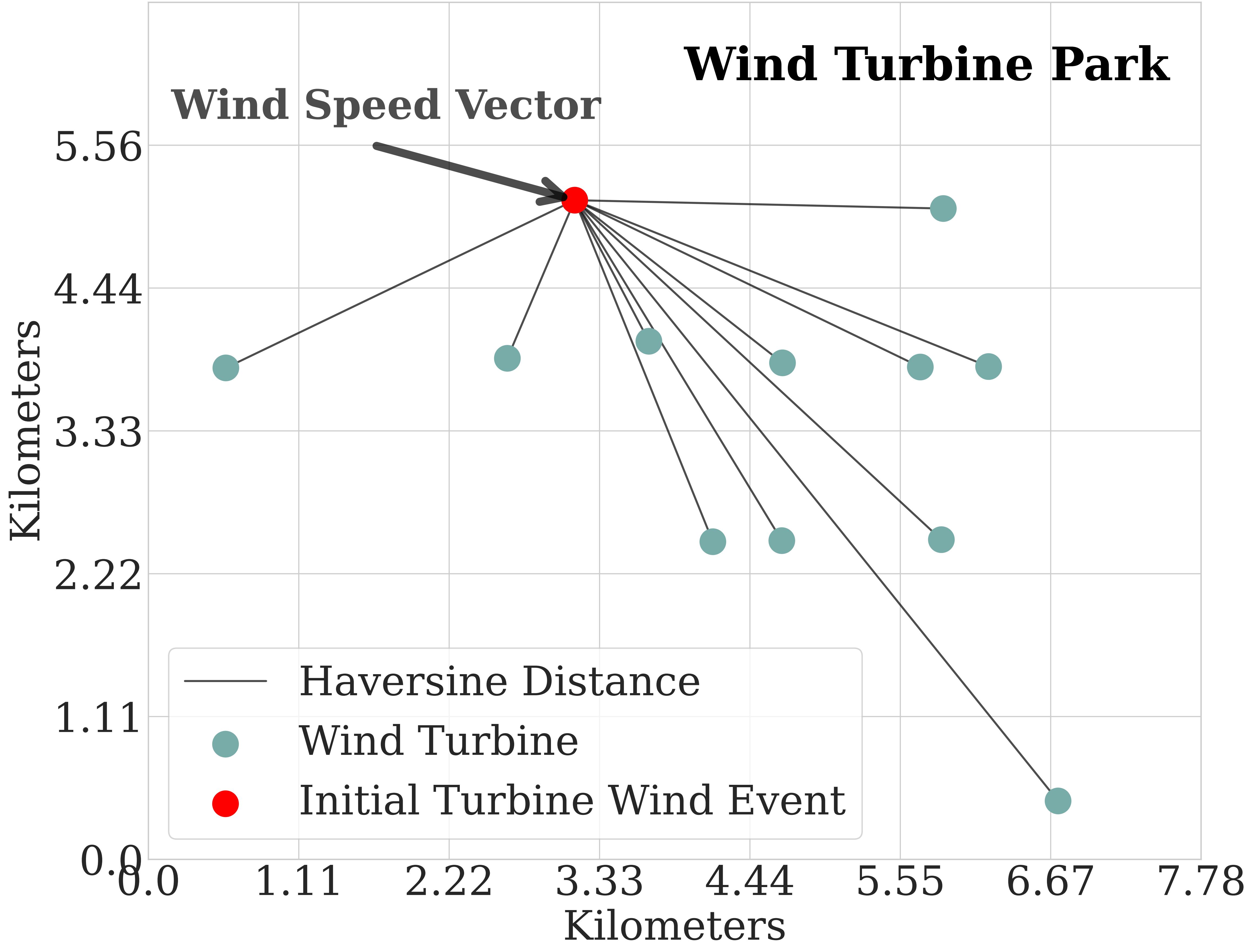
2. Can we leverage ML to enhance known physics and develop more robust models with limited data?



Method (cont.)

Physics Model

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



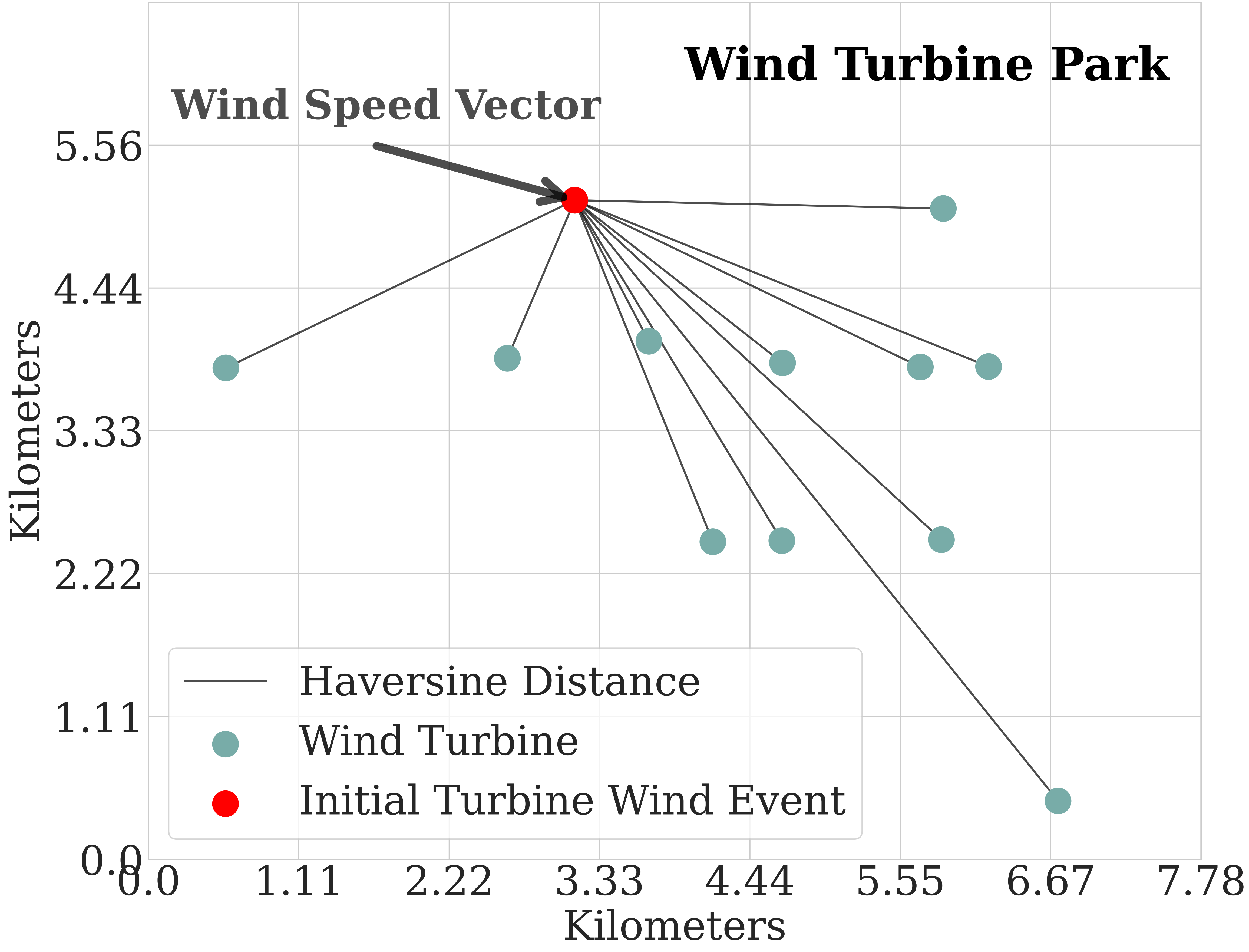
Method (cont.)

Physics Model

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

Wind speed, v, 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 ML.



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ML Physics Hybrid Model

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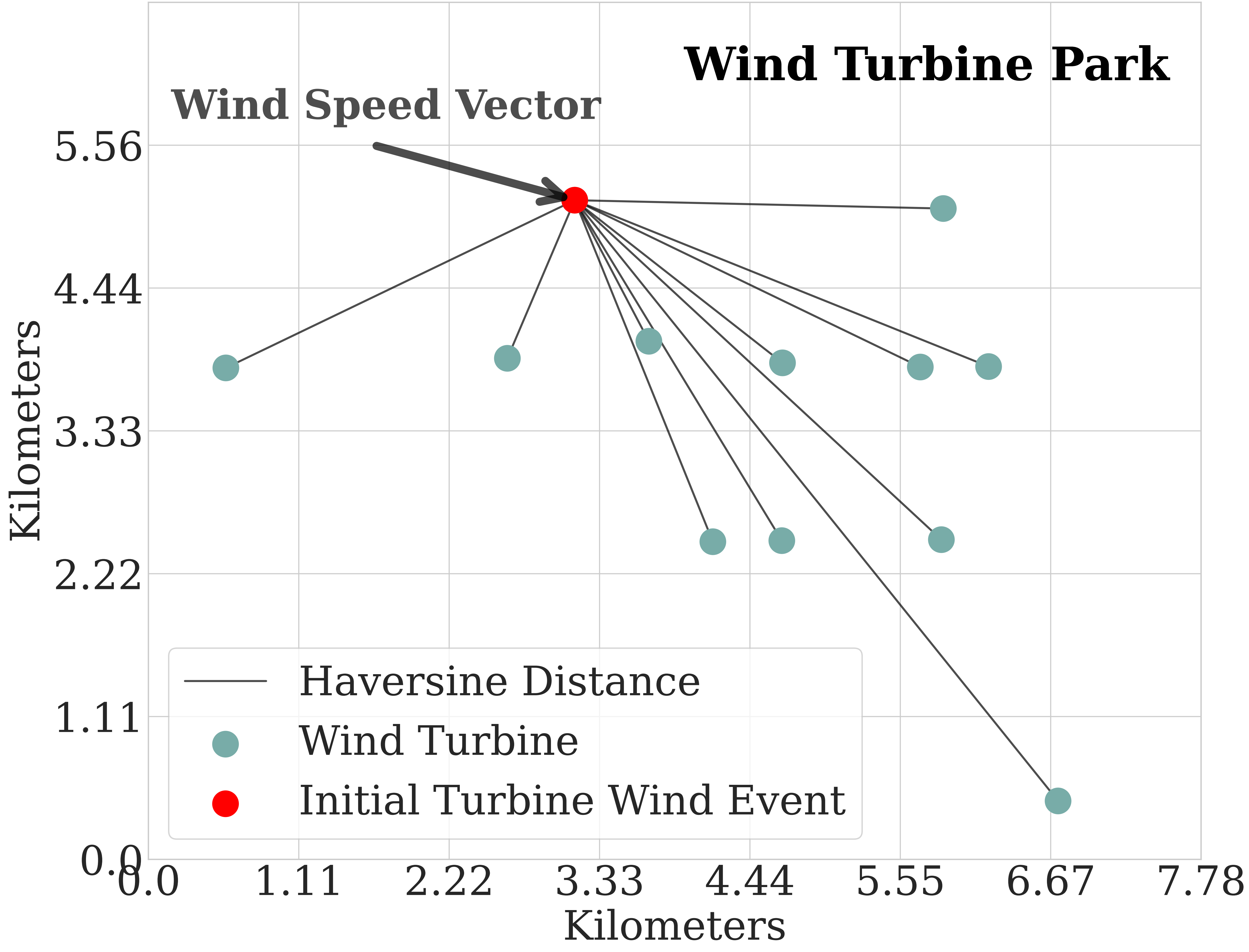

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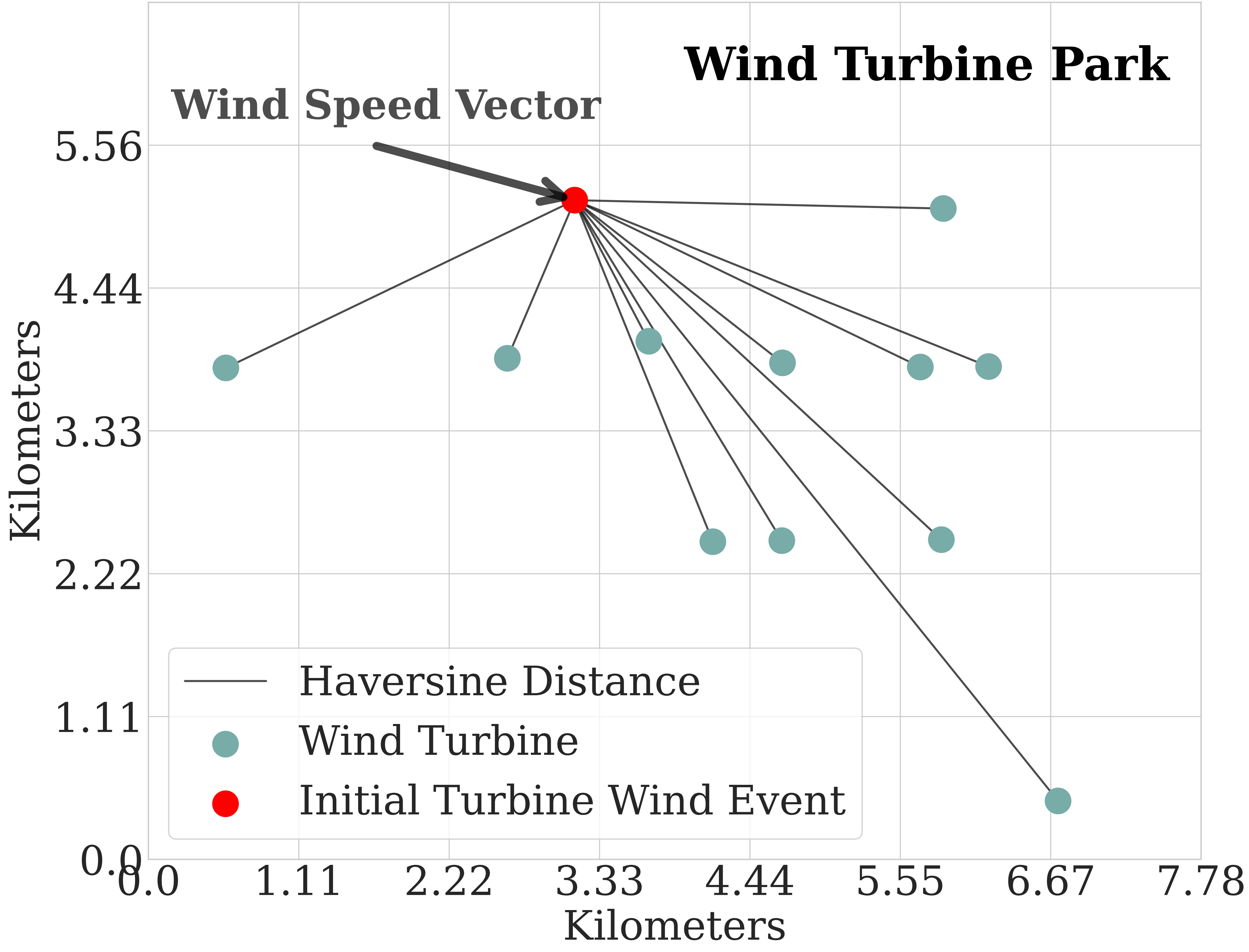
$$s = f_\theta(x)$$

Since ***s*** is learned as a function of the feature space, ***s*** is unique to each turbine.



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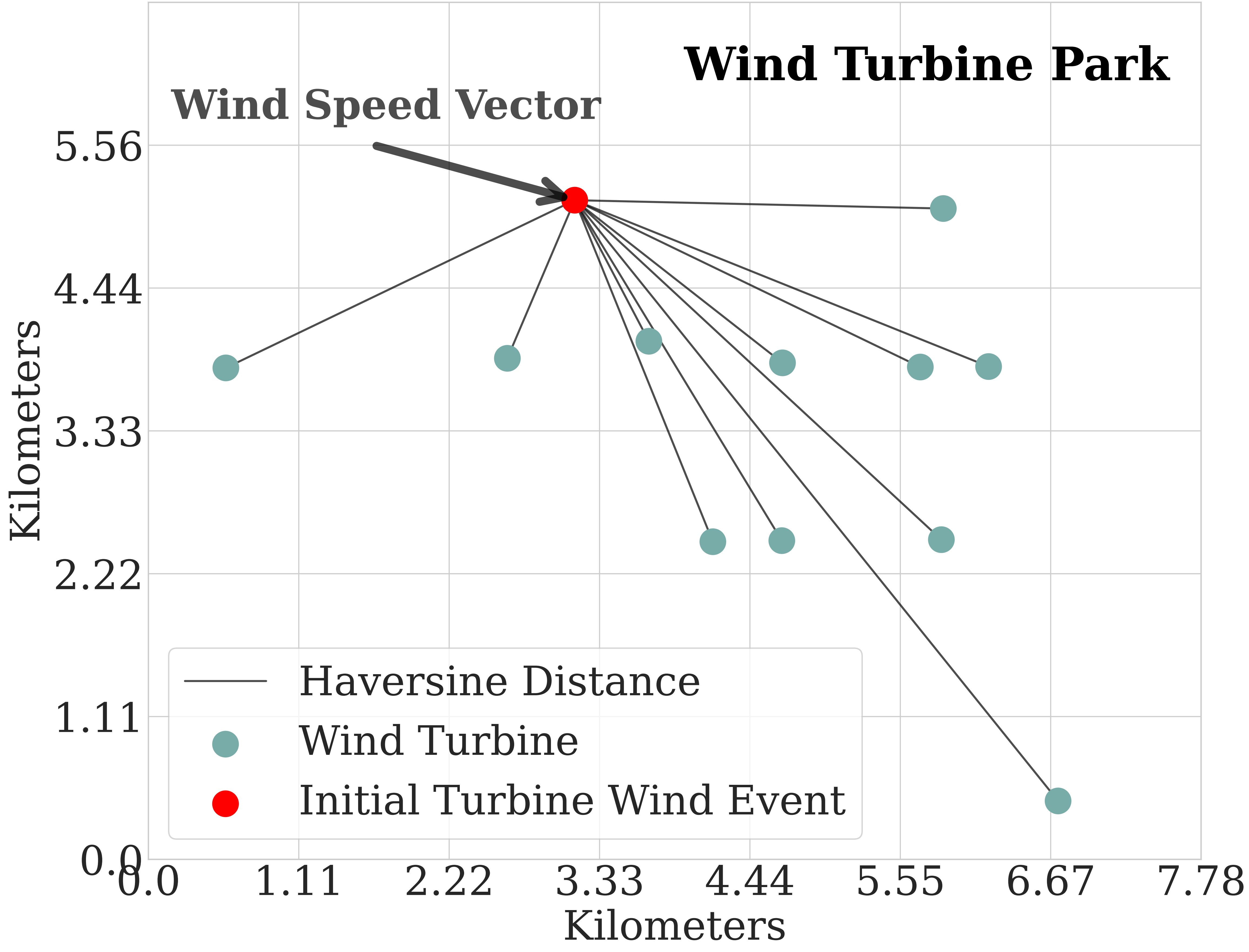
$$x \in \mathbb{R}^{N \times C}$$

Where $\boldsymbol{N}$ is the number of turbines and $\boldsymbol{C}$ is the number of features.



Results

MAE (standard deviation)					
Baselines					Proposed
Average	Physics		ML		ML Physics Hybrid
$\hat{t} = \bar{t}$	$\hat{t} = \frac{d}{v}$	$\hat{t} = \frac{d_t}{v_t}$	$\hat{t} = MLP(x)$	$\hat{t} = DSM(x)$ [1]	$\hat{t} = \frac{d}{v \cdot s}$
45.57 (7.03)	6.79 (6.19)	5.03 (4.45)	12.72 (6.94)	6.62 (5.43)	**2.61 (4.02)**

1. 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.

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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.**

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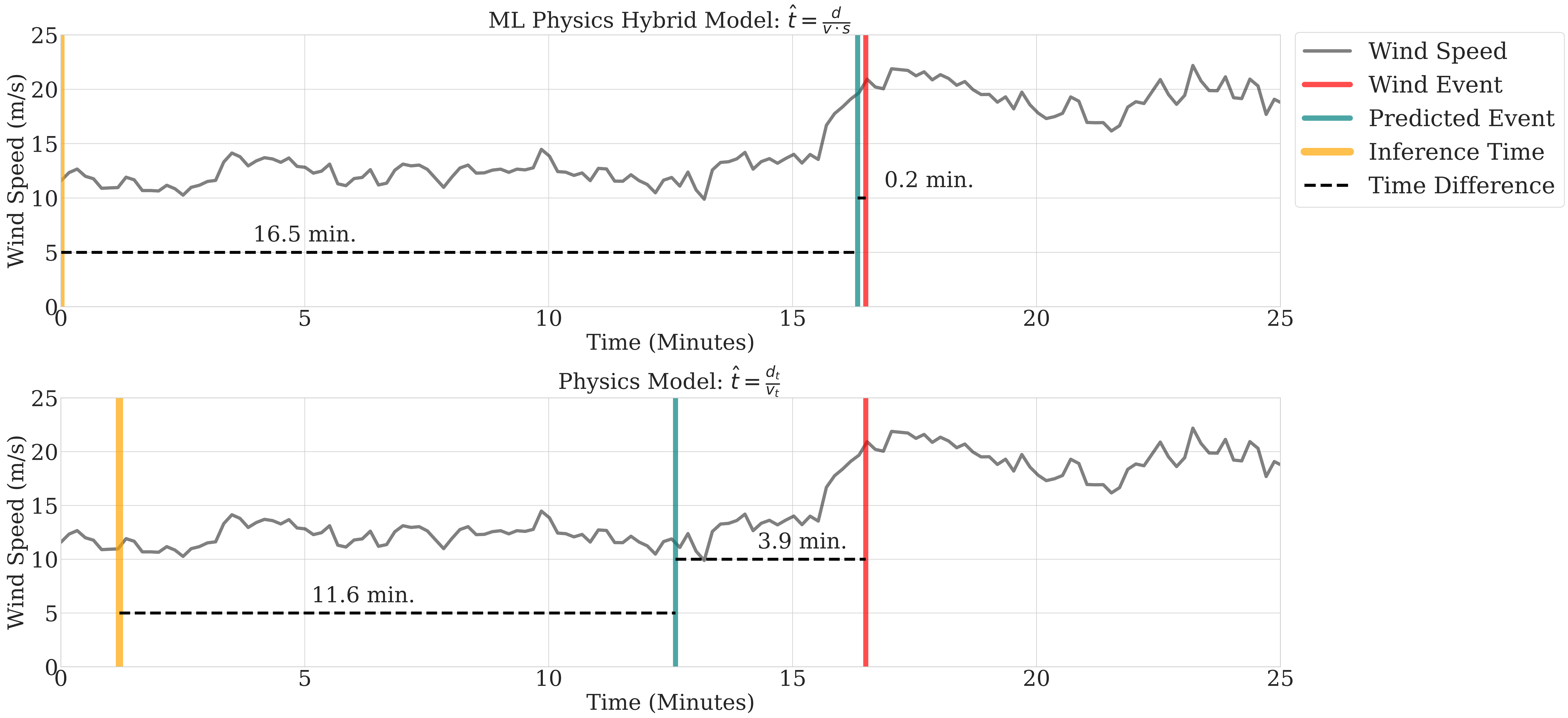

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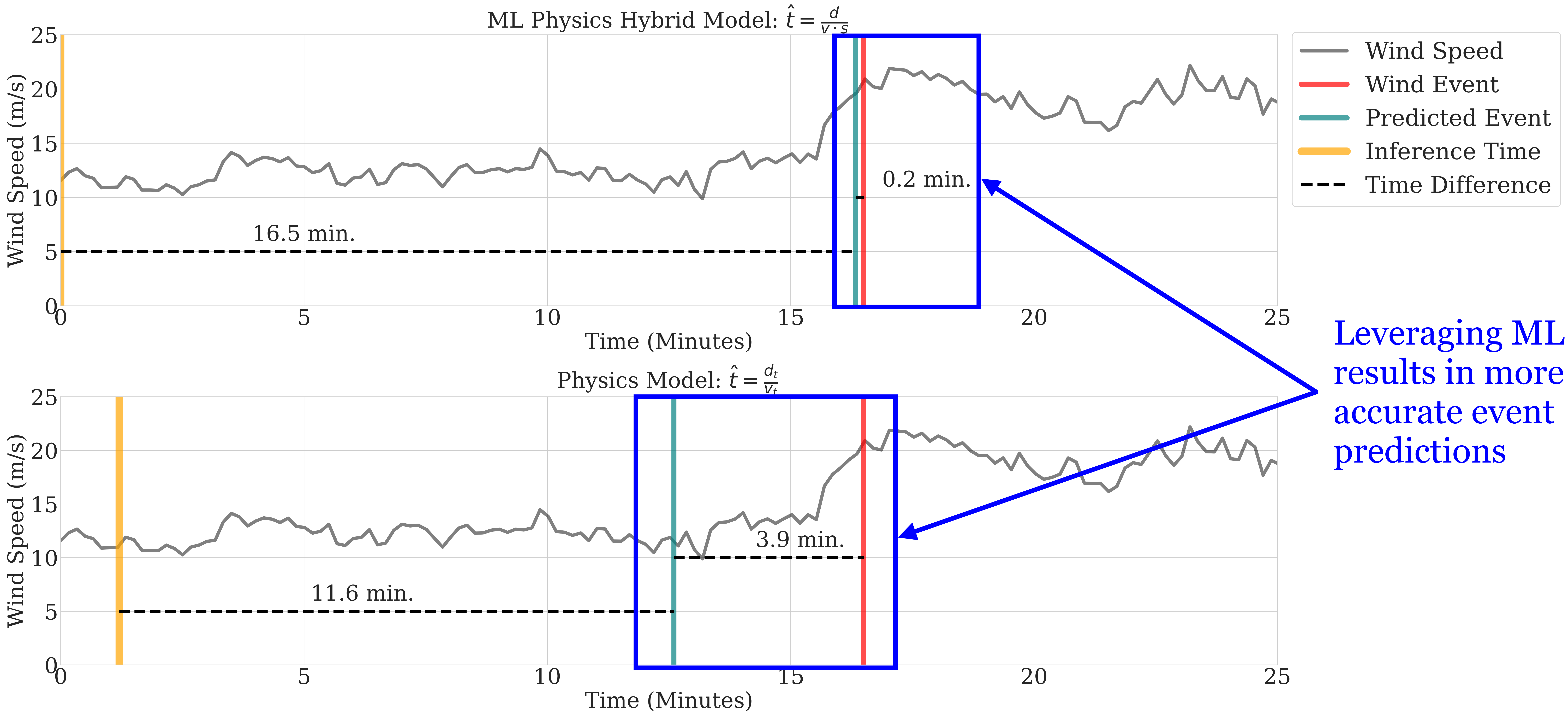
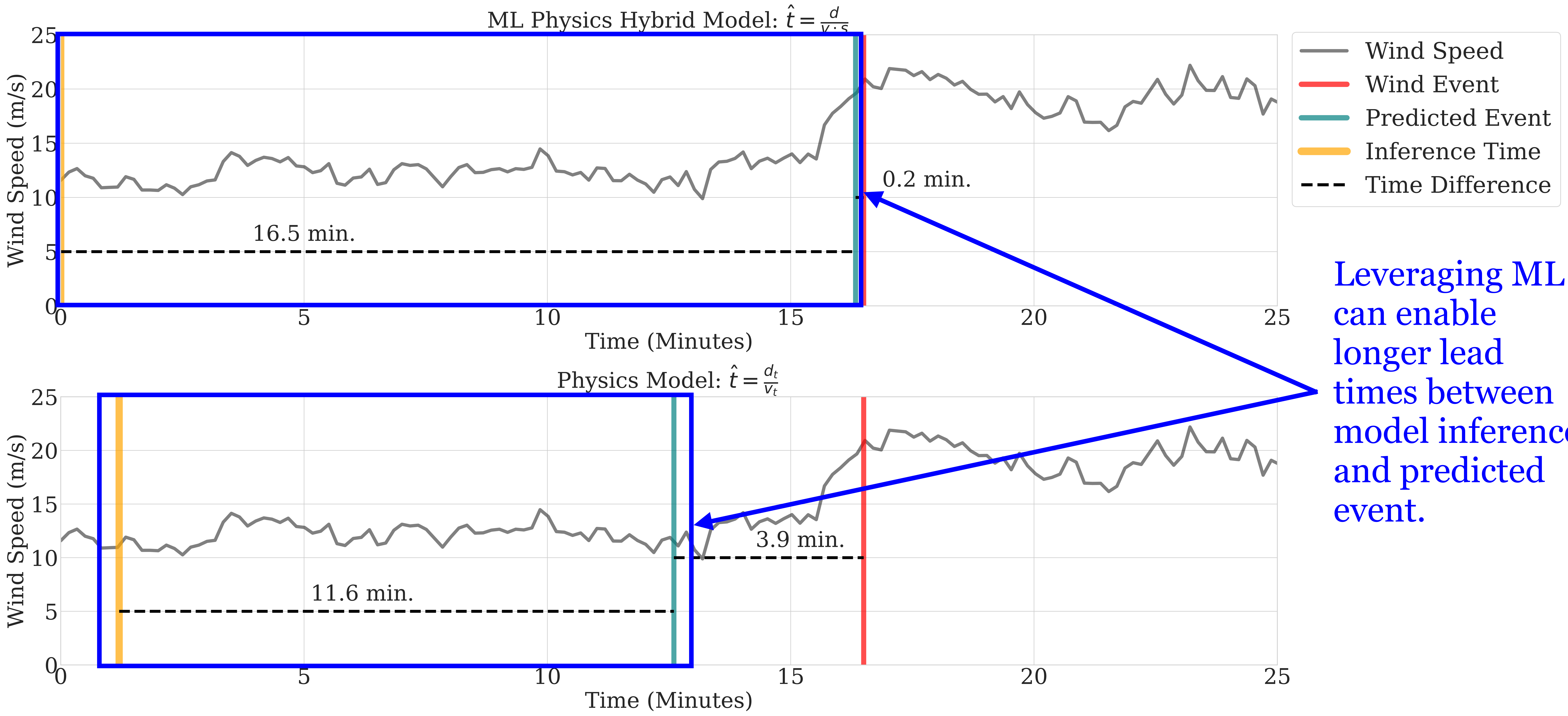


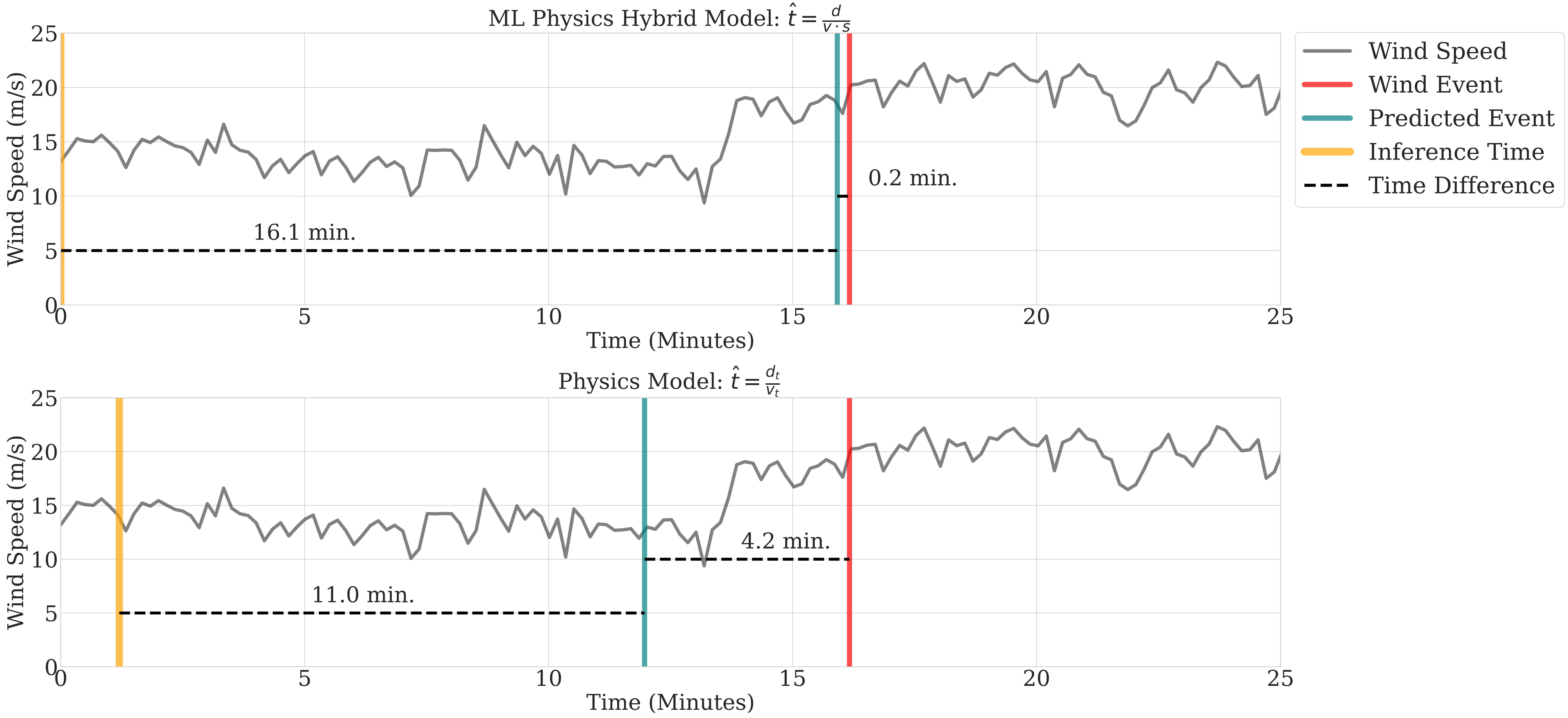
Leveraging ML results in more accurate event predictions

Results (cont.)



Leveraging ML can enable longer lead times between model inference and predicted event.

Results (cont.)



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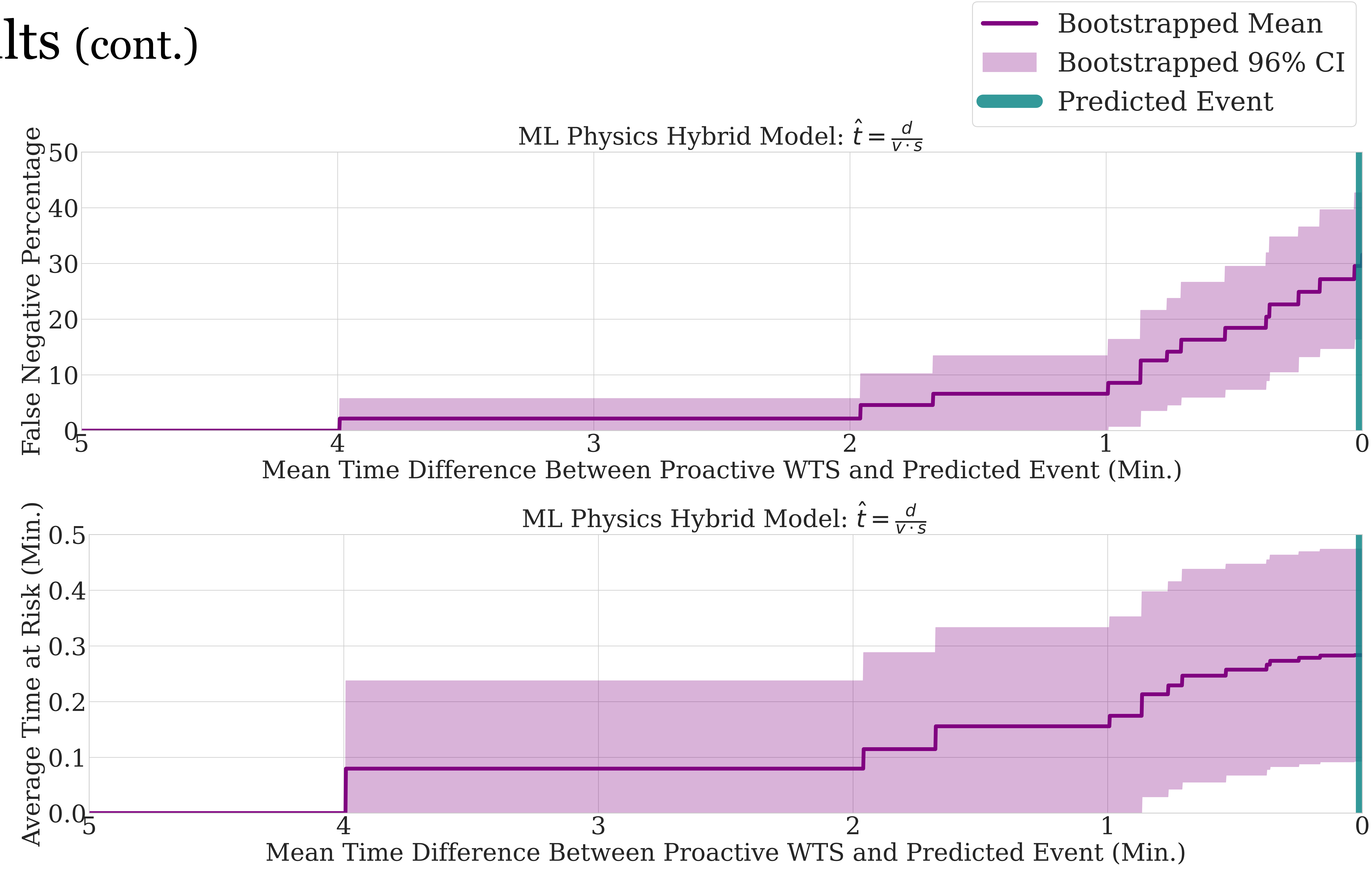
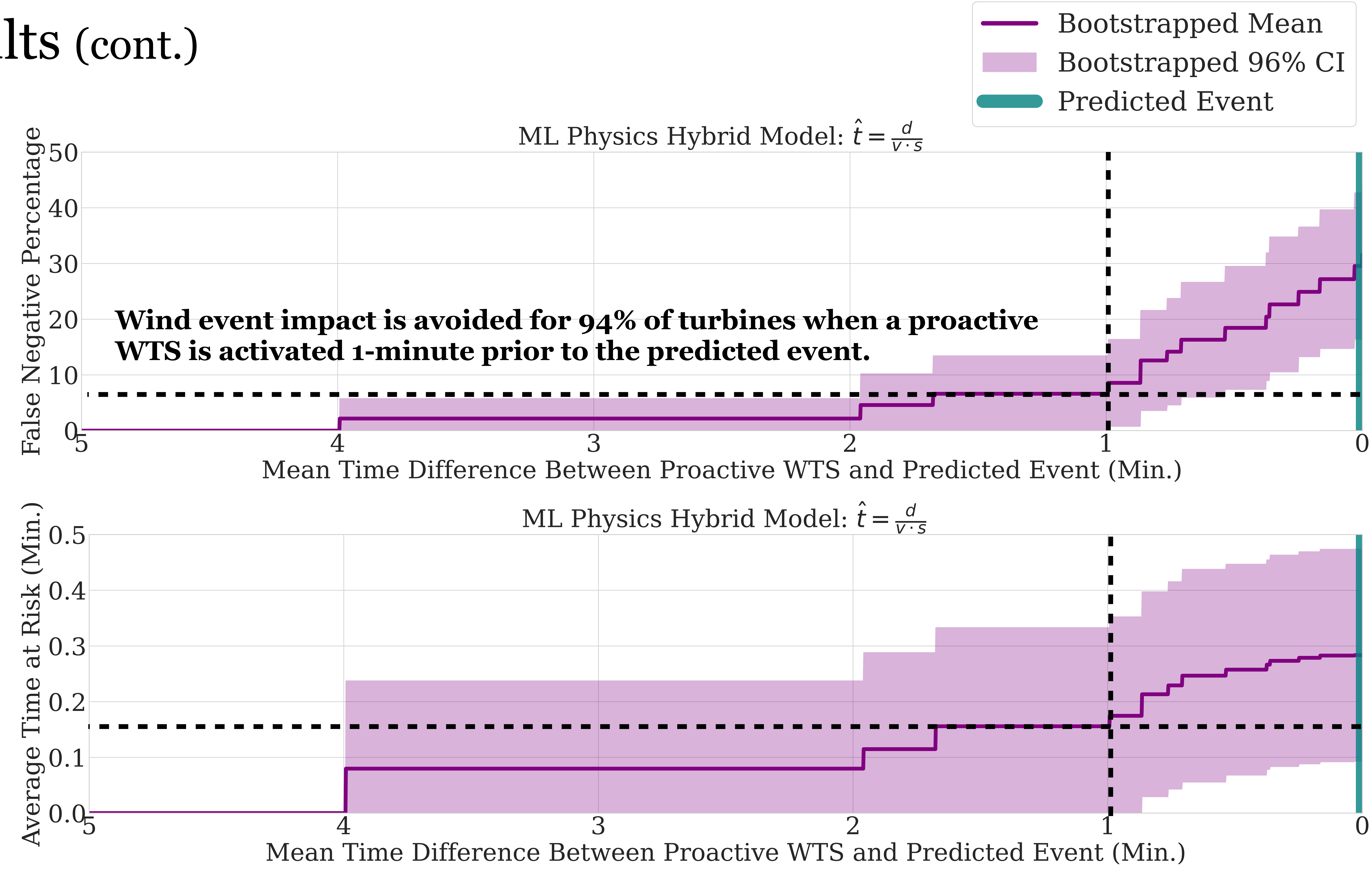


Results (cont.)

Wind event impact is avoided for 94% of turbines when a proactive WTS is activated 1-minute prior to the predicted event.



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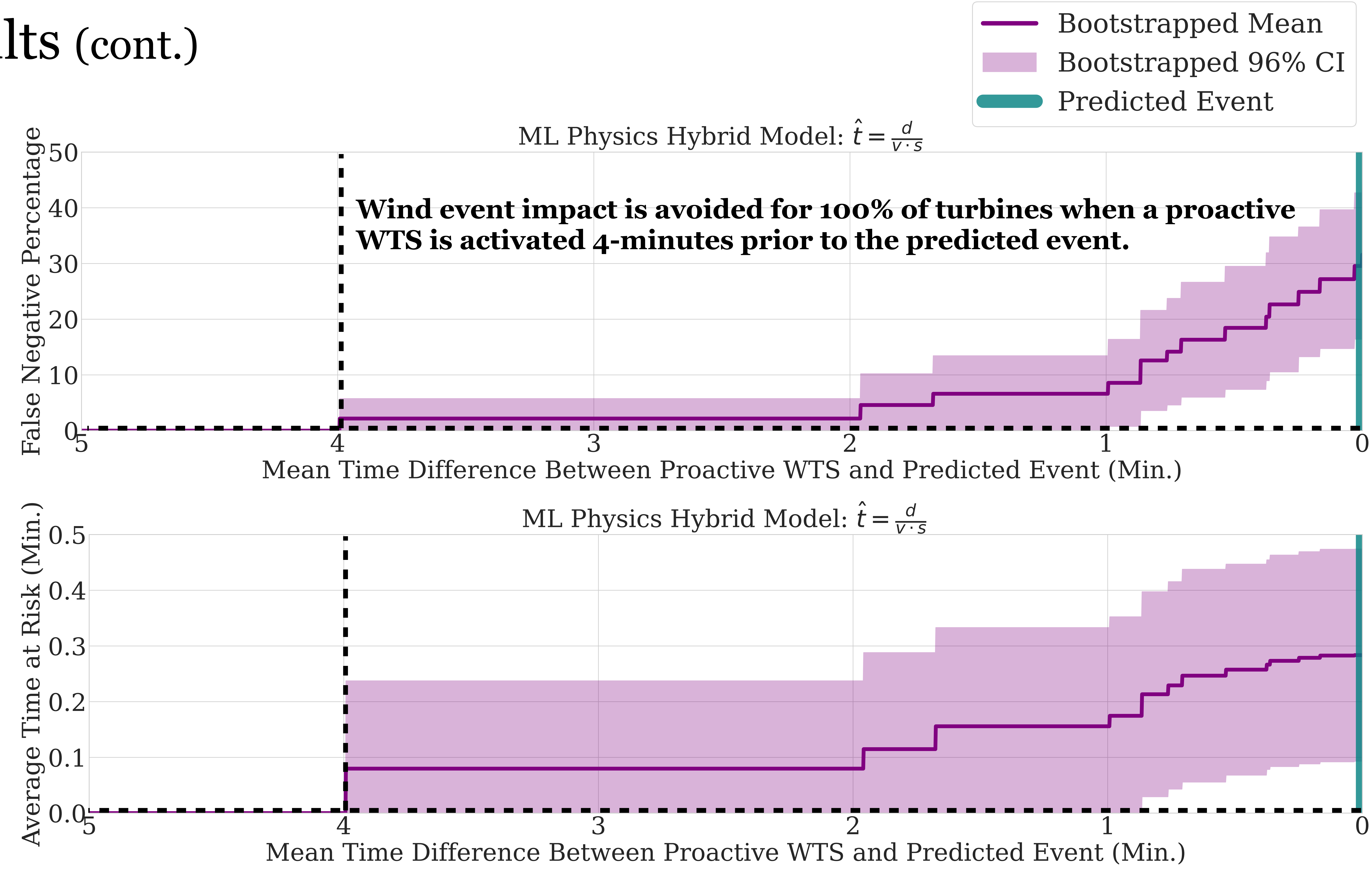

Proposed Model Extensions

Wind speed exhibits time-varying characteristics. As such, we propose to extend our preliminary ML physics hybrid model to leverage time series data across multiple turbines to infer time-dependent velocity representations or scaling factors.

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We propose leveraging attention mechanisms to weight the importance of neighboring turbine time series used to generate velocity representations for wind event predictions.

For example, Graph Attention Networks (GATs) [1] offer a promising deep learning approach to harness spatial-temporal information recorded across wind turbines.

1. Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. Graph attention networks, 2018.