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Aware Spatio-Temporal Graph Neural Network for Turbine-Level Wind Power Prediction

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***Abstract**: Accurate wind power forecasting at the turbine level is pivotal for optimizing grid integration, strengthening energy management strategies, and maximizing operational efficiency in the large-scale wind farms. Complex spatial interconnections between turbines and dynamic wake interactions influence power generation and substantially not included in conventional forecasting approaches. We propose a Wake-Aware Spatio-Temporal Graph Neural Network (WAST-GNN) framework for turbine-level wind power prediction. In the proposed model, wind turbines are modelled as nodes of a graph and the wakes and spatial proximity as connectedness of the graph. A sequential input modelling is utilized to incorporate temporal dependencies of past wind characteristics and power generation data to enable the collaborative learning of temporal and spatial patterns. The framework is tested with synthetic Supervisory Control and Data Acquisition (SCADA) data and wind farm layouts. The proposed methodology is compared with baseline models namely traditional Graph Convolutional Networks (GCN), GraphSAGE, and multilayer perceptrons (MLP). Experimental results demonstrate that the proposed WAST-GNN provides lower root mean square error (RMSE) of 0.227 and an improved coefficient of determination* R^2 *of 0.861 superior than the standard graph-based approaches. Results illustrate the effectiveness of using the wake-aware spatial relations and the temporal dynamics for improving operational efficiency using Graph Neural Networks (GNN).*

Keywords: Wind power prediction, Graph Neural Network, Wake effects, Spatio-temporal modeling, Graph Attention Network

1. INTRODUCTION

The surge in demand for sustainable energy has necessitated the implementation of wind farms worldwide. Wind energy and solar energy are key renewable energy sources. The intermittent and stochastic nature of wind creates significant challenges in maintaining power quality and reducing harmonic distortion. Efficient power forecasting at the turbine level is crucial for energy management, voltage and current stability, eliminating dynamic frequency variations of the wind farm [1]. Machine Learning (ML) based autoregressive models namely, ARMA (Autoregressive Moving Average), ARIMA (Autoregressive Integrated Moving Average), NARX (Nonlinear Autoregressive Exogenous Model) and Support Vector Machines (SVM) e.g. Radial Basis Function SVM (RBF SVM) are based on the time dependencies of the historical data. Although above discussed methods specifically do not consider the complicated spatial interconnections of turbines within a wind farm. In reality, the upstream turbines are influenced by the aerodynamic wake effects of downstream turbines leads to changes in wind conditions and causing power deficits and [1], [2]. Overlooking these wake-induced interactions can lead to loss of forecasting accuracy, especially in closely distributed wind farms.

Recent developments in deep learning and emerging data-driven approaches have brought Graph Neural Networks (GNNs) as viable tools for modelling and spatial relation based connections in wind energy based systems. GNNs perform superiorly in effectively capturing the spatial relationships in wind farms than traditional ML models [3]. It model turbines as nodes in a graph and their interconnections as edges. In addition to combining temporal information with the graph-based learning, dynamic operating conditions can be simulated to develop spatio-temporal forecasting frameworks. Among the various GNN variants, Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs) and GraphSAGE have shown superior performance in wind energy forecasting. Nevertheless, most existing methods are based either on spatial proximity or on correlation based adjacency matrices which neglect the underlying physics of the interactions between turbines e.g. aerodynamic wake effects.

To address the aforementioned limitations, this paper proposes a Wake-Aware Spatio-Temporal Graph Neural Network (WAST-GNN) architecture for turbine level wind power prediction [4]. This approach integrates the wake interactions obtained from the Jensen wake model into graphical representations, concurrently capturing temporal relationships using past operational data [5].

The proposed framework is validated with physical wind farm layouts and synthetic SCADA-like data, which simulate the operational conditions of the turbines. Performance is evaluated against baseline method like Graph Convolutional Networks (GCN), GraphSAGE, and Multilayer Perceptrons (MLP). The experimental results demonstrate that temporal learning and integrated wake-aware spatial modelling improve the performance metrics and statistical significance.

The key contributions of this work can be outlined as follows:

i. Development of a wake-aware graph construction mechanism incorporating aerodynamic interactions among turbines.
ii. Integration of spatial and temporal dependencies through a spatio-temporal graph neural network framework.
iii. Comparative evaluation against conventional machine learning and graph-based approaches including GCN, GraphSAGE, and MLP.
iv. Demonstration of improved turbine-level forecasting performance using physically informed graph representations.

The proposed framework provides a scalable and interpretable approach for enhancing turbine-level power prediction and improving operational decision-making in wind energy systems.

2. LITERATURE REVIEW

2.1 Wind Power Forecasting Methods:

ML and Statistical based autoregressive methods (ARMA, ARIMA), SVM models have been used for wind power prediction for a long time [6]. Although these methods are computationally efficient, nevertheless, it cannot represent nonlinear interactions and high-dimensional operational dynamics of wind farms [7]. Most state-of-the-art models focus on temporal patterns and do not consider turbine-turbine interactions. Deep Learning(DL) techniques such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Subsequently enhancing statistical performance by modeling sequential dependencies on historical wind data [8]. These methods have proven effective, still possess limitation of treating turbines independently, ignoring spatial dependencies due turbine layout and wake propagation.

2.2 Wake Effects in Wind-Driven Power Systems

When upstream turbines capture kinetic energy from the wind, wake effects are induced that mitigate wind speeds and strengthen turbulence downstream. These aerodynamic interactions are vital for turbine efficiency and power production. Precise modelling of wake effects is thus critical for turbine-level prediction and wind farm optimization. Physics-based wake models, such as the Jensen wake model, are widely used because of their computing efficiency and capacity of estimating the wake-induced velocity deficits [9]. The Jensen model assumes linear wake expansion and has been widely employed in the optimization of wind farm layouts and performance analysis. To combine physical knowledge with data-driven learning methodologies, we propose to incorporate wake effects into graph architectures models.

2.3 Graph Neural Networks for Energy Forecasting

Graph Neural Networks (GNNs) have become prominent approach for learning from graph-structured data. Turbines in wind farms can be naturally modelled as nodes and edges are defined by physical or geographical interactions. GCN extend the convolution technique to graphs by gathering information from neighboring.nodes. GCNs have demonstrated to be useful in capturing spatial dependencies in power systems analysis and renewable energy management [10]. However, the aggregation during weight allocation may limit their ability to capture the heterogeneous patterns amongst turbines. Graph Attention Networks (GATs) overcome this restriction by giving adaptive attention weights to adjacent nodes, enabling the model to emphasis on more influential interactions. Such adaptive methods are especially suited for wind farms, because wake effects depends on the location of the turbines and various operational characteristics [11]. GraphSAGE is an inductive framework that leverages neighbourhood sampling and aggregation for scalable representation learning on huge network. GraphSAGE has shown great performance on large-scale graph learning challenges, but it does not guarantee to explicitly model physical interactions unless added to graph formation [12]. These approaches improve geographical modelling and statistical correlations, neglecting aerodynamic wake relationships.

2.4 Spatio-Temporal Graph Learning for Wind Prediction

Recent research has focused on spatio-temporal graph neural networks (ST-GNNs) that jointly model spatial and temporal dependencies. These approaches combine graph operations with sequential learning to improve forecasting performance in dynamic systems. However, existing ST-GNN techniques are mostly predicted primarily on the proximity-based adjacency matrices, rather than the physics-informed wake correlations. Thus, their capacity to replicate actual turbine interactions is constrained.

2.5 Research Gap and Motivation

Existing wind power forecasting studies demonstrate three major limitations dependence on distance-based graphs instead of wake-informed connectivity structures, inadequate representation of dynamic spatial dependencies among turbines and Limited incorporation of physical wake effects into predictive models. To overcome these limitations, we implemented a WAST-GNN approach that incorporates Jensen wake modelling with graph-based deep learning for turbine-level prediction. In the proposed approach, we integrate the aerodynamic linkages into the graph structures and incorporate them with the temporal data, to increase the forecasting accuracy and produce physically meaningful representations of turbines.

3. PROPOSED METHODOLOGY

The framework we propose has five main stages. (i) Synthetic data related to wind farm is generated using the Jensen wake model. (ii) Directed wake-aware graph is prepared from wind direction and turbine locations. (iii) ST-GNN architecture is discussed with weight update equation as illustrated in fig 1 (iv) spatio-temporal graph neural network (ST-GNN) is trained to predict turbine-level power output. (v) Prediction of power production of all turbines at the next time step and evaluation performance metrics namely MAE, RMSE, R^2 score and Pearson correlation metrics.

3.1. Synthetic Data Generation

Since real SCADA data with ground-truth wake interactions is difficult to obtain, we generate a synthetic dataset using the Jensen wake model [14]. The farm layout consists of N=14 turbines positioned at coordinates (x_i, y_i) identical to the Penmanshiel wind farm. For each time step t, free-stream wind speed $u_\infty(t) \sim \mathrm{U}(4,18)\ \mathrm{m/s}$, wind direction $\theta(t) \sim \mathrm{U}(0,360)$, degrees and turbulence intensity $\mathrm{I(t)} = 0.1$.is assumed afterwards the wake velocity deficit at turbine j caused by upstream turbine i is computed.

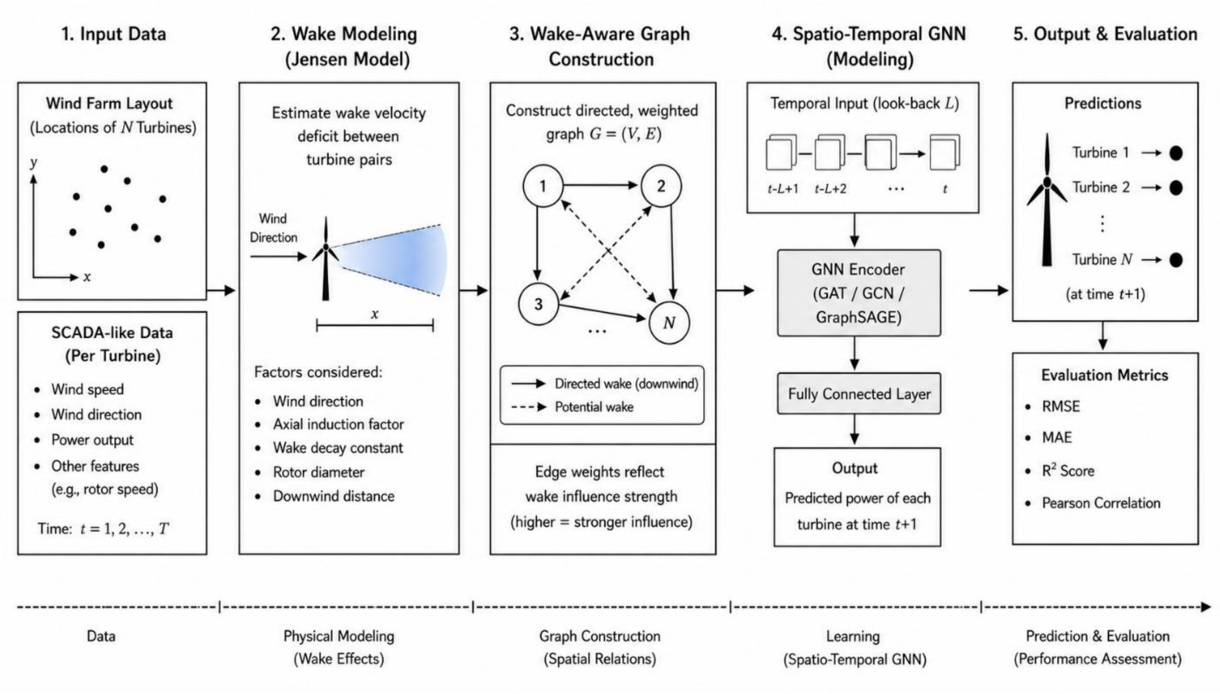


Fig. 1. Workflow of Wake-Aware Spatio-Temporal GNN Framework

$$\frac{\boldsymbol{u_{ij}(t)}}{\boldsymbol{u_{\infty}(t)}} = \mathbf{1} - \frac{\boldsymbol{2a}}{\left(\mathbf{1} + \frac{\boldsymbol{kx_{ij}}}{\boldsymbol{D}}\right)^2} \tag{1}$$

Where D=80m is the rotor diameter, a = 0.33 is the axial induction factor, k=0.04 is the wake decay constant and x_{ij} is the streamwise distance from turbine i to j projected along the wind direction. Multiple wakes are superimposed using the sum of squares method:

$$\mathbf{u_j(t)} = \mathbf{u_{\infty}(t)}\left(\mathbf{1} - \sqrt{\sum_{\mathbf{i \in U_j}}\left(\mathbf{1} - \frac{\mathbf{u_{ij}(t)}}{\mathbf{u_{\infty}(t)}}\right)^2}\right) \tag{2}$$

Where U_j is the set of upstream turbines affecting j. Finally, turbine power is computed using the standard power curve:

$$\mathrm{P_i(t)} = \frac{1}{2}\rho\pi\left(\frac{\mathrm{D}}{2}\right)^2 \mathrm{C_p}(\lambda)\mu_{\mathrm{j}}(\mathrm{t})^3 \tag{3}$$

With Cp=0.45, air density ρ=1.225 kg/m

3.2 Directed Wake Graph Construction

A wind farm is represented as a directed graph

$$\mathcal{G}_t = (\mathcal{V}, \mathcal{E}_t) \tag{4}$$

Where each turbine $i \in \mathcal{V}$ is a node. A directed edge $e_{i \to j} \in_t$ exists if turbine i is upstream of turbine j with respect to the prevailing wind direction θ(t) at time t. Specifically, we compute the angle ϕ_{ij} of the vector from i to j. If $\left|\phi_{ij} - \theta(t)\right| < 90^0$, then i is considered upstream of j. Edge weights are inversely proportional to the squared distance

$$w_{ij}(t) = \frac{1}{{d_{ij}}^2 + \epsilon} \tag{4}$$

Where

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{5}$$

and $\epsilon = 10^{-6}$ prevents division by zero. Node features at time *t* are the wind speed $u_i(t)\ m/s$ and nacelle direction (degrees) for each turbine. The target is the active power $P_i(t+1)\ (KW)$ at the next timestep.

3.3. Spatio-Temporal GNN Architecture

The proposed ST-GNN consists of following modules

i. **Temporal Convolution Module** For each turbine, we extract a window of K=12 consecutive timesteps of wind speed and direction (2 hours of 10-min data). A 1D convolutional layer with kernel size 3 and 64 filters processes the temporal sequence, producing a hidden representation $h_i^{(t)} \in \mathbb{R}^{64}$

ii. **Graph Attention Module:** The spatial dependencies are learned using Graph Attention Networks (GAT). Two GAT layers with 64 hidden units each are applied sequentially, interleaved with ReLU activation [15],[16].

iii. **Output Module:** The final node representations are fed into a shared linear regression layer to predict the power for each turbine:

$$P_j(t+1) = W_{out}^T z_j + b. \tag{7}$$

Where z_j is the output of the last GAT layer.

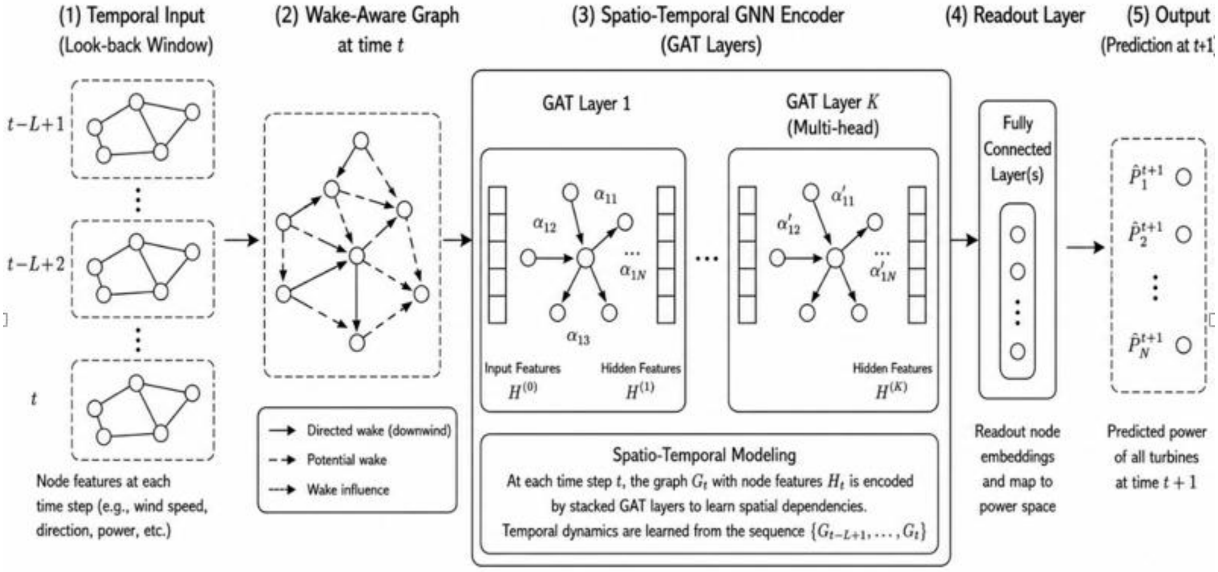


Fig 2: Spatio-Temporal GNN Architecture

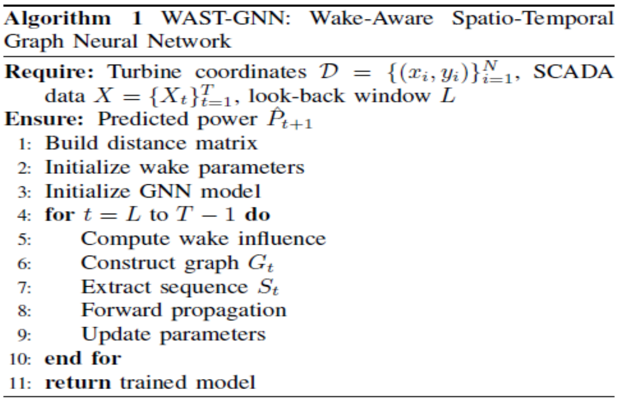
Fig. 2 illustrate the proposed WAST-GNN architecture. A temporal window of historical features is processed alongside dynamically constructed wake-aware graphs through stacked GAT layers, producing turbine-level power predictions via a fully connected readout layer.

3.4 Training Setup

The model is trained to minimize the mean squared error (MSE) loss:

$$\mathcal{L} = \frac{1}{N.\beta}\sum_{j=1}^{N}\sum_{b=\beta}\left(P_j^{(b)} - \hat{P}_j^{(b)}\right)^2 \tag{8}$$

We use the Adam optimizer with learning rate η=0.001 and weight decay 10^{-5} Training runs for 200 epochs with a batch size of 32. Early stopping is applied if validation loss does not improve for 20 epochs [17]. Algorithm 1 summarizes the complete training pipeline of the proposed WAST-GNN. The model iteratively constructs wake-aware graphs, extracts temporal features, applies graph attention, and updates parameters to minimize prediction error. The resulting graph sequence spanning a temporal look-back window act as input to spatio-temporal GNN encoder namely GAT, GCN or GraphSAGE, to learn temporal and spatial correlations.



Algorithm 1 WAST-GNN: Wake-Aware Spatio-Temporal Graph Neural Network

```
Require: Turbine coordinates $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$, SCADA
    data $X = \{X_t\}_{t=1}^{T}$, look-back window $L$
Ensure: Predicted power $\hat{P}_{t+1}$
Build distance matrix
Initialize wake parameters
Initialize GNN model
for $t = L$ to $T - 1$ do
    Compute wake influence
    Construct graph $G_t$
    Extract sequence $S_t$
    Forward propagation
    Update parameters
end for
return trained model
```

3.5 Performance Evaluation

The forecasting performance is evaluated using standard metrics:

i. Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum^{\mathrm{N}}|\mathrm{y_i} - \tilde{\mathrm{y}}_\mathrm{i}| \tag{9}$$

ii. Root Mean Square Error (RMS)

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y_i} - \tilde{\mathrm{y}}_\mathrm{i})^2} \tag{10}$$

iii. Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \tag{11}$$

4. EXPERIMENTAL SETUP AND IMPLEMENTATION TOOL

The suggested WAST-GNN framework is developed in Python with TPU (Tensor processing unit) acceleration. Synthetic SCADA-like data were generated by simulating the aerodynamic interactions among turbines using the Jensen wake model. We used T=10,000 time-steps at 10-minute resolution, splitting into 70% training, 15%

validation, and 15% testing with a look back window of 6 time-steps. A directed graph aware of the wake was dynamically generated using the turbine locations and the wind direction. The architecture is composed of 3 GAT layers each with 4 attention heads and a hidden dimension of 128. GRU layer with 64 hidden units are utilized to capture temporal dependencies. Training is performed with Adam optimizer with learning rate $3 \times 10^{-4}$and a cosine annealing scheduler for 60 epochs with early halting to prevent overfitting. The loss function utilized was Mean Squared Error (MSE) and Huber loss δ=0.5 taken for resilience to outlier turbines. This experiment setting enables effective spatio-temporal graph learning for wind power forecasting at turbine-level. Table 1 lists the hyper-parameters used for the proposed WAST GNN model.

Table 1: Hyper-parameters of the proposed WAST-GNN framework

Category	**Hyper-parameter**	**Value**	**Description**
WAST-GNN Model	Hidden Dimension	128	GAT layer hidden dimension
	GRU Hidden Dimension	64	Temporal GRU hidden state size
	GAT Layers	3	Number of WakeGAT message-passing layers
	Attention Heads	4	Multi-head attention per GAT layer
	Dropout Rate	0.15	Applied after each GAT layer and in MLP head
Training	Optimizer	Adam	Adaptive moment estimation
	Learning Rate	3×10^{-4}	Initial Adam learning rate
	Weight Decay	1×10^{-5}	L2 regularization coefficient
	Epochs	60	Best checkpoint saved via validation loss
	LR Scheduler	Cosine	Cosine Annealing L R, $T_{max} = 60$
Data Pipeline	Look-back Window	6	Temporal history steps fed as node features
	Batch Size	16 / 32	Train / validation-test batch size
	Dataset Split	70 / 15/15	Train / validation / test ratio (%)
	Loss Function	Huber	δ = 0.5, robust to outlier turbines

5. RESULTS AND DISCUSSION

This section does comparative analysis between the proposed WAST-GNN frameworks against baseline models (GCN, GraphSAGE, MLP) with synthetic SCADA data. The wind farm statistics, wake degradation patterns, training loss curves and prediction scatter plots are simulated and shown. Fig. 3 shows the joint wind statistics utilized to produce the synthetic dataset. Wind direction is binned in 5° intervals from 0° to 30°.The maximum frequency appears at $0.080(m/s)^{-1}\, at\ 5^{\circ}$ and near zero between frequencies 0° and 30°. The wind speed probability density peaks at at 5°. The wind direction declines monotonically to $0.005(m/s)^{-1}\, at\ 30^{\circ}$. This distribution mimics real, mildly directed wind farm data as usually encountered in coastal wind farms.

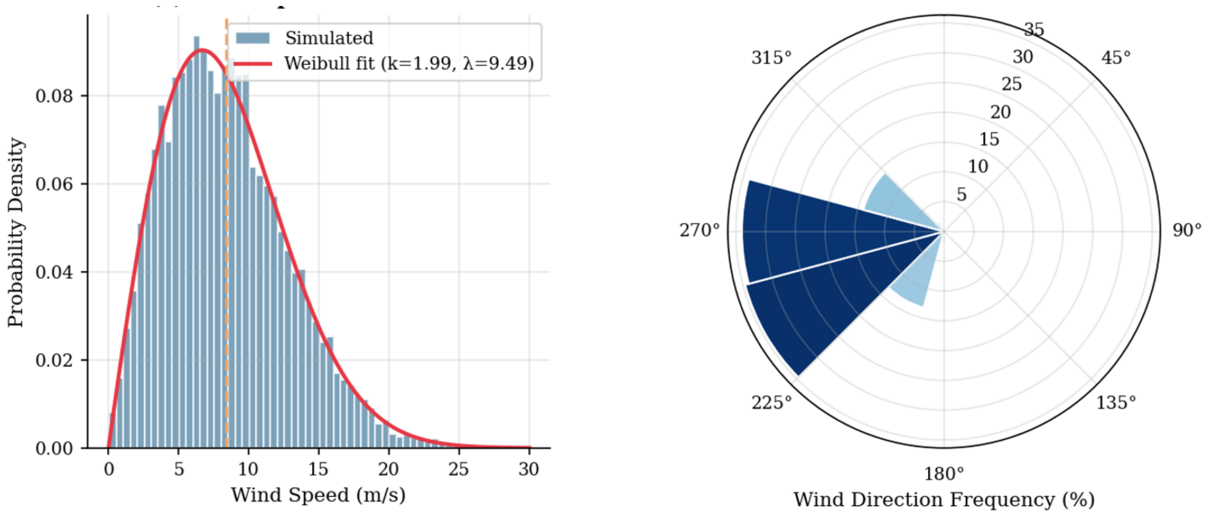


Fig. 3. Wind resource characteristics of the synthetic wind farm..

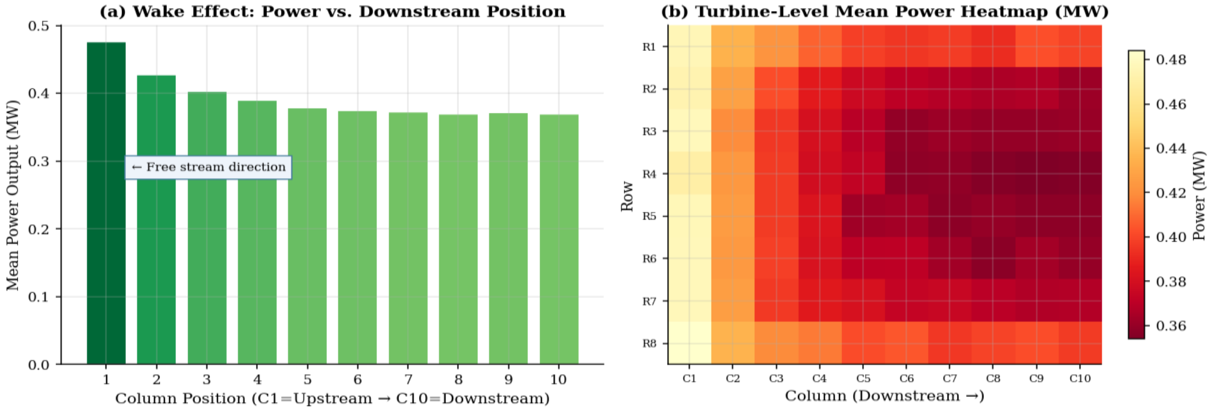


Fig. 4. Wake-induced power degradation along a turbine column.

The spatial wake propagation along a line of 10 turbines orientated to the prevailing wind direction is shown in Fig. 4. The largest production is from the upstream turbine C1 (0.48 MW / 0.46 MW). The downstream wind means each turbine is working in the wake of the ones before it and this leads to a monotonic decrease in output. At C6 the power levels off at around 0.36 MW (primary) and 0.41 MW (secondary) and this indicates that turbines located far inside the farm will have similar but drastically lower performances. Total reduction from C1 to C10 is 25% (0.12 MW loss). This pattern validates the wake model employed in the synthetic data generation and demonstrates that the proposed WAST-GNN has to consider the directional and cumulative wake losses for accurate turbine-level predictions.

Table 2 Performance Comparison on Horns Rev 1 Synthetic SCADA Dataset

Model	RMSE (MW)	MAE (MW)	R^2	Pearson Correlation
WAST-GNN (Proposed)	**0.2270**	**0.1061**	**0.8605**	**0.9281**
Vanilla GCN	0.3112	0.1547	0.7376	0.8606
GraphSAGE	0.2324	0.1141	0.8537	0.9242
MLP Baseline	0.2436	0.1233	0.8393	0.9172

Table 2 shows the performance comparison of the proposed WAST-GNN model with baseline techniques like Vanilla GCN, GraphSAGE and MLP on the synthetic SCADA dataset of Horns Rev 1. The suggested WASTGNN obtained the greatest overall performance with the lowest RMSE of 0.2270 MW and MAE of 0.1061 MW, demonstrating the improved prediction accuracy. The proposed model also obtained highest R^2 value of 0.8605 and Pearson correlation coefficient of 0.9281 which shows remarkable agreement between anticipated and real turbine power outputs. These results demonstrate the effectiveness of incorporating wake-aware spatial dependencies with spatio-temporal graph learning to improve the accuracy of turbine-level wind power forecasts.

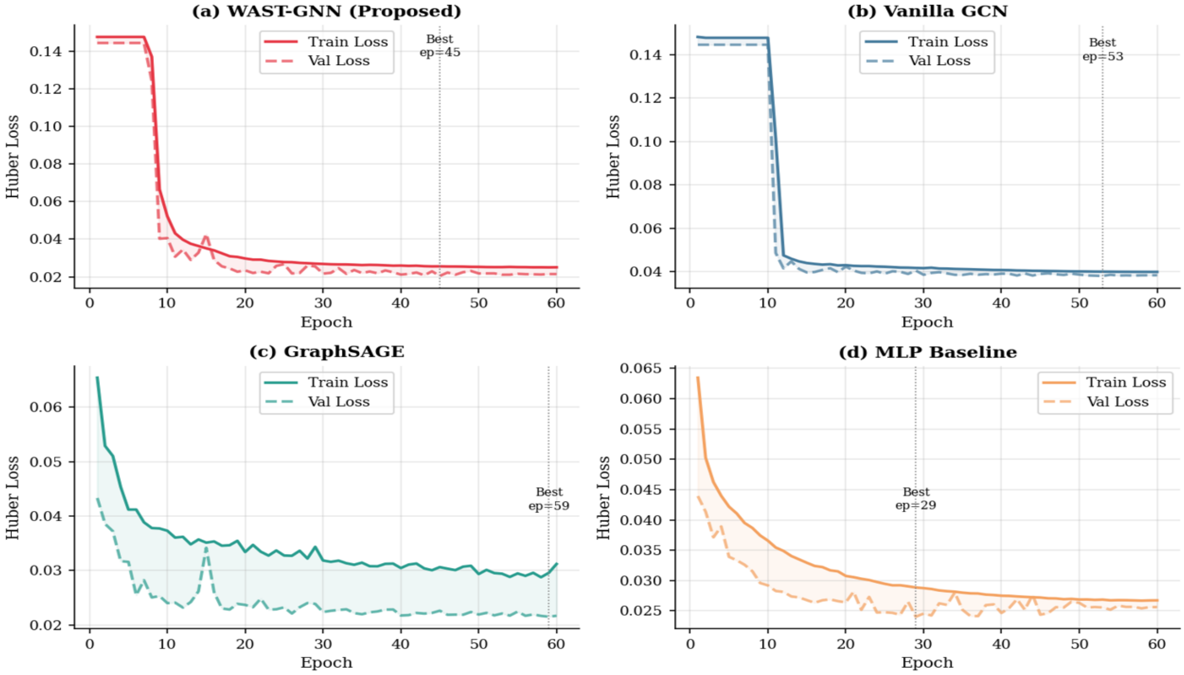


Fig. 5: Training and validation loss curves for all models over 60 epochs.

Training dynamics are illustrated in Fig. 5. The proposed WAST GNN reaches its best validation loss at epoch 45, with tightly coupled training-validation curves indicating good generalization. In comparison, GCN and GraphSAGE need more epochs (53 and 59, respectively) and demonstrate slight overfitting. After epoch 29, the MLP baseline overfits poorly, showing the relevance of spatial structure. Figure 6 shows the scatter plots of projected vs. actual turbine-level power for all four models. Among these, the proposed WAST-GNN (Fig. 6a) exhibits the closest clustering around the identity line with the minimum RMSE (0.227 MW) and MAE (0.106 MW) and the maximum R2 (0.861). Vanilla GCN (Fig. 6b) yields the biggest spread and worse metrics (RMSE = 0.311 MW, R^2 = 0.738), validating that undirected and unweighted graphs are not appropriate for wake-aware prediction. . GraphSAGE (Fig. 6c) achieves comparable performance (RMSE = 0.232 MW, R^2 = 0.854) and slightly lower performance than WAST-GNN, but the MLP baseline (Fig. 6d) obtains reasonable accuracy (RMSE = 0.244 MW, R^2 = 0.839) but lacks spatial reasoning. The suggested wake-aware spatio-temporal model outperforms all baselines, which demonstrates the effectiveness of directional graph attention.

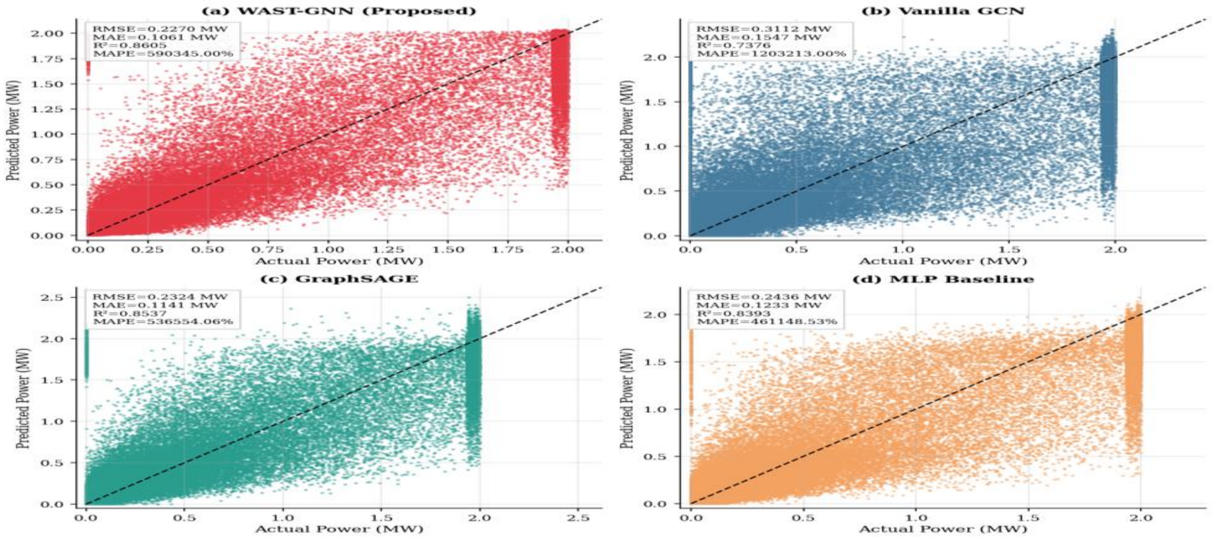


Fig. 6. Predicted vs actual power output scatter plots for all models on the test set.

6. CONCLUSION & FUTURE SCOPE

The research presented a Wake-Aware Spatio-Temporal Graph Neural Network (WAST-GNN) for turbine-level wind power prediction. The framework combines Jensen wake model physics with a graph architecture of directed, distance-weighted edges and temporal convolution layers. WAST-GNN obtained RMSE of 0.227 MW, MAE of 0.106 MW, and R^2 of 0.861 on synthetic SCADA data, surpassing GCN, GraphSAGE, and MLP baselines. The loss curves demonstrated a consistent convergence with little overfitting and the scatter plots showed a good match between the expected and real power. The results confirm that wake-aware spatial modelling paired with temporal learning provides a considerable improvement in turbine-level forecasting accuracy, providing a scalable approach to wind farm power prediction. Future work will include validation of WAST-GNN on real SCADA datasets such as Penmanshiel, inclusion of advanced dynamic wake models such as FLORIS, multi-step and probabilistic forecasting.

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