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Enhancing Numerical Weather Predictions with Spatiotemporal Graph Neural Networks

Graph Deep Learning – MeteoSwiss project

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Introduction

Motivation & problem statement
Introduction

The challenge of post-processing NWP ensembles

- Accurate wind-speed forecasts drive energy, transport and safety decisions.
- **Numerical Weather Prediction (NWP)** produces *ensemble* guidance but suffers from:
  - Limited grid resolution.
  - Simplified physical parameterisations.
- Raw output therefore needs statistical post-processing.

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Why spatiotemporal GNNs?

Weather = space + time dependency

- Classic post-processing calibrates *each* station in isolation ⇒ ignores spatial flow.
- **Spatiotemporal GNNs (STGNNs)** model:
  - **Graph edges**: geographical relations between 152 Swiss stations.
  - **Temporal dynamics**: multi-scale convolutions / RNN / attention.
- Project goal: quantify the added skill of STGNNs vs. strong temporal baseline for wind-speed post-processing.

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Related work

Key literature
Related work

- Neural post-processing of ensembles [1]
- STGNNs for wind farms [2]
- Learnable adjacency ST-GCNs [3]
- Attention-GNN temperature post-processing [4]
- **Competitive Backbone**: MultiScale Graph WaveNet (MS-GWN) [5]

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Methodology

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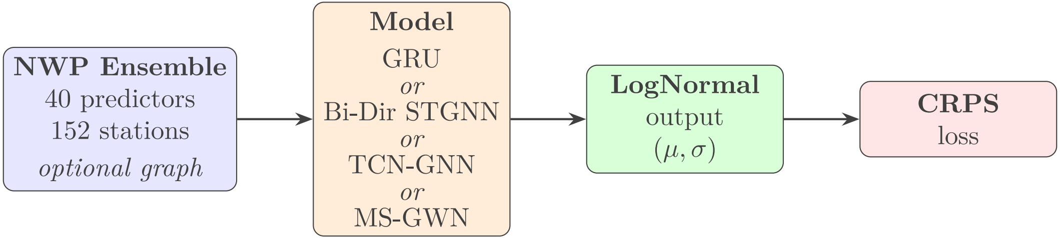
Modelling Pipeline

Methodology



All architectures share this pipeline: raw ensemble (with or without station graph) $\rightarrow$ chosen neural model $\rightarrow$ LogNormal wind-speed distribution $\rightarrow$ optimisation via CRPS.

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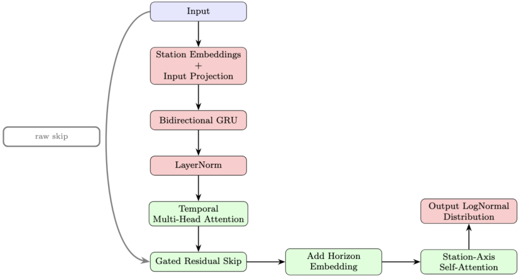
Baseline Model

Methodology

- Bidirectional GRU extracts local temporal context.
- Temporal self-attention re-weights lead-times adaptively.
- Station embeddings $\rightarrow$ station-wise attention.
- LogNormal head outputs μ, σ for wind speed.



Baseline Architecture Design

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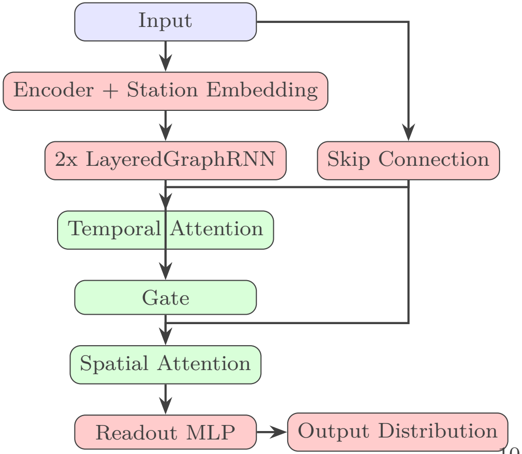
Enhanced Bi-Directional STGNN
Methodology

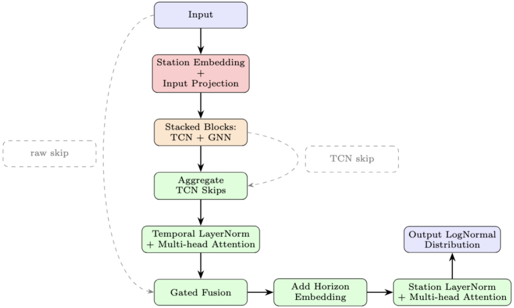
- Two **LayeredGraphRNNs** apply Message Passing on the fixed station graph forwards and backwards in time.
- Added Gating
- Added Temporal & spatial self-attention layers with LayerNorm.



Enhanced TCN-GNN

Methodology

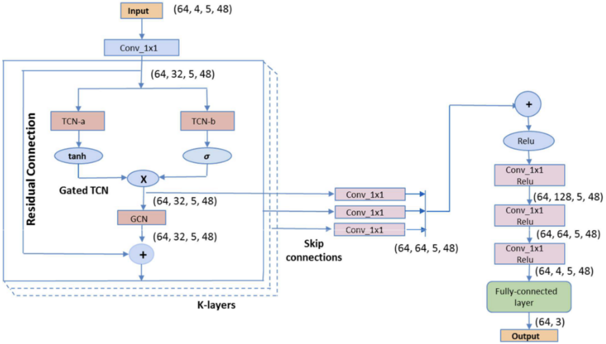
- Stacks of dilated causal TCN blocks capture long-range time-dependencies.
- Graph message passing after each TCN layer (fixed topology).
- Horizon & station embeddings + self-attention.
- Sigmoid gate fuses raw inputs with learned features.



MultiScale Graph WaveNet (MS-GWN)

Methodology

- Multi-scale dilated temporal convolutions (non-causal for post-processing).
- Adaptive graph convolutions with learnable edge weights.
- Edge / history dropout + BatchNorm for regularisation.
- Learnable node embeddings; dynamic weighting of dilation scales.



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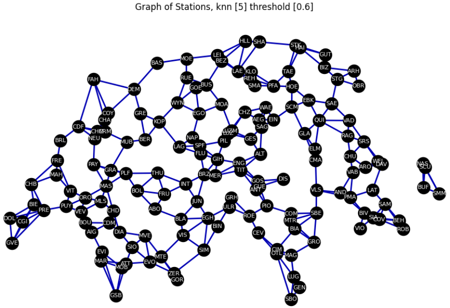
Dataset overview

Methodology

- 40 features: 18 ICON-CH2-EPS [6] forecasts + terrain & time data for 152 stations
- Training & Validation: Feb 2020 - Sep 2023
- Test: May 2024 – Jan 2025
- Distance-based k-Nearest Neighbors graph (default k=5, $threshold$=0.6).



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Evaluation metrics

Methodology

- **CRPS**: $\mathrm{CRPS}(F, x) = \int_{-\infty}^{\infty} \big(F(y) - H(y - x)\big)^2 \, \mathrm{d}y$
- **MAE**: $\frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - y_i|$
- **Calibration check**: Talagrand rank histograms and predictive distribution.
- **Significance**: Diebold–Mariano test [**diebold˙comparing˙2002**] & Benjamini–Hochberg FDR [7]

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Results

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Convergence

Results

Our enhanced TCN-GNN has better convergence than theirs.

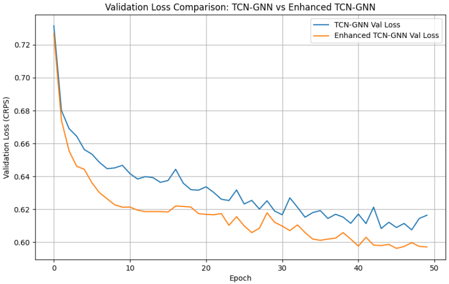

Figure: Validation Loss Comparison

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Test results

Results

Table: Experimental results MAE

Methods	Overall	1h	24h	48h	96h
Baseline	0.90±0.009	0.85±0.012	0.86±0.009	0.89±0.009	1.01±0.010
ST-GNN	1.00±0.01	0.98±0.02	0.97±0.01	1.01±0.01	1.07±0.01
TCN-GNN	0.90±0.010	0.86±0.010	0.85±0.010	0.89±0.010	0.98±0.012
MSGWN	0.87±0.01	0.82±0.01	0.84±0.01	0.87±0.01	0.97±0.01

Table: Experimental results CRPS

Methods	Overall	1h	24h	48h	96h
Baseline	0.63±0.003	0.59±0.003	0.60±0.004	0.62±0.003	0.70±0.004
ST-GNN	0.70±0.006	0.67±0.008	0.68±0.007	0.70±0.006	0.75 ± 0.005
TCN-GNN	0.62±0.004	0.59±0.004	0.59±0.004	0.62±0.005	0.68±0.005
MSGWN	0.61±0.004	0.56±0.005	0.58±0.004	0.60±0.004	0.67±0.04

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Masking Protocols

Masks for Wind Speed

Masking Protocols

Two Masking Protocols considered:

- **Naive**: Takes the whole wind speed distribution and censors the 0.02, and 0.98 percentiles.
- **Station Wise**: Develops a mask looking at the wind speed distribution for each station.

Masks for Wind Speed

Masking Protocols

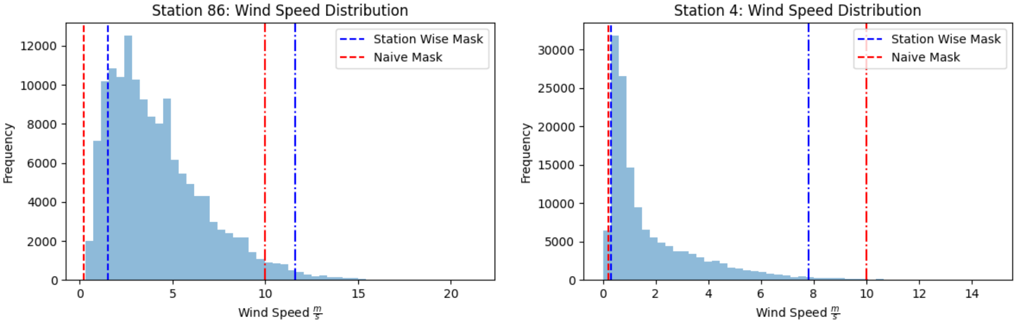

Figure: Wind Speed Distribution with Masks

Loss Evolution

Masking Protocols

Loss evolution for Unmasked and Masked TCN-GNN on validation set for 50 epochs.

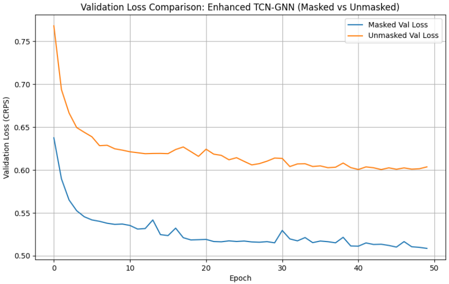

Figure: Loss Evolution: Unmasked v. Masked

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Test results with naive anomaly masking

Masking Protocols

Table: Experimental results MAE - anomaly masked

Methods	Overall	1h	24h	48h	96h
Baseline	0.88±0.034	0.84±0.039	0.84±0.029	0.87±0.037	0.97±0.032
ST-GNN	0.95±0.007	0.90±0.011	0.92±0.008	0.94±0.007	1.00±0.009
TCN-GNN	0.83±0.005	0.80±0.006	0.79±0.009	0.82±0.006	0.90±0.003
MSGWN	0.82±0.006	0.76±0.006	0.78±0.006	0.81±0.006	0.89±0.006

Table: Experimental results CRPS - anomaly masked

Methods	Overall	1h	24h	48h	96h
Baseline	0.60±0.015	0.57±0.018	0.57±0.013	0.59±0.016	0.65±0.012
ST-GNN	0.65±0.004	0.62±0.005	0.63±0.004	0.65±0.004	0.69±0.004
TCN-GNN	0.57±0.002	0.55±0.002	0.55±0.003	0.57±0.002	0.62±0.001
MSGWN	0.57±0.003	0.52±0.003	0.54±0.003	0.56±0.003	0.61±0.002

Test results with 2nd anomaly masking

Masking Protocols

Table: Experimental results MAE - anomaly masked

Methods	Overall	1h	24h	48h	96h
Baseline	0.78±0.015	0.74±0.012	0.75±0.011	0.77±0.018	0.86±0.0221
ST-GNN	0.82±0.006	0.80±0.009	0.80±0.006	0.82±0.008	0.88±0.009
TCN-GNN	0.76±0.014	0.73±0.014	0.72±0.014	0.75±0.015	0.82±0.015
MSGWN	0.75±0.004	0.70±0.007	0.72±0.003	0.75±0.004	0.82±0.007

Table: Experimental results CRPS - anomaly masked

Methods	Overall	1h	24h	48h	96h
Baseline	0.53±0.008	0.51±0.007	0.52±0.006	0.53±0.009	0.58±0.009
ST-GNN	0.57±0.003	0.56±0.004	0.55±0.004	0.57±0.003	0.60±0.004
TCN-GNN	0.52±0.007	0.50±0.007	0.50±0.008	0.52±0.008	0.56±0.007
MSGWN	0.51±0.002	0.48±0.002	0.49±0.002	0.51±0.0018	0.56±0.003

Effect of anomaly masking

Masking Protocols

- Mask 2–98% wind-speed quantiles during train/val.
- MS-GWN CRPS improves to 0.57 ± 0.003 (overall) for Naive Masks.
- Largest gains for TCN-GNN (up to $\sim$47% stations better by DM test) for Naive Masks.

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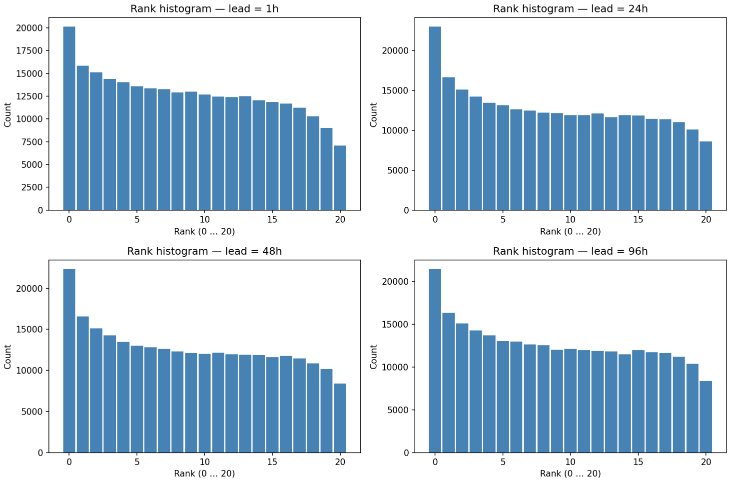
Calibration and Plots

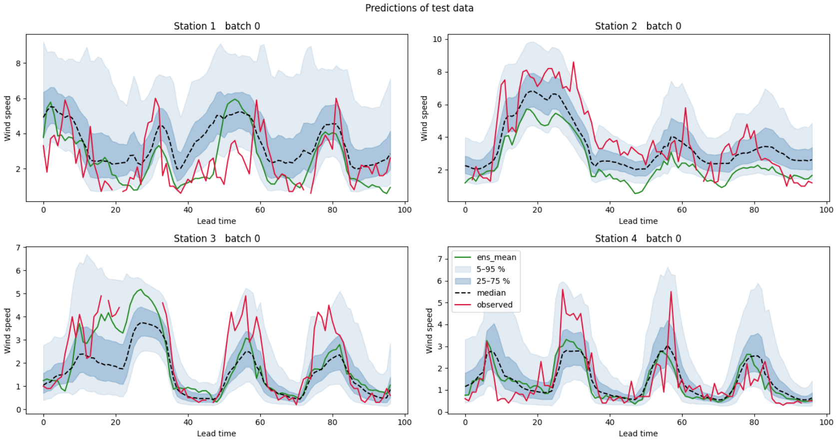
Rank histogram (MS-GWN)

Calibration and Plots



Predictive distribution (MS-GWN)

Calibration and Plots



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Discussion

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Insights
Discussion

- Rich temporal modelling + embeddings capture majority of skill.
- Graph adds modest gain; terrain-aware topology likely needed for Alps.
- Data quality fixes (outlier masking) on par with architectural upgrades.
- Calibration still an open issue – consider heavier-tailed heads or flows.

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Future directions

Discussion

1. Learnable/topography-aware adjacency.
2. Hybrid physics-ML constraints.
3. Heavy-tailed or mixture predictive distributions.
4. Targeted augmentation for extreme winds.

Encountered Difficulties

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1. Environment Installation/Setup (Poetry, Dependencies)
2. Getting used to the provided Pipeline (MLflow, OmegaConf)

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Thank you!

Discussion

Questions?

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Key references
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[3] Tomasz Stańczyk and Siamak Mehrkanoon. *Deep Graph Convolutional Networks for Wind Speed Prediction*. arXiv:2101.10041 [cs]. Jan. 2021. DOI: 10.48550/arXiv.2101.10041. URL: http://arxiv.org/abs/2101.10041 (visited on 04/30/2025).

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[5] Neetesh Rathore et al. "Multi Scale Graph Wavenet for Wind Speed Forecasting". In: *2021 IEEE International Conference on Big Data (Big Data)*. Dec. 2021, pp. 4047–4053. DOI: 10.1109/BigData52589.2021.9671624. URL: https://ieeexplore.ieee.org/abstract/document/9671624 (visited on 04/30/2025).

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[6] *ICON Forecasting Systems - MeteoSwiss — meteoswiss.admin.ch*. `https://www.meteoswiss.admin.ch/weather/warning-and-forecasting-systems/icon-forecasting-systems.html`. [Accessed 29-05-2025].

[7] Yoav Benjamini and Yosef Hochberg. "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing". en. In: *Journal of the Royal Statistical Society: Series B (Methodological)* 57.1 (1995). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.2517-6161.1995.tb02031.x, pp. 289–300. ISSN: 2517-6161. DOI: `10.1111/j.2517-6161.1995.tb02031.x`. URL: `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.2517-6161.1995.tb02031.x` (visited on 05/19/2025).