Physics-Induced Graph Neural Network for Probabilistic Spatio-Temporal Forecasting of Wind Power

Annika Schneider

***Abstract*—The power output of several wind farms or turbines is correlated in time and space. Representing wind farm configurations as graphs and using neural networks on this graph-structured data recently led to promising results in wind power point forecasting. The aim of this research project is to (1) integrate physical knowledge into the graph training procedure, (2) employ historical weather forecast data to increase accessible information for the model, and (3) extend this approach to probabilistic forecasting, equipping forecast stakeholders with valuable information about the underlying distribution and uncertainty of the given forecast. We will provide a novel, physics-induced graph neural network architecture tailored to the use case of wind farm configurations, which optimally captures their spatial correlation structure. Generative networks will be employed to model the probability distribution corresponding to each node (site) in the network. The framework will be applied to three open-source, real-world wind data sets, both on wind farm and wind turbine level, and results will be compared to state of the art spatio-temporal probabilistic forecasting frameworks.**

I. Introduction

Wind energy is the largest renewable energy supplier in most developed countries. In 2023, wind power covered roughly 19% of the entire electricity production in Europe ([16]) and this share will increase substantially in the upcoming years. However, the intermittent nature of wind power imposes challenges for reliable grid operation and grid security. Therefore, accurate wind power forecasting plays a crucial role in the energy transition.

This study focuses on short-term probabilistic forecasting (up to one day-ahead). Short-term prediction is mainly oriented to the spot (daily and intraday) market, system management and scheduling of some maintenance tasks, being of interest to system operators, electricity companies and wind farm promoters ([5]). For short-term forecasting, data driven approaches proved to be superior to the highly accurate, but computational expensive numerical weather prediction (NWP) ([7], [17]). However, as opposed to NWP, data-driven approaches often-times lack of the physical knowledge of the underlying system. To overcome this, graph neural networks (GNNs) had been employed recently in different studies, to capture the geographical allocation of wind power generators. Using spatial information of wind turbines or farms can have several benefits:

- Neighboring wind farms or turbines produce a similar amount of wind power. Therefore, integrating neighboring wind power data adds significant information to the model, leading to a better forecasting performance (*real-time correlation*).
- Neighboring wind turbines shadow each other, directly influencing their resulting wind power output (*real-time causation*).
- A wind farm which is located upstream of another wind farm will produce similar wind power as the downstream wind farm, with a certain time lag. The wind power generation data of the downstream wind farm is therefore highly informative for the upstream short-term wind farm power forecast (*lagged correlation*).

The recent GNN forecasting results benefited strongly from the additional information via graph-structured data and outperformed other state-of-the-art methodologies, even those, who already use spatial information in addition to the historical data (spatio-temporal models). However, these recent studies did not provide any distributional information of the given forecast, making it impossible for forecast stakeholders to estimate forecast uncertainty or plan scenario-based operation. On the other hand, GNN forecasting models have been used for probabilistic forecasting in other domains, for example, demand forecasting and spatio-temporal forecasting of solar irradiance. These models, however, are not tailored to the use case of wind power prediction and do not incorporate physical knowledge, nor historical weather forecasts.

II. Research Question

This study addresses the research gap we outlined above: a probabilistic, spatio-temporal GNN forecasting model, which incorporates physical information of the wind turbine/farm allocation and weather forecasts. We will develop a methodology which provides a generative distribution of each node (site), enabling scenario generation based on the predicted wind power distribution per wind power site. In addition, we will tailor the network architecture to the use case of wind turbines/farms, providing physical information, like the distance of two neighboring wind farms and physical wake-deficit models, in contrast to solely data-driven graph learning. Our aim is to research on several (novel) ways to integrate physical knowledge in graph training, as opposed to only following existing methodologies (as the wake-deficit model). Moreover, we will experiment on different GNN ensembling techniques. These could also cover ensembling over several physics-based graphs and data-driven graphs. Lastly, we will investigate the benefit of integrating historical weather forecasts into the graph embeddings.

III. Literature Review

Since the first approaches of GNNs for wind power forecasting were published in 2019 and achieved outstanding results, the number of subsequent, similar studies increased heavily. While we could find two publications in 2019 and 2020 each, there where at least four studies in 2021, six studies in 2022, and 15 publications in 2023. We could already find two new studies published in 2024.[1] As supplementary material to this research proposal we provide a table overview of the mentioned papers, stating the name of the proposed model, the kinds of data the model has been applied to, whether data or code is available, the journal, publication year and its number of citations (as of January 2024). Only one out of these 31 studies provides some form of probabilistic forecasting via delivering prediction intervals. This gives a first idea of uncertainty, however, by far not as much information as an entire distribution, which describes possible extreme behaviours of wind power output and enables sampling, i.e., scenario generation of future wind power output. Thus, as discussed, there is a clear research gap in providing a probabilistic forecasting approach with GNNs for wind power forecasting.

The two key papers closest to our research question are [9] and [6]. In [9], a wind farm configuration is represented as a graph and a physical wake interaction is used to impose physically plausible interactions among the nodes when processing the graph (updating the embedding) during training. This method enables wind power computation given wind speed, but has two main limitations: In its current form, it can not be used for (probabilistic) forecasting, and the analysis is based on simulated data only.

In [6], a framework for probabilistic forecasting for solar irradiance with GNNs is proposed. In their method, solar measurement sites are modelled as undirected graph, where edges reflect the correlation between sites. Then, a convolutional graph autoencoder architecture is employed to model the distribution at the nodes (sites), incorporating the information on the edges. This results in a probabilistic, distributional forecast at each measurement site, which enables scenario generation of future irradiance. As opposed to [9], this approach is not tailored to wind power and no physical knowledge apart from correlation observed in the historical data is employed.

A. Data Availability

Many of the 31 mentioned studies worked with open-source wind speed data which we could re-use, and we will consider doing so for those with time resolution higher or equal to 10 minutes (highlighted in the supplementary material). In addition, we plan to employ the AEMO ([1]), the Penmanshiel ([11]), and the Kelmarsh ([10]) data set. Some relevant metadata is listed in Table I. All of these data sets are real-world wind speed or power measurements and open-source. In Figure 1, we visualize the Kelmarsh data set.

[1]For sake of brevity, we omit citation of all papers here and refer to our supplementary material.

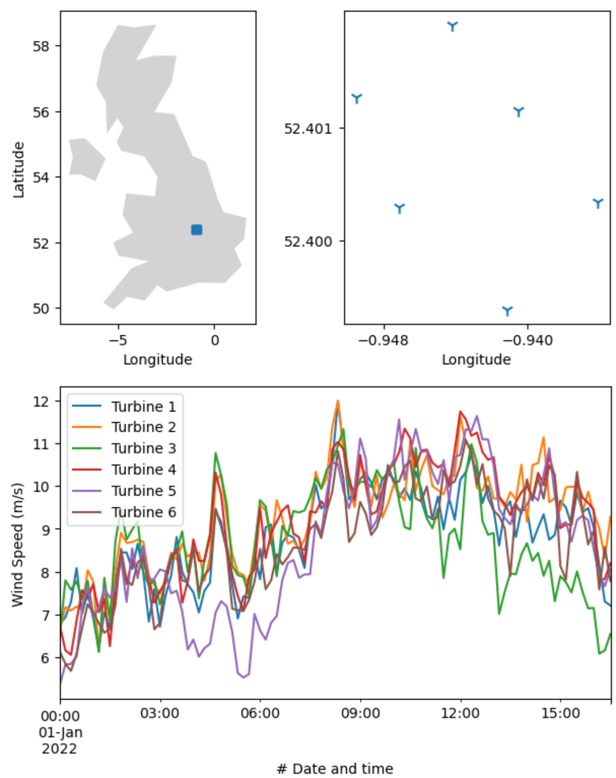

Fig. 1. Location of the Kelmarsh wind farm (upper left) and the six wind turbines in the wind farm (upper right) and wind speed measurements over time (bottom).

In addition to wind data, we will integrate historical weather forecast data, wherever possible. For most of Europe and North America, we can employ the NWP forecast data from the European Centre for Medium-Range Weather Forecasts High Resolution model [18].

TABLE I
Open-source wind speed/power data sets.

Name	Level	Region	Time Res. & Scope	#Sites
AEMO	Farm	Australia	5min, 2010–2023	79
Penmanshiel	Turbine	UK	10min, 2016–2021	14
Kelmarsh	Turbine	UK	10min, 2016–2022	6

B. Code Availability

Out of the 31 researched papers on GNN for wind power forecasting, there are six papers ([4], [8], [13], [14], [3], [15]) where the code was either published alongside the paper, or the authors sent the code after we requested the code via email. For all remaining papers, we also asked the authors but did not hear back yet, or received the answer that the code cannot be made public.

This means, even though we do not have the code from our key papers [9] and [6], we still have some implementations we can build upon, which will speed up our work and facilitates thorough benchmarking. This repositories include on the one hand many key components we need for our implementation (like how to design the graph for a wind farm configuration and provide it as a Data Loader for training), and on the other hand many benchmark methods (other GNN architectures or even models like ARIMA) we can use for performance evaluation.

IV. Research Approach

Our research approach comprises the following steps:

1) **Designing the input data**: First, we need to decide how we would like to represent our data as a graph object, i.e., how do we choose the node and edge embeddings, such that we can optimally capture the wind farm configuration and prevalent correlations. In particular, we will decide on a feasible way to integrate weather forecast data into the embeddings.
2) **Defining the updating procedure**: Similar to hidden layers for classical feed-forward neural networks, a GNN consists of several graph layers, where going from one graph layer to the next, the node and edge embeddings get updated. For example, when updating the embedding of one node, the information of neighboring nodes and edges can be taken into account via *message passing*. Similar to [9], we want to design the updating function such that we induce physical knowledge, as in their case, integrating an engineering wake-deficit model. We aim to develop novel techniques to support the training with physical knowledge in an ideal manner.
3) **Designing the output graph**: Our output graph should carry the distributional information of each node (site), integrating generative networks, as in [6]. It is part of this research project to figure out, how we can achieve this in our physics-induced setting.Moreover, we plan to experiment with ensembling techniques, to further improve our forecasting performance and reduce uncertainty in the distribution.
4) **Evaluating the results**: Our method will be benchmarked with other probabilistic, spatio-temporal methods, for example, GSTAR ([12]) and copula models ([2]). In addition, we plan to compare our performance to non-spatial methods, as state-of-the-art global forecasting models. Identifying the most appropriate benchmarks is also part of this research.

V. Result Outlook

Using typical measures to compare probabilistic forecasts, like the quadratic or the continuous ranked probability score, we will provide summary statistics of the performance of our method compared to the benchmark. We will discuss advantages and disadvantages of our framework, taking aspects like run time, model complexity, and interpretability into account. Moreover, the code of our method, as well as the one for our benchmark method, will be provided as open-source repository. As future research, we plan to extend this repository to a usable and efficient wind power forecasting library. With this project, we aim to make a significant contribution to (1) graph neural network architecture and training methodology and (2) wind power forecasting performance and interpretability.

References

[1] AEMO. *Nemweb SCADA Data*. 2024. URL: https://www.nemweb.com.au/REPORTS/CURRENT/Dispatch_SCADA/.

[2] Mario Arrieta-Prieto and Kristen R. Schell. “Spatio-temporal probabilistic forecasting of wind power for multiple farms: A copula-based hybrid model”. In: *International Journal of Forecasting* 38 (1 Jan. 2022), pp. 300–320. ISSN: 01692070. DOI: 10.1016/j.ijforecast.2021.05.013.

[3] Dogan Aykas and Siamak Mehrkanoon. “Multistream Graph Attention Networks for Wind Speed Forecasting”. In: 2021, pp. 1–8. DOI: 10.1109/SSCI50451.2021.9660040.

[4] Lars Ødegaard Bentsen et al. “Spatio-temporal wind speed forecasting using graph networks and novel Transformer architectures”. In: *Applied Energy* 333 (2023), p. 120565. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2022.120565. URL: https://www.sciencedirect.com/science/article/pii/S0306261922018220.

[5] Alexandre Costa et al. “A review on the young history of the wind power short-term prediction”. In: *Renewable and Sustainable Energy Reviews* 12 (6 2008), pp. 1725–1744. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2007.01.015. URL: https://www.sciencedirect.com/science/article/pii/S1364032107000354.

[6] Mahdi Khodayar et al. “Convolutional graph autoencoder: A generative deep neural network for probabilistic spatio-temporal solar irradiance forecasting”. In: *IEEE Transactions on Sustainable Energy* 11 (2 Apr. 2020), pp. 571–583. ISSN: 19493037. DOI: 10.1109/TSTE.2019.2897688.

[7] Yaxin Liu et al. *Recent advances in data-driven prediction for wind power*. 2023. DOI: 10.3389/fenrg.2023.1204343.

[8] Minbo Ma et al. “HiSTGNN: Hierarchical spatio-temporal graph neural network for weather forecasting”. In: *Information Sciences* 648 (2023), p. 119580. ISSN: 0020-0255. DOI: https://doi.org/10.1016/j.ins.2023.119580. URL: https://www.sciencedirect.com/science/article/pii/S0020025523011659.

[9] Junyoung Park and Jinkyoo Park. “Physics-induced graph neural network: An application to wind-farm power estimation”. In: *Energy* 187 (Nov. 2019). ISSN: 03605442. DOI: 10.1016/j.energy.2019.115883.

[10] Charlie Plumley. *Kelmarsh wind farm data*. Feb. 2022. DOI: 10.5281/zenodo.5841834. URL: https://doi.org/10.5281/zenodo.5841834.

[11] Charlie Plumley. *Penmanshiel Wind Farm Data*. Feb. 2022. DOI: 10.5281/zenodo.5946808. URL: https://doi.org/10.5281/zenodo.5946808.

[12] Jianhua Z Huang Arash Pourhabib and Yu Ding. "Short-Term Wind Speed Forecast Using Measurements From Multiple Turbines in A Wind Farm". In: *Technometrics* 58 (1 2016), pp. 138–147. DOI: 10.1080/00401706.2014.988291. URL: https://doi.org/10.1080/00401706.2014.988291.

[13] Victor Oliveira Santos et al. "Spatiotemporal analysis of bidimensional wind speed forecasting: Development and thorough assessment of LSTM and ensemble graph neural networks on the Dutch database". In: *Energy* 278 (2023), p. 127852. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2023.127852. URL: https://www.sciencedirect.com/science/article/pii/S036054422301246X.

[14] Yue Song et al. "Short-Term Forecasting Based on Graph Convolution Networks and Multiresolution Convolution Neural Networks for Wind Power". In: *IEEE Transactions on Industrial Informatics* 19 (2 2023), pp. 1691–1702. DOI: 10.1109/TII.2022.3176821.

[15] Tomasz Stańczyk and Siamak Mehrkanoon. "Deep graph convolutional networks for wind speed prediction". In: 2021, pp. 147–152. DOI: https://doi.org/10.14428/esann/2021.ES2021-25.

[16] Statista. *Anteil der Energieträger an der Nettostromerzeugung in der EU in den Jahren von 2021 bis 2023*. 2024. URL: https://de.statista.com/statistik/daten/studie/182159/umfrage/struktur-der-bruttostromerzeugung-in-der-eu-27/.

[17] Xiaochen Wang, Peng Guo, and Xiaobin Huang. "A Review of Wind Power Forecasting Models". In: *Energy Procedia* 12 (2011). The Proceedings of International Conference on Smart Grid and Clean Energy Technologies (ICSGCE 2011, pp. 770–778. ISSN: 1876-6102. DOI: https://doi.org/10.1016/j.egypro.2011.10.103. URL: https://www.sciencedirect.com/science/article/pii/S1876610211019291.

[18] Dazhi Yang, Wenting Wang, and Tao Hong. "A historical weather forecast dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) for energy forecasting". In: *Solar Energy* 232 (2022), pp. 263–274. ISSN: 0038-092X. DOI: https://doi.org/10.1016/j.solener.2021.12.011. URL: https://www.sciencedirect.com/science/article/pii/S0038092X21010604.