# Physics-Informed Neural Network for Hindcasting Wind Components with Globally Available Dataset

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***Abstract*—To promote wind energy, modeling the behavior of wind in the atmosphere is an indispensable initiative. However, atmospheric variables are highly complex to simulate due to their intermittent nature within a non-linear dynamic system, which increases the complexity for modeling their behavior. Additionally, the simulations using current forecasting models are approximate, time-consuming, and associated with high computational costs. This work proposes a case study using a globally available dataset from ERA5, targeting the nearby São João de Cariri anemometer station located in northeast Brazil. We built two types of Multi-Layer Perceptron networks: one without physics constraints and another with physics constraints. Then, we compared the performance of the models across hindcasting horizons using the statistical metrics (NRMSE, RMSE, MSE, MAE and R2). We conclude that improvements with physics-informed neural networks are consistent across different hindcast horizons and enhance prediction accuracy for wind components.**

***Index Terms*—Physics-informed Neural Networks, Wind Hindcasting, Wind Components, Artificial Intelligence.**

## I. Introduction

The United Nations Sustainable Development Goals, also known as the Global Goals, were adopted as a universal call to action to achieve a better and more sustainable future addressing global challenges. Despite efforts to meet these goals, fossil fuels remain the world's primary energy source and are also recognized for their significant contribution to air pollution. Environmental degradation has amplified these adverse effects of climate change, making the mitigation of these impacts a global challenge. This work focuses on the development of technology for wind energy, which is closely connected to some Global Goals, for example, Affordable and Clean Energy and Climate Action.

Over recent years, there has been more investments in renewable energies than fossil fuels, indicating an energy trend towards more sustainable alternatives. In this transition, wind energy demonstrates a considerable expansion in terms of energy production, in which experts predict that wind energy could represent a quarter to a third of the global energy supply by 2050, highlighting the potential of this energy source to fulfill local and global electricity requirements and contribute to the mitigation of environmental challenges [1].

The application of mathematical, statistical and computational methods in wind energy is grounded in a thorough comprehension of the physical mechanisms. The energy generation process involves the kinetic energy associated with the movement of air masses, which is influenced by the local terrain and captured within the circular areas swept by the blades of wind turbines. In physics, the Navier-Stokes equations are applied to simulate the movement of air masses from areas of high pressure to low pressure, which manifests as wind. Thereby enabling the prediction of future states of wind components.

The most common method applied to wind predictions is Numerical Weather Prediction (NWP), which uses numerical modeling to simulate wind behavior, accounting for variables that change over time, such as wind speed and direction, as well as natural phenomena like turbulence. In meteorology, this approach represents the most advanced tool employed for weather forecasting. Although NWP represents the forefront of modern meteorology, there are some challenges in terms of complexity in adjusting parameters and high computational costs associated to the simulations [2].

Innovative Artificial Intelligence (AI) techniques emerge as a complementary tool for combating the adverse effects of global warming. AI-based methods leverage in performance, analyzing vast datasets, identifying complex patterns, and predicting atmospheric phenomena with high accuracy and fast inferences. Deep Neural Networks demonstrate potential as a supplementary method to NWP, effectively meeting these criteria.

In some scenarios characterized by limited, uncertain and nonlinear variables, such as those associated to the Earth's atmosphere, training traditional neural networks with a huge amount of data may still be insufficient for developing an accurate wind forecast model. When considering NWP models in these scenarios, this challenge become even more pronounced. Nevertheless, there is a new method called Physics-Informed Neural Networks (PINNs) that combines AI methods with the partial differential equation used in numerical approaches that has shown a greater ability to generalize from less data and produce predictions with enhanced physical consistency in chaotic behaviors [3].

The landscape of Physics-Informed Neural Networks has experienced swift advancement, with valuable contributions from Raissi, Perdikaris and Karniadakis (2019), who demonstrated the use of PINNs to solve inverse engineering problems

[4]. Raissi, Yazdani and Karniadakis (2020) that explored applying the Navier-Stokes equations in fluid mechanics, uncovering hidden fluid dynamics through images [5]. Furthermore, CAI et al. (2021) implemented a physics-informed model to tackle heat transfer problems of industrial complexity [6].

In this context, this research is designed to investigate, train, evaluate PINNs for wind forecasting with a study case. This work proposes developing models with physics-informed features to predict wind components. This approach seeks to closely mimic the outcomes of complex numerical modeling simulations to accurately predict wind components targeting regions that host wind farms to enhance the accuracy of wind forecasts and to promote better wind energy generation estimates.

This paper is organized as follows. The literature review is presented in Section 2. The dataset, preprocessing data and exploratory data analysis is discussed in Section 3. The Physics-informed approach, model development and training, model validation and assessment is discussed in Section 4. Section 5 summarizes the methodology and the main results, discussions and final remarks of the proposed method.

## II. Literature review

### A. Numerical Modeling

Technological advancements, improvements in data acquisition equipment and new data analysis approaches have contributed to the refinement of computational modeling approaches. This evolution has made numerical modeling essential for simulating weather patterns. Numerical models, such as those developed by the National Oceanic and Atmospheric Administration (NOAA) and the European Centre for Medium-Range Weather Forecasts (ECMWF), have become fundamental tools for optimizing and enhancing the efficiency of wind energy through atmospheric forecasts, providing essential data for the assessment of wind resources, planning, and operation of wind farms.

This work explore trends, techniques, and recent developments in numerical weather forecasting modeling in this subsection, with an emphasis on the analysis of wind behavior and its interaction with wind energy systems.

Andrade and Bessa (2016) utilize a grid of NWP applied to wind energy and solar energy. The methodology integrates the gradient boosting trees algorithm, a machine learning method for classification and regression, combined with feature engineering techniques to extract information from the grid. The author reports that the combination of temporal and spatial indices for solar energy and the PCA approach for wind energy led to improvements in both deterministic and probabilistic forecasts. The paper emphasizes the need to test the methodology in different locations and atmospheric conditions, as well as to compare it with other techniques [7].

Olson et al. (2019) developed numerical weather forecasting models to predict wind in complex terrains, aiming for short-term applications (1-24 hours) using the NOAA's Rapid Refresh and High-Resolution Rapid Refresh models based on the Weather Research and Forecasting Model (WRF). The simulations from the models show improvements, emphasizing the importance of the physical processes associated with wind flow around wind farms, focusing on the development of tailored physical parameterizations in the model and the application of numerical methods. The authors mention the need to apply the model in different geographical contexts and atmospheric conditions for its validation [8].

Optis et al. (2021) are focused on aspects that influence the sensitivity of numerical weather prediction models for wind energy applications, considering various configurations of the WRF model, particularly in offshore environments. The research reports significant variability in wind forecasts, demonstrating the need for robust methods to quantify and communicate the sensitivity in modeled wind speed forecasts by NWP. There is also a limitation regarding the generalization of the results and the need for comparison with other forecasting methodologies [9].

It is clear that efforts are being made to find more accurate and reliable wind energy forecasting models, addressing the combination of NWP with other techniques and challenges presented by complex landscapes.

### B. Neural Networks

This subsection explore the development of neural networks models and new architectures proposed in the literature in recent years, focusing on predicting wind speed and direction in the atmosphere and applications in wind energy.

Khosravi et al. (2018) tackle the forecasting of wind speed and direction and the output power of a wind turbine, using three machine learning algorithm models: multilayer feedforward neural network, support vector regression with radial basis function, and adaptive neuro-fuzzy inference system optimized with particle swarm optimization. The models incorporate variables such as temperature, pressure, relative humidity, and local time across a broader set of climatic and geographical conditions [10].

Zucatelli et al. (2020) address short-term forecasting of wind speed using data from measurements on towers with anemometers at heights of 100 meters, 120 meters, and 150 meters in three locations in Bahia. This study utilized supervised machine learning and different artificial neural network techniques, exploring various MLP and RNN network topology, and applying wavelet packet decomposition to determine the most efficient one. The best performance was achieved with an RNN combined with wavelet. The results indicate a promising approach with lower computational load and higher forecast accuracy [11].

Nascimento, Melo, and Moreira (2023) introduce a new deep neural network architecture based on transformers, integrated with wavelet transform for predicting wind speed and wind power generation for a 6-hour forecast horizon, using multiple meteorological variables as inputs for multivariate time series forecasting. To assess the performance of the proposed model, different case studies were investigated using data collected by anemometers installed in three different regions in Bahia. The model's performance was compared with

an LSTM model, as well as related work in the literature. The forecast performance results were evaluated using statistical metrics, training and inference times, through both quantitative and qualitative analysis. The proposed method is effective for predicting wind speed and power generation, showing superior performance to the LSTM model and comparable performance to state-of-the-art models, demonstrating potential for extension to general-purpose multivariate time series forecasting [12].

There is limited exploration of comparative analysis between the proposed models and other machine learning techniques applied to this task. There is also a need for validation of the studies in different scenarios, as the dependence on historical data specific to one region can limit the generalization of the models to other geographical areas. However, some researches provided a comparison with related work and offer methods for predicting wind speed and direction.

### *C. Physics-informed Neural Networks*

This research seeks to investigate the use of PINNs with the Navier-Stokes equations used in numerical methods for fluid simulation. The goal is to assess the accuracy and computational cost of predicting wind speed, direction, and energy production in wind farms for a specific region. Three main approaches were found in the literature for the development of physics-informed neural networks for weather and meteorological processes: spatio-temporal forecasting; emulation of complex physical processes; and downscaling of coarse data.

Spatio-temporal forecasting is an approach commonly used in computational fluid dynamics and artificial intelligence to predict data that varies both in space and time.

Howland and Dabiri (2019) introduced physics-informed statistical models aiming at forecasting energy production in wind farm configurations. They underscore the fact that turbulent wakes from wind turbines adversely affect both energy output and efficiency for turbines located downstream. Consequently, understanding and modeling these disturbances is crucial for optimizing wind farm designs. The authors show that the physics-based wake model offers benefits for approaches focused on control, and that physics-informed statistical models decrease the error in predicting power output within wind farms [13].

Zhang and Zhao (2021) proposes a methodology that integrates LIDAR measurements with flow physics to forecast the spatio-temporal wind field. A Deep Neural Network was modeled and trained, incorporating the Navier-Stokes equations. Only the sparse sensor data was required to enable the prediction of the wind field across the domain after training. This method was able to discover complex wind patterns that was not presented in the training data. The outcome demonstrates the capability to forecast spatio-temporal flow velocities under various scenarios with limited measurements, underscoring the method's effectiveness. This innovative methodology proves beneficial for assessing wind resources and managing wind farms [14].

Mammedov, Olugu, and Farah (2022) presents a weather forecasting method divided into two models: one for wind speed prediction and another for the atmospheric system. The first model is data-driven, incorporating wavelet transform and recurrent neural networks to predict wind speed. The second uses a physics-informed echo state network to learn the chaotic behavior of the atmospheric system. The results of this proposal demonstrate that the PINN captures the nonlinear behavior of atmospheric systems, showing promise for wind energy forecasting [15].

Data sparsity can inhibit the learning process of neural networks. However, PINNs, which leverage not just data but also physical laws, effectively navigate through information scarcity. With proper parameters, these networks frequently achieve successful generalization from sparse data, yielding inferences that are physically consistent and interpretable.

The approach based on the emulation of complex physical processes refers to the use of mathematical and computational models to replicate these phenomena computationally, through simulations of the process in a controlled environment.

Snaiki and Wu (2019) presents a deep learning algorithm with knowledge enhancement to simulate the wind field within the tropical cyclone boundary layer, using 1D and 2D Navier-Stokes equations to improve the regularization mechanism during deep network training for tropical cyclone boundary layer wind dynamics, through storm input parameters. This study highlights the need for a relatively small number of training data sets for the implementation of an early warning system [16].

Zhang and Zhao (2021) introduces a physics-informed deep learning model to reconstruct the three-dimensional (3D) spatio-temporal wind field in front of a wind turbine, combining 3-D Navier-Stokes equations and LIDAR measurements. The results indicate that the wind vector field across the entire 3D domain is accurately predicted using only LIDAR measurements at sparse locations. Furthermore, it was possible to infer turbulent viscosity, which can be used to characterize wind turbulence in other applications. The accuracy of the predictions was confirmed by the mean square errors of the reconstructed wind fields, demonstrating the high precision of the proposed method [17].

Vadyala, Betgeri, and Betgeri (2022) implemented Physics-Informed Neural Networks for real-time physical simulation and geometry optimization of the advection equation in one dimension. Simulations presented that the conventional approach incorporates an effect almost as significant as the effect of the turbulent diffusion model, making the numerical solution inconsistent with the PDEs, while the PINN approximation accurately predicted the outcome. The author emphasizes that traditional numerical methods to find a consistent solution led to inaccurate results and that PINNs can transform physical simulation, enabling real-time simulations without the need for large supercomputers [18].

The downscaling approach is used to obtain detailed information about geographic areas from large-scale data derived from global climate models.

Jiang et al. (2020) introduces a framework called MeshfreeFlowNet for performing super-resolution based on deep learning with physical constraints. This study aims to generate continuous spatio-temporal solutions for turbulent flows in the 2D Rayleigh–Bénard convection problem from low-resolution inputs. The authors believe this framework can revolutionize applications in turbulence modeling [19].

Chen et al. (2022) proposes a framework based on physics-informed neural networks called DeepUrbanDownscale for high-resolution and high-accuracy detailing of urban surface temperature. The network captures large-scale influences through atmospheric force and extracts information from land surface geometry. This approach combines process-based modeling and deep learning approaches to provide computationally efficient super-resolution predictions of urban surface temperature. The authors highlight that this network can be adopted in other urban surface climate forecasting applications without the need for computationally expensive dynamic detailing [20].

Accurate predictions of wind speed and direction are essential in the operations of wind farms, given that wind energy generation is irregular and unreliable. Therefore, wind energy generation can be enhanced by effective wind forecasting.

This review identifies existing gaps related to numerical modeling, artificial neural networks, and physics-informed neural networks in the forecasting and simulation of atmospheric variables for wind energy generation. However, it was found that few studies have made significant advances in these areas, highlighting gaps in the current state of the art of this research field. The research revealed limitations in existing forecasting methods, including prolonged forecasting periods, reduced accuracy, slow convergence, lack of parameter optimization, and a shortage of analytical resources. These gaps compromise the effectiveness of the predictive process.

This research is designed to investigate, train, evaluate PINNs for wind hindcasting and aims to contribute with gaps related to computational efficiency and the accuracy of spatio-temporal wind forecasting.

## III. Data Preparation and Analysis

The initial stage of this research involves exploring datasets available in public domain repositories that provide reliable atmospheric data. It is essential for these datasets to include variables such as temperature, wind components or wind speed and wind direction, atmospheric pressure, and others. Potential data sources may include weather stations, satellites, climate models, and more.

Several repositories have been identified for use in this research, such as ERA5, the National Centers for Environmental Information (NOA NCEI), the Goddard Earth Sciences Data and Information Services Center (GES DISC), the National Environmental Data Organization System (SONDA), the National Institute of Meteorology (INMET). SONDA and INMET are meteorological institutes based in Brazil. Due to its global availability, we chose ERA5 for dataset acquisition. This climate and weather tool combines information from a variety of sources to create a consistent representation of global climate over time.

This work presents a case study for wind speed hindcasting to predict up to six hours ahead for the region near the anemometer station of São João de Cariri, situated in Paraíba, Brazil, from January to December of 2008. The study uses the ERA5 dataset, which is globally and publicly available and obtained through climate reanalysis from ECMWF. The dataset was acquired using the Copernicus Climate Data Store (CDS) API as follows:

- Acquire and Configure the CDS API Key: Install the CDS API client and create a Python script that uses the CDS API to retrieve the desired data. It is necessary to configure the script with parameters including the variables, year, month, day and time.
- Data Collection: This research collected hourly reanalysis data nearby the São João de Cariri station for the entire year of 2008. This dataset included twenty-nine atmospheric variables, enabling the analysis of climatic conditions throughout the year.
- Data Extraction: The selected atmospheric data were extracted at a horizontal resolution of 0.25° by 0.25°, ensuring precision in capturing the climatic conditions pertinent to the station's location. It is required selecting variables from the grid closest to the geographical coordinates (latitude and longitude) of the station.

The second stage corresponds to preprocessing data and conduct an exploratory data analysis (EDA). In this stage, it is necessary to treat raw data to avoid incorrect interpretations and potentially inaccurate outcomes. The primary reasons include null data, outliers and interpolations. EDA is the initial process of exploring, visualizing, and describing the dataset. In other words, it is an analysis of the data in search of patterns, identification of outliers, hypothesis testing, and verification of assumptions based on statistics and graphical representations.

At this point, it is necessary to analyze the descriptive statistics of the data, understand the main characteristics of the dataset, and comprehend its structure and nature.

TABLE I
Descriptive statistics of wind components at 100 meters

| Features | U component | V component |
|---|---|---|
| count | 8781 | 8781 |
| mean | -5.418 | 3.014 |
| std | 1.983 | 2.525 |
| min | -10.782 | -5.828 |
| 25% | -6.800 | 1.232 |
| 50% | -5.498 | 3.052 |
| 75% | -4.116 | 5.080 |
| max | 5.439 | 9.996 |

The analysis of Table 1 indicates that there are 8781 samples of wind components, where u and v represent the longitudinal (x-axis) and lateral (y-axis) components of the wind. The U component have a negative prevailing wind direction, while the V component's prevailing direction is positive. The V component presents greater variability in its values than the

U component. The distribution of the U component might be slightly skewed towards the lower end, while the V component appears more symmetrical based on the close proximity of the mean and median values (50%).

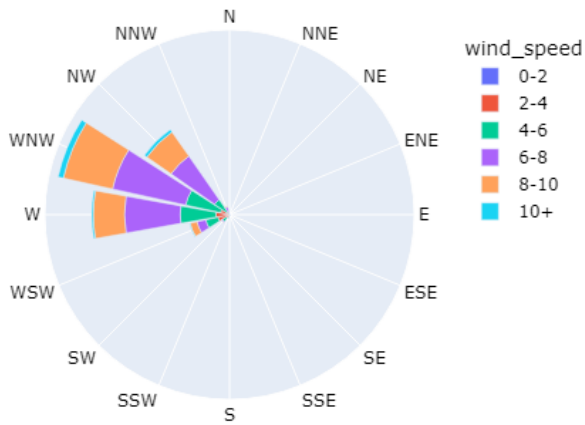


Fig. 1. Wind Rose Nearby São João do Cariri Station.

The Figure 1 represents dataset extracted from ERA5, as previously described. The data exhibits a distribution among different wind direction categories, namely ”NW,” ”WNW,” ”W,” and ”WSW,” with a notable prevalence of data directed towards the ”WNW” direction. Wind speed values span from the lower range of 0-2 (m/s) up to the higher range of 10+ (m/s). Upon closer examination, it becomes evident that winds within the orange color range (8-10 m/s) and purple color range (6-8 m/s) are more frequent in the main wind directions.

This work aims to predict the u and v components of the wind, as highlighted in the Exploratory Data Analysis. However, it is worth noting that the dataset extracted from ERA5 also includes other atmospheric variables. Mapping the wind patterns is useful for various applications, including the planning and design of wind farms, and for general weather and climate modeling. It assists in understanding the wind behavior in a particular region over a certain period.

## IV. Physical Constraints in Neural Networks

The partial differential equations that governs the behavior of moving fluids are the Navier-Stokes equations, which derive from the conservation of mass and momentum equations, describing how the velocity field of a fluid evolves over time. The general form of the continuity equation and the momentum equations for the $x$-direction and $y$-direction in an incompressible flow in two-dimensional Cartesian coordinates can be represented in 1, 2 e 3, respectively [21].

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \mathbf{V}) = 0 \tag{1}$$

$$\rho \left( u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} \right) = -\frac{\partial p}{\partial x} + \mu \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) \tag{2}$$

$$\rho \left( u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} \right) = -\frac{\partial p}{\partial y} + \mu \left( \frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right) \tag{3}$$

Where $\rho$ is the fluid density, $\mathbf{V}$ is the velocity vector, $u$ is the velocity component in the $x$-direction, $v$ is the velocity component in the $y$-direction, $p$ is the pressure, and $\mu$ is the fluid's dynamic viscosity. These are the partial differential equations (PDEs) that should be incorporated into the regularization terms of the loss function of the neural network.

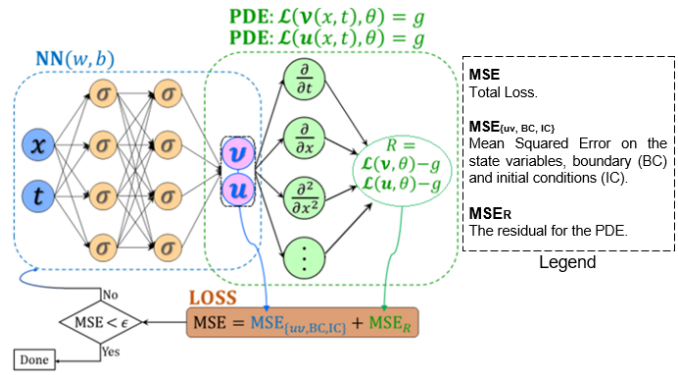


Fig. 2. Schematic of a physics-informed neural network [22].

Figure 2 represents a PINN structure that incorporates the constraints of PDEs into its training process at the network's output u and v.

This case study was modelled using SciANN, a Keras wrapper for scientific computations and physics-informed neural networks, to train the model comparing computing derivatives through automatic differentiation and minimizing the equation's residual. For experimental purposes, we have designed both our neural networks using the Multilayer Perceptron (MLP) architecture.

The MLP consists of multiple layers of perceptrons, each fully connected to the next via weighted links. The MLP aims to approximate the function by mapping input data to an associated output response. Throughout the training, the connection weights are adjusted based on the errors observed in the output, enabling the network to learn the parameter values that best approximate the desired function.

In this architecture, a total of 8781 samples were used, with 29 features extracted from ERA5, including the 10m and 100m u-component and v-component of wind, surface pressure, 2m temperature, among others. The input data consisted of 56% for training, 24% for validation, and 20% for testing. The model comprised three hidden layers with 32, 128, and 16 neurons, respectively. The output data included six horizons and two features, specifically designed to predict the 100m u and v components six steps ahead. The activation function was “tanh”, and the optimizer was “adam”. The model was trained using 16 batches across 100 epochs.

For the physics-informed neural network, we have the same architecture and hyperparameters, however, for scientific computations some adaptations were required. In the context of the SciANN framework, we convert our inputs into “Variables”, which are symbolic placeholders that not only holds the data but is also designed to allow for differentiation operations. The remaining layers were restructured as “Functionals”, designed

to facilitate the creation and manipulation of complex scientific models. Then, "Data" constraints were integrated to impose specific conditions directly on the loss terms of the PINN model. At this point, we conducted a comparative evaluation between MLP and PINN models.

## V. Results

The table presents a comparison of the performance metrics for wind components, predicted by two Multi-Layer Perceptron networks: one without physics constraints (referred to as MLP) and one with physics constraints (referred to as PINN).

TABLE II
Evaluation Metrics of Wind Predictions (U Component) at Different Hindcast Horizons for MLP Model

| Horizon | NRMSE | RMSE | MSE | MAE | R2 |
|---|---|---|---|---|---|
| 1h | 0.205 | 0.541 | 0.293 | 0.413 | 0.889 |
| 2h | 0.335 | 0.888 | 0.788 | 0.677 | 0.702 |
| 3h | 0.389 | 1.027 | 1.055 | 0.795 | 0.600 |
| 4h | 0.428 | 1.129 | 1.276 | 0.891 | 0.516 |
| 5h | 0.459 | 1.207 | 1.457 | 0.960 | 0.446 |
| 6h | 0.456 | 1.198 | 1.436 | 0.948 | 0.453 |
| Mean | 0.379 | 0.998 | 1.050 | 0.781 | 0.601 |

TABLE III
Evaluation Metrics of Wind Predictions (U Component) at Different Hindcast Horizons for PINN Model

| Horizon | NRMSE | RMSE | MSE | MAE | R2 |
|---|---|---|---|---|---|
| 1h | 0.172 | 0.455 | 0.207 | 0.340 | 0.922 |
| 2h | 0.292 | 0.773 | 0.597 | 0.585 | 0.774 |
| 3h | 0.378 | 0.998 | 0.996 | 0.777 | 0.623 |
| 4h | 0.413 | 1.090 | 1.188 | 0.862 | 0.549 |
| 5h | 0.434 | 1.143 | 1.306 | 0.910 | 0.504 |
| 6h | 0.465 | 1.220 | 1.489 | 0.985 | 0.433 |
| Mean | 0.359 | 0.946 | 0.964 | 0.743 | 0.634 |

TABLE IV
Evaluation Metrics of Wind Predictions (V Component) at Different Hindcast Horizons for MLP Model

| Horizon | NRMSE | RMSE | MSE | MAE | R2 |
|---|---|---|---|---|---|
| 1h | 0.094 | 0.393 | 0.154 | 0.305 | 0.963 |
| 2h | 0.135 | 0.561 | 0.315 | 0.437 | 0.925 |
| 3h | 0.173 | 0.720 | 0.519 | 0.567 | 0.875 |
| 4h | 0.208 | 0.866 | 0.749 | 0.685 | 0.820 |
| 5h | 0.219 | 0.911 | 0.830 | 0.719 | 0.801 |
| 6h | 0.241 | 1.003 | 1.006 | 0.797 | 0.759 |
| Mean | 0.178 | 0.742 | 0.595 | 0.585 | 0.857 |

The results demonstrate the overall performance through the coefficient of determination (R2) values for both MLP and PINN models indicate a generally good fit to the data, with PINN models showing a slightly better fit in most cases. This suggests that incorporating physical laws improves the model's predictive capability.

The Root Mean Square Error (RMSE) values are lower for the PINN models across all U components, and for most V components, except 6h where MLP has a slightly better score. Lower RMSE values in PINN models indicate better

TABLE V
Evaluation Metrics of Wind Predictions (V Component) at Different Hindcast Horizons for PINN Model

| Horizon | NRMSE | RMSE | MSE | MAE | R2 |
|---|---|---|---|---|---|
| 1h | 0.079 | 0.328 | 0.108 | 0.250 | 0.974 |
| 2h | 0.134 | 0.558 | 0.311 | 0.435 | 0.925 |
| 3h | 0.170 | 0.707 | 0.500 | 0.555 | 0.880 |
| 4h | 0.200 | 0.835 | 0.696 | 0.659 | 0.833 |
| 5h | 0.228 | 0.949 | 0.901 | 0.748 | 0.784 |
| 6h | 0.240 | 1.002 | 1.004 | 0.788 | 0.759 |
| Mean | 0.175 | 0.730 | 0.587 | 0.572 | 0.859 |

model performance and accuracy. Consistent with the RMSE findings, Mean Squared Error (MSE) values are also lower for PINN models in almost all cases, which further supports the higher accuracy of physics-informed models. Similarly, Mean Absolute Error (MAE) values are generally lower for PINN models. This shows that on average, the errors between the predicted values and actual values are smaller when physics constraints are applied.

As the forecast horizon increases (from 1h to 6h), the performance of both models tends to decrease, as indicated by increased error metrics and decreased R2 values. This is a common trend in predictive modeling, where accuracy often decreases as the prediction horizon extends.

## VI. Final Remarks

The incorporation of physics constraints generally yields better predictive performance over traditional MLP models, however it has the cost of increased computational time, as evidenced by the faster training time for MLP (Wall time: 6min 40s) compared to PINN (Wall time: 33min 31s) for this experiment. The improvements with PINNs are consistent across different forecast horizons and underscore the advantages of integrating the knowledge of physical constraints to enhance prediction accuracy in complex systems like wind forecasting.

This comparison also highlights the trade-off between the computational intensity, speed and efficiency. In contexts where precision is of utmost importance, the benefits of PINNs may justify the longer training times, especially when such models can lead to more reliable decision-making. It is also important to consider the inference times for both models, the MLP had a faster inference of 1.42 seconds, while PINN has a slightly longer inference of 2.55 seconds. Despite PINN's longer training, its inference remains relatively quick. This indicates that once trained, the additional complexity of the PINN does not significantly restrain its operational efficiency.

For real-world applications where models need to be retrained frequently with new data, the longer training times of PINNs might be a limiting factor. However, if the model can be used for extended periods without retraining, the slight increase in inference time may be a reasonable trade-off for the improved accuracy provided by PINNs. Future studies should explore other techniques, compare the proposed PINN model against other methods and consider a broader evaluation, testing the model across different geographical locations.

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