Optimizing Wind Energy Production: Leveraging Deep Learning Models Informed with On-Site Data and Assessing Scalability through HPC

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Abstract: This study suggests employing a deep learning model trained on on-site wind speed measurements to enhance predictions for future wind speeds. The model uses a gated recurrent unit (GRU) derived from the long short-term memory (LSTM) variant, and is trained using actual measured wind velocity data collected at both 10-minute and hourly intervals. The approach relies on using same-season data for predicting wind velocity, necessitating regular updates to the model with recent measurements to ensure accurate predictions in a timely manner.

The results from the prediction model, particularly at a 10-minute interval, demonstrate a significant alignment with the actual data during validation. Comparative analysis of the employed model over a two-year span, with a 24-year distinction, indicates its efficiency across different time periods and seasonal conditions, contingent upon frequent updates with recent on-site wind velocity data.

Given the reliance of sequential deep learning models on extensive data for enhanced accuracy, this study emphasizes the importance of employing high-performance computing (HPC). As a recommendation, the study proposes equipping the wind farm or wind farm cluster with an HPC machine powered by the wind farm itself, thereby transforming it into a sustainable green energy resource for the HPC application. The recommended approach in this work is enforcing the smart power grid to respond to the power demand that is connected to predictable wind farm production.

Keywords: Deep Learning; Wind Energy; Wind Turbine; Smart Grid; Renewable Energy Prediction; High-performance computing

1 Introduction

1.1 Wind Energy Resource

The paramount global challenge is climate change, and each nation bears the responsibility and capacity to invest in renewable energy as a means to mitigate the emission of greenhouse gases [1, 2].

In recent years, the remarkable expansion of wind energy has emerged as a noteworthy development in the worldwide energy scenario [3]. Wind energy currently stands as the swiftest-growing form of renewable energy, boasting a cumulative installed capacity of 763 GW in 2020—a substantial increase from the modest 24 GW recorded in 2000 [4, 5]. This extraordinary growth can be attributed to technological advancements, cost reductions, and favorable policies that encourage the shift from fossil fuels to renewable sources.

In recent times, advancements in artificial intelligence (AI) have enhanced the prediction and management of power generation in wind energy [6]. Wind power presents numerous advantages, positioning it as a compelling alternative to conventional energy sources. Unlike fossil fuels, wind energy is renewable and environmentally friendly, as it does not emit harmful greenhouse gases or pollutants. The modular and scalable nature of wind turbines makes them suitable for a diverse range of applications, spanning from large-scale utility projects to small-scale residential systems. Additionally, wind energy stands out as a dependable and cost-effective electricity source, with the leveled cost of wind energy experiencing a significant decline over the past decade [3].

Forecasts suggest that the global capacity for wind energy will achieve 2,110 GW by the year 2030, constituting roughly 20% of the world's electricity generation [7]. This upward trajectory is propelled by various factors, including the rising demand for clean energy, supportive policies, and technological advancements that contribute to the enhanced efficiency and cost-effectiveness of wind turbines [7].

1.2 Wind Turbine

Wind energy production involves converting kinetic energy from moving wind into electrical power. There are two main types of wind turbines: horizontal axis wind turbines (HAWTs) and vertical axis wind turbines (VAWTs) [1]. The efficiency of the HAWTs is much larger than that of VAWTs; however, both of these types have advantages and disadvantages [8, 9]. The power potential of a wind turbine is proportional to the cubic power of the wind velocity [10]. Wind speed has a turbulence behavior and diverse fluctuations [11]. Moreover, the power potential of the wind turbine is proportional to the density of air. As a result, cold air has a higher wind power potential than warm air [10]. These nonlinear and random features of the wind makes its forecasting a crucial issue for wind power producers.

Power production from wind farms depends on the wind velocity. Furthermore, it is crucial issue that the producer be aware of the kind of farm production to respond to the demand for electricity on the power grid. Moreover, the smart grid technology is a function of the smart components that supply the power grid. In fact, if the wind farm has the capability to predict the wind speed in the short and long-term, it has forecasting for electricity production [3, 6]. This leads to smart wind farm production and enforcement of the smart power grid [12]. Figure 1 displays how wind power production prediction could assist the power supplier in managing the response to the power grid demand.

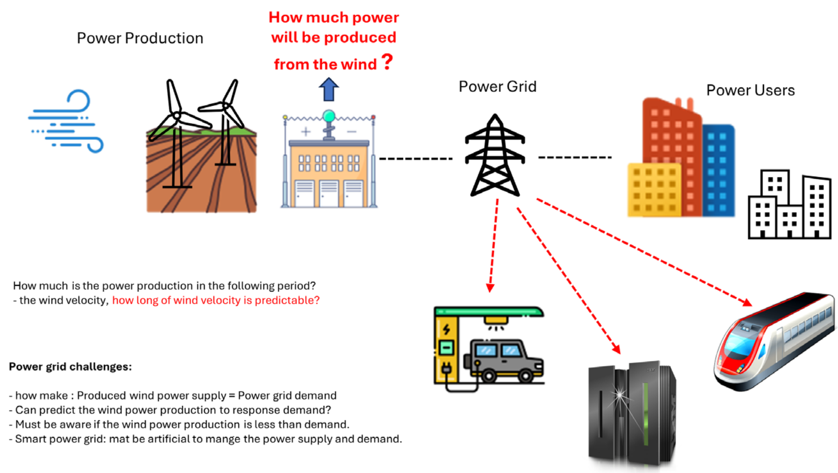

Figure 1
A schematic representation of how wind power production prediction could assist the power supplier in managing the response to the power grid demand

1.3 Deep Learning and Wind Farm

The deep learning model, based on the sequential models, displayed the successful capability to predict the nonlinear phenomenon [13]. In order to optimize the accuracy of the DL model for the wind velocity, using the appropriate period and size of the data is essential. Additionally, depending on the wind park location, the wind speed has a different pattern for monthly, seasonal, bi-annual, and annual datasets. Based on the author's experiences in Nordic countries like Iceland, the wind speed in the winter is extremely higher than in the summer. Because of this difference, the previous study demonstrated a DL model for summer that should not be used for winter prediction [6]. Thus, it is essential to have an online and updated DL model for a wind park. This leads to updating the DL model with measured data from many years ago to a few minutes before.

1.4 Literature Review

In recent years, the DL model for wind velocity forecasting was developed with different DL layers architecture [6, 14]. The majority of the available studies focused on short-term prediction [6, 15]. The dataset used to train the DL model consists of 5-10 minutes and 1-2 hours [6]. The measured data in the previous studies from onshore wind farms [6, 16]. The literature displays 1-6 hour prediction with different DL models. However, there is no universal model to be used globally, and they are specified for a particular site location where trained data has been measured [6, 17].

Looking at the above-mentioned aspects of the proposed DL model for wind speed prediction leads to a novel approach and perspective proposal. Since the wind farm's location, air temperature, month, season, and year of the measured data impact the prediction [3, 6], it dictates an essential local DL model design for each specified wind farm, and the model training must be updated per hour or daily.

The present study proposes a DL model for wind velocity prediction that is updated with training data depending on effective factors such as hour, daily, cold, and warm air and season. The result of the study is a remarkable capability that can cause long-term prediction in addition to short-term forecasting. Hence, this paper is organized as follows. The applied methodology is presented in Section 2. In Section 3, the result and discussion are presented and at the end the conclusion is presented.

2 Methodology

2.1 Measured Wind Velocity

This study applies on-site measured wind velocity data from the Vedurstofan (the Metrological Office) of Iceland. The data involves a time step of 10 minutes for specific years and an hour time step for other years. Figure 2 displays December 1995 to February 1996 and December of 1996 to February 1997.

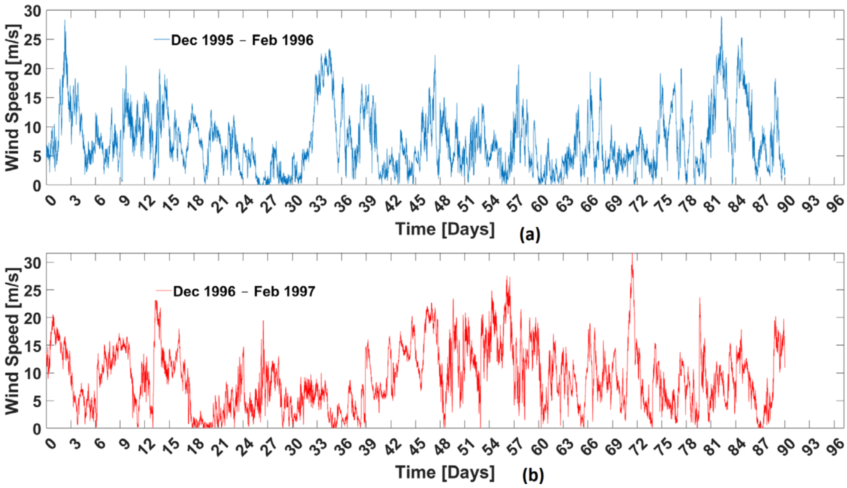

Figure 2

Presentation of the measured wind velocity for two different time periods in Iceland. (a) December 1995 to February 1996, (b) December 1996 to February 1997

These are the same period of time for two years. It can be seen that the wind velocity does not have a similar pattern to be able to use the previous year's data and simulate the next year.

Moreover, two different time periods (seasons) can be seen in Figures 3 and 4. These presentations reveal how owning a distinct pattern is from September 1996 to November 1996 to December 1996 to February 1997. In Figure 4, the same period of September 2021 to February 2022 is displayed. The illustration of these two figures uncovers that the wind speed has nonlinear and random features, and there is no known equation or pattern to use the previous wind velocity of the earlier time to simulate the next time.

As pointed out in the introduction, in recent years, DL networks have been employed to predict a sequential nonlinear dataset, such as wind speed, which has turbulence behavior in the fluid dynamics area. However, the models depend on the specific site location and measured data. The present study suggests using online and recent data to train each wind park's DL model to overcome this defect. To make this application possible in the actual wind farm, it is essential to connect the measured data online to the DL model and update the training in a short time. Additionally, this study would emphasize the fact that using training data from the same period of time will be much more efficient. For example, the speed data from the summer train in the DL model may not be sufficient to predict the wind speed in the winter and needs to be merged with data from winter time. This concept is used in the current study.

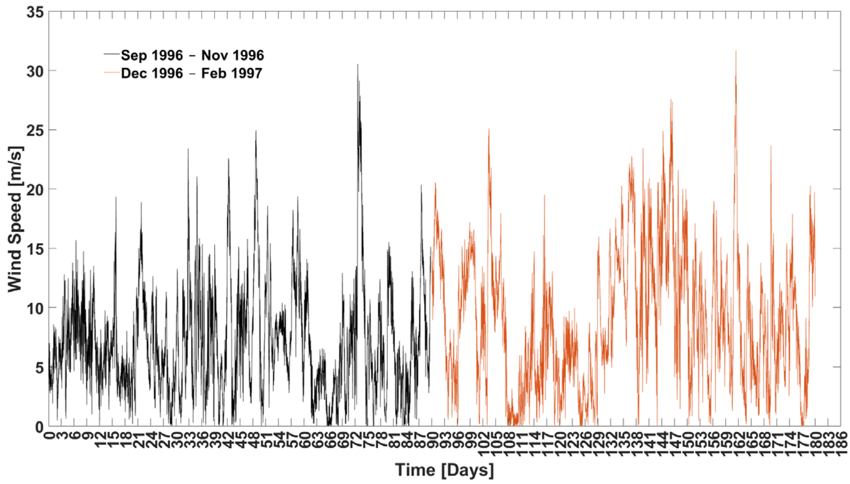

Figure 3

On-site measured wind velocity for two different seasons in Iceland, black color curve, September 1996 to November 1996 and red color curve, December 1996 to February 1997

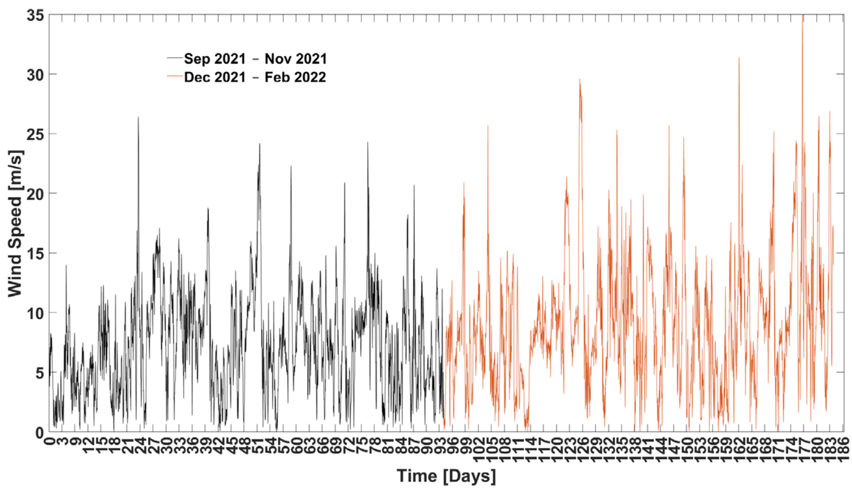

Figure 4

On-site measured wind velocity for two different seasons in Iceland, black color curve, September 2021 to November 2021, and red color curve, December 2021 to February 2022

2.2 Deep Learning Models

Among available DL models for sequential data, LSTM for sequential nonlinear and random datasets displayed successful application. Additionally, the Transformer as an up-to-date DL model from the attention mechanism provided appropriate prediction for the random sequential dataset. The current study employs a gated recurrent units (GRUs) model trained with on-site measured wind velocity and forecasts the wind speed for the following period of time. Based on the literature, GRU is a variant of LSTM and has a simpler architecture. It is reported that GRU has the same efficiency as LSTM with less data.

The model has been assessed with two datasets, one from 1996 with a time step of 10 minutes and the second dataset from 2021 with an hour time step. For each model, 60% of the data was used for training, and 40% of the rest of the data was employed for testing the model prediction. The present study shows that reducing the training data ratio to lower than 60% will reduce the model prediction accuracy. The mean absolute error and squared R (R^2) are measured as metrics for the models. Figure 5, a diagram shows the required dataset for DL model training with HPC resources, and the target is a prediction of the wind speed.

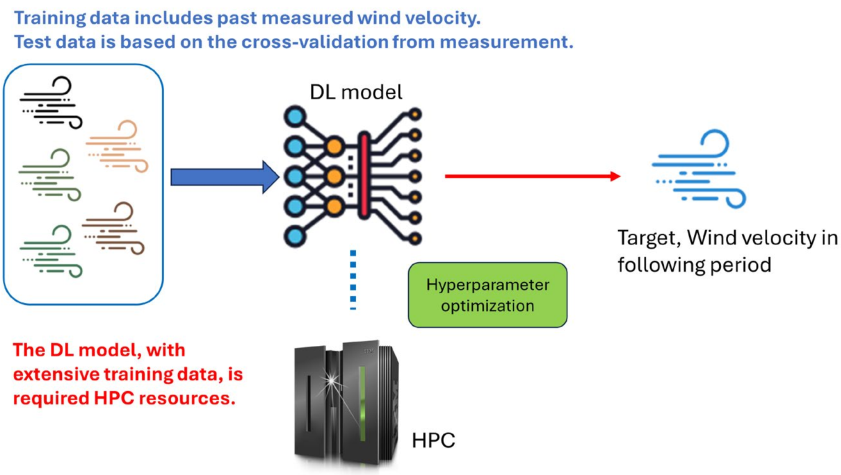

Figure 5
The DL model is trained and tested with measured wind speed. Training data are 60% of the measured data, and 40% of the rest of the data are used to test the model prediction

2.3 High-Performance Computing in Wind Farm

The sequential model of DL will lead to an accurate model with a larger amount of training data. The extensive training data and the DL architecture make it essential to use high-performance computing (HPC). As discussed earlier in this study, the suggestion is to use an online DL model training with up-to-date measured data at the wind farm site.

Having access to HPC to train a DL model with extensive data that is related to scalability is a crucial issue.

However, since the wind frame produces power, it will be an option for each wind farm to own its HPC system or install an HPC system for cluster wind farms that share the computing between them; this will make the HPC supported with green energy, which is a remarkable achievement since many of the HPC clusters using traditional and fossil fuel resources.

3 Result and Discussion

This section presents and discusses the result of the proposed approach, which is composed of the on-site measured data and GRU model.

Figure 6 shows the GRU model result that used measured wind speed data with a period of September 1996 to November 1996 with time step 10 minutes. To train the GRU model, 60% of the data is used to train the GRU model, and 40% to validate the model prediction. The metric evaluation shows MAE 0.019 and R^2 is 0.97. this model used data with short time steps.

Figure 7 illustrates the wind velocity prediction result of the GRU model that trained with actual wind speed from in-site measurement with a period of September 2021 to November 2022 with time step an hour. In this model, 60% of the data is used for training and 40% as validation. The prediction of the model has MAE 0.059 and R^2 is 0.71. This model used data with longer time steps.

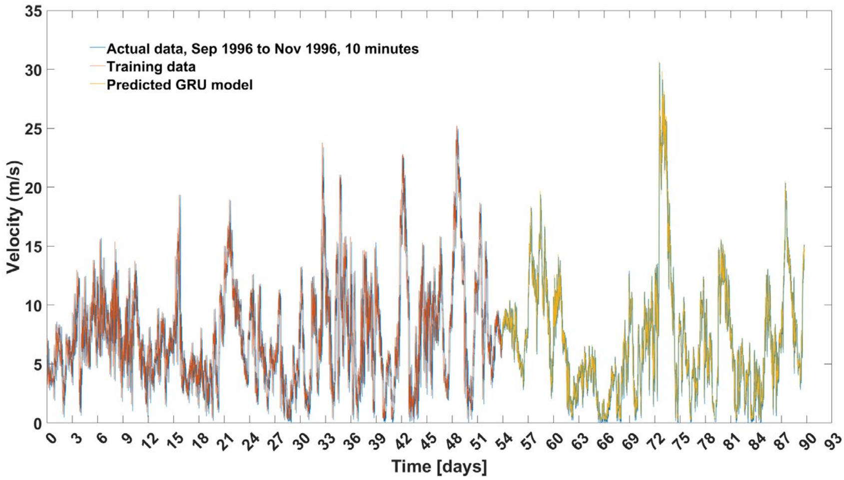

Figure 6
Presentation of GRU model prediction that is trained with on-site measured wind velocity with time step 10 minutes with a period of September 1996 to November 1996, with 60% training ratio and 40% validation. Blue colors the actual measured data, red colors the training ratio, and yellow colors the prediction of the model.

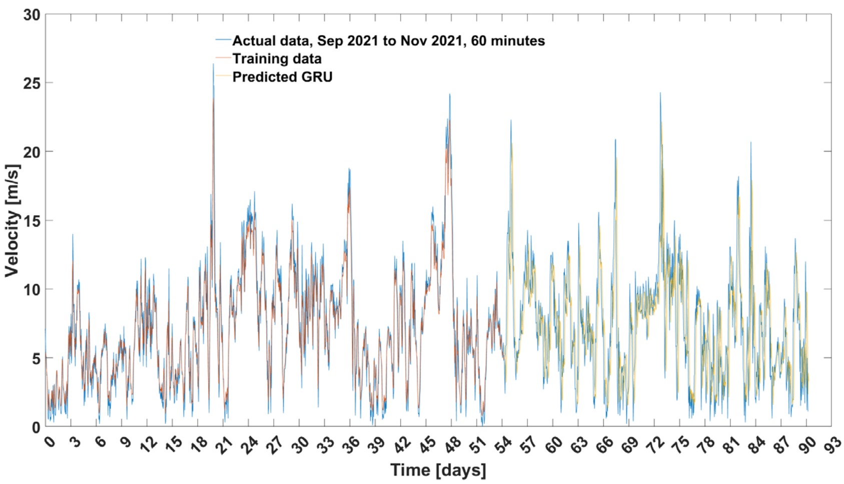

Figure 7
Representation of GRU model prediction that is trained with on-site measured wind velocity with time step an hour with a period of September 2021 to November 2022, with 60% training ratio and 40% validation. Blue colors the actual measured data, red colors the training ratio, and yellow colors the prediction of the model.

The illustrated results in Figures 6 and 7 show a remarkable observation. The GRU model that trained with shorter time steps is much more accurate. In contrast, to the model trained with an hour time step, shorter time step data caused a 36% increase in the R^2 and a 67% decrease in the MAE. Therefore, measuring in-site and speed with short time steps makes the prediction model more efficient and accurate.

Additionally, the current study used one GRU model with a distinct period of time from 24 years ago (1996 and 2021). For each model, the training data was updated, and the model resulted in an appropriate wind speed prediction. These remarkable achievements show that the training update significantly affects the model's accuracy. It could be taken into account that the season of the data for wind speed training should match the target wind speed time.

Conclusions

The current study proposes an approach to using time series data of in-site measured wind speed to predict the wind velocity in the following period of time with the application of deep learning capability. A GRU model from the LSTM variant was designed and trained with a specific ratio of the measured data, and its prediction was validated by the actual data.

The superiority of the present work suggests the use of updated data to predict wind velocity. Furthermore, the study used data from the same season (winter or summer) to train and predict the wind velocity. The study results uncovered that the shorter time step, 10 minutes, makes the model extremely accurate than the model trained with a longer time step, an hour (60 minutes).

The present study recommends using a DL model as software in wind frames that are trained with updated measured wind speed via online connection and updated training to be able to have short and long-term predictions with desirable accuracy. This application makes it possible for the wind energy producer to have a period of wind velocity and wind energy production, and this capability leads to an efficient smart power grid to respond to the power demand. It is planned to evaluate the wind speed prediction via updated data with a Transformer as an attention mechanism and compare it to LSTM variants.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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Conflicts of Interest

The authors declare no conflicts of interest.

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