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Wind Turbine Efficiency Optimization Using Deep Neural Networks

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***Abstract*— Using a Deep Neural Networks' architecture, a novel wind turbine controller addon element is presented. The aim is to optimize wind power generation and at the same time minimize power losses, operational costs and structural fatigue thus extending wind turbines operational lifetime. The scheme was based on data collected from the field using a 50kW small scale wind turbine.**

Keywords—deep learning;wind turbine, small-scale wind turbines; fatigue load reduction;yaw-controller;efficiency optimazation

I. INTRODUCTION

According to United Nations in order to prevent the severe effects of climate change, emissions must be cut by nearly half by 2030 and reach net-zero by 2050. Renewable energy sources are, accessible, sustainable, and dependable alternative sources and reduce world's dependency on fossil fuels [1]. Wind power is one of the least expensive and fastest-growing electricity sources, and it is expected to continue increasing quickly. In 2022, wind-generated power demonstrated the second-highest growth with more than 2100 TWh, an all-time high rise of 265 TWh (up 14%) [2,3]. Although there are tremendous technological advances in the wind power generation industry in recent years, there is always the drive for production optimization. Research is currently concentrating its efforts on ways to increase wind energy capture efficiency and wind turbine reliability. Both of these elements are influenced by the stochastic nature of the wind flow, which directly affects the performance of the Wind Turbine (WT), the mechanical loads it receives (thus its maintenance costs and lifetime) and the quality of the generated energy supplied to the grid [4].

Wind speed and direction demonstrate spatial and more importantly temporal changes during the day and the seasons. A turbine's output is determined by the cube of wind speed, a nonlinear relationship that magnifies the impact of even tiny variations in wind speed [5]. Yaw misalignment is a phenomenon that occurs when the inflow wind direction and the turbine nacelle orientation are not aligned, resulting in a deviation of the yaw angle from the optimal position (see Fig. 1). For the best possible power output, the WT blades must be perpendicular to the incoming wind, and so the yaw error is 0 degrees. Wind turbine yaw system aims to keep the nacelle aligned with the direction of the wind when the wind direction changes.

Power production variation is proportional to the square of cosine of the angle φ of misalignment [6,7] thus making yaw controller very crucial for WT power generating efficiency and overall performance. Both static and dynamic yaw misalignment can negatively impact the power output of a WT. Published research

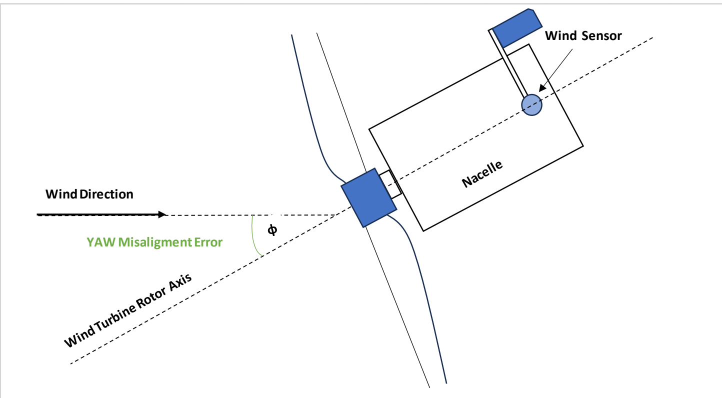

Fig. 1. Yaw Misalignment

report that over 50% of turbines operate with more than 6° of static yaw misalignment [8].

The inaccuracy in wind turbine alignment results in fatigue loads [9] (thus increasing maintenance costs), ultimately shortening the wind turbine's service life [10] reducing the amount and the quality of the produced power [11].

Under typical operating conditions, the rotor torque variations brought on by yawing movements can seriously fatigue the turbine's structure. Yaw system is the second most frequent mechanical part that affects a turbine's total failure rate, which is determined by how many turbines break in a year [12] To ensure the safe operation of a wind turbine, these variations and the problems caused by steady-state and transient-state yaw misalignment must be considered and addressed [13].

In a typical WT the yaw controller is equipped with a wind direction and speed sensor positioned at the rear of the nacelle. This approach is low cost but not optimal since the sensors are under disturbed air flow due to their position behind the rotor blades and not sensing the same air flow that the rotor utilizes.

Most production level WTs utilize traditional control approaches for yaw control based on wind vane sensors in conjunction to rotor speed and produced power [14]. Other control approaches take into account load variations of the flap and edgewise moments [15] or use analytical models to consider the wake effects and the power sensitivity to yaw error [16]. For large wind farms a state-of-the-art approach to the problem is the addition of advanced measuring devices such as Laser Imaging Detection and Ranging [17]. Lidar devices can be used to measure the wind speed and direction ahead of the turbine by sending laser beams into the air ahead of the turbine. This solution though is not always justified for large-scale deployment due to the very high costs involved [17]. For the same reason, in small WTs (those below 50KW) the use of lidars is prohibited.

The objective of the present short paper is to propose a state of the art, high performing low-cost solution to predict the yaw misalignment in real-time using machine learning methods that was developed under project PARALOS^2.

II. EXPERIMENTAL SETUP

For the purposes of the project the wind turbine of interest is a stall-controlled 50kW small scale wind turbine, according to the IEC 61400-12-1 [18], the hub height is 22m and the rotor diameter is 16m. The terrain of installation is complex and of type C, for this reason, a meteorological mast has been erected at a distance of 2.5 Diameters from the wind turbine, to perform the site calibration [18].

Two datasets of 1-minute averaged wind data recorded from the meteorological mast and the wind turbine have been analyzed and used for this work. The wind data available consists of wind speed and wind direction from the nacelle and the met mast, power production, and yaw misalignment.

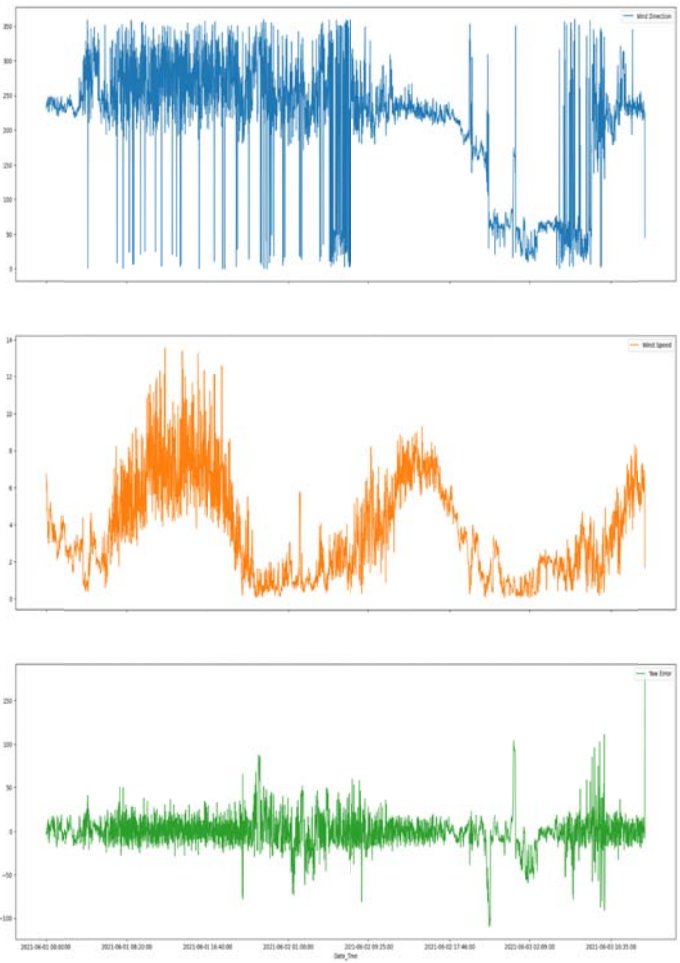

Fig. 2. A time-varying plot of a) Wind Direction (Top), Wind Speed (Middle) and Yaw Error (Bottom), for a 3 day sample from the dataset.

III. DATA ANALYSIS

Following the two data collection campaigns from the field, the datasets were preprocessed.

Missing values, outliers, and inconsistencies where examined addressed at this stage. Since the data are in the form of time-series additional processing was performed regarding data seasonality (repeating patterns) and trends (long-term changes). Techniques such as seasonal decomposition, differencing, and detrending were applied.

After the filtering process of the data, the reference mast measurements have been compared to the wind turbine ones. The scatter plot of the vanes data is shown in Fig. 2.

As can be noted, there are two areas of the plot with disturbances. The more scattered data between 90 and 135 degrees are due to the shadow of the wind turbine on the met mast, and scattered data between- 60 and -90 degrees are due to the met mast shadow on its vane.

The reference mast can be considered to be a reliable reference for the wind direction measurement, especially because its vane is not affected by the rotor and the nacelle geometry. The accuracy between the two vanes resulted in an R2=0.93

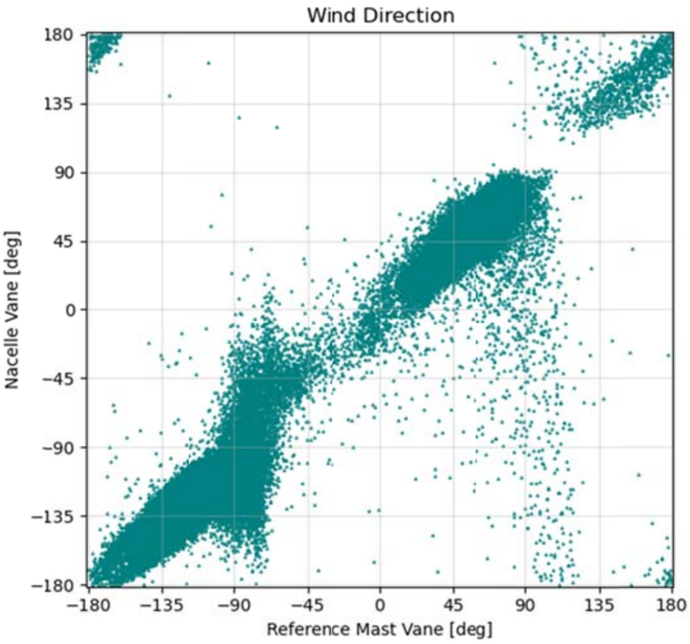

Fig. 2: Reference vane measurement vs. Nacelle vane measurement

IV. Deep Learning model for Yaw Misalignment prediction

Recurrent Neural Networks (RNNs) are artificial neural networks designed for processing sequences of data and are particularly good for tasks where the order and context of the data are important, such as time series analysis, natural language processing and speech recognition, [19]. RNNs due to their architecture have the ability to maintain some form of memory about the previous inputs, making them able to capture sequential patterns more easily than other Neural Networks' architectures.

The idea that makes RNNs work well with sequential data is that they use the same weights and biases for each step in a sequence so the way they process data is consistent and doesn't change as they move through the sequence, ensuring that the network applies the same learned parameters consistently throughout. This shared parameterization is instrumental in enabling RNNs to grasp and encode sequential dependencies.

Crucial to the RNN's operation is its hidden state. At each step in the sequence, the RNN takes the current input and combines it with the hidden state from the previous step, resulting in a new hidden state. This hidden state acts as a memory, preserving information and insights from the network's previous calculations updating the internal state allowing the RNN to adapt to the changing context and dependencies within the sequence.

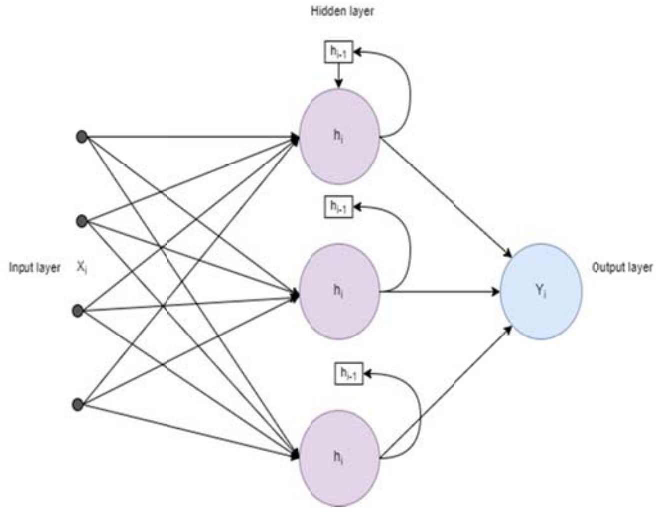

Fig4. General Representation of RNN

Where the variables used are as follows:
X_i=Input for the current iteration i
h_i= State of hidden layer at the iteration i
h_{i-1}=State of previous iteration i-1
Y_i=Output for the current iteration i

For the purposes of the current short paper a RNN following the Long Short-Term Memory type was developed. As inputs were used measurenments from the wind speed and wind direction sensors. Output was the Yaw Misalignment (yaw error). The dataset was split in training, validation and test subsets.
The evaluation of the model performance used the Root Mean Square Error metric:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}},$$

where:

N is the number of data points,
y(i) is the i-th measurement for a specific set of inptuts,
y^(i) is model output/prediction for the same inputs.

The proposed model achieved and RMSE=4.737 degrees of Yaw Misalignment.
Fig. 5 presents a time-series plot of a subset from the test dataset overlaid by the model predictions for the same period. As it can be seen the model was able to capture the yaw error dynamics for the small wind turbine in the specific complex terrain of installation.

V. Conclusions

A Deep Learning model for a small wind turbine yaw misalignment prediction was presented. Yaw misalignment has a tremendous effect on the wind turbine's ability to capture energy, the quality of its

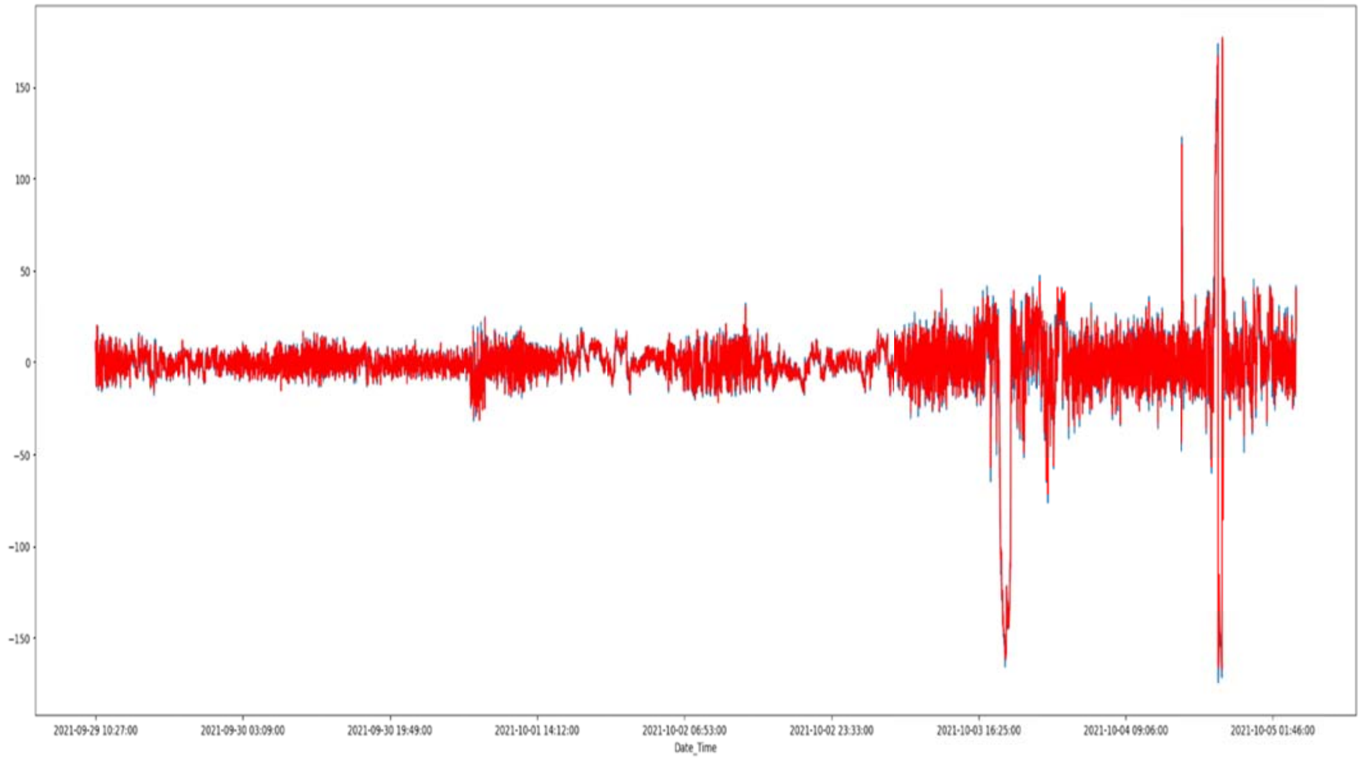

Fig 5. A time-varying plot depicting model performance: in blue is the actual measured data found in the test set and in red are the deep learning model predictions.

output, and its structural fatigue. However, the majority of current sensing or detection techniques provide suboptimal performance or call for additional very expensive sensors, while the intricate operating conditions of any wind turbine significantly skew the sensing function. Machine learning techniques offer a viable solution for optimized WT performance, increasing producer's revenue by minimizing power loses. At the same time, they reduce operating cost by minimizing component fatigue and extent the operational lifetime of the investment. The authors will present in future publications results from more machine learning based models that reinforce the idea that data driven solutions are cost effective and optimize wind power generation.

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