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USING FORECASTS AND SCADA DATA FOR WIND FARM OPERATIONS E-

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Accurate forecasting of wind power production plays a critical role in enabling more reliable load management and optimizing power distribution. Nonetheless, wind power forecasting remains a technically demanding task, primarily due to the stochastic nature of the wind and the non-stationary behavior of the turbine’s power response curve. Wind power forecasting methods are commonly divided into four categories: physical models, statistical models, machine learning-based models, and hybrid models. Moreover, persistence models, which operate under the assumption that the wind turbine’s power output at time t equals that at time *t–1*, remain a standard benchmark for assessing the performance of more advanced forecasting methods. The ongoing progress in computer science has contributed to the growing adoption of machine learning techniques in energy systems modeling, particularly in power forecasting. Several artificial intelligence-based models have been proposed in the literature, including least squares support vector machine (LSSVM), Kalman filter, fuzzy logic method, support vector machine (SVM), extreme learning machine (ELM), Elman network, multi-layer perceptron (MLP), and generalized regression neural network (GRNN). Moreover, examples of deep learning-based models are also available: convolutional neural network (CNN), auto-encoder (AE), deep belief network (DBN), and long short-term memory (LSTM) [1].

This work presents a data-driven power forecasting framework which utilizes real-time turbine operational data from SCADA systems alongside gridded NWP forecasts to downscale meteorological conditions to the precise turbine location. The model leverages time series data collected from SCADA systems, encompassing operational states like active power, Revolution Per Minute (RPM) of the rotor, and pitch angle, complemented by NWP data such as wind speed, wind direction and gust at different altitudes. Moreover, experiments are conducted both by considering individual turbine-level models (Single Models approach) and a farm-level model (Aggregate Model approach). The results demonstrate that the Aggregate Model combined with the spatial regression step, significantly outperforms state-of-the-art industrial approaches, such as persistence methods. Datasets are pre-processed separately, Fig. 1,with spatial regression applied to the NWP data. The processed data is used to create two datasets: one at wind farm level and one at turbine level. These are then used to train two modeling approaches: the Aggregate Model, which uses the wind farm-level data to forecast total power, and the Single Models, in which each turbine's data is used to train an individual forecasting model [2, 3].

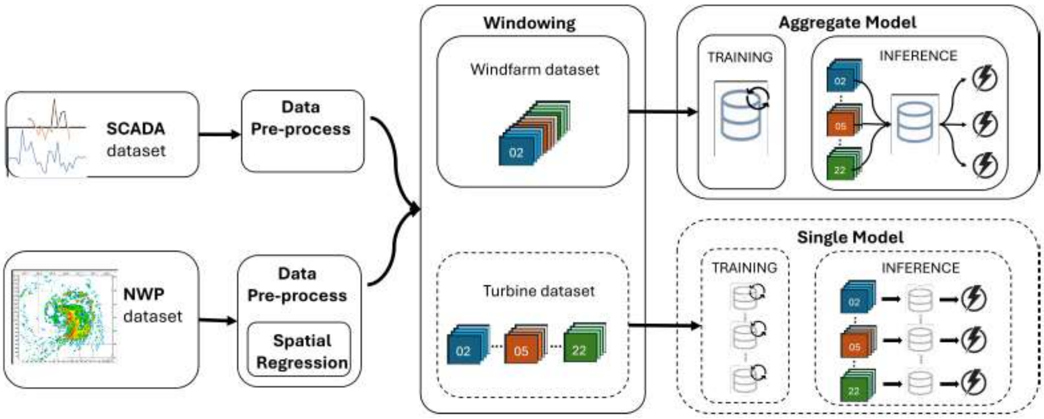

Figure 1. The method for global wind farm power forecasting

In order to provide a more general representation of the underlying physics, the intrinsic similarity among the turbines is used to construct a larger training dataset. Since the turbine fleet belongs to the same wind farm and consists of identical models, it can reasonably be assumed that they are exposed to similar atmospheric conditions and respond to them according to the same control laws. Based on this assumption, a unique model, referred to as the Aggregate Model, is trained on an input dataset obtained by concatenating the individual datasets of each turbine. Once trained, the model in the inference phase takes data from the single turbine as input and provides as output the prediction of the power produced by the turbine. To compare the performance of the proposed approach, a more common prediction technique is used, referred to in this paper as Single Models, in which each turbine is used to train a turbine-specific model and used exclusively for inference on that same turbine. In both cases, during inference, the predicted power outputs of the individual turbines are summed to obtain the overall farm power prediction.

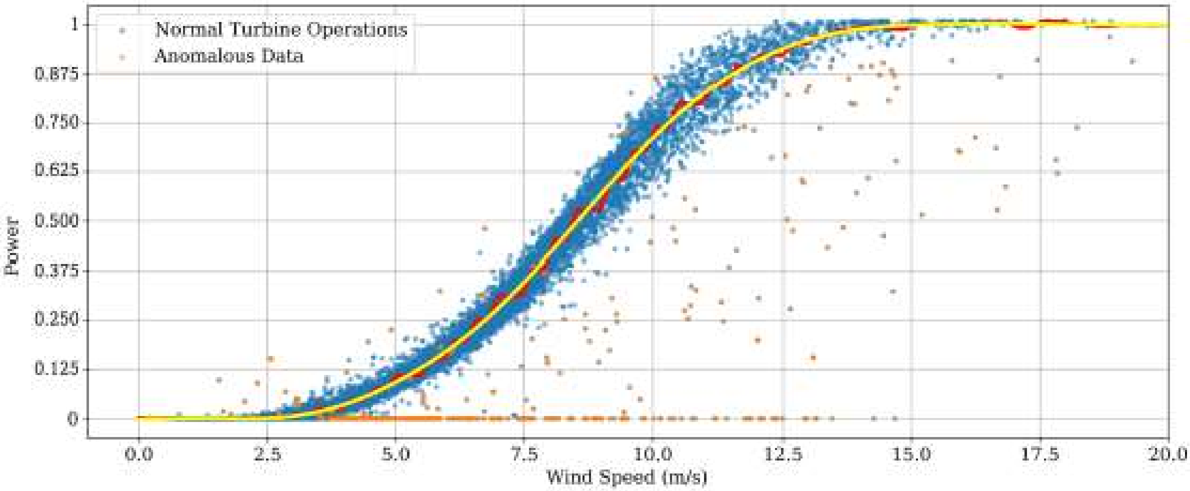

Figure 2. Scatter plot of operational data points on the wind-power plane for the turbine

Data Fig. 2 are not just downscaled to the farm location, but mapped directly to turbine-level power outputs by training a data-driven model able to capture wind patterns over larger areas. In this way, the model learns the downscaling transfer function of the turbines altogether. The past SCADA data are represented as a matrix of shape $N \times P$, where N is the number of variables and P the number of historical time steps, also referred to as the look-back period. Future covariates, derived from NWP models, form a matrix of shape $M \times F$, with M being the number of forecasted features and F the number of future time steps, defining the forecast horizon. The output associated with each window is a vector of shape $1 \times F$, representing the predicted values of a single target variable across the F lead times [4, 5]. The persistence model forecasts a feature's value by assuming it remains unchanged from the previous timestamp. Despite its simplicity, it serves as a reference for evaluating the performance of more complex methods. Ridge Regression is a regularized version of linear regression that includes a penalty term to prevent overfitting, especially useful when the model includes many correlated predictors. Finally, XGBoost (Extreme Gradient Boosting) is an ensemble learning algorithm based on decision trees. It builds models sequentially, with each new model aiming to correct the errors made by the previous ones.

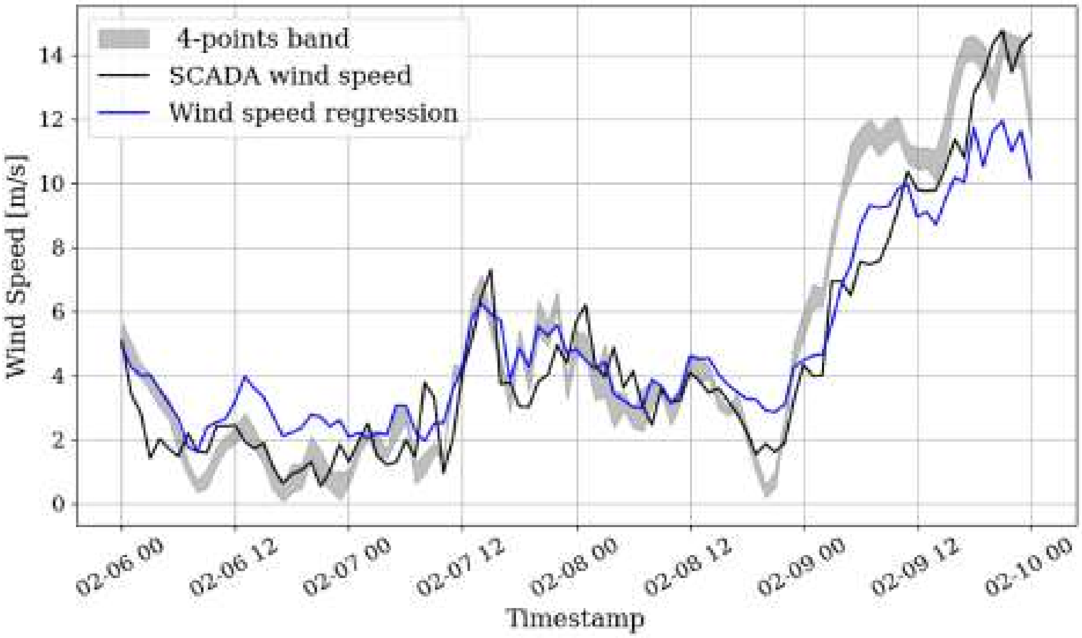

Figure 3. Comparison of downscaled wind speed and NWP Grid Points Against SCADA Ground Truth

The figure refers to a single turbine, and for clarity, the time window shows a subset of test period. The MAE of the wind speed regression, computed over the full test period, is 1.359 m/s. For the 4-point band, the MAE is calculated using the average of the four NWP wind speed forecasts, resulting in a value of 1.804 m/s. Wind speed regression outperforms the original forecast data, leading to a 24.7 % reduction in MAE. The blue dashed line represents the mean error of the regression, while the grey dashed line indicates the mean error of the 4-point band, computed as the average of the four NWP wind speed forecasts. The regression shows a higher concentration of small errors, whereas the 4-point band exhibits a greater frequency of positive errors [6, 7]. This confirms the tendency of raw NWP forecasts to overestimate wind speed, as well as the ability of the regression model to mitigate this bias. The normalized datasets serve as inputs for training various predictive models, including XGBoost, Linear Regression, Ridge Regression, and a Persistence baseline. Moreover, different subsets of input features are selected to assess the impact of the feature composition on forecasting performance. Experimental results demonstrate that the Aggregate Model outperforms the turbine-based approach, confirming that the aggregation of turbine data not only enhances the robustness of the model but also enables better generalization, ultimately leading to more accurate and reliable power forecasts. In particular, the best result in terms of MAE is obtained using the XGBoost regressor with the inclusion of features derived from the spatial regression layer applied to high-resolution NWP data, achieving an MAE of 1,13 on the total farm power.

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GRID SUSTAINABILITY USING PHOTOVOLTAIC POWER PLANTS AND FORECASTING THE CAPACITY OF DISTRIBUTION NETWORKS

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Introduction. The initial phase of research in this area focused on symbolic AI and knowledge-based systems. Early power grid forecasting relied on predefined models and expert systems that encoded domain knowledge about grid behavior, environmental factors, and operational rules. These systems typically used rule-based approaches, where expert insights were embedded to estimate grid performance under various conditions. However, their reliance on static knowledge bases made them inflexible in the face of unforeseen events. Moreover, they were computationally intensive and struggled with the complexity of large-scale grid operations and dynamic, real-time data. Despite these limitations, such approaches provided foundational insights into grid behavior and paved the way for more advanced methods. Despite the progress in data-driven forecasting, current methods still encounter limitations. These include the need for large volumes of high-quality data, difficulty in interpreting model outputs, and limited adaptability to