Neural Network-Based Estimation of Onshore and Offshore Wind Power Generation in Germany

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Abstract: Wind power generation has become increasingly important in Germany, where the installed capacity of wind sources currently reaches 75.75 GW. Accurate wind power generation forecasting is essential for predicting spot prices and grid management. Deep learning approaches have emerged as promising alternatives for renewable energy forecasting due to their ability to capture complex nonlinear relationships in time-series data. This study develops and compares two neural network architectures for estimating hourly wind power generation using Copernicus ERA5 reanalysis data in Germany. Models in this study are simple regression model with separate onshore/offshore branches and Convolutional Neural Network (CNN). For training, we used the wind components (u_{100}, v_{100}) from ERA5 reanalysis, representing the eastward and northward wind speeds, matched with hourly generation data and monthly data of installed capacity for wind offshore and onshore from Energy-Charts transparency platform. Training and validation data span from 2019 to 2024, testing is performed on first 5 months in 2025 to evaluate performance. Data from Copernicus are standardized, while data of installed capacity and generation are normalized. The regression model achieved validation/test Mean Square Error (MSE)/Mean Absolute Error (MAE) of 0.0765/0.0937; the CNN achieved 0.0497/0.0517, outperforming the simple model and demonstrating the effectiveness of convolutional layers for capturing spatial wind patterns. Estimation of power generation was better in onshore case than offshore case in both models. The results highlight the potential of CNNs for wind power forecasting and suggest further improvements by incorporating additional meteorological variables such as pressure, temperature, and humidity and exploring other architectures, such as CNN Long Short-Term Memory Networks.

Keywords: Electricity Market; Wind Power Forecasting; Deep Learning; Renewable Energy; Convolutional Neural Network

1 Introduction

The global demand for electricity rose by 2.2% in 2024, and renewables sources of energy shared largest growth in global energy suply [1]. The International Energy Agency (IAE) forcasts that global installed capacity of onshore wind will reach 732 GW by 2030, highlighting wind's growing strategic role [2]. Germany, a leader in European wind, aims for 115 GW onshore capacity by 2030, although current trends suggest this target may be missed [3], [4]. The integration of wind into electricity markets, particularly within the coupled European power market, has significantly affected market operations, price volatility, and cross-border power flows. It is important to study ways to predict wind generation and its effect on electricity market. Based on our previous research, studying capture rate for solar and wind energy sources, in terms of economic profitability, wind does not experience big decline in its economic capability compared to solar, in the past decade [5]. Analysis of capture rates for solar are better described in [6]. Energy market is evolving, and over past years, volatility of prices has increased drastically [7]. Based on facts mentioned above, our research is focusing on studies in energy market and its behavior, and to research better predictions for multiple factors affecting price formation. In this work, we apply neural network methods to estimate wind power output in Germany, using high-resolution meteorologicaldata from Copernicus (ERA5) and generation and installed capacity data provided by Energy-Charts [8], [9]. By comparing a baseline regression approach with a CNN, we assess the accuracy and market relevance of advanced deep learning for wind forecasting in a highly interconnected European market.

2 Literature Overview

Wind power forecasting is a crucial area of research, given wind's growing share in electricity markets. Early approaches relied on statistical physical models, such as autoregresive, ARMA/ARIMA, and numerical weather prediction methods, each with their own limitations, Recent reviews highlight that deep learning techniques, such as Artificial Neural Networks, Convolutional Neural Networks and reccurent architectures, offer improved performance in short and multi-hour wind prediction tasks [10]. Using Web of Science's smart search, we provide quick review of recent trends, papers from 2024 and 2025, that use neural networks for wind power generation predictions.

Authors in [11] presents a novel hybrid deep learning model, combining Temporal Convolutional Network and Long Short-Term Memmory with parallel architecture. They used Savitzky-Golay filter to deonise and smooth wint speed data. Experiments were conducted on real SCADA data from wind turbine in

Turkey, comparing multiple models. Hyperparameter optimization gave best results with 64 filters for TCN and LSTM layers, with filter size 3 and Tanh activation. Proposed model outperformed simpler models.

Publication [12] proposed hybrid model for ultra-short-term wind power forecasting combining LSTM networks with Vision transformers to capture temporal and spatial correlations in meteorological data. Model was tested on real-world wind farm data from the USA and data were devided into seasonal subsets. Proposed model outperformed several baseline models. The results demostrate the capacity and capability of proposed model to learn and comprehend complex nonlinear dependencies, enhance forecasting accuracy and better adapt to climatic conditions. In future work, authors want to optimize hyperparameters and reduce model complexity.

Authors in [13] proposed wind power forecasting framework that combines deep and dense Convolutional neural networks with spatial context-aware maps of turbines. The turbine map encodes turbine locations and capacities on the spatial grid of numerical weather prediction (NWP) variables, enabling the model to learn spatial patterns effectively across multiple bidding zones. This approach helps manage distribution shifts caused by changing turbine mixes, capacity expansions, and operational factors. Evaluation was done on EEM20 dataset [14], covering Swedish bidding zones. The DenseNet-based CNN outperforms other architectures like ResNet and transformers, and conformal prediction calibration significantly improves uncertainty quantification compared to uncalibrated methods. The proposed SCDRF model efficiently produces full predictive distributions with practical value for risk-aware operation.

Publication [15] proposed a hybrid wind power forecasting system conmbining data decomposition, algorithm optimization and deep learning to improve accuracy. Hybrid Adaptive Decomposition Denoising algorithm was proposed to reduce noise in wind speed data, and Improved Seagull Optimization Algorithm was used to oprtimize LSTM model parameters. Augmentation of data was also used, to better quantify uncertainties.

Wind power forecasting is a vital research area due to wind energy's increasing role in electricity markets, with early methods like statistical and physical models having notable limitations. Recent deep learning techniques have shown improved forecasting accuracy over short and medium time horizons. Recent studies present hybrid deep learning models combining Temporal Convolutional Networks and LSTM, or Vision Transformers with LSTM, demonstrating enhanced accuracy on real turbine data by capturing complex temporal and spatial patterns. Additionally, spatially aware CNN-based frameworks using turbine maps address distribution changes in regional forecasting while improving uncertainty quantification. These advances underscore the growing efficacy of hybrid and spatially informed deep learning approaches in wind power prediction.

3 Data Procesing and Model Training

In this study, we acquired onshore and offshore wind generation data for Germany via the Energy-Charts API and extracted ERA5 Copernicus meteorological data over Germany, specifically u_{100} and v_{100} wind speed components. Data procesing was conducted using pandas and xarray Python libraries. Both wind speed and wind power generation data are structured at hourly resolution, while installed capacity is recorderd monthly. The ERA5 dataset provides wind data on 5 x 5 km spatial grid, where each grid cell contains 2 value, the east–west (u_{100}) and north–south (v_{100}) wind speed components. For illustrative purposes, in Figure 1 we present picture of wind speed map over Europe, where wind speed at each grid point is computed using formula *wind speed =* $\sqrt{(u_{100} * v_{100})}$.

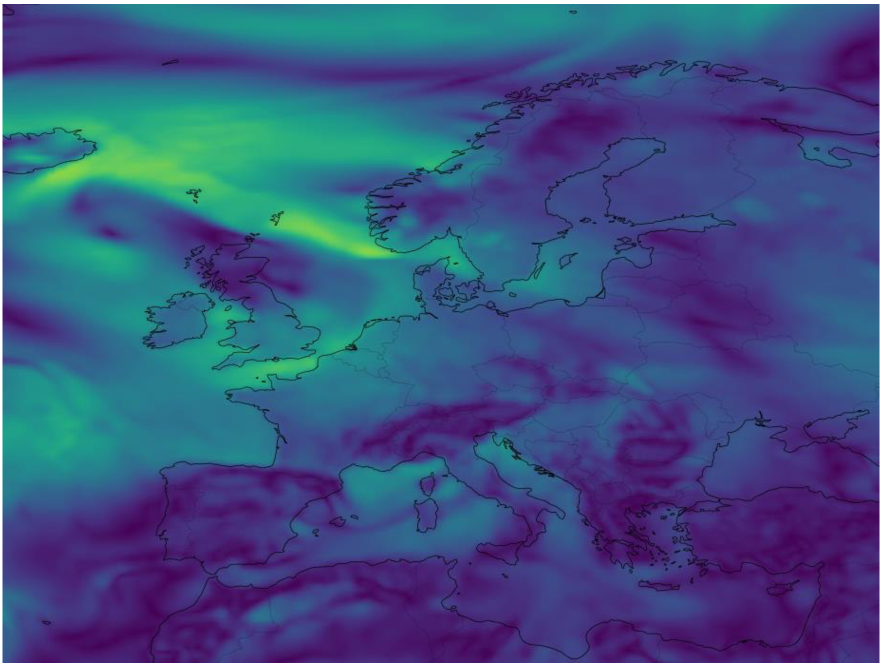

Figure 1

Wind speed above Europe, time 2024-01-01 00:00

Following data acquisition, we standardized wind speed components data using z-score normalization. Conversely, wind power generation and installed capacity values were normalized using min-max scaling with buffers to prevent boubdary effects. Specifically, for generation values (both onshore and offshore) we used 10% buffer, and for installed capacities (both onshore and offshore) we used 20% buffer relative to their respective data ranges.

Our dataset comprises six years of hourly wind meteorological and generation data (2019-2024) and data from january till may for year 2025. To establish robust model validation we partitioned dataset for training, validation and testing. The 2019-2024 period was devided into training (80%) and validation (20%) subsets, with shuffle implemented from scikit-learn Python library. Testing periond represents first five months of 2025, ensuring evaluation on distinct data from the training horizon. This approach enable us to create models for estimation of wind power generation from one sample, instead of multi-hour samples.

To estimate hourly wind power generation for onshore and offshore wind farms in Germany, we compared two neural network architectures, a simple fully-connected regression model and a Convolutional Neural Network (CNN). For model develompent we used Tensorflow Python framewrok. Both models process wind field data and installed capacity as inputs, with separate prediction branches for onshore and offshore generation.

The simple regression model takes as input wind data arranged on a grid and capacity values for offshore and onshore wind farms separately. The wind data is first flattened into a single vector, removing spatial structure. This flattened input passes through two fully connected layers with Rectified Linear Unit (ReLU) activation to learn key features. Then the model splits into two branches, one for offshore and one for onshore prediction. Each branch concatenates its capacity input to the features before producing its final output through a sigmoid-activated dense layer. The sigmoid activation restricts predictions between 0 and 1, matching the normalized scale of target power values. Outputs from both branches are combined into a final two-dimensional prediction vector, representing onshore and offshore generation simultaneously. In Figure 2 we present architecture of simple regresion model.

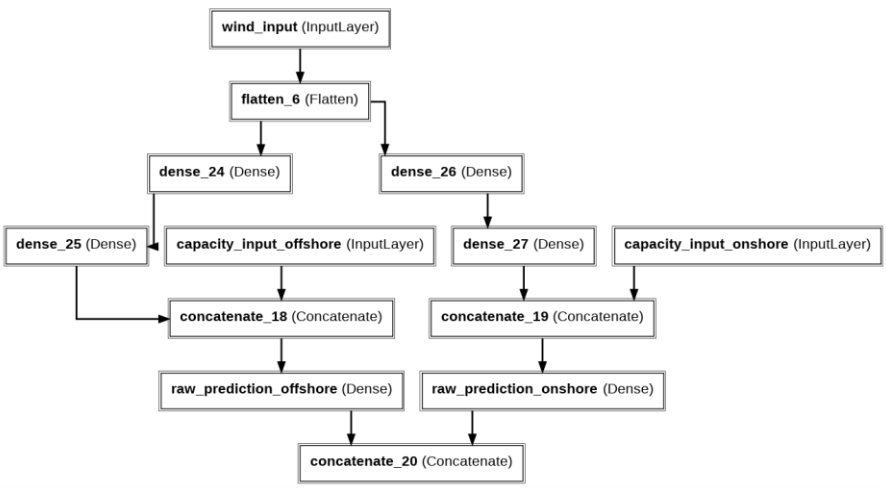

Figure 2

Architecture of simple regresion model

The CNN model is designed to capture spatial wind patterns from ERA5 grid data and produce separate power generation estimates for offshore and onshore wind. It takes wind data arranged on a grid and installed capacities for both wind types. The input wind data is first processed through three convolutional layers, each increasing the number of filters (32, 64, 128), with ReLU activations and max pooling for dimensionality reduction. The extracted features are then flattened and split into two branches, one for offshore, the other for onshore predictions. Each branch has two dense layers with ReLU activations, concatenated with its respective installed capacity input for contextual scaling. The outputs are passed through sigmoid activation to ensure results stay within the normalized range of power values before being merged into a final two-element output. In Figure 2 we present structure of both models. In Figure 3 we present architecture of prepared CNN model.

Figure 3
Architecture of CNN model

Both models were trained using the Adam optimizer with mean squared error (MSE) as the loss function and mean absolute error (MAE) as the evaluation metric. Training was conducted for a maximum of 10 epochs with early stopping based on validation loss to prevent overfitting. Batch size was set to 32, and models were trained on GPU hardware to accelerate computation. Custom Keras Sequence generators were implemented to efficiently load wind field data, capacity inputs, and target power values during training, handling the multi-dimensional spatial structure and temporal alignment of hourly data.

4 Results

As we menntioned above, both models were evaluated on data from january to may of 2025. The CNN model demonstrated performance improvements over the baseline regresion aproach. Specifically, the CNN model achieved a validation MAE of 0.0497 compared to the regression model's 0.0765, and on the test set, the CNN attained 0.0517 MSE versus 0.0937 for regression model. The CNN model showed superior capability in capturing spatial wind patterns from ERA5 meteorological data, particularly for onshore predictions. Onshore generation forecasting proved more accurate for both models, suggesting that the spatial patterns encoded in the 100-meter wind speed components better represent onshore wind resource variability. In contrast, offshore wind predictions exhibited larger errors, which may be caused by smaller spatial grid area representing offshore wind speeds. Additional meteorological variables (pressure, temperature, humidity) beyond wind speed components or hybrid architectures combining CNNs with temporal models like LSTMs can improve generation estimates.

In Figure 4 and Figure 5 we showcase actual and estimated values for onshore and offshore wind generation from our simple regresion model. Offshore wind predictions show substantial variability and consistently underestimate peak generation, indicating the model struggles with extreme weather conditions typical of maximum resource availability. Onshore wind predictions display better performance, tracking observed values more closely throughout the test period. The simple regression model proves insufficient for capturing the spatial complexity of wind fields.

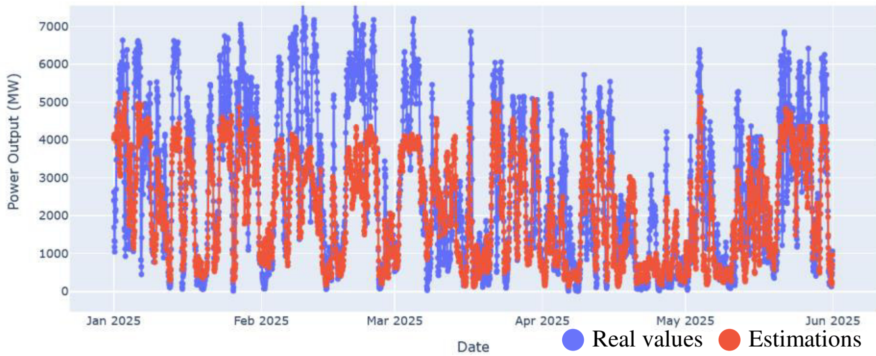

Figure 4

Real and Estimated values for **offshore** wind generation from **simple regression model**

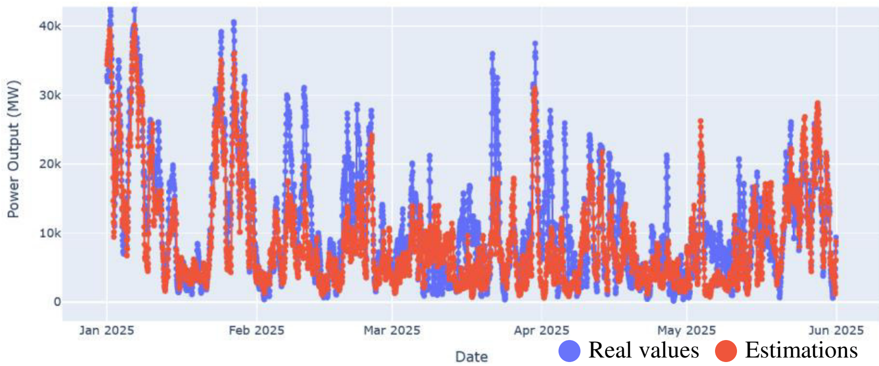

Figure 5

Real and Estimated values for **onshore** wind generation from **simple regression model**

In Figure 6 and Figure 7 we present actual and estimated values over testing period for CNN model. The CNN model substantially outperforms the simple regression model, with estimated values tracking observed generation significantly more closely. Onshore estimates show better agreement with observations, with the model effectively following rapid generation ramps. In case of offshore generation, model did not performed as good as in case of onshore estimates, which may be caused by smaller spatial grid area representing offshore wind speed components. These results confirm that the convolutional architecture's spatial feature learning enables substantially improved wind power forecasting compared to dense fully-connected networks.

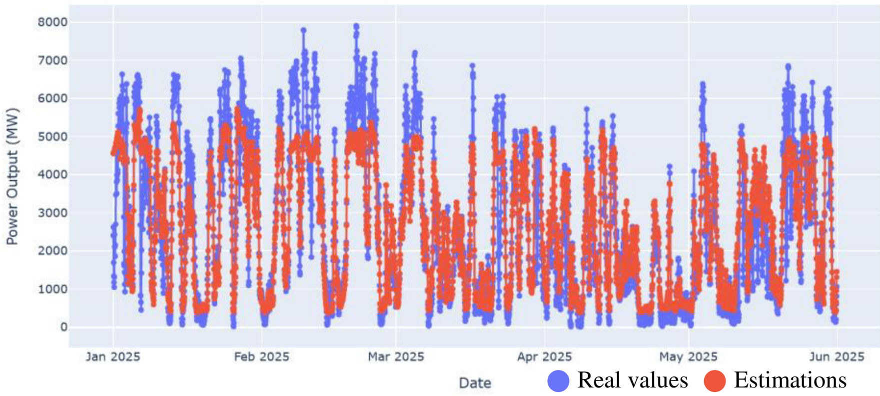

Figure 6

Real and Estimated values for **offshore** wind generation from **CNN model**

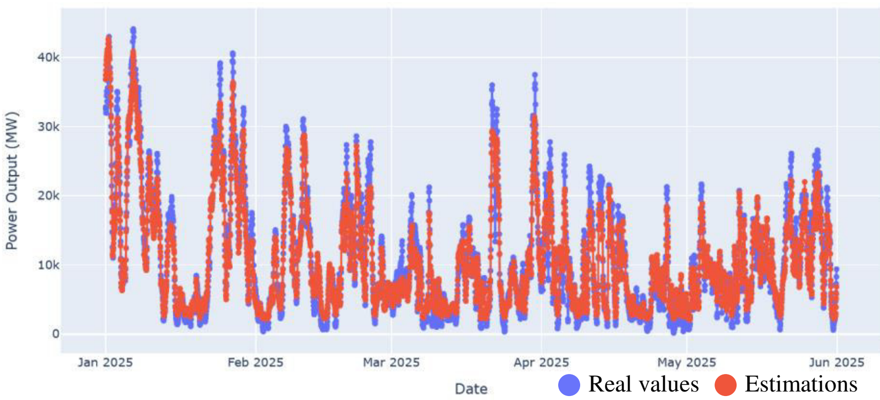

Figure 7

Real and Estimated values for **onshore** wind generation from **CNN model**

Conclusions

This study succesfully demonstrated the application of deep learning techniques on wind power generation estimation in Germany using ERA5 meteorological reanalysis data with installed capacity data. Comparison of simple regression model and CNN model proved, that CNN model can better comprehend spatial data for wind power generation estimation. In case of onshore wind, estimated values better followed real world values than in case of offshore wind, which is caused by small spatial grid area representing offshore wind speeds, suggesting new approach, where new meteorological data should be added to dataset, such as humidity, temperature and atmospheric pressure.

European market price formation mechanism are directly influenced by the trend of renewable energy sources. Accurate wind power forecasting directly influences balancing operations, reserve deployment, and price formation and is crutial for grid operators and market participants.

Future work should explore several promising directions to further improve accuracy. Incorporating additional meteorological variables may enhance offshore wind modeling by capturing more complete data. Hybrid architectures combining CNNs for spatial feature extraction with LSTM could better capture multi-scale wind variability.

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