Transferability of site-dependent wind turbine performance predictions using machine learning

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Abstract. Within this work, machine learning models of site-specific machine learning models of wind turbine power curves of the Beberibe Wind Farm in Brazil, which consists of 32 turbines and one met mast, were developed. Previous work already showed that machine learning models taking into account site-specific effects can increase power prediction accuracy of single wind turbines by a factor of three compared to the standard power curve binning method. The main goal was to investigate the transferability of these models through power output predictions of various turbines depending on the distance from the met mast. It was found that transferring models within a wind farm is possible, but a decrease of prediction accuracy by up to 30% in certain cases could be observed. Neither the combination of various turbine data, nor the incorporation of site-specific data had an apparent effect on the transferability performance. It was thus concluded that a further investigation is needed, where a larger and more distributed subset of turbines should be used.

1. Introduction

Site-specific conditions such as turbulence intensity and shear can have a significant effect on the power output of turbines. It has been shown in previous studies that these effects can change the power output by more than 10% for a given wind speed [1, 2, 3, 4, 5, 6]. When planning a wind turbine (WTG), or even a whole wind farm project, these differences can have a tremendous influence on the estimation of the Annual Energy Production (AEP) and thus on the Levelized Cost Of Electricity (LCOE) and the Return on Investment (ROI). Clifton et al. [7] estimated a lost income of $1,000 per year per turbine based on a 1.5 MW wind turbine and an underestimated rated power of just 1%.

As the commonly used ‘method of binning’, standardised in the IEC-61400-12 [8], does not consider site-specific conditions apart from the wind speed, it can lead to inaccuracies and therefore higher financial risks. In recent years, power curves have been improved by incorporating machine learning algorithms that use site-specific input data such as turbulence intensity and shear [7, 9] and it has been shown that power curve prediction accuracy can be increased by a factor of three.

The values of these site-specific conditions are commonly obtained through met mast measurements within a wind farm. However, usually only a limited number of met masts at specific positions within a wind farm are set up, which can span several kilometers in length. It is therefore of interest of how well machine learning models, trained with this kind of data, can be transferred to different locations within a wind farm that are not close to met masts.
Therefore, in this work, power curve machine learning models based on measured wind speed and power data of wind turbines within a wind farm together with turbulence intensity and shear values obtained from a nearby met mast are developed. Their transferability within the wind farm is then tested through power output predictions of turbines located at various positions within the wind farm.

2. Measurement Data
The measurement data used in this work was based on SCADA data of 13 Enercon E-48 wind turbines with a hub height of 75 m and a IEC-compliant met mast with a height of 100 m. Each measured point represents a ten-minute averaged value, which were recorded between August 2013 and July 2014. The wind speed and the power output data were obtained at the nacelle of each turbine and the turbulence intensity (TI) and the shear factor (α) were determined based on the met mast data. As the available wind turbine data was restricted to the ten-minute averaged wind speed and power output, the TI at the wind turbine locations could not be established and was obtained instead at the met mast. For the calculation of TI the wind speed and the standard deviation of the wind speed at met mast height 80 m were used. The shear factor α was determined based on the power law assumption at met mast heights 40 m and 100 m.

The turbines and the met mast are part of the Beberibe Wind Farm (‘UEBB’) in Brazil [10], which consist of 32 WTGs in total. Figure 1 shows a map of the site, with the three turbines used for the model development marked by red circles, the met mast in blue and the ten turbines for the transferability assessment in green. The prevailing wind on the site blows in the east-west direction.

Figure 1. The Enercon E-48 wind turbines at the Beberibe Wind Farm (‘UEBB’) in Brazil.
Figure 2 shows the environmental conditions at the met mast in terms of average wind speed, turbulence intensity, $TI$, and the shear factor, $\alpha$. On the diagonal part of the matrix the histograms are depicted, whereas the lower matrix shows scatter plots. As can be seen, for lower wind speeds $TI$ and $\alpha$ are much more broadly distributed, reaching high turbulence values and strong wind shear both positive and negative. Towards higher wind speeds the turbulence intensity decreases and mainly slightly positive shear factors are prevalent.

![Figure 2](image)

**Figure 2.** Histograms (diagonal) and scatter plots (lower matrix) showing the distributions and relationships, respectively, of the average wind speed, the turbulence intensity, $TI$, and the shear factor, $\alpha$.

Turbines $WTG\ 12$, $WTG\ 13$ and $WTG\ 14$ were chosen for the power curve models due to the proximity to the met mast. The evaluation turbines were chosen for various distances from the met mast, ranging from close proximity to the met mast to distances of $2.6\ km$ apart, which helps to better paint a picture of the transferability. A distance matrix is presented in Figure 3, showing the Haversine distance - the shortest distance on a sphere - between two points.

The power curves of turbines $WTG\ 12$, $WTG\ 13$ and $WTG\ 14$ are shown in Figure 4 and the total number of available samples per turbine are listed in Table 1.
3. Wind turbine performance predictions using the gradient boosting method

The power curve models developed within this work are based on the gradient boosting technique. More specifically, the ‘extreme’ version of this algorithm — implemented in the Python library XGBoost — was chosen, which has been successfully used for a variety of complex data problems [11]. This technique offers a computationally efficient way to easily and readily generate various power curve models.

3.1. Pre-processing

The data of the different wind turbine generators used within this work was pre-processed before using it for the model training. Firstly, power values below 1.0 kW for wind speeds above the cut-in wind speed of 3 m/s were filtered out. After that the data was binned into 1 m/s bins.

Figure 3. Distance matrix of selected wind turbines in the Beberibe Wind Farm (‘UEBB’) in Brazil. The lighter the color, the further the distance (km) between two points.

Table 1. Number of samples for the used wind turbines.

|        | WTG 12 | WTG 13 | WTG 14 | Combined |
|--------|--------|--------|--------|----------|
| No. samples | 37,202 | 36,678 | 36,664 | 110,544  |
Figure 4. Measured power curves for the three wind turbines used for model development.

and the power distribution for each bin was calculated. Power values exceeding more than three standard deviations were then filtered out, resulting in a representative power curve without any outliers.

Furthermore, site-specific turbulence intensities, $TI$, and wind shear factors, $\alpha$, taken from the met mast, were combined with the wind speed and power data of the turbines. In previous studies [7, 9] the incorporation of these site-specific conditions resulted in power curve prediction accuracy improvements by a factor of three, which is why these parameters were considered within this work as well.

3.2. Model training

The data was split into a training and a test set, based on 80% and 20% of the whole data set, respectively, where the test set is used for assessing generalization performance of the predictor. For the training, the data was further split into five equal parts, which were used for cross validation. In order to assess the performance of each model, the Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{P}_i - P_i)^2} \tag{1}$$

and the Mean Absolute Error

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{P}_i - P_i| \tag{2}$$

were calculated, where $n$ is the number of observations, $\hat{P}_i$ is the predicted power and $P_i$ is the actual power.

Six different power curve models were trained; for each of the three wind turbine generators $WTG\ 12$, $WTG\ 13$ and $WTG\ 14$ a model with only the wind speed as an input parameter as well as with the three input parameters wind speed, $TI$ and $\alpha$. Additionally, two models were trained based on a combined data of all three turbines, which will be denoted as the Combined data set in the following sections.
In order to determine the most optimal model parameters, a hyper-parameter search was conducted with the Combined data set, where the mean square error loss function was minimised. The parameters considered for the tuning were:

- The number of gradient boosted trees.
- The maximum tree depth.
- The minimum child weight, which controls the node splitting depending on the node’s sample size.
- The learning rate.
- The booster method – in XGBoost the three boosters gbtree, dart and gblinear are available.
- The cross-validation score, which is to be optimised.

The best cross-validation score was achieved with the parameter values shown in Table 2. As for the booster, the gbtree booster performed better than the dart and the gblinear boosters.

Table 2. Values of the optimised XGBoost model parameters.

| No. of boosted trees | Max. depth | Min. child weight | Learning rate | Score   |
|----------------------|------------|-------------------|---------------|---------|
| 500                  | 4          | 10                | 0.05          | 0.99351 |

Based on these optimal model parameters, learning curves for the Combined data set as well as the individual data sets for the turbines WTG 12, WTG 13, WTG 14 were created, which are a means to assess whether additional data might potentially improve the prediction accuracy or not. Figures 5 and 6 depict the learning curves for one and three input parameters, respectively, where the dependence of the RMSE on the data sample size can be observed. The RMSE is determined for the training set (line) and the cross-validation set (dashed line).

As can be seen, for all wind turbine generator data sets and the combined data set, but the WTG 14 set, the training and cross-validation losses approach each other, indicating that additional data will not further benefit the model performance. The WTG 14 case shows a gap between the two different losses, meaning that this model does not perform as well on unseen data.

As for the case with the three inputs, wind speed, turbulence intensity $TI$ and shear factor $\alpha$, the training and cross-validation losses did not converge for all four turbine data sets. This means that additional data, if available, would potentially improve the model performance and the models in the current state suffer from overfitting and are not able to sufficiently make a generalised prediction. Even for the Combined data set, additional data, by incorporating more turbines in the data set, might potentially further reduce the prediction errors. This set, however, also results in the highest cross-validation and training losses.

Figures 7 and 8 show the prediction errors based on the RMSE and the MAE, respectively, for one and three input parameters. The error metrics were calculated with the test set mentioned above, which was not used for the model training itself. For all models an immediate improvement can be observed by adding the $TI$ and $\alpha$ parameters, confirming the results based on simulation data mentioned above [9]. Overall, the model based on the WTG 12 data resulted in the lowest RMSE and MAE values, whereas the model with the WTG 14 data resulted in the highest errors. The Combined model performed slightly better than the WTG 13 model. Interestingly, the Combined model compensated for the poor performance of the WTG 14 model.

As the error trends are the same for RMSE and MAE, for the sake of brevity, only the MAE will be looked at in the following sections.
4. Results
In order to assess the transferability of the eight models, data from WTGs at various distances from the met mast (Figure 1) was used to determine the prediction performance. As a result,
the prediction performance - the MAE - is obtained as a relationship to the distance to the met mast. The specific distances between the chosen WTGs and the met mast are shown in the distance matrix in Figure 3.

Figure 9 shows the MAE versus the distance, denoted by the respective wind turbines, for the one input parameter case, with ascending distance from left to right. As can be seen, there is no apparent trend and the prediction based on the furthest wind turbine data set, WTG25, which is about 2.6 km away from the met mast, is even better than some of the closer turbines. Furthermore, there does not seem to be a ‘best’ model between the WTG 12, WTG 13, WTG 14 and Combined models for distances up to 1 km (WTG2) from the met mast, as each of them perform better or worse for different turbines. However, for the three furthest turbines...
the model based on WTG14 performs best. This is interesting, considering that the WTG14 model performance was worst based on its own test set, as observed in Section 3.2.

The same conclusions can be drawn for the three input parameter case, shown in Figure 10. The addition of the turbulence intensity, $TI$, as well as the shear factor, $\alpha$, has almost no positive effect on the prediction losses. This might be due to the fact that the site-specific conditions are less relevant for the other WTGs as for WTG 12, WTG 13 and WTG 14 because of the larger distance to the met mast.

![Figure 9](image9.png)

**Figure 9.** Transferability of the power curve models based on WTG 12, WTG 13, WTG 14 and their combination for the one input parameter case.

![Figure 10](image10.png)

**Figure 10.** Transferability of the power curve models based on WTG 12, WTG 13, WTG 14 and their combination for the three input parameters case.

Additionally, for each individual turbine shown in the previous plots (WTG 1, WTG 2, WTG 30, etc.) two models, with one and three input parameters respectively, based on their own data were trained and tested. The data sets were also pre-processed according to the procedure given
in Section 3.1. For the training the same model parameters as listed in Table 2 were used. The model performances were then compared to the WTG 12, WTG 13, WTG 14 and Combined model performances. In order to do so the differences in the prediction losses were calculated, which are shown in Figures 11 and 12. The first thing to notice is that each individual turbine model performs better than the WTG 12, WTG 13, WTG 14 and Combined models used for predictions on these turbines. However, for some turbines the differences are very small, showing good model performance on unseen data. Especially the WTG 14 model stands out when considering the three furthest turbines WTG 26, WTG 30 and WTG 25, indicating great transferability for the given data. As already observed above, the Combined model shows mixed prediction performance for all considered turbines.

![Figure 11](image_url)  
**Figure 11.** Differences between the prediction losses based on the WTG 12, WTG 13, WTG 14 and Combined models and the prediction losses for the individual turbine models for the one input parameter case.

5. Conclusions

Based on these results, some important conclusions can be drawn. Firstly, incorporating site-specific conditions such as turbulence intensity, $TI$, and the shear factor, $\alpha$, has a positive effect on the prediction performance on single turbines, reducing the RMSE by almost 5% when considering the boosted tree models. However, this was only the case for the data based on the trained models and not for unseen data of wind turbines some distance apart. Secondly, more training data is needed when site-specific conditions are to be considered, as revealed by the learning curves. The bundling of data of various wind turbines and combining them in one model helped tackle this problem and even compensated for poor model performance, as seen for WTG14. Hence, it is advisable to combine data sets of several turbines in order to achieve a more robust result. However, these advantages were not observed in terms of transferability. Thirdly, transferring models within a wind farm is possible, but a decrease of prediction accuracy by up to 30% in certain cases could be observed. Furthermore, neither the combination of turbine data, as in the case of the Combined model, nor the incorporation of site-specific data, had an apparent effect on the transferability performance and further analysis is needed.

This leads to the overall conclusion that the transferability performance needs to be further investigated with a larger and more distributed subset of turbines, which is part of our ongoing
work. Other site-specific variables like air density and wind direction, if available, should be considered as well in order to improve model accuracy [1]. At certain wind directions, for example, turbine wakes will affect neighboring turbines and hence have a direct impact on the power production. Wake effects might also be one possible explanation for the observed prediction performance behavior in relation to the distance. Another important variable influencing the power production of a turbine is the yaw error, occurring when the wind direction and the rotor axis are not perpendicular to each other [12]. Transferability considerations could also benefit from further wind farm analysis techniques and methods, like spatio-temporal analysis, in order to gain more insights into the flow patterns and relationships between turbines within a wind farm.

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