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# Wind power prediction in complex terrain using analog ensembles

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## 1. Introduction

The intermittent power generation from wind energy industry influence both power grid stability, energy system operators and the power marked economics. Accurate wind power predictions may reduce the cost impact of wind energy, and several forecasting techniques and methods have been proposed during the last decades [1, 2]. The performance of different forecasting methods is normally evaluated using root mean square error (RMSE) or mean absolute error (MAE), and the performance in general decreases for wind sites in complex terrain [3, 4].

In this paper we investigate the use of analog ensembles (AnEn) for wind power prediction [5] with focus on five wind power parks in northern Norway. This cold climate region can in general be characterized with good wind resources, but is challenging with the complex terrain consisting of large mountains, valleys and fjords [6, 7]. As input to the AnEn forecast method, we have used wind data from the open and operational weather forecast provided by the Norwegian Meteorological Institute [1]. The AnEn wind power prediction is compared to downscaling by the high-resolution WindPRO park modelling, using the same weather forecast as input. In addition, the naive persistence output model is included as a reference.

The paper is organized as follows: Section 2 describe the wind parks, the wind power forecasting methods and the verification statistics used. Results are shown and discussed in Section 3, followed by recommendations and conclusions in Section 4

## 2. Method

### *2.1. Wind parks*

The location of the five wind parks in this study are shown in Fig. 1. The overview shows the terrain elevation in northern Norway in gray tones from black to white, corresponding to 0m and 2000m height above sea level, respectively, and the ocean is also shown in white. Nygårdfjellet wind park is found south west in this figure, quite close to the border to Sweeden. This wind park is located at an elevation of about 400m, in a valley going west-east and with high mountains close by to the north, and where high wind from east is common during the winter season [7]. Fakken wind park is located on a small island on the coast, on a small hill at 40-200m elevation, with open sea to north, close by mountains to the west and a mountain range to the south dividing with two large fjords. Havøygavlen is located on a flat low island, at about 200m

[1] http://thredds.met.no

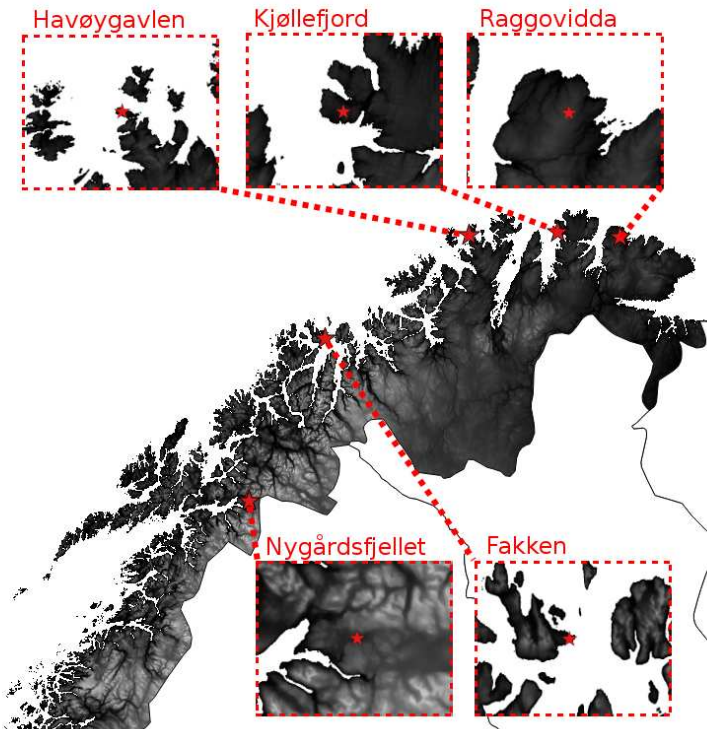


**Figure 1.** Northern Norway. Ocean shown in white. Gray tones from black to white shows terrain height from 0m to 2000m, respectively.

**Table 1.** Description of wind park sites.

| Name | MW | Location °N/°E | RIX | Terrain features |
|---|---|---|---|---|
| Fakken | 54.0 | 70.098 / 20.081 | 5-10 | Small hill, high steep mountains and fjords |
| Havøygavlen | 40.5 | 71.012 / 24.589 | 10-20 | Flat low island, steep cliffs and fjords |
| Kjøllefjord | 39.1 | 70.922 / 27.268 | 0-5 | Low flat mountains and fjords |
| Nygårdfjellet | 32.2 | 68.504 / 17.879 | 5-10 | Inland valley, high steep mountains |
| Raggovidda | 45.0 | 70.769 / 29.094 | 0-5 | Flat inland mountain, close to coast |

elevation. No nearby high mountains, but the island has steep cliffs down to the ocean and there are several fjords and narrow straits close by. Kjøllefjord is located at a low flat mountain area, at about 260m elevation, and with a large fjord to the west going north-south and some smaller fjords north and south going in the east-west direction. Raggovidda is the newest wind park in this region, is located at about 430m elevation on a large flat mountain area, with good wind resources and a capacity factor above 45% the last three years.

These wind parks are compared and summarized in terms of location, turbine types, site ruggedness (RIX)[8] and nearby terrain features in Table 1. The close by and steep cliffs down to the ocean make a large impact on the site ruggedness for Havøygavlen. The large mountains and fjords around Fakken and Nygårdsfjellet could also be challenging for wind prediction using numerical weather modelling.

### 2.2. Wind power forecasting

The weather forecast used in this paper is the Meteorological Cooperation on Operational numerical weather prediction (MetCoOp) run by Norwegian Meteorological Institute and Swedish Meteorological and Hydrological Institute. The forecast covers both countries with a horizontal resolution of 2.5km, using a horizontal grid of 739x949 points centered at 63.5°N and 15°E, and is issued at 00, 06, 12 and 18UTC with a 66 hour lead time. The MetCoOp is a branch of HARMONIE model developed within the High Resolution Limited Area Model consortium with several European meteorological institute, and was the main operational forecast in Norway from 2014 to 2016. This high resolution model has been shown to improve the wind, temperature and precipitation forecast in complex terrain [9]. The MetCoOp data set had some missing data in 2016, and in those cases, the succeeding MEPS or the similar Arctic AROME forecast data is used as a replacement.

Based on the current MetCoOp weather forecast $F_t$, at lead time $t$, the AnEn method search through historical weather forecasts to find similarities based on a set of physical variables. The ranking of similarities between current forecast and a historical forecast $A_t$ is found following the distance metric [10]

$$||F_t, A_t|| = \sum_{i=1}^{N_v} \frac{w_i}{\hat{\sigma}_i} \sqrt{\sum_{j=-\tau}^{\tau} \left(F_{i,t+j} - A_{i,t+j}\right)^2} \tag{1}$$

where $N_v$ is the number of physical variables to consider, $w_i$ is the weighting chosen for the $i$-th parameter, $\hat{\sigma}_i$ is the estimated standard deviation of the variable, $F_{i,t}$ is the forecast for the $i$-th variable at lead time $t$, and $\tau$ describe the window of smoothing along the lead times of the forecasts. The $N_A$ highest ranked historical forecast at that particular lead time $t$ are the set of analog ensembles $A_{t_n}$, and the mean of the observed analog ensembles power output is the AnEn power forecast $PW_t^{\{anen\}}$ for lead time

$$PW_t^{\{anen\}} = \frac{1}{N_A} \sum_{n=1}^{N_A} PW^{\{anen\}} \left[A_{t_n}\right]. \tag{2}$$

The $PW^{\{anen\}} \left[A_{t_n}\right]$ are the power forecast ensemble which can be used to investigate the statistical properties of the forecast, e.g. standard deviation or interquartile range, and it is also possible to weight the analog outputs differently and/or use Kalman filtering to improve the forecast [10, 5].

The physical variables in the AnEn power forecast using Eq. (1) are 10m $W_t$ and direction $D_t$ interpolated to the wind park position shown in Table 1. The AnEn power forecast can use wind speed from 10m directly, even if the wind turbine nacelle typically are placed around 80m above the terrain, as the observed historical output from the nearest historical forecast is used as predicted forecast. The AnEn power estimate have 66 hourly forecast lead times, as this is the underlying wind forecast form the MetCoOp model.

Our AnEn wind power forecast is the mean value using $N_A = 20$ analogs, with equal weights on wind speed $W_t$ and direction $D_t$, with window smoothing $\tau = 1$ and without bias correction [11].

We will compare the results from AnEn power forecast method with the naive persistence model (PRE), where the current power output as the forecast for all lead times, $PW_t^{pre}$. PRE is often used as a starting point both in operational use and for comparing different forecast techniques. We have this method as a base line, as the persistence methods performs well for short time periods [1].

The second type of forecasting we have included in this study uses power curves from the park wind turbines and numerical weather prediction for the wind estimate (PNWP). This

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method use the same 10 meter wind speed and direction data as the AnEn method, but now in combination with a wind park model from WindPRO software. As the WindPro park model assumes wind speed at turbine height, we have included a park depended wind scaling constant $c$ giving park power output as

$$PW_t^{pnwp} = ppc\left[cW_t, D_t\right], \tag{3}$$

where the park power curve function $ppc[\cdot]$ is a linear interpolation from the park specification covering wind ranges $0,5$-$29,5$ m/s and 12 wind directions (N, NNE, NE, ...) of the WindPRO Park Power Verification Model (PPV) [12]. The input to the PPV model is based on N50 maps of Norway from Norwegian Mapping Authority, with 20 meter elevation levels and terrain roughness index, and the PPV model takes into account the power curve for each turbine, the placement of the turbine, the local topography and the wake effects between turbines [12]. The wind scaling constant $c$ is chosen for each wind park site by optimizing the model output RMSE using the training data set, as described in Eq. (5).

Using the same input data for both PNWP and AnEn, allows for a fair comparison between the models as they share the same inherent variability from the numerical modeling of a changing weather pattern.

### *2.3. Forecast performance*

The wind power data in this study are measured hourly total output, $PW_t^o$, during 2016 for each site listed in Table 1 provided by the Norwegian Water Resources and Energy Directorate (NVE)[2]. The power production time series are normalized with the corresponding wind park installed capacity, as listed in Table 1, as this allows a direct comparison between the different wind parks.

The wind forecast data is chosen so that all lead times are within 2016, creating a total of 1456 power forecast time series each of 66 lead times, $PW_{t,i}^m$, where $m$ corresponds to the $anen$, $pnwp$ or $pre$ forecast method, $t$ is the lead time and $i$ is the forecast time series. The forecast data is split into a training set consisting of the first $N_T = 1200$ times series, and the last $N_P = 200$ time series are used to calculate the prediction performance for each method.

Based on the error $e_{t,i}^m$ between the predicted and observed power production

$$e_{t,i}^m = PW_{t,i}^m - PW_{t,i}^o \tag{4}$$

the root mean square error (RMSE) at each lead time $t$ is defined as [13]

$$RMSE_t^m = \sqrt{\frac{1}{N_P}\sum_{i=1}^{N_P}\left(e_{t,i}^m\right)^2}. \tag{5}$$

The training set consisting of the first $N_T = 1200$ time series, corresponds to the period from January 1st to October 26th, is used to find the optimal RMSE scaling factor $c$ for each wind park combining Eq. (3) and Eq. (5). The verification period runs from November 9th to December 29th, and the no overlap period between those ensure that there is no overfitting for the scaling factor.

The different power forecast methods is further analyzed using the bias $b_t^m$, or the mean error $\overline{e_t^m}$,

$$b_t^m = \overline{e_t^m} = \frac{1}{N_P}\sum_{i=1}^{N_P} e_{t,i}^m, \tag{6}$$

[2] https://www.nve.no/energiforsyning-og-konsesjon/vindkraft/

standard deviation of the error,

$$\sigma_t^m = \mathrm{std}\left(e_t^m\right) = \sqrt{\frac{1}{N_P - 1}\sum_{i=1}^{N_P}\left(e_{t,i}^m\right)^2} \tag{7}$$

and the skill score $ss_t^m$ based on the mean square error and the *pre* basic persistence forecast

$$ss_t^m = 1 - \frac{\left(RMSE_t^m\right)^2}{\left(RMSE_t^{pre}\right)^2}. \tag{8}$$

Note that $ss_t^{pre} = 0$, and that the skill score can be interpreted as the effective improvement in other two method compered to the basic persistence forecast. A value above zero shows that the method is better than the PRE method, and the value can also be interpreted as the improvement in percent [14].

The last statistical quantity used in the comparison of the methods is the Pearson correlation coefficient defined as [15]

$$r_t^m = \frac{1}{N_P - 1}\sum_{i=1}^{N_P}\left(\frac{PW_{t,i}^m - \overline{PW_t^m}}{\mathrm{std}\left(PW_t^m\right)}\right)\left(\frac{PW_{t,i}^o - \overline{PW_t^o}}{\mathrm{std}\left(PW_t^o\right)}\right), \tag{9}$$

where $\overline{PW_t^m}$ and std$(PW_t^m)$ is the mean and standard deviation of the forecast methods, using the notations and definitions in Eq. (6) and Eq. (7), respectively. The correlation coefficient $r_t^m \in [-1, 1]$ describe the linear relationship between the forecast and measured value, where a value close to 1 (or -1) indicates a strong relationship and a value close to 0 means that these to quantities are uncorrelated [16].

## 3. Results

The RMSE for each power forecast method as a function of lead time are shown in Fig. 2, where the number in the parenthesis is the lead time averaged RMSE of the corresponding forecast method. The persistence method (PRE), shown as black solid lines, performs as expected with low RMSE at low lead times, but RMSE increases rapidly as $t$ increases for all wind parks. Comparison between the wind parks shows that Nygårdsfjellet has the highest RMSE values, which may indicate a more rapid change of wind pattern at this park. The differences between the parks are in general quite small, and the average RMSE across wind parks, shown in lower right plot Fig. 2, shows that RMSE increases the first 20 hours and then stabilizes at RMSE $0.45 - 0.5$.

The numerical weather forecast results, PNWP, are shown as a red dashed-dotted lines in Fig. 2. For this forecast method, the RMSE starts around 0.2-0.25 at $t = 1$ hour, and increases almost linearly with lead time for all parks up to lower average RMSE value 0.35-0.4 than the other three, which indicates that the meteorological forecast is more precise here. The PNWP results are significantly lower than PRE for $t > 2$ for all wind parks, but at shortest lead time the persistence method still preforms better. Note also that the PNWP seems to increase slower in the 12-36 lead time region for Fakken and Nygårdsfjellet wind parks compared to the three other wind parks, indication that this method could provide good input for day-a-head trading.

The AnEn forecast results, shown as a blue dashed line in Fig. 2, provides a lower RMSE than the PNWP in all case. The overall results shows a RMSE with more than 10% improvement for all lead times. The improvement is highest and lowest for Havøygavlen and Nygårdsfjellet, respectively. The AnEn method shows in overall a consistent linear increase in RMSE from 0.2 to 0.3 for lead time 1 to 66 hours, and the performance variation is very small between the different parks.

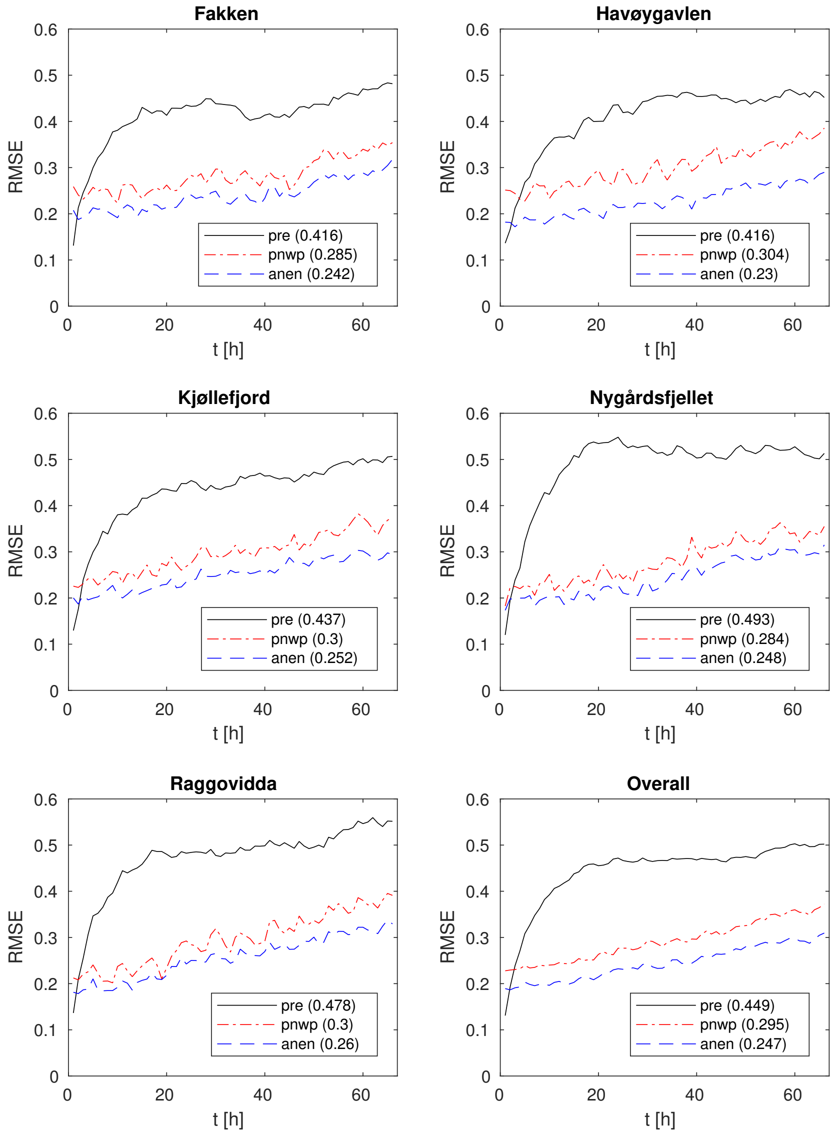


**Figure 2.** RMSE results for each wind park as function of lead time, with the lead time averaged RMSE in legend parenthesis. Lower right plot shows the overall RMSE averaged all wind parks.

The upper left plot in Fig. 3 shows the overall bias of the different forecast methods. PRE has a bias close to zero, while PNWP and AnEn are slightly over- and underestimating the power output, respectively. The bias increases for higher lead times, but the lead time averaged bias is under 2%. This bias in the AnEn case might come because of yearly variation of wind speeds, as the verification period at the end of the year might include more high wind events.

The overall standard deviation of the errors are shown in the upper right plot of Fig. 3. The standard deviation for all methods are almost identical to the RMSE results plotted in the lower right corner of Fig. 2. This shows that the prediction error is mainly caused by high variation in all cases, and not from bias.

The PRE method has a high correlation coefficient close to 0.92 for $t = 1$, but the correlation drops rapidly and falls below 0.50 at $t = 7$ hours. The PNWP and AnEn forecast methods, on

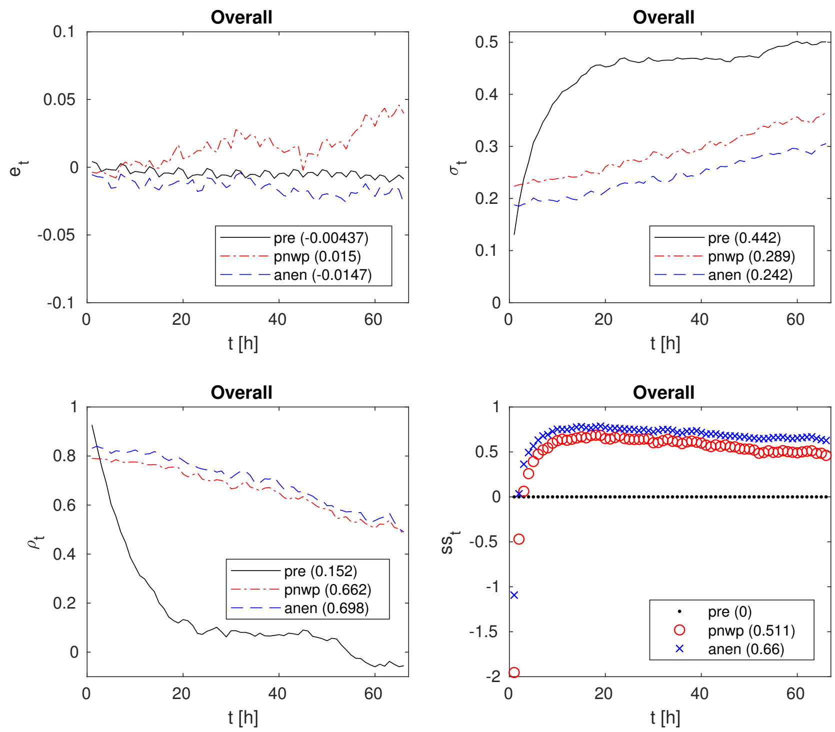


**Figure 3.** Overall performance of PRE, PNWP and AnEn methods. Upper left: Bias. Upper right: Standard deviation of error. Lower left: Correlation. Lower right: Skill score

the other hand, starts with a correlation close to 0.8 but the decay is significantly slower and the correlation does not drop below 0.5 even for the longest lead time $t = 66$. The AnEn method has a slightly higher correlation with measurement compared to the PNWP method.

The last plot is the skill score results, shown in the lower right corner of Fig. 3. To allow for easier readout for each lead time, the hourly results are shown as black dots, red circles and blue crosses, for PRE, PNWP and AnEn forecasting method, respectively. This figure shows that PRE performers best for $t = 1$, for $t = 2$ the PRE and AnEn methods performs equally good as $SS_1^{anen} = 0$, but for all other lead times the AnEn forecast performs best. The average improvement of AnEn and PNWP compared to PRE is 66% and 51%, respectively, and for lead times $t \in [12, 36]$ relevant for day ahead energy trading, these numbers increases to 75% and 65%.

## 4. Conclusions

In this paper we have investigated five different wind parks in northern Norway with respect to power prediction using three different prediction methods: PRE, PNWP and AnEn.

We have shown that the AnEn method provides a robust power forecast at all wind parks in this study. Overall, the RMSE for this method is 44% lower than the persistence method and 16% lower than optimized wind speed from numerical weather prediction and power curves. The performance of all methods is also investigated using standard deviation of error, skill score and Pearson correlation coefficient, and the AnEn method perform better than persistence for $t \geq 2$ hours lead time and better than PNWP for all lead times.

The large improvement in RMSE from PNWP to AnEn method in the case of Havøygavlen wind park might be explained by the high ruggedness index for this site. It is well known that numerical weather models have higher errors in complex terrain, but the AnEn method seems to be successful in handling those cases. Our results about the robustness and improvement using AnEn method compared to PNWP in complex terrain are similar to those represented in [4], although the latter uses all ensembles to create a probabilistic power forecast and we have used a deterministic approach. Furthermore, the results in this paper expands the use of the AnEn method into several wind parks located in a coastal complex terrain, which add some new insight into the performance of both AnEn and PNWP based methods.

The site ruggedness (RIX) has been used in the literature to classify the complexity of the terrain, and it is well known that the performance of short-time forecasting of wind speed and direction strongly depends on the terrain complexity [3]. The MetCoOp weather forecast has been used in this study, and the wind power forecast from the PNWP method have almost identical large variance both at Havøygavlen with a RIX value of 10-20, and for Kjøllefjord and Raggovidda where the RIX values are in the 0-5 class. On the other hand, the Fakken and Nygårdsfjellet wind park have the lowest RMSE errors, although these parks have the highest nearby mountains. Our results indicates that both nearby mountains and mountain range, valleys, fjords and sharp cliffs can create local events that affects the performance, in both negative and positive direction. The RIX value alone do not provide a clear indication to the trustfulness of the PNWP forecasting method in our case, and a closer evaluation of the NWP performance in general may be necessary in complex terrain.

When it comes to operational wind power forecast systems, it is important to keep in mind that the numerical weather prediction results are not available immediately. The MetCoOp forecast at initiation time (00, 06, 12 and 18 UTC), uses some time both to collect receive and process all observations and to do the numerical simulation, which implies that the forecast typically is available for public 2.5 hours after the initiation time. The AnEn method is not computer intensive and does not add extra time in this setting, but in practice both AnEn and PNWP method results should be shifted two leads hours forward because of the NWP processing time for a fair comparison with the PRE method. Thus, we could expect that the PRE method performers best up to $t = 3$ lead hours, and AnEn best after this. As day-a-head power trading typically has to be submitted before 12:00 the day before, this corresponds to lead time in the 12-36 hour region. For these lead times, the wind power forecast system is less effected by the NWP processing time and the AnEn method should be a natural choice among the methods investigated in this paper.

In this paper, the input wind parameters to the PNWP and the AnEn power prediction models are limited to a numerical weather prediction model with 2.5 km horizontal resolution taken 10 meter above the ground. If the input came from a higher resolution model, and/or the wind parameters at turbine hub heights were used, we would expect a decrease in RMSE for the PNWP. Changing the input parameters could also improve the AnEn performance, and it would have been interesting to quantify the ratio on improvements in these models.

Our results are limited to five wind parks and about one year of data, and some forecasts time series from other models had to be included. With longer training data, using a single operational forecast model and more advanced versions of analog ensembles, we can expect increased performance in AnEn.

## 5. Learning objectives

The paper introduces different classes of short-time power prediction, and explain an experimental setup for the investigation of model performance. The wind parks included represents different complex terrain types, including high steep mountains, valleys, fjords and sharp cliffs. This might create significant localized speed up or wind shadow area effects. Out results indicates that the analog ensembles method provide an robust and efficient method to short-time power production in complex terrain.

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