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Modelling Energy Production of Wind Farms under Transmission Capacity Constraints

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1 Introduction

Climate change and environmental concerns have shifted energy production towards renewable energy sources, whereby wind power offers a sustainable option (Cavanagh and Viswanthan, 2016; Steinberger and Yeh, 2016). Wind is increasingly cost-effective, and an inexhaustible source of renewable energy that produces no pollution (Peltola et al., 2017; Islam et al., 2013).

Nevertheless, wind power industry has experienced some challenges. Wind turbines have been considered noisy and ugly, the technology has been relatively expensive, and wind is intermittent which causes systemic challenges. In spite of these obstacles, the wind energy industry is starting to boom (Weissman et al., 2017). Currently, onshore wind is one of the most competitive sources of energy, and the technology is still developing (IRENA, 2018). Additionally, many governments are offering incentives to spur wind energy development (Behrendt, 2015; Steinberger, 2017).

Wind energy is converted into electrical energy by wind turbines. Electricity is fed into a transmission line, which has a capacity limit to transmit the power. Because wind power is not dispatchable and it varies according to the weather, the energy production from the turbines is usually below or above the transmission capacity. Therefore, wind power must be balanced with other energy sources to keep the system in balance as a whole; a necessity for power system operations. Additionally, when all produced wind cannot be transmitted due to the transmission line capacity limits, the owner of the wind production facility faces a profit loss.

In this study, we consider a situation in which a curtailment due to the transmission capacity limit may cause such profit losses on wind production facilities. This is a real case study from Norway but wind farms are discussed anonymously as wished by the client of Kjeller Vindteknikk. The plan under study includes a system of seven wind farms. Six of them have the privilege to use the transmission line out of the system into the larger grid. This means that if the total production of wind farms in the system exceeds the limit, the seventh wind farm must restrain its power production first. Distance from the southernmost wind farm to the northernmost wind farm is approximately 86 km.

The objective of this study is to find out how much wind farm 7 may have to cut down its annual production due to this transmission line capacity limit. In order to determine this, we construct a model to represent energy production time series and merit curves for the wind farms in the system.

Scenarios with and without wind farm 7 are considered.

Section 2 presents data and model formulation. Results are presented in Section 3 and conclusions in Section 4.

2 Methods

2.1 Data

The model formulation in this study was based on the supervisory control and data acquisition (SCADA) data of energy production from wind farm 1 during years 2013-2015. The data was available on an hourly basis for each of the 25 turbines in the wind farm. The layout of wind farm 1 can be found in Figure 1. To be able to build the model, the SCADA data was filtered and cut, to produce uncorrupted data without technical problems. The model was constructed with MATLAB.

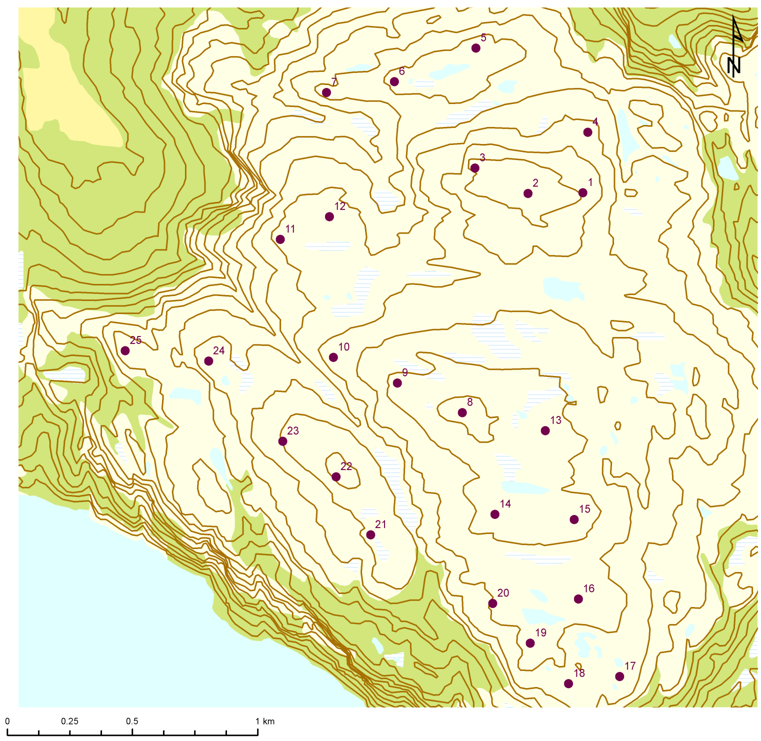

Figure 1: Layout of the wind farm 1

The wind dataset, including wind speed and direction for each wind farm for the years 2000-2016, was produced with the publicly available meso-scale meteorological model WRF (Weather Research and Forecast Model), with a horizontal resolution of 4 km x 4 km and a temporal resolution of 1 hour. Each wind farm is represented by a WRF grid point and the model describes the geographical differences in wind conditions between all seven wind farms. Details on this model are in Appendix A.

Wind speed for each wind farm was scaled so that the modelled energy production was able to reach the expected AEP (Annual Energy Production). Net production was assumed to be 85 % of the gross production. Wind roses, which show the frequency distribution of the long-term wind direction binned according to different wind speed intervals, are given in Appendix B for each wind farm with the scaled wind for years 2000-2016.

Information on the 7 wind farms is in Table 1. The turbine type of wind farm 6 is not known, so a Vestas V117, which is used in many of the other wind farms, has been selected for this study. The number of turbines in wind farm 6 is calculated based on the turbine capacity and the total capacity of the wind farm.

Table 1: Features of the wind farms. Status meanings: IO = In operation, UC = under construction, IP = In planning. Net annual energy production = Net AEP.

Wind farm	Number of turbines	Status	Capacity/ turbine (MW)	Total capacity (MW)	Net AEP (GWh)	Turbine type
1	25	IO	2.3	57.5	172.5	Enercon E70
2	71	UC	3.6	255.6	766.8	Vestas V117
3	80	UC	3.6	288.0	864.0	Vestas V117
4	30	UC	3.6	108.0	324.0	Vestas V117
5	28	UC	3.6	100.8	302.4	Vestas V117
6	36	IP	3.6	129.6	390.0	Not decided
7	32	IP	3.6	115.2	345.0	Vestas V117

2.2 Smoothing function

Because we have energy production data only for wind farm 1 from the SCADA data, the production for the other six wind farms has to be based on modelling. For this, we need wind speed data for each wind farm location and power curves for different turbine types to construct the energy production time series. Turbine type specific power curves are in Appendix C.

To develop a realistic model for total production of a wind farm, we need a smoothing function. SCADA data for wind farm 1 was used for studying the smoothing effect on the production within each wind farm. Without smoothing, our model assumes the correlation between energy productions of different turbines within a wind farm to be 1, which is not realistic. This is because geographical dispersion of wind energy production decreases volatility in total energy production.

Figure 2 shows how the correlation between the production levels of two different turbines in wind farm 1 decreases as the distance between them increases. The reference turbine is turbine 18 in the south-east corner. Correlations are calculated and the linear fit of correlation as a function of distance is made based on the available SCADA data.

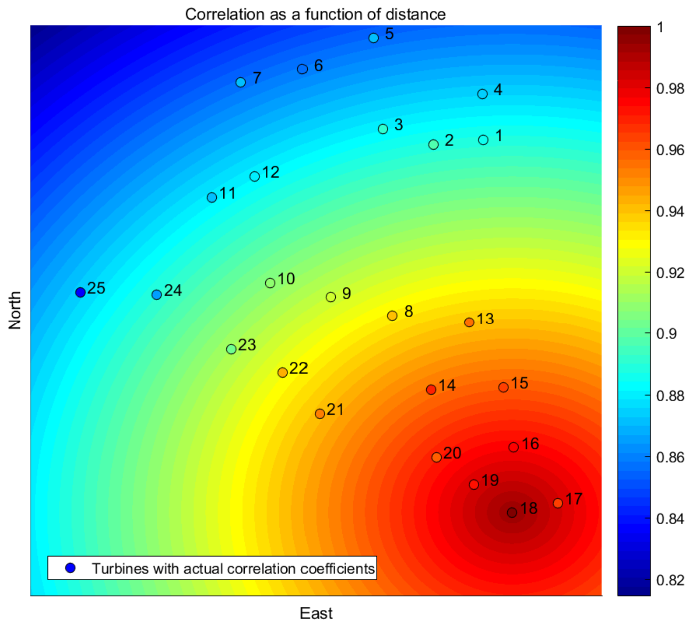

Figure 2: Wind energy production correlation as a function of distance and the actual correlation coefficients for wind farm 1. Reference turbine is turbine 18.

The effect of smoothing can be seen clearly in merit curves, especially on production close to the maximum of the production capacity. The merit curve shows the share of hours above a certain production capacity. The horizontal axis shows the time as a percentage of total time and the vertical axis shows the percentage with which the turbine/wind farm is producing. For example, Figure 3 shows that without smoothing, the model assumes that turbine produces approximately 10 % of the time with full power; with smoothing the time with full power decreases to around 6 %, which is closer to real production in view of the average of the SCADA data.

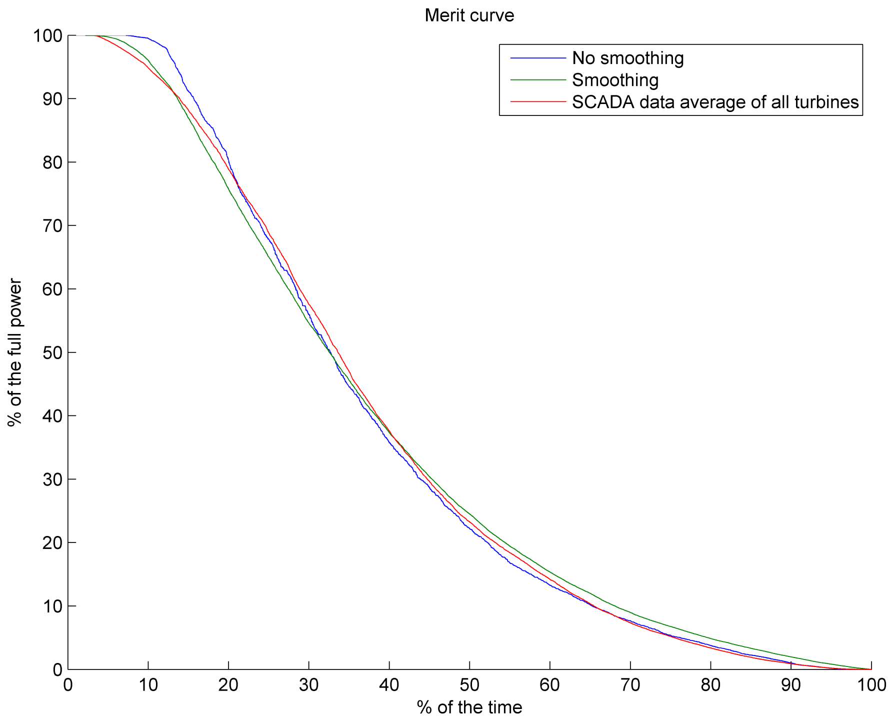

Figure 3: Effect of smoothing on the merit curve of wind farm 1.

The final smoothing function combines two techniques. The first one focuses on critical evaluation of the power curves (Sohoni et al., 2016). Three different power curves are produced based on one, turbine-specific power curve, after which they are aggregated based on weights. The second technique focuses on the geographical dispersion within a wind farm by using time shifts in production time series. Lastly, shifted time series are aggregated based on weights.

2.2.1 Power curve shift in the smoothing function

Power curve shift allows the model to consider also extreme values and not only values around the mean. The strategy is to create three different power curves by adding 1 m/s and, correspondingly, subtracting 1 m/s from the wind speed (Olauson and Bergkvist, 2015; Norgaard and Holttinen, 2004). This is shown in Figure 4.

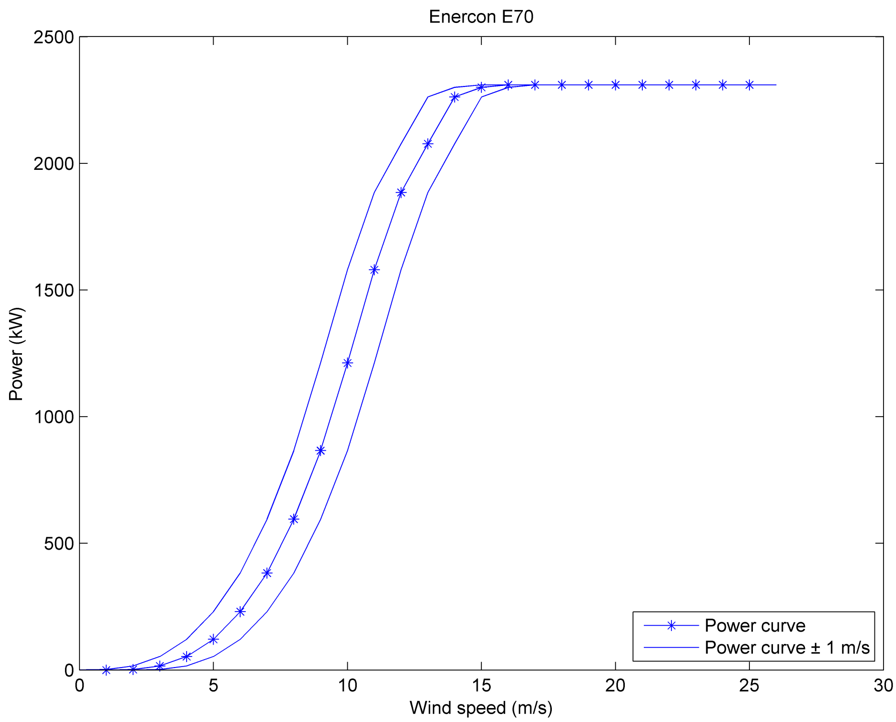

Figure 4: Original and shifted power curves of Enercon E70 turbines.

Once the three power curves were created, they were combined to generate an aggregated power curve. This resulted in a smoothed multi-turbine power curve, that is representative for the aggregated power output for the wind turbines within the area.

2.2.2 Time shift in the smoothing function

For the time shift, the relation of the distance between two turbines and the correlation between their energy production levels was studied based on the available SCADA data. The following linear fit was made by MATLAB:

$$c_1 = -0.0542d + 0.9944, \tag{1}$$

where c_1 is the correlation between the energy production levels of two turbines, and d is the distance (km) between turbines x_1 and x_2.

The fit and the actual correlation coefficients of the turbines compared to the reference turbine 18, the southernmost turbine, are in Figures 5 and 2, respectively.

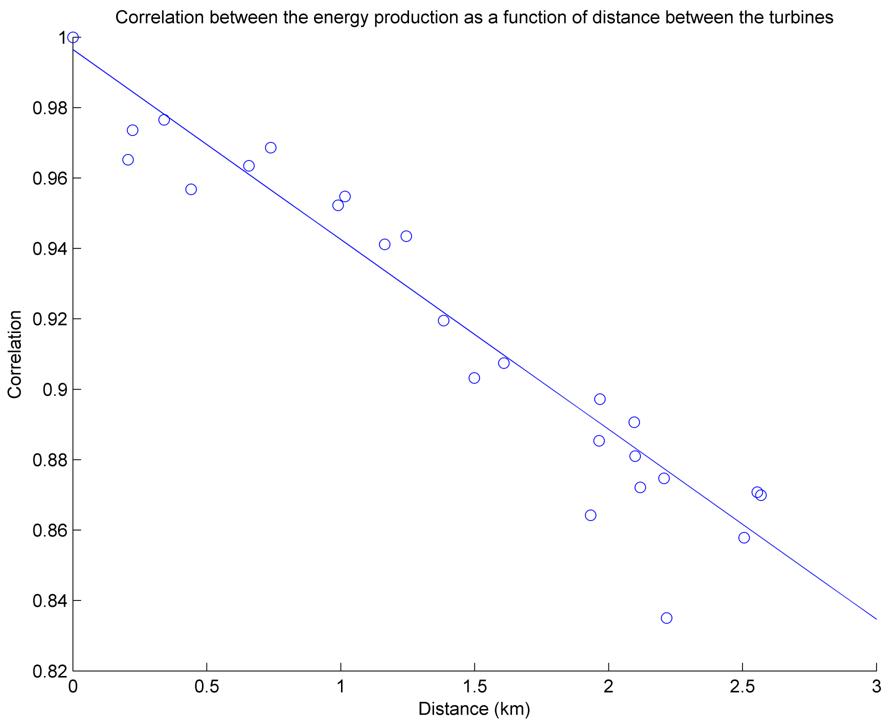

Figure 5: Correlation between the energy production of two turbines as a function of their distance.

Other parameters than the distance also have effects on the variation. For example, complex terrain and turbulence affect the variation of production within a wind farm, but are not studied here.

The correlation between the original and the shifted production time series was studied with MATLAB. The following second-degree polynomial fit was made:

$$s = 36.7693c_2^2 - 80.1266c_2 + 43.4363, \tag{2}$$

where s is the time shift (h) and c_2 is the correlation between original and shifted time series. The fit with the actual correlation coefficients can be seen in Figure 6.

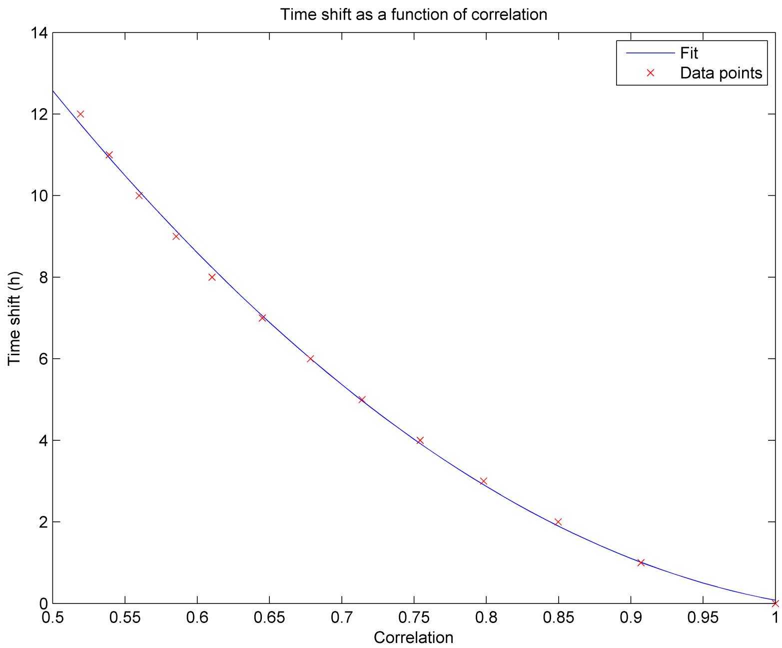

Figure 6: Time shift as a function of correlation between the shifted and the original time series.

By using the size of each wind farm, the correlations between turbines within the farm were estimated by using equation (1). Average correlation was estimated by using the mean of the length and width of the wind farm. By applying the estimated correlation, the correct time shift for smoothing for each wind farm was calculated by using equation (2). The time shifts for each wind farm are in Table 2.

Table 2: Time shifts used in smoothing for different-sized wind farms.

Wind farm	Mean of length & width	Time shift (h)
1	2.25	2
2	8.50	11
3	6.50	7
4	3.50	3
5	3.75	3
6	4.75	4
7	4.25	4

Time shifts were used to shift the energy production time series back and, correspondingly, the same amount of time ahead so that we had three production time series similarly to Norgaard and Holttinen (2004). These three time series were combined to produce one, more realistic, time series with less volatility.

2.2.3 Weights for the smoothing function

For the final smoothing function, the change in the power curves had to be combined with the change in the production time series. This was made by creating the combined power curve by using weights and using it to calculate one production time series. This time series was shifted to create three time series, which were then combined by using weights to produce the final, smoothed time series.

Six parameters had to be decided for the smoothing function. To find the appropriate mix of the three power curves, as well as the mix of the three time series, weights for the power curves and similarly weights for the time series had to be chosen carefully.

As the smoothed model should correspond to an average turbine of a wind farm, it was compared with the average of the available SCADA data of wind farm 1. In the comparison, average observations and modelled data points were fitted to align on the merit curve. The appropriate weights were found by manual iteration similarly to Norgaard and Holttinen (2004). The weights in Table 3 and Table 4 were applied to all wind farms 1-7.

Table 3: Weights for combining three different power curves in the smoothing function.

	Weight
Power curve - 1 m/s	0.2
Power curve	0.6
Power curve + 1 m/s	0.2

Table 4: Weights for combining three different time series, shift x hours, in the smoothing function. The time shift x depends on the size of the wind farm according to Table 2.

	Weight
Production time series - x h	0.2
Production time series	0.6
Production time series + x h	0.2

2.3 Modelling losses

To create a net production time series for each wind farm and merit curves for the total net production of all the wind farms, some losses had to be accounted for. Modelling losses is important to produce a realistic model of energy production. If the total decrease in production due to different losses would be modelled similarly at every time period, the focus would be on the average and consequently the extremes would not be modelled realistically. This would not affect total production, but it would have a big effect on the merit curves and on the calculation of annual profit losses in wind farm 7, which is our objective in this study. Four kinds of losses were modelled with MATLAB: icing and blade degradation losses, wake losses, unavailability losses, and electrical losses. The estimations of the percentage for different types of losses were based on the expertise and previous experience of Kjeller Vindteknikk. The distribution of different losses is in Table 5.

Icing and blade degradation losses include the production losses due to ice formation on the blades, and due to the successive degradation of the blade surface that occurs due to wear and tear and exposition to icing and dirt. The turbines continue producing with degraded performance (Turkia et al., 2013; Zidane et al., 2016; Sareen et al., 2014), and the resulting losses were modelled by a decreased wind speed. The seasonal variation by the icing was not taken into account, as it was considered to have only a small effect on the total losses, and the effect of cold weather was taken into account when considering the unavailability losses. The reduced production was estimated by decreasing wind speed until the desired percentage of blade degradation losses was reached. This means that the turbine will still be able to produce at full power, but the wind speed will have to be slightly higher to reach the full power.

Wake losses are the production losses caused by a wake effect generated by the turbines of the wind farm. Wind turbines extract energy from the wind and, thus, downstream from the wind turbine, there is a wake, which means that the wind has reduced speed and is turbulent (González-Longatt et al., 2012). It is important to consider the wake effect when designing a wind farm and to account for wake losses when modelling the production. Wake losses are modelled by a decreased wind speed similarly to icing and blade degradation losses.

Unavailability losses were modelled as random production breaks in turbines. These losses occur mostly in periods when the turbine is unavailable to produce energy due to technical reasons. The turbine with a break was chosen randomly as well as the start of the break. The duration of the break was chosen randomly from the distribution of halt durations made of the SCADA data of wind farm 1. The breaks were added one by one until the unavailability losses reached the defined baseline percentage. In addition, at low temperatures, the wind turbine system can shut down or produce at reduced efficiency. Due to this, extra halts were added during winter time (from October to March), until the determined level of total unavailability losses was achieved.

Lastly, electrical losses were added. Electrical losses were estimated to be proportional to the square of the production on each moment. Losses were scaled to reach the defined percentage of electrical losses.

The final percentages for the different types of losses are in Table 5. Losses were added one after another so the total loss percentage was a multiplication of different types of losses. The actual total loss percentage sums up to 14.4 %. The total effect of the modelled losses on the production is in Figure 7.

In summary, the total production of the wind farms never reaches the installed capacity due to the losses. The merit curve does not reach the maximum mainly because of the electrical losses. Unavailability losses have an effect mostly on the shape of the merit curve close to the maximum, and icing and blade degradation and wake losses on the middle production. Effects of the different losses on the merit curve are in Figure 8.

Table 5: Different types of losses and the percentages the production is decreased because of the each loss.

Type of the loss	Distribution of the production losses
Icing and blade degradation	1 %
Wake effect	8 %
Unavailability	4 %
Electrical	2 %

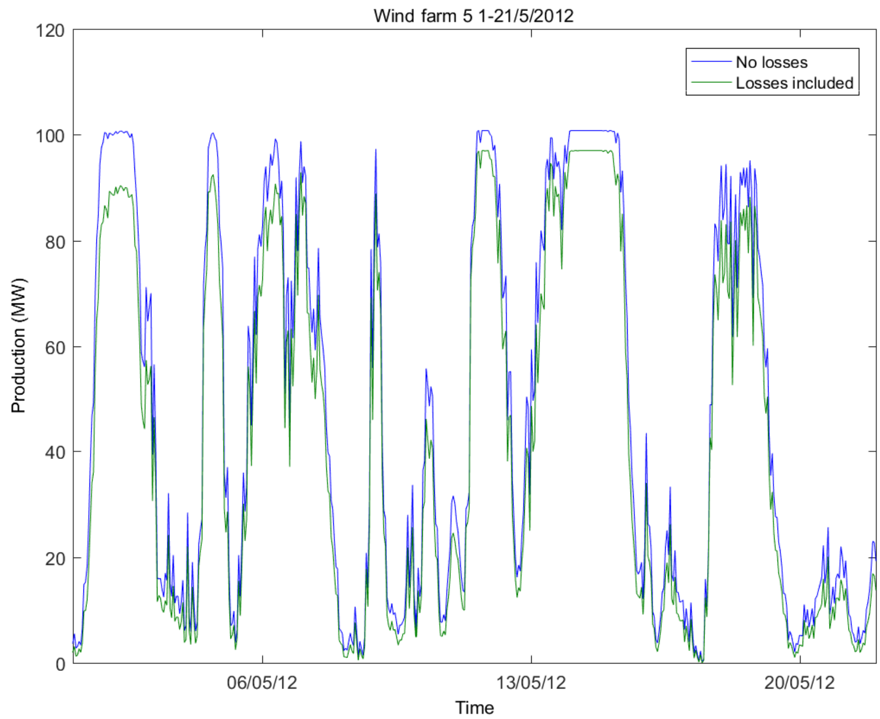

Figure 7: An illustrative time series of modelled energy production in wind farm 5 with and without modelled losses.

3 Results

3.1 Time series and merit curves

By using the smoothing function and acknowledging production losses, a time series for realistic net production in 2000-2016 were calculated for each wind farm. The effects of smoothing and losses are in Figure 9 for an example

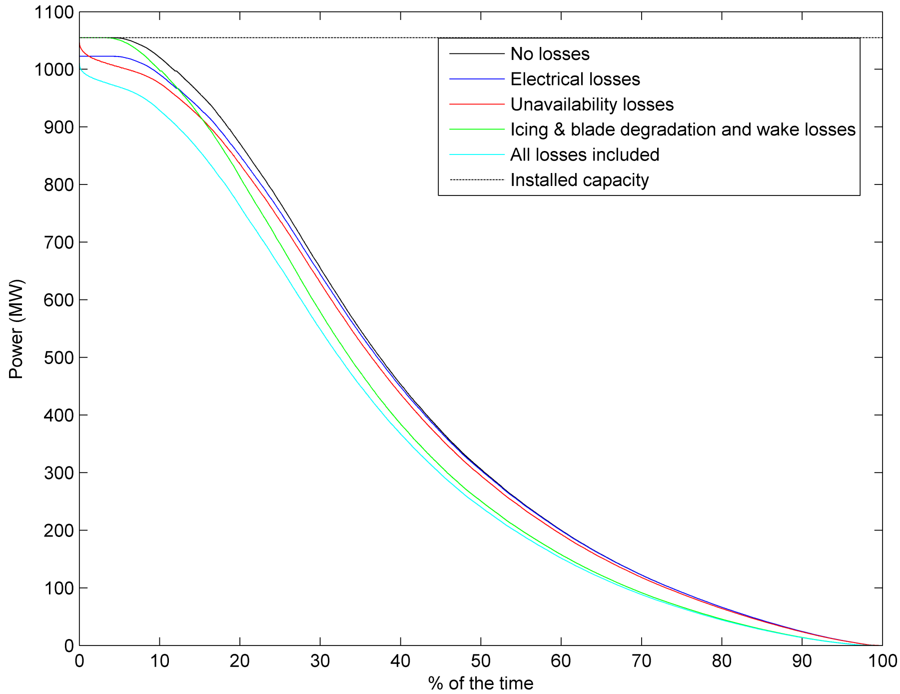

Figure 8: Comparison of the effects of different loss types on the unsmoothed merit curve.

one-week time series of the modelled power production for a turbine in wind farm 1.

Merit curves were constructed by using the production time series. Merit curves for the total production of the wind farms both with and without wind farm 7 are in Figure 10, along with the installed capacity of all wind farms. The total production of the wind farms never reaches the installed capacity due to the losses.

3.2 Curtailment due to the transmission line capacity limit

Seven wind farms are planned to be in the same local grid, but there is a limited power transmission capacity in the system consisting of seven wind farms. Because the wind farms 1 through 6 have the privilege to use the transmission line, there are occasional profit losses for wind farm 7, when

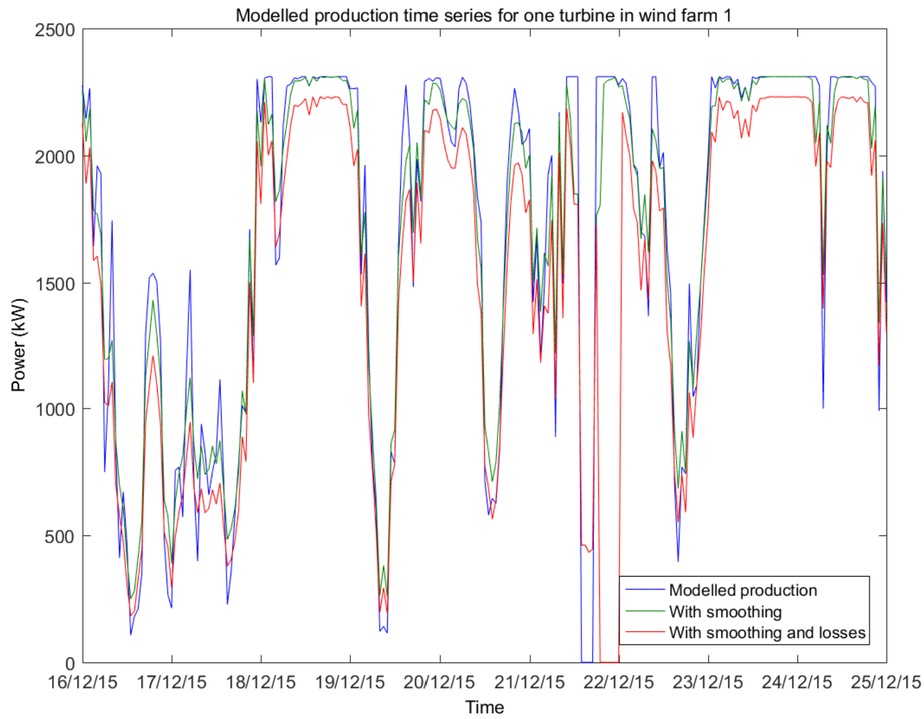

Figure 9: An example time series of modelled production by using wind data and power curve, adding smoothing and the losses.

the produced power cannot be exported to the grid due to the limit on transmission line capacity. This happens whenever the total production of the wind farms exceeds the transmission line capacity constraint.

The level of the curtailment due to the transmission limit was calculated by using merit curves. The curtailment of the power production of wind farm 7 was calculated by integrating the area between the merit curves with and without wind farm 7, above the power that is equal to the transmission line capacity limit.

Different transmission limits are considered, as we do not know the real limit. Therefore, different levels of the curtailment are presented in energy and as a percentage of the annual energy production of wind farm 7 in Table 6. The sum of the installed wind power capacity is 1055 MW and the modelled annual energy production of wind farm 7 is 345 GWh. This is an estimation based on the weather data of the location. Due to the losses, the power of all farms never reaches the total installed capacity but is 1003 MW at the

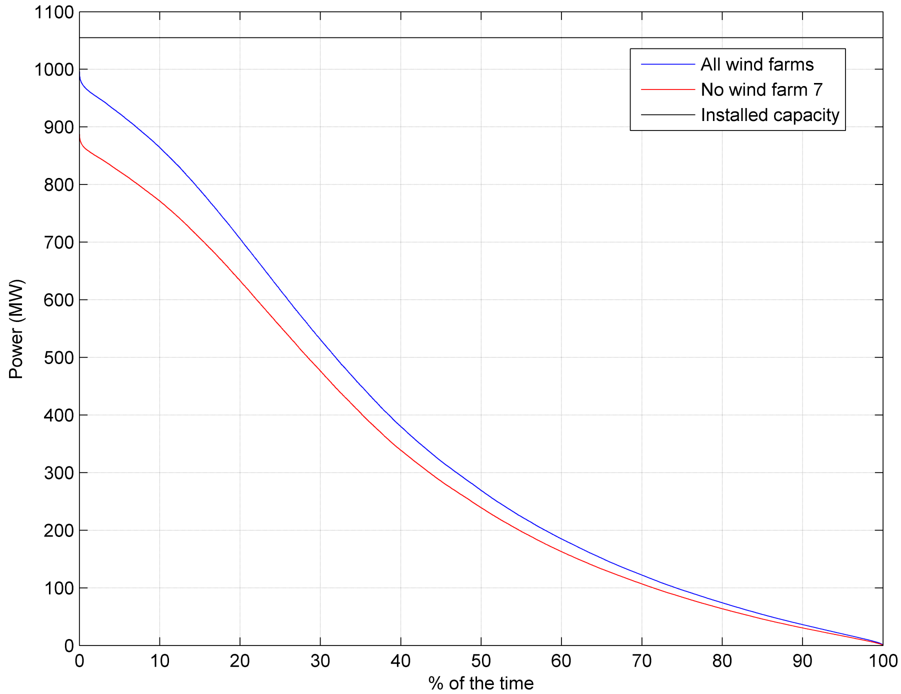

Figure 10: Merit curves for the total production of the wind farms with and without wind farm 7 along with the total installed capacity of the wind farms.

maximum.

Table 6: Levels of the curtailment in wind farm 7 with different transmission line capacity limits in energy and as a percentage of the annual energy production of wind farm 7.

Limit (MW)	Curtailment (GWh)	Curtailment as a percentage
1055	0	0 %
1003	0	0 %
950	3	1 %
900	24	7 %
850	62	18 %
800	97	28 %
750	125	36 %
700	148	42 %

The level of average curtailment due to transmission constraints is 2-3 % in the United States (Wiser et al., 2015). From Table 6, we can see that if the transmission line capacity limit is below 1003 MW, the energy production in wind farm 7 is curtailed.

If the transmission line capacity limit is below 950 MW, the curtailment increases significantly. However, if the transmission line capacity limit is below the total production capacity of the other six wind farms, there can be curtailment in their production as well. The total installed capacity of wind farms 1-6 sums up to 940 MW but due to the losses the real production capacity is below this. If all the wind farms are producing energy close to their maximum and the limit is below their total production capacity, the production in the other wind farms must be curtailed as well. Therefore, the transmission line capacity limit has also an effect on the other wind farms but that is not studied here.

Transmission limit of 700 MW equals to the curtailment of 148 GWh. As the annual energy production of wind farm 7 is 345 GWh (Table 1), this means the level of curtailment is nearly half, 42 %, of the AEP of wind farm 7. With the limit of 850 MW, the curtailment is still nearly one fifth, 18 %, of the AEP of wind farm 7. However, in these cases the transmission limit effects on the other wind farms as well at times, because the total production of wind farms 1-6, with wind farm 7 entirely curtailed, may exceed the transmission line capacity. Hence, the level of the annual curtailment in wind farm 7 is actually smaller.

The significant level of the curtailment depends case by case. For example, Jorgenson et al. (2017) defines 15.5 % as a significant level of wind curtailment and studies how it can be reduced through transmission expansion.

3.3 Discussion

Different sources of uncertainty affect the results. The most sensitive choice is likely to be the assumption of total losses to be 15 %. The assumption was made based on the Kjeller Vindteknikk's experience. This has an effect on the estimated net AEP and, thus, on the wind scaling, as well as the amount of losses added to the production model. Also the distribution of losses has uncertainties, and it has to be estimated well to be able to model the energy production realistically.

Other model limitations include, for example, omission of the effect of the geography within wind farms. In the construction of the smoothing function, the choices of the weights for combining three power curves and the three time series involve uncertainties, as they are found by manual iteration and merit curve inspection. Also, the estimation of the sizes of wind farms and the choice to use the mean of length and width can affect the results through the smoothing function.

The estimation of the profitability of wind farm 7 is left to the client. As the transmission line capacity is not known for this study, no exact value for the curtailment is given. Rather, the modelled levels of curtailment for different capacity limits are stated.

4 Conclusions

In this study, we have examined a system of seven wind farms in Norway. Six of the farms are privileged to use the transmission line to transmit the produced energy to the grid from the system of the seven wind farms. We constructed a model to represent energy production of different wind farms realistically. With the energy production time series, we constructed merit curves and found the level of annual curtailment in wind farm 7 due to the transmission capacity limit.

The results suggest that, depending on the transmission line capacity, a significant curtailment in wind farm 7 can lead to profit losses. Therefore the level of the energy production in the other wind farms should be taken into account when implementing transmission line capacity limits on the energy production at wind farm 7.

The study also examined the effect of the smoothing of the modelled energy production within each wind farm as well as between the wind farms. The study indicates that the smoothing is necessary to model energy production realistically. Merit curves are useful when studying smoothing effects as well as the effects of losses. The importance of modelling different types of losses was demonstrated as well.

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A Weather Research and Forecast model

Meso-Scale Model WRF

The Weather Research and Forecast (WRF) model is a state-of-the-art meso-scale numerical weather prediction system, aiming at both operational forecasting and atmospheric research needs. A description of the modelling system in on the home page http://www.wrfmodel.org/. Details about the modelling structure, numerical routines and physical packages available can be found for example in Klemp et al. (2007)[1] and Michalakes et al. (2001)[2]. The development of the WRF-model is supported by a strong scientific and administrative community in U.S.A. The number of users is large and growing rapidly internationally. In addition the code is freely accessible for the public.

The meso-scale model WRF solves coupled equations for all important physical processes (such as winds, temperatures, stability, clouds, radiation etc.) in the atmosphere based on the initial fields and the lateral boundary values derived from the global data.

Input data

The most important input data are geographical data and meteorological data. The geographical data is from the National Oceanic and Atmospheric Administration (NOAA). The data includes topography, surface data, albedo and vegetation. These parameters have high influence for the wind speed in the layers close to the ground. The WRF model uses land use data input from NOAA.

For solving the model equations, boundary conditions of the area are required. Such lateral boundary data is available from the National Centers for Environmental Protection (NCEP). The data originates from the Final Global Data Assimilation System (FNL) and is available as global data with 1 degree resolution every 6 hours. FNL is an operational assimilation model that incorporates all available observation data globally, and uses this data to

[1]Klemp, Joseph B., William C. Skamarock, and Jimy Dudhia. "Conservative split-explicit time integration methods for the compressible nonhydrostatic equations." Monthly Weather Review 135.8 (2007): 2897-2913.

[2]Michalakes, J., et al. "Development of a next-generation regional weather research and forecast model." Developments in Teracomputing. 2001. 269-276.

create a global analysis dataset, or a snapshot of the atmosphere, four times every day. The assimilation model incorporates data from several thousand ground based observation stations, vertical profiles from radiosondes, aircrafts, and satellites.

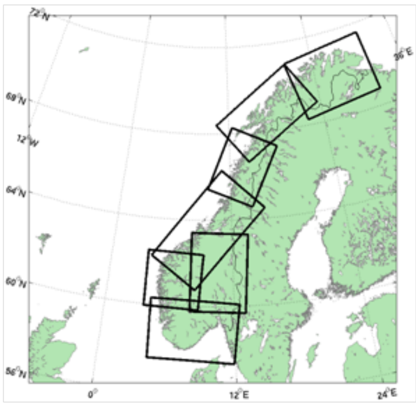
Model Setup

The model setup used in this study is shown in Figure 11a. The simulations of the northern European region have been performed for 18 years covering the period 2000-2017. The model has been set up with 2 nested domains. The horizontal resolution is 4 km x 4 km.

With the current setup, the WRF-model calculates the change in the meteorological fields for each grid-cell for a time step from 5 to 108 seconds in the different domains with increasing time step for lower horizontal resolution. In this way a realistic temporal development of the meteorological variables is achieved. Data is stored every 1 hours of simulation.

The domain setup of the high resolution model used in this analysis is shown in Figure 11b. The 7 simulations of Norway have been performed for 1 year (2005). The model has been set up with 3 nested domains. The horizontal resolution is 1 km x 1 km. The NCEP–FNL dataset is used as input for the 1 km simulations.

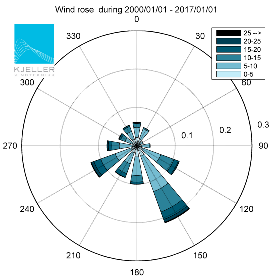
(a) Model setup for WRF4km simulation.



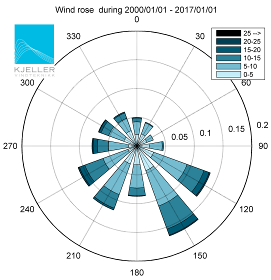
(b) Inner model domains from all available simulations from WRF1km.

Figure 11: Domain setups for WRF.

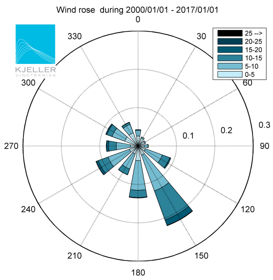
B Wind roses



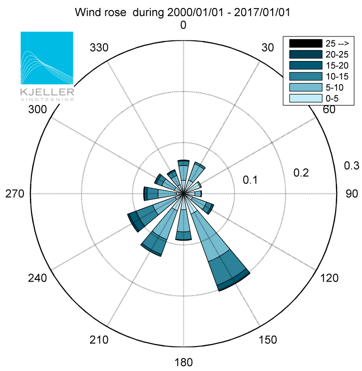
(a) Wind farm 1



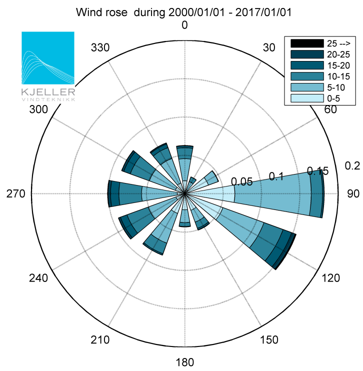
(b) Wind farm 2



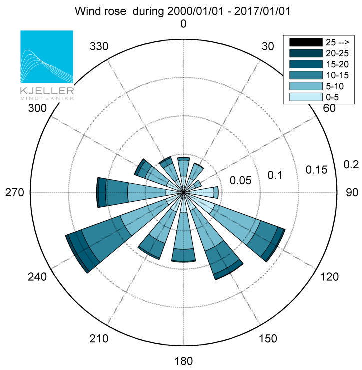
(c) Wind farm 3



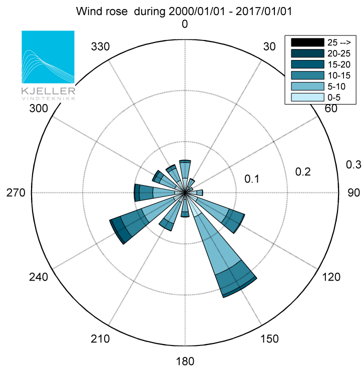
(d) Wind farm 4



(e) Wind farm 5



(f) Wind farm 6



(g) Wind farm 7

Figure 12: Wind roses for each wind farm

C Power curves

Table 7: Turbine type specific power curves

Wind speed [m/s]	Enercon E70 [MW]	Vestas V117 [MW]
1	0	0
2	2	0
3	16	11
4	53	134
5	121	318
6	230	587
7	383	967
8	596	1467
9	866	2106
10	1212	2835
11	1580	3405
12	1885	3600
13	2077	3600
14	2262	3600
15	2300	3600
16 – 25	2310	3600