Impact of turbine availability and wake effect on the application of dynamic thermal rating of wind farm export transformers

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A B S T R A C T

Dynamic thermal rating allows transformers to operate beyond the nameplate rating according to the actual weather and loading conditions. This paper proposes a methodology to improve the application of this technology in the design of new transformers or in the operation of existing transformers connected to wind farms by accurately predicting their load profiles, accounting for the influence of wake effect and turbine availability. Specifically, the variation of turbine availability due to the intermittent wind is considered in the load profile estimation. Additionally, a correction method, which can be incorporated into any wake model, is proposed to improve the accuracy of wake loss computation. A case study shows that the wake effect and the changing turbine availability shorten the time that the transformers maintain at full load, thereby reducing the aging rate of the wind farm export transformers. The findings suggest that considering these two factors in the DTR application can benefit the longevity and efficiency of wind farm exported transformers.
Regarding turbine availability, few papers link it with the load profiles of WFETs except in Kazmi et al. (2021), in which the turbine availability is assumed as a constant when building a probabilistic model to estimate the annual load profile of a WFET. Nevertheless, the previous studies still provide valuable information on how turbine availability influences wind power generation (Sulaeman et al., 2017; Nguyen et al., 2019) and how to build probabilistic models to estimate the load profile of WFETs considering the turbine availability (Sayas and Allan, 1996; Karki et al., 2006; Leite et al., 2006; Manco and Testa, 2007; Nguyen and Mitra, 2017; Bhaumik et al., 2018). However, as Sulaeman et al. (2017), Nguyen et al. (2019) indicates, the turbine availability varies due to the intermittent nature of wind. Under high wind speed, it is unclear if the transformers suffer accelerating aging due to full loading or if the aging of transformers is reduced due to the variation of the turbine availability. Hence, the variation of the turbine availability due to the intermittent wind cannot be ignored when evaluating the load profile of WFETs.

It can be observed that the impact of the factors (wake effect and turbine availability) on the load profile of WFETs is crucial to be analyzed when applying DTR to WFETs but has not been well implemented in the previous papers. In this paper, a methodology is introduced to consider the wake effect and the turbine availability in the load profile estimation of WFETs. The accuracy of the proposed methodology is verified by the measured data from an onshore wind farm located in the north of Sweden. Furthermore, the impact of the turbine availability and the wake effect on the load profile of the WFETs is assessed.

Compared to the existing research works, the main contribution of this paper can be summarized as follows. A methodology is proposed to assess the impact of wake effect and turbine availability on the load profile and aging rate of WFETs. Regarding the wake effect part, a Wake Impact Factor (WIF) correction method is proposed to correct the measured data to improve the accuracy of wake loss estimation. The proposed WIF method can be incorporated into any wake model and it requires wind data from only one turbine to estimate the wind speed of the rest turbines on the wind farm. Regarding the turbine availability part, a Markov model is proposed to consider the influence of the turbine availability in the load profile estimation of WFETs. The impact of wind speed on the change of turbine availability is taken into account.

The rest of this paper is organized as follows. Methodology description and modeling are given in Section 2. Section 2.1 illustrates how to implement the correction method in the wake loss computation.
Section 2.2 explains the principle of the proposed Markov model and how to consider the variable turbine availability in the estimation. Section 2.3 exhibits the transformer thermal model. Section 3 presents the analysis of the data resource and a case study to verify the accuracy of the proposed model. Finally, this paper is ended with conclusions in Section 4.

2. Methodology

2.1. Estimation of wake effect

2.1.1. Jensen model

Compared to the Jensen model, the wake models in Larsen (1988), Ishihara et al. (2004), Frandsen et al. (2006), Yang and Sotiropoulos (2016) generate more accurate results at the price of high computational costs, which is not suitable for the scenario and time horizon in this paper. Hence, the Jensen wake model is used in this paper to consider the power loss caused due to the wake effect considering its simplicity. The model principle is shown in Eq. (1) and Fig. 1. Assuming the incoming wind speed $U_{\text{nowake}}$ (the direction of the incoming wind) is not changed, the reduced wind speed $U_{\text{wake}}$ (m/s) of the $j$th turbine considering the wake effect due to other turbines is calculated based on the speed of the incoming wind $U_{\text{nowake}}$ (m/s).

$$U_{\text{wake}_{j}} = U_{\text{nowake}}[1 - \sum_{i=1}^{N-1} (1 - C_i) \left(\frac{d_{x_j}}{d_{X_j}}\right)^2]$$

In Eq. (1), $U_{\text{nowake}}$ is the incoming wind speed of the whole wind farm and $U_{\text{wake}_{j}}$ is the downstream wind speed of WTj considering the cumulative wake effect of the rest ($N-1$) turbines. $C_i$ is the thrust coefficient of the wind turbine, $d_{X_j}$ is the diameter of the expanded wake area, which equals to,

$$d_{X_j} = d + 2r_j = d + 2kx_j$$

where $d$ is the rotor diameter and $x_j$ is the distance between WTj and WTj. A wake decay constant $k = 0.075$ is used in this onshore wind farm scenario (Zigras and Moennich, 2006). The wind shade effect due to upstream obstacles (turbines) is ignored.

2.1.2. Wake impact factor correction

For a wind farm in operation, a rough method to estimate the wind power generation is to use the average value of the measured wind speed from all turbines. The average value is used to minimize the impact of the wake effect on the estimation accuracy. However, the estimation using the average value differs from the real case. It is also challenging to collect accurate measured data from all turbines (due to the offline of some anemometers). Commonly, only data from a limited number of turbines is of high quality. A wake impact factor (WIF) correction method is proposed to solve this issue. This correction method requires wind data from only one turbine from the wind farm and the wind farm layout to estimate the wind speed of other turbines considering the influence of the wake effect.

In order to estimate the diminished wind speed of each turbine on a wind farm, $U_{\text{wake}}$ used in the Jensen model must be the incoming wind speed for the entire wind farm, in other words, the upstream wind for all turbines. The measured wind from the anemometer of one turbine can be upwind or downwind for other turbines on the wind farm depends on the wind direction and the location of the anemometer. Hence, the wind data measured by the anemometers (on the meteorological tower or on the turbine nacelle) is not usable directly as input for the Jensen model since the wind may have already suffered reduction before the measurement due to the wake effect. It is unclear if the measured wind speed from one turbine is upstream or downstream with regard to the rest turbines on the wind farm due to the changes in wind direction.

The intention of the wake impact factor correction (WIF) method is to correct the measured data before the data is proceeded with the Jensen model. The WIF method only requires wind speed from one turbine and can correct the wind speed from the “non-incoming” direction. Before the data is input to the Jensen model, it needs to be corrected to the incoming wind speed for the whole wind farm using the WIF method. Initially, it is assumed that $U_{\text{mea}}$ represents the measured wind speed from the anemometer of the $j$th wind turbine (WTj). A test incoming wind speed $U_{\text{nowake}}$ (with a variable wind direction $\theta_{\text{nowake}}$) is defined in a certain range. This step aims to evaluate the influence of the wind farm layout on $U_{\text{nowake}}$ before $U_{\text{wake}}$ reaches WTj. The combination of $U_{\text{nowake}}$ and $\theta_{\text{nowake}}$ in the defined range include all possible cases of wind. Using the Jensen wake model, the reduced wind speed $U_{\text{wake}}$ of WTj under all possible wind conditions can be calculated. After $U_{\text{wake}}$ is derived based on $U_{\text{nowake}}$ and $\theta_{\text{nowake}}$, the wake impact factor (WIF) for the wind farm under different wind conditions is calculated using Eq. (3).

$$\text{WIF}(U_{\text{mea}}, \theta_{\text{nowake}}) = \frac{U_{\text{wake}}}{U_{\text{nowake}}}$$

Assuming the imported wind direction $\theta_{\text{nowake}}$ is not changed, the wind speed $U_{\text{mea}}$ from WTj can be corrected to the corresponding incoming wind speed $U_{\text{wake}}$, for the whole wind farm using Eq. (4).

$$U_{\text{nowake}}(\text{wif}) = \frac{U_{\text{mea}}}{\text{WIF}(U_{\text{mea}}, \theta_{\text{nowake}})}$$

2.1.3. Wind power evaluation

After the corrected incoming wind speed $U_{\text{nowake}}(\text{wif})$ is calculated using the WIF method, Eq. (1) is used again to calculate the reduced wind speed $U_{\text{wake}}(\text{wif})$ of each turbine to estimate the generated power from the wind farm. The power curve of the chosen turbine is used to estimate the power output from the turbine based on the wind speed. The corrected wind speed $U_{\text{wake}}(\text{wif})$ of each turbine is fitted into the power curve to get the corresponding real-time power output $P_{\text{adv}}$. The ideal real-time power output $P_{\text{out}(\text{est})}$ on the condition that all turbines are in operation is calculated as,

$$P_{\text{out}(\text{est})} = P_{\text{adv}}N$$

Since the final objective of the paper is to operate transformers according to the thermal limit, the load factor is chosen to represent the load profile of transformer, similar to the setting in Arguence and Cadoux (2020). The total power output $P_{\text{out}}$ from the wind farm is converted into load factor $K$, which is a ratio between load current $I_{\text{load}}$ and rated current $I_{\text{rated}}$. This variable is an input in the calculation of the transformer operating temperature. If the voltage drop across the leakage reactance is ignored and the output voltage $U$ is assumed as
a constant, $K$ can be expressed by the generated power using Eq. (6).

The denominator $P_{\text{rated}}$ is the rating of the selected-size transformer and the numerator $P_{\text{load}}$ depends on the real-time generated power from the wind farm.

$$K = \frac{I_{\text{out}}}{I_{\text{rated}}} = \frac{P_{\text{out}}/U_{\text{rated}}}{P_{\text{rated}}/U_{\text{rated}}} = \frac{\sum_{i=1}^{N} P_{\text{indiv},i}}{P_{\text{rated}}/U_{\text{rated}}}$$  \hspace{1cm} (6)

Load factor can also be used to check the simulation accuracy by comparing the results between the simulation duration curve $K_{\text{SIM}}$ and the measurement duration curve $K_{\text{real}}$. Mean-squared error (MSE) is used as an indicator to evaluate the quality of simulation result compared to the measured data.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (K_{\text{SIM},i} - K_{\text{real},i})^2$$  \hspace{1cm} (7)

Since this paper focuses on the influence of the wind power on the transformer insulation, more attention should be paid to when the transformer load is high. Hence, a weighted factor $w_i = K_{\text{real},i}$ is added to neutralize the influence of zero values in the load factor. The weighted mean square error (WMSE) is calculated to evaluate the simulation accuracy.

$$\text{WMSE} = \frac{1}{n} \sum_{i=1}^{n} w_i (K_{\text{SIM},i} - K_{\text{real},i})^2$$  \hspace{1cm} (8)

2.2. Turbine availability

Production-based availability (PA) is used in this section for the estimation of the transformer load. It is a simplified index to evaluate the availability of turbines when the wind speed $u_{\text{ind}}$ satisfies the requirement of power generation. When $U_{\text{cut-in}} \leq u_{\text{ind}} \leq U_{\text{cut-out}}$, the corresponding WT is considered production-based unavailable if it cannot produce power in either out-of-service (OOS) mode or in non-operative (NO) mode according to standard (Anon, 2019). This definition considers the WT as a whole and aims to avoid confusion with the reliability of the wind turbines sub-assemblies. In this way, the availability of wind turbines can be combined with wind power prediction to improve the estimation of the transformer load.

To calculate the turbine availability, the failure and repair rate of turbines should be evaluated first. It has to be noted that the 'failure' here means the turbine stops rotation when the wind speed is in the range $(U_{\text{cut-in}} \leq u_{\text{ind}} \leq U_{\text{cut-out}})$ and the 'repair' means the whole process after the failure and before the turbine re-starts operation.

2.2.1. Failure & repair rate

After Type III data (the data influenced by the failure and maintenance of wind turbines) is included, the turbine availability should be taken into account. The wind turbines stop operation and cannot produce power during the failure or maintenance period. In this paper, the failure rate and repair rate is defined in a per turbine per year format.

A filter is defined to select the data in which the wind speed satisfies the condition of power generation $(U_{\text{cut-in}} \leq u_{\text{ind}} \leq U_{\text{cut-out}})$. It is assumed the repair is initiated immediately when the failure occurs. A data-based method is defined to calculate the failure and repair rate in Fig. 2. Based on $n$ and $Z$ derived in Fig. 2, the availability of the wind farm can be determined. For the wind turbine, which is a repairable system, the repair/down time cannot be ignored compared to the operating/up time. According to Carroll et al. (2014), Wallnerström and Hilber (2014), Spinato et al. (2009), Tavner et al. (2007), for a repairable system with data in hours, the yearly based MTTF, MTTR and MTBF can be expressed as.

$$\text{MTTF} = \frac{T - Z}{n}$$  \hspace{1cm} (9)

$$\text{MTTR} = \frac{Z}{n}$$  \hspace{1cm} (10)

$$\text{MTBF} = \text{MTTF} + \text{MTTR}$$  \hspace{1cm} (11)

The yearly based failure rate $\lambda$, repair rate $\mu$ and the availability $q$ can be expressed as,

$$\lambda = \frac{1}{\text{MTTF}}$$  \hspace{1cm} (12)

$$\mu = \frac{1}{\text{MTTR}}$$  \hspace{1cm} (13)

$$q = \frac{\text{MTTF}}{\text{MTBF}}$$  \hspace{1cm} (14)
2.2.2. Markov model

The binomial distribution (BD) equation is used to calculate the probability distribution of the number of running turbines based on a constant wind turbine availability $q$. The probability distribution that a certain number of turbines in operation is given by the binomial probability density,

$$A_x = \binom{N}{x} p^x q^{N-x} = \frac{N!}{(N-x)!x!} p^x q^{N-x} \quad (15)$$

where

1. $x$ is the number of real-time running turbines, varying from 0 to $N$
2. $p$ is the unavailability of wind turbine, $p = 1 - q$

Next, the uniform pseudo-random number generator in Matlab is used to generate a sequence of random number based on the binomial probability distribution, which simulates the variation of the real-time number of operational turbines $N_{\text{run}}$ in time series. The improved estimated wind power output $P_{\text{wind}+\text{BD}}$ from the wind farm, which considers the influence of turbine unavailability, can be calculated as:

$$P_{\text{wind}+\text{BD}} = P_{\text{indiv}} N_{\text{run}} \quad (16)$$

2.2.3. Transformer thermal model

In the BD model, the variation of turbine failure and repair rate under different weather conditions is not considered. In reality, the failure rate and the repair rate of turbines are influenced by environmental conditions. The correlation between the wind speeds and the failure rates of turbine sub-assemblies is determined to be negative in Tavner et al. (2006). Based on this conclusion, a discrete Markov chain model is proposed in Nguyen et al. (2019) to take the variation of turbine unavailability under different weather conditions into consideration.

However, the turbine population considered in Tavner et al. (2006) is too large and spread unevenly over Denmark. Clearer correlations can be found between WT failures and weather data if a limited population of identical WTs at several locations is used (Tavner et al., 2013). Besides, the wake effect, an important factor influencing the wind farm operation and power generation, is not considered in Nguyen et al. (2019). In this session, a new Markov-chain method considering the wake effect is proposed to check the correlation between the wind turbine availability and the wind speed of a wind farm with $N$ wind turbines. In this way, the accuracy of wind power prediction can be developed further.

The wind farm is sometimes restricted to achieve full power rating due to turbine maintenance. When the corrective/preventive maintenance is implemented, the repair time might be extended when the wind speed is above a certain limit. The repair crew might be forbidden to climb the turbine tower due to weather issues (e.g. strong wind, icing problems). Hence, considering the influence of wind speed on turbine failure and repair, the wind speed is divided into three states:

1. $U_L$: low wind speed, low failure rate, one crew is arranged to repair
2. $U_M$: medium wind speed, failure rate increases, one crew is arranged to repair
3. $U_H$: high wind speed, high failure rate, repair is not allowed

The failure and repair rate at different wind speed range is defined as:

1. $\lambda_L$: failure rate at low wind speed
2. $\lambda_M$: failure rate at medium wind speed
3. $\lambda_H$: failure rate at high wind speed
4. $\mu_L$: repair rate at low wind speed
5. $\mu_M$: repair rate at medium wind speed
6. $\mu_H$: repair rate at high wind speed

The transition rates between different wind speed states can be defined as:

1. $\rho_{LH}$: transition rate from low to medium wind speed
2. $\rho_{MH}$: transition rate from medium to high wind speed
3. $\rho_{LM}$: transition rate from low to medium wind speed

The transition probability distribution $f(x)$, $f(x)_L$, $f(x)_M$, and $f(x)_H$ that describes the number of operational turbines under low, medium and high wind speed is calculated using Eqs. (12) and (13). The transition rate is calculated using Eq. (17),

$$\bar{\rho}_{ij} = \frac{N_{ij}}{D_i} \quad (17)$$

where $N_{ij}$ is the number of transitions from state $i$ to state $j$ and $D_i$ is the duration of state $i$ before switching to other states.

Using the parameters shown above, the state transition matrix for the Markov model is shown in Fig. 3. In the Markov model, $\lambda_L \neq \lambda_M \neq \lambda_H$ due to the variation of wind speed. The repair rate varies ($\mu_L \neq \mu_M \neq \mu_H$) since the turbine maintenance might be postponed due to the extreme weather conditions (e.g. fierce wind, icing).

The probability distribution $f(x)$, $f(x)_L$, $f(x)_M$, and $f(x)_H$ that describes the number of operational turbines under low, medium and high wind speed is calculated based on the Markov model. The number of operational turbines is generated using the pseudo-random number generator according to $f(x)$, $f(x)_L$, $f(x)_M$, and $f(x)_H$. In this way, the real-time number of operational turbines, $N_L$, $N_M$ and $N_H$ in time series under different wind states is simulated. The improved estimated wind power output $P_{\text{wind}+\text{Markov}}$ from the wind farm, which considers the influence of turbine unavailability under different wind speed, can be calculated as:

$$P_{\text{wind}+\text{Markov}} = P_L N_L + P_M N_M \quad (18)$$

2.3. Transformer thermal model

The degradation rate of the transformers is determined by the operating temperature. Two corresponding variables, hot spot temperature.
(HST) and top oil temperature (TOT), reflect the heat dissipation from winding to oil and from oil tank to the surrounding air respectively due to the eddy loss (Kulkarni and Khaparde, 2017; Rommel et al., 2021). IEEE standard (Anon, 2012) indicates that transformers (with thermally upgraded insulation paper) operating the winding HST of 110 °C has a life expectancy of about 20 years. In this paper, simplified equivalent thermal circuits in the standard (Anon, 2018b) is used instead to estimate the HST and evaluate the aging rate of transformers.

According to Anon (2018b), the lifetime duration of WFET is determined by the insulation paper of the chosen transformer. The expected lifetime of the insulation paper mostly depends on the variation of ambient temperature and transformer load, i.e. the real-time generated power from the wind farm. Due to the failure and maintenance of WTs, even at high wind speed, the load of WFET cannot always reach the power rating of the connected wind farm. A thermal model is built to assess the impact of the variation of transformer load and ambient temperature on the transformer insulation.

A scenario is assumed to calculate the aging rate of the chosen WFET. In this case, a mineral-oil-filled transformer is assumed to operate in ONAF (Oil Natural Air Forced) mode and the thermal upgraded paper is chosen for transformer insulation. The thermal characteristics of the upgraded insulation paper (free from air at 1.5% moisture condition) are referred from Laneryd and Gustafsson (2020), in which a transformer is designed for wind power application and working in ONAF cooling mode. The thermal characteristics and the assigned values used in the equations are shown in Table 1.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Thermal characteristics.</th>
</tr>
</thead>
<tbody>
<tr>
<td>For exponential equations in ONAF mode</td>
<td>Value</td>
</tr>
<tr>
<td>Exponential power of total losses versus top-oil (in tank) temperature rise (oil exponent)</td>
<td>( x = 0.8 )</td>
</tr>
<tr>
<td>Exponential power of current versus winding temperature rise (winding exponent)</td>
<td>( y = 1.3 )</td>
</tr>
<tr>
<td>For thermal upgraded paper in ONAF mode free from air at 1.5% moisture condition</td>
<td>Value</td>
</tr>
<tr>
<td>Pre-exponential factor</td>
<td>( A = 3.0 \times 10^9 \text{ h}^{-1} )</td>
</tr>
<tr>
<td>Activation energy</td>
<td>( E_A = 86 \text{ kJ/mol} )</td>
</tr>
<tr>
<td>Rated top oil temperature rise</td>
<td>( \Delta \theta_{op} = 52.8 \text{ K} )</td>
</tr>
<tr>
<td>Rated winding gradient</td>
<td>( g_h = 12.8 \text{ K} )</td>
</tr>
<tr>
<td>Rated hot spot factor</td>
<td>( H = 1.43 )</td>
</tr>
<tr>
<td>Ratio of load loss over no-load loss</td>
<td>( R = 13.74 )</td>
</tr>
</tbody>
</table>

where \( \theta_h \) is the hot-spot temperature in the \( t_{90} \) 10-min interval. If the yearly profile of the transformer load is defined as a cycle and count the number of cycles throughout its lifetime, the life expectancy of the thermally upgraded paper \( t_{\text{exp}} \) (Anon, 2018b) based on the measured data in this period can be calculated as,

\[
t_{\text{exp}} = \frac{1}{R} \left( \frac{1}{A \cdot 24 \cdot 365} \cdot \exp \left[ \frac{E_A}{R(\theta_{90} + 273)} \right] \right)
\]

where \( R \) is a gas constant equal to 8.314 J/(K mol); The insulation DP value at the end of life criterion or the moment of the sampling \( DP_{\text{end}} = 200 \); The initial insulation DP value \( DP_{\text{start}} = 1000 \).

Since the official regulation about service lifetime of transformers varies in each country, a relative aging rate is calculated instead to evaluate the transformer lifetime. According to IEC thermal model (Anon, 2018b), the aging rate of the paper insulation is given as follows:

\[
k = A \cdot \exp \left[ -\frac{E_A}{R(\theta_{90} + 273)} \right]
\]

A rated insulation condition “free from air and 0.5% moisture” is defined in the standard for thermally upgraded paper. The relative aging rate is defined to relate the aging rate at a certain insulation condition to the rated rate (Susa et al., 2011):

\[
V = \frac{k}{k_r} = A \cdot \exp \left[ \frac{1}{R} \left( \frac{E_A}{R(\theta_{90} + 273)} - \frac{E_A}{R(\theta_{90} + 273)} \right) \right]
\]

The value of \( V \) reflects the aging rate of the transformer. If \( V = 1 \), the transformer in the analyzed case has the same aging rate as in the rated condition. If \( V > 1 \), the transformer in the analyzed case is aging faster than in the rated condition, and vice versa.

3. Validation & discussion

3.1. Data analysis

In this section, the available data is classified according to the dominant factor influencing the load profile of WFETs at each moment. There are multiple factors influencing the power generation of a wind farm. Apart from the persistent wake effect, three other factors, in which each shows an evident impact on the load profile of WFETs, are discussed in this paper. The data is classified according to the dominant factor influencing the power generation at each unit time period.

- Type I — icing: turbine operation during winter is more likely to be influenced by icing.
- Type II — wind power curtailment: the power generation is operationally reduced below what the system is capable of producing (Qi et al., 2018).
- Type III — turbine availability: the output of turbine is zero or negative (due to the self-consumption of wind turbine) when the turbine is under failure or maintenance.
- Type IV — wake effect: all the turbines are in service and only the disturbance of wake effect influences the power generation.
temperature and the icing accretion on the turbine blades restricts the raise of HST. For type II data, the analysis of power curtailment is outside the scope of this paper since it is more related to power system operation.

3.2. Case study

The proposed methodology is validated by comparing the simulation outcome with the measured data. The measurement record is from a wind farm called Stor-Rotliden (SRL). SRL is a 77.8 MW onshore wind farm with forest and semi-natural landscape, located in Vasterbotten, Sweden. The wind farm got commissioned in 2011, consisting of forty Vestas Wind Systems V90 turbines (eleven with rating of 1.8 MW and twenty-nine with rating of 2 MW).

The measurement record contains two year measured data from the wind farm based on a ten-minute interval (52560 measuring records in one year). The records include the following items.

- The measured wind speed from all turbines in the horizontal direction, $U_{\text{mea}}$, m/s
- The measured wind direction from all turbines in the horizontal direction, $\theta_{\text{mea}}$, m/s
- Power curtailment setpoint at SRL in time sequence
- Ambient temperature of the turbine closest to the substation, $\theta_{\text{a}}$, °C
- Active power output from SRL, $P_{\text{real}}$, MW

The curtailment setting record shows when the turbine rating is limited due to power curtailment operation. $P_{\text{real}}$ is used to verify the accuracy of the model by comparing the simulation with the measured data. It is assumed that the turbine operation not in the period from 1st of March to 31st of October in each year is influenced by icing. Using the algorithm shown in Fig. 4, the data is classified according to the factors dominant at each measurement interval. The results are shown in Table 2.

The results in Table 2 show that for the SRL wind farm, the operation period influenced by the turbine availability is much longer compared to that influenced by the power curtailment. As stated in 3.1, Type I and Type II data is not included into analysis. Based on comparison with the ‘filtered’ measured data (Type III+IV), the influence of these factors on the load profile of transformers can be analyzed individually.

3.3. Validation of WIF method & wake model

Based on self-defined $U_{\text{nowake}}$ (varying in [5, 25], unit: m/s), wind direction $\theta_{\text{nowake}}$ (varying in [0, 360], unit: degree) and the wind farm layout in Fig. 5, the wake impact factor (WIF) for SRL under different wind conditions is calculated using Eqs. (3) and (1). The WIF map at SRL is shown in Fig. 6. It is worth noting again that Fig. 6 reflects the reduction of the incoming wind speed under the assumption that the incoming wind direction $\theta_{\text{nowake}}$ is the same for each turbine.

Type IV data is used to check the accuracy of WIF and the Jensen wake model. Choosing the measured data from turbine B10 as an input $U_{\text{mea}B10}$, the corrected incoming wind speed for the whole wind farm $U_{\text{wake}(wif)}$ is calculated based on Eq. (4) and Fig. 6. Next, the Jensen model in Eq. (1) is used to calculate the reduced wind speed $U_{\text{wake}(wif)}$ of each turbine. The real-time power output of each turbine is derived by fitting the corresponding wind speed into the power curve of Vestas V90 in Fig. 8. As indicated in Section 2.3, the power output variables ($P_{\text{nowake}(wif)}$, $P_{\text{wake}(wif)}$, $P_{\text{real}}$) are converted into the corresponding load factors ($K_{\text{nowake}(wif)}$, $K_{\text{wake}(wif)}$, $K_{\text{real}}$) using Eq. (6). The simulation results and measured data are compared by the duration curve (load factor versus time), which is shown in Fig. 9(a) and Fig. 9(b). $K_{\text{nowake}(wif)}$ in Figs. 9(a) and 9(b) indicate the calculated load factor assuming the wind speed of each turbine is the same as turbine B10 (the turbine chosen for WIF correction). MSE is calculated between

Table 2

<table>
<thead>
<tr>
<th>Data classification according to influencing factors.</th>
<th>I (%)</th>
<th>II (%)</th>
<th>III (%)</th>
<th>IV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019/01-2019/12/31</td>
<td>32.88%</td>
<td>0.96%</td>
<td>25.78%</td>
<td>40.39%</td>
</tr>
<tr>
<td>2020/01-2020/12/31</td>
<td>32.88%</td>
<td>7.27%</td>
<td>15.29%</td>
<td>44.56%</td>
</tr>
</tbody>
</table>

Fig. 4. Flow chart to label the data type (I: icing; II: power curtailment; III: turbine availability; IV: wake effect).
the simulation and measurement result and shown in Tables A.7 and A.8.

Besides, the effect of WIF and Jensen wake model correction can also be seen from the comparison of the annual energy production (AEP) of each turbine, which is shown in Figs. 10(a) and 10(b).

3.4. Validation of turbine availability model

After the verification of WIF and the Jensen wake model, the turbine availability is involved to see its influence on the load factor prediction. The data (type II+III+IV) is used in this case to guarantee the time continuity of data in the calculation of failure and repair date. Next, the data (type III+IV) are used to verify the accuracy of the proposed turbine availability model.

3.4.1. BD model

According to the output \( n \) and \( Z \) derived from the algorithm shown in Fig. 2, the failure and repair rates of turbines for the BD model in these two years are calculated using Eqs. (12)–(14) and the results are shown in Table 3.

Based on the binomial distribution curve generated by Eq. (15), random number is generated in time sequence according to the constant turbine availability \( q \) to simulate the variation of the operational turbines. The new duration curve considering the constant turbine availability is included in Figs. 11 and 12. Considering that this model is used to size the transformer, more attention should be paid to when the load factor is higher than 0.5. Hence, partial enlarged view is given to the time range of 0%–15%. The MSE between the simulation and the measurement is shown in Tables A.7 and A.8.

3.4.2. Markov model

To consider the variation of turbine availability under different wind conditions, the wind speed is divided into low, middle and high state. The range of low, middle and high wind speed defined in Arwade et al. (2011) is based on the average daily wind speed. In this paper, the three variables are defined according to \( U_{\text{cut-in}}, U_{\text{rated}} \) and \( U_{\text{cut-out}} \) of the Vestas V90 power curve.

- \( U_L \): Low wind speed (4.0–9.0 m/s)
- \( U_M \): Medium wind speed (9.0–13.9 m/s)
- \( U_H \): High wind speed (13.9–25.0 m/s)

After classifying the data according to the wind speed, \( n \) and \( Z \) under different wind speed state can be counted using the algorithm shown in Fig. 2. The failure and repair rate of the turbines under low,
Fig. 9. Duration curve using WIF correction & Jensen model. in (a) 2019 (b) 2020.

Fig. 10. Annual energy production of individual turbine in (a) 2019 (b) 2020.

Fig. 11. Duration curve 2019 (a) nowake (b) wake.
Fig. 12. Duration curve 2020 (a) nowake (b) wake.

Fig. 13. Difference of duration curves between simulated cases and $K_{\text{real}}$ in 2019 (a) nowake (b) wake.

Fig. 14. Difference of duration curves between simulated cases and $K_{\text{real}}$ in 2020 (a) nowake (b) wake.
middle and high wind speed are calculated using Eq. (12), Eq. (13) and Eq. (14) and the results are shown in Tables 4 and 5. Using Eq. (17), the transition rates between \( U_L \), \( U_M \) and \( U_H \) are calculated and shown in Table 6. Random number is generated in time sequence according to the turbine availability \( q \) in each wind state to simulate the variation of the operational turbines. The new duration curve considering the changing turbine availability is included in Figs. 11 and 12. Since it is challenging to distinguish the curves due to the overlapping, the differences between \( K_{\text{nowake(wif)}} \), \( K_{\text{wake(wif)+BD}} \), \( K_{\text{wake(wif)+markov}} \) and \( K_{\text{real}} \) are plotted in Figs. 13 and 14.

### 3.5. Transformer lifetime estimation

The data of the ambient temperature is selected from the database of SMHI, measured by a station at Fredrika, which is closest to Stor-Rotliden. Using Eqs. (20), (21) and (22), the relative aging rate of the transformer insulation lifetime is calculated and shown in Figs. 15(a) and 15(b).

### 3.6. Discussion

Combining the layout of wind farm (SRL) in Fig. 5 and the WIF map in Fig. 6, it can be seen that the wake effect influences the wind power generation especially when the wind speed is in 5–12 m/s and the wind direction is in [120, 180] and in [300, 340] degree. The wind farm suffers more wake loss in 2019 since Fig. 7 shows a more even distribution of the wind rose in 2020 than in 2019.

The WIF correction and the wake model improves the accuracy of wind power prediction. It can be seen in Figs. 9(a) and 9(b) that the simulated duration curves \( (K_{\text{wake(wif)+markov}}) \) based on \( U_{\text{real}} \) fit the measured duration curve \( K_{\text{real}} \) better than the duration curve \( (K_{\text{wake(wif)+markov}}) \) based on \( U_{\text{avg}} \). Tables A.7 and A.8 also show that the WMSE between \( K_{\text{real}} \) and \( K_{\text{wake(wif)}} \) is the minimum. Besides, the simulated annual energy production (AEP) of each turbine fits better with the measured data in Figs. 10(a) and 10(b) after applying the WIF correction and the Jensen wake model.

It can be found in Figs. 9(a) and 9(b) that the wake effect reduces the load of WFETs and to some extent reduces the aging rate of WFETs according to Figs. 15(a) and 15(b). However, the influence of the wake effect is limited when the transformer is close to fully loaded. Hence, even the wake effect affects the aging rate, it is not the dominant factor influencing the HST of WFETs when the load is close to the installed capacity of the connected wind farms.

After considering the impact of the turbine availability using BD/Markov model, according to Figs. 13 and 14, the duration curve is corrected further. Combining with the MSE results shown in Tables A.9 and A.10, it shows that the simulation results using the Markov model fits the measured data better compared to the BD model since the BD model ignores the variation of turbine failure and repair rate. Tables 4 and 5 reflect that the correlation between the wind speed and the wind power generation is not strictly positive. High wind speed leads to a lower turbine availability compared to low or middle wind speed. The reduction of the operational turbines at high wind speed reduces the wind power generation and the load profile of the WFETs, especially when the wind speed satisfies the condition of generating power close to the installed capacity of the wind farm.

This finding is beneficial for the DTR application since the hot spot temperature of transformer increases sharply when the WFET is fully loaded or overloaded. The decrease of turbine availability at high wind speed mitigates the risk of overloading transformers.

As can be seen from Figs. 15(a) and 15(b), the crosspoint between \( V_{\text{nowake(wif)}} \) and \( V_{\text{rated}} \) indicates the transformer capacity would allow expansion of the wind farm by 63%. After considering the wake effect and turbine availability, the crosspoints between \( V_{\text{wake(wif)+markov}} \) and \( V_{\text{rated}} \) indicate that the installed capacity of the wind farm could be increased by 74%–77% (11%–14% more than the \( V_{\text{nowake(wif)}} \) case) in the expansion stage without causing the transformer aging rate higher than in the rated condition.

The inconsistency between \( K_{\text{markov}} \) and \( K_{\text{real}} \) can be due to the differences in operation and maintenance strategies between actual
implementation and the model’s assumption (e.g. the defined range of low, middle and high wind speed, numbers of crews). The inconsistency may also arise due to the finite states included in the Markov model.

4. Conclusion

This paper proposes a new methodology to estimate the transformer load profile based on wind speed to improve the underutilization issue of the wind farm exported transformers (WFETs). The case study and discussion show that it is critical to incorporate turbine availability as well as wake effect analysis in order to get an accurate estimation of the load of transformers. The correction method (WIF) can pre-process limited wind data to eliminate the measurement error caused by the wake effect. The Markov model outperforms the BD model in predicting transformer loads by effectively incorporating the variable turbine availability. However, the BD model maintains its utility, offering a simpler evaluation of turbine availability’s impact on load profiles due to its lower input requirements.

The results show that the changing turbine availability and the wake effect both reduce the aging rate of the WFETs, even the wake effect has limited influence when the transformer is close to fully loaded compared to the turbine availability. This methodology allows for a more accurate assessment of the aging rate of the existing transformers and the transformers in the planning stage. If components such as cables and breakers can be upgraded synchronously, it is possible to under-size the WFETs during the planning stage with the application of dynamic thermal rating. The WFETs can be better utilized based on a trade-off between economical cost and acceptable aging losses. After suitable parameter adjustments in the wake model, this methodology may also be applied to analyze the substation construction of offshore wind farms. As one of the heaviest components on offshore platforms, optimally rated export transformers help reduce construction costs and difficulty.

CRediT authorship contribution statement

Zhongtian Li: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Writing – original draft. Patrik Hilber: Project administration, Supervision, Visualization, Writing – review & editing. Tor Laneryd: Supervision, Writing – review & editing. Gonzalo Pablo Navarro Díaz: Resources, Writing – review & editing. Stefan Ivanell: Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix. MSE comparison


References

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