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Article

Iceland wind farm assessment case study and development: An empirical data from wind and wind turbine

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A R T I C L E I N F O

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A B S T R A C T

This study aimed to apply empirical data to assess wind energy production at the Búrfell site in Iceland based on the E44 turbine model. The empirical data are 5 years of recordings at the site location by the Iceland Metrological office. The wind speed data are measured at a 10 m height from 2017 to 2021. There are two E44 wind turbines test installed on the site. In the previous studies, the wind farm capacity and Levelized cost of energy (LCOE) were reported without investigating the wake loss model and its impacts on LCOE and have an estimation applied. The previous research was based on the two installed wind turbines at the site, which are located in a straight line and perpendicular to the prevailing wind speed. This study applies the Jensen-Katic model to investigate wake loss. Downwind and crosswind ten-rotor diameters and five-rotor diameters are calculated respectively as the best options. Afterward, an appropriate number of wind turbines is suggested for 80MW production. In addition, this study's optimum capacity factor (CF) is 26.08%, which was reported at 37.9% - 38.38% before. On average, the turbines produce less than 30% of their rated power, which has been reported at 38.15% in prior studies. This study presents the LCOE as equal to 0.0659 USD/kWh, which is less than 0.0703 USD/kWh in the previous studies and the LCOE reported by the 2020 LCOE European report. The obtained LCOE in this study is based on the weighted average cost of capital in the energy project by Landsvirkjun, the national power company of Iceland. The obtained result from the model used, which matched the empirical measurements, displays Iceland's best rank for wind energy LCOE metric among European countries. The proposed method provides a vision to use the wake loss model output in deep learning training to predict power production, leading to a sustainable and reliable power grid.

1. Introduction

Iceland is the most sustainable energy country in the world, profiting from geothermal energy and hydropower. Moreover, Iceland has an extraordinary wind energy source (Nawri et al., 2014) which will be the next alternative resource (Ragnarsson et al., 2015). There is ongoing practical research for wind production by Landsvirkjun, the national power company of Iceland, and universities. In a particular location called Búrfell, which has extreme wind potential and a nonlimited open area to construct a wind farm, two E44 wind turbines test have been installed (Ragnarsson et al., 2015). In prior studies, the recorded data from the mentioned site was employed to report the LCOE (Ragnarsson et al., 2015; Samuel et al., 2015); however, there was no technical aspect of the wind farm layout based on the wake loss model.

In research focusing on a single wind turbine performance, the calculation will provide the outcome for the highest-rated power, which causes considerable error in LCOE. Moreover, the single-performance wind turbine leads to incorrect downwind and crosswind distances, which will calculate the number of turbines in the wrong direction for a specific production. Ragnarsson et al. (Ragnarsson et al., 2015) have specified LCOE for the Búrfell site with these assumptions: seven-rotor diameter downwind and four-rotor diameter crosswind. But there has not been a consideration of the wake loss effect, which considerably impacts the LCOE and financial aspects.

Six well-known wake loss models are applied in wind farm layout: Jenson-Katic, Larsen, Frandsen, Gaussian-Bastankah, Porté-Agel (BPA), Gaussian-Xia and Archer (XA), and Geometric (Cristina et al., 2018). Jansen-Katic model (Jensen, 1983; Katic et al., 1987) is built based on two principal assumptions; first, the cross-stream integral of the velocity deficit is preserved because the wake expands linearly downstream of the wind turbine, and second, the velocity deficit is only a function of the distance x downstream of the turbine. Larsen (Larsen, 1988) has

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developed an analytical wake loss model using self-similarity and assuming that the wake region behind a wind turbine is defined via Prandtl turbulent boundary layers equations (Cristina et al., 2018). The Frandsen model (Frandsen et al., 2006) applies the momentum equation to a control volume by assuming self-similarity (Cristina et al., 2018). The Frandsen model, similar to the Jensen model, also assumes that the velocity deficit is only a function of distance x downstream of the turbine and that wind speed has a constant profile. The Frandsen module is recommended for small and large regular wind farms with rectangular shapes and spacing between turbines equal in both directions and lower than 10-rotor diameters (Cristina et al., 2018, Renkema, 2007). Gaussian is a category in wake loss models based on the assumption that the wind speed deficit δ follows a Gaussian distribution; thus, it is a function of both axial distance x and radial distance r (Cristina et al., 2018, Majid and Fernando, 2014, Xie and Archer, 2015). Two models were developed based on Gaussian distribution: BPA (Majid and Fernando, 2014) and XA (Xie and Archer, 2015). The BPA model is an explicit dependency on y and z, where y and z are the spanwise and vertical coordinates, respectively; the formation is such that it is effectively axis-symmetric. The XA wake loss model was inspired by the Gaussian plume model used in air pollution studies to simulate the evolution of a plume of inert pollutants from a stationary elevated stack. The XA model is the only wake loss model that is genuinely dependent on z and y as it predicts a wake that is not axis-symmetric or conical but ellipsoidal, which is a more realistic approximation, in particular in the presence of wind shear (Xie et al., 2017). A specific equation gives the wind speed deficit in the BPA and XA models. The geometric model (Ghaisas and Archer, 2016) is a hybrid wake loss model that estimates the relative power generated by any downstream turbine with respect to the power generated by the front-row turbines. It does not simulate the physical process occurring in wakes.

Among all described wake loss models, the literature well addressed the Jensen-Katic, and the XA models are generally recommended because of their consistently strong performance for all directions and all farms (Cristina et al., 2018). The Jensen-Katic is recommended for layout optimization with annual energy production because of satisfied performance in the correlation coefficient (Cristina et al., 2018). The literature mentions that the XA is suitable for the wake loss model along the direction of alignment (Cristina et al., 2018). The subject of this study is to apply a wake loss model for annual energy production and contrasts the model output with actual recorded data from test turbines. Hence, based on the mentioned studies, the Jensen-Katic model is used. Therefore, the model is employed to calculate the LCOE of the wind farm site to evaluate and correct previous reports, which did not consider the wake loss issue in the production and LCOE.

Furthermore, it must be noted that recently deep learning presents a strong capability in wind speed forecasting (Gu and Li, 2022), which is in context to essential for power producers to respond and cover the electricity demand. In deep learning, it is vital to have enough datasets available for a reliable prediction. Usually, the training dataset obtains from in-site measurements or computational fluid dynamics (CFD), which are costly and have many constraints. The proposed model in this study provides an output dataset in the kind of velocity and power applicable for training data in deep learning and is possible to implement without the necessity of in-site measurement or costly CFD simulation.

This study is done to supplement the wake loss model and farm layout to the previous reports (Ragnarsson et al., 2015; Samuel et al., 2015), and it has corrected the rated power of the E44 turbine and the LCOE on the mentioned site location. We used the Jensen-Katic model for the wind farm layout with the technical specifications of turbine E44, which this turbine was selected by Landsvirkjun, the national power company of Iceland. Landsvirkjun has installed two turbines E44 in the desired wind farm location for research and development.

Although, in a recent study Enercon E44 was the best option technically and financially (Samuel et al., 2015) instead of Enercon E82, which was suggested in 2012 and 2015 (Ragnarsson et al., 2015; Helgason, 2012). Hence this paper is organized as follows. The applied method is introduced in Section 2. The results and discussion are provided in Section 3, and the conclusion is presented in Section 4.

2. Methodology

2.1. Burfell site and measured data

Búrfell site is located south of Iceland (see Fig. 1). Two wind turbines of Enercon E44 900 KW have been installed at the site. In this study, wind speed data gathered from the Icelandic Meteorological Office were wind speed data measured at a 10 m height in the years 2017–202l (Data bank of Meteorological Office of Iceland, 2022); the measurement was conducted by using a “Young Wind Monitor”, which is a wind speed sensor with four blade helicoid propellers.

2,2. Logarithmic wind profile (log law)

The wind measurement is taken at the height of 10 m; however, the hub height of an E44 turbine is 55m (Enercon). Hence, the logarithmic wind profile (log law) in Eq. 1 is applied to scale the wind speed (Manwell et al., 2004; Hansen, 2019):

$$U(y) = \frac{U^*}{K_v} ln\left(\frac{y}{y_0}\right) \tag{1}$$

where U^* is defined as the friction velocity, y_0 is the surface roughness length, which characterizes the roughness of the ground terrain and y is the desired height, K_v=0.4 is von Karman’s constant.

The log law equation can be used to estimate wind speed from a reference height to another level using the following relationship (Manwell et al., 2004; Hansen, 2019):

$$\frac{U_h}{U_m} = \frac{\ln\left(\frac{y_h}{y_0}\right)}{\ln\left(\frac{y_m}{y_0}\right)} \tag{2}$$

where y_h is the hub height, y_m is measurement height, y_0 is the surface roughness length. The log law is a method for modeling the vertical wind speed profile, and it was developed for flat and homogenous terrain (Manwell et al., 2004). Regarding Búrfell, from visiting and Landsverkjun data (Burfellslundur), the terrain is a sand surface (see Fig. 2); however, the surface is covered by snow in the wintertime. From the roughness length (Hansen, 2019; Troen and Petersen, 1989), we applied the terrain as land with a closed appearance $y_0 = 0.1\ m$ to be able to cover both terrain surfaces. The results show that this terrain option is appropriate and provides the wind speed profile and, thus, power output E44 wind turbine, which matches the experiment measurement at the site. Besides the corresponding result, from (Gu and Li, 2022) the land with few trees matches the site condition in actual view with similar terrain roughness to the selected one. From Eq. 2, the scale factor is obtained and leads to the value of the mean wind speed $\bar{U}$ and standard deviation σ_U of the wind speed.

2,3. Weibull distribution and wind rose

Statistical analysis can be used to determine a given site’s wind energy potential and estimate the wind energy output at this site. If the projection of measured data from one coordinate to another is required or only summary data are available, then analytical representation for the probability distribution of wind speed has distinct advantages (Manwell et al., 2004).

Generally, two probability distributions are used in wind data analysis: Rayleigh and Weibull. The Rayleigh probability density function uses one parameter, the mean wind speed. The Weibull distribution function is based on two parameters and thus can better represent a wider variety of wind regimes (Manwell et al., 2004). In this study, we applied the Weibull probability density function.

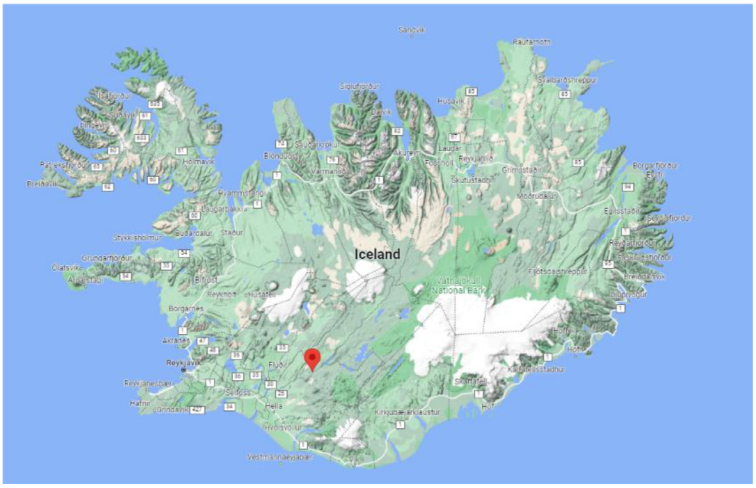

Fig. 1. Location of the Búrfell site in Iceland, Latitude: 64° 7′ 39”, Longitude: -19° 43′ 43.6" coordinates at a geographic coordinate system from the Icelandic Metrological Office (The wind power).

Fig. 2. A landscape of Búrfell wind park, two E44 turbines are seen in this picture (Rúnar et al., 2016).

Determination of the Weibull probability density function requires a knowledge of two parameters: k, a shape factor, and c, a scale factor. Both these parameters are a function of $\bar{U}$ is the mean wind speed from the scaled data, and σ_U is the corresponding standard deviation. The gamma function, Γ, is used to find the constant c. The Weibull probability density function is given by (Manwell et al., 2004):

$$p(U) = \left(\frac{k}{c}\right)\left(\frac{U}{c}\right)^{k-1} exp\left[-\left(\frac{U}{c}\right)^{k}\right] \tag{3}$$

where based on the empirical method (Justus, 1978) (Manwell et al., 2004) k calculated as follows:

$$k = \left(\frac{\sigma_U}{\bar{U}}\right)^{-1.086} \tag{4}$$

and thus, c can be calculated via Eq. 5:

$$c = \frac{\bar{U}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{5}$$

as a recap, the gamma function is, $\Gamma(x) = \int_0^\infty e^{-t} t^{x-1} dt$.

Eqs. 3-5 are used in this study to obtain the Weibull probability density function, which is presented in the result section. The wind rose is applied in this study to find the prevailing wind speed direction. The wind direction is sorted into 12 bins ranging from 0 to 360 degrees: 30 degrees per bin and the probability of each bin is calculated.

2.4. Wind farm configuration and wake loss model

Landsvirkjun, the National power company of Iceland, has considered and suggested three areas called plans 1, 2, and 3 (Rúnar et al., 2016). These areas have distinct spaces varied from 33 to 40 km^2. The plans investigation has included the technical, capacity, financial and environmental assessment. In this study, we apply area plan 1, which has 34 km^2 (see Fig. 3). First, the long edge of the area is orientated along the prevailing wind speed direction, which will be represented in the results section. Second, the site has overlap space covered with two other plans, which makes this study result applicable in the two plans to extend the downwind distance, undoubtedly leading to increased power rate and reduced wake loss. However, the selected area must meet other requirements, particularly environment assessment, which is not the subject of this study.

The area approximately has a rectangular shape. The site's dimensions have about 10 km long edge and a 3.4 km short edge, which is a fair assumption to apply the Jensen-Katic wake loss model. It must

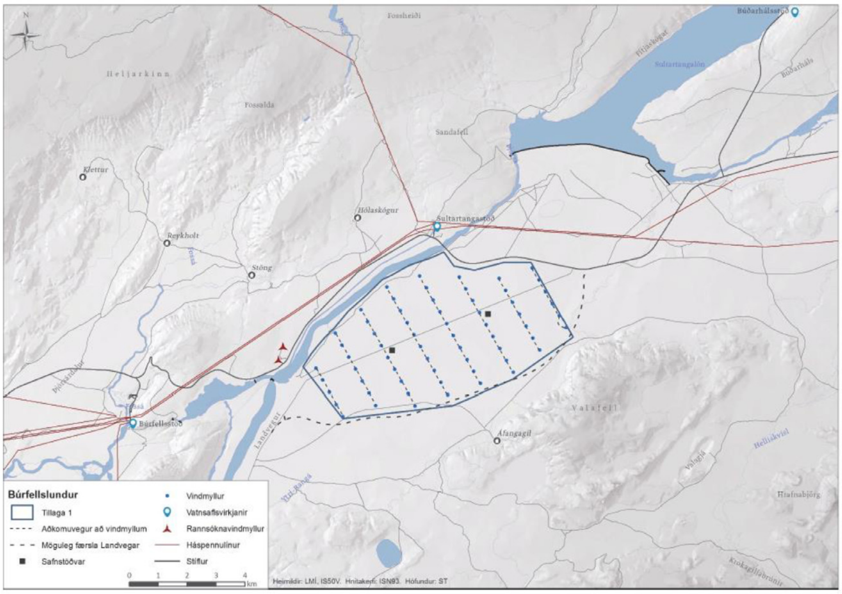

Fig. 3. The area for the Búrfell wind farm is called plane 1. The three area options suggested by Landsvirkjun feasibility study vary from 33 to 40 km^2 of space. In this study, we apply plane 1, which has a 34 km^2 area (Rúnar et al., 2016).

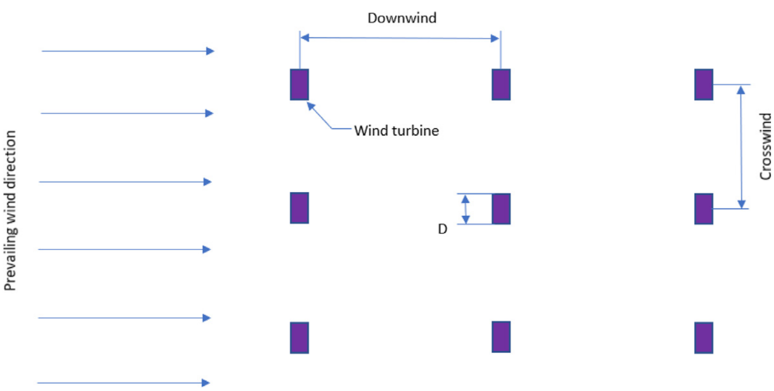

Fig. 4. Draft of the configuration of the wind farm. Note only a limited portion of the farm is displayed

be noted that the area is nonlimited by obstacles, and this assumption provides us with the downwind and crosswind along the long and short edges, respectively.

The wind farm is set up in a rectangular pattern primary assumption, as Fig. 4 depicts. The literature has reported that the wind farm configuration with 8–10 rotor diameters, D, in the downwind direction and 5 rotor diameters in the crosswind direction results in array losses below 10% (Manwell et al., 2004). Therefore, a crosswind spacing of 5D is chosen, but the analysis based on the Jensen-Katic wake loss model has taken five downwind spacing: 8D, 8.5D, 9D, 9.5D, and 10D, and optimal spacing is determined. The rotor diameter of the E44 turbine is 44 m (Enercon), the crosswind spacing is thus 220 m, and the downwind ranges from 352 m to 440 m.

In this study, we employed the Jensen-Katic wake loss model. Based on this model, the diameter of the wake grows linearly with distance from the rotor, see Fig. 5. The local velocity deficit, δ, at a distance X from the rotor is described with the following equation (Manwell et al., 2004; Hansen, 2019):

$$\delta = 1 - \frac{U_X}{U_0} = \frac{1-\sqrt{1-C_T}}{\left(1+2q\frac{X}{D}\right)^2} \tag{6}$$

where q is the decay constant, C_T is the trust coefficient, which can be derived from the axial induction factor as follows:

$$a = \frac{1}{2}\left(1-\sqrt{1-C_T}\right) \tag{7}$$

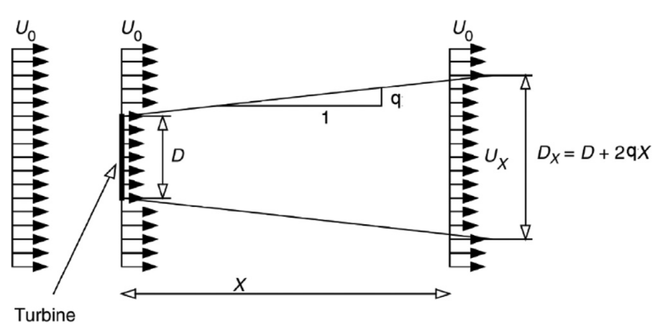

Fig. 5. Schematic view of the Jesen-Katic wake loss model. Where U_0 is the initial free stream velocity, D the turbine diameter, U_X the velocity at a distance X, D_X, wake diameter at a distance X, and q the wake decay constant (Manwell et al., 2004).

This study has taken $a = 1/3$ (Manwell et al., 2004), which resulting in $C_T = 0.89$. Wake decay constant, q, is a function of numerous factors, including ambient turbulence intensity, turbine-induced turbulence, and atmospheric stability. Katic notes that q=0.11 is appropriate for the downstream turbine (Manwell et al., 2004).

Jensen-Katic wake loss model assumes that the local velocity deficit for each turbine in a row is calculated independently with Eq. 6. The total deficit for each turbine has been calculated as a sum of squares of the local deficit upwind to the turbine, which is described with the

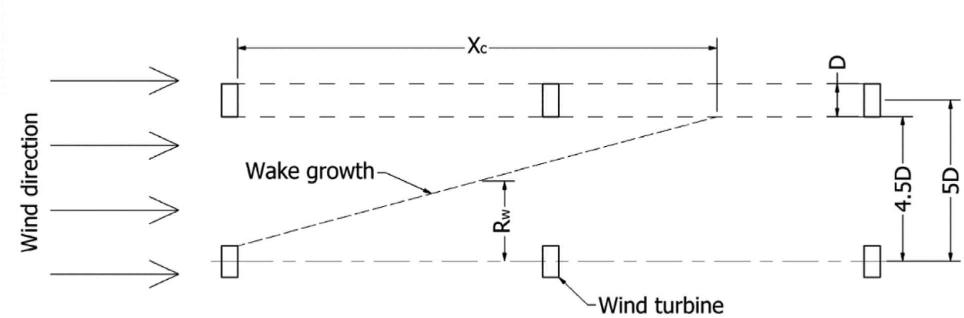

Fig. 6. Schematic drawing of the wake growth between turbine rows

equation below:

$$\left(1-\frac{U_X}{U_0}\right)^2=\left(1-\frac{U_{X,1}}{U_0}\right)^2+\left(1-\frac{U_{X,2}}{U_0}\right)^2 \tag{8}$$

The total velocity deficit, ξ, for the n-th turbine is thus:

$$\xi_n=\sqrt{\sum_{i=1}^{n}\delta_i^2} \tag{9}$$

and the velocity at the n-th turbine is given as $U_n=U_0(1-\xi_n)$.

Row independence is determined first by applying the wake model to the whole wind farm; thus, the wake of one row affects the neighboring row. As previously mentioned, the wake's diameter, and hence the radius, expands linearly with distance from the rotor. Since the rows are spaced 5D apart, the wake from one row will interact with its neighboring rows once the radius of the trailing wake, R_w, becomes 4.5D, as Fig. 6 illustrates. The radius of the wake is described with the following equation:

$$R_w=\frac{D}{2}+qX \tag{10}$$

where D is the rotor diameter.

The average production of turbines in wind farm configuration will be specified and will use to calculate the capacity factor (CF) via the following equation (Manwell et al., 2004; Hansen, 2019):

$$CF=\frac{\bar{P}}{P_{name}} \tag{11}$$

where $\bar{P}$ is the average power production, and P_{name} is the nameplate production, which is 900kW for the E44 turbine (Enercon). The ratio of operating time for the turbines is assumed to be 0.97.

2.5. Levelized Cost of Energy (LCOE)

The Levelized Cost of Energy (LCOE) criterion is defined by the International Renewable Energy Agency and is a widely used indicator for comparing and evaluating energy technologies. The LCOE measure is defined as the cost value of an energy project at the time of construction divided by the current value of all energy produced during the project's lifetime. LCOE is a helpful tool for comparing different energy technologies and assuming 25 years of operation. The equation for LCOE is (Manwell et al., 2004):

$$LCOE=\frac{\sum_{n=0}^{N}\frac{I_n+M_n+F_n}{(1+d)^n}}{\sum_{n=1}^{N}\frac{Q_n}{(1+d)^n}} \tag{12}$$

where I_n is the initial capital expenditure (ICE), M_n is the maintenance and operation costs (MOC), F_n is fuel costs, which is negligible in this case, d is the weighted average cost of capital (WACC), and Q_n is the total annual production (TAP) in year n. In the LCOE calculation, energy production in the planned lifetime is crucial, and therefore it is essential to provide a valid estimation and simulation of the project in energy production. In the wind farm, the wake loss model has a considerable effect, and it is essential to assess its effects. In this context, this study considered the LCOE of a wind farm project in the specified site in Iceland in the presence of a wake loss model. The examination presents different results in contrast to previous studies that only considered the rated power production of a single wind turbine without wake loss.

Table 1
Mean and standard deviation from wind speed data from 2017 to 2021, before and after height scaling

Height, m	Mean Velocity, m/s	Standard Deviation, m/s
10	6.80	4.30
55	9.32	5.89

3. Results

3.1. Wind speed

Based on log law Eq. 2, the wind speed scale factor is 1.37 for wind speed data used in this study, which dictates a 37% increase in velocity in the turbine E44 hub relative to the measurement height. Table 1 shows the changes in mean and standard deviation, and Fig. 7 displays the logarithmic wind profile.

We used mean velocity and standard deviation from Table 1, and the constants k and c were calculated to equal 1.674 and 10.427, respectively. The achieved Weibull probability distribution curve is presented in Fig. 8. Regarding the prevailing wind direction, the wind rose is illustrated in Fig. 9. For the wind rose, 0 degrees are defined to the east, and a counterclockwise is considered positive. The primary wind speed direction from 5 years of measured data is between 30 and 60 degrees or Northeast. Búrfell site, based on plan 1 considered and suggested by Lansdvirkjun, has a long edge oriented to the prevailing wind speed direction and a short edge approximately perpendicular to the wind speed direction. Therefore, the area has a desired condition to specify wind turbine layout and optimized power production.

Based on the given wind data, each wind speed is linearly interpolated with the power production data to determine the power production of a wind turbine. The power curve for an E44 turbine is applied (see Fig. 10) (Enercon). For the given wind speed data, the average production of an E44 turbine is calculated as 387.3 kW, so to achieve an annual average of 80 MW, 206 turbines would be required. But this estimation is without the wake loss impact, which is highly reduced production when it is taken into effect—the applied method calculated the average output as 387.3 kW, which means 43.03% capacity factor. The onsite measurement for two installed turbines, the capacity factor from February 2013 to January 2014, has been reported in the range of 37.28%–40.39% (Ragnarsson et al., 2015), which shows that our model provides significantly similar CP.

3.2. Wind farm layout

From Eq. 10, the critical distance in a downstream direction where the trailing wake starts interacting with the neighboring rows and makes

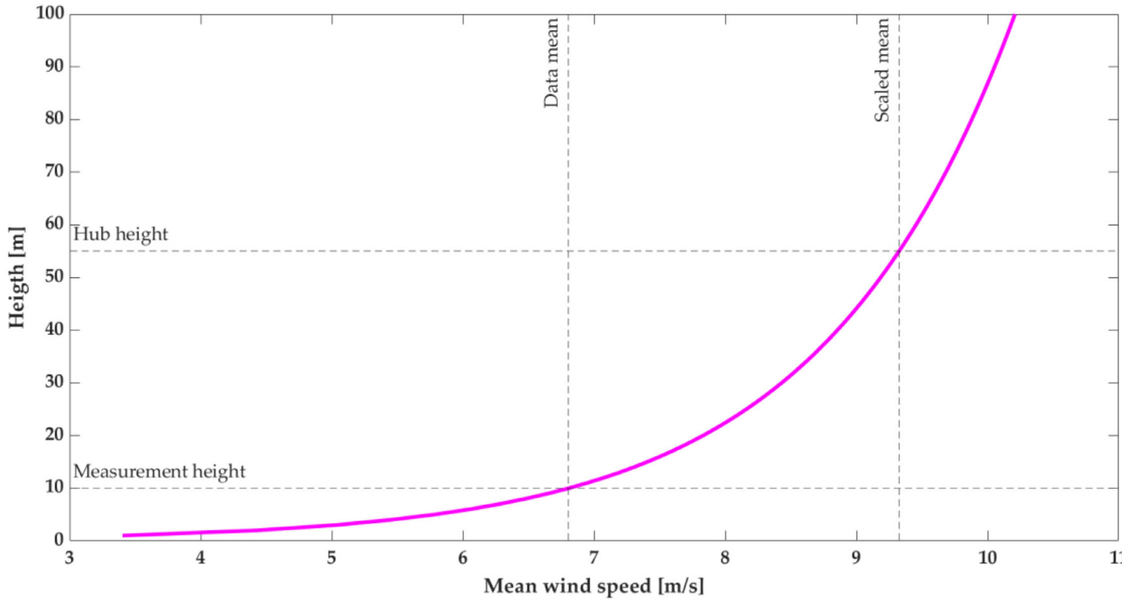

Fig. 7. Logarithmic wind profile considering a sand surface roughness of 0.1 m

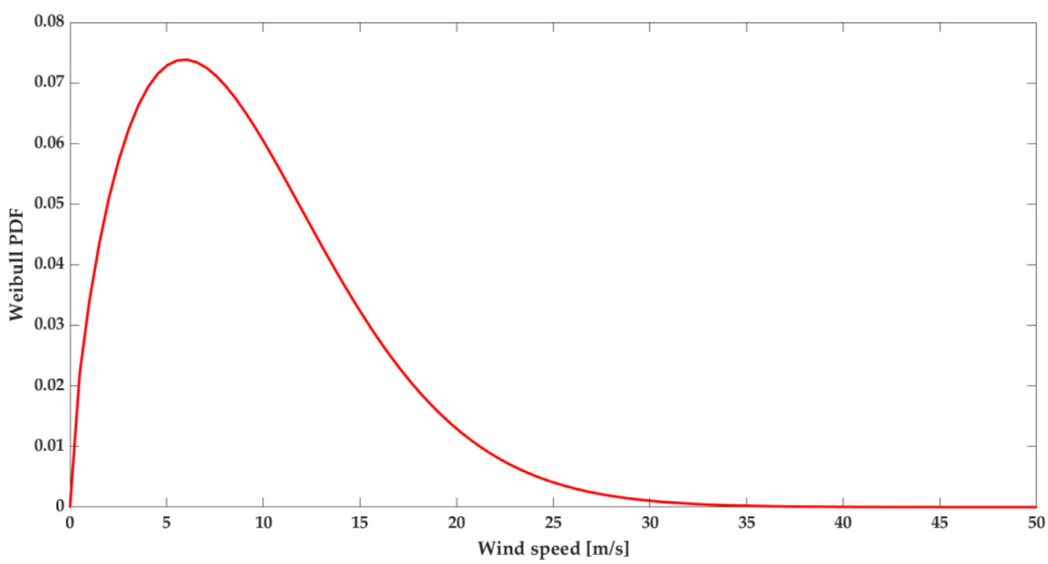

Fig. 8. The Weibull probability distribution for the scaled wind speed

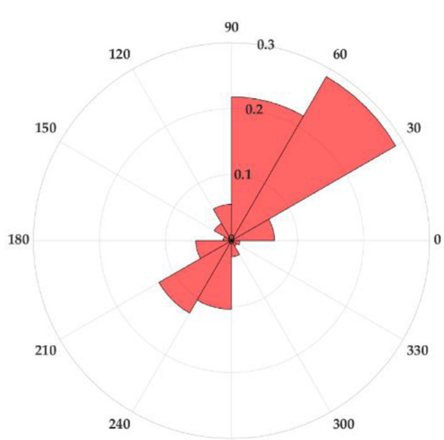

Fig. 9. The wind rose to display the probability of each wind direction bin

to velocity deficit is 1600 m. The calculation from Eq. 6 represents the velocity deficit of 0.82%, which could be considered negligible, making it possible to assume the wind turbine rows are independent of each other.

This study looks for a layout design with an optimized distance between wind turbine rows. Based on the determined assumption for the independent wind turbine rows, the production calculation is applied to a single row, and thus the number of rows in the defined area will determine the possible production. For each row, the power for a given wind speed is specified via an interpolation function. In each row, the first turbine has the maximum possible power rate, but from the second wind turbine to the end of the row, the power rate of each turbine is affected by velocity deficit based on the Jensen-Katic wake loss model in this study.

To illustrate a downstream distance variation, we calculated the average production per turbine in a row, and Table 2 displays the result. Fig. 11 shows how the average power production in a row reduced with a shorter distance downwind. The results mention layout configuration

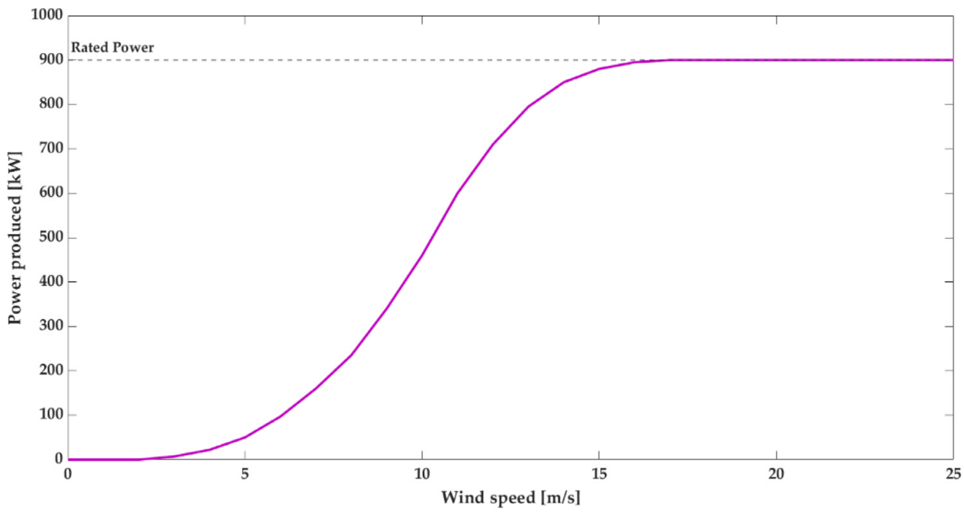

Fig. 10. E44 Turbine power curve (Enercon)

Table 2
Results from production calculations for each downwind spacing analyzed, showing average and total production per row, number of rows and turbines needed, and total production of the windfarm layout

Downwind spacing	Turbines per row	Average production per turbine in a row [kW]	Total production per row [kW]	Number of rows to achieve 80MW	Total number of Turbines	Total production [MW}
8D	28	200.88	5.62	15	420	84.4
8.5D	26	210.72	5.48	15	390	82.2
9D	25	219.18	5.48	15	375	82.2
9.5D	23	227.60	5.23	16	368	83.8
10D	22	234.73	5.16	16	352	82.6

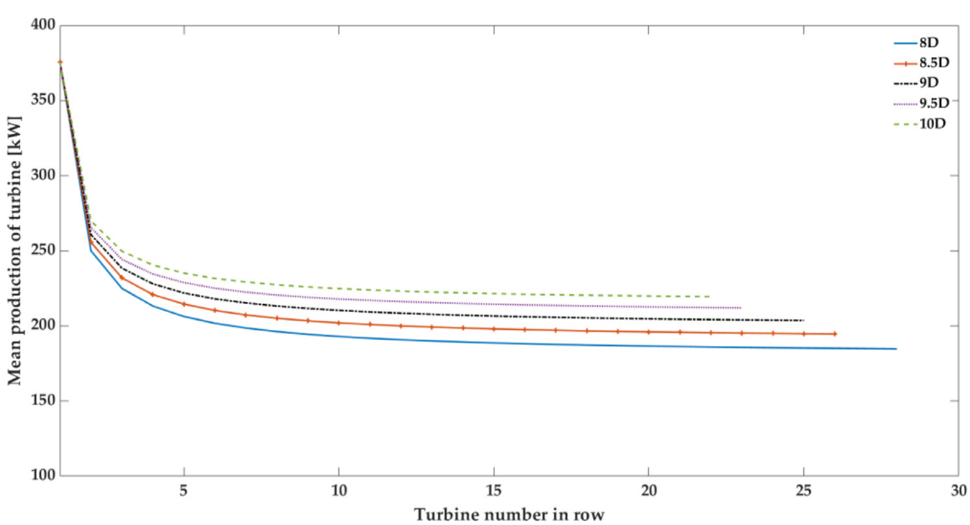

Fig. 11. Mean production of each turbine as a function of turbine number, turbine number 1 being the front wind turbine

Table 3
The capacity factor for average production per row

Downward spacing	8D	8.5D	9D	9.5D	10D
CF	0.2232	0.2341	0.2435	0.2529	0.2608

with a 10D downwind distance will provide much better power. This study suggested the layout in Table 2 with 80MW production. The capacity factor (CF) corresponding to each investigated layout configuration is presented in Table 3. The results for capacity factor show the turbines produce less than 30% of their related power on average. Table 4 shows how the spatial configuration occupies the available land for the total production of 80MW.

3.3. LCOE for Búfrell layout configurations

LCOE is a reliable index to assess an energy project's feasibility. According to Eq. 12, gathering financial information regarding the project's construction, commissioning and maintenance are necessary. The inflation rate is affecting the project cost, which has been taken into assessment. Based on the information regarding two E44 wind turbines installed and commissioned, the cost data have been acquired from Landsvirkjun. The reported data from 2014 are composed of 2299 USD/kWh for ICE and 0.015 USD/kWh for OPM. To update the project cost information, we used the inflation rate from Hagstofa Íslands (Statistics Iceland) from 2014 to 2021. The up-to-date project cost for this evaluation is investigated by ICE=2800 USD/kWh and OPM=0.018 USD/kWh (Ragnarsson et al., 2015). The project time life is assumed to

Table 4
Land utilization for the different configurations analyzed

Downwind spacing	Number of rows	Cross distance [m]	The ratio of available land utilized
8D	15	3300	0.97
8.5D	15	3300	0.97
9D	15	3300	1.03
9.5D	16	3520	1.03
10D	16	3520	1.03

Table 5
Levelized Cost of Energy according to different configurations analyzed

Option	Number of wind turbines	TAP[MW]	LCOE, d=6%	LCOE, d=10%
1	420	84.4	0.0659 USD/kWh	0.0894 USD/kWh
2	390	82.2	0.0659 USD/kWh	0.0894 USD/kWh
3	375	82.2	0.0659 USD/kWh	0.0894 USD/kWh
4	368	83.8	0.0659 USD/kWh	0.0894 USD/kWh
5	352	82.6	0.0659 USD/kWh	0.0894 USD/kWh

be 25 years, and for these 25 upcoming years, the inflation rate will affect the OPM (Ragnarsson et al., 2015). The average of the current eight years inflation rate in Iceland was calculated at 2.5%, which is applied as the annual inflation rate for the following years. The European wind projects determine WACC is 10% (Ragnarsson et al., 2015); however, Landsvirkjun in Iceland applies it equal to 6% (Ragnarsson et al., 2015). To compare this project to the European rate, both WACC is calculated and reported in Table 5. Total annual production is varied depending on the site configuration, and Table 5 mentions the LCOE of the Búfrell site based on suggested layouts.

This study employed a wake loss model to set up the wind farm layout and investigate power production. Previous studies have applied a few assumptions which have impacted the results severely, and we are listing literature assumption and their effects:

- The capacity factor has been used equally to the CP of two E44 wind turbines installed, but we must notice that the applied CP is without wake loss effects for a single wind turbine, and it is well known the wake impacts the CP extensively.
- The E44 test turbines' CP measurements are modified and scaled for an E82 wind turbine. First, it is crucial to notice that E82 has a larger rotor diameter than E44, which directly affects the wake loss model and changes in the CP amount. (E82 rotor diameter is 82 m) (Xie and Archer, 2015). Hence, the ICE and OPM for an E44 wind turbine for the test turbine could not be used for the E82 wind turbine project without an accurate correction factor because E82 has a much higher height (hub height 78 m) than E44, which will make distinct cost effect. Regarding the OPM, there are similar issues that must be taken into consideration.

As mentioned above, having a correct LCOE calculation first must simulate the wind farm with the effect of the wake loss model. It is apparent that the rated power of a single wind turbine is far from actual power production in a wind farm with a number of turbines and wakes loss effects. In this study, the wake loss model application indicates the optimum capacity factor (CF) is 26.08%, which was reported at 37.9% - 38.38% in the previous study (Ragnarsson et al., 2015). Moreover, the turbines produce less than 30% of their rated power, which has been reported at 38.15% in prior studies (Ragnarsson et al., 2015). From a previous study with WACC=10%, the LCOE is calculated at 0.0873 USD/kWh. Furthermore, the previous work reported 5% and 20% wake loss impact assumptions taken into consideration without modeling and simulation; the LCOE will be 0.0907 USD/kWh and USD 0.1047 USD/kWh, respectively. With the Jensen-Katic model, which is a reliable method, current study displays LCOE as 0.0659 USD/kWh. The impacts of wake loss are considerable and apparent in calculated characteristics.

4. Conclusions

In this study, we applied empirical data from wind speed measured from 2017 to 2021 at the 10 m height at the Búrfell location, which has two E44 turbines installed by Landsvirkjun, the national power company of Iceland. We modified the wind speed profile by log law and obtained the mean velocity and standard deviation at the hub height of the E44 wind turbine. Weibull probability function and the prevailing wind speed direction are also specified. Based on the applied method, the wind power production capacity factor is calculated by the technical specification and power curve of the E44 wind turbine. The calculated CF is 43.03% which considerably matches the CF measurement from two wind turbines installed at the location from February 2013 to January 2014 in the range of 37.28%–40.39% (Ragnarsson et al., 2015) and dictates the applied method and the surface roughness selected in this study could be used to design this wind farm. In the context of wind farm design and wind power production, wake loss is a crucial issue. Previous studies for the nominated location applied an individual power production of an E44 turbine to calculate the wind farm capacity, and they assumed the production equal to how many wind turbines with a nominal power rate. However, wake loss is a critical issue and impacts the wind production rate. This study applied the Jensen-Katic model to examine the wake loss effect on the wind turbine power rate. The result shows that with a 5D crosswind and 10D downwind design, the wind farm layout can be an optimized design for power production based on this study's modified wind speed profile. The optimized capacity factor is 26.08% which is lower than CP reported in the previous research at Búrfell without wake loss examination. It leads to different numbers of wind turbines producing a specified total power production. The investigated site, with plan 1 specification from Landsvirkjun, can produce 80 MW power with 352 of E44 wind turbines and will cover 103% of the area space with an optimized design.

With financial data from installed turbines and economic factors, particularly inflation, the LCOE of a potential wind farm was examined via this design for 25 years. The results show for optimized design, if WACC is 10% applied from European projects, the LCOE is 0.0894 USD/kWh, and with WACC=6%, which Landsvirkjun often takes in Iceland, the LCOE is 0.0659 USD/kWh. The obtained LCOE, in contrast to the European report in 2020 with WACC= 10%, is lower (Ragnarsson et al., 2015), and it is displayed that Iceland has excellent technical and economic conditions to produce wind power technically and economically. However, the WACC of Landsvirkjun is 6%, leading to a much lower LCOE than the European metric.

The applied approach in most results matches the empirical measurement, which makes this model applicable to predicting power production. This study provided a wind speed profile model analogous to experiment measurement.

Recently, deep learning has been applied to turbulent flow Hassanian et al., 2022, and the assessment indicates it can predict the fluid flow Hassanian et al., 2022. Since wind speed is in the range of turbulent flow Hassanian et al., 2023, it is a crucial issue that power producers must have wind speed forecasting to be able to respond to the demand for electricity. This topic has been investigated for an extended period and is still ongoing. The matter in deep learning to have a reliable prediction is the recorded input data to train the model and predict. Besides, the period of the recorded data is a practical subject to have enough data. Deep learning in wind energy production has been used in many studies from in-site measured data, but the wind speed measurement in every coordinate and condition deals with many constraints.

In this study, the applied wake loss model generated wind speed data in different coordinates that have been matched the actual data. Hence, this approach could create a data set with a specific period, employ it as input data in deep learning, and conduct wind power forecasting for the power producer. It is not essential to measure the wind speed for every single turbine or the wind speed at the turbine blade height. The only requirement characterization is the average speed in a determined height and then using the proposed method to create datasets for a wind farm as input of deep learning. The planned future study will aim to investigate and present this capability.

Therefore, it is possible to employ the model to predict the wind speed via artificial intelligence (Gu and Li, 2022), such as Long short-term memory, convolutional neural networks, and Gated Recurrent Units, which are capable of creating appropriate production for sequential datasets based on recent applications (Gu and Li, 2022). Truly wind speed prediction model in wind energy power leads to a sustainable power grid that has considerable outcomes in clean, stable, green, and reliable energy resources. Artificial intelligence has been opened an exciting landscape in wind forecasting, which is a function of training input datasets; hence study in this area to reinforce the deep learning training data from arithmetic models besides practical measurements and CFD simulation is essential and effective.

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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.

CRediT authorship contribution statement

Reza Hassanian: Conceptualization, Methodology, Software, Data curation, Visualization, Writing – original draft. **Ásdís Helgadóttir:** Writing – review & editing. **Morris Riedel:** Resources, Writing – review & editing, Supervision.

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Conflict of Interest

The authors declare no conflict of interest.

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