A study of onshore wind turbine spatial arrangement in Thailand

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ABSTRACT

This study examines the impact of wind turbine spatial arrangement on electricity generation efficiency in onshore wind energy farms within Thailand's meteorological and geographical context. An empirical analysis was conducted on 20 operational wind energy farms representing approximately 96% of Thailand's installed onshore wind capacity. Geographic information system (GIS) techniques were applied to measure the spacing and layout of the turbines, and the National Renewable Energy Laboratory's (NREL's) system advisor model (SAM) was employed to simulate the amount of electricity generated each year, considering wake effects, terrain, and site-specific wind resources. Capacity factors were calculated and compared against operational data. Results indicate capacity factors range from 16.34% to 31.32%, with a mean of 23.34%. Research reveals that wind turbine spacing is not the primary determinant of wind energy farm performance in Thailand. When the wind resources and site characteristics are good, the wind energy farms can have good performance from many different spacing setups. On the other hand, layout optimization by itself can't make up for bad wind conditions. These findings demonstrate the need for a more comprehensive design for wind energy farms in areas with moderate wind resources.

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1. INTRODUCTION

The transition toward renewable energy sources in Thailand has accelerated dramatically in recent decades [1], driven by concerns over climate change, energy security, and sustainable development [2]. Wind energy, in particular, has emerged as one of the most cost-effective renewable technologies [3]. Thailand has ambitious targets to increase the share of renewables in its energy mix to 30% by 2037 [1]. Onshore wind energy represents a significant component of Thailand's renewable energy strategy. However, wind energy remains a relatively underutilized resource with significant untapped potential, while solar photovoltaic systems have dominated Thailand's renewable energy expansion [4]. Thailand's onshore wind energy sector faces unique challenges, including spatially uneven wind resources, predominantly low-to-moderate wind speeds at wind turbine hub heights, and complex terrain characteristics that influence wind flow patterns and wind turbine performance [5].

The spatial arrangement of wind turbines, which includes the positioning, spacing, and orientation of turbines within a wind energy farm, serves as a critical factor for overall performance. This importance arises largely from the physical phenomenon of wake effects. When downstream turbines operate in the disturbed airflow created by upstream turbines, the system experiences significantly reduced energy capture and increased mechanical stress on turbine components [6], [7]. Research indicates that poorly designed layouts can result in efficiency losses of 10% or higher, depending on specific site conditions and wind patterns [8]. On the other hand, designing efficient wind turbine layouts can increase power output without additional costs [9]. However, the complexity of optimizing onshore wind energy farm layouts arises from multiple physical factors. A primary technical challenge involves the wake effect, where downstream turbines experience reduced wind speeds and increased turbulence. Terrain effects influence wind flow patterns and turbulence intensity [10]. Also, seasonal and diurnal variations in prevailing wind direction affect the determination of optimal turbine positioning [11].

A critical challenge for wind energy farm development worldwide is the substantial gap between simulated pre-construction predictions and actual operational performance. Recent validation studies document systematic discrepancies. Prediction errors range from 5% to 28% in capacity factors across diverse wind regimes [12], [13]. These errors arise from multiple compounding sources [14].

Wind speed errors reach 45% and uncorrected capacity factor errors range from 30% to 50% at sites with complex terrain [15], [16]. Grid curtailment constraints also materially reduce realized generation under technical potential [17]. In addition, pre-construction simulation models systematically overestimate actual operational capacity factors by 2.5% to 11.5% [13]. These losses include availability degradation, electrical losses, and environmental effects. Consequently, the relative contribution of spatial arrangement versus other factors remains poorly understood. These factors include topographic complexity, wind resource quality, and grid integration constraints. This knowledge gap is particularly evident in tropical moderate-wind regimes like Thailand, where systematic validation studies are scarce.

Despite extensive international research on wind energy farm layout optimization, there remains a significant knowledge gap regarding spatial arrangements for Thailand's specific meteorological and geographical conditions. Most previous studies on wind energy in Thailand focus on wind resource assessment and wind turbine technologies. While Thailand has developed several onshore wind energy farms, particularly in the southern and northeastern regions, systematic studies examining the effect of spatial arrangement on the electricity generation efficiency of wind energy farms in Thailand are scarce.

To fill the gaps, this research investigated the wind turbine spatial arrangement and electricity generation efficiency of the 20 onshore wind energy farms in Thailand. Their total installed capacity is 1,447 MW, whereas current total installed capacity of all wind energy farms in Thailand is 1,504 MW [1]. Therefore, the results of this research can be representative of wind energy farms in Thailand. This study provides empirical evidence for best practices in wind energy farm design and offers practical recommendations for future wind energy development in Thailand and similar tropical climates. The study contributes to the growing body of knowledge on renewable energy optimization and has direct implications for energy policy, investment decisions, and sustainable development planning.

2. THE COMPREHENSIVE THEORETICAL BASIS

2.1. The importance of spatial arrangement of onshore wind energy farms

The spatial arrangement of wind turbines within an onshore wind energy farm is a critical determinant of overall electricity generation efficiency and economic viability. Onshore wind energy farm layout optimization can result in substantial wake losses, where downstream turbines operate in the disturbed flow created by upstream turbines, leading to reduced power output and increased mechanical stress. Research consistently demonstrates that wake effects can account for significant total energy losses in wind energy farms, representing a vast amount of foregone revenue over a wind power project's lifetime [18], [19]. Wind turbine layout optimization involves determining the optimal positions and configurations of turbines to maximize energy capture while minimizing wake interference, land use conflicts, and operational costs. This multidimensional optimization problem is particularly complex in Thailand's context, where moderate wind resources necessitate maximizing every percentage point of electricity generation efficiency to achieve economic viability. The spacing between wind turbines, their alignment relative to prevailing wind directions, wind turbine hub height variations, and terrain interactions significantly influence the performance of a wind energy farm [20].

2.2. Wake effects and their impact

Wake effects represent the critical aerodynamic physical phenomenon governing wind energy farm performance. When wind flows through an upstream turbine, it generates a velocity deficit and higher turbulence intensity in the downstream area. This formation creates a wake zone where subsequent turbines experience reduced wind speeds and increased mechanical loading [21]. These regions of reduced wind speed and elevated turbulence extend kilometers downstream. A single turbine can reduce wind speed by 30% to 50% immediately downstream, and these effects persist for 10 to 20 rotor diameters (D_T) before atmospheric turbulence restores the flow [22]. The physical mechanisms that control wake behavior include turbulence mixing, atmospheric stability, and geometric spacing. Furthermore, simulations demonstrate that turbine spacing and layout configuration significantly influence wake recovery through vertical kinetic energy flux. Studies on wind energy farm layout optimization provide evidence that strategic spatial rearrangement can reduce wake losses by 2% to 3% compared to conventional layouts [23]. Comprehensive reviews of analytical wake models indicate that energy production estimates can vary by several percentage points [24], [25]. Therefore, accurately modeling these wake interactions is essential for layout optimization because wake losses typically reduce wind energy farm output by 5%–20%, depending on configuration and site conditions.

2.3. Onshore wind turbine spacing requirements and wind energy farm layout configurations

A review of the literature reveals consistent patterns regarding spacing requirements and configuration. For streamwise spacing, conventional practice employs a distance of 5 to 10 D_T in the direction of the predominant wind. The value of 5 D_T represents a conservative baseline that balances wake losses against land use efficiency [26]. Research indicates that spacing under 5 D_T results in substantial wake losses, whereas spacing beyond 10 D_T provides diminishing returns in wake recovery. In terms of crosswind spacing, a lateral distance of 3 to 5 D_T is typical. It is also permissible to use closer spacing when turbines are not aligned with the prevailing winds [27]. Nevertheless, industry practice has converged on general wind turbine spacing guidelines based on empirical experience and modeling studies. The most commonly cited recommendations suggest a minimum wind turbine spacing of 2 to 3 D_T to avoid extreme wake effects. Moreover, according to previous studies on onshore wind energy farm layout patterns [28], [29], the comparative studies of aligned, staggered, and triangular layouts demonstrate that staggered and triangular configurations generally outperform aligned grids by reducing wake overlap. Staggered layouts can maximize land-use power density while maintaining acceptable wake losses. The previous study also reveals that non-uniform hub heights (hub height variation) can exploit vertical wind shear and reduce wake interference in complex terrain [30]. Figure 1 presents a typical layout of an onshore wind energy farm, as described in the literature.

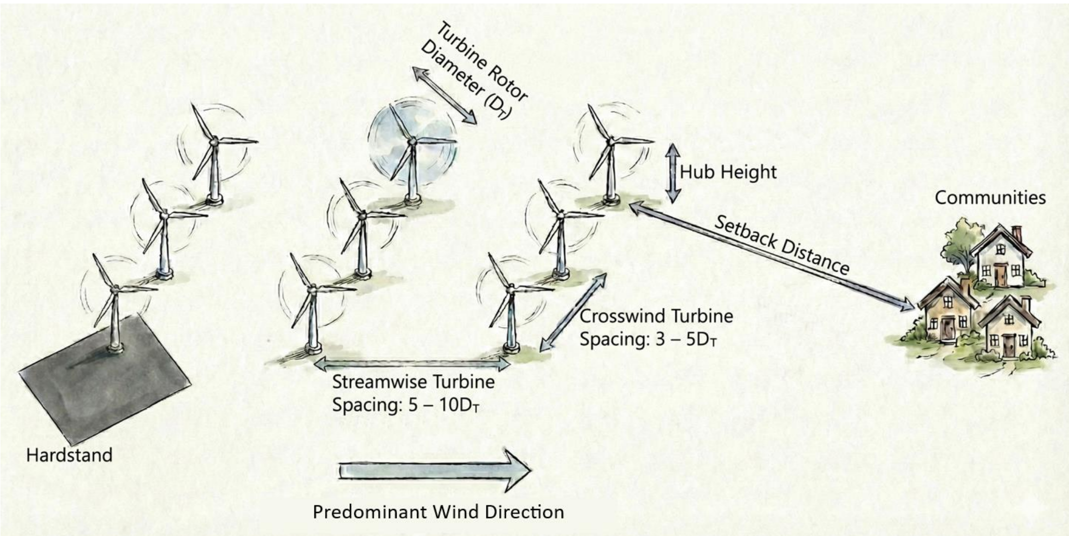

Figure 1. A typical spatial arrangement of an onshore wind energy farm

Shekar and Shivakumar [31] proposed a multi-objective framework for optimizing wind energy farm layouts that takes into account maximizing energy yield, minimizing convex hull area, and reducing the Euclidean minimum spanning tree (EMST) at the same time. Their results demonstrate that designing a wind energy farm layout is inherently a trade-off problem, where maximizing energy output does not necessarily correspond to minimizing land usage or cable length. Extrapolating this to other contexts, this viewpoint bolsters the assertion that turbine spacing alone cannot dictate wind energy farm efficacy, especially in moderate wind resource contexts like those present in Thailand.

3. METHOD
3.1. Data collection

This study presents data related to installed capacities; yearly electricity generation; hub height; and the number of wind turbines of the 20 onshore wind energy farms being operated in Thailand, as presented in Table 1. These data were collected from the Energy Regulatory Commission of Thailand (ERC) [32]. The yearly electricity generation of each wind energy farm used to calculate capacity factors was referred to [32], [33]. The wind speeds at the locations of the 585 wind turbines were collected from https://globalwindatlas.info, which is a well-known source providing data on wind power throughout the world. Also, the prevailing wind directions at each wind energy farm were collected from https://power.larc.nasa.gov/docs/services/api/application/windrose/.

Table 1. Data of onshore wind energy farms in Thailand [32], [33]

Wind energy farm ID	Installed capacity per wind turbine (MW)	Number of wind turbines installed	Rotor diameter of wind turbines (m)	Hub height (m)	Location at the top of the wind energy farm	Location at the bottom of the wind energy farm	Yearly electricity generation (kWh)	The first operation date
α	2.3	90	101	80	15.234894N 101.447895E	15.128792N 101.474577E	314,065,777.50	14th November 2012
β	2.5	24	120	85	16.709865N 100.986120E	16.681931N 100.986299E	85,863,239.50	5th August 2016
γ	1.8	70	110	137	8.29662N 100.26136E	7.80573N 100.35558E	256,733,012.00	3rd March 2017
δ	2.5	20	124	137	14.990025N 101.435596E	14.922255N 101.452593E	112,461,075.50	20th June 2018
ε	2.5	19	126	153	15.484966N 101.417219E	15.444933N 101.406542E	108,138,867.50	22nd March 2019
ζ	2.5	16	126	153	15.518272N 101.451512E	15.451110N 101.449851E	76,329,005.00	30th March 2019
η	2.0	30	116	80	15.440720N 101.486132E	15.400383N 101.468679E	141,908,861.50	24th December 2016
θ	2.5	4	118	90	8.341284N 100.250539E	8.331501N 100.253742E	14,430,137.00	6th November 2015
ι	3.0	30	130	134	15.272991N 101.484740E	15.205682N 101.494120E	207,758,650.00	16th March 2019
κ	2.0	12	117	94	14.834788N 101.556336E	14.809825N 101.554250E	63,593,172.77	20th April 2018
λ	3.45	13	133	136	16.378161N 104.411672E	16.370361N 104.409122E	67,261,616.00	1st April 2019
μ	3.0	30	136	132	15.387257N 101.509687E	15.342163N 101.412947E	237,125,630.00	28th September 2018
ν	2.5	32	121	120	15.625277N 101.568923E	15.581513N 101.533659E	124,483,950.00	16th December 2016
ξ	2.045	33	112	153	15.190646N 101.490924E	15.153458N 101.494052E	126,780,715.00	27th March 2018
ο	3.0	30	136	132	15.359080N 101.465254E	15.317248N 101.468054E	242,443,022.50	28th September 2018
π	3.0	30	130	134	15.308257N 101.492670E	15.242147N 101.460509E	246,910,242.50	21st November 2018
ρ	3.0	30	130	134	15.110140N 101.491479E	15.045136N 101.530873E	216,596,324.50	28th December 2018
σ	2.5	36	126	153	15.669494N 101.694623E	15.602124N 101.643872E	153,011,285.00	25th January 2019
τ	2.5	32	126	153	15.566394N 101.564582E	15.507242N 101.538247E	146,030,422.50	13th April 2019
υ	2.5	4	121	90	8.307226N 100.239821E	8.296956N 100.241316E	16,731,600.00	11th April 2019
Total		585						

3.2. Utilizing geographic information systems

A geographic information system (GIS) software was used to investigate the locations of all wind turbines installed at each wind energy farm (585 wind turbines distributed throughout the 20 wind energy farms). Also, this software was used to measure the spacings between the wind turbines. ArcGIS Pro 3.3.2 version and the associated GIS database were used in this research under a valid license.

3.3. Simulation of the electricity generation of the wind energy farms

The wind power model in the National Renewable Energy Laboratory's (NREL's) system advisor model (SAM) was used to simulate the annual electricity generation of 20 wind energy farms. SAM is a robust tool for simulating onshore wind energy farms because its algorithms achieve precise energy output forecasts [34]. The analysis covers the wind energy farm layout and wind turbine specifications, wind resource data, hub-height adjustments, terrain/orographic effects, and power curve adjustments for site conditions. National Aeronautics and Space Administration (NASA) prediction of worldwide energy resources (POWER) data provides historical wind statistics derived from the modern-era retrospective analysis for research and applications, version 2 (MERRA-2) global reanalysis model. NASA POWER provides the hub-height wind speed frequency distribution summarized by Weibull parameters. The wind energy farm terrain was characterized using a digital elevation model (DEM). A rotor-averaged Gaussian wake model was implemented to quantify wake losses. Lastly, the average air density at the site was estimated using NASA power data for atmospheric pressure and temperature.

3.4. Calculation of capacity factors of wind energy farms

The capacity factor is the parameter that represents the ratio of average power. The capacity factor used is given by (1).

$$CF = \frac{Generated\ power\ during\ analysis\ period}{Nominal\ power \times Analysis\ period} \tag{1}$$

The definitions of symbols used in (1) are given as follows: i) CF is the capacity factor (%); generated power during analysis is yearly electricity generation from wind (kWh); nominal power is the total installed capacity of a wind energy farm (MW); and analysis period is 8,760 hours. In this research, the analysis period used to calculate capacity factor covers 8,760 hours, which represents one full year. This calculation does not consider the downtime and maintenance of the wind energy farms because the operational data of the 20 wind energy farms is confidential and unavailable for data collection.

4. RESULTS AND DISCUSSION

4.1. The wind turbine spatial arrangement of the 20 wind energy farms

Firstly, Figure 2 displays the locations of the 20 wind energy farms on Thailand's wind map. Subsequently, Figures 3 to 22 present wind turbine spatial arrangements, while Figures 23 to 42 show the terrain of each wind energy farm. Lastly, Table 2 presents a comparison of the simulated versus actual yearly electricity generation and capacity factors.

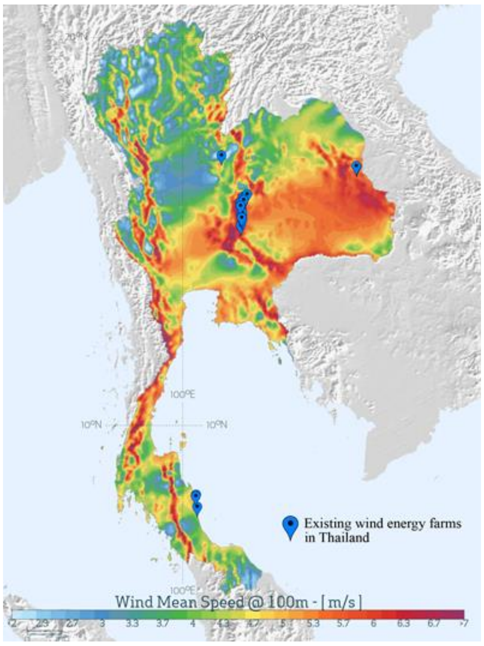

Figure 2. The locations of the 20 existing wind energy farms in Thailand [35]

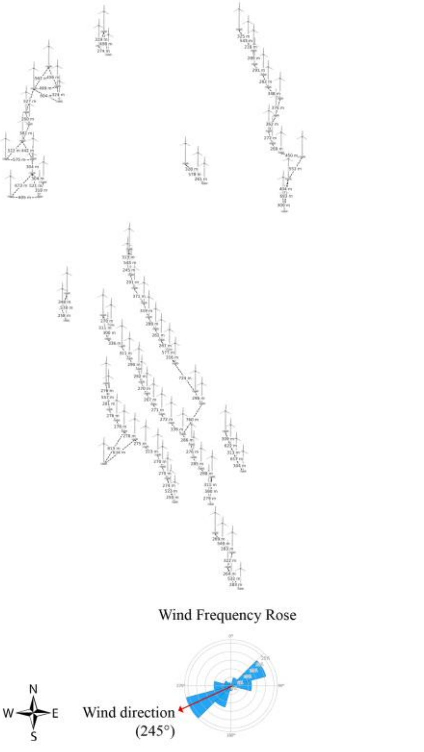

Figure 3. The wind turbine spatial arrangement of wind energy farm α

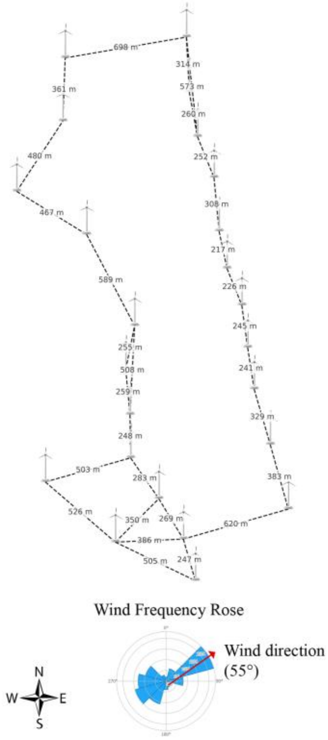

Figure 4. The wind turbine spatial arrangement of wind energy farm β

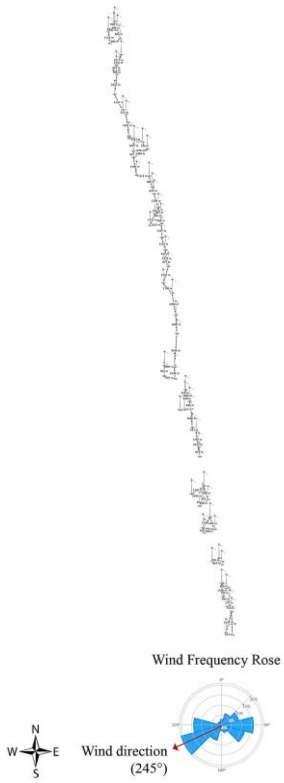

Figure 5. The wind turbine spatial arrangement of wind energy farm γ

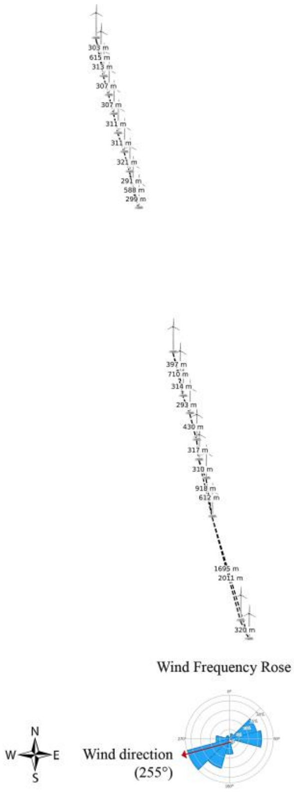

Figure 6. The wind turbine spatial arrangement of wind energy farm δ

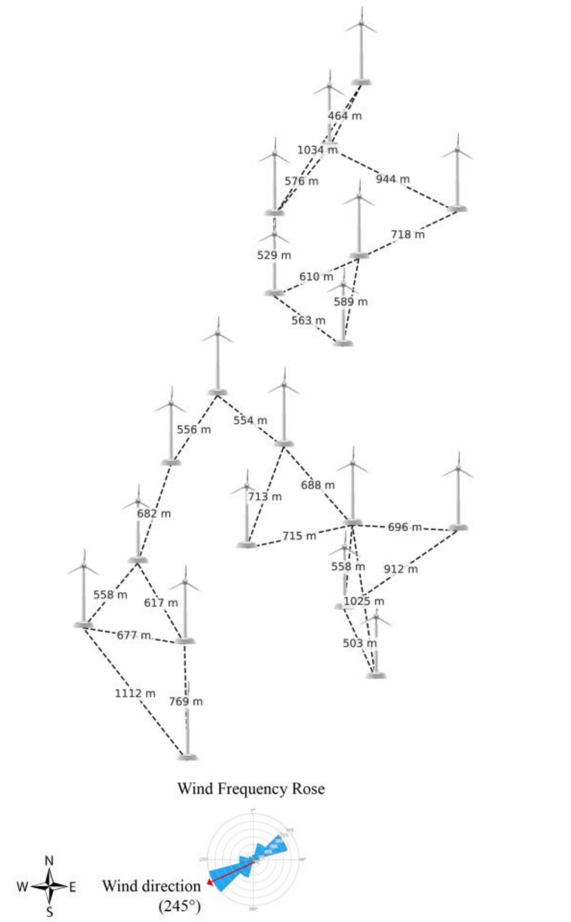

Figure 7. The wind turbine spatial arrangement of wind energy farm ε

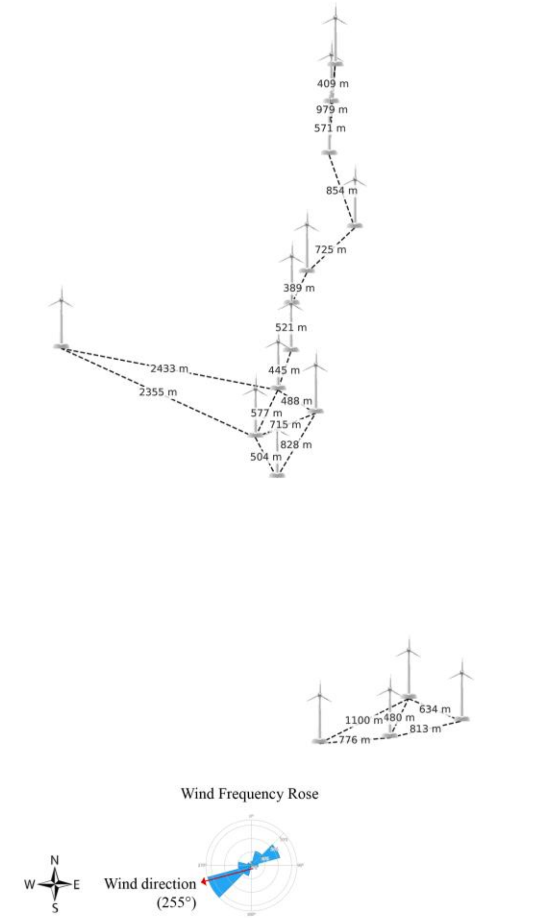

Figure 8. The wind turbine spatial arrangement of wind energy farm ζ

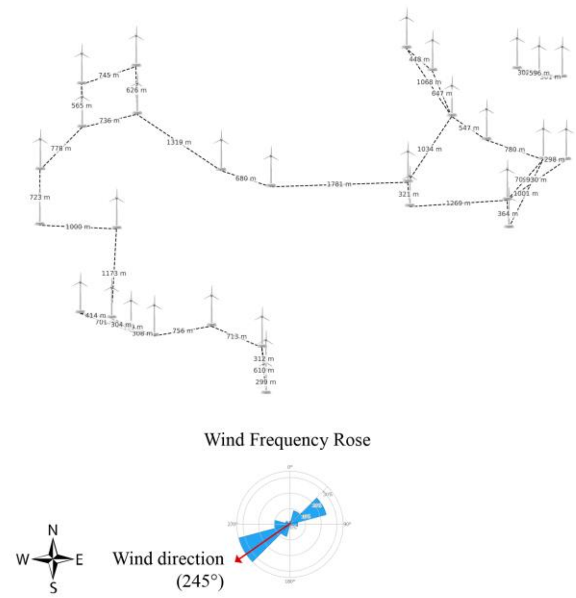

Figure 9. The wind turbine spatial arrangement of wind energy farm η

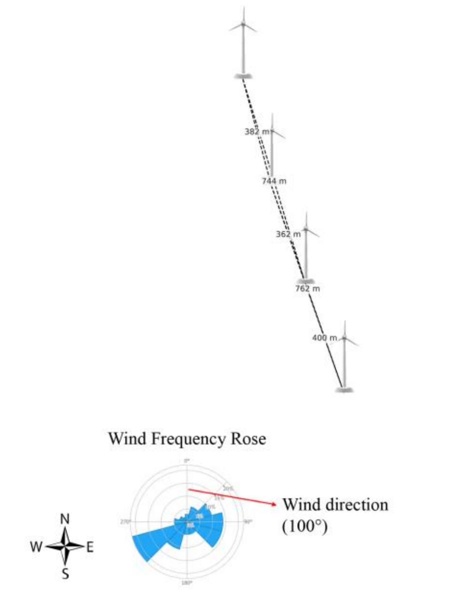

Figure 10. The wind turbine spatial arrangement of wind energy farm θ

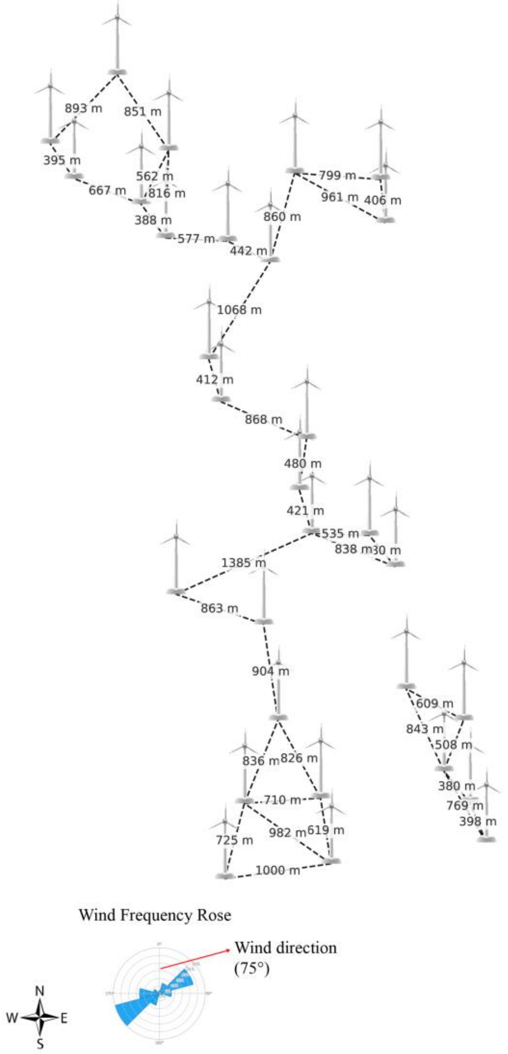

Figure 11. The wind turbine spatial arrangement of wind energy farm ι

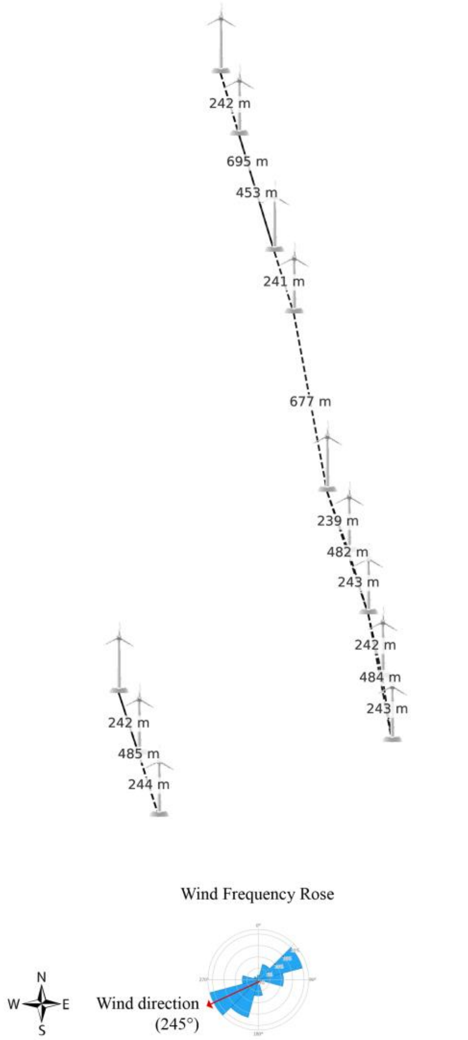

Figure 12. The wind turbine spatial arrangement of wind energy farm κ

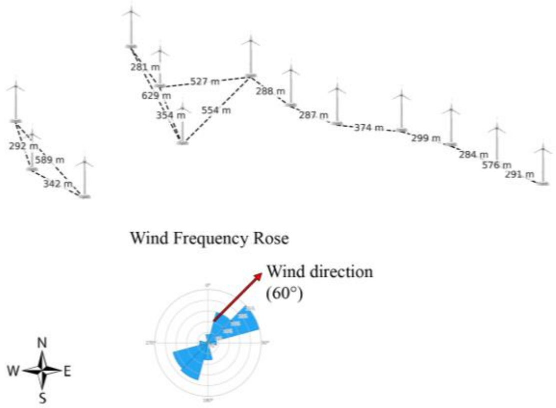

Figure 13. The wind turbine spatial arrangement of wind energy farm λ

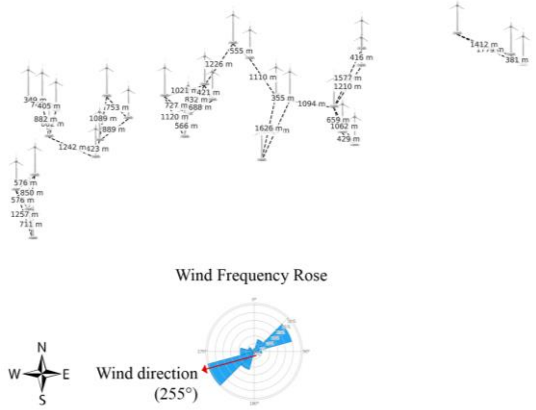

Figure 14. The wind turbine spatial arrangement of wind energy farm μ

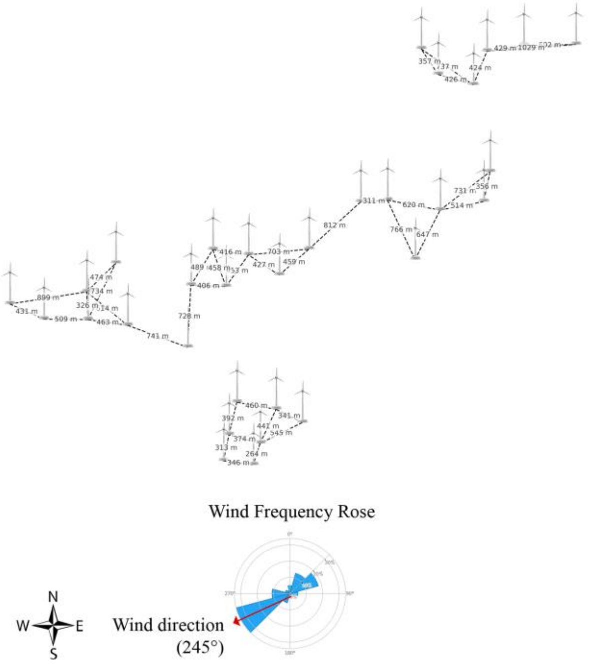

Figure 15. The wind turbine spatial arrangement of wind energy farm ν

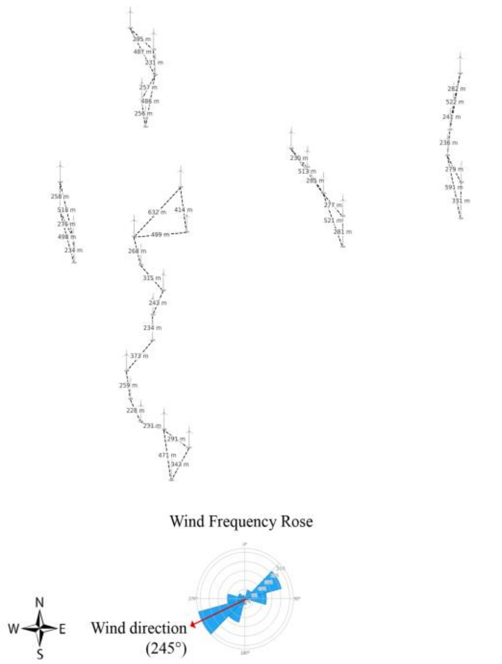

Figure 16. The wind turbine spatial arrangement of wind energy farm ξ

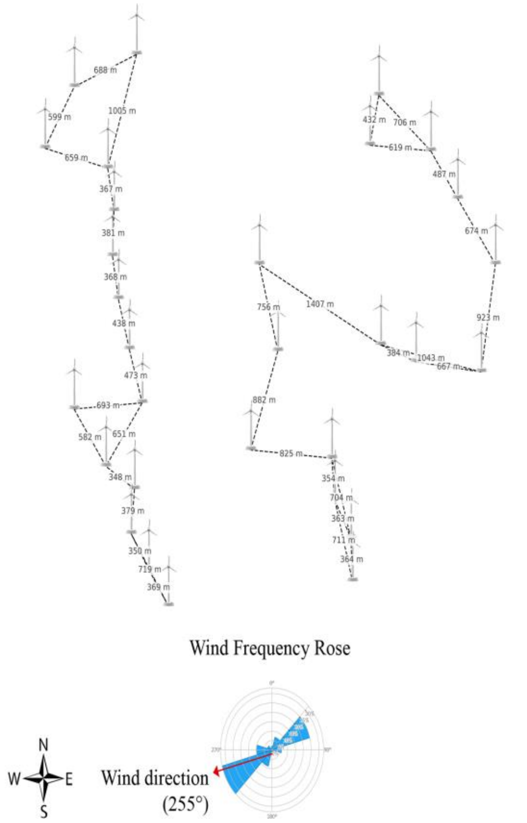

Figure 17. The wind turbine spatial arrangement of wind energy farm ο

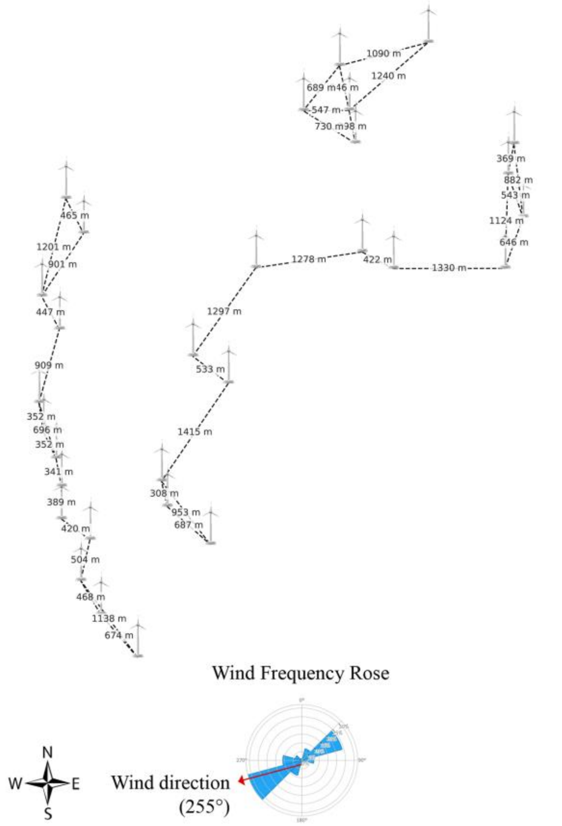

Figure 18. The wind turbine spatial arrangement of wind energy farm π

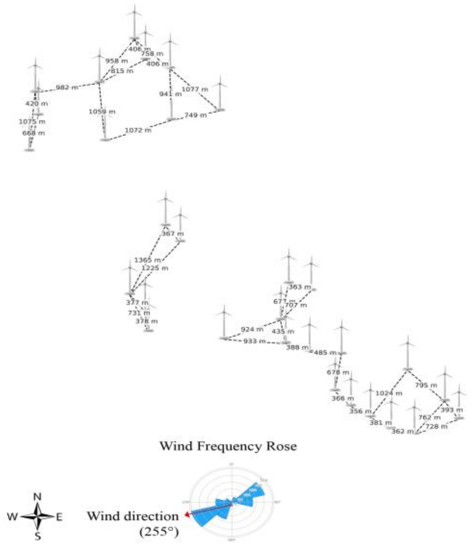

Figure 19. The wind turbine spatial arrangement of wind energy farm ρ

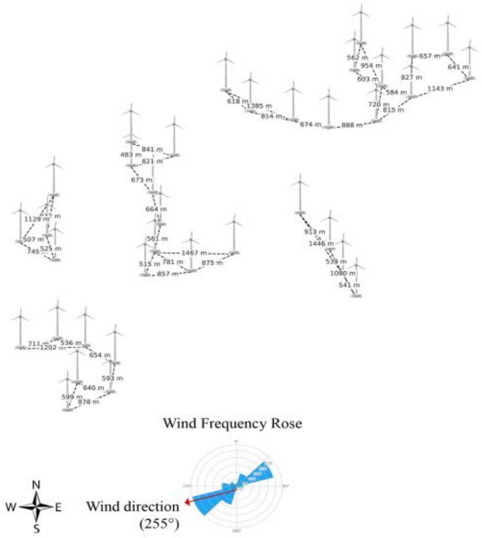

Figure 20. The wind turbine spatial arrangement of wind energy farm σ

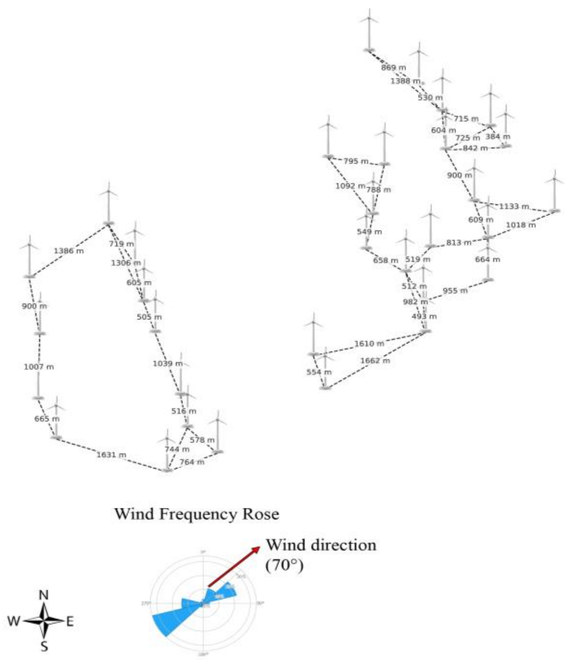

Figure 21. The wind turbine spatial arrangement of wind energy farm τ

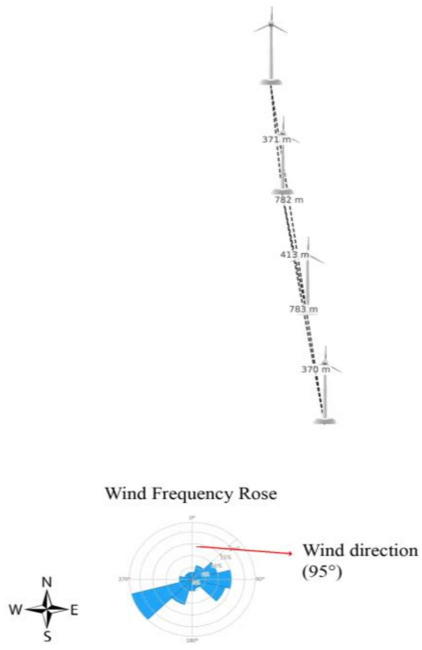

Figure 22. The wind turbine spatial arrangement of wind energy farm υ

4.2. Electricity generation efficiency of onshore wind energy farms in Thailand

The results of the research demonstrate that the actual capacity factors of the 20 wind energy farms vary from 16.34% to 31.32. The average simulated and actual capacity factors for these wind energy farms are 29.53% and 23.34%, respectively. Compared to capacity factors of onshore wind energy farms in other countries detailed in Table 3, even the average simulated capacity factor for wind energy farms in Thailand, which does not include the losses from downtime or maintenance, is relatively low. The reason is that the wind energy farms in Thailand were located in medium-to-low wind density areas, as illustrated in Figure 2.

Table 2. Wind turbine spatial arrangement and electricity generation efficiency

Wind energy farm ID	Region in Thailand	Installed capacity (MW/turbine)	Estimated wind speed at the hub height (m/s)	Wind turbine spacing (m)	Wind turbine spacing (D_T)	Simulated yearly electricity generation (kWh)	Actual yearly electricity generation (kWh)	Simulated capacity factor (%)	Actual capacity factor (%)
α	North-East	2.3	6.18	218–834	2–8	419,420,455.40	314,065,777.50	23.13	17.32
β	North-East	2.5	5.59	217–698	2–6	85,739,598.65	85,863,239.50	16.12	16.34
γ	South	1.8	4.69	257–3,009	2–27	376,096,635.40	256,733,012.00	34.07	23.26
δ	North-East	2.5	6.82	291–2,011	2–16	153,427,679.00	112,461,075.50	35.03	25.68
ε	North-East	2.5	6.60	464–1,112	3–9	77,333,978.52	108,138,867.50	18.59	25.99
ζ	North-East	2.5	6.82	389–2,433	3–19	121,602,587.70	76,329,005.00	34.70	21.78
η	North-East	2.0	6.19	298–1,781	2–15	160,950,756.00	141,908,861.50	30.62	25.71
θ	South	2.5	4.23	362–762	3–6	13,853,191.41	14,430,137.00	15.81	16.47
ι	North-East	3.0	6.74	380–1,385	3–11	194,268,956.90	207,758,650.00	24.64	26.35
κ	North-East	2.0	6.40	239–695	2–6	63,212,343.47	63,593,172.77	30.07	30.25
λ	North-East	3.45	6.79	281–629	2–5	139,612,336.20	67,261,616.00	35.54	17.12
μ	North-East	3.0	6.80	349–1,779	2–13	258,964,807.90	237,125,630.00	32.85	30.08
ν	North-East	2.5	5.99	264–1,029	2–9	238,704,661.20	124,483,950.00	34.06	17.76
ξ	North-East	2.045	6.84	228–632	2–6	204,761,862.90	126,780,715.00	34.63	20.88
ο	North-East	3.0	7.13	348–1,407	2–10	248,647,553.80	242,443,022.50	31.54	30.75
π	North-East	3.0	6.88	308–1,415	2–11	195,577,980.90	246,910,242.50	24.81	31.32
ρ	North-East	3.0	6.53	356–1,365	2–11	295,388,760.70	216,596,324.50	37.47	27.47
σ	North-East	2.5	6.25	483–1,467	3–12	311,170,221.60	153,011,285.00	39.47	19.41
τ	North-East	2.5	6.48	384–1,662	3–13	170,000,000.00	146,030,422.50	24.26	20.84
υ	South	2.5	4.12	370–783	3–7	13,826,371.47	16,731,600.00	15.78	19.10
Capacity-weighted average								29.53	23.34

Table 3. Country-specific average capacity factors for onshore wind energy farms [36]–[40]

Country	Capacity factor (%)
Brazil	49
Canada	38
China	33
Denmark	39
France	32
Germany	34
India	33
Indonesia	30–35
Italy	33
Japan	35
Mexico	36
New Zealand	28–44
Philippines	25–28
Spain	38
Sweden	38
Turkey	37
United Kingdom	37
United States	43
Vietnam	32

This study analyzes the discrepancies between simulated and actual electricity generation of the wind energy farms in Thailand. The results indicate a systematic over-prediction bias of 6.19% on average. The errors across all 20 farms range from −20.06 to +7.40 percentage points, with 65% showing over-prediction. A significant finding demonstrates that higher simulated capacity factors are strongly associated with larger over-predictions. The correlation coefficient is -0.7884 with a p-value of less than 0.0001. The wind speed analysis reveals that simulation models perform effectively at the extremes (very low and very high) wind speeds but show systematic over-prediction in the moderate-to-good wind speed range (5-7 m/s). Furthermore, the spacing analysis indicates that wake model accuracy does not improve monotonically with increased spacing. Tight spacing shows expected over-prediction due to wake effects. Conversely, the very wide spacing category also presents large errors. This suggests that non-wake factors become dominant at wide spacing. These findings imply that simulation tools might rely too heavily on wake models. Consequently, these tools may inadequately account for atmospheric, terrain, and operational factors.

This research draws upon turbine location data, site characteristics, and comprehensive literature regarding wind energy farm simulation validation to identify seven possible causes of the discrepancy between simulation and reality. The first significant factor involves the wake model and the associated parameter uncertainties. Secondly, atmospheric effects can be inadequately represented in simulations. Thirdly, terrain complexity and micro-siting can affect simulations. Following terrain complexity, operational losses can contribute to the discrepancies between simulated and actual electricity generation. Following operational losses, wind data used for simulation is possible to identical to the actual wind at sites. Furthermore, degradation of the wind turbines can affect electricity generation. Finally, grid constraints and curtailment or downtime act as external limitations on electricity generation. These findings provide significant implications for wind energy farm development in Thailand and offer actionable recommendations for improving simulation accuracy.

4.3. The wind turbine spacing of the wind energy farms

The comparative analysis of high-efficiency (capacity factor ≥ 23.34%) and low-efficiency (capacity factor < 23.34%) farms in this study reveals patterns that further illuminate the limited role of spacing as a standalone performance determinant. High-performing farms exhibited an average spacing of 3.936 D_T, while low-performing farms averaged 3.535 D_T. This finding indicates that the performance differential between the two groups cannot be attributed to systematic differences in turbine spacing, reinforcing the discussion that other factors dominate capacity factor outcomes. However, an analysis of individual high-efficiency wind energy farms shows distinct variations. Wind energy farm γ achieved a capacity factor of 23.26% with notably wide spacing of 6.618 D_T, while wind energy farm μ attained an exceptional capacity factor of 30.08% with moderate spacing of 4.221 D_T. This variability demonstrates that high performance is achievable through multiple pathways. Some projects utilize wider spacing, whereas others rely on alternative optimization strategies. Consequently, the data suggests that no single-spacing value guarantees superior outcomes.

The superior performance of certain farms despite moderate or tight spacing suggests favorable combinations of wind resource quality, terrain characteristics, and turbine technology compensating for narrow spacing. Wind energy farm μ achieved a capacity factor of 30.08% with a spacing of 4.221 D_T, likely from high wind speeds and favorable wind flow. Wind energy farm κ achieved a capacity factor of 30.25% with tight spacing of 2.059 D_T, suggesting exceptionally strong wind resources overwhelming wake losses. These examples illustrate that spacing represents one variable within a multidimensional optimization space, and superior performance emerges from holistic site development strategies rather than spacing adjustments alone.

Conversely, low-performing wind energy farms across the spacing range indicate that inadequate spacing is not the primary cause of underperformance. Wind energy farm β, with a capacity factor of 16.34% and spacing of 2.5 D_T, and wind energy farm θ, with a capacity factor of 16.47% and spacing of 3.195 D_T, both exhibit poor performance despite different spacing configurations. These wind energy farms face fundamental limitations in wind resource availability, adverse terrain effects, or suboptimal turbine technology that cannot be remedied through spacing adjustments alone. The literature emphasizes that effective wind farm design is a highly complex, multi-dimensional problem; maximizing performance requires advanced modeling that simultaneously accounts for turbine sizing, partial wake interactions, and atmospheric stability [41]. Furthermore, modern optimization studies demonstrate that optimal turbine spacing and power density are highly sensitive to the total available land area, meaning layout modifications must be dynamically adapted to specific site constraints rather than relying on generalized spacing rules to reduce the levelized cost of energy [42]. These cases represent site selection or turbine technology choices that impose binding constraints that geometric arrangement cannot overcome.

The comparative analysis also reveals that highly efficient wind energy farms tend to occupy larger average farm areas (82.82 km^2) compared to low-efficiency wind energy farms (27.17 km^2), although this difference is not statistically significant. This pattern may reflect several underlying mechanisms. Larger wind energy farm areas provide greater flexibility for micro-siting, allowing developers to selectively place turbines on the most favorable terrain features and avoid adverse flow zones, thereby improving average capacity factors through strategic positioning rather than uniform spacing [43], [44]. Additionally, larger wind energy farms may be developed in regions with more extensive favorable wind resources, where the economic viability of large-scale development indicates superior underlying wind potential. However, the lack of statistical significance for this relationship suggests that farm area alone does not determine performance, and that the quality of site selection and micro-siting within the available area matters more than the absolute size of the development.

4.4. Terrain and site-specific factors

The terrain profiles of the 20 wind energy farms presented in Figures 23 to 42 illustrate the dual nature of topographic effects on wind energy farm performance. Complex terrain can enhance or degrade electricity generation depending on the specific land configuration and turbine placement. Flow acceleration over ridges increases local wind speeds, while separation, recirculation, and terrain-induced turbulence can reduce performance for poorly sited turbines [43]. The terrain complexity metric calculated in this study (the sum of latitude and longitude ranges) captures spatial extent of elevation variations but does not distinguish favorable and unfavorable topographic configurations. Wind energy farms with similar terrain complexity scores may experience different performance outcomes depending on turbine positioning relative to topographic features. This interpretation aligns with the literature emphasizing micro-siting as a critical determinant of performance in complex terrain, where precise turbine placement relative to topographic features can yield performance differences exceeding those achievable through spacing optimization [44].

The literature on wind resource assessment and wind energy farm optimization in Thailand provides context for these geographic patterns. The northeastern region possesses the most favorable wind resources from monsoon patterns and topographic channeling, while the southern peninsula benefits from coastal wind regimes and the central plains exhibit modest wind speeds [45]. However, within each region, substantial site-to-site variability exists from local terrain, surface roughness, and meteorological patterns. This heterogeneity explains latitude's inability to predict capacity factor. The implication is that regional-scale wind resource assessments must be complemented by site-specific wind measurements and flow modeling to accurately predict performance and optimize layouts.

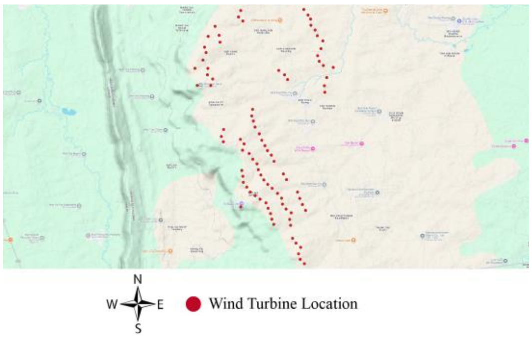

Figure 23. The terrain of wind energy farm α

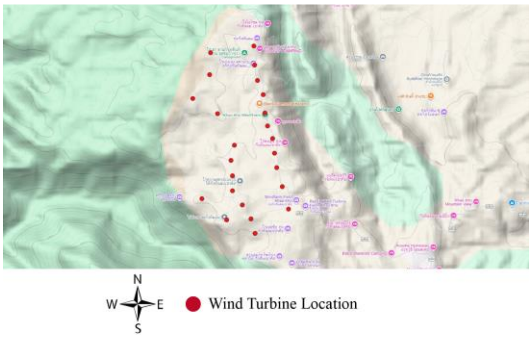

Figure 24. The terrain of wind energy farm β

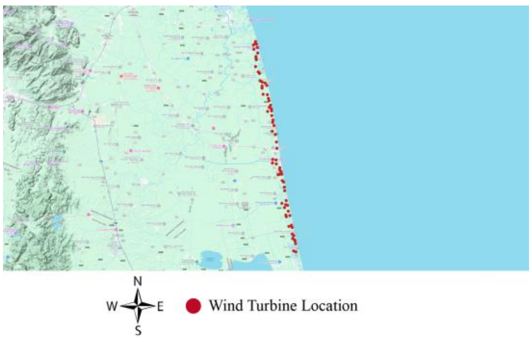

Figure 25. The terrain of wind energy farm γ

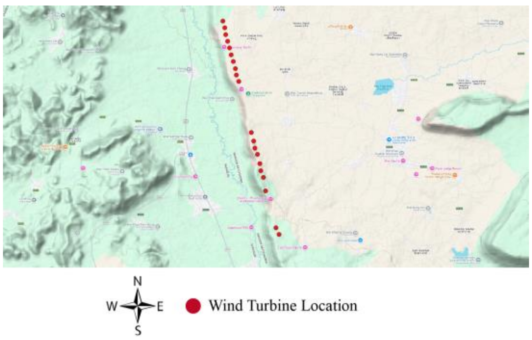

Figure 26. The terrain of wind energy farm δ

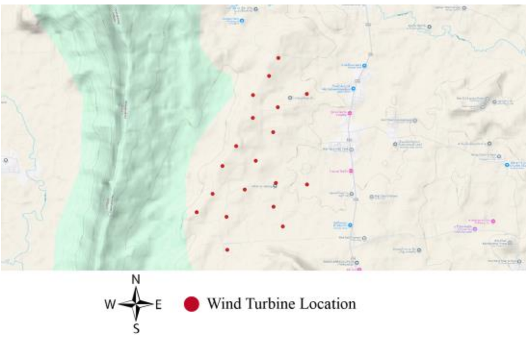

Figure 27. The terrain of wind energy farm ε

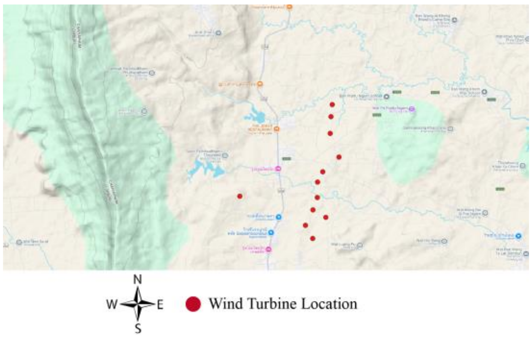

Figure 28. The terrain of wind energy farm ζ

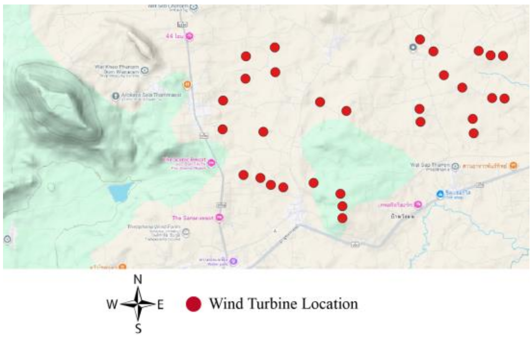

Figure 29. The terrain of wind energy farm η

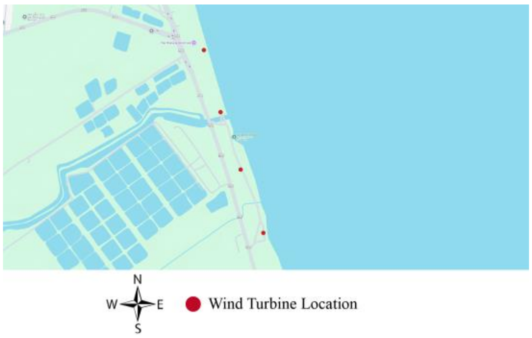

Figure 30. The terrain of wind energy farm θ

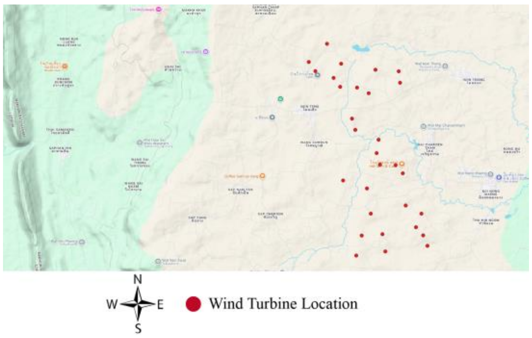

Figure 31. The terrain of wind energy farm ι

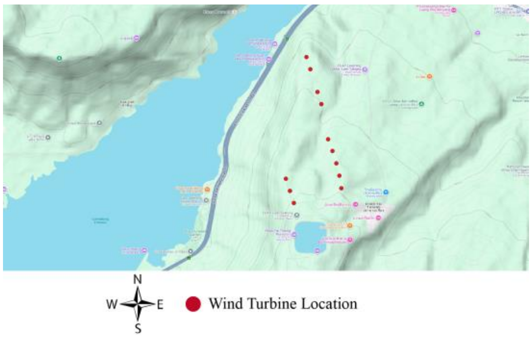

Figure 32. The terrain of wind energy farm κ

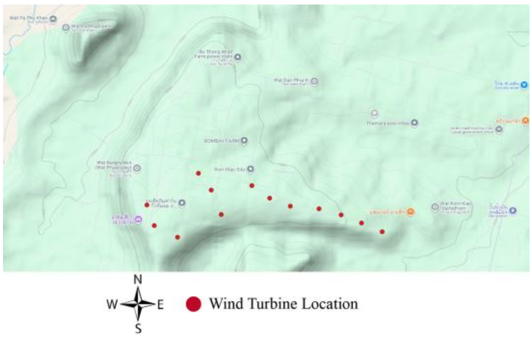

Figure 33. The terrain of wind energy farm λ

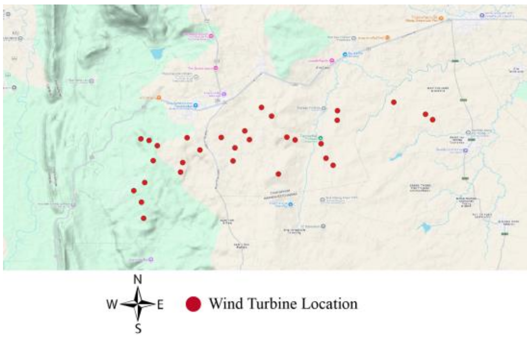

Figure 34. The terrain of wind energy farm μ

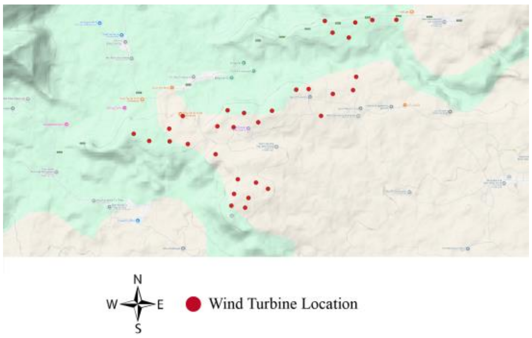

Figure 35. The terrain of wind energy farm ν

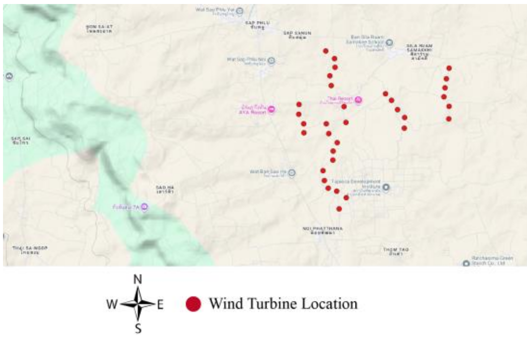

Figure 36. The terrain of wind energy farm ξ

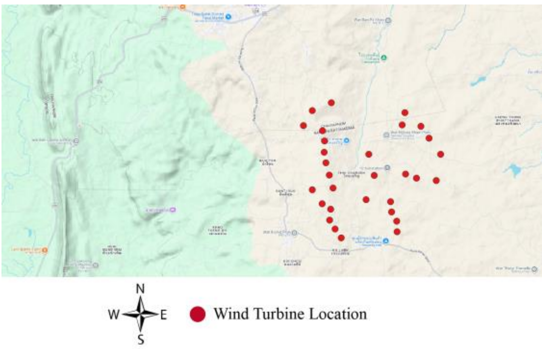

Figure 37. The terrain of wind energy farm ο

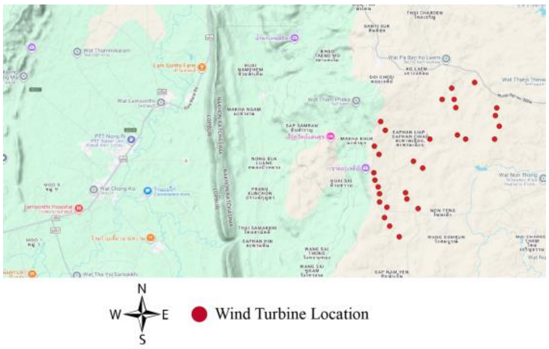

Figure 38. The terrain of wind energy farm π

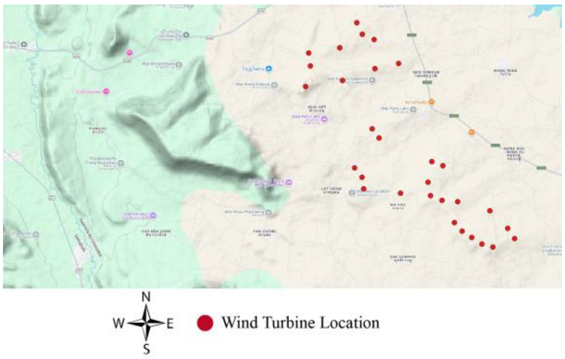

Figure 39. The terrain of wind energy farm ρ

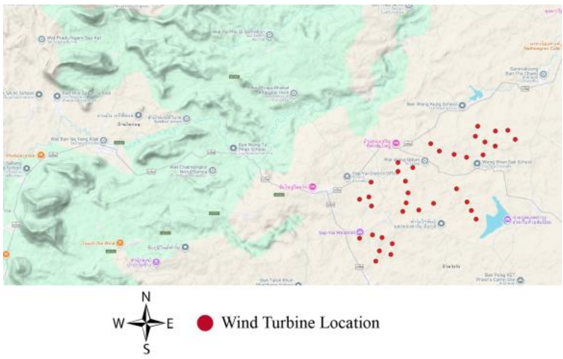

Figure 40. The terrain of wind energy farm σ

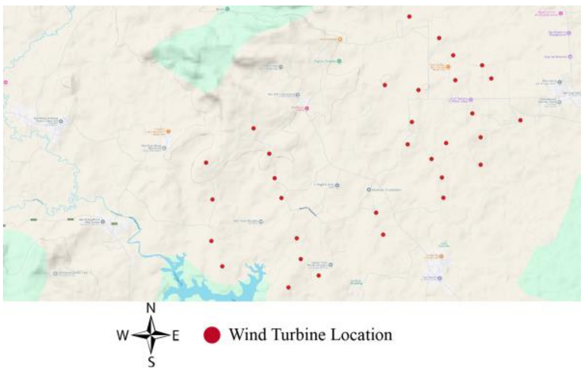

Figure 41. The terrain of wind energy farm τ

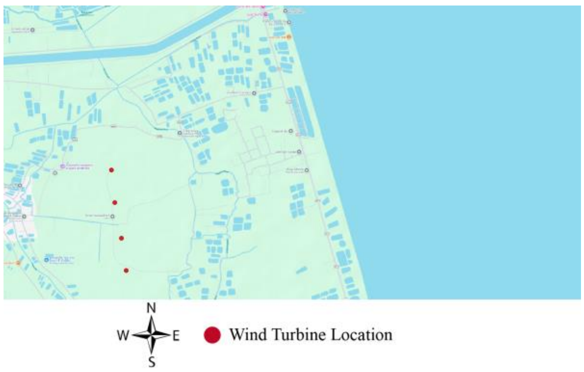

Figure 42. The terrain of wind energy farm υ

The finding that farm area does not correlate significantly with capacity factor, despite high-performing farms averaging larger areas, suggests that the relationship between farm size and performance is mediated by other factors. Larger farms may be developed in regions where extensive favorable wind resources justify investment, creating an indirect association between size and performance driven by resource quality rather than solely by wind energy farm area. Larger wind energy farms also provide spatial diversification, allowing developers to capture a broader range of wind conditions and potentially variability in output [46]. However, small wind energy farms with excellent wind resources and optimal micro-siting can achieve comparable capacity factors, indicating wind energy farm size alone does not guarantee superior performance.

4.5. Hub height and rotor diameter sensitivity to capacity factor

A parametric sensitivity analysis of hub height and rotor diameter across the 20 wind energy farms reveals engineering trade-offs relative to site-specific wind resources. Hub heights range from 80 to 153 m yet correlate weakly with actual capacity factor (Pearson's $r = 0.23$); wind energy farms at mid-range heights (120–137 m) achieve the highest average capacity factor of 25.53%, while the tallest-hub group (153 m) averages only 21.78%, indicating that increased hub height cannot guarantee improved performance when wind resources are inadequate. Rotor diameter (101–136 m) shows a moderate positive correlation with capacity factor (Pearson's $r = 0.45$), confirming that lower specific power turbines better exploit Thailand's moderate wind speeds [3], [30], [43]. Wind speed at the hub height remains the strongest predictor (Pearson's $r = 0.51$), reinforcing that turbine technology selection offers only incremental gains unless matched with favorable site resources.

4.6. Data transparency and alignment with international standards

The analytical framework of this study aligns with internationally recognized standards for wind turbine assessment and geospatial analysis. Turbine selection across the 20 farms reflects the wind class classification in International Electrotechnical Commission (IEC) 61400-1:2019 [47], which categorizes sites by reference wind speed (Vref) and annual mean wind speed; Thailand's sites, with mean wind speeds predominantly in the 5–8 m/s range, correspond to IEC wind class III ($V_{mean} \leq 7.5$ m/s) and class II ($V_{mean} \leq 8.5$ m/s), validating the turbine models deployed. The capacity factor derivation—actual annual generation divided by installed capacity and 8,760 operating hours—is consistent with the power performance framework of IEC 61400-12-1:2022 [48], which derives annual energy production (AEP) from the measured power curve applied to site-specific wind speed frequency distributions, with air density normalization. The GIS-based spatial analysis using ArcGIS and DEM data adheres to ISO 19115-1:2014 [49] metadata principles, ensuring spatial reference consistency, dataset traceability, and data quality lineage for all geospatial inputs.

5. CONCLUSION

This study evaluated the influence of the spatial arrangement of wind turbines on the electricity generation efficiency of 20 operational onshore wind energy farms in Thailand. The actual capacity factors ranged from 16.34% to 31.32%, with an average of 23.34%, compared with an average simulated capacity factor of 29.53%. The results demonstrate that turbine spacing alone is not the primary determinant of wind energy farm performance. Wind resource quality, terrain characteristics, and turbine technology are more influential, as high-performing farms were observed across different spacing configurations. The comparison between simulated and actual electricity generation also revealed a tendency for the model to overpredict electricity generation, particularly under moderate wind conditions, highlighting the importance of accounting for site-specific atmospheric, terrain, and operational factors. Therefore, future onshore wind energy development in Thailand should prioritize detailed wind resource assessment, appropriate site selection, turbine–site matching, and site-specific layout design rather than relying primarily on generalized turbine-spacing criteria. These findings support a more comprehensive and site-specific approach to improving the performance of onshore wind energy farms in moderate-wind regions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Suparatchai Vorarat	✓	✓		✓	✓				✓	✓		✓		
Watcharapong Tantawat	✓	✓	✓	✓		✓	✓	✓		✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

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

INFORMED CONSENT

This section not applicable. This study did not involve human participants or patient data, and therefore, informed consent was not required.

ETHICAL APPROVAL

This section not applicable. This article does not contain any studies with human participants or animals performed by any of the authors. No ethical approval was required for the research method described in this work.

DATA AVAILABILITY

The data that support the findings of this study are openly available on the website of the Energy Regulatory Commission, reference number [1] and the Thailand Greenhouse Gas Management Organization (Public Organization), reference number [33].

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