JMES The International Journal of
Mechanical Engineering and Sciences
https://iptek.its.ac.id/index.php/jmes
e-ISSN 2580-7471

Precision Computational Modeling of Wind Flow Dynamics to Optimize Wind Turbine Deployment in Nigeria's Varied Geographical Terrains

H. C. O. Unegbu[1]*, D. S. Yawas[1]*

[1]Department of Mechanical Engineering, Ahmadu Bello University, Zaria, Nigeria

Received: 28 August 2025, Revised: 28 November 2025, Accepted: 26 February 2026

Abstract

This study presents a precision computational framework to assess and optimize wind energy potential across three major geographic zones in Nigeria: the northern highlands, coastal areas, and savannah regions. By integrating high-resolution computational fluid dynamics (CFD), geographic information systems (GIS), and hybrid optimization algorithms, region-specific wind flow characteristics and turbine layouts were modeled and evaluated. Wind resource data from ERA5 reanalysis and local meteorological observations were combined with digital elevation models to simulate site-specific atmospheric conditions and topographic effects. The CFD simulations, validated against empirical datasets, revealed that the northern highlands exhibit superior wind energy characteristics, with mean wind speeds of 7.2 m/s at 80 m hub height and turbulence intensity below 10%. Optimized turbine layouts in this region yielded an annual energy output of 3,600 MWh per turbine and a capacity factor of 42%, with minimal wake losses. Coastal and savannah regions demonstrated lower wind potential, with higher turbulence levels and reduced energy yields, highlighting the need for adaptive deployment strategies. The findings underscore the importance of terrain-sensitive modeling and hybrid optimization techniques in wind energy planning. This work provides actionable insights to guide wind farm development and policy planning in Nigeria and similar regions with heterogeneous wind profiles.

Keywords: Wind Energy, Computational Fluid Dinamics, Turbine Optimization, GIS, Renewable Energy

1. Introduction

The transition to renewable energy has become a global priority, driven by the dual imperatives of mitigating climate change and ensuring long-term energy security. Among renewable sources, wind energy offers several strategic advantages, including scalability, low operational emissions, and declining costs, making it a viable alternative to conventional fossil fuels. Recent advancements in computational modeling—particularly computational fluid dynamics (CFD) and geographic information systems (GIS)—have enhanced the precision of wind flow analysis and turbine placement strategies [1], [2]. In Nigeria, energy insecurity remains a persistent challenge, with over 40% of the population lacking access to reliable electricity [3]. The country's continued dependence on fossil fuels contributes to environmental degradation and exposes its energy sector to the volatility of international oil prices. While Nigeria possesses significant renewable energy resources, particularly solar and wind, these remain largely underutilized due to infrastructural, technical, and policy-related barriers [4].

The urgency of developing sustainable and decentralized energy solutions is underscored by Nigeria's rapidly growing population and industrial demands. However, current energy policies and infrastructure strategies have generally overlooked the potential of advanced computational tools in renewable energy planning, leading to inefficient site selection and sub-optimal resource use [5], [6]. A key constraint in wind energy development is the difficulty in identifying suitable turbine locations, especially in regions with complex terrain and variable wind conditions [4]. Nigeria's geographic diversity—including coastal areas, savannahs, and highland plateaus—presents both challenges and opportunities for wind energy deployment. Elevated terrains such as the northern highlands offer promising wind conditions, but variations in surface roughness, atmospheric stability, and turbulence complicate accurate resource assessment [7], [8], [9]. Overcoming these challenges requires a region-specific and data-driven approach to wind energy modeling.

Furthermore, Nigeria's strategic position in sub-Saharan Africa underscores the regional relevance of wind energy research tailored to complex terrains. Successful deployment of wind power systems in such environments can serve as a blueprint for neighboring countries with similar geographical challenges [10], [11], [12]. Despite the progress in global wind energy modeling, there is a no-

*Corresponding author. Email: chidieberehyg@gmail.com, phone: +2348055603083

table lack of precision studies that account for the specific terrain-induced variability found within the Nigerian landscape. To address this gap, this study employs a precision computational framework that integrates CFD simulations, GIS-based spatial analysis, and advanced optimization algorithms to assess wind flow dynamics and energy potential across three representative regions of Nigeria: the northern highlands, coastal areas, and savannah zones. Each of these regions presents distinct topographical and atmospheric conditions that influence wind behavior, turbine siting, and overall system performance.

By capturing localized wind characteristics such as turbulence intensity, surface roughness, and wake interactions, the study aims to enhance the accuracy of wind resource assessments and inform efficient turbine placement. While regions such as the northern highlands exhibit favorable wind conditions, traditional modeling methods often fail to quantify the site-specific constraints and performance trade-offs required for scalable deployment [7], [8], [9]. This research contributes to both academic and practical domains by offering a geospatially and aerodynamically informed methodology for wind energy planning. The expected outcomes include detailed wind flow maps, optimized turbine layouts, and region-specific performance metrics, all of which are intended to support policymakers, energy planners, and developers in designing sustainable wind energy systems across Nigeria.

2. Literature Review

2.1. Overview of Wind Deployment

Wind energy is increasingly recognized as a critical pillar of global renewable energy strategies, offering a clean, renewable, and cost-effective alternative to fossil fuels. By 2023, global installed wind energy capacity surpassed 900 GW, driven by technological innovations in turbine design and favorable government policies worldwide [13], [14], [15]. The efficiency of wind energy systems depends heavily on the ability to optimize turbine placement, taking into account wind resource variability, terrain complexity, and logistical constraints [16], [17], [18]. In sub-Saharan Africa, wind energy development remains limited, with less than 1% of the region's total energy generation attributed to wind power [19]. Challenges such as inadequate wind resource data, insufficient technical expertise, and financing barriers have hindered large-scale deployment. However, several studies highlight the untapped potential for wind energy in Africa, with countries like Nigeria showing promising wind resource availability, particularly in the northern highlands [20].

2.2. Computational Modeling in Wind Flow Dynamics

Computational fluid dynamics (CFD) has revolutionized wind energy research by providing high-resolution simulations of wind flow behavior over diverse terrains. CFD models solve the Navier-Stokes equations to simulate airflow, capturing complex phenomena such as turbulence, flow separation, and wake effects [21]. Turbulence modeling, including large-eddy simulation (LES) and Reynolds-averaged Navier-Stokes (RANS) methods, has further improved the accuracy of CFD models, particularly in capturing small-scale wind dynamics [22].

GIS-based approaches complement CFD by enabling spatially explicit analyses that integrate wind flow data with terrain and land use information. Hybrid GIS-CFD frameworks are especially effective for wind resource assessments in regions with heterogeneous topographies, such as Nigeria [23]. For instance, these methods have been used to map wind potential across varying altitudes, demonstrating the value of coupling computational models with geospatial data [24]. Advancements in computational power and machine learning techniques have further enhanced CFD applications. For example, machine learning algorithms are now integrated into CFD workflows to predict wind resource variability and optimize computational efficiency [25]. These advancements are particularly valuable for assessing wind energy potential in regions like Nigeria, where diverse terrains and limited empirical data complicate traditional modeling approaches [26].

2.3. Optimization Techniques for Wind Energy Systems

Optimization is central to maximizing the efficiency of wind energy systems. Multi-objective optimization methods, including genetic algorithms (GAs), particle swarm optimization (PSO), and differential evolution (DE), are widely used to determine the optimal placement and configuration of wind turbines [27]. These techniques account for factors such as wake interactions, turbulence intensity, and land use constraints, balancing energy yield with economic and environmental considerations [28].

Machine learning (ML) has transformed wind energy optimization by enabling data-driven decision-making. Techniques such as artificial neural networks (ANNs) and support vector machines (SVMs) have been employed to model the complex relationships between wind dynamics and turbine performance [29]. Reinforcement learning (RL) has also gained prominence for its ability to adaptively optimize wind farm operations based on real-time wind conditions [30]. Recent studies highlight the benefits of hybrid optimization frameworks that combine traditional algorithms with machine learning. These approaches enhance the accuracy and computational efficiency of optimization processes, making them particularly suitable for regions with complex wind patterns, such as Nigeria [31]. By leveraging these techniques, researchers have demonstrated significant improvements in energy yield and cost efficiency across diverse terrain types [32].

2.4. Challenges in Wind Energy Deployment in Nigeria

Despite its significant wind energy potential, Nigeria faces multiple barriers to large-scale deployment. Geographical diversity, including coastal areas, savannahs, and plateaus, creates complex wind flow patterns that require advanced modeling to accurately assess energy potential [33]. Additionally, inadequate wind resource data and limited access to high-resolution terrain information hinder precise assessments of wind energy viability [34]. Infrastructure deficits, such as a poorly developed electricity grid and insufficient transmission capacity, further complicate wind energy deployment in Nigeria. Sociopolitical issues, including regulatory uncertainty and land ownership disputes, also deter investment in wind energy projects [35]. However, regions such as the northern highlands, characterized by average wind speeds exceeding 6 m/s, present significant opportunities for wind energy development if these challenges can be addressed [36].

2.5. Research Gaps and Opportunities

While advancements in computational modeling and optimization have significantly improved wind energy planning globally, their application in Nigeria remains underexplored. Many studies on wind energy in sub-Saharan Africa rely on generalized models that do not account for the region's unique geographical and climatic conditions [37]. For example, most existing models fail to address terrain-induced wind flow complexities and the impact of land use constraints on turbine placement [38]. This study seeks to bridge these gaps by developing an integrated computational framework tailored to Nigeria's diverse terrains. By combining advanced CFD modeling, GIS analysis, and state-of-the-art optimization techniques, the research aims to provide actionable insights for policymakers and developers. Furthermore, this framework can serve as a replicable model for other regions facing similar challenges, contributing to the global advancement of renewable energy technologies [39].

3. Materials and Methods

3.1. Study Area Description

This study focuses on three representative regions in Nigeria selected for their distinct topographical and meteorological characteristics: the northern highlands, coastal areas, and savannah zones. These regions were chosen to reflect the geographical diversity of the country and to evaluate the variability in wind energy potential across different terrains. The coastal region includes urbanized zones such as Lagos and Calabar, where wind patterns are influenced by maritime conditions, vegetation, and built environments. Savannah regions, located in central Nigeria—including areas such as Abuja and Minna—exhibit rolling landscapes that create intermediate wind flows with higher surface friction. The northern highlands, including the Jos Plateau and its surrounding areas, represent elevated terrains with reduced surface roughness and relatively stable wind profiles. At 80-meter hub heights, the highlands record average wind speeds exceeding 6 m/s, making them particularly attractive for utility-scale wind projects [40], [41], [42].

3.2. Data Collection and Preparation

To achieve accurate wind resource estimation, the study integrates multiple high-resolution datasets. Wind speed and direction data were sourced from the ERA5 global reanalysis dataset, which offers hourly climate variables at a spatial resolution of approximately 31 km. To enhance local reliability, these data were validated using point-based measurements obtained from the Nigerian Meteorological Agency (NiMet), thereby correcting for model bias and increasing spatial fidelity. Digital Elevation Models (DEMs) were derived from Shuttle Radar Topography Mission (SRTM) data with a resolution of 30 meters, providing detailed topographical inputs for terrain-sensitive CFD simulations.

Preprocessing involved the application of statistical smoothing algorithms to eliminate outliers and interpolate missing data points. Key wind parameters—including wind speed, direction, and turbulence intensity—were extracted and subjected to spatial interpolation for GIS integration. The Weibull distribution function was applied to model wind speed probability distributions across the selected regions. This probabilistic model enabled the calculation of site-specific mean wind speeds and energy densities, both critical for evaluating turbine performance and annual energy output [43], [44], [45], [46], [47].

3.3. Computational Modeling Framework

The core of the analysis relies on high-resolution CFD simulations to model wind flow over complex Nigerian terrains. OpenFOAM, an open-source CFD platform, was used due to its flexibility in handling atmospheric boundary layer simulations and its proven utility in wind energy applications. The Reynolds-Averaged Navier–Stokes (RANS) equations were solved using the standard $k-\varepsilon$ turbulence model, which provides a reliable balance between computational cost and accuracy for simulating turbulent wind flows in heterogeneous landscapes.

Simulation domains were constructed based on DEM data, capturing elevation gradients, slope effects, and surface roughness elements derived from land-use classifications. Boundary conditions were defined using climatological data from validated wind profiles, with inlet boundaries assigned logarithmic wind velocity profiles to represent atmospheric boundary layer behavior. Lateral boundaries were treated as symmetry planes, and the ground surface was defined using rough wall functions to simulate frictional losses due to terrain and vegetation.

Each simulation was run until residual convergence was achieved, with time-step independence and mesh sensitivity studies performed to ensure numerical stability. Mesh refinement was applied near the surface and around obstacles to capture fine-scale turbulence and flow separation effects. Outputs from CFD simulations were exported into GIS platforms to spatially analyze wind flow characteristics, overlay exclusion zones, and identify viable turbine placement locations [48], [49], [50], [51]. Figure 1 shows the schematic diagram of the computational modelling framework.

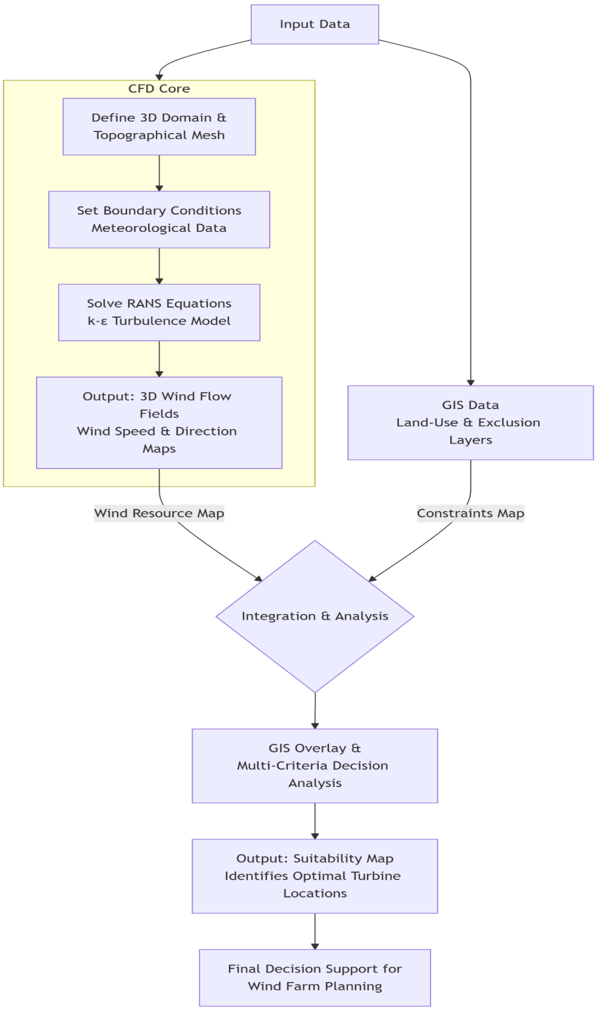


Figure 1. Schematic diagram of the integrated computational fluid dynamics (CFD) and geographic information system (GIS) framework for wind turbine siting.

3.4. Optimization Techniques

Turbine placement was optimized using a hybrid framework that integrates Genetic Algorithms (GAs) and machine learning (ML) techniques. The optimization objectives included maximizing net energy yield, minimizing wake-induced losses, and reducing the environmental footprint of wind farm layouts. The Jensen wake model was used to quantify wake effects based on turbine spacing and prevailing wind direction, accounting for energy losses behind upstream turbines. The GA component generated multiple layout configurations across the defined study areas, each evaluated using a custom fitness function.

This fitness function incorporated critical constraints, including land-use restrictions (e.g., exclusion of urban areas, agricultural zones, and protected lands), turbine spacing requirements to reduce wake interference, and simplified financial indicators such as land availability and access considerations. To accelerate convergence and enhance layout accuracy, machine learning models were trained on CFD-derived wind field outputs, learning to predict high-performance placement zones. Furthermore, reinforcement learning (RL) was implemented to simulate real-time adaptation of turbine positioning in response to fluctuating wind conditions, enhancing the resilience of optimized layouts [52], [53], [54].

3.5. Simulation Parameters and Assumptions

All simulations were conducted using standardized specifications for modern onshore wind turbines. Turbine hub heights were set at 80 meters, with rotor diameters of 120 meters, reflecting utility-scale designs suitable for the Nigerian context. The turbines' operational thresholds included a cut-in wind speed of 3 m/s and a cut-out speed of 25 m/s, consistent with industry standards.

Surface roughness was incorporated into the CFD domain using land classification maps and vegetation indices, allowing site-specific modeling of frictional drag. Roughness lengths were assigned based on terrain type (e.g., urban areas, shrubs, open land), and logarithmic wind profiles were applied near the ground surface to simulate atmospheric boundary layer behavior. Exclusion zones were enforced using GIS overlays of land-use categories, ensuring compliance with national siting regulations and international best practices [55], [56].

3.6. Model Validation

The validity of the computational modeling framework was assessed using empirical data from small-scale wind installations in regions with similar topographic and climatic conditions to the study areas. Simulated wind speeds and energy outputs were compared against observed data using statistical performance indicators, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The results showed strong correlation, with coefficient values exceeding 0.9, indicating high model reliability in predicting wind behavior and turbine performance. To further ensure robustness, cross-validation was performed by splitting the available data into training and test subsets, allowing independent verification of model accuracy. CFD wind fields were also qualitatively validated using wind rose diagrams and velocity contours to confirm realistic flow patterns. These validation steps ensured that the integrated CFD-GIS-optimization framework could produce reliable and actionable insights for wind energy planning [57], [58].

4. Results and Discussion

4.1. Wind Flow Dynamics Across Selected Regions

The CFD simulations revealed distinct wind flow characteristics across the northern highlands, coastal areas, and savannah regions, with strong correlations between geographic features and local wind behavior. In the northern highlands, the elevated terrain and low surface roughness created stable atmospheric boundary layers, re-

Table 1. Wind flow characteristics across regions.

Region	Average Wind Speed (m/s)	Turbulence Intensity (%)	Key Features
Northern Highlands	7.2	10	High elevation, low roughness
Coastal Areas	5.1	18	Maritime influence, urban-induced roughness
Savannah Regions	4.8	15	Seasonal variability, moderate roughness

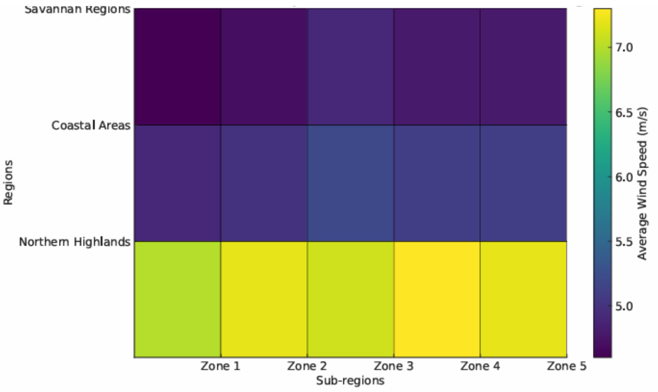


Figure 2. Simulated wind speed distribution across selected regions.

sulting in an average wind speed of 7.2 m/s at an 80-meter hub height. Turbulence intensity in this region remained below 10%, primarily due to the uniform topography and minimal obstructions, which favored consistent wind acceleration and lower vertical shear.

In contrast, the coastal areas exhibited more irregular wind behavior. Although maritime influence contributed to moderate average wind speeds of 5.1 m/s, turbulence intensity reached 18%, significantly impacting wind quality. This high turbulence was attributed to a combination of vegetation cover, urban infrastructure, and humidity-related thermal gradients, all of which disrupted laminar flow and introduced frequent directional shifts.

The savannah regions demonstrated intermediate wind performance, with mean wind speeds of 4.8 m/s and turbulence intensity around 15%. These patterns were shaped by undulating terrain and seasonal vegetation changes, which introduced moderate surface roughness and variable thermal conditions. Seasonal flow reversal and diurnal thermal shifts were particularly evident, resulting in increased directional variability during dry-to-wet transitions. Figure 2 illustrates spatial wind speed distribution across all three regions, emphasizing the strong wind corridors observed in the highlands. The model captured micro-scale accelerations at ridge crests and wind channeling effects in valleys, both critical for siting high-yield turbines. These effects were visualized using horizontal velocity contours and vertical profile plots, which provided insight into shear gradients and flow stratification.

4.2. Optimal Turbine Placement Strategies

Using the hybrid optimization framework combining Genetic Algorithms (GAs), Machine Learning (ML), and Reinforcement Learning (RL), region-specific turbine layouts were developed based on simulated wind flow characteristics and wake loss minimization strategies. In the northern highlands, the optimal layout maintained a 600-meter spacing between turbines. This distance was sufficient to suppress wake overlap due to strong prevailing wind directionality and low turbulence, limiting energy loss to 8%.

For the coastal region, the optimization algorithm recommended a denser 300-meter turbine spacing to compensate for lower wind speeds. However, this configuration led to a higher wake loss of 12%, as increased turbulence and multidirectional wind flow reduced wake recovery distance. The savannah zone adopted an intermediate spacing of 450 meters, balancing land availability, wind variability, and wake interactions. Here, wake losses reached 15%, due to less predictable flow paths and increased vertical turbulence. GIS-based spatial overlays were used to integrate land-use constraints, ensuring that all optimized layouts avoided protected zones, densely populated areas, and agricultural corridors. Figure 3 shows the turbine placement map for the northern highlands, highlighting wind corridors and exclusion zones derived from GIS layers.

4.3. Energy Yield and Performance Metrics

The energy yield analysis confirmed the superior performance of the northern highlands in wind energy generation. With a stable wind regime and low turbulence, turbines in this region produced an average of 3,600 MWh/year per unit, achieving a capacity factor of 42%. This performance is attributed to consistent wind alignment, minimal shear distortions, and reduced wake interference due to effective turbine spacing. The CFD-predicted flow fields indicated uniform flow structures with minimal velocity deficits downstream of turbines, va-

Table 2. Optimized turbine configurations and wake losses.

Region	Turbine Spacing (m)	Wake Loss (%)	High-Potential Zones (%)
Northern Highlands	600	8	70
Coastal Areas	300	12	45
Savannah Regions	450	15	55

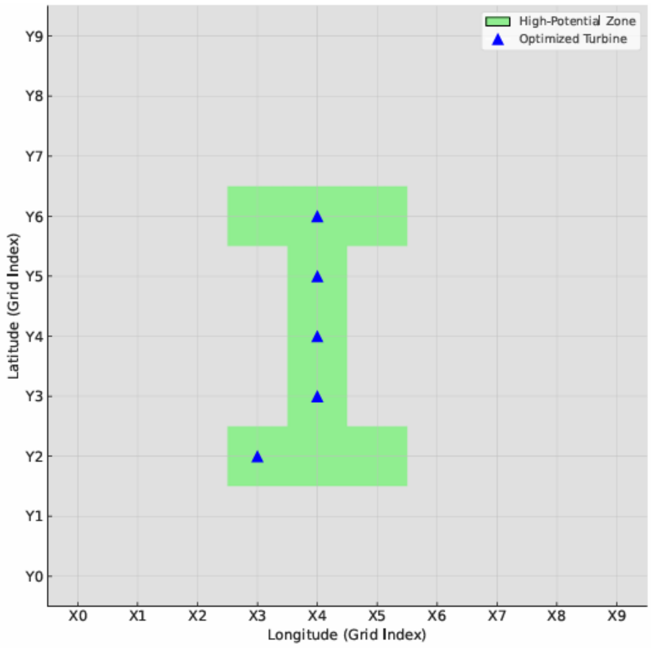


Figure 3. GIS-based optimized turbine placement for the northern highlands.

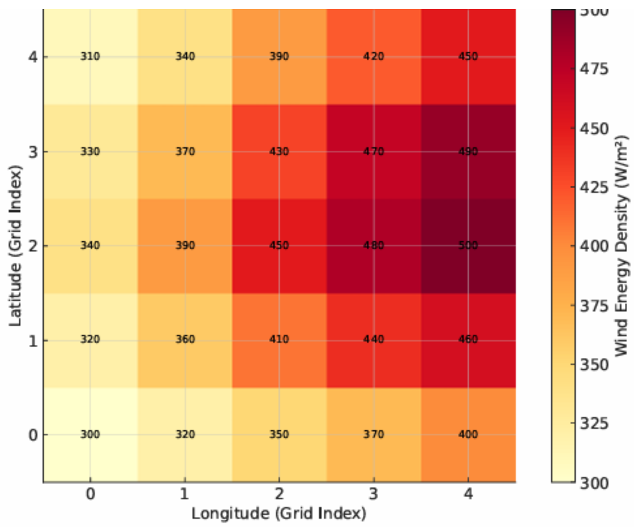


Figure 4. Energy density distribution for the northern highlands.

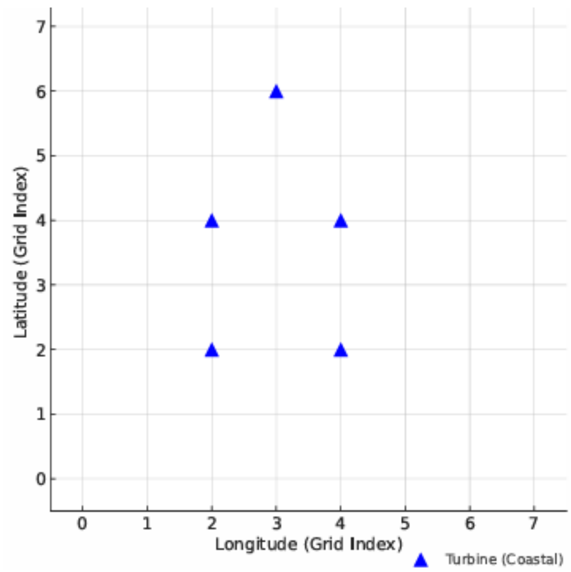
lidating the placement strategy. In contrast, coastal areas achieved an average energy yield of 2,200 MWh/year per turbine and a capacity factor of 28%. This lower yield reflects the compounded effect of higher turbulence, multidirectional flow, and wake overlapping in denser layouts. Although wind speeds were moderate, flow instability reduced effective operating hours, increasing wake-induced variability in turbine output.

The savannah region, with its transitional wind conditions and moderate terrain complexity, yielded approximately 1,900 MWh/year per turbine at a 24% capacity factor. Intermittent wind flow, seasonal variability, and elevated turbulence intensity limited overall system efficiency. Despite a relatively open terrain profile, wake losses and frequent directional shifts reduced the operational performance of turbines. Performance metrics such as wake losses, turbulence impacts, and efficiency were extracted from CFD results and optimization outputs to quantify inter-regional differences. The results validate the suitability of the highlands for large-scale deployment, while coastal and savannah regions may be better suited for hybrid or distributed systems.

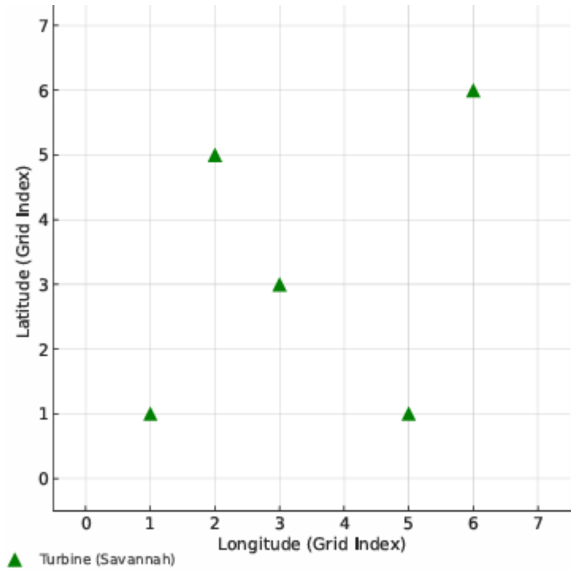
4.4. Visualization of Results

Visual outputs from the CFD-GIS integration were crucial in interpreting the spatial distribution of wind potential and guiding turbine siting decisions. Figure 2 depicted the wind speed distribution, while Figure 3 presented the GIS-based turbine layouts. Figure 4 provided an energy density map of the northern highlands, highlighting regions with annual average wind power density exceeding $450 \mathrm{W/m^2}$, a threshold typically favorable for commercial-scale turbines. These visualizations revealed key aerodynamic features such as wind channeling through valleys, acceleration zones along ridgelines, and shadow zones behind elevated terrain. Such flow characteristics were captured through horizontal velocity fields, vertical shear profiles, and turbulence intensity contours, all extracted from OpenFOAM post-processing.

Furthermore, Figure 5(a) & 5(b) compared the turbine layout maps for the coastal and savannah regions, demonstrating how turbine spacing and orientation adapted to regional constraints. The use of layered GIS maps—combining terrain, land-use, and wind resource data—allowed the identification of exclusion zones and high-potential micro-siting opportunities within broader regions. This integrative visual analysis supported not only performance prediction but also practical deployment planning.



(a)



(b)

Figure 5. (a) Optimized turbine layout coastal region; (b) Optimized turbine layout savannah region.

Table 3. Energy yield and capacity factors across regions.

Region	Energy Yield (MWh/year)	Capacity Factor (%)	Turbulence Impact (%)
Northern Highlands	3600	42	10
Coastal Areas	2200	28	18
Savannah Regions	1900	24	15

4.5. Discussion of Findings

4.5.1. Interpretation of Results in the Context of Nigeria's Energy Goals

The results of this study strongly support the viability of wind energy as a strategic component of Nigeria's renewable energy transition. The northern highlands demonstrated a high potential for utility-scale wind power deployment, achieving a capacity factor of 42%, which is competitive with global wind farm benchmarks [59], [60]. The region's favorable wind regime, low turbulence intensity, and topographic consistency make it ideal for large-scale, grid-connected wind projects.

These findings align with Nigeria's Vision 30:30:30 plan, which aims to generate 30 GW of electricity by 2030, with at least 30% from renewable sources. Harnessing highland wind resources could contribute significantly toward meeting this target, while also enhancing energy access in underserved northern communities. By contrast, the coastal and savannah regions may be more suitable for small-scale or hybrid systems that combine wind, solar, and storage technologies to buffer intermittency and site constraints [61].

4.5.2. Comparison with Prior Studies

This study significantly extends existing research on Nigeria's wind energy potential by applying high-resolution CFD-GIS modeling and hybrid optimization. Earlier studies, such as those by Ajayi and Adaramola [62], relied primarily on empirical wind measurements and statistical extrapolation, often lacking terrain-specific turbulence modeling or wake effect analysis.

Unlike previous works that treated Nigeria's wind potential as uniform or broadly regional, this study introduces spatially differentiated insights based on topography, land use, and atmospheric dynamics. The inclusion of turbulence intensity, wake modeling, and performance validation provides a much more realistic estimate of achievable energy yield across regions. This enhanced approach allows policymakers and developers to make data-driven siting and investment decisions [63].

4.5.3. Implications for Large-Scale Wind Energy Deployment

The energy yield and wake loss results for the northern highlands indicate strong technical feasibility for grid-

Table 4. Summary of key performance metrics across regions.

Metric	Northern Highlands	Coastal Areas	Savannah Regions
Average Wind Speed (m/s)	7.2	5.1	4.8
Turbulence Intensity (%)	10	18	15
Wake Loss (%)	8	12	15
Energy Yield (MWh/year)	3600	2200	1900

scale wind farms. The region's capacity factor of 42% places it well above the industry threshold (typically 30-35%) for financial viability. These outcomes support prioritizing infrastructure investment in transmission lines, substations, and access roads for highland wind corridors. For coastal and savannah regions, where wind conditions are more variable, the integration of wind energy into distributed systems or hybrid configurations is more appropriate. For example, coastal microgrids could combine wind with solar and battery storage to serve fishing and off-grid communities. In these cases, the turbine layout must be carefully adapted to minimize wake interactions under unstable atmospheric conditions [64], [65].

Overall, the differentiated deployment strategy suggested by this study allows for resource optimization across Nigeria's diverse landscapes, reducing over-dependence on fossil fuel infrastructure and supporting decentralized energy access.

4.5.4. Limitations of the Study and Areas for Improvement

While the integrated CFD-GIS-optimization framework presented in this study offers a robust tool for wind energy planning, several limitations remain. First, the study relies on simulated data, which—although validated against available observations—may not fully capture extreme weather events, long-term seasonal shifts, or microclimatic anomalies. The limited availability of high-resolution local wind measurements in many parts of Nigeria restricts empirical validation [66].

Second, the study does not incorporate detailed financial modeling, including capital cost estimation, payback periods, or levelized cost of electricity (LCOE). These are essential for investment-grade feasibility assessments. Lastly, social, regulatory, and land acquisition challenges—especially in rural or protected areas—were not explicitly modeled, though they could impact real-world implementation.

4.5.5. Recommendations for Policy and Infrastructure Development

To support wind energy deployment in Nigeria, several policy and infrastructural actions are recommended:

- Invest in Wind Resource Assessment

  Establish more meteorological monitoring stations across diverse terrains, and deploy remote sensing technologies such as LiDAR and SODAR for accurate vertical wind profiling [67].

- Expand Grid Infrastructure

  Develop transmission corridors connecting high-yield wind zones (particularly in the highlands) to major demand centers. This includes substations, smart grid integration, and load management systems [68].

- Incentivize Private Sector Participation

  Introduce feed-in tariffs, tax credits, and low-interest financing to attract investment in wind farms and manufacturing components [69].

- Promote Local Research and Capacity Building

  Support academic-industry partnerships, workforce training, and university research programs focused on renewable energy system design, modeling, and optimization [70].

4.5.6. Future Research Directions

Future work should integrate long-term climate projections to understand how changing wind patterns might affect turbine performance and regional energy planning. The use of downscaled regional climate models (RCMs) can provide insight into climate-induced shifts in wind behavior over decadal time scales. Additionally, future models should include multi-objective economic optimization, factoring in capital cost, operation and maintenance (O&M), LCOE, and land-use costs to support bankable feasibility studies. The integration of socio-environmental factors—such as community acceptance, ecological impacts, and legal frameworks—would also provide a more holistic assessment.

Finally, expanding the modeling framework to include hybrid energy systems that integrate solar photovoltaics (PV), wind, and battery storage will be crucial for improving energy resilience in variable wind zones [71], [72].

5. Conclusions

This study presented a comprehensive, data-driven framework for evaluating and optimizing wind energy potential across Nigeria's diverse geographical terrains using an integrated approach combining computational fluid dynamics (CFD), geographic information systems (GIS), and hybrid optimization techniques. By simulating wind flow dynamics over three representative regions— the northern highlands, coastal zones, and savannah areas—the research highlighted the significant spatial variability in wind resources, turbulence characteristics, and turbine performance. The northern highlands emerged as the most viable region for large-scale wind energy deployment, with average wind speeds of 7.2 m/s, low turbulence intensity, and a capacity factor of 42%. Optimized turbine layouts in this region achieved annual energy yields of 3,600 MWh per turbine with minimal wake losses, making it well-suited for grid-connected utility-scale wind farms. In contrast, coastal and savannah regions demonstrated moderate wind potential, with higher turbulence and directional variability. These areas are more appropriate for distributed or hybrid systems that combine wind with solar photovoltaic and energy storage technologies.

The use of CFD allowed for high-resolution modeling of terrain-induced wind behaviors, including flow acceleration, shear, and wake effects, which are often overlooked in conventional resource assessments. The integration of GIS enabled spatial filtering of turbine siting zones based on land-use, topographic constraints, and exclusion criteria, ensuring practical deployment feasibility. Hybrid optimization—leveraging genetic algorithms (GA), machine learning (ML), and reinforcement learning (RL)—further improved turbine layout efficiency under site-specific constraints.

The validated modeling framework demonstrated strong correlation with observed data, confirming its robustness for wind energy planning in complex terrains. The results offer not only technical insights but also strategic direction for national energy development. In the context of Nigeria's Vision 30:30:30 energy policy, the northern highlands represent a high-impact opportunity for integrating wind energy into the national grid and reducing dependence on fossil fuels. However, realizing this potential will require complementary investments in grid infrastructure, localized wind resource monitoring, financial incentives for private developers, and regulatory reform to streamline project approvals. Equally important is the development of local capacity through academic research, workforce training, and public-private partnerships in renewable energy technology development.

Future research should focus on incorporating climate change projections to assess long-term shifts in wind regimes, performing full economic feasibility studies including levelized cost of electricity (LCOE), and expanding the modeling framework to support hybrid systems. Furthermore, including socio-environmental impact assessments will be critical to ensure that wind energy deployment is sustainable, equitable, and aligned with national development goals. Overall, this study provides a replicable, terrain-sensitive computational framework that can guide both policymakers and developers in the strategic deployment of wind energy infrastructure across Nigeria. By combining high-resolution simulation with spatial intelligence and optimization, the research advances the precision and reliability of wind energy planning and contributes to a cleaner, more resilient energy future.

Acknowledgments

I want to appreciate the support and inspiration of my supervisor Professor D. S. Yawas for guiding me in writing this manuscript.

References

[1] M. I. Blanco, “The economics of wind energy,” *Renewable and Sustainable Energy Reviews*, vol. 13, no. 6–7, pp. 1372–1382, 2009.

[2] H. Çetinay, F. A. Kuipers, and A. N. Guven, “Optimal siting and sizing of wind farms,” *Renewable Energy*, vol. 101, pp. 51–58, 2017.

[3] A. Adewuyi, “Challenges and prospects of renewable energy in nigeria: A case of bioethanol and biodiesel production,” *Energy Reports*, vol. 6, pp. 77–88, 2020.

[4] J. Dai, Y. Tan, and X. Shen, “Investigation of energy output in mountain wind farm using multiple-units SCADA data,” *Applied Energy*, vol. 239, pp. 225–238, 2019.

[5] A. Odubiyi and I. Davidson, “Distributed generation in nigeria's new energy industry,” *Power Engineer*, vol. 17, no. 5, pp. 18–20, 2003.

[6] B. Olomiyesan, O. D. Oyedum, P. E. Ugwuoke, and M. Abolarin, “Assessment of wind energy resources in nigeria – a case study of north-western region of nigeria,” *International Journal of Physical Research*, vol. 5, no. 2, p. 83, 2017.

[7] B. Blocken, A. van der Hout, J. Dekker, and O. Weiler, “CFD simulation of wind flow over natural complex terrain: Case study with validation by field measurements for ria de ferrol, galicia, spain,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 147, pp. 43–57, 2015.

[8] T. Uchida and Y. Ohya, “Large-eddy simulation of turbulent airflow over complex terrain,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 91, no. 1–2, pp. 219–229, 2003.

[9] M. Elgendi, M. AlMallahi, A. Abdelkhalig, and M. Y. E. Selim, “A review of wind turbines in complex terrain,” *International Journal of Thermofluids*, vol. 17, p. 100289, 2023.

[10] A. Z. Dhunny, M. R. Lollchund, and S. D. D. V. Rughooputh, "Wind energy evaluation for a highly complex terrain using Computational Fluid Dynamics (CFD)," *Renewable Energy*, vol. 101, pp. 1–9, 2017.

[11] M. Szubel, M. Filipowicz, K. Papis-Frączek, and M. Kryś, *Computational Fluid Dynamics in Renewable Energy Technologies: Theory, Fundamentals, and Exercises*. CRC Press, 1 ed., 2023.

[12] Z. Wang, Y. Tu, K. Zhang, Z. Han, Y. Cao, and D. Zhou, "An optimization framework for wind farm layout design using CFD-based kriging model," *Ocean Engineering*, vol. 293, p. 116644, 2024.

[13] R. Sharma, H. Kodamana, and M. Ramteke, "Multi-objective dynamic optimization of hybrid renewable energy systems," *Chemical Engineering and Processing - Process Intensification*, vol. 170, p. 108663, 2022.

[14] S. Pookpunt and W. Ongsakul, "Optimal placement of wind turbines within wind farm using binary particle swarm optimization with time-varying acceleration coefficients," *Renewable Energy*, vol. 55, pp. 266–276, 2013.

[15] H. AlShannaq and A. M. Aly, "Review of artificial neural networks for wind turbine fatigue prediction," *SDHM Structural Durability and Health Monitoring*, vol. 18, no. 6, pp. 707–737, 2024.

[16] Y. He, X.-H. Liu, H.-L. Zhang, W. Zheng, F.-Y. Zhao, M. A. Schnabel, and Y. Mei, "Hybrid framework for rapid evaluation of wind environment around buildings through parametric design, CFD simulation, image processing, and machine learning," *Sustainable Cities and Society*, vol. 73, p. 103092, 2021.

[17] Global Wind Energy Council, "Global wind report 2023," 2023.

[18] K. Liu, W. Chen, G. Chen, D. Dai, C. Ai, X. Zhang, and X. Wang, "Application and analysis of hydraulic wind power generation technology," *Energy Strategy Reviews*, vol. 48, p. 101117, 2023.

[19] O. K. Bishoge, G. G. Kombe, and B. Mvile, "Renewable energy for sustainable development in sub-saharan african countries: Challenges and way forward," *Journal of Renewable and Sustainable Energy*, vol. 12, no. 5, p. 053702, 2020.

[20] IRENA, "Renewable energy opportunities in africa," 2022.

[21] W. Zhang, J. Calderon-Sanchez, D. Duque, and A. Souto-Iglesias, "Computational Fluid Dynamics (CFD) applications in floating offshore wind turbine (FOWT) dynamics: A review," *Applied Ocean Research*, vol. 138, p. 104075, 2024.

[22] T. Ma and C. Sun, "Large eddy simulation of wind turbulence over non-breaking and breaking waves," *Ocean Engineering*, vol. 305, p. 117898, 2024.

[23] G. López, P. Arboleya, D. Núñez, A. Freire, and D. López, "Wind resource assessment and influence of atmospheric stability on wind farm design using Computational Fluid Dynamics in the andes mountains, ecuador," *Energy Conversion and Management*, vol. 284, p. 116972, 2023.

[24] G. Bangga and T. Lutz, "Aerodynamic modeling of wind turbine loads exposed to turbulent inflow and validation with experimental data," *Energy*, vol. 223, p. 120076, 2021.

[25] F. Elyasichamazkoti and A. Khajehpoor, "Application of machine learning for wind energy from design to energy-water nexus: A survey," *Energy Nexus*, vol. 2, p. 100011, 2021.

[26] M. Abkar, N. Zehtabiyan-Rezaie, and A. Iosifidis, "Reinforcement learning for wind-farm flow control: Current state and future actions," *Theoretical and Applied Mechanics Letters*, vol. 13, no. 6, p. 100475, 2023.

[27] M. A. M. Ramli, H. R. E. H. Bouchekara, and A. H. Milyani, "Wind farm layout optimization using a multi-objective electric charged particles optimization and a variable reduction approach," *Energy Strategy Reviews*, vol. 45, p. 101016, 2023.

[28] W. Hu, Q. Yang, Z. Yuan, and F. Yang, "Wind farm layout optimization in complex terrain based on CFD and IGA-PSO," *Energy*, vol. 288, p. 129745, 2024.

[29] H. Sun, C. Qiu, L. Lu, X. Gao, J. Chen, and H. Yang, "Wind turbine power modelling and optimization using artificial neural network with wind field experimental data," *Applied Energy*, vol. 280, p. 115880, 2020.

[30] J. J. Yang, M. Yang, M. X. Wang, P. J. Du, and Y. X. Yu, "A deep reinforcement learning method for managing wind farm uncertainties through energy storage system control and external reserve purchasing," *International Journal of Electrical Power & Energy Systems*, vol. 119, p. 105928, 2020.

[31] I. Itodo, "Obstacles and way forward in promoting renewable energy in nigeria," *Journal of Technology Innovations in Renewable Energy*, vol. 3, no. 4, pp. 166–170, 2014.

[32] O. O. Ajayi, "Assessment of utilization of wind energy resources in nigeria," *Energy Policy*, vol. 37, no. 2, pp. 750–753, 2009.

[33] M. S. Adaramola and O. M. Oyewola, "On wind speed pattern and energy potential in nigeria," *Energy Policy*, vol. 39, no. 5, pp. 2501–2506, 2011.

[34] A. O. Adelaja, "Barriers to national renewable energy policy adoption: Insights from a case study of nigeria," *Energy Strategy Reviews*, vol. 30, p. 100519, 2020.

[35] H. Abedi, "Assessment of flow characteristics over complex terrain covered by the heterogeneous forest at slightly varying mean flow directions: A case study of a swedish wind farm," *Renewable Energy*, vol. 202, pp. 537–553, 2023.

[36] A. S. Aliyu, J. O. Dada, and I. K. Adam, "Current status and future prospects of renewable energy in nigeria," *Renewable and Sustainable Energy Reviews*, vol. 48, pp. 336–346, 2015.

[37] G. López, P. Arboleya, D. Núñez, A. Freire, and D. López, "Wind resource assessment and influence of atmospheric stability on wind farm design using Computational Fluid Dynamics in the andes mountains, ecuador," *Energy Conversion and Management*, vol. 284, p. 116972, 2023.

[38] J. Hu, Z. Song, Y. Tan, and M. Tan, "Optimizing integrated energy systems using a hybrid approach blending grey wolf optimization with local search heuristics," *Journal of Energy Storage*, vol. 87, p. 111384, 2024.

[39] S. M. Malakouti, F. Karimi, H. Abdollahi, M. B. Menhaj, A. A. Suratgar, and M. H. Moradi, "Advanced techniques for wind energy production forecasting: Leveraging multi-layer Perceptron + Bayesian optimization, ensemble learning, and CNN-LSTM models," *Case Studies in Chemical and Environmental Engineering*, vol. 10, p. 100881, 2024.

[40] M. Jamil, S. Parsa, and M. Majidi, "Wind power statistics and an evaluation of wind energy density," *Renewable Energy*, vol. 6, no. 5–6, pp. 623–628, 1995.

[41] J. A. Carta, P. Ramírez, and S. Velázquez, "A review of wind speed probability distributions used in wind energy analysis," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 5, pp. 933–955, 2009.

[42] J. V. Seguro and T. W. Lambert, "Modern estimation of the parameters of the weibull wind speed distribution for wind energy analysis," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 85, no. 1, pp. 75–84, 2000.

[43] C. G. Justus, W. R. Hargraves, and A. Yalcin, "Nationwide assessment of potential output from wind-powered generators," *Journal of Applied Meteorology*, vol. 15, no. 7, pp. 673–678, 1976.

[44] J. F. Manwell, J. G. McGowan, and A. L. Rogers, "Wind energy explained: Theory, design and application," *John Wiley & Sons*, 2009. Book.

[45] T. Burton, D. Sharpe, N. Jenkins, and E. Bossanyi, "Wind energy handbook," *John Wiley & Sons*, 2011. Book.

[46] IEC, "Iec 61400-1: Wind turbines – part 1: Design requirements," *International Electrotechnical Commission*, 2019. International Standard.

[47] T. Ackermann, "Wind power in power systems," *John Wiley & Sons*, 2012. Book.

[48] E. Hau, "Wind turbines: Fundamentals, technologies, application, economics," *Springer*, 2013. Book.

[49] D. A. Spera, "Wind turbine technology: Fundamental concepts of wind turbine engineering," *ASME Press*, 2009. Book.

[50] F. D. Bianchi, H. De Battista, and R. J. Mantz, "Wind turbine control systems: Principles, modelling and gain scheduling design," *Springer*, 2007. Book.

[51] M. O. L. Hansen, "Aerodynamics of wind turbines," *Routledge*, 2015. Book.

[52] G. Giebel and G. Kariniotakis, "Wind power forecasting—a review of the state of the art," *Renewable Energy*, vol. 136, pp. 1053–1064, 2019.

[53] M. Shafiee and F. Dinmohammadi, "An fmea-based risk assessment approach for wind turbine systems: A comparative study of onshore and offshore," *Energies*, vol. 7, no. 2, pp. 619–642, 2014.

[54] J. K. Kaldellis and D. Zafirakis, "The wind energy (r)evolution: A short review of a long history," *Renewable Energy*, vol. 36, no. 7, pp. 1887–1901, 2011.

[55] O. S. Ohunakin, "Wind resource evaluation in six selected high altitude locations in nigeria," *Renewable Energy*, vol. 36, no. 12, pp. 3273–3281, 2011.

[56] G. M. Argungu, E. J. Bala, M. Momoh, M. Musa, and K. A. Dabai, "Analysis of wind energy resource potentials and cost of wind power generation in sokoto, northern nigeria," *International Journal of Engineering Research and Technology (IJERT)*, vol. 2, no. 5, 2013.

[57] A. D. Mukasa, E. Mutambatsere, Y. Arvanitis, and T. Triki, "Wind energy in sub-saharan africa: Financial and political causes for the sector's underdevelopment," *Energy Research & Social Science*, vol. 5, pp. 90–104, 2015.

[58] A. Hodgkin, G. Deskos, and S. Laizet, "On the interaction of a wind turbine wake with a conventionally neutral atmospheric boundary layer," *International Journal of Heat and Fluid Flow*, vol. 102, p. 109165, 2023.

[59] O. O. Ajayi, "The potential for wind energy in nigeria," *Wind Engineering*, vol. 34, no. 3, pp. 303–311, 2010.

[60] T. Kamal, R.-E. Precup, and S. Z. Hassan, *Advanced Control and Optimization Paradigms for Wind Energy Systems*. Singapore: Springer, 2019.

[61] W. Hu, Q. Yang, Z. Yuan, and F. Yang, "Wind farm layout optimization in complex terrain based on cfd and iga-pso," *Energy*, vol. 288, p. 129745, 2024.

[62] M. El-Shimy, M. Said, and M. A. Abdelraheem, "Improved framework for techno-economical optimization of wind energy production," *Sustainable Energy Technologies and Assessments*, vol. 23, pp. 57–72, 2017.

[63] Y. Back, P. Kumar, P. M. Bach, W. Rauch, and M. Kleidorfer, "Integrating cfd-gis modelling to refine urban heat and thermal comfort assessment," *Science of The Total Environment*, vol. 858, p. 159729, 2023.

[64] C. C. Crossett, A. K. Betts, L.-A. L. Dupigny-Giroux, and A. Bomblies, "Evaluation of daily precipitation from the era5 global reanalysis against ghcn observations in the northeastern united states," *Climate*, vol. 8, no. 12, p. 148, 2020.

[65] A. Hodgkin, G. Deskos, and S. Laizet, "On the interaction of a wind turbine wake with a conventionally neutral atmospheric boundary layer," *International Journal of Heat and Fluid Flow*, vol. 102, p. 109165, 2023.

[66] J.-W. Ding, M.-J. Chuang, J.-S. Tseng, and I.-Y. L. Hsieh, "Reanalysis and ground station data: Advanced data preprocessing in deep learning for wind power prediction," *Applied Energy*, vol. 375, p. 124129, 2024.

[67] M. Szubel, M. Filipowicz, and K. Papis, *Computational Fluid Dynamics in Renewable Energy Technologies: Theory, Fundamentals and Exercises*. 2023.

[68] S. Nielsen, P. A. Østergaard, and K. Sperling, "Renewable energy transition, transmission system impacts and regional development – a mismatch between national planning and local development," *Energy*, vol. 278, p. 127925, 2023.

[69] M. Appiah, S. Ashraf, A. K. Tiwari, B. A. Gyamfi, and S. T. Onifade, "Does financialization enhance renewable energy development in sub-saharan african countries?," *Energy Economics*, vol. 125, p. 106898, 2023.

[70] J. Ugwu, K. C. Odo, L. O. Oluka, and K. O. Salami, "A systematic review on the renewable energy development, policies, and challenges in nigeria with an international perspective and public opinions," *International Journal of Renewable Energy Development*, vol. 11, no. 1, pp. 287–308, 2022.

[71] F. Bai, X. Ju, S. Wang, and W. Zhou, "Wind farm layout optimization using adaptive evolutionary algorithm with monte carlo tree search reinforcement learning," *Energy Conversion and Management*, vol. 252, p. 115047, 2021.

[72] M. R. Maghami and A. Mutambara, "Challenges associated with hybrid energy systems: An artificial intelligence solution," *Energy Reports*, vol. 9, pp. 924–940, 2023.