Control System Technique for Wind Energy Optimization: A Systematic Review Process

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Abstract
Intermittency has continued to threaten the reliability of energy produced by wind. This paper presents a review on control system strategies for wind energy optimization. The study assessed the potential of wind energy in Nigerian regions, highlighting their variability across zones and stated, considering wind and speed. In addition, the quantification of wind energy generation potential, proving important insight for energy policy makers to achieve sustainable clean energy development. Furthermore, wind energy pitch control strategies were discussed. Optimization of wind energy strategies were also explored in the paper. Their strength and weakness were all stated, while considering their relevance to energy sustainability. Findings showed that hybrid control strategy and also intelligent control system, offers improved adaptive in optimization of wind energy output. In conclusion, there should be target deployment of advance control system in regions characterized with highly unstable wind energy so as to improve Nigerian wind energy potential and then support the clean energy suitability goal and overall capacity of power generation in Nigeria.

Keywords: *wind turbine, energy, Nigeria, control system, intelligent control, power sector*

1. INTRODUCITON

The global demand for clean energy has triggered major shift from the traditional fossil fuel to the sustainable energy sources (Okedu et al., 2024). Among these sources which are major characterized by renewable energy generators, wind energy has emerged as one of the fasting growing sources of sustainable energy. wind energy offers several advantages which include abundance, low cost of energy generation, sustainability and zero dirty energy; however, one major constraint which has impacted on the reliability of wind adoption as energy source is intermittency and stochastic nature of wind (Kamel et al., 2013). This problem has affected the stability of power generated by wind turbines over a long period of time, and remained open for solution in the scientific community. Currently the integration of control system has resonated as approach to help optimize wind energy and ensure power output stability (Tiwari nd Babu, 2016); however, while there are several control solutions proposed to help optimize wind energy, and each studies tend to argue and recommended proposed controller as the best; meanwhile the issues of intermittency, and impacts on wind power generation has not been addressed. In addition, there are limited works which have experimented or explored the positives and negative impacts of control system techniques for the optimization of wind energy. This therefore underscores the need for this paper, which is aimed at investigating different control system techniques for wind energy optimization.

1.1 The paper organization

The organization of this paper is structured around four key objectives. First, it aims to assess the wind energy resources available across various regions in Nigeria, identifying areas with the most promising wind conditions for energy generation. Second, it explores the overall wind energy potential of the country, quantifying the capacity that can be harnessed for sustainable development. Third, the paper evaluates various wind turbine control strategies, analyzing their effectiveness in optimizing energy output and ensuring operational stability. Finally, it examines the different methods of wind energy optimization and control, including both conventional and advanced approaches, to determine the most efficient techniques applicable to Nigeria's unique wind profile.

1.2 Contributions of the paper

i. Provides a comprehensive assessment of wind energy resources across Nigeria, highlighting regional variations in wind potential.
ii. Quantifies the wind energy generation capacity in selected Nigerian states, offering valuable data for policymakers and investors.
iii. Reviews and compares various wind turbine control strategies, including conventional, model-based, data-driven, and hybrid methods.

2.0 Assessment of Wind Energy Resources in Nigeria

In Ojosu et al. (1995), wind patterns across Nigeria was analyzed and found that the northern regions particularly Nguru and Sokoto exhibited the highest wind speeds, ranging from 1.5 to 4.1 m/s with power densities between 5.7 and 22.5 W/m². The peak wind periods occurred between April and August. In contrast, the southern region produced less wind, between 1.40 to 3.00 m/s, making it less viable for large-scale wind energy deployment. The estimated annual mean energy production ranged from 2.24 to 12,521.55 MWh, showing regional differences in energy yield potential. Anyanwu et al. (1995) study in Owerri indicated relatively low wind energy potential, with an annual mean power density of 7.66 W/m² and an energy yield of 60.29 kWh/m². Such values suggest that wind applications in this location may only be feasible for micro-scale or supplemental power generation. Ngala et al. (2007) studies in Oyo State, wind power densities at a 25-meter height ranged between 4712 and 27,449 MWh/month. The average wind speeds recorded were between 2.85 and 5.20 m/s, with corresponding power densities of 27.08–164.48 W/m². These values show moderate wind availability, making it suitable for mid-scale applications if optimized with appropriate turbines. In Fafare, (2008) an assessment of wind turbine at a 10-meter hub height in Enugu showed a mean wind speed of 2.5 ± 0.3 m/s. The study used Weibull parameters: a scale factor of 4.31 m/s, shape factor of 2.21, and skewness of −0.46, indicating low to moderate wind energy potential. Ajayi et al. (2014), investigation in Southwest Nigeria showed spatial and seasonal variability in wind speeds, ranging from 2.9 to 5.8 m/s. In Abeokuta, the lowest mean annual power was 4.21 kW/year using DeWind 48, while Lagos recorded the highest at 430.10 kW/year with DeWind D7-1.5 MW. Power densities varied across cities Lagos (387.07 W/m²), Osogbo (87.34), Abeokuta (65.09), Akure (145.07), and Ibadan (176.96), indicating practical potential for grid-connected or hybrid systems.

Paul et al. (2012) This study broadly covered the southern region, noting annual mean wind speeds between 3.09 and 4.15 m/s. The relatively low values suggest suitability only for small wind turbines or hybrid renewable systems. A GIS-based fuzzy analytical model was used to determine optimal locations for wind energy deployment across Nigeria. This model integrated multiple criteria such as wind speed, terrain, and land use, providing a spatial decision-making tool for turbine siting (Fagbenle et al., 2011). Ohunakin (2011) revealed that Maiduguri and Bauchi had peak wind speeds of 6.10 m/s and 7.04 m/s, respectively, with corresponding power densities of 173.70 W/m² and 299.88 W/m². Potiskum had slightly lower values with 4.80 m/s and 103.14 W/m². These locations are suitable for commercial wind projects. While Ikpo. An unusual result was reported where the highest average wind speed at 10 meters was given as 7925 m/s, with a minimum of 3675 m/s, which is clearly a data or typographical error. This requires verification (Ikpotokin et al., 2019). At 10 m height, wind speeds ranged from 3.21 to 4.19 m/s. Power densities varied between 6.28 and 102.90 W/m², with annual energy outputs from 422 to 747 kWh/m². The coastal region showed better potential with 2.1 to 3.0 m/s wind speed and 6.0 to 16.3 W/m² power density using Weibull models (Diemuodeke et al., 2019).

Akure recorded mean power densities of 22.26 W/m² and 18.51 W/m² under Rayleigh and Weibull models, respectively. The mean wind speed was around 2.70–2.71 m/s, suggesting marginal wind potential for micro-scale generation (Okeniyi et al., 2015). Wind speeds were reported to range from 0.9 to 13.1 m/s with a mean absolute percentage error of 8.9%. Annual wind speeds were between 2.75 and 4.57 m/s. Power densities fell between 16.57 and 76.40 W/m², indicating varying wind energy feasibility depending on location (Fadare, 2010). Wind energy output ranged from 4.07 to 145.6 MWh annually. A 35-kW wind turbine was recommended, suggesting that the area supports medium-sized wind projects if sited appropriately (Adaramola et al., 2014). Okokpujie et al. (2020) revealed that tn Umudike, the annual wind energy potential was estimated at 3101 kWh/m², indicating localized potential for wind energy development.

Table 1: Summary of Reviewed Wind Energy Works in Nigeria

Ref.	**Location**	**Work Done**	**Results**	**Findings**
Ojosu et al. (1995)	Nigeria (General)	Assessment of wind speed and energy across regions	Wind speed: 1.5–4.1 m/s, Power density: 5.7–22.5 W/m², Energy: 2.24–12,521.55 MWh	North has better wind resources than the South
Anyanwu et al. (1995)	Owerri	Estimation of power density and energy yield	Power density: 7.66 W/m², Energy: 60.29 kWh/m²	Low wind potential; suitable for micro-generation
Ngala et al. (2007)	Oyo State	Evaluation of wind speed and density at 25 m height	Wind speed: 2.85–5.20 m/s, Power density: 27.08–164.48 W/m²	Moderate wind resource, feasible for mid-scale applications
Fafare, (2008)	Enugu	Weibull distribution analysis at 10 m hub height	Mean speed: 2.5 m/s ± 0.3, Scale: 4.31 m/s, Shape: 2.21	Moderate wind potential with seasonal variation

Ajayi et al. (2014)	Southwest Nigeria	Analysis using commercial turbines (DeWind)	Wind speed: 2.7–7.7 m/s, Power: 4.21–430.10 kW/year, Density: 65.09–387.07 W/m²	Medium to small-scale wind systems feasible
Paul et al. (2012)	Southern Nigeria	General estimation of annual mean speeds	Wind speed: 3.09–4.15 m/s	Suitable for small turbines only
(Fagbenle et al., 2011)	Nigeria (GIS-based)	GIS fuzzy model for wind site suitability	Location-specific scores using terrain, wind, and access data	A decision-support tool for site selection
Ohunakin (2011)	Maiduguri, Bauchi, Potiskum	Wind analysis in NE Nigeria	Wind speed: 4.8–7.04 m/s, Power density: 103.14–299.88 W/m²	Best wind performance in Bauchi and Maiduguri
(Ikpotokin et al., 2019)	Omu-Aran (Kwara)	Wind speed data at 10 m	Wind speed (likely error): 7925 m/s max	Data error; re-evaluation needed
(Diemuodeke et al., 2019)	South-South Region	Wind speed and density at 10 m height	Wind speed: 2.1–4.2 m/s, Power density: 6.28–102.90 W/m²	Coastal areas have seasonal and marginal potential
(Okeniyi et al., 2015).	Akure	Rayleigh and Weibull model comparison	Wind speed: ~2.7 m/s, Power density: 18.51–22.26 W/m²	Low wind; only feasible for micro wind systems
(Fadare, 2010)	North-central Nigeria	Wind speed assessment across region	Wind speed: 2.75–4.57 m/s, Power density: 16.57–76.40 W/m²	Mixed performance; some areas marginal, others viable
(Adaramola et al., 2014).	Niger Delta	Annual energy estimation	Energy output: 4.07–145.6 MWh	Recommends 35 kW turbine; moderate viability
Okokpujie et al. (2020)	Umudike	Wind power estimation	Energy: 3101 kWh/m²	Small-scale generation possible

2.1 Wind energy potential in Nigeria

Vegetation cover and topographic aspects are among the dynamics that influences variation in wind patterns (Oladigbolu et al, 2019). With an average wind speed of 3.0 m/s for the entire Nigeria, the country has a great potential from wind energy (Oluleye and Adeyewa, 2016), though the country possesses a low wind speed profile (Idris et al, 2020). The average wind speed of the different geographic zones of the country shows the following - 3.88 – 9.39 m/s (North-West); 1.77 – 4.5 m/s (South-West); 2.46 – 5.36 m/s (North-Central); 3.30 – 4.65 m/s (South-South) (Oluleye and Adeyewa, 2016). With an average air density of 1.1 kg/m^3, the strength of wind energy at right angles to the wind direction ranges between 44 W/m^2 at the coastal regions to 352 W/m^2 at the far northern region of Nigeria (Olatomiwa et al, 2015). The northern regions of Nigeria therefore have greater wind resources compared to the southern part, and therefore they are the most appropriate for wind energy exploration. Accordingly, hybrid system (small-scale) is more appropriate for southern Nigeria, except in the coastal areas that exhibits viable wind energy potential. In the northern, the occurring wind speed shows that large-scale wind turbine is feasible.

In Nigeria, the peak wind speed occurs in April to August, across the country. Further, relative to dry season, the rainy season is more turbulent for wind energy because of fluctuation in wind speed (Idris *et al*., 2020).

In spite of the feasibility of wind energy in Nigeria, the resources do not contribute to the national grid or even off-grid. For example, the only large-scale onshore wind turbine in Nigeria is situated in Rimi Local Government Area of Katsina State, producing only an estimated 10 MW. Other wind turbines (small-scale) installed in Nigeria is the 5 kW wind turbine in Sokoto State and the 1 kW wind turbine in Bauchi and Katsina States, deployed for water abstraction (Okonkwo et al, 2021).In a study conducted by Akorede et al (2018), it is roughly estimated that about 70,218 MWh of wind energy will be generated from 31 cities in Nigeria with a capacity factor ranging from 0.1 to 0.2. Wind speed, the designed wind speed factors such as cut-in, rated and cut-off wind speeds greatly affects the performance of a wind turbine (Adaramola et al, 2012). Table 2 presents wind energy distribution in 14 selected Nigerian states, while Table 3 presents the wind energy distribution in Nigeria across zones.

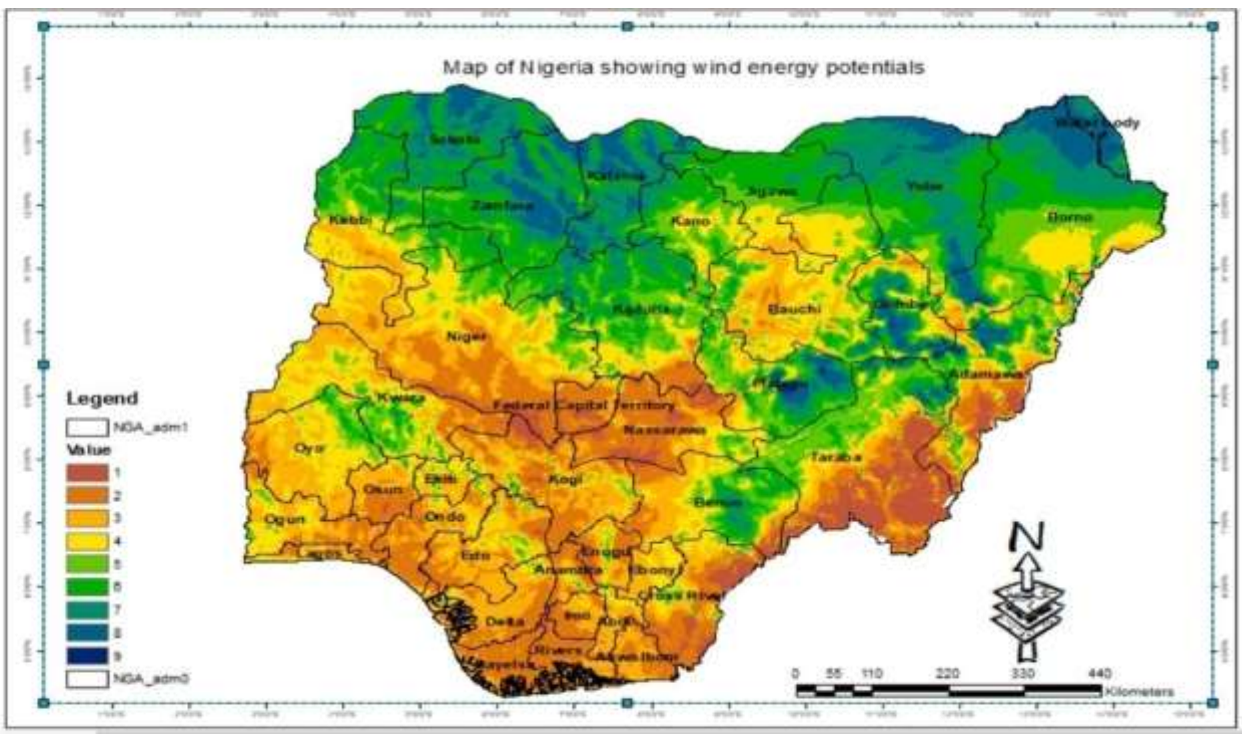

Figure 1: Wind energy map of Nigeria (Okedu et al., 2024)

Table 2: Wind Energy Potential in 14 Selected Nigerian States (Dvorak et al., 2013).

State	Land Area (km²)	% Area with Wind Speed > 4 m/s	1% of Suitable Area (km²)	Installed Capacity (MW)	Annual Generation (MWh)
Adamawa	37,957	45%	170	854	2,244
Bauchi	48,197	50%	240	1,204	3,166
Borno	72,767	100%	727	3,638	9,561
Gombe	17,428	100%	174	871	2,290
Jigawa	23,415	100%	234	1,170	3,076

Kaduna	44,217	60%	265	1,326	3,486
Kano	20,389	90%	183	917	2,411
Kebbi	23,822	100%	238	1,191	3,130
Katsina	36,320	25%	90	454	1,193
Plateau	26,539	90%	238	1,194	3,318
Sokoto	32,146	90%	289	1,446	3,801
Taraba	59,180	40%	236	1,183	3,110
Yobe	44,880	100%	448	2,244	5,897
Zamfara	33,667	80%	269	1,346	3,539
Total			**3,808**	**19,043**	**50,046**

Table 3: Annual energy distribution in Nigerian Geopolitical Zones (Akorede *et al,* 2018)

Zone	Average Annual mean wind speed (m/s) at 10m height	Average Annual wind speed (m/s) at 70 m height	Average Capacity Factor	Estimated Annual Energy (MWh)
South-West	3.75	4.83	0.151	11,940
South-South	3.86	4.97	0.154	4,067
South-East	4.26	5.49	0.200	3,506
North-West	6.47	8.33	0.447	27,438
North-Central	3.91	5.04	0.160	7,040
North-East	5.78	7.45	0.370	16,227
Total				70,218

Inshore, the wind is strong in mountainous sections of the North, while hilly topographies of the middle belt and northern peripheries have huge potential to harvest abundant wind energy. There is also existence of substantial variations within the same area because of different topography and unevenness of the country. However, it is predicted that the potential of wind energy development in Nigeria experiences a continuous decline. This is based on unplanned urban development and other human-activities which are depleting suitable topography for wind generation. The conditions for generation of wind energy potential are wind speed of ≥3 m/s, a buffer from built-up environment of 2000 m, 2,500m buffer from airfields or airports and others (Chiemelu et al, 2019). This suggests the criticality of environmental considerations in socio-economic development of the country, since the environment is a vital resource offering many benefits, among which include renewable energy resources.

2.4 Wind Turbine Pitch Control Strategies for Energy Optimization

Wind turbine pitch controllers play a crucial role in optimizing energy output by adjusting the blade angle to regulate aerodynamic power extraction. The control strategies for pitch regulation can be broadly classified into five main categories: Hybrid Pitch Controllers, Hydraulic Pitch Controllers, Maximum Power Point Tracking (MPPT) Control Strategies, Conventional Controllers, and Soft Computing Controllers. These classifications, illustrated in Figure 2, represent a spectrum of solutions ranging from classical control methods to advanced intelligent systems, each tailored to improve the performance, reliability, and adaptability of wind energy conversion systems under varying wind and operational conditions. Figure 2 presents the wind turbine pitch control approaches.

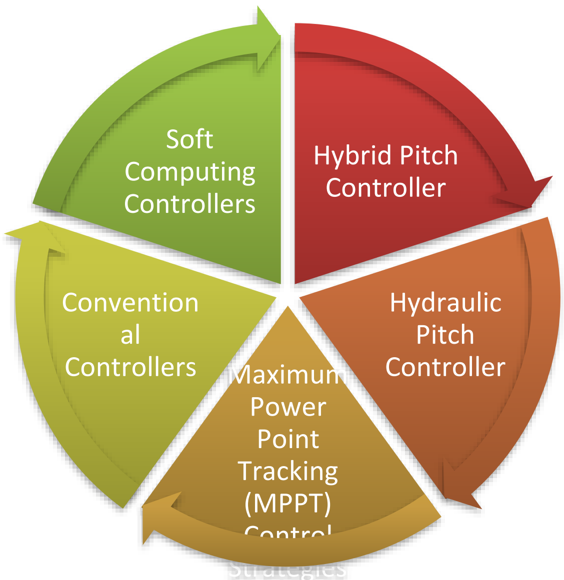

Figure 2: Methods of wind pitch control strategies

1. Hybrid Pitch Controller

Hybrid pitch controllers combine robust control techniques with soft computing methods to address the limitations of conventional control approaches in wind turbine (WT) systems. They are designed to enhance the dynamic performance and system stability while managing system complexity. According to Abdullah et al. (2012), hybrid controllers provide reliable solutions for nonlinear WT systems and contribute to optimized power output. However, their implementation may introduce additional costs due to the integration of multiple control layers and algorithms.

2. Hydraulic Pitch Controller

The hydraulic pitch controller operates the turbine blades using a hydraulic actuator coupled with an accumulator tank, which supplies the necessary linear motion. A hydraulic pump located in the nacelle of the WT provides the energy required for blade rotation. Recent research efforts have focused on the dynamic modeling, reliability, and efficiency of hydraulic systems for pitch control. While effective for large turbines due to high actuation force, their complexity and maintenance demands remain concerns.

3. Maximum Power Point Tracking (MPPT) Control Strategies

MPPT algorithms are essential in WT systems for ensuring the maximum extraction of energy across varying wind conditions. These algorithms continuously adjust operational parameters to align with optimal power output points. As Lin and Hong (2010) explained, MPPT not only improves power efficiency but also protects generators from overloads and surges, particularly when wind speeds exceed rated values.

4. Conventional Controllers

Conventional pitch control methods, particularly PID and PI controllers, are widely used in small-scale wind energy conversion systems (WECS). These controllers generate pitch angle references based on parameters like rotor speed, generator power, and wind speed. Knight (2005) highlighted their high response time and effectiveness in managing rotor speed and power. However, their reliance on accurate wind speed measurements and limited adaptability under dynamic environmental changes are major drawbacks. They are best suited for systems where simplicity and cost-effectiveness are prioritized.

5. Soft Computing Controllers

Soft computing controllers utilize artificial intelligence techniques to manage uncertainties and nonlinearities in WT systems. Common approaches include fuzzy logic control (FLC), artificial neural networks (ANN), and genetic algorithms (GA) as shown in figure 3.

i. Fuzzy Logic Control (FLC)

FLC is gaining popularity for pitch angle regulation due to its adaptability and simplicity. It does not require exact mathematical modeling and allows real-time tuning of controller parameters. Kamel, Chaouachi, and Nagasaka (2011) demonstrated the effectiveness of FLC in microgrid applications by improving frequency regulation without relying on battery storage. Similarly, Chowdhury, Hosseinzadeh, and Shen (2012) employed a fuzzy pitch controller to smooth wind power fluctuations, especially under low wind speed conditions. Despite its strengths, FLC depends on the expert knowledge of the designer and requires significant memory allocation.

ii. Artificial Neural Networks (ANN)

ANNs are capable of learning from system data and estimating complex nonlinear relationships in WT systems 9Kekong et al., 2019). They use input variables such as rotor speed, torque, wind speed, pitch angle, and voltage to produce optimal control actions. ANN-based pitch control is particularly effective in optimizing power output when wind speeds exceed the rated values (Ata, 2015; Pucci & Cirrincione, 2011). Their main limitation lies in the need for large training datasets and computational resources.

iii. Genetic Algorithms (GA)

GA-based controllers are a class of metaheuristic optimization algorithms used to fine-tune pitch angles under low wind speed conditions. Tiwari and Babu (2016) noted that GA-based pitch control helps maintain system stability and improve power extraction by adjusting the generator speed to match the optimal reference speed. These controllers are adaptive and global in scope but are best suited for offline or semi-online optimization due to their processing time (Sochima et al., 2025).

2.4 Methods of Wind Energy Optimization and Control

Efficient wind energy conversion depends not only on the mechanical and electrical design of wind turbines but also on the effectiveness of control strategies used to regulate their operation. Control systems play a vital role in optimizing power output, ensuring system stability, and extending the lifespan of wind energy components under variable wind and environmental conditions (Pucci and Cirrincione, 2011).

Over the years, several control approaches have been developed, ranging from traditional model-based techniques to advanced data-driven and hybrid methods. This section presents a detailed overview of the key wind energy optimization and control strategies, including Data-Driven Approaches, Model-Based Approaches, Hybrid Control Techniques combining both methods, Classical Control Methods, and specialized Model-Based Controls tailored for Floating Offshore Wind Turbine (FOWT) systems. Each method is discussed with respect to its principles, applications, advantages, and limitations (Oluleye and Adeyewa, 2016). Figure 4 presents the methods of wind energy optimization.

i. Data-Driven Approach

The data-driven approach focuses on using historical and real-time operational data from wind turbines to develop control strategies through machine learning, statistical inference, and artificial intelligence. This method avoids the need for explicit physical modeling by learning patterns and system behavior directly from the data (Kamet al., 2013). Techniques such as artificial neural networks (ANN), support vector machines (SVM), fuzzy logic systems, and reinforcement learning are used to optimize pitch control, torque regulation, fault detection, and power forecasting. The major strength of this approach lies in its adaptability and ability to handle nonlinearities and uncertainties in wind conditions, though it often requires large datasets and may lack interpretability (Ata, 2015).

ii. Model-Based Approach

Model-based control relies on well-defined mathematical representations of the wind turbines dynamics, including aerodynamics, mechanics, and electrical systems. Controllers such as PID, LQR, and model predictive control (MPC) are designed based on these models to optimize performance, improve stability, and ensure system safety (Ata, 2015). This approach provides a structured and predictable control mechanism, especially effective when accurate physical models are available. It is suitable for large-scale wind energy systems where operational dynamics are well-understood and measurable. Figure 4 presents the methods of energy optimization.

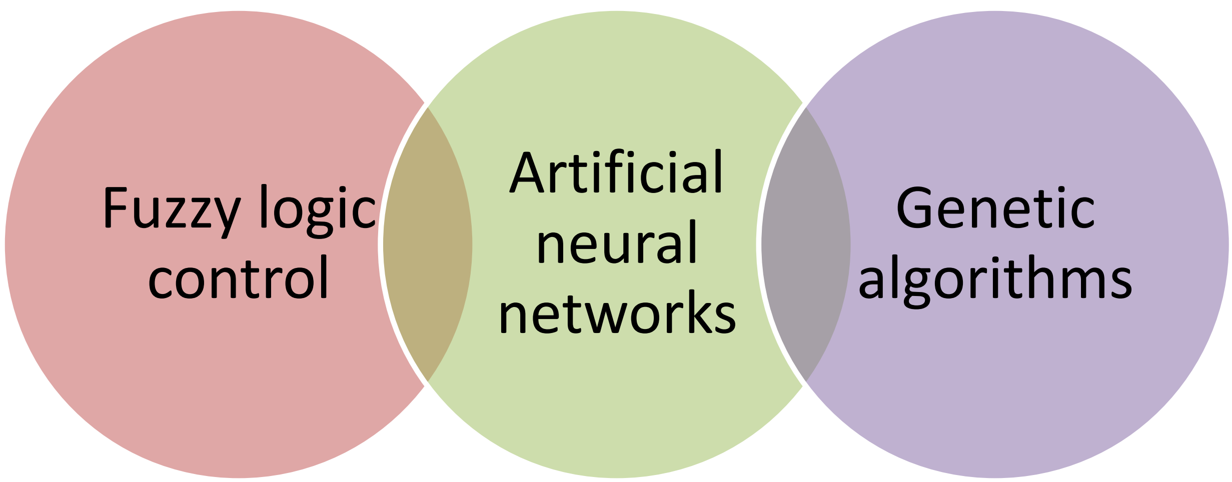

Figure 3: Soft Computing Controllers

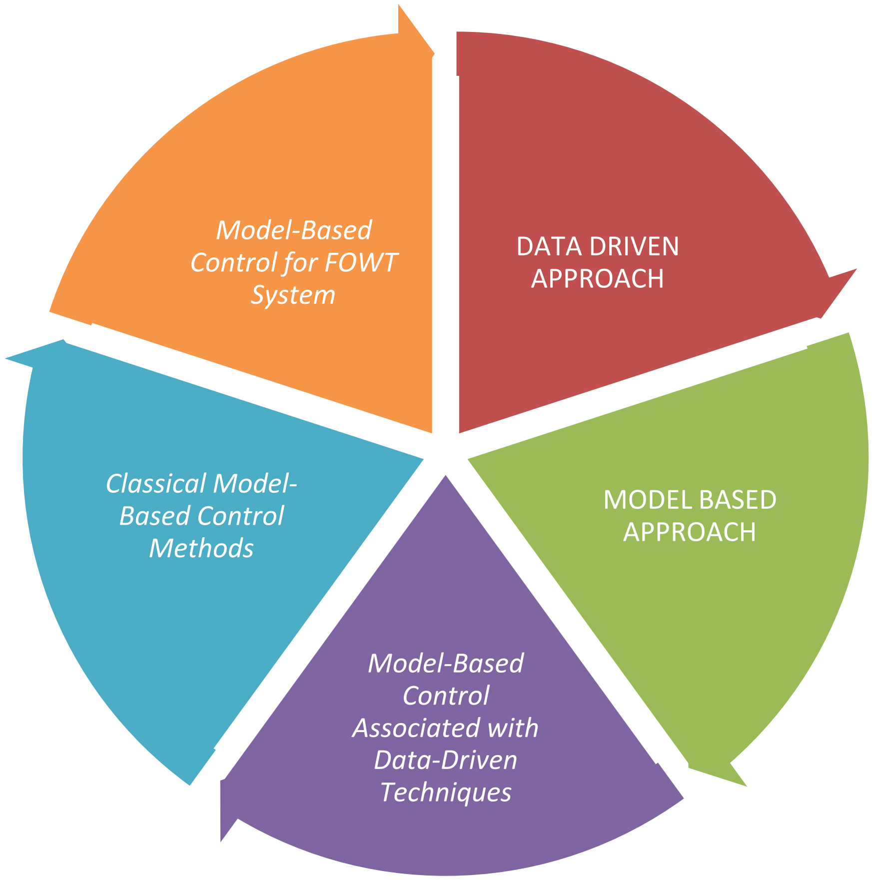

Figure 4: Methods of wind energy optimization

iii. Model-Based Control Associated with Data-Driven Techniques

This hybrid method combines the precision of model-based control with the adaptability of data-driven approaches. It uses physical models to establish control frameworks while incorporating machine learning techniques to enhance prediction, fault tolerance, and real-time adaptation (Fagbenle et al., 2011). For instance, model predictive control may use neural networks for disturbance estimation, or Kalman filters may be augmented with data-driven forecasting tools. This synergy enables more robust and intelligent wind turbine control, particularly useful in complex, variable environments with partial model uncertainty.

iv. Classical Model-Based Control Methods

Classical model-based methods involve traditional control theory techniques such as PID, PI, and PD controllers, which are simple, easy to implement, and widely used in small and medium wind energy systems. These controllers adjust rotor speed (Tiwari and Babu, 2016) pitch based on real-time inputs like wind speed and generator power, assuming a linear approximation of system dynamics. Though limited in handling complex nonlinearities and external disturbances, their low computational cost and reliability make them effective for basic wind turbine operations and grid support functions.

v. Model-Based Control for FOWT Systems

For floating offshore wind turbines (FOWTs), model-based control strategies are specifically tailored to handle coupled dynamics between wind loads, wave-induced motion, and platform stability. These methods often include multivariable control techniques such as linear quadratic regulators (LQR), MPC, and dynamic feedback control to simultaneously regulate power output and mitigate platform motion (Ata, 2015). Accurate modeling of aero-hydro-servo-elastic interactions is critical in this context. The goal is to enhance energy capture while ensuring structural safety and minimizing fatigue caused by environmental disturbances. Table 4 presents the summary of wind energy optimization and control methods.

Table 4: Summary of Wind Energy Optimization and Control Methods

Method	Advantages	Disadvantages	Suggestions/Applications
Data Driven Approach	Adaptable to system changes Handles nonlinearities Learns from realtime/historical data	Requires large, highquality datasets Limited interpretability May overfit	Use for fault detection, predictive control, and performance optimization in variable conditions
Model Based Approach	Welldefined structure Predictable and deterministic response Suitable for control design	Inflexible under modeling errors Complex to model real wind behavior accurately	Best for largescale systems with accurate physical models; use for pitch and torque control
Model Based + Data Driven Techniques (Hybrid)	Combines accuracy and adaptability Enhances robustness under uncertainty Realtime learning	Increased complexity Integration challenges Requires high computational resources	Ideal for smart wind farms; apply in dynamic environments with partial model knowledge
Classical Model Based Control Methods	Simple and cost effective Easy to implement Low computation demand	Poor performance under nonlinearities Limited flexibility Requires tuning	Use in small/medium turbines; enhance with gain scheduling or adaptive tuning
Model Based Control for FOWT Systems	Specifically designed for complex offshore dynamics Manages coupled wavewind loads Reduces fatigue loads	Requires precise modeling of aerohydroservoelastic behavior High complexity	Use in offshore farms; incorporate MPC and LQR with realtime environmental data

Given the wide range of environmental conditions and technical requirements associated with wind energy systems, various control methods have been developed to ensure optimal performance. Each control strategy whether data-driven, model-based, hybrid, or tailored for specific systems like floating offshore wind turbines offers unique strengths and limitations. To provide a concise comparison, the Table below summarizes these methods in terms of their advantages, disadvantages, and recommended applications. This overview supports informed decision-making for selecting or designing suitable control strategies in different wind energy scenarios.

5. Summary of Key Findings

This section uses Table to summarize the findings from the study. This was classified considering different focus area of the research and findings made as shown in Table 5.

Table 5: Research findings

Focus Area	Findings
Wind Energy Resource Distribution	Northern states such as Borno, Sokoto, and Bauchi exhibit the highest wind speeds, exceeding 6 m/s, while southern regions show lower wind potential.
Wind Power Potential	States like Borno, Yobe, and Jigawa have the highest installed capacity and annual generation potential, indicating suitability for large-scale wind farms.
Wind Turbine Control Strategies	Advanced control methods such as fuzzy logic and neural networks outperform classical PID controllers in adapting to nonlinear and variable wind conditions.
Data-Driven Control	Machine learning models (e.g., ANN) are effective in handling uncertainties, improving power output, and enabling real-time control adaptation.
Model-Based Control	PID and MPC controllers are efficient for structured systems with known dynamics but struggle with sudden changes and unmodeled disturbances.
Hybrid Control (Model + Data)	Combining model-based and data-driven approaches enhances robustness, particularly in complex environments like offshore or fluctuating wind regimes.
FOWT (Floating Offshore Wind Turbines)	Require specialized control strategies due to coupled wind-wave-platform dynamics; model-based approaches like LQR and MPC are most effective.
Nigeria's Implementation Gaps	Despite potential, limited infrastructure, lack of localized control technologies, and insufficient data hinder wind energy development.

6. Recommendations

Based on the findings of this study, it is recommended that Nigeria prioritizes the development of region-specific wind energy systems by investing in accurate wind resource assessments and selecting appropriate turbine technologies that align with local wind characteristics. Policymakers should support the integration of advanced control strategies particularly data-driven and hybrid approaches to enhance the efficiency and reliability of wind energy conversion systems. Furthermore, there is a need for increased research and capacity building in intelligent control methods such as fuzzy logic and neural networks, which have shown significant potential for optimizing wind power output under variable conditions. Establishing pilot projects and incentivizing private sector participation can also accelerate the adoption of these modern control technologies in Nigeria's renewable energy sector.

7. Conclusion

This study has provided a comprehensive assessment of wind energy resources across Nigeria, revealing significant regional variations in wind potential and identifying key areas suitable for wind power development. By quantifying the wind energy generation capacity in selected states, the paper offers crucial data that can guide policymakers, investors, and energy planners in making informed decisions. Furthermore, the review and comparison of various wind turbine control strategies including conventional, model-based, data-driven, and hybrid approaches underscore the importance of selecting context-specific control methods to enhance the efficiency, reliability, and adaptability of wind energy systems in Nigeria. Overall, the findings contribute to advancing the knowledge base required for the sustainable integration of wind power into the national energy mix.

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