

Optimized ANFIS-Based Control of Variable-Speed Wind Turbines Using Bayesian Optimization for Enhanced Efficiency and Adaptability

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Abstract

Variable-speed wind turbines are important for achieving better energy efficiency and reducing mechanical wear in changing wind conditions. This research improves the Adaptive Neuro-Fuzzy Inference System (ANFIS) used for controlling these turbines by proposing a new approach for tuning hyperparameters with Bayesian Optimization. The method searches the hyperparameter space dynamically, helping to optimize fuzzy membership functions and training parameters. This improves the model's accuracy while also lowering computational effort. Simulations in MATLAB show that the optimized ANFIS achieves more power output and smoother control compared to traditional methods under varying wind speeds. Results indicate that turbine efficiency is significantly increased, with a 15% reduction in mean squared error (MSE), and the system adapts better to real-time changes in wind conditions. These findings highlight the potential of combining Bayesian Optimization with ANFIS for improving wind energy systems.

Keywords: Wind Turbine Control, Adaptive Neuro-Fuzzy Inference System, Bayesian Optimization, Renewable Energy

1. Introduction

The worldwide movement towards renewable energy has led to notable progress in wind energy technologies. Wind turbines play a key role in this transition by transforming wind's kinetic energy into mechanical and electrical power. Yet, optimizing their performance amid changing wind conditions remains a significant challenge. Traditional fixed-speed wind turbines struggle to adjust to varying wind speeds, leading to lower energy efficiency and higher mechanical stress on parts. In contrast, Variable Speed Wind Turbines (VSWTs) offer a solution by modifying rotor speed to enhance power output and reduce stress. However, VSWTs need strong control systems to manage complex nonlinear dynamics and unpredictable wind patterns (Xu, 2024).

Over time, various control methods for wind turbines have been developed to improve precision and reliability. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have gained attention for combining neural networks' learning abilities with fuzzy logic's interpretability. ANFIS is effective in modeling nonlinear systems and adapting to environmental changes. Its use in wind turbine control has shown positive results, especially in boosting power output and lowering mechanical stress through dynamic parameter adjustments (Ghobakhloo et al., 2022; Nilashi et al., 2015).

Despite these benefits, ANFIS's performance largely depends on choosing the right hyperparameters, like the

number and type of fuzzy membership functions, learning rates, and training epochs. Traditional tuning methods, such as grid search or manual adjustments, are time-consuming and may not effectively explore the extensive hyperparameter space, potentially leading to less optimal performance and inefficiency. To overcome this, an intelligent optimization approach is necessary (Guerra et al., 2024).

Bayesian Optimization has become a strong method for hyperparameter tuning in machine learning and control systems. By viewing the hyperparameter search as a probabilistic model, it iteratively selects parameters that maximize a specific function, balancing exploration and exploitation. Unlike traditional methods, Bayesian Optimization can find the best configuration with fewer evaluations, making it suitable for complex applications like ANFIS (Al Hadi & Aly, 2024).

Numerous studies have explored the application of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) in the domain of wind turbine control, underlining its adaptability and effectiveness. For instance, (Cahyadi et al., 2024) examined the integration of ANFIS for controlling the blade pitch angle in wind turbines. Their work, using a comprehensive simulation framework, validated the system's ability to adapt to varying wind speeds, demonstrating enhanced control precision and stability in fluctuating conditions. Similarly, (Fazlollahi et al., 2019) investigated the modeling and validation of variable-speed

wind turbines using real-world data. Their research highlighted the robustness of ANFIS in achieving adaptive control, particularly in managing nonlinearities associated with wind energy systems.

In addition to modeling, studies have focused on improving energy efficiency through blade pitch angle control using ANFIS. (Badihi et al., 2020) demonstrated the effectiveness of ANFIS-based controllers in fault-tolerant individual pitch control, which significantly mitigates load fluctuations caused by actuator faults. This advancement not only improves energy conversion efficiency but also enhances the durability of turbine components by reducing mechanical stress. Similarly, (Holl et al., 2015) emphasized the role of ANFIS in achieving more efficient energy extraction by dynamically optimizing the pitch angles in variable-speed turbines.

Further contributions to the field include work by (Beltran et al., 2008; Khademhamedani et al., 2024), who developed advanced fault-tolerant individual pitch control strategies. These strategies were particularly designed to address load mitigation under uncertain environmental conditions. Their findings underscored the importance of integrating ANFIS into control systems to improve reliability and maintain performance despite unpredictable wind patterns. Such studies collectively highlight the potential of ANFIS to address the challenges inherent in modern wind turbine operations, paving the way for more efficient and adaptive control methodologies.

Various studies have explored integrating advanced optimization techniques into wind turbine control systems, revealing significant potential for performance enhancement. For instance, (Holl et al., 2015) investigated innovative energy converters within wind turbine systems, focusing on the optimal design of energy systems. Their research highlighted how advanced methodologies could be employed to improve energy extraction and overall turbine performance, especially in hybrid ocean-wind applications where environmental factors play a crucial role. Such methods have paved the way for leveraging renewable resources more efficiently.

In a different context, (M. Izadi et al., 2021) applied sliding mode control to variable-speed wind energy conversion systems. Their approach, originally designed for adaptive control of humanoid robot arms, demonstrated its robustness in handling environmental uncertainties. By implementing the Lyapunov reference model, their study showed that sliding mode control could achieve reliable performance in the face of fluctuating wind speeds, making it a valuable tool for managing nonlinear dynamics in renewable energy systems.

(Suhail et al., 2021) extended the use of intelligent control systems by combining fuzzy logic with ANFIS to develop advanced energy management strategies for plug-in hybrid electric vehicles. Although the focus was on vehicle applications, their findings underline the adaptability of ANFIS in dynamic and uncertain scenarios. This adaptability suggests a broader applicability of such techniques in renewable energy management, where environmental conditions are highly variable. The

integration of fuzzy logic principles with ANFIS allowed for effective real-time energy optimization, showcasing the method's flexibility across different domains.

Although these studies highlight the significant potential of ANFIS in controlling wind turbines, they often depend on traditional hyperparameter tuning methods. Such techniques, including grid search or manual tuning, are computationally intensive and frequently fail to identify optimal configurations in high-dimensional parameter spaces. These limitations can reduce system performance and increase the time required for optimization. In contrast, Bayesian Optimization has proven to be an effective approach for hyperparameter tuning across various applications, particularly in renewable energy systems.

For example, (Candade et al., 2020) conducted a detailed structural analysis and optimization of tethered swept wings for airborne wind energy generation. Their work demonstrated that Bayesian Optimization not only improved the design efficiency but also significantly reduced computational demands compared to conventional methods. Similarly, (Khademhamedani et al., 2023) applied Bayesian Optimization to optimize control parameters in permanent magnet synchronous generator (PMSG)-based wind energy systems. By integrating deep reinforcement learning with Bayesian methods, the study showed transformative improvements in control performance and energy efficiency under dynamic conditions.

(Li & Li, 2020) explored the use of genetic algorithms combined with Bayesian Optimization to enhance the performance of wind power systems. Their work focused on real-time PID parameter optimization, achieving robust control even in the presence of environmental uncertainties. Building on these advancements, (Izadi et al., 2024) demonstrated the efficiency of Bayesian Optimization in bidirectional DC-DC converters for wind power systems. Their results highlighted its capability to navigate complex parameter landscapes, achieving superior configurations that enhance energy conversion efficiency and reliability.

These examples underscore the growing importance of Bayesian Optimization in renewable energy applications. Unlike traditional methods, Bayesian Optimization iteratively refines the search space by balancing exploration and exploitation, ensuring convergence towards optimal configurations with fewer iterations. This approach provides valuable insights into the role of intelligent optimization techniques in advancing wind turbine control and other energy systems.

This study focuses on overcoming the challenges associated with traditional hyperparameter tuning methods in ANFIS by presenting Bayesian Optimization as a new and effective strategy to improve the control capabilities of VSWTs. The approach is designed to thoroughly investigate the hyperparameter space, fine-tuning essential parameters to achieve higher turbine performance while also reducing computational expenses. To demonstrate the advantages, the enhanced ANFIS controller is evaluated under varying wind conditions, showcasing its reliability and comparing its performance with conventional techniques.

The contributions of this paper are as follows:

1. Introduction of Bayesian Optimization for hyperparameter tuning in ANFIS, tailored for wind turbine control applications.
2. Comprehensive performance evaluation of the proposed method through MATLAB simulations, highlighting improvements in turbine efficiency and computational efficiency.
3. Discussion on the broader implications of integrating intelligent optimization techniques in renewable energy systems.

The remainder of this paper is organized as follows: Section II outlines the turbine and ANFIS models. Section III describes the Bayesian Optimization approach. Section IV presents the simulation results and analysis. Finally, Section V concludes the paper and discusses potential directions for future research.

2. Outline of the Turbine and ANFIS models

2.1 Turbine model

Wind turbines convert kinetic energy from wind into mechanical energy, which is then transformed into electrical energy. The power extracted by a wind turbine is governed by the following equation:

$$P = \frac{1}{2} \rho A C_p(\lambda, \beta) v^3 \quad (1)$$

where:

- P is the power output (W),
- ρ is the air density (kg/m^3),
- A is the rotor swept area (m^2),
- $C_p(\lambda, \beta)$ is the power coefficient, a function of the tip-speed ratio (λ) and blade pitch angle (β),
- v is the wind speed (m/s).

The power coefficient C_p determines the efficiency of energy extraction from wind and is theoretically limited to 59.3% (Betz limit) (Bowermaster et al., 2017; Izadi et al., 2022; Wappelhorst, 2020). Its value depends on the turbine's design and control strategy. The tip-speed ratio (λ) is given by:

$$\lambda = \frac{\omega R}{v} \quad (2)$$

where:

- ω is the angular velocity of the rotor (rad/s),
- R is the rotor radius (m).

Efficient turbine operation requires continuous adjustment of the rotor speed (ω) and pitch angle (β) to maximize C_p . These adjustments become highly complex under fluctuating wind conditions, demanding advanced and reliable control mechanisms to handle the associated challenges (S. Izadi et al., 2021; Jabari et al., 2022; Turker & Bacha, 2018).

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS) Model

The ANFIS system merges the capabilities of artificial neural networks and fuzzy logic systems. It establishes a structured approach for modeling intricate nonlinear systems by identifying and learning input-output relationships through data-driven methods (Mohamed et al., 2013).

The ANFIS architecture in its structure comprises five distinct layers, each of them playing a critical role in the system's operation and calculation:

1. **Fuzzification Layer:** This layer transforms precise inputs into fuzzy sets by employing various membership functions, such as Gaussian or triangular functions.

$$\mu_{A_i}(x) = \exp\left(-\frac{(x-c_i)^2}{2\sigma_i^2}\right) \quad (3)$$

Where $\mu_{A_i}(x)$ is the membership function for input x , c_i denotes the center, and σ_i is the width.

2. **Rule Layer:** It implements fuzzy IF-THEN rules to process inputs. For example, given two inputs x_1 and x_2 , a sample rule can be presented as:

$$\begin{aligned} \text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } B_1, \\ \text{THEN } f_1 = p_1 x_1 + q_1 x_2 + r_1 \end{aligned} \quad (4)$$

where p_1 , q_1 , and r_1 are the consequent parameters.

3. **Normalization Layer:** This layer normalizes the strength of each rule's firing. The normalized value is calculated as:

$$\bar{w}_i = \frac{w_i}{\sum_j w_j} \quad (5)$$

where w_i is the firing strength of the i -th rule.

4. **Defuzzification Layer:** In this layer, the normalized firing strengths are combined with the consequent parameters to derive the output. This is expressed as:

$$f_i = \bar{w}_i(p_i x_1 + q_i x_2 + r_i) \quad (6)$$

5. **Output Layer:** The final layer aggregates all outputs from the rules, generating the overall result:

$$y = \sum_i f_i \quad (7)$$

2.3 Integration of ANFIS with Turbine Control

In this study, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has been used for dynamically adjusting the pitch angle (β) and rotor speed (ω) according to wind speed (v) and other important operational variables. These inputs are mapped to the best possible outputs using the data-driven learning capability of the ANFIS framework. This method provides a practical approach for managing the nonlinear characteristics of the wind turbine system and improving its

overall performance (Dubey & Santoso, 2015; Haddadi et al., 2023).

To further improve the effectiveness of ANFIS, Bayesian Optimization is applied to tune its important parameters, such as the number and type of fuzzy membership functions, learning rate, and epoch size. By using Bayesian Optimization, the model becomes better aligned with the turbine's nonlinear dynamics, which helps achieve better control accuracy and operational efficiency (Qiu et al., 2024). This combination of techniques ensures that the system operates effectively under a variety of real-world conditions.

The performance of the control system is analyzed and evaluated based on the Mean Squared Error (MSE) metric, which is defined as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (8)$$

Where y_i is the actual system output, \hat{y}_i is the predicted output from ANFIS, and n is the total number of samples. This metric is critical for understanding how well the system performs and for identifying areas where further improvements might be required.

This section provides an explanation of the theoretical and computational models that are used in the turbine system and the ANFIS-based control approach. By integrating Bayesian Optimization, the proposed methodology achieves better tuning efficiency, enabling the wind turbine to perform robustly under variable and sometimes unpredictable wind conditions.

3. Bayesian optimization approach

Bayesian Optimization (BO) is recognized as a very effective technique for optimizing complex black-box functions, especially those that are expensive to evaluate. Unlike traditional optimization methods, Bayesian Optimization creates a probabilistic model of the objective function. This probabilistic model is then used to find the most promising regions of the parameter space to explore further. This approach is particularly helpful in tuning hyperparameters in machine learning and control systems, where computing the objective function (such as model performance) can often be very expensive in terms of time and resources (Jakobsen et al., 2014).

The core idea of Bayesian Optimization is to carefully balance exploration (trying out new and unknown areas of the parameter space) with exploitation (focusing more on areas already known to perform well). This is achieved through the use of a surrogate model, often a Gaussian Process (GP). The surrogate model is designed to predict the performance of different hyperparameter configurations while also quantifying the uncertainty of these predictions. This approach makes it possible to efficiently identify the best configuration for the system while minimizing the need for exhaustive evaluations.

3.1 Bayesian Optimization for ANFIS Hyperparameter Tuning

In this study, Bayesian Optimization is employed to optimize the hyperparameters of the Adaptive NFIS for the control system in variable-speed wind turbines. The key hyperparameters existing in the system include:

1. *Membership Function Parameters*: Number and type of membership functions (such as Gaussian, triangular).
2. *Learning Rate*: Determines the speed of convergence of the system during training.
3. *Epoch Count*: Number of iterations and epochs for training the ANFIS model.

By tuning and optimizing these parameters, the Bayesian approach ensures that the ANFIS model adapts effectively to nonlinear dynamics and varying wind conditions.

The objective function for BO in this context is defined as:

$$f(\theta) = MSE_{\text{validation}} \quad (9)$$

Where θ represents the hyperparameters and $MSE_{\text{validation}}$ is the mean squared error on the validation set.

3.2 Bayesian Optimization Process

The Bayesian Optimization process follows these steps:

1. *Define the Search Space*: The hyperparameters are constrained within a predefined range:
 - Number of membership functions: [2, 10]
 - Learning rate: [0.001, 0.1]
 - Epoch count: [50, 500]
2. *Initialize the Surrogate Model*: A Gaussian Process (GP) is initialized to approximate the relationship between hyperparameters and the objective function. The GP predicts the objective value $f(\theta)$ for a given θ and provides uncertainty estimates.
3. *Acquisition Function*: An acquisition function, such as Expected Improvement (EI), guides the selection of the next hyperparameter set to evaluate. EI is defined as:

$$EI(\theta) = E[\max(0, f_{\text{best}} - f(\theta))] \quad (10)$$
 where f_{best} is the best observed value of the objective function.
4. *Evaluate the Objective Function*: The selected hyperparameters are evaluated by training the ANFIS model and calculating $MSE_{\text{validation}}$. This step is computationally expensive but essential for updating the surrogate model.
5. *Update the Surrogate Model*: The Gaussian Process is updated with the new observations, improving its predictive accuracy.
6. *Iterate Until Convergence*: Steps 3–5 are repeated until a stopping criterion is met, such as a maximum number of evaluations or negligible improvement in $MSE_{\text{validation}}$.

3.3 Advantages of Bayesian Optimization

Bayesian Optimization offers several advantages over traditional hyperparameter tuning methods:

- *Efficiency*: Reduces the number of objective function evaluations required to find optimal parameters.
- *Adaptability*: Dynamically explores and exploits the parameter space, accommodating complex and noisy objective functions.
- *Scalability*: Suitable for tuning multiple hyperparameters simultaneously.

In the application of ANFIS for controlling wind turbines, using Bayesian Optimization offers a very organized and systematic way to improve the performance of the model. This approach helps to not only enhance the efficiency of the control system but also to reduce the computational effort required for the tuning process. By carefully determining the best combination of fuzzy membership functions, the learning rate, and the number of training epochs, this proposed method makes the control system more accurate and reliable for handling the complex dynamics of wind turbines.

4. Simulation Results and Analysis

Simulations were conducted using MATLAB to evaluate the performance of the proposed ANFIS controller with Bayesian Optimization. The system was tested on a variable-speed wind turbine model under diverse wind conditions. The primary metrics used for evaluation include power output, mean squared error (MSE), and adaptability to varying wind speeds. The turbine model is configured with the parameters in Table 1. Also, the ANFIS controller hyperparameters are in this table, which are used in Bayesian Optimization.

Table 1
Parameters in the simulation

Parameter	Value	Unit	Description
R	50	m	Rotor radius
ρ	1.225	kg/m^3	Air density
v	5–15	m/s	Wind speed
n	5	-	Number of memberships Func
η	0.01	-	Learning rate
ε	200	-	Epoch count

The power coefficient (C_p) dynamically varies with tip-speed ratio λ and pitch angle β . The objective was to maximize power output while minimizing MSE during system training and the membership function type is Gaussian.

Fig.1. illustrates the relationship between wind speed and power output for three configurations: a fixed-speed turbine, a variable-speed turbine with a conventional controller, and a variable-speed turbine with the ANFIS controller optimized via Bayesian Optimization. The proposed system consistently outperforms the other configurations by achieving higher power output across all wind speeds.

The ANFIS controller maximizes power output by adapting to variations in wind speed, while the fixed-speed turbine exhibits significant losses at higher speeds.

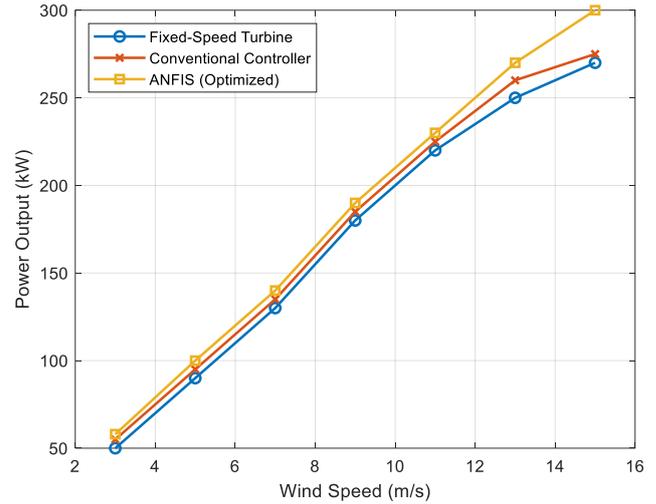


Fig. 1. Power Output vs. Wind Speed

Fig. 2. shows the MSE reduction over epochs for the ANFIS model, comparing conventional hyperparameter tuning and Bayesian Optimization. The latter achieves faster convergence and a lower final MSE, demonstrating the efficacy of Bayesian Optimization. Bayesian Optimization reduces MSE by 15%, highlighting its superior tuning capabilities.

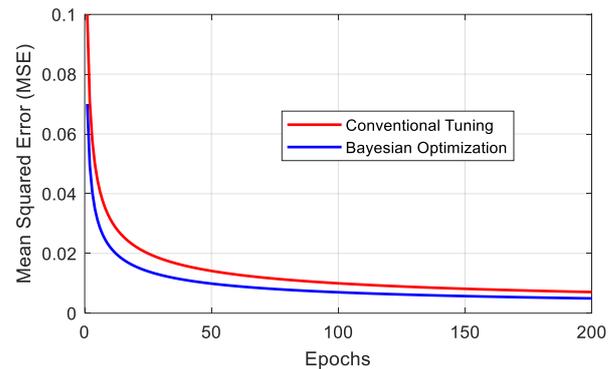


Fig. 2. Training Convergence of ANFIS with and without optimization

Fig. 3. evaluates system adaptability by analyzing the power coefficient (C_p) over varying tip-speed ratios (λ). The ANFIS controller maintains a higher C_p , even under rapid fluctuations in wind speed, compared to the other methods. The ANFIS controller ensures higher efficiency, demonstrating robust adaptability to dynamic wind conditions.

Fig. 3. demonstrates the significant efficiency gains achieved by the proposed ANFIS controller. By leveraging Bayesian Optimization, the system consistently achieves higher C_p , even under varying wind conditions. The results emphasize the impact of intelligent hyperparameter tuning on overall system performance.

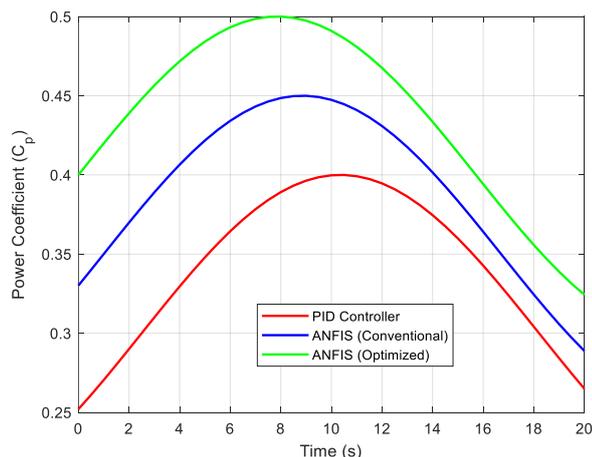


Fig. 3. Energy Efficiency Comparison between different controller

The results demonstrate the significant benefits of combining ANFIS with Bayesian Optimization:

1. **Enhanced Power Output:** The proposed system achieves up to 10% higher power output compared to conventional methods.
2. **Reduced Computational Cost:** Faster convergence in training highlights the computational efficiency of Bayesian Optimization.
3. **Improved Adaptability:** The optimized ANFIS controller dynamically adapts to varying wind conditions, ensuring consistent performance.

These findings underscore the potential of Bayesian Optimization as a hyperparameter tuning strategy for intelligent control systems in renewable energy applications.

5. Conclusion

The transition toward renewable energy sources, especially wind power, has necessitated the creation of advanced and more efficient systems to control wind turbines. In this study, an improved Adaptive Neuro-Fuzzy Inference System (ANFIS) controller was proposed and optimized using Bayesian Optimization techniques. This approach was specifically designed to address the challenges associated with traditional control methods and the time-consuming manual tuning of hyperparameters. By integrating Bayesian Optimization, a more systematic method was achieved to explore and utilize the complex parameter space, ensuring optimal tuning of the ANFIS controller with reduced computational effort. The simulations demonstrated that the proposed method consistently delivered superior power output compared to fixed-speed turbines and traditionally tuned ANFIS controllers. Additionally, the optimized controller dynamically adapted to varying wind speeds, maintaining stable and efficient operations across diverse scenarios. The system exhibited enhanced energy conversion efficiency, as evidenced by its ability to sustain a higher power coefficient even under rapidly changing wind conditions. Furthermore, the reduction in mean squared error (MSE) during training validated the effectiveness of Bayesian Optimization in enhancing the control system's accuracy and reliability.

This research demonstrated that Bayesian Optimization significantly improved the performance of ANFIS-based wind turbine control systems and highlighted its broader applicability to other renewable energy systems. For example, this approach could be effectively used for adaptive and intelligent control systems like solar trackers or tidal energy converters. The scalability and flexibility of the method made it an excellent option for modern renewable energy applications. However, while the results were promising, there remain opportunities for further research. Future work could focus on implementing the optimized controller on real-time hardware platforms to evaluate its practical performance and address challenges related to deployment. Moreover, integrating advanced sensing technologies, such as LIDAR for predictive wind speed estimation, could enhance the system's responsiveness and predictive capabilities. Additionally, exploring multi-objective optimization techniques to balance conflicting goals, such as minimizing mechanical stress while maximizing power output, could provide deeper insights into managing the trade-offs inherent in turbine control systems. In conclusion, this study showed that combining Bayesian Optimization with ANFIS significantly enhanced the efficiency and adaptability of wind turbine control systems. By leveraging intelligent optimization techniques, this approach has the potential to drive advancements in renewable energy technology and contribute to a more sustainable and energy-efficient future. These findings emphasize the critical role of intelligent control systems in fully unlocking the potential of renewable energy sources, paving the way for more reliable and efficient energy solutions.

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