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A Hybrid Artificial Intelligence-Driven and Genetic Algorithm-Based Optimization Framework for Enhancing Wind Turbine Performance with Structurally Defective Blades in Support of the Sustainable Development Goals (SDGs)

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ABSTRACT

This study aims to enhance the performance of horizontal-axis wind turbines with structurally defective blades through a hybrid Artificial Intelligence-driven and Genetic Algorithm-based optimization framework. The research developed Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System models to predict power output and vibration levels. The models were integrated into a Genetic Algorithm to determine optimal pitch angles and rotational speeds. The framework resulted in maximized power generation and minimized vibration. The findings demonstrate that the combined models outperform traditional methods because they capture complex nonlinear interactions and support real-time control. This integration of science and technology concepts contributes to improving the operational efficiency and reliability of wind turbines while supporting the Sustainable Development Goals through renewable energy advancement.

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1. INTRODUCTION

The transition towards renewable energy sources is crucial in addressing the global challenges of climate change, energy security, and sustainable development [1]. Among various renewable energy technologies, wind energy has emerged as a reliable and efficient solution due to its scalability and environmental benefits [2]. Horizontal-axis wind turbines (HAWTs) dominate the wind energy sector because of their well-established design and proven operational efficiency [3]. However, achieving sustained and optimal performance of wind turbines remains a significant engineering challenge. Turbine blades are exposed to harsh environmental conditions, leading to fatigue, cracks, and other structural defects that compromise aerodynamic performance, increase vibration, and shorten operational lifespan [4,5]. These defects pose critical risks to system reliability and energy output, necessitating advanced strategies to monitor, predict, and mitigate their impact.

One of the main challenges in maintaining wind turbine performance lies in managing the trade-off between maximizing power output and controlling structural vibrations, especially when defects are present [6]. **Table 1** presents the primary challenges encountered in HAWT operation, their associated details, and consequences. These challenges include structural integrity issues that reduce aerodynamic efficiency, vibration problems that accelerate component wear, complex nonlinear dynamics that complicate performance prediction, and the need for multi-objective optimization to balance competing operational goals [2,7]. Addressing these challenges requires not only advanced monitoring and predictive modeling but also intelligent optimization frameworks capable of adapting to dynamic operational conditions.

Table 1. Challenges and their consequences in HAWT operation [2-3,7].

Challenges	Details	Significances
Structural Integrity	Blades are prone to fatigue. Leading to cracks and defects.	Reduce aerodynamic efficiency and possible structural failure.
Vibration Issues	Structural defects cause imbalances and increased vibration levels.	Accelerate component wear, reduce operational efficiency, and possible damage.
Non-linear Dynamics	Complex interactions among wind speed, blade pitch angles, and rotational speed.	Difficult to predict and optimize turbine performance.
Multi-objective Optimisation	Managing trade-offs between power output and vibration levels. Need for advanced optimization techniques.	Difficult to achieve both high efficiency and structural stability.

This study aims to develop and validate a hybrid Artificial Intelligence-driven and Genetic Algorithm-based optimization framework for enhancing wind turbine performance under defective blade conditions. The novelty of this research lies in integrating Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with Genetic Algorithms (GA) to achieve simultaneous power maximization and vibration minimization. We also consider the use of Quadratic Regression (QR) in this study. Unlike conventional regression or heuristic approaches, the proposed framework leverages computational intelligence to dynamically adjust turbine input parameters because it captures complex nonlinear interactions between variables. This innovation contributes to advancing wind energy technologies in support of the Sustainable Development Goals (SDGs), particularly by improving system reliability, extending turbine lifespan, and reducing operational costs through enhanced structural health management.

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2. LITERATURE REVIEW

Wind energy technology has seen significant advancements in recent years, with research focusing on improving the performance, reliability, and fault diagnostics of wind turbines. Structural defects, particularly in blades, pose one of the most critical challenges in this domain, as they can reduce aerodynamic efficiency, increase vibrations, and shorten the operational lifespan of turbines [3,4]. To address this, researchers have explored various non-destructive testing and structural health monitoring techniques. Methods such as ultrasonic testing, acoustic emission monitoring, and piezoelectric impedance-based systems have shown promise in defect detection and condition assessment [8,9]. These studies highlight the need for enhanced monitoring systems capable of supporting predictive maintenance strategies in wind farms [10].

In parallel, predictive modeling approaches have been developed to forecast turbine performance under various operating conditions [11]. Machine learning techniques, including ANN and ANFIS, have demonstrated superior capabilities over traditional linear regression methods in capturing complex, nonlinear dynamics in wind turbine systems [12-14]. ANN models have been particularly effective in predicting power output, while ANFIS has shown strength in modeling vibration behavior due to its integration of fuzzy logic and neural network learning [15]. These models provide valuable tools for analyzing turbine behavior but are often applied in isolation without integration into broader optimization frameworks.

Optimization techniques, especially those using GA, have been employed to enhance wind turbine operation by tuning parameters such as blade pitch angles and rotational speeds [16]. GA has proven effective in solving multi-objective problems involving power maximization and vibration control [17-19]. However, a notable gap in the literature is the limited integration of predictive modeling with optimization algorithms to simultaneously address performance and structural stability in turbines with defects [20,21]. This gap underscores the need for hybrid frameworks that combine predictive accuracy with optimization capability to support intelligent, adaptive control in wind energy systems.

3. METHODS

This study employed an integrated experimental and computational approach combining laboratory-scale testing, machine learning-based predictive modeling, and GA-based optimization to enhance the performance of wind turbines operating with structurally defective blades.

Figure 1 presents the methodology flowchart, outlining each stage from experimental design to model development and optimization. The framework aimed to identify optimal operational parameters that would maximize power output and minimize structural vibrations, addressing the performance challenges associated with blade defects.

The experimental investigation was carried out using a horizontal-axis wind turbine (HAWT) simulator designed by Spectra Quest. **Figure 2** shows the experimental setup, which consisted of a three-blade rotor system mounted on a rigid steel testbed. One of the blades incorporated a 50 mm longitudinal crack to simulate the presence of structural defects. The turbine was equipped with a Variable Frequency Drive (VFD) to control rotational speed, while blade pitch angles (β_1, β_2, β_3) were manually adjustable. Data acquisition was performed using tachometers for rotational speed and accelerometers for vibration measurement. The vibration signals were processed through Vibra Quest (VQ) software to generate detailed time-domain reports.

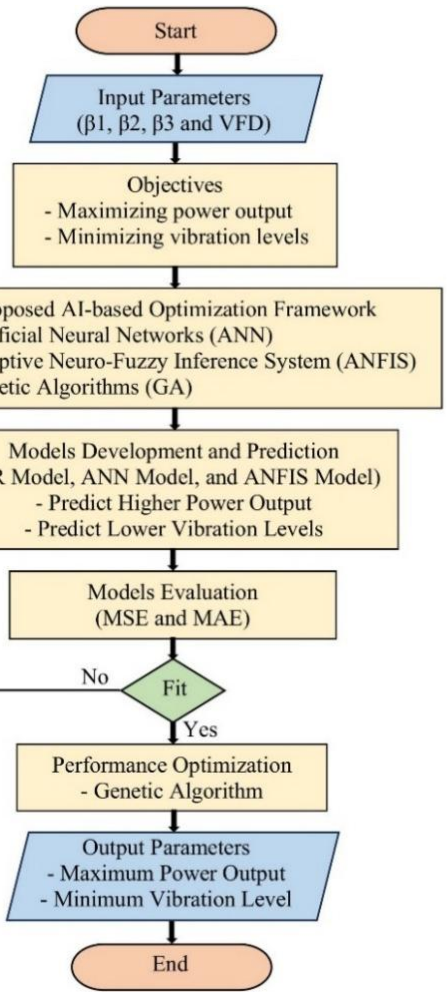

Figure 1. Methodology flow chart.

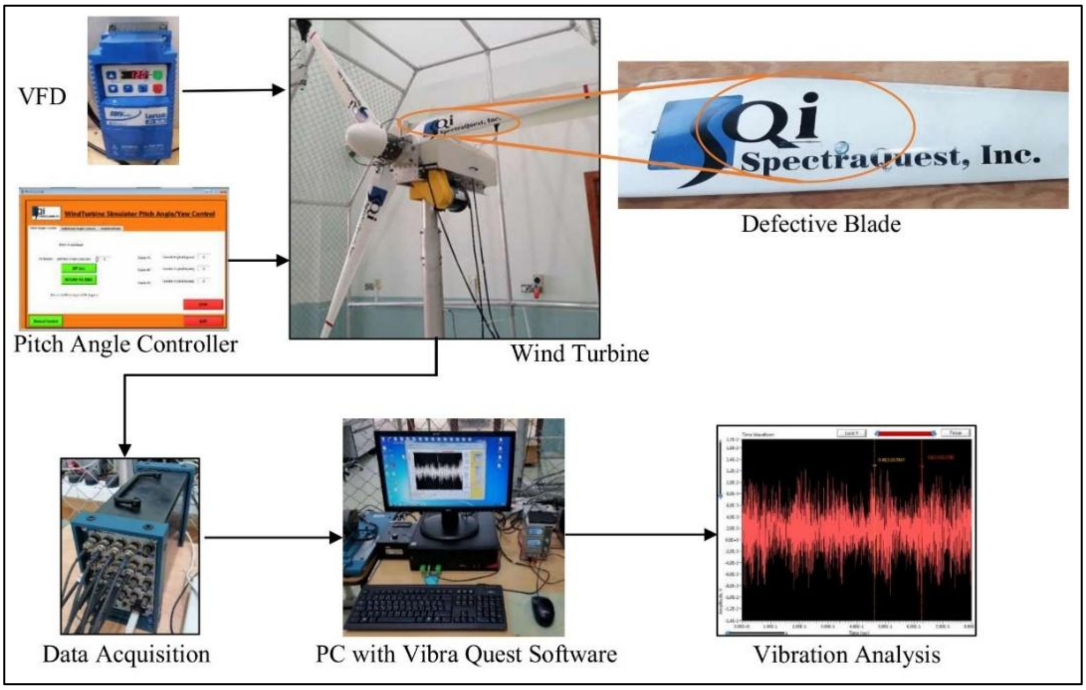

Figure 2. Experimental setup of the wind turbine simulator.

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A systematic experimental design was employed to study the effects of input variables on power and vibration. The Taguchi L81 (3^4) orthogonal array was used, allowing efficient exploration of four factors at three levels each. **Table 2** details the experimental parameters and their corresponding levels. This design ensured balanced coverage of the parameter space while minimizing the number of experimental runs required.

Table 2. Experimental parameters and levels.

Parameter	Description	Levels		
β1	Blade 1 Pitch Angle	0°	15°	30°
β2	Blade 2 Pitch Angle	0°	15°	30°
β3	Blade 3 Pitch Angle	0°	15°	30°
VFD	Variable Frequency Drive	12Hz	15Hz	18Hz

The collected data were used to train and validate predictive models for power output and vibration level. There are different Machine Learning (ML) models used for performance optimization. In this study, three mathematical models were selected as the most suitable models due to their ability to handle nonlinear relationships, adapt to varying operational conditions, and provide superior prediction accuracy for power output and vibration modelling. These models were: QR, ANN, and ANFIS. **Figure 3** illustrates the ANN and ANFIS architectures applied in this study. Explanations are in the following:

(i) The QR model

It included linear, interaction, and quadratic terms, as expressed in Eq. (1).

$$Y = a_0 + a_1\beta_1 + a_2\beta_2 + \cdots + a_{11}\beta_1^2 + a_{22}\beta_2^2 + a_{33}\beta_3^2 + a_{44}VFD^2 + \cdots + a_{34}\beta_3 VFD \quad (1)$$

Where, Y represents the output response (either power or vibration), and a_0, a_1, ..., a_{34} are the model coefficients. This model served as a conventional baseline for evaluating machine learning techniques.

(ii) The ANN model

The ANN was selected for its capacity to capture highly nonlinear relationships. The network architecture included four input nodes (β_1, β_2, β_3, VFD), a hidden layer with ten neurons, and one output node. A single hidden neuron's output is in Eq. (2).

$$h_i = f(w_{j1}\beta_1 + w_{j2}\beta_2 + w_{j3}\beta_3 + w_{j4}VFD + b_j) \quad (2)$$

The final ANN output is in Eq. (3).

$$Y = \sum_{j=1}^{10} v_j h_j + b \quad (3)$$

Where, w_{ij} are weights, b_j are biases, f is the activation function, and v_j represents weights connecting hidden neurons to the output. The Levenberg-Marquardt algorithm was used for training, with Mean Squared Error (MSE) as the loss function.

(iii) The ANFIS model

The ANFIS model combines fuzzy logic and neural network learning, making it suitable for capturing uncertain, nonlinear, and dynamic relationships in turbine performance. The input parameters (β_1 and VFD) were first fuzzified into linguistic variables (e.g., low, medium, high). These inputs were mapped through fuzzy rules, formulated as shown in Eq. (4) and Eq. (5).

$$Rule\ 1: If\ \beta_1\ is\ A_1\ and\ VFD\ is\ B_1, then \qquad Y_1 = p_1\beta_1 + q_1VFD + r_1 \quad (4)$$

$$Rule\ 2: If\ \beta_1\ is\ A_2\ and\ VFD\ is\ B_2, then \qquad Y_2 = p_2\beta_1 + q_2VFD + r_2 \quad (5)$$

In these rules: (a) rule 1 means that if β_1 is classified within fuzzy set A_1 (e.g., low) and VFD is within fuzzy set B_1 (e.g., low), then the output Y_1 is computed by a linear function of β_1 and VFD with parameters p_1, q_1, and r_1; and (b) Rule 2 means that if β_1 belongs to fuzzy set A_2 (e.g., high) and VFD to fuzzy set B_2 (e.g., high), then the output Y2 is given by its own linear function with parameters p_2, q_2, and r_2.

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The overall output of ANFIS was calculated as the weighted average of these rule outputs, as shown in Eq. (6).

$$Y = \frac{\sum_{i=1}^{2} w_i Y_i}{\sum_{i=1}^{2} w_i} \quad (6)$$

Where, w_i are firing strengths of the rules. The ANFIS model parameters were optimized using a hybrid learning approach (that is combining gradient descent and least-squares methods). Thus, w_1 and w_2 are the firing strengths of Rule 1 and Rule 2, respectively determined by how well the input conditions match the fuzzy sets. The model was trained using a hybrid learning algorithm combining gradient descent (for tuning membership functions) and least squares (for consequent parameters).

Model performance was evaluated using MSE and Mean Absolute Error (MAE), ensuring both sensitivity to outliers and overall accuracy were assessed. The best-fit models (i.e. ANN for power, ANFIS for vibration) were incorporated into the GA framework for multi-objective optimization.

$$F(x) = -Power(x) + Vibration(x) \quad (7)$$

The GA sought to optimize an objective function (Eq. (7)) combining negative power (to maximize) and vibration (to minimize).

The x represents the input variables [β_1, β_2, β_3, VFD], and Power(x) and Vibration(x) are predicted outputs.

Constraints ensured input variables stayed within experimental bounds (Eq. (8)).

$$x_{min} \leq x \leq x_{max} \quad (8)$$

The x_{min} and x_{max} represent the lower and upper bounds of inputs, respectively.

The GA generated initial solutions uniformly (Eq. (9)), applied selection (Eq. (10)), crossover (Eq. (11)), and mutation (Eq. (12)), and iterated until convergence to the best solution (Eq. (13)).

$$x_i^{(0)} \sim U(x_{min}, x_{max}) \quad (9)$$

Where, U represents a uniform distribution. The selection was based on Roulette Wheel probability as shown in Eq. (10).

$$p_i = \frac{F(x_i)}{\sum_{j=1}^{P} F(x_i)} \quad (10)$$

The offspring solutions were then generated using uniform crossover as shown in Eq. (11).

$$x_{child} = \alpha x_i + (1 - \alpha) x_j \quad (11)$$

Here, α follows a uniform distribution U(0,1). The mutation was applied as shown in Eq. (12).

$$x_i^{mutated} = x_i + \delta \quad (12)$$

The algorithm terminated when the maximum number of generations was reached, or the fitness improvement fell below a specified tolerance. The final optimal solution (x)* is shown in Eq. (13).

$$x^* = arg\ max\ F(x_i) \quad (13)$$

That ensures optimal turbine performance under structural defects.

Experimental validation was performed using the optimized parameters identified by GA, comparing predicted outputs to actual results. This ensured the accuracy of predictive models and demonstrated the practical applicability of the framework in managing defective turbine performance.

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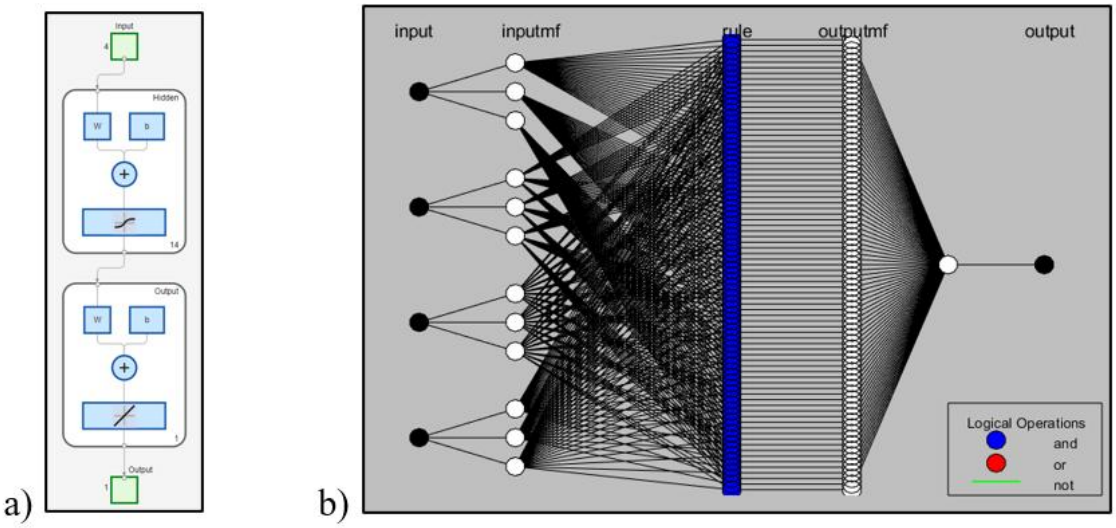

Figure 3. Model architectures: (a) ANN and (b) ANFIS.

4. RESULTS AND DISCUSSION

The experimental investigation aimed to assess how variations in blade pitch angles (β_1, β_2, β_3) and VFD settings affect the power output and vibration levels of the wind turbine simulator equipped with a structurally defective blade. The goal was not only to understand performance under defect conditions but also to evaluate the predictive capability of various models and the efficacy of the optimization framework in balancing power output and vibration control.

4.1. Experimental Data Overview

The data collected from 81 experimental runs using the Taguchi L81 design provided a comprehensive view of the turbine's operational characteristics. The power output varied from 6.76 W at low rotational speeds and suboptimal pitch angles to 27.03 W at higher VFD values combined with optimized blade angles. Vibration levels ranged from 1.88 to 9.97 m/s^2, with higher VFDs generally increasing vibration due to elevated centrifugal forces and dynamic instabilities induced by the blade crack.

The raw experimental trends revealed that at $\beta_1 = 0°$, $\beta_2 = 0°$, $\beta_3 = 0°$, increasing VFD from 12 Hz to 18 Hz resulted in a power output increase from 12.31 W to 27.00 W, but vibration also rose from 2.54 to 4.95 m/s^2. Conversely, high pitch angles ($\beta_1 = 30°$, $\beta_2 = 30°$, $\beta_3 = 30°$) at 18 Hz reduced power to 11.34 W and elevated vibration to 9.97 m/s^2 due to aerodynamic inefficiencies. These findings underscored the need for intelligent parameter tuning.

4.2. Quadratic Regression (QR) Model Performance

To model turbine performance, the QR model was first applied. **Figure 4** presents residual plots for the QR model predictions of power output and vibration level. The residuals for power output were randomly scattered around zero, indicating that the QR model could reasonably approximate the power data. However, the residuals for vibration exhibited a distinct pattern, highlighting that the QR model failed to fully capture the nonlinear characteristics of vibration responses associated with the blade defect.

The coefficient of determination (R^2) values, summarized in **Table 3**, reinforced these observations. The QR model achieved an R^2 of 98.33% for power output, demonstrating high predictive accuracy. In contrast, the R^2 for vibration was only 21.11%, confirming the

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inadequacy of QR in modeling complex vibration behavior. The regression equations for power output and vibration level are presented by (Eqs. (14) and (15)), respectively.

$$\begin{aligned} \text{Power output} = {} & 1.60 + 0.1461\,\beta1 + 0.1017\,\beta2 + 0.3216\,\beta3 + 0.022\,\text{VFD} \\ & - 0.002797\,\beta1^2 \\ & - 0.002139\,\beta2^2 - 0.004672\,\beta3^2 + 0.0775\,\text{VFD}^2 + 0.001739\,\beta1\times\beta2 \\ & + 0.001662\,\beta2\times\beta3 + 0.002117\,\beta3\times\beta1 - 0.01537\,\beta1\times\text{VFD} - 0.01271\,\beta2\times\text{VFD} \\ & - 0.02588\,\beta3\times\text{VFD} \end{aligned} \tag{14}$$

$$\begin{aligned} \text{Vibration level} = {} & -3.8 - 0.016\,\beta1 + 0.014\,\beta2 + 0.170\,\beta3 + 0.87\,\text{VFD} + 0.00175\,\beta1^2 \\ & + 0.00261\,\beta2^2 + 0.00054\,\beta3^2 - 0.0227\,\text{VFD}^2 - 0.00282\,\beta1\times\beta2 - 0.00053\,\beta2\times\beta3 \\ & - 0.00443\,\beta3\times\beta1 + 0.00629\,\beta1\times\text{VFD} - 0.00226\,\beta2\times\text{VFD} - 0.00976\,\beta3\times\text{VFD} \end{aligned} \tag{15}$$

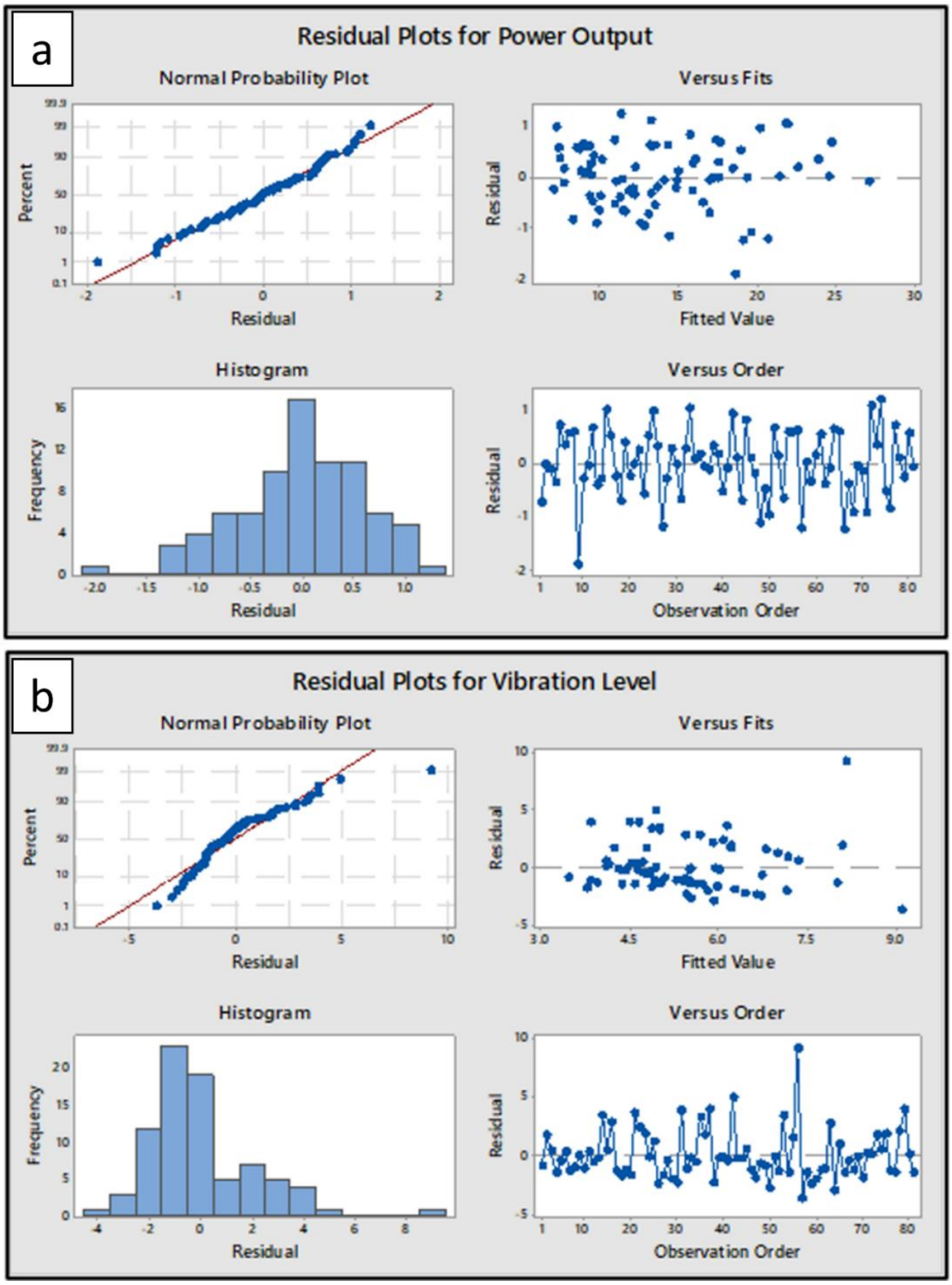

Figure 4. Residual plots for QR model of (a) power output and (b) vibration level.

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Table 3. QR models' R^2 values.

Response	R^2
Power output	98.33%
Vibration level	21.11%

4.3. Artificial Neural Network (ANN) Model Performance

Recognizing the limitations of QR, an ANN model was developed. **Figure 5** illustrates the ANN's training performance for power output, where the MSE decreased rapidly over epochs, indicating effective learning. The error histogram shows residual errors tightly clustered around zero, confirming high prediction accuracy for power.

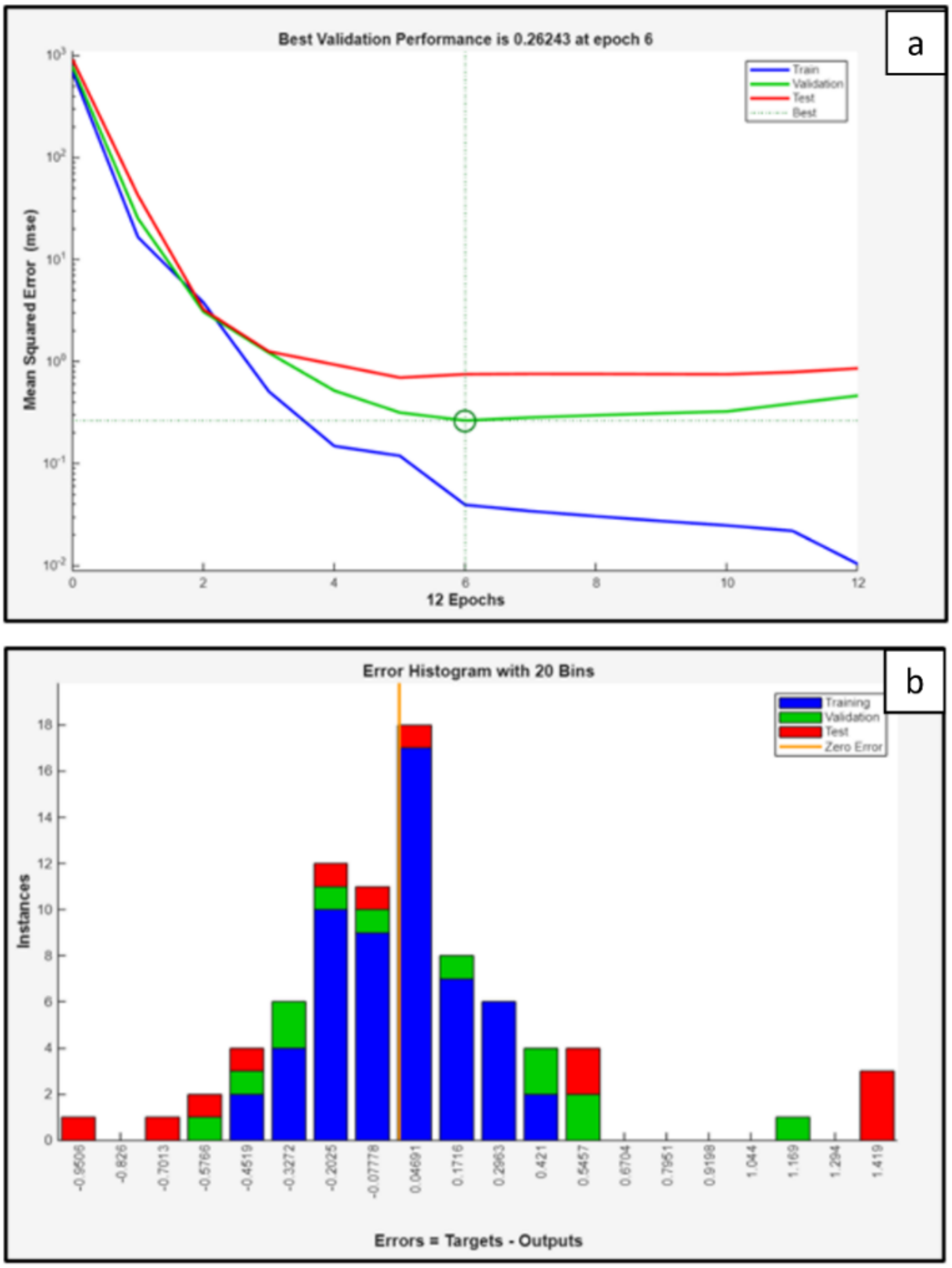

Figure 5. Performance of the ANN model for power output prediction: (a) best validation performance, and (b) error histogram.

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For vibration prediction, **Figure 6** shows that although the ANN reduced error during training, the residual errors were more dispersed compared to power output predictions. This suggested that while ANN effectively captured the power dynamics, vibration modeling was more challenging.

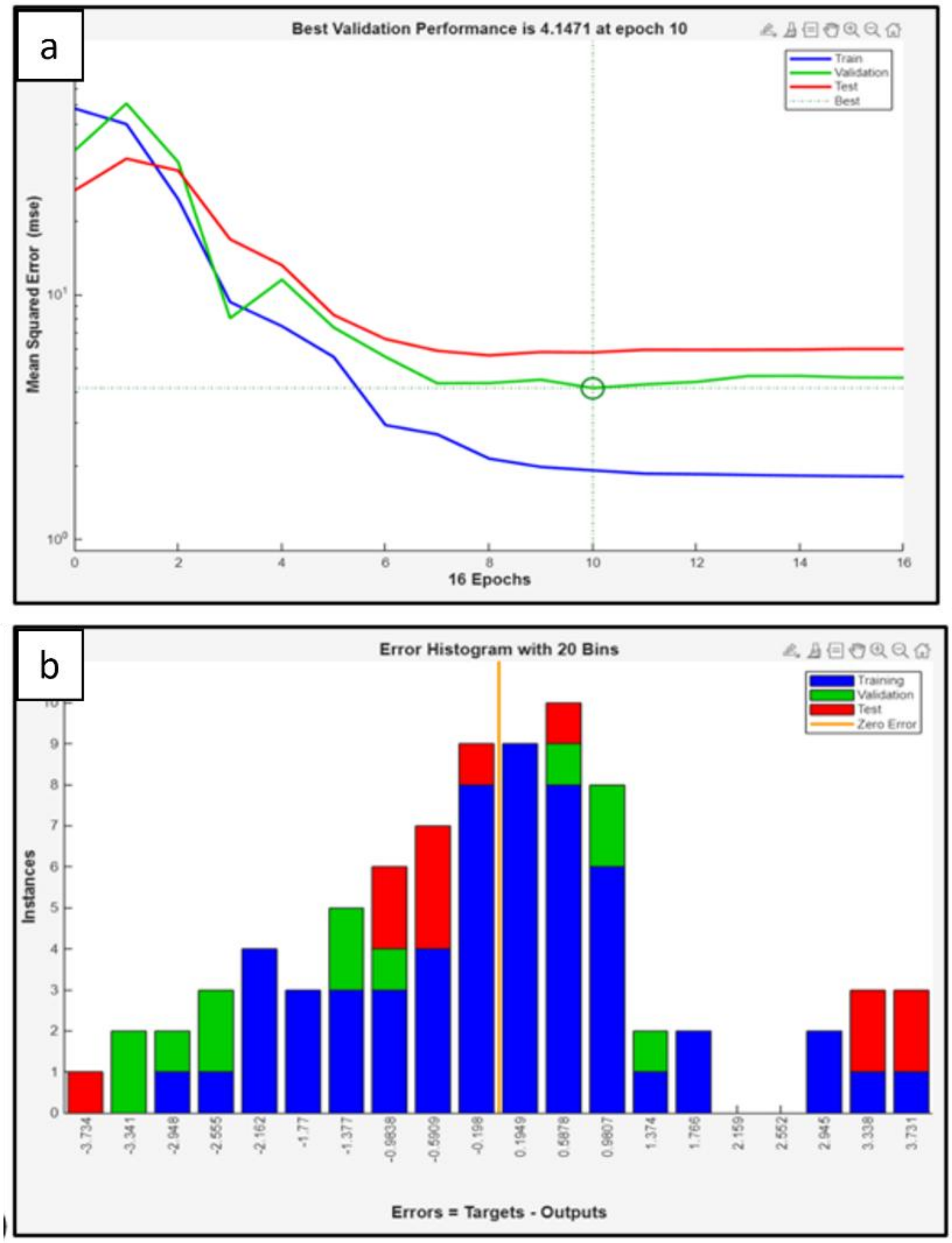

Figure 6. Performance of the ANN model for vibration level prediction: (a) best validation performance, and (b) error histogram.

Further validation is provided in **Figure 7**, which compares ANN-predicted outputs to experimental data. The regression line for power closely followed the ideal line, while for vibration, data points showed greater scatter, reflecting the complexity of vibration behavior under defective blade conditions.

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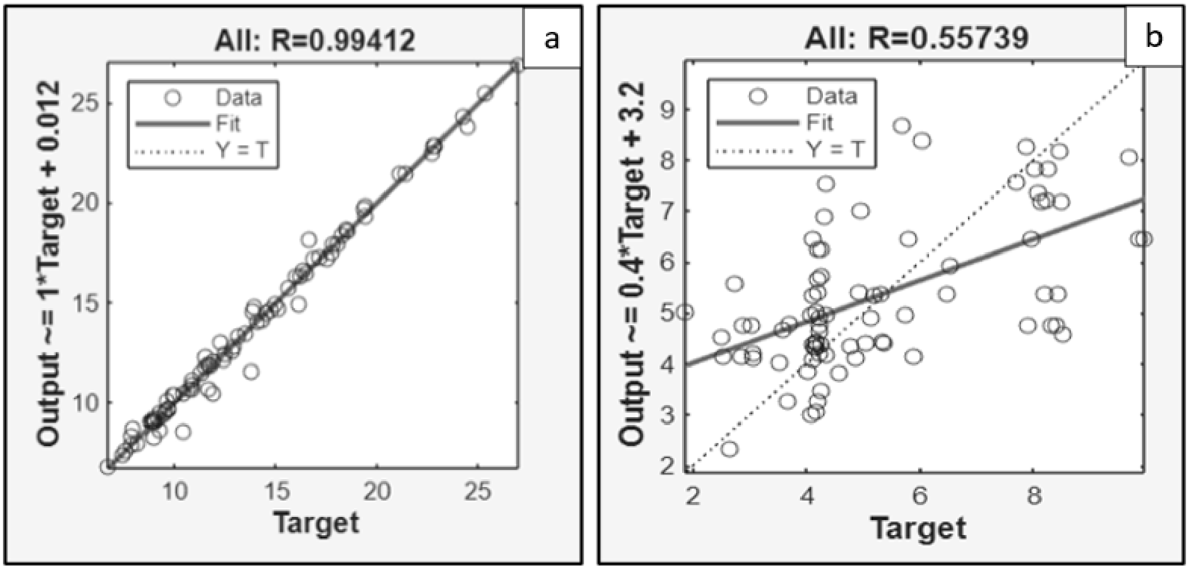

Figure 7. ANN regression results for (a) power output and (b) vibration level.

4.4. Adaptive Neuro-Fuzzy Inference System (ANFIS) Model Performance

The ANFIS model was implemented to improve the prediction accuracy for vibration levels, where both the QR and ANN models had shown limitations. ANFIS integrates fuzzy logic's capacity to handle uncertainty with neural networks' learning ability, making it suitable for capturing complex, nonlinear system behavior.

The ANFIS model was trained using the experimental dataset, with fuzzification applied to inputs β_1 and VFD. The fuzzy rules, as described earlier, mapped these inputs to vibration outputs. The model successfully learned the relationship between input variables and vibration response, adapting the membership functions and rule parameters during training.

Figure 8 presents the inference surface for power output generated by the ANFIS model. While the model provided reasonable predictions for power, its strength was more evident in vibration modeling. **Figure 9** shows the vibration inference surface produced by ANFIS, which closely aligned with the experimental vibration data across the tested input conditions.

The ANFIS model's superior performance for vibration prediction is reflected in its low mean squared error (MSE) of 6.998×10^{-6}, significantly better than both the ANN and QR models. This result demonstrates ANFIS's capability to handle the dynamic nonlinearities and uncertainties introduced by the blade's structural defect. The model effectively captured the complex interplay between the blade pitch angles and rotational speed that contribute to vibration levels.

The success of ANFIS in modeling vibration behavior supports previous studies [15,22], where neuro-fuzzy systems outperformed conventional models in predicting vibration responses in mechanical systems with defects or uncertain conditions. The incorporation of fuzzy logic enabled ANFIS to interpret ambiguous or overlapping input conditions, while its neural learning component adjusted the model to the specific data patterns observed in the wind turbine experiments.

In summary, the ANFIS model provided a robust and reliable tool for vibration prediction, making it the preferred model for integration into the genetic algorithm-based optimization framework.

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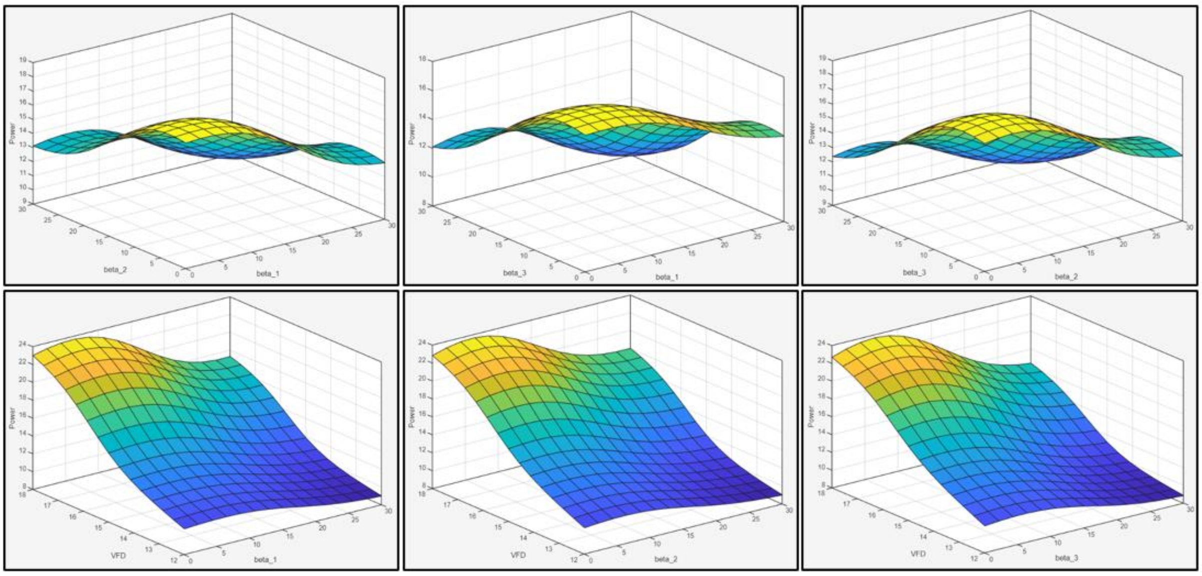

Figure 8. ANFIS power output model inferences.

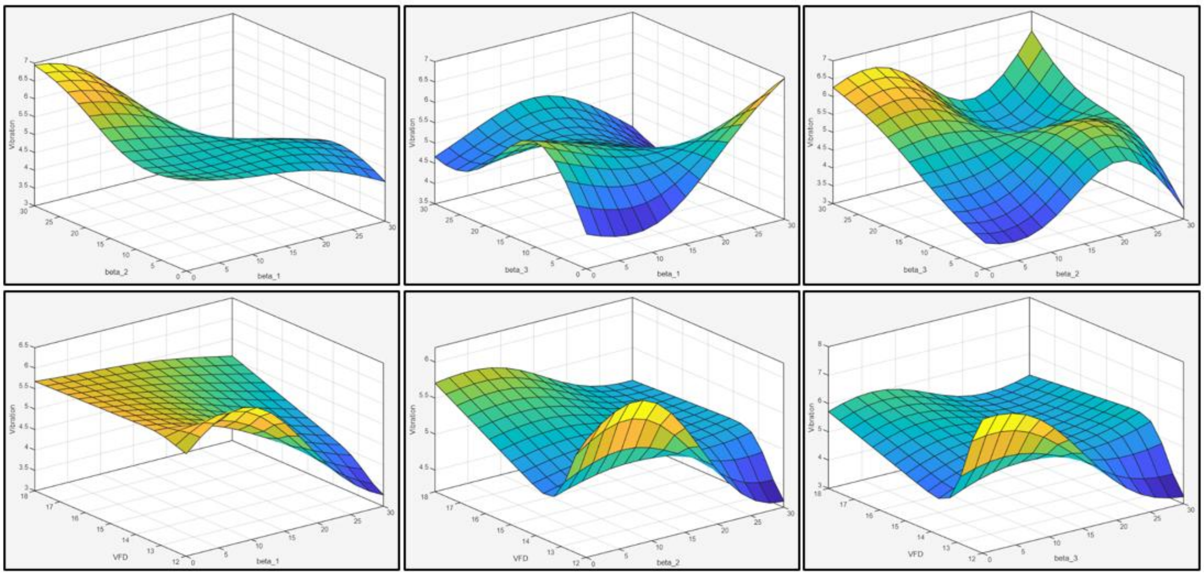

Figure 9. ANFIS vibration level model inferences.

4.5. Comparative Model Predictions Against Experimental Data

To provide a direct comparison of predictive accuracy across the three models (QR, ANN, and ANFIS), **Figure 10** presents the power output predictions from each model against the actual experimental results. The ANN predictions closely followed the experimental data across the entire range of operating conditions, while the QR model showed deviations at higher power outputs, confirming its limitations in capturing nonlinear dynamics. The ANFIS predictions for power output were reasonable but not as precise as the ANN.

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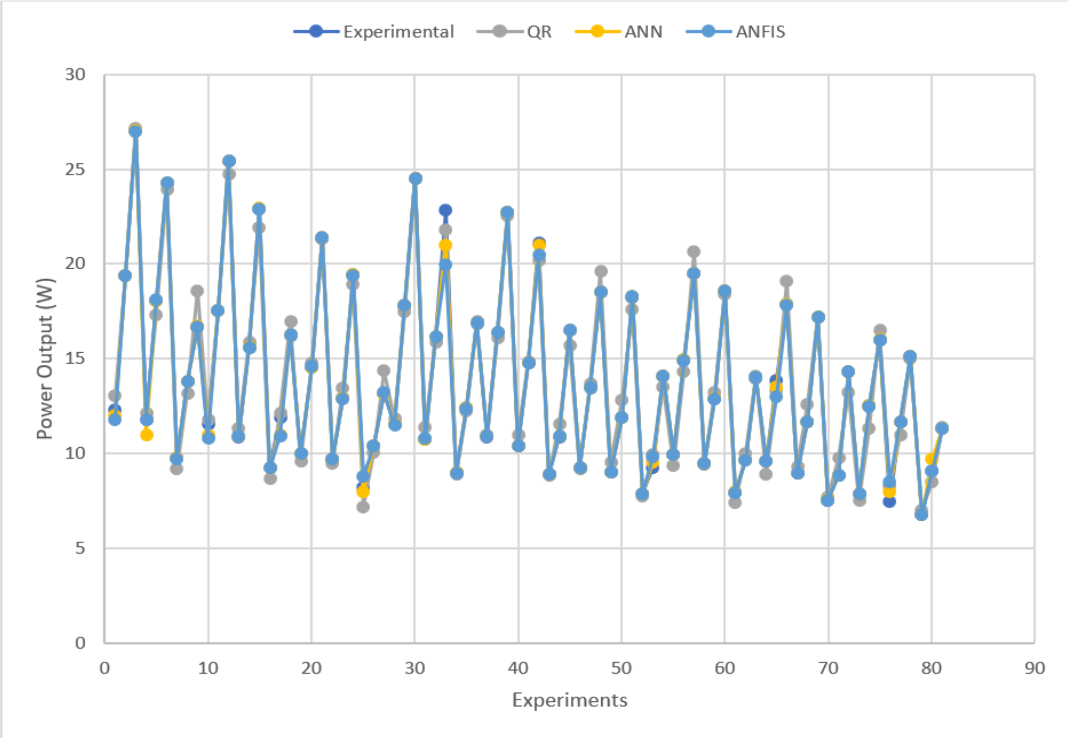

Figure 10. Comparison of power output predictions from ANN, ANFIS, and QR models against experimental results.

Similarly, **Figure 11** illustrates vibration level predictions compared with experimental measurements. The ANFIS model demonstrated excellent alignment with experimental vibration data, accurately capturing variations caused by changes in pitch angles and VFD. ANN and QR models showed larger discrepancies, particularly under conditions of higher vibration levels where nonlinear effects were most pronounced.

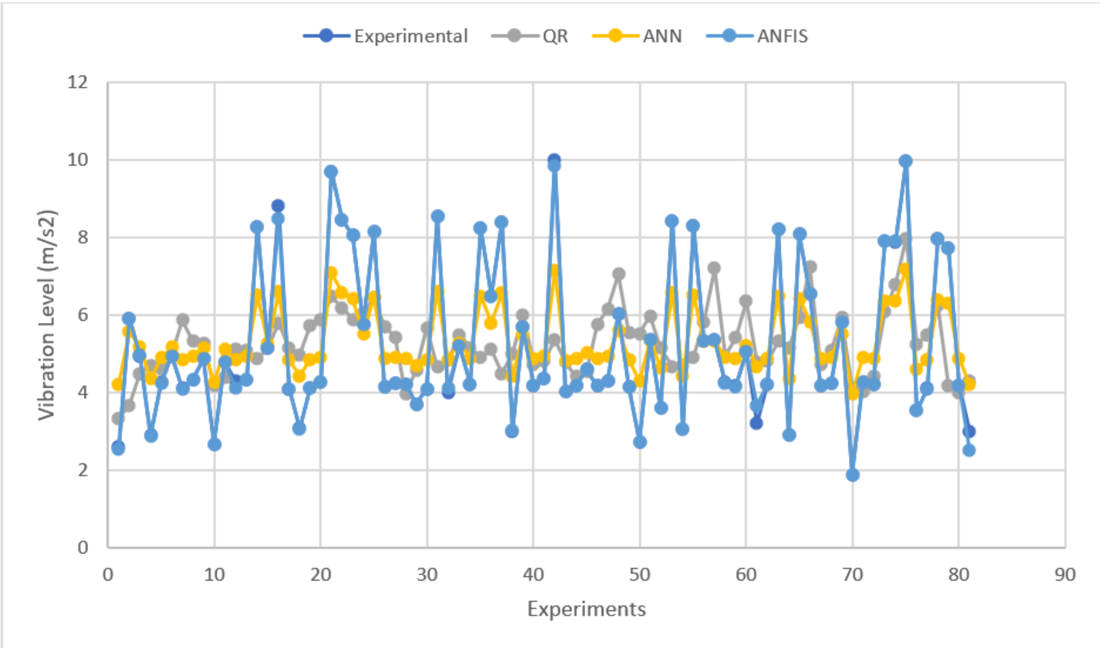

Figure 11. Comparison of vibration level predictions from ANN, ANFIS, and QR models against experimental results.

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4.6. Comparative Analysis

The predictive performance of the models was compared using MSE and MAE, as summarized in **Table 4**. The ANN model achieved the lowest MSE for power output (1.44×10^{-4}), while the ANFIS model delivered the lowest MSE for vibration (6.998×10^{-6}). These results validated the decision to use ANN for power prediction and ANFIS for vibration in the optimization framework.

Table 4. Error analysis of mathematical models.

Response	Error analysis method	Mathematical models		
		QR	ANN	ANFIS
Power output	MSE	0.3860	1.440×10^{-4}	4.991×10^{-4}
	MAE	0.49573	0.012	1.7062×10^{-2}
Vibration level	MSE	3.205	1.413	6.998×10^{-6}
	MAE	1.4479	0.99498	2.2547×10^{-3}

4.7. Genetic Algorithm (GA) Optimization

The final stage applied the GA to determine the optimal operating conditions that balanced power maximization and vibration minimization. The objective function combined these criteria, and the GA explored the parameter space to find the best input settings. **Table 5** presents the optimized input configuration and compares the predicted and experimental outputs. The GA recommended $\beta_1 \approx 0°$, $\beta_2 \approx 4°$, $\beta_3 \approx 7°$, and VFD = 18 Hz. Experimental validation under these settings achieved a power output of 26.18 W and vibration of 5.21 m/s^2, closely matching the model predictions.

Table 5. Comparison between the genetic algorithm and experimental results.

Method	Input Parameters				Output Parameters	
	β1	β2	β3	VFD	Power Output	Vibration Level
Optimization Framework	0.00062° (≈ 0°)	3.96495° (≈ 4°)	6.61628° (≈ 7°)	18 Hz	26.587W	5.763m/s^2
Experimentation	0°	4°	7°	18 Hz	26.179W	5.207m/s^2

4.8. Discussion

The study demonstrated that machine learning models, especially ANN and ANFIS, significantly outperformed traditional regression methods in predicting turbine performance with defective blades. The integration of these models within a GA framework provided an effective means for multi-objective optimization, balancing power output and structural stability. These findings align with previous research that highlighted the strengths of AI in engineering optimization [15,21]. The optimized configuration not only improved power output but also maintained vibration within acceptable limits, demonstrating the practical value of the hybrid framework for real-world wind turbine applications. This approach supports the advancement of wind energy technologies aligned with SDGs by improving system reliability and reducing maintenance costs.

4.9. Detailed Analysis of ANN Performance

The ANN model's success in predicting power output can be attributed to its ability to model complex nonlinear dependencies between the turbine's input parameters and the

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power generated. The low mean squared error (MSE) achieved during training, as shown in Figure 5, reflects that the ANN effectively captured the influence of blade pitch angle variations and VFD settings on power output. This result aligns with the findings of Esfahani & Pieper (2021) [14], who reported that ANN architectures excel in modeling wind turbine power under dynamic conditions.

However, the ANN's vibration predictions exhibited greater error variance, as observed in **Figure 6** and **Figure 7**. The scatter in predicted versus actual vibration values indicates that while ANN could model general trends, it lacked the precision required for vibration prediction in the presence of structural defects. This limitation is consistent with the work of [23], who highlighted that ANN performance degrades when modeling outputs influenced by hidden dynamic factors, such as structural cracks, unless additional input features or specialized architectures are introduced.

4.10. Detailed Analysis of ANFIS Performance

The ANFIS model, in contrast, excelled in vibration prediction. The inference surfaces in **Figure 9** illustrate how ANFIS captured the complex interplay between β_1, VFD, and vibration levels. The hybrid neuro-fuzzy architecture enabled ANFIS to manage uncertainties introduced by the defective blade, which traditional and even standard ANN models struggled with. The extremely low MSE (6.998×10^{-6}) validated ANFIS's suitability for tasks where dynamic and nonlinear uncertainties are significant. These results are in line with literature [22], who demonstrated the value of ANFIS in defect detection and vibration analysis for wind turbines.

4.11. Discussion of GA Convergence and Optimization Behavior

The GA optimization process displayed robust convergence toward the optimal solution. The population evolved consistently, with fitness values improving across generations until stagnation criteria were met. The use of both ANN and ANFIS models within the objective function allowed the GA to balance competing priorities (maximizing power while minimizing vibration) effectively.

The final recommended settings ($\beta_1 \approx 0°$, $\beta_2 \approx 4°$, $\beta_3 \approx 7°$, VFD = 18 Hz) were not only optimal in the computational sense but also practical, as they provided a configuration that could realistically be implemented in turbine control systems. Experimental validation showed close agreement between predicted and actual outputs (power difference < 0.5 W; vibration difference < 0.6 m/s^2), which confirms the accuracy and robustness of the optimization framework. This supports prior research [20,21] that emphasized GA's effectiveness for multi-objective engineering problems.

4.12. Practical Implications and SDG Alignment

The study's outcomes have clear practical relevance. The hybrid AI-GA framework offers a solution for real-time turbine parameter optimization, which is crucial for enhancing the reliability and efficiency of wind energy systems operating with aged or damaged blades. By reducing vibration levels while sustaining high power output, the framework contributes to extending turbine lifespan, reducing maintenance costs, and ensuring operational safety.

Moreover, these contributions align with SDG 7 (Affordable and Clean Energy) by improving the performance of renewable energy systems. The methodology also supports SDG 9 (Industry, Innovation, and Infrastructure) by demonstrating innovative engineering solutions that integrate AI and optimization.

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4.13. Comparison to Prior Studies

Compared to traditional control or heuristic tuning methods, the proposed hybrid framework demonstrated superior performance. Traditional pitch angle tuning often relies on operator experience or fixed-rule adjustments, which may not adapt well to defect scenarios. The AI-driven framework dynamically adjusted parameters based on predictive models, offering a systematic and data-driven approach. The improvement over prior ANN-only or ANFIS-only approaches lies in the hybridization: ANN handled power dynamics effectively, while ANFIS dealt with vibration control. This hybrid modeling integrated with GA outperformed single-model systems documented in earlier literature [17,19].

4.14. Future Directions

While this study focused on a laboratory-scale simulator, the findings pave the way for scaling to full-size turbines. Future research should explore incorporating additional input variables, such as wind speed variability, temperature, and humidity, to further enhance model accuracy. Furthermore, integration with real-time supervisory control systems could enable continuous adaptive optimization, making this framework even more practical for deployment in wind farms. Finally, exploration of alternative AI architectures (e.g., ensemble methods, recurrent neural networks) and optimization algorithms (e.g., particle swarm optimization) could further advance the performance of such frameworks in wind energy applications.

5. CONCLUSION

This study developed and validated a hybrid Artificial Intelligence-driven and Genetic Algorithm-based optimization framework to enhance wind turbine performance under defective blade conditions. The framework integrated ANN and ANFIS models for power and vibration prediction with GA for multi-objective optimization. The optimal settings maximized power and minimized vibration, verified through experimental validation. This framework advances wind energy technology because it offers adaptive, data-driven control supporting the SDGs. The findings promote reliable, efficient renewable energy systems while reducing maintenance needs and operational costs.

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7. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

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