Neuro-fuzzy control on a permanent magnet synchronous generator integrated in a wind system

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ABSTRACT

This paper introduces a control strategy for a synchronous generator in a wind energy system using an adaptive neuro-fuzzy approach. The suggested controller, based on neuro-fuzzy logic (NFLC), is meant to govern a permanent magnet synchronous generator (PMSG) often utilized in wind power applications. The generator's output voltage phase, phase current, reactive power, active power, angular velocity, and DC voltage are all under control. The adaptive neuro-fuzzy controller efficiently stabilizes all variables in a brief amount of time, according to simulation results. The effectiveness and robust performance of the suggested control system are verified by a number of simulated scenarios. The resilience of fuzzy logic control (FLC) and NFLC systems was compared. The study carefully tested the performance of both control techniques under varied operating settings and disturbance situations to determine their relative stability, flexibility, and efficacy in sustaining desired system behavior.

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1. INTRODUCTION

Over the past decade, wind energy has seen significant expansion, driven by its environmental advantages, advancements in technology, and supportive government incentive programs. In addition to large-scale production facilities, small standalone units are becoming increasingly popular for powering remote or isolated locations [1]. Today, permanent magnet synchronous generators (PMSGs) are widely used in wind turbines due to their advantages, including higher reliability, reduced maintenance requirements, and greater efficiency [2], [3]. Additionally, operating under variable speed conditions enables the system to achieve optimal efficiency [4]. For remote areas not connected to the main power grid, a practical solution for electricity generation is to use a variable-speed wind turbine in a standalone system. These systems often incorporate batteries to supply power when wind energy is insufficient. When wind conditions are favorable, autonomous wind systems can deliver low-cost electricity. Surplus energy generated during high wind periods can be stored in batteries, which in turn supply power when the wind is not strong enough to meet the demand [5]. Moreover, artificial intelligence (AI) methods have proven highly beneficial in the domain of electrical power systems [6], [7], with applications extending far beyond traditional areas like image processing [8], [9].

In this paper, we suggest a control technique for a synchronous generator in a wind energy system utilizing an adaptive neuro-fuzzy approach. The influence of parameter fluctuations such as stator resistance, inductance, and torque constant is effectively mitigated by dynamically adjusting a neuro-fuzzy-based model reference adaptive system to match the real behavior of the PMSG. This neuro-fuzzy-tuned estimator maintains great resilience against parameter variations while reliably estimating rotor position and speed across a broad operational range. The MATLAB/Simulink environment is used to carry out the simulation.

2. THE PERMANENT MAGNET SYNCHRONOUS MACHINE AND TURBINE MODEL
The theoretical power available to the wind turbine is expressed by (1), where ρ represents the air density, S denotes the swept area of the turbine blades, β is the blade pitch angle, and v is the wind speed in meters per second [10].

$$P_t = C_p(\beta,\lambda)\frac{1}{2}\rho S v^3 \tag{1}$$

The (2), where R_t is the blade radius, and Ω_m is the turbine's angular velocity, defines the ratio between the wind speed and the turbine's rotational speed.

$$\lambda = Rt\frac{\Omega_{turbine}}{v} \tag{2}$$

The power coefficient (Cp) has a theoretical maximum value of 0.593, known as the "Betz limit," which cannot be achieved in practice [6]. An estimate of this coefficient can be calculated using (3) [11].

$$C_p(\beta,\lambda) = \big(0.5 - 0.0167(\beta-2)\big)sin[\frac{\pi(\lambda+0.1)}{18.5-0.3(\beta+2)} - 0.00184(\lambda-3)(\beta-2) \tag{3}$$

The (4) provides the mechanical torque C_m that the wind turbine produces based on the mechanical power.

$$C_m = \frac{P_t}{\Omega_m} \tag{4}$$

The (5) is the mechanical equation of the system, where J_t and J_m are the turbine and generator's respective moments of inertia, f_v is the generator's viscous friction coefficient, and Ω_m is the rotational speed of the generator. The (6) provides the dynamic model of the PMSG in the dq reference frame. Rs stands for stator resistance, L_d and L_q for inductances along the d and q axes, I_{sd} and I_{sq} for stator currents, Ω for the PMSG's electrical angular speed, and ϕ for the machine's residual magnetic flux [12], [13].

$$(J_t + J_m)\frac{d\Omega_m}{dt} + f_v\Omega_m = C_m - C_{em} \tag{5}$$

$$\frac{d}{dt}\begin{bmatrix} I_{sd} \\ I_{sq}\end{bmatrix} = \begin{bmatrix} \frac{-R_s}{L_d} & \frac{\Omega L_q}{L_d} \\ \frac{-\Omega L_q}{L_q} & \frac{-R_s}{L_q}\end{bmatrix}\begin{bmatrix} I_{sd} \\ I_{sq}\end{bmatrix} + \begin{bmatrix} \frac{v_{sd}}{L_d} \\ \frac{v_{sq}-\Omega\varphi}{L_q}\end{bmatrix} \tag{6}$$

The following equations are used to calculate the active and reactive powers supplied to the network [14], [15].

$$\begin{cases} P = v_d I_d + v_q I_q \\ Q = v_q I_d - v_d I_q \end{cases} \tag{7}$$

Figure 1 shows the overall model of the generator PMSG connected to the electrical networks. Figure 2 illustrates the wind profile used in the analysis of the studied system.

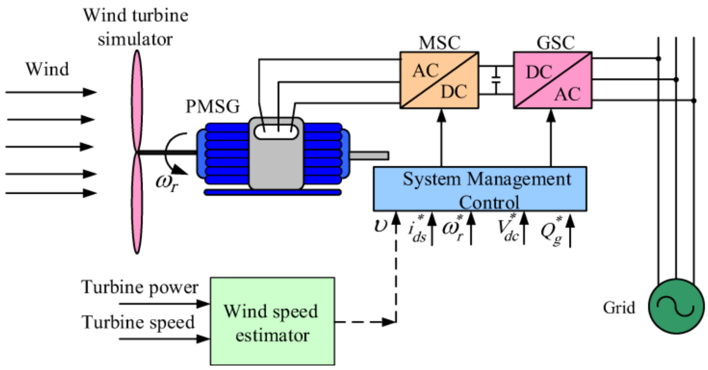

Figure 1. Grid-connected wind turbine system block schematic using the PMSG

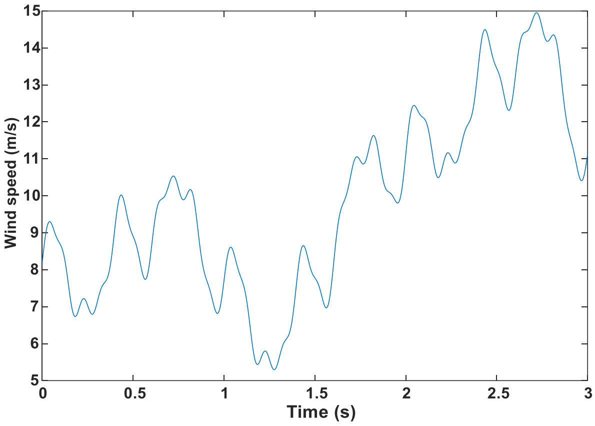

Figure 2. Wind profile

3. NEURO-FUZZY CONTROL

This section focuses on the application of neuro-fuzzy logic for speed and power control of a permanent magnet synchronous machine. Fuzzy logic is widely used in decision-making, pattern recognition, modeling, and especially in process control, its most common industrial application. In systems with a single input variable, the fuzzy controller typically takes as inputs the error (the difference between the desired setpoint and the actual process output) and the error variation, which reflects the system's dynamic behavior [16], [17]. In this context, the two inputs to the fuzzy controller are the speed error and its rate of change.

The speed error, represented by e, is defined as shown in (8) [18].

$$e = \Delta\Omega = \Omega_{ref} - \Omega_r \tag{8}$$

The change in speed error, denoted as Δe, is defined as (9).

$$\Delta e = e(t + \Delta t) - e(t) = e(k + 1) - e(k) \tag{9}$$

The output of the controller represents the change in the control signal or electromagnetic torque, denoted as Δu. The three variables e, Δe, and Δu are normalized as (10).

$$E = G_e.e, \Delta E = G_{\Delta e}.\Delta e, \Delta U = G_{\Delta u}.\Delta u \tag{10}$$

Here, G_e, $G_{\Delta e}$, and $G_{\Delta u}$ are scaling or normalization factors that significantly influence the control system's static and dynamic performance [19], [20].

The inference rules define the behavior of the fuzzy controller and require intermediate steps to convert real-world values into fuzzy values and back. These steps are known as fuzzification and defuzzification, as illustrated in Figure 3. Triangular and trapezoidal membership functions were selected for each variable, as illustrated in Figure 4.

Based on the analysis of the system's behavior, control rules can be formulated to link the output to the inputs. As previously noted, each of the two linguistic input variables in the fuzzy controller is divided into five fuzzy sets, leading to a total of twenty-five rules. These rules can be organized in the form of the following inference matrix [21], [22].

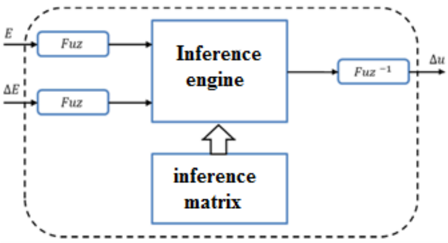

Figure 3. Illustration of the internal stages of fuzzy regulation

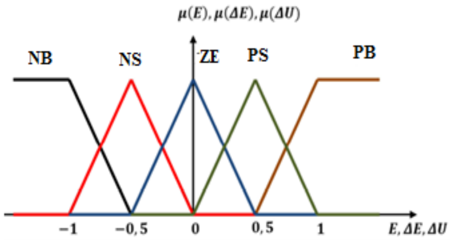

Figure 4. The inputs and output of the membership functions

The rule matrix is derived from a broad, qualitative understanding of the system's behavior. For instance, it is expected that a change in the reference torque ΔU\Delta UΔU occurs when both the error in the PMSG output speed relative to its setpoint and its variation are positive big (PB), as shown in Table 1. An example rule is: If *E* is PB and ΔE is PB, then ΔU is PB. After computing the fuzzy output, it must be converted into a precise numerical value. Several defuzzification methods exist, with the center of gravity method being the most commonly used and the one applied in this study [23], [24]. The output value of the controller corresponds to the abscissa of the center of gravity, calculated using (11).

$$x_{Gr} = \Delta U = \frac{\int_{-1}^{1} x_r u_{RES}(x_r) dx_r}{\int_{-1}^{1} u_{RES}(x_r) dx_r} \tag{11}$$

In the case of the sum-product inference method, this expression is represented in the following discrete form.

The performance of the fuzzy controller described above is analyzed and assessed through its application to a permanent magnet synchronous machine. This is done to maintain the rotational speed setpoint of the wind turbine at the optimal point. The optimal point corresponds to the optimal tip-speed ratio λopt and the maximum power coefficient Cpmax [25].

Neural networks are widely recognized for their capability to learn and approximate any continuous function. They have been used for parameter identification and state-space estimation in control systems for reciprocating engines. Unlike traditional programming, artificial neural networks (ANNs) operate through a learning process. They are particularly well-suited for tasks such as association, classification, pattern recognition, prediction or estimation, and the control of complex systems [26]. The multi-layer perceptron (MLP), especially with a single hidden layer, is commonly used in system identification and control, as it serves as a "universal approximator". The neural network diagram of the proposed method is shown in Figure 5. The neuro-fuzzy logic control (NFLC) structure of the proposed method is illustrated in Figure 6. Table 2 illustrates the parameters of the permanent magnet synchronous generator.

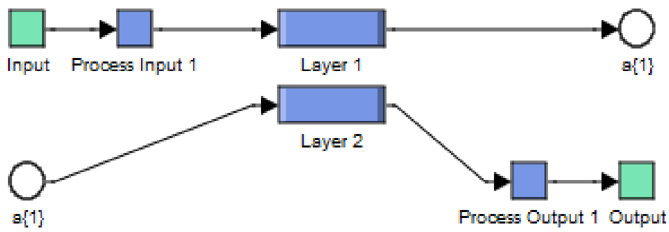

Figure 5. The neural network architecture of the proposed approach

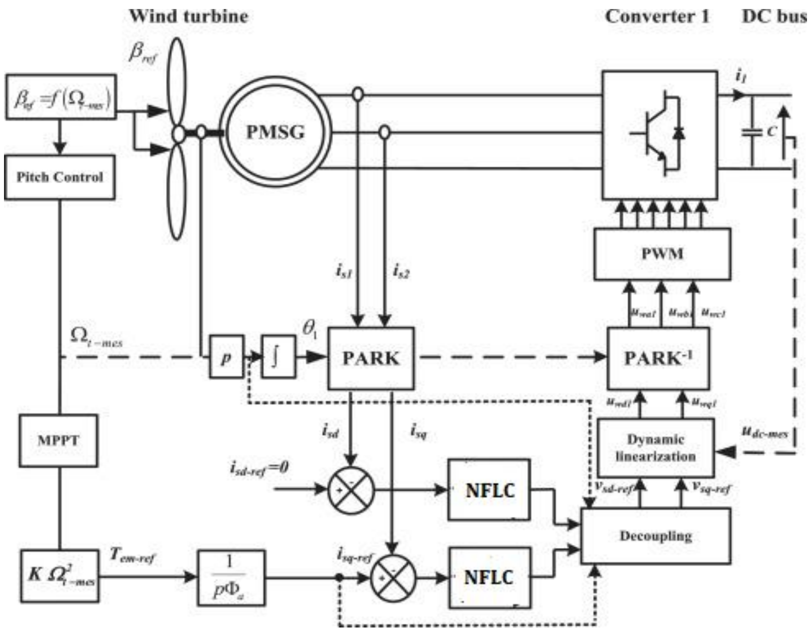

Figure 6. Diagram illustrating the speed control of the PMSG in a wind energy system

Table 1. Fuzzy rules inference matrix

ΔE	E				
	NB	NS	ZE	PS	PB
NB	*NB*	*NB*	*NS*	*NS*	*ZE*
NS	*NB*	*NS*	*NS*	*ZE*	*PS*
ZE	*NS*	*NS*	*ZE*	*PS*	*PS*
PS	*NS*	*ZE*	*PS*	*PS*	*PB*
PG	*ZE*	*PS*	*PS*	*PB*	*PB*

Table 2. Parameter of PMSG

Parameter	Unit
Rs = 0.89	Ω
L_d = 0.012	H
L_q = 0.021	H
P = 3	-
Coefficient of friction F = 0.001	Nm/rd/s
The turbine and generator assembly's inertia = 0.0014	Kg.m^2

4. SIMULATION RESULTS AND DISCUSSION

The performance of the NFLC strategy was evaluated through a series of tests designed to assess key control characteristics. These included setpoint tracking accuracy, dynamic response time, the qualitative analysis of output signal waveforms, and the overall quality of the electrical energy delivered to the grid. The results obtained provide insight into the NFLC controller's effectiveness in maintaining precise reference tracking, ensuring rapid system responsiveness, preserving signal integrity, and sustaining high power quality under operational conditions. Additionally, tests were conducted to evaluate the system's decoupling performance and its ability to maintain a unity power factor (PF = 1).

As evidenced by the results presented in Figures 7 and 8, both active and reactive power components closely tracked their respective reference values, demonstrating high setpoint accuracy. Furthermore, the system exhibited a notable improvement in dynamic performance, with a response time reduced by approximately 0.1 seconds and a significant decrease in signal ripple. Figure 9 illustrates that the current waveforms are sinusoidal, indicating low harmonic distortion. This observation is further supported by the total harmonic distortion (THD) analysis shown in Figure 10, where the THD remains below 5%, signifying that the power injected into the grid meets established quality standards [27].

Figure 11 confirms effective decoupling between positive and negative-sequence current components. In this context, the current component Iq is associated with active power generation, while Id corresponds to reactive power control. Additionally, Figures 12 and 13 demonstrate that by maintaining the reactive power reference at zero, the system can achieve unity power factor operation, ensuring efficient energy transfer with minimal reactive losses.

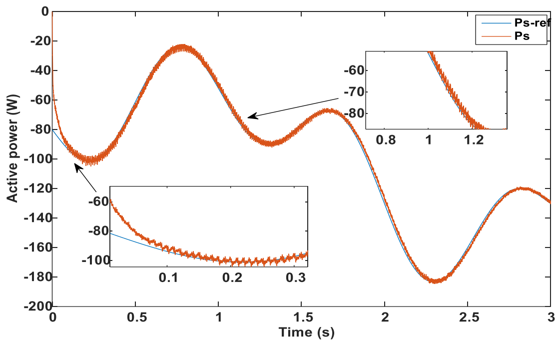

Figure 7. Active power

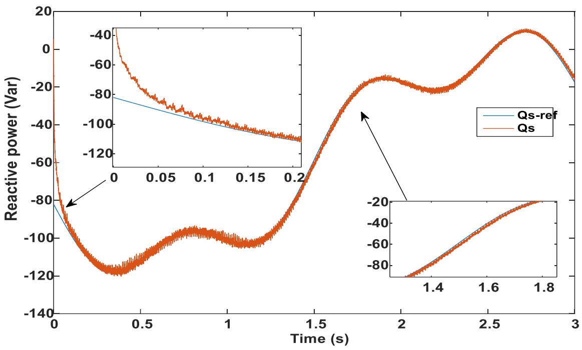

Figure 8. Reactive power

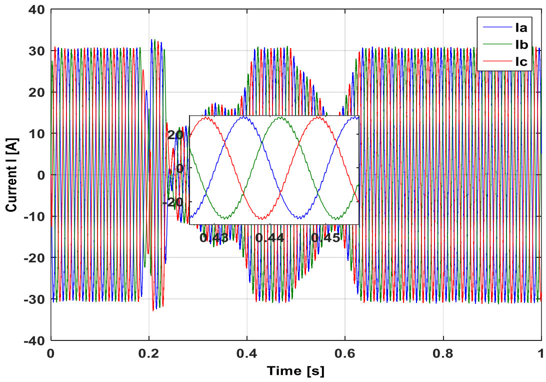

Figure 9. Current injected into the network

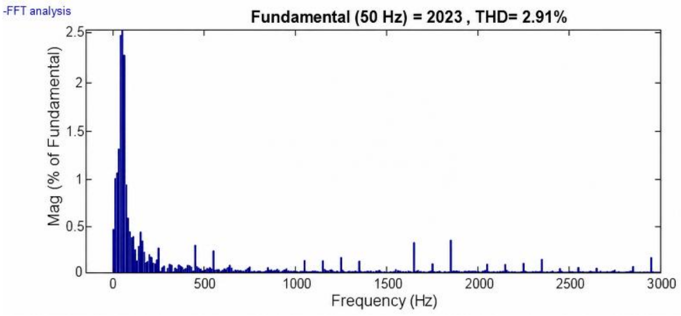

Figure 10. Total harmonic distortion of NFLC

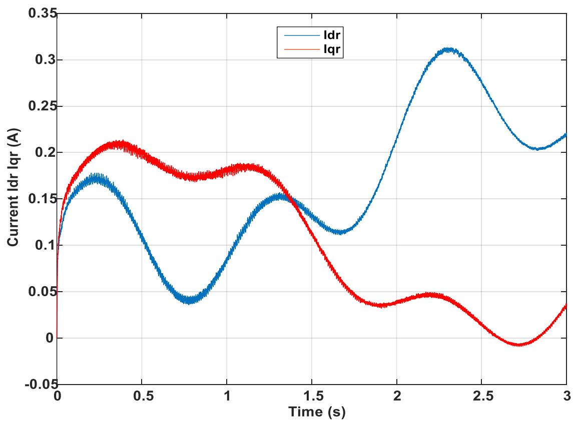

Figure 11. Currents Id, Iq of the PMSG generator

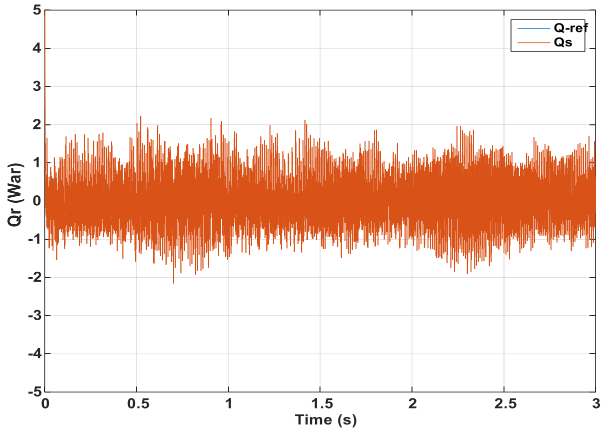

Figure 12. Grid reactive power

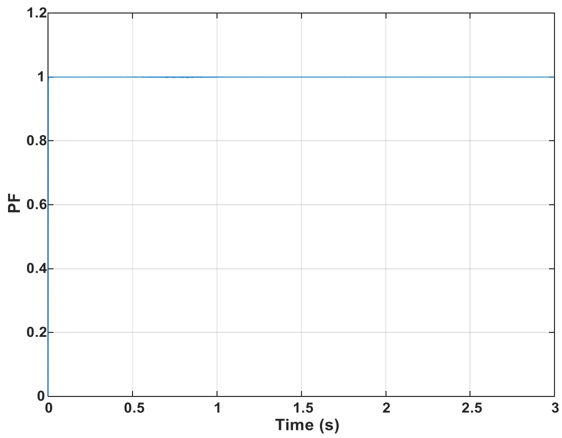

Figure 13. Power factor on the grid side

5. ROBUSTNESS TEST

To assess the robustness of the controllers, specific parameter variations were introduced to simulate system uncertainties and disturbances. The robustness tests involved: a 50% variation in stator inductance (Ls) and resistance (Rs). These disturbances were implemented to assess the ability of the controllers to maintain stable and accurate performance despite significant variations in key machine parameters.

The results illustrated in Figures 14 and 15 indicate that the NFLC strategy demonstrates superior robustness in comparison to the conventional fuzzy logic control (FLC) approach. This enhanced robustness is evidenced by the NFLC controller's improved ability to maintain system stability and performance in the presence of parameter variations and external disturbances. Specifically, the NFLC exhibited more consistent tracking behavior, reduced sensitivity to fluctuations in system parameters, and greater resilience under nonideal operating conditions, thereby affirming its effectiveness in ensuring reliable control across a broader range of scenarios.

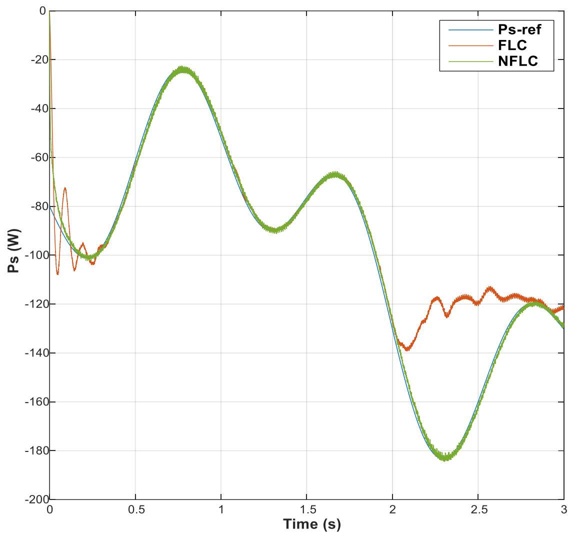

Figure 14. Active power

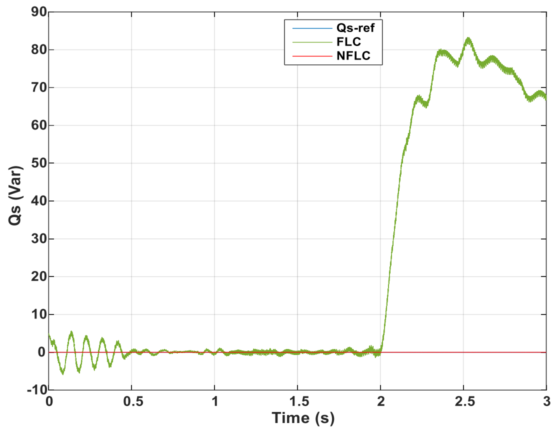

Figure 15. Reactive power

6. CONCLUSION

The primary objective of this research was to develop and optimize an NFLC strategy for a PMSG, with a focus on its application within a variable-speed wind turbine system. To achieve this goal, the study encompassed several key components, including a comprehensive review of the state of the art in wind energy conversion systems, detailed modeling of the PMSG-based system, and an in-depth analysis of its operational characteristics and control strategies.

The proposed NFLC architecture demonstrated multiple advantages over conventional control approaches. Notably, it exhibited superior dynamic performance, precise tracking of power setpoints, and effective decoupling between the direct and quadrature current components, as well as between active and reactive power. Additionally, the system ensured high power quality, as evidenced by low THD, with the injected grid currents maintaining a near-sinusoidal waveform. The NFLC approach also contributed to enhanced stability of electrical parameters at the grid interface, reinforcing its suitability for robust and efficient integration in modern wind energy systems.

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AUTHOR CONTRIBUTIONS STATEMENT

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

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Ibrahim Yaichi	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓
Harrouz Abdelkader	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	
Patrice Wira	✓	✓	✓	✓	✓	✓				✓		✓		

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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