# Adaptive Neuro-Fuzzy Reinforcement Learning Control for Grid Stability and LVRT Enhancement in PMSG-Based WECS

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**Abstract:** In this work, an Adaptive Neuro-Fuzzy Reinforcement Learning (ANF-RL) control framework is developed to improve the grid-integration performance of Permanent Magnet Synchronous Generator (PMSG)-based Wind Energy Conversion Systems (WECS). The proposed controller integrates neural-network-based nonlinear approximation, fuzzy reasoning for uncertainty handling, and reinforcement-learning-based adaptive optimization. It is coordinated with a Dynamic Voltage Restorer (DVR) and a 31-level Cascaded H-Bridge Multilevel Inverter (CHBMLI) to address voltage sags, DC-link instability, torque ripple, harmonic distortion, and Low Voltage Ride Through (LVRT) requirements. The system is formulated for MATLAB/Simulink evaluation under variable wind profiles and grid disturbances, with performance assessed using LVRT capability, Total Harmonic Distortion (THD), DC-link voltage regulation, torque ripple, grid synchronization, voltage recovery, and settling time. The study also establishes a system-level baseline for a broader postdoctoral programme that subsequently extends intelligent LVRT control toward physics-informed reference-current generation and converter-level control in DFIG-based WECS.

**Keywords:** Wind Energy Conversion System (WECS); Permanent Magnet Synchronous Generator (PMSG); Adaptive Neuro-Fuzzy Reinforcement Learning (ANF-RL); Low Voltage Ride Through (LVRT); Grid Stability.

## I. Introduction

The increasing penetration of renewable energy resources has intensified the need for wind-energy control strategies that remain effective under variable environmental and grid conditions [1]. PMSG-based WECS are attractive because of high efficiency, gearless operation, high power density, and variable-speed capability [2]. However, fluctuating wind input and grid disturbances can produce voltage variations, DC-link oscillations, torque ripple, harmonic distortion, and reduced ride-through capability. Modern grid-connected wind turbines are expected to remain connected during temporary voltage sags; therefore, LVRT performance, power quality, and converter stability must be considered simultaneously [3].

Conventional PI/PID controllers are simple and effective around fixed operating points, but fixed gains and model dependence restrict their performance when the plant is nonlinear or operating conditions change rapidly. Fuzzy logic and neuro-fuzzy control improve uncertainty handling [8], neural networks provide nonlinear learning capability [9] and reinforcement learning offers adaptive optimization for changing operating conditions [10], [11]. Recent PMSG-WECS studies also demonstrate the value of robust adaptive fuzzy control for performance enhancement [4]. In parallel, DVR-based LVRT support and intelligent multilevel-converter control have been investigated for grid-stability and power-quality improvement [5], [6], while emerging ANF-RL concepts motivate the integration of learning and adaptation within a unified framework [7].

Accordingly, this paper develops a unified ANF-RL framework integrated with a DVR and a 31-level CHBMLI for PMSG-based WECS. The immediate objective is to coordinate learning-based control and power-electronic compensation so that LVRT capability, grid voltage support, DC-link stability, harmonic reduction, torque-ripple mitigation, and synchronization can be evaluated within one architecture [3], [6], [7]. The performance objectives established here are subsequently extended to DFIG-based WECS through physics-informed dq-frame reference-current generation, optimized DC-link regulation, and converter-level active/reactive power control. Thus, the later DFIG work is treated as a distinct technical extension rather than as the same controller applied to a different generator.

**II. Related Work and Research Gap**

In the available power-converter control methods, PI and PID controllers are widely utilized because of their simple implementation; however, their tuning performance is affected by changes in the operating point. Fuzzy controllers provide improved disturbance-rejection capability without requiring an exact plant model, whereas their effectiveness mainly depends on the selection of membership functions and formulation of the rule base [8]. ANN-based methods are capable of learning nonlinear relationships from operating data, but their performance is influenced by training quality and adaptability under varying dynamics [9]. RL provides online decision-making and adaptive optimization; however, computational complexity, the exploration-exploitation balance, and safe learning under power-system constraints remain important practical limitations [10], [11].

Hardware-supported grid compensation is considered as a complementary solution. DVR-based compensation injects the required voltage during sag conditions and thereby improves LVRT performance [12]. Multilevel converters, particularly cascaded H-bridge structures, provide improved output waveform quality together with reduced switching stress [13]. From the existing literature, it is observed that intelligent control, DVR compensation, and multilevel conversion are generally investigated as separate functions, or the analysis is limited to a small number of control objectives [5], [11]-[14]. The resulting research gap is the limited treatment of a coordinated architecture that combines ANN learning, fuzzy reasoning, RL adaptation, DVR voltage support, and multilevel conversion while simultaneously considering LVRT, THD, DC-link regulation, torque ripple, and grid synchronization.

**III. Proposed Methodology**

**A. Overall System Architecture—**The proposed WECS consists of a variable-speed wind turbine mechanically coupled to a PMSG. The generator output is processed through an AC-DC converter and a regulated DC-link capacitor before grid interfacing through a 31-level Cascaded H-Bridge Multilevel Inverter (CHBMLI). A Dynamic Voltage Restorer (DVR) is connected in series with the utility grid so that compensating voltage can be injected during voltage-sag events, thereby supporting LVRT operation [3], [12], [13]. The architecture is therefore designed to coordinate generator-side energy conversion, DC-link regulation, inverter-based grid interfacing, and series voltage compensation within a single control framework.

**B. Adaptive Neuro-Fuzzy Reinforcement Learning Controller—**The controller continuously receives wind speed, generator output voltage, grid voltage, grid current, and DC-link voltage measurements and uses them to determine coordinated control actions for the DVR and CHBMLI. The neural-network component provides nonlinear approximation of relationships between measured operating states and required control actions [9]. Fuzzy inference handles uncertainty and imprecise transient conditions without requiring an exact mathematical description of every operating state [8]. Reinforcement learning updates the control policy from interaction with the simulated power-system environment, enabling adaptive optimization as the wind and grid conditions change [10], [11]. The combined ANF-RL structure therefore brings nonlinear learning, uncertainty handling, and adaptive policy improvement into one controller rather than treating them as independent functions [7].

**C. Dynamic Voltage Restorer and Multilevel Inverter Integration—**During grid disturbances, the DVR provides the direct voltage-support function by injecting the required compensating voltage to reduce the depth and duration of the sag seen by the wind-energy system [5], [12]. At the grid interface, a 31-level CHBMLI is utilized to generate a near-sinusoidal output waveform with lower harmonic content and reduced switching stress in comparison with conventional two-level conversion [13]. Based on the measured electrical states, the ANF-RL layer coordinates the DVR and CHBMLI operations so that voltage recovery, DC-link response, waveform quality, and continuous grid connection are considered within the same control process. This coordinated arrangement extends earlier intelligent-controller and DVR/multilevel-inverter approaches [3], [6] by emphasizing simultaneous control of multiple grid-support objectives.

**D. Proposed Control Strategy—**The proposed controller operates in six recurring steps: (1) acquire wind speed, grid voltage, grid current, generator output, and DC-link voltage measurements; (2) use the neural-network component to estimate nonlinear system behavior; (3) apply fuzzy inference to represent uncertainty during transients; (4) update the control action through reinforcement learning according to the received reward; (5) generate the required switching/control commands for the DVR and CHBMLI; and (6) maintain LVRT capability, voltage stability, grid synchronization, DC-link regulation, and acceptable power quality as the operating condition changes [3], [10], [11]. This sequence follows the original system concept while making the interaction between the learning layer and the power-electronic compensation devices explicit.

**E. Coordinated Control Objectives—**The integrated ANF-RL, DVR, and 31-level CHBMLI arrangement is intended to address several objectives simultaneously rather than optimize a single response variable. Therefore, the proposed control framework considers LVRT capability, grid-voltage recovery, THD reduction, DC-link voltage stability, torque-ripple mitigation, and synchronized grid operation under variable wind and grid conditions [5]-[7], [12], [13]. By coordinating intelligent decision-making with voltage compensation and multilevel conversion, the methodology provides a common platform in which these performance indices can be evaluated under the same operating cases.

## IV. Simulation and Performance Evaluation

In this work, the ANF-RL framework is formulated for MATLAB/Simulink implementation using a system model consisting of the wind turbine, PMSG, AC-DC converter, DC-link capacitor, DVR, 31-level CHBMLI, utility grid, and intelligent controller [3], [14]. The simulation cases considered from the original study include normal operation at rated wind speed, variable wind speed, balanced three-phase voltage sag, unbalanced grid fault, and sudden load variation [12]. For comparative assessment, the same plant and disturbance conditions are applied to PI, fuzzy-logic, ANN, RL, and the proposed ANF-RL controllers [10].

Performance is evaluated using LVRT capability, THD, DC-link voltage regulation, torque-ripple reduction, grid synchronization, voltage-recovery time, and dynamic settling time [10], [12]. The final simulation report should also state the wind-turbine and PMSG ratings, nominal DC-link and grid voltages, switching frequency, simulation duration, and MATLAB/Simulink version to support reproducibility. Quantitative performance claims are reserved for validated simulation outputs.

## V. Results and Discussion

The final results section will contain only the validated MATLAB/Simulink comparison of the ANF-RL, PI, fuzzy, ANN, and RL controllers. Discussion will be limited to the measured LVRT response, THD, DC-link deviation, torque ripple, and settling behavior; quantitative improvement will be stated only after the simulation outputs are finalized.

## VI. Conclusion and Research Continuity

This paper establishes a coordinated ANF-RL control framework for PMSG-based WECS by integrating neural learning, fuzzy reasoning, reinforcement-learning adaptation, DVR compensation, and a 31-level CHBMLI. The main emphasis is the proposed architecture and control sequence for simultaneous LVRT support, DC-link regulation, power-quality improvement, torque-ripple mitigation, and grid synchronization. From the defined simulation cases and performance indices, a systematic basis is obtained for the subsequent quantitative validation.

As the initial stage of the postdoctoral programme, the proposed study establishes a technical baseline for the subsequent DFIG-based investigation. In the forthcoming conference studies, the same LVRT, THD, DC-link, and grid-stability objectives are retained, while DQ-PINN-based reference-current generation and FLO-PI-based DC-link regulation are introduced as separate technical developments. Hardware-in-the-loop and real-time validation can follow the completed simulation studies.

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