Controlling and Modeling of a Doubly-Fed Induction Generator Based Wind Turbine by using Adaptive Techniques

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ABSTRACT

Traditionally, Droop control models have been used to characterize the response of systems. However, this work demonstrates that when droop control is applied to doubly-fed induction generators, these models fail to predict the system's stability and dynamic response accurately. Therefore, this paper presents adaptive techniques like Fuzzy Logic Control and Artificial Neural Networks, which overcome the limitations of droop control models. The proposed model, validated by simulation in MATLAB/Simulink, accurately analyzes the stability and dynamic response of the system under study. This model serves as a valuable tool for future work in designing and adjusting grid-forming controllers for Doubly-Fed Induction Generators.

Keywords: Doubly Fed Induction Generator, Wind Turbine, Renewable Energies, Droop Control, Fuzzy Logic Controllers, Artificial Neural Network.

I. INTRODUCTION

In the contemporary landscape of power generation, the shift from traditional fossil-fuel-based energy sources to renewable energy is not just a trend but a necessity. [1] Among various renewable energy sources, wind power stands out due to its sustainability and minimal environmental impact. Central to the efficiency and effectiveness of wind power generation are wind turbines, particularly those equipped with Doubly-Fed Induction Generators [2] (DFIGs). DFIGs have gained prominence in the variable speed onshore wind turbine market, offering advantages such as improved energy efficiency and reduced mechanical stress. However, the integration of [2-5] DFIG- based wind turbines into the power grid presents unique challenges, primarily related to grid stability and control. [6]

Traditionally, power grids have been dominated by Synchronous Generators (SGs) of large conventional fossil-fuel power plants. These generators have been the backbone of grid stability, dictating the frequency and voltage levels. However, as renewable energy sources like DFIG wind turbines increasingly replace SGs, concerns about grid stability have surfaced. The Grid-Following Control (GFL) [10] [12] strategies, which are prevalent in most power converters, rely on the presence of a strong grid, a condition that SGs fulfill. The gradual replacement of SGs with renewable energy sources necessitates the development of new control techniques to ensure grid stability.

In response to these challenges, the research community has shifted its focus towards developing Grid-Forming (GFM) control strategies. [9] These strategies are pivotal in addressing the complexities involved in the large-scale integration of renewable energies, ensuring a stable and safe operation of the power system [10]. One of the critical aspects of integrating DFIG wind turbines into the power grid is the management of load sharing among different generating units. Traditionally, this has been achieved through droop control. However, when applied to DFIGs, [11] conventional Root Mean Square (RMS) models, typically used to characterize the response of droop-controlled systems, fall short. They fail to accurately predict the system's stability and dynamic response, necessitating the development of more sophisticated models.

To address these limitations, this paper presents a linearized small-signal model that surpasses the capabilities of RMS models [13]. This model is designed to effectively control and model a grid-connected DFIG wind turbine, optimizing system stability and dynamic response. The innovation does not stop at the development of a new model; it extends to the implementation of adaptive techniques for control. Specifically, the use of Fuzzy Logic Controllers and Artificial Neural Networks (ANN) is proposed [15-16]. These advanced control techniques are known for their ability to handle nonlinearities and uncertainties, characteristics inherent in wind power generation.

The effectiveness of the suggested control is validated using MATLAB/SIMULINK. This validation is crucial, as it demonstrates the practical applicability of the proposed model in real-world scenarios. By leveraging the strengths of adaptive techniques, this research contributes significantly to the field of renewable energy, particularly in enhancing the efficiency and stability of DFIG-based wind turbines within the power grid.

A. OBJECTIVE

The objective of this research is to develop adaptive control techniques for modeling and controlling of Doubly-Fed Induction Generator (DFIG) wind turbines. With a focus on enhancing grid stability during the transition from fossil-fuel power to renewable energy, the study aims to overcome limitations in traditional control methods like Root Mean Square (RMS) models and Droop Control models. The research also includes the validation of these techniques using Fuzzy Logic Controllers and Artificial Neural Networks (ANN), with the ultimate goal of optimizing system stability and dynamic response.

B. PROBLEM STATEMENT

As the global energy landscape transitions towards renewable sources, wind power plays a significant role in reducing our reliance on fossil fuels. Doubly- Fed Induction Generators (DFIG) are widely used in onshore wind turbines due to their variable-speed capabilities. However, this shift from conventional fossil-fuel power plants to renewable energy sources like wind introduces a challenge related to grid stability. The traditional power grid relies heavily on Synchronous Generators (SG) found in conventional power plants, and their Grid-Following Control (GFL) strategies depend on the presence of a stable grid with frequency and voltage provided by SGs. With the increasing integration of DFIG wind turbines and other renewable sources, there's a risk that the grid's stability could be compromised. To address this challenge, researchers have been developing Grid-Forming Control (GFM) strategies that enable renewable energy sources to actively contribute to grid stability and ensure safe and reliable power system operation. One crucial aspect of DFIG wind turbine control is the implementation of droop control, commonly used to regulate load sharing among multiple generating units in parallel operation. Traditionally, Root Mean Square (RMS) models have been used to characterize the response of droop-controlled systems. However, when applied to DFIGs, RMS models have limitations in predicting system stability and dynamic responses accurately.

The study will explore the use of Fuzzy Logic Controllers and Artificial Neural Networks (ANN) to validate the effectiveness of the proposed control strategy. The goal is to demonstrate that the suggested control approach can successfully implement a linearized small-signal model for controlling and modeling grid-connected DFIG wind turbines while optimizing system stability and dynamic response.

II. METHODOLOGY

A. DOUBLY FED INDUCTION GENERATOR

A Doubly Fed Induction Generator (DFIG) is a type of electrical generator commonly utilized in wind turbines. It is characterized by its ability to generate electricity at varying rotor speeds, making it highly effective for efficiently harnessing wind energy. Unlike conventional fixed-speed generators that operate at constant rotational speeds, a DFIG is part of a larger wind turbine system that allows the rotor to spin at speeds that fluctuate with the wind speed.

The core of a DFIG system is its wound rotor, which is connected to the electrical grid via slip rings and brushes, allowing for a variable speed operation as shown in Fig.1. This is in contrast to the stator, which is directly connected to the grid. The rotor is fed with electrical power from the grid through a back-to-back converter comprising of two converters rectifier and inverter connected by a DC link. This setup allows the DFIG to absorb or inject reactive power, which aids in the control of the grid voltage and the flow of active power.

The back-to-back converter can control the rotor's speed within a certain range around the synchronous speed of the electrical grid. This enables the DFIG to extract the maximum possible energy from the wind across a range of wind speeds. Additionally, by adjusting the phase and magnitude of the rotor voltage, the DFIG can also provide system services like voltage regulation and reactive power support, which can enhance the stability and efficiency of the power grid.

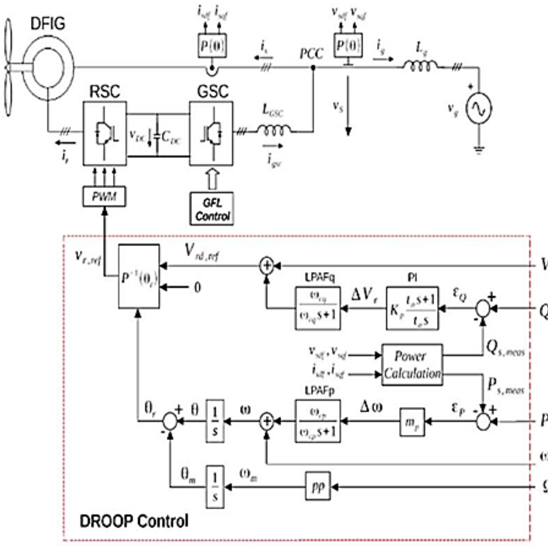

Figure 1: Droop Control Implementation for a DFIG Wind Turbine

DFIGs are known for their cost-effectiveness and improved energy capture efficiency, especially in regions with variable wind speeds. They are also capable of reducing mechanical stresses within the turbine during gusts of wind, leading to a longer operational lifespan for the turbine. However, the complexity of their design and the need for slip rings and brushes can result in higher maintenance costs and potential reliability issues compared to other types of generators. Despite these challenges, DFIGs remain a popular choice in modern wind energy systems due to their overall benefits in terms of control, efficiency, and grid support.

B. CONTROL STRATEGIES

Control strategies for Doubly Fed Induction Generators (DFIGs) in wind turbines are crucial for optimizing performance, ensuring stability, and managing power output. The fig.2 shows the Control strategy

i. Rotor-Side Control:

The rotor-side converter controls the rotor current to regulate the electromagnetic torque and the reactive power of the generator. This is essential for adjusting the power factor and managing the rotor speed to track the optimal power coefficient of the turbine for different wind speeds .Vector control, often implemented with a Proportional-Integral (PI) controller, allows separate control of active and reactive power by decoupling the stator flux from the rotor current. Slip control is used to maintain the rotor speed at a level where the generator can efficiently convert the kinetic energy of the wind into electrical energy.

ii. Grid-Side Control:

The grid-side converter maintains the DC link voltage at a constant level, which is crucial for the stable operation of the rotor-side converter. It also controls the exchange of reactive power with the grid, contributing to voltage regulation at the point of common coupling. Power quality issues are addressed by filtering harmonics and balancing the power supplied to the grid.

iii. Adaptive Control Techniques:

Modern DFIGs often employ adaptive control strategies, such as Fuzzy Logic or Artificial Neural Networks (ANN), to handle non-linearities and uncertainties inherent in wind energy conversion.

These adaptive controllers can adjust control parameters in real-time, responding to sensor data and historical performance to optimize efficiency and resilience to disturbances.

iv. Pitch Control:

Besides electrical control, the mechanical pitch control of the turbine blades is also utilized to restrict the power captured by the turbine at high wind speeds. This mechanism safeguards the turbine against excessive mechanical stress and averts the overproduction of electricity.

v. Fault Ride-Through:

DFIGs are equipped with control strategies to deal with grid disturbances. These strategies ensure that the turbine can maintain operation during short periods of grid faults, a requirement in many grid codes.

vi. Energy Storage Integration:

The incorporation of energy storage systems, such as batteries or super capacitors, can be controlled to mitigate the variability of wind power, store excess energy, and release it when needed, thus stabilizing the output.

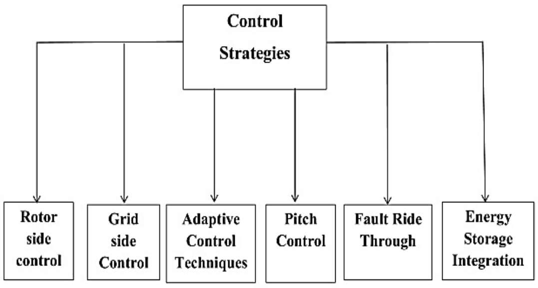

Figure.2: Flowchart for control strategy

Each control strategy for DFIGs is designed to respond to specific aspects of wind turbine operation, from day-to-day efficiency optimization to rare but critical fault conditions. The sophistication of these controls is a testament to the complexity and advanced engineering behind modern wind energy technology.

Doubly-Fed Induction Generator (DFIG) Wind Turbine: The primary input is the DFIG wind turbine system, which is the subject of the research. The challenges associated with integrating renewable energy sources, like DFIG wind turbines, into the existing power grid, including issues related to grid stability and control strategies. Knowledge and data on Grid-Forming Control (GFM) strategies used to address the challenges of large-scale renewable energy integration. Information on droop control, its traditional use in power converters, and its application in DFIG wind turbines. Understanding of the limitations of Root Mean Square (RMS) models when applied to DFIG systems.

Grid Stability Enhancement, The research aims to enhance grid stability as fossil-fuel power plants are replaced by renewable energy sources. One of the main outputs is the development of control techniques that contribute to grid stability. Optimized Wind Turbine Operation, The research seeks to optimize the operation of DFIG wind turbines, resulting in improved energy capture and conversion efficiency. Observations and results obtained from using Fuzzy Logic Controllers and Artificial Neural Networks to validate the effectiveness of the suggested control techniques.

ADAPTIVE CONTROL TECHNIQUES

A. FUZZY LOGIC CONTROL

Fuzzy logic Control, particularly as it applies to Doubly- Fed Induction Generators (DFIG) in wind turbines:

i. Designing Fuzzy Logic Controllers (FLCs):

Fuzzy Sets and Membership Functions: The first step in designing a Fuzzy Logic Controller is to define fuzzy sets for each input and output variable. A fuzzy set is a mathematical representation of a qualitative concept like "slow" or "fast" in terms of a continuum of values between 0 and 1.Each fuzzy set is associated with a membership function that determines the degree to which a specific input value belongs to the set. These sets are then used to create control rules. Control rules are the heart of the FLC, capturing expert knowledge about the system's behavior. For instance, a rule might state, "IF the rotor speed is high, THEN reduce power output."

ii. Defining Input and Output Variables:

In the context of DFIGs, inputs might include measurable parameters like wind speed, rotor speed, or power demand. These inputs are used to make decisions about how to control the turbine. The outputs are the control actions the FLC will take. For example, adjusting the blade pitch or generator torque.

iii. Developing Control Rules:

Rules in a FLC are typically formulated in an IF-THEN structure. These rules dictate the controller's response to various input combinations. The development of the rule base is a critical step that involves understanding the dynamics of the DFIG and the desired outcomes (like maximizing efficiency or minimizing stress on the turbine).

iv. Fuzzification:

This is the process of converting real- world numerical inputs into degrees of membership in the relevant fuzzy sets. It is an essential step that transforms crisp values into a form that can be processed by fuzzy rules.

v. Inference Engine Processing:

Rule Application is the inference engine applies the fuzzy control rules to the fuzzified inputs. Aggregation is the outputs of individual rules are combined (or aggregated) to form a single fuzzy set for each output variable.

vi. Defuzzification:

This is the process of converting the aggregated fuzzy output set into a single crisp output value. This value is then used as the actual control action for the DFIG system.

B. ANN CONTROL

ANN Control, specifically for Doubly-Fed Induction Generator (DFIG) wind turbines:

i. Data Collection and Preprocessing:

Operational data is collected from various sensors and systems within the DFIG. This includes parameters like wind speed, rotor speed, electrical output (voltage, current, power), and mechanical stresses. Preprocessing Steps include the collected data often requires cleaning and normalization. This might involve filtering out noise, handling missing values, or scaling the data to a uniform range. The preprocessing stage is crucial for ensuring that the data fed into the ANN is of high quality and suitable for training.

ii. Designing the Neural Network:

Choosing the right architecture involves deciding on the number of layers (input, hidden, and output layers) and the number of neurons in each layer. The architecture is dictated by the complexity of the control task and the nature of the data. Different types of neurons and activation functions can be selected based on the specific requirements of the application. Common activation functions include sigmoid, tanh, and ReLU (Rectified Linear Unit).

iii. Training the Network:

The most common learning algorithm for ANNs is backpropagation, where the network learns by adjusting weights to minimize the error between its predictions and actual values. Optimization Techniques, Gradient descent or its variants (like stochastic gradient descent) are used to find the optimal set of weights. This involves iteratively updating the weights in the direction that reduces the overall error.

iv. Validation and Testing:

Cross-Validation involves dividing the dataset into a training set and a validation set. The model is trained on the training set and validated on the validation set to check for overfitting. Performance Metrics like mean squared error (MSE), accuracy, or others relevant to the specific application are used to evaluate the model's performance.

v. Implementation for Control:

The trained ANN is integrated into the DFIG's control system, where it uses real-time data to make predictions and control decisions. The ANN can adjust operational parameters like blade pitch or generator torque to optimize performance.

vi. Continuous Learning and Adaptation:

The ANN can be designed to adapt to new data, learning from ongoing operations and improving its control strategies over time. Online Learning involves updating the ANN model incrementally as new data is collected, allowing the system to respond to changing environmental and operational conditions.

ADVANTAGES

i. Improved Grid Stability: The use of adaptive control techniques can enhance the stability of electrical grids as they transition from conventional fossil-fuel power plants to renewable energy sources like DFIG wind turbines. This contributes to a more reliable and resilient power supply.

ii. Optimized Power Generation: Adaptive control strategies, such as Fuzzy Logic Controllers and Artificial Neural Networks, can optimize the operation of DFIG wind turbines, enabling them to capture more wind energy and improve overall energy conversion efficiency.

iii. Enhanced Dynamic Response: The development of a linearized small-signal model can lead to better prediction and management of the DFIG system's dynamic response. This can result in quicker and more accurate adjustments to changing wind conditions, ensuring stable grid interaction.

iv. Grid-Forming Capability: The research focuses on Grid-Forming Control (GFM) strategies, which enable DFIG wind turbines to actively contribute to grid stability. This capability is crucial for large-scale integration of renewable energy and grid support during contingencies.

v. Reduced Environmental Impact: By improving the efficiency and stability of wind turbine operations, the research indirectly supports the reduction of greenhouse gas emissions and environmental impact associated with fossil-fuel-based power generation.

vi. Research Innovation: The research contributes to the ongoing innovation in the field of wind energy technology, advancing the understanding of DFIG wind turbines' behavior and control mechanisms.

IV. VALIDATION OF THE PROPOSED MODEL THROUGH SIMULATION

It presents the outcomes of applying Fuzzy Control and Artificial Neural Network (ANN) Control to manage active and reactive power in Doubly-Fed Induction Generator (DFIG) wind turbines. It highlights the effectiveness of these adaptive control techniques in addressing the uncertainties in wind energy systems and underscores their role in improving DFIG wind turbine performance. The section concludes that these techniques offer a flexible and effective framework for optimizing wind energy system control, particularly for DFIG-based turbines.

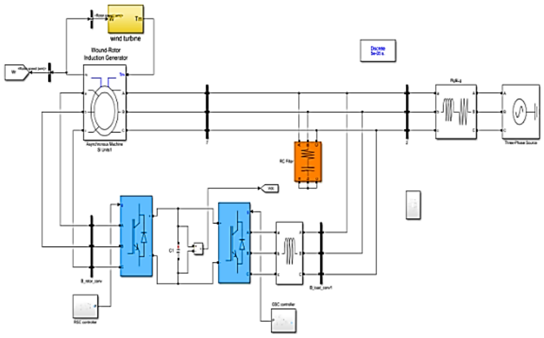

Figure 3: Simulation Diagram for Fuzzy Logic Control

Fig.3 presents simulation diagram demonstrating the application of Fuzzy Control in managing the active and reactive power of a Doubly-Fed Induction Generator (DFIG) wind turbine. This figure is part of the research exploring the effectiveness of Fuzzy Control techniques in optimizing the performance and stability of DFIG systems within wind turbines

Output Response for case.1:

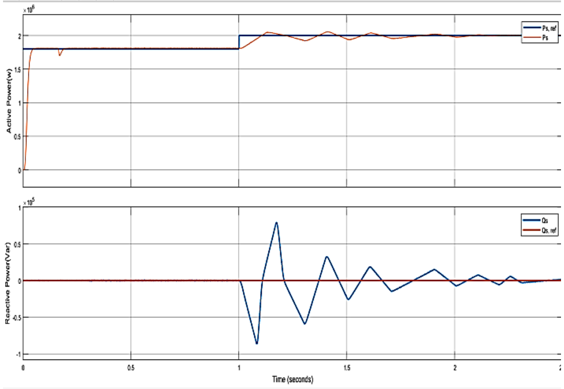

Figure 4: Fuzzy Logic Control Active and Reactive Power at 1050 RPM.

Fig.4 would illustrate the performance of Fuzzy Control in regulating both active and reactive power in a doubly-fed induction generator (DFIG) wind turbine operating at a speed of 1050 RPM. The figure likely includes graphical representations showing how Fuzzy Control effectively manages power output under these specific operational conditions.

Output Response for case.2:

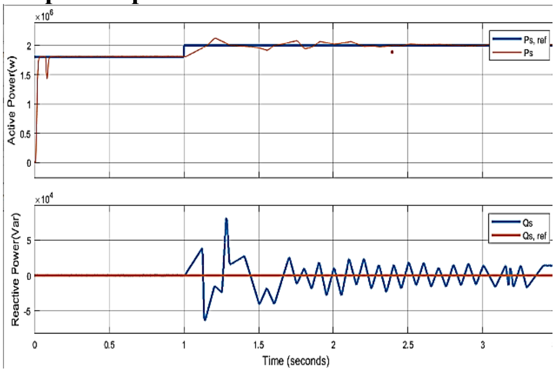

Figure 5: Fuzzy Logic Control Active and Reactive Power at 1800 RPM

This fig.5 demonstrates the performance of Fuzzy Control in managing both active and reactive power in a Doubly-Fed Induction Generator (DFIG) wind turbine, particularly at an operational speed of 1800 RPM. It probably includes graphical visualization that showcase the effectiveness of Fuzzy Control in optimizing power output under these specific conditions.

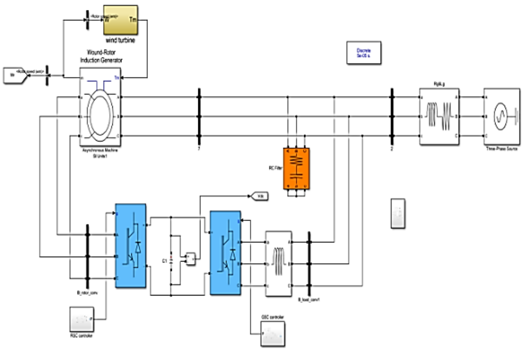

Figure 6: Simulation Diagram ANN Control

This fig.6 would depict the application of Artificial Neural Network (ANN) Control in a Doubly-Fed Induction Generator (DFIG) wind turbine. The figure would likely illustrate how ANN Control is used to manage the performance of the DFIG, potentially focusing on aspects such as power output, efficiency, or stability. The figure might include graphical data or simulations demonstrating the effectiveness of ANN Control in optimizing the operation of DFIG wind turbines.

Output response for case. 1:

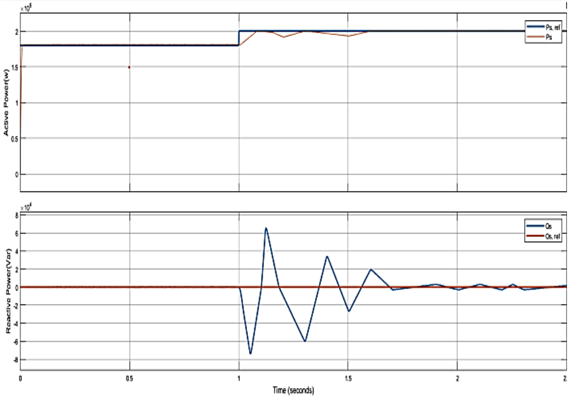

Figure 7: ANN Control Active and Reactive Power at 1050 RPM

The fig.7 would illustrate the performance of Artificial Neural Network (ANN) Control in managing both active and reactive power in a Doubly-Fed Induction Generator (DFIG) wind turbine at an operational speed of 1050 RPM. It is likely to include graphs or visual data that demonstrate the effectiveness of ANN Control in optimizing the power output and efficiency of the wind turbine under these specific conditions.

Output response for case. 2:

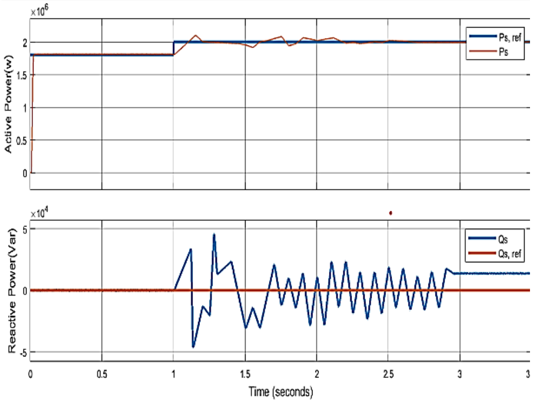

Figure 8: ANN Control Active and Reactive Power at 1800 RPM

This fig.8 would demonstrate the application of Artificial Neural Network (ANN) Control in managing active and reactive power in a Doubly-Fed Induction Generator (DFIG) wind turbine at an operational speed of 1800 RPM. The figure likely includes graphical representations, showing how ANN Control optimizes the power output and operational efficiency of the DFIG under these specific operational conditions.

V. CONCLUSION

"Fuzzy Control and Artificial Neural Network (ANN) Control bring significant advantages in addressing the Active and Reactive power control to the uncertain nature of wind energy systems. These adaptive techniques provide a flexible framework for enhancing the performance of DFIG wind turbines".

It emphasizes the effectiveness of Fuzzy Control and ANN Control in managing the complexities of wind energy systems, specifically in the context of a Doubly-Fed Induction Generator (DFIG) based wind turbine. The adaptive nature of these controls is highlighted as a key factor in improving the performance of DFIG wind turbines.

REFERENCES

[1] Hansen, A. D., & Hansen, L. H. (2004), " The low-voltage ride-through capability of doubly fed induction generators," IEEE Transactions on Power Electronics, 19(5), 1292-1299.

[2] Chaves, E. M., & Faria, H. A. (2015), " An adaptive fuzzy sliding mode controller for doubly fed induction generator based wind turbine systems," Renewable Energy, 83, 663-674.

[3] Wang, C., Wang, Y., & Ni, Y. X. (2013), " Wind turbine control strategies using adaptive dynamic programming," IEEE Transactions on Sustainable Energy, 4(1), 1-10.

[4] Tan, Y., & Zhu, Z. (2011), " Adaptive fuzzy control of DFIG-based wind turbines for maximum power point tracking," IEEE Transactions on Energy Conversion, 26(3), 877-888.

[5] Chaudhuri, N. R., & Chatterjee, K. (2016), "Model predictive control of doubly fed induction generator-based wind turbines with maximum power point tracking," IEEE Transactions on Energy Conversion, 31(1), 86-96.

[6] Zhang, C., Hu, X., & Fu, M. (2012), " Adaptive sliding-mode control of doubly fed induction generator-based wind turbine with uncertainty and disturbance," IEEE Transactions on Industrial Electronics, 59(1), 458-466.

[7] Li, J., Wang, L., & Li, G. (2010). Fuzzy neural network control of wind turbines with doubly fed induction generators for maximum power point tracking," IEEE Transactions on Energy Conversion, 25(1), 71-82.

[8] Liu, Y., Shi, J., & Li, H. (2014), "Adaptive neuro-fuzzy controller for maximum power point tracking of wind turbine with doubly fed induction generator," IEEE Transactions on Industrial Electronics, 61(4), 1817-1825.

[9] Yu, W., Li, Y., & Li, X. (2011), "Control and modeling of a doubly fed induction generator for wind turbines," IEEE Transactions on Energy Conversion, 26(3), 755-766.

[10] Rui, X., & Xiaosong, H. (2013). "Wind turbine modeling and control with doubly fed induction generator and battery energy storage," IEEE Transactions on Sustainable Energy, 4(3), 826-833.

[11] Oraa J. Samanes J. Lopez and E. Gubia, "Modeling of a Droop-Controlled Grid- Connected DFIG Wind Turbine," in IEEE Access, vol. 10, pp. 6966-6977, 2022. DOI: 10.1109/ACCESS.2022.3142734.

[12] T. Telsnig, "Wind energy technology development report 2020," Publications Office of the European Union, Luxembourg, Tech. Rep. JRC123138, 2020. Available online: ResearchGate Link. DOI: 10.2760/742137.

[13] R. Rosso, X. Wang, M. Liserre, X. Lu, and S. Engelken, "Grid-forming converters: Control approaches, grid-synchronization, and future trends—A review," IEEE Open Journal of Industrial Applications, vol. 2, pp. 93–109, 2021.

[14] K. V. Kkuni, S. Mohan, G. Yang, and W. Xu, "Comparative assessment of typical control realizations of

grid forming converters based on their voltage source behaviour," 2021. arXiv:2106.10048. Available online: arXiv Link.

[15] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuna, and M. Castilla, "Hierarchical control of droop-controlled AC and DC microgrids—A general approach toward standardization," IEEE Transactions on Industrial Electronics, vol. 58, no. 1, pp. 158–172, January 2011.

[16] J. Rocabert, A. Luna, F. Blaabjerg, and P. Rodríguez, "Control of power converters in AC microgrids," IEEE Transactions on Power Electronics, vol. 27, no. 11, pp. 4734–4749,
May 2012.