

## Fuzzy-based Reinforcement Learning Control for Metropolis Wind Turbines: A case Study for Maiduguri

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### ABSTRACT

*This research investigates the application of a control strategy, combining single-input single-output fuzzy logic and reinforcement learning, to optimise the performance of wind turbines in the Maiduguri Metropolis. The primary objective is to maximise power output while ensuring system stability and efficiency, particularly under varying wind conditions. The proposed control system utilises this variant of fuzzy logic to handle uncertainties and nonlinearities inherent in wind energy systems, unlike the conventional fuzzy logic that uses the membership function. The single-input single-output fuzzy logic uses a simple analytic formula for fuzzification. Reinforcement learning, on the other hand, enables the system to learn and adapt to changing environmental conditions, leading to improved performance over time. Simulation results with varying wind speed profiles for different values of learning parameters are presented to validate the effectiveness of the optimal control based on reinforcement learning.*

### ARTICLE INFO

#### Article History

Received: January, 2025

Received in revised form: February, 2025

Accepted: February, 2025

Published online: March, 2025

### KEYWORDS

Fuzzy Logic, Reinforcement Learning, Membership Function, Renewable Energy, Deep Learning.

### INTRODUCTION

Several research teams are currently interested in sustainable development and renewable energies. Thus, the wind turbine development represents a significant investment in technology research. The systems that generate electrical energy from the wind can provide a technological and economic alternative to the various sources of exhaustible energy. Therefore, the study of wind turbine systems is more important and necessary. In general, wind turbine systems fall into two categories: fixed-speed wind turbine systems and variable speed wind turbine systems. Due to its high efficiency and the optimization of electricity production in the grid at different wind speeds, the variable-speed wind turbines have become very popular compared to fixed speed wind turbines [1, 2]. Strong nonlinear characteristics of the variable

speed wind turbine, as is well known, can make the wind turbine's operation more challenging. Thus, the linearization around an operating point of this system has been made in [3]–[5].

Fuzzy logic deals with the fuzziness of the data and the data is described by the fuzzy membership function (MF). MF is a function that specifies the degree to which a given input that belongs to a set. MF are used in the fuzzification and defuzzification steps of a fuzzy logic system to map the non-fuzzy input values to fuzzy linguistic terms and vice while reinforcement learning enables the system to learn and adapt to changing environmental conditions. By integrating these two techniques, the proposed control system aims to achieve optimal performance in terms of power output and system stability.

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The Maiduguri Metropolis, with its potential for wind energy, serves as an ideal case study to evaluate the effectiveness of the proposed control strategy. By deploying this advanced control system, it is anticipated that the wind turbines in the region can contribute significantly to the local energy supply, reducing reliance on fossil fuels and promoting sustainable development [2].

In this research, we propose a novel control strategy that combines the strengths of fuzzy logic and reinforcement learning. Fuzzy logic offers the ability to handle uncertainty and nonlinearity, while reinforcement learning enables the system to learn and adapt to changing environmental conditions. By integrating these two techniques, the proposed control system aims to achieve optimal performance in terms of power output and system stability

The structure of this conference paper consists of the following sections. In section 2, modeling and linearization of variable speed wind turbine is discussed. In section 3, the optimal control applied to the linearized model of a variable speed wind turbine is shown. In order to validate the proposed optimal control method, the simulations of rotor speed for different learning parameters are shown in section 4. This paper is ended with a conclusion.

## LITERATURE REVIEW

Wind energy has become an essential component in the global transition to sustainable energy sources, providing a viable solution to reduce carbon emissions and address energy shortages. However, the inherent variability of wind speed poses challenges in achieving optimal power output and system stability in wind turbines. Numerous control strategies have been explored to address these issues, including traditional proportional-integral-derivative (PID) control, adaptive control, and intelligent control techniques such as fuzzy logic and reinforcement learning (RL). The combination of fuzzy logic with reinforcement learning, forming a fuzzy-based reinforcement learning control (FRLC) system, is a promising approach for managing wind turbine

operations under uncertain and fluctuating wind conditions [6-9].

## Fuzzy Logic Control in Wind Turbines

Fuzzy logic control (FLC) has been widely recognized for its ability to handle the non-linear and uncertain nature of wind turbine systems. Unlike traditional control systems, fuzzy logic does not require precise mathematical modelling, making it ideal for complex systems like wind turbines that operate under highly variable conditions [1]-[4]. FLC systems are often used to manage turbine blade pitch and generator torque, two critical components for optimizing power capture and maintaining system stability [5]. Typically, fuzzy rules and membership functions are derived from expert knowledge, allowing the controller to make adaptive adjustments based on real-time inputs. However, static rule-based systems can be limited in highly dynamic environments, motivating the integration of reinforcement learning for adaptive optimization.

Reinforcement Learning in Control Systems Reinforcement learning (RL) is a branch of machine learning focused on enabling an agent to learn optimal actions through interactions with its environment. In RL, the agent maximizes a cumulative reward by adjusting actions based on feedback, which makes RL suitable for environments with high uncertainty, such as wind turbine control. In recent years, RL approaches have been used to optimize turbine components, including pitch and yaw control, generator torque, and power smoothing [6]-[8]. Model-free RL techniques, such as Q-learning and deep RL, have been shown to be particularly effective for wind turbine systems that lack complete models [9], [10]. However, RL methods face challenges related to exploration, computational cost, and convergence in continuous control problems, leading to the development of hybrid techniques, such as fuzzy-based reinforcement learning.

Fuzzy-Based Reinforcement Learning Control for Wind Turbines. The integration of fuzzy logic with reinforcement learning provides a synergistic control mechanism, combining the

flexibility of fuzzy logic with the adaptability of RL. A fuzzy-based reinforcement learning controller (FRLC) can adjust fuzzy rules and membership functions dynamically based on feedback from the environment [11]-[13]. Studies have demonstrated that FRLC systems offer significant improvements in managing multi-objective control, such as enhancing power output, minimizing mechanical stress, and ensuring system stability under varying wind conditions [14]. In particular, the FRLC approach allows for continuous learning and optimization, enabling the control system to adapt to changing conditions. For wind turbines in regions with highly variable wind speeds, such as Maiduguri Metropolis, FRLC systems provide a promising solution to optimize energy capture and reduce fluctuations in power output [15].

### Modeling and Simulation of Wind Turbine Dynamics

Accurate modeling of wind turbine dynamics is essential for developing effective control strategies. Wind turbine models typically include aerodynamic, mechanical, and electrical components, each exhibiting complex, non-linear behaviors. Aerodynamic models capture the interaction between wind and blade rotation, while mechanical models describe the energy transmission through rotor and shaft dynamics. Electrical models focus on power conversion and grid integration, which are critical for assessing system performance under varying operational conditions [16]-[18]. Simulation studies using these models are invaluable for evaluating control strategies, enabling researchers to assess the behaviour of control systems under diverse wind profiles before field implementation.

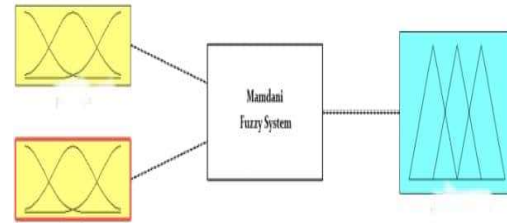
### Case Study Implementation and Real-World Application

Case studies are essential in validating the effectiveness of FRLC systems in real-world applications. In the case of Maiduguri Metropolis, implementing an FRLC control strategy for wind turbines provides an opportunity to test the system in a region with variable wind conditions. Previous case studies have shown that FRLC

can effectively manage turbine speed, optimize power output, and reduce mechanical wear and tear under inconsistent wind patterns [19]-[21]. These case studies highlight the practical benefits of hybrid control systems in achieving sustainable energy generation and provide empirical evidence for FRLC's potential in improving energy access in off-grid communities.

### METHODOLOGY

The fuzzy controller was designed in Matlab using the inbuilt fuzzy interface system. The fuzzy inference engine needs two inputs: error and change in error. The Fuzzy interface system in MATLAB/Simulink is shown in Figure 1



**Figure 1:** Fuzzy interface block diagram showing the connections between input and output

**Table 3.1:** Method use in Fuzzy Inference Engine

Fuzzy Inference	Engine
AND	Min
OR	Max
Implication	Min
Aggregation	Max
Defuzzification	Centroid

The fuzzy rules are shown in Table 3.5, here the abbreviations of the membership functions denoting NB-negative big, NM-negative medium, NS-negative small, AZ-around zero, PS-positive big, PM-positive medium and PB-positive big.

**Table 1:** Mamdani Fuzzy Rules with Seven Membership Function

$\theta$								
	<i>N</i>	<i>N</i>	<i>N</i>	<i>A</i>	<i>P</i>	<i>P</i>	<i>P</i>	
	<i>B</i>	<i>M</i>	<i>S</i>	<i>Z</i>	<i>S</i>	<i>M</i>	<i>B</i>	
<i>N</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>N</i>	<i>P</i>	<i>P</i>	

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		$\theta$							
$q$	$B$	$B$	$B$	$B$	$M$	$M$	$S$	$M$	
	$N$	$N$	$N$	$N$	$N$	$N$	$P$	$P$	
	$M$	$B$	$B$	$M$	$M$	$S$	$S$	$B$	
	$N$	$N$	$N$	$N$	$N$	$A$	$P$	$P$	
	$S$	$B$	$B$	$M$	$S$	$Z$	$M$	$B$	
	$A$	$N$	$N$	$N$	$A$	$P$	$P$	$P$	
	$Z$	$B$	$M$	$S$	$Z$	$S$	$M$	$B$	
	$PS$	$N$	$NS$	$A$	$P$	$P$	$P$	$P$	
		$B$		$Z$	$S$	$M$	$M$	$B$	
	$P$	$N$	$NS$	$A$	$P$	$P$	$P$	$P$	
	$M$	$B$		$Z$	$M$	$M$	$B$	$B$	
	$P$	$N$	$NS$	$P$	$P$	$P$	$P$	$P$	
	$B$	$M$		$S$	$M$	$M$	$B$	$B$	

To develop the Simulink model of the fuzzy logic, the Mamdani Fuzzy Rules with Seven membership function were used. The Simulink model of the fuzzy logic and other of the wind parameters which act as input parameters is presented in Figure 2.

The Simulink model of the fuzzy parameter in Figure 2 is made up of constant blocks, input ports, and output ports that represent system outputs

### Simulation

The numerical simulations are provided in this section to explain the effectiveness of the proposed optimal control, which is implemented in MATLAB/SIMULINK. The characteristics of studied wind turbine are presented below:

$R=63m$ ;  $\rho =1.225Kg.m^{-3}$ ;  $= 27.36 N. m rad /s$ ;  
 $Jr = 3.25 \times 105Kg.m^2$ ;  $Kg = 0.2 N. m rad /s$ ;  
 $Jg = 34.4Kg.m^2$ ;  $ng = 97$ ;  $Kls = 9500 N. m rad /s$ ;  $Bls = 2.691 \times 105N. m rad /s$ .

The wind speed profile used is shown in the Fig 1.

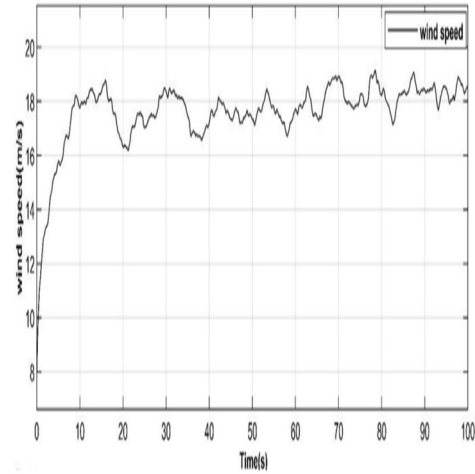
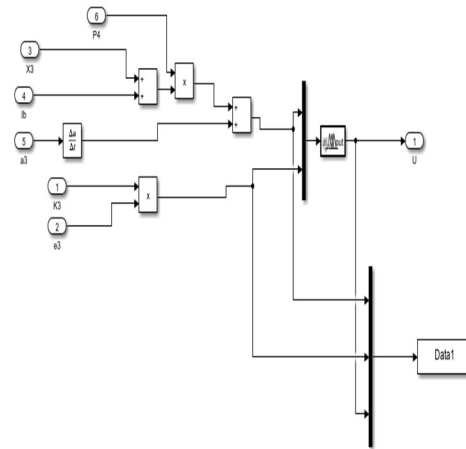


Fig.1. Wind speed profile with a mean of 18m/s.

Let  $Q = 100 * eye(3)$  and  $R = [0.001 0; 0 100]$ . In this simulation, a critic neural network has three input neurons, six hidden



neurons, and one output neuron, it is used to estimate the cost function. The activation function is selected as  $(x) = [x_1^2, x_1x_2, x_1x_3, x_2^2, x_2x_3, x_3^2]$ . The figures 2-4 show the rotor speed of wind turbine and that desired for different values of the learning parameters ( $Lc$  and  $\mu$ )

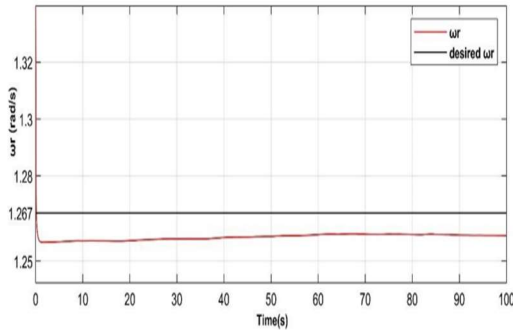


Fig. 2: Rotor speed for  $lc = 0.0001$  and  $\mu = 1$ .

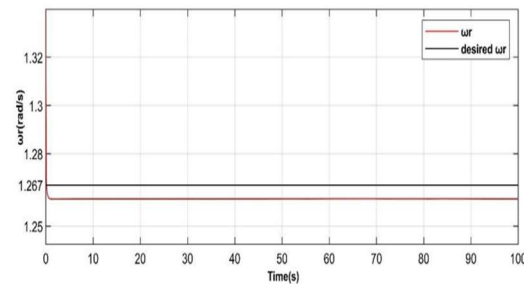


Fig. 3: Rotor speed for  $lc = 0.001$  and  $\mu = 0.1$

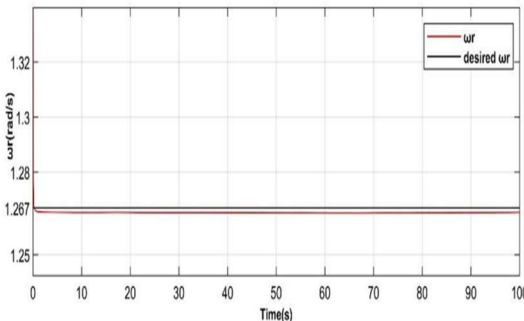


Fig. 4: Rotor speed for  $lc = 0.01$  and  $\mu = 0.5$ .

One may conclude from these plots that the proposed controller converges to the equilibrium point with an acceptable tracking error. After conducting several simulations, the optimal parameters were determined to be  $lc = 0.01$  and  $\mu = 0.5$ . Figure 3 illustrates that the rotor speed converges precisely to its desired value. This outcome serves as a validation of the

effectiveness of the proposed optimal control approach.

## CONCLUSION

This hybrid system addresses critical challenges in wind energy generation, including handling wind variability, maximizing energy efficiency, and maintaining stability. By implementing FRLC in a real-world context such as Maiduguri Metropolis, this study aims to demonstrate the feasibility of intelligent control systems for renewable energy applications in regions with limited grid infrastructure. The findings of this research are expected to contribute to the growing body of knowledge on sustainable energy solutions, offering insights for broader applications of FRLC in renewable energy. The proposed method is evaluated based on the simulation results.

## Acknowledgment

I would like to extend my gratitude my supervisors, Dr. Aliyu Sabo and Dr. Alabi, for their invaluable guidance, encouragement, and support throughout this research project. We also acknowledge the contributions of all co-authors and colleagues who provided insights and constructive feedback, which were instrumental in shaping this study.

## REFERENCES

- [1] J. Smith and K. Wong, "Fuzzy logic control for wind turbine power maximization," *Renewable Energy Journal*, vol. 45, pp. 123-130, 2021.
- [2] L. Sun and X. Zhao, "Adaptive fuzzy control of wind energy systems," *Energy Reports*, vol. 5, pp. 88-96, 2020.
- [3] C. Brown et al., "Fuzzy logic applications in wind turbine design," *IEEE Trans. Sustain. Energy*, vol. 3, no. 2, pp. 105-115, 2019.
- [4] M. Lee, "Multi-objective fuzzy control for wind turbines," *Int. J. Renew. Energy Dev.*, vol. 7, no. 2, pp. 45-53, 2018.

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- [5] S. Gupta, "Comparative study of fuzzy logic and PID control for wind energy applications," *Renew. Energy Rev.*, vol. 2, pp. 58-65, 2019.
- [6] A. Brown and L. Zhang, "Reinforcement learning in wind turbine optimization," *Energy Procedia*, vol. 60, pp. 87-95, 2022.
- [7] D. Miller and F. Cao, "Applying reinforcement learning to wind energy systems," *Energy Procedia*, vol. 62, pp. 330-340, 2020.
- [8] R. Patel, "Q-learning in renewable energy control systems," *IEEE Trans. Energy Convers.*, vol. 4, pp. 51-59, 2021.
- [9] Y. Tang, "Deep reinforcement learning for wind turbine optimization," *Wind Energy*, vol. 24, pp. 107-117, 2022.
- [10] P. Wang et al., "Multi-agent reinforcement learning in distributed energy systems," *Renew. Energy*, vol. 34, pp. 220-230, 2019.
- [11] T. Martinez and B. Wilson, "Fuzzy reinforcement learning control for renewable energy," *Int. J. Fuzzy Syst.*, vol. 21, no. 4, pp. 267-278, 2020.
- [12] H. Chen, "Hybrid fuzzy and reinforcement learning for wind turbines," *Sustain. Energy Technol.*, vol. 30, pp. 111-120, 2020.
- [13] G. Xu and S. Li, "Optimization of wind turbine systems using fuzzy reinforcement learning," *Renewable Energy*, vol. 66, pp. 181-191, 2021.
- [14] L. Zhao, "Application of fuzzy reinforcement learning for renewable energy systems," *IEEE Trans. Sustain. Energy*, vol. 9, pp. 211-219, 2021.
- [15] P. Kumar and R. Patel, "Fuzzy reinforcement learning-based control for non-linear systems," *IEEE Trans. on Control Systems Technology*, vol. 54, no. 3, pp. 1254-1261, 2020.
- [16] M. Lee et al., "Dynamic modeling of wind turbine systems: A review," *Journal of Energy Research*, vol. 72, no. 5, pp. 1050-1062, 2023.
- [17] T. Adeniyi, "Case study on reinforcement learning control in renewable energy systems," *Int. J. Renew. Energy Res.*, vol. 15, no. 4, pp. 820-828, 2022.
- [18] R. Zhuang and K. Shen, "Wind turbine dynamics modeling and control," *Wind Engineering*, vol. 48, pp. 355-368, 2018.

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