ISSN: 0974-5823 Vol. 7 No. 5 May, 2022

International Journal of Mechanical Engineering

AN ARTIFICIAL INTELLIGENT USED IN HYBRID PV OR DFIG BASED GRID CONNECTED SYSTEM

Rahul Mishra[1] , Dr. Rakesh Bhandari[2] , Dr. S. P Pandey[3]

Research Scholar, Mechanical Engineering Department, Sangam University, Bhilwara , Rajasthan,

Associate Professor, Mechanical Engineering Department, Sangam University, Bhilwara , Rajasthan,

Vice Chancellor, IIMT University, Meerut, Uttar Pradesh & AICTE Margdarshak

Abstract- A hybrid sun PV device and wind power device can enhance the reliability of power deliver. In case of deficiency of energy all through quick intervals, resulting from the failure of each sun irradiation and wind, a battery backup is blanketed withinside the energy device. Such a provision facilitates to render the uninterrupted energy deliver to the crucial loads. Energy control may be very critical in a hybrid device. The device includes reassets whose availability is unpredictable.

Keyword- Artıfıcıal Intellıgent, Hybrıd Ststem , Energy Disrtibution Or Connection System

Introduction

The MPPT set of rules serves an important important characteristic in renewable power structures for generating most energy below fluctuating climate circumstances [4][5]. The sun photovoltaic device creates power with relation to amount of irradiance absorbed with the aid of using the PV modules.

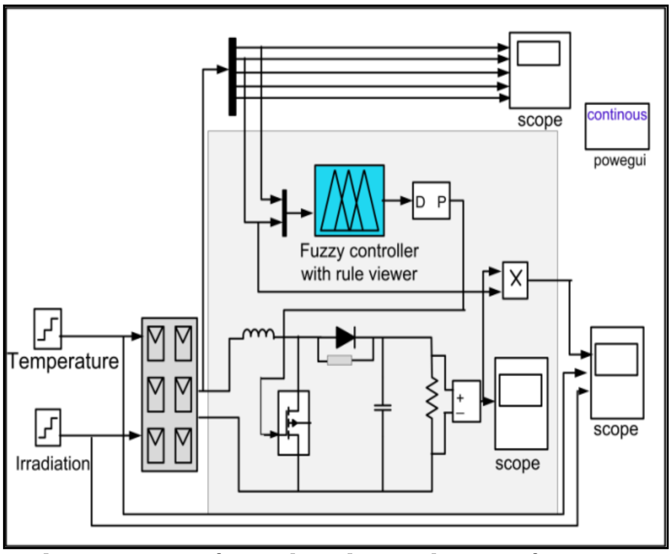


Figure 1: Simulation version for 10 kW device the use of FL MPPT controller

There will now no longer be sufficient strength generated with the aid of using the PV modules because of sun radiation's nonlinearity. MPPT set of rules primarily based totally at the fuzzy logic (FL) controller has been evolved withinside the thesis. Figure 1 indicates the MATLAB code for the improve converter-primarily based totally PV MPPT device.

Methodology

Design of Fuzzy Logic Controller for PV MPPT

Two inputs and one output are supplied through the bushy good judgment controller model. In Figure 2, the obligation cycle of the PV raise converter is displayed as an enter characteristic, even as PV voltage and contemporary are proven as output functions. This characteristic classifies the voltage inputs of fuzzy PVs as LV, MV or HV primarily based totally at the degrees of the enter voltages (HV). Low-contemporary (LI), medium-contemporary (MI), and high-contemporary (HI) are all classifications for the bushy PV contemporary enter club characteristic (HI). LD, MD, and HD are the 3 fuzzy obligation cycle output degrees that make up the club characteristic of the bushy obligation cycle output club characteristic (HD). The fuzzy club characteristic layout is primarily based totally on trapezoidal approach for fuzzification technique as proven in Figure 4.three and makes use of centroid approach for defuzzification technique. The fuzzy policies are fashioned primarily based totally on enter statistics evaluation and obligation cycle at diverse conditions. It is represented withinside the Table 4.1[14].

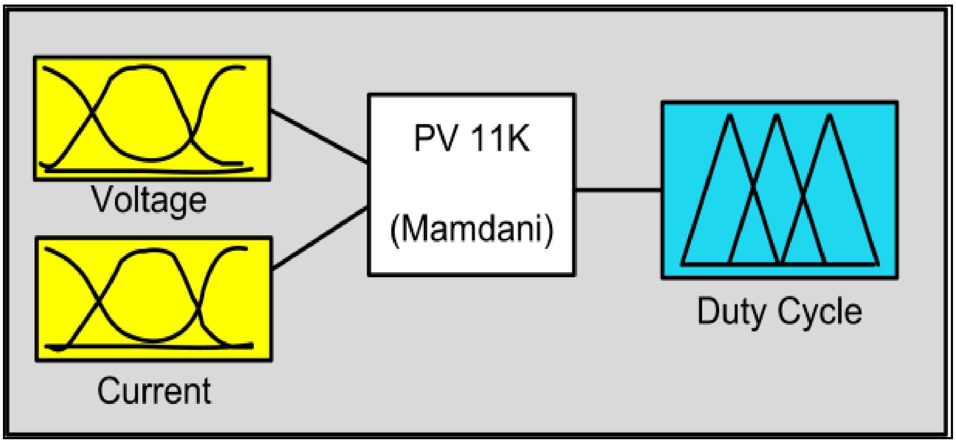


Figure 2: Fuzzy controller structure for MPPT controller

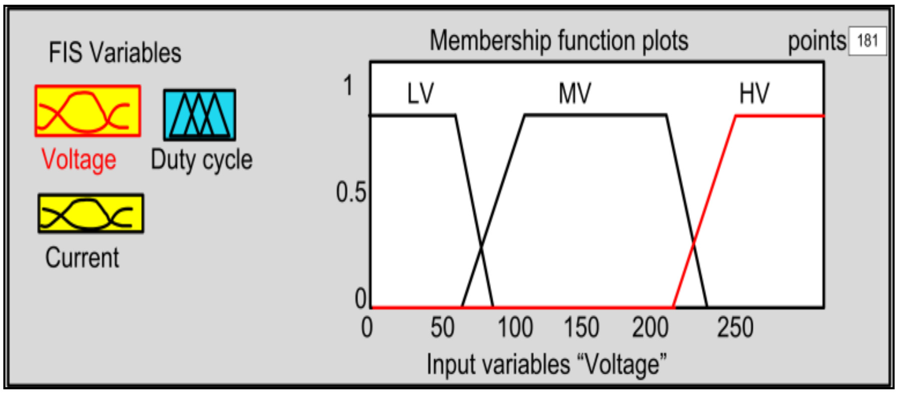


Figure 3a: Input Fuzzy membership functions for PV MPPT FL

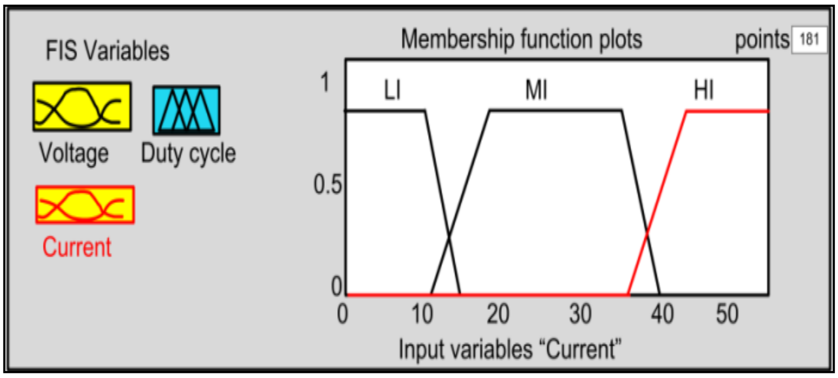


Figure 3b: Input Fuzzy membership functions for PV MPPT FL

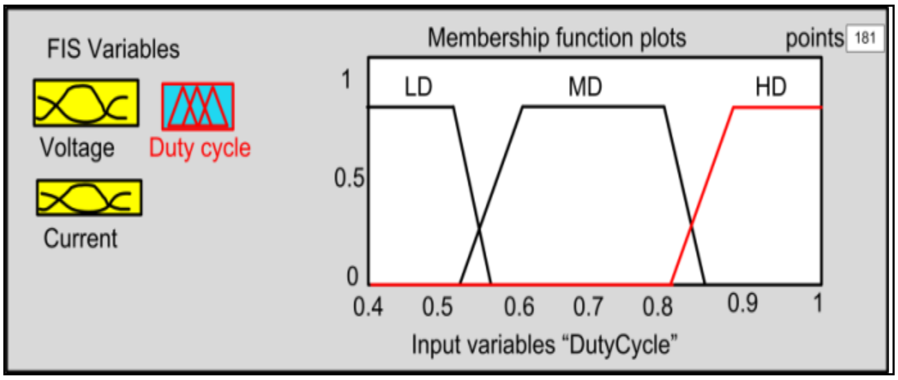


Figure 3c: Output Fuzzy membership functions for PV MPPT FL

The proposed fuzzy control-primarily based totally PV MPPT controller is simulated at variable irradiance and temperature. In the simulation, the irradiance values implemented at diverse time durations are 250W/m2, 500 W/m2, 750W/m2, 900W/m2 and a thousand W/m2. Also, the temperature values implemented at diverse time durations are 250C, 260C, 280C, 290C and 250C. The above climatic situations are implemented in proposed simulation version and the ensuing PV output energy waveform offered in Figure 4. The PV increase converter voltage and contemporary waveforms are proven in Figure 5. The above effects acquired in Figure 6 suggest that because the sun irradiance will increase the PV output energy will increase while boom in temperature reasons lower withinside the PV output energy as proven in Figure 4c. Hence at irradiance of a thousand W/m2and temperature of 250 C, the PV device is producing 10 kW of output energy.

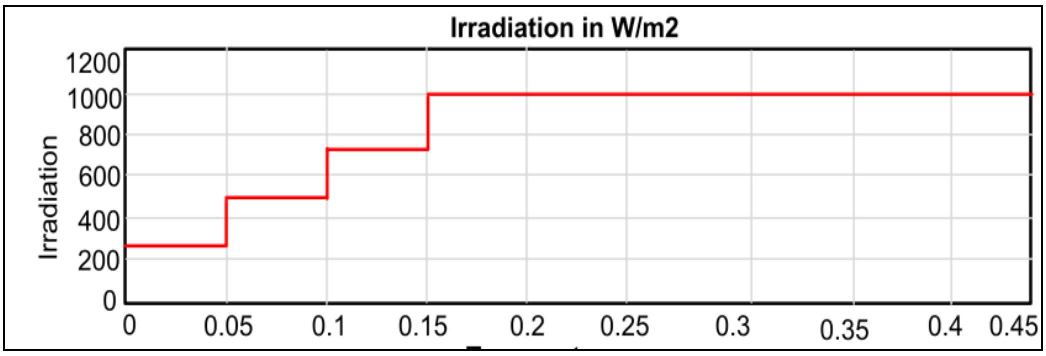


Figure 4a: PV irradiance variation with time

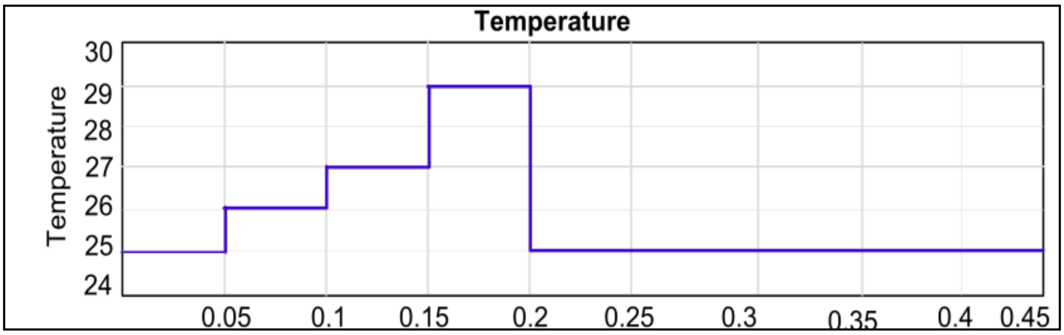


Figure 4b: PV temperature variation with time

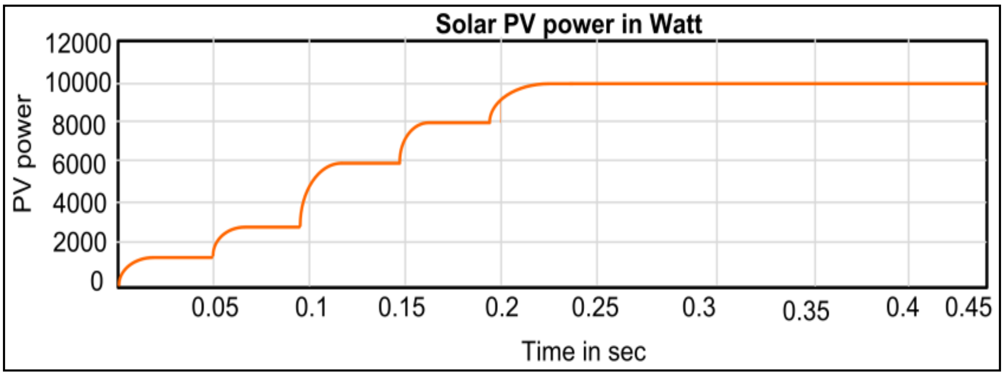


Figure 4c: PV power variation for variable irradiance and temperature

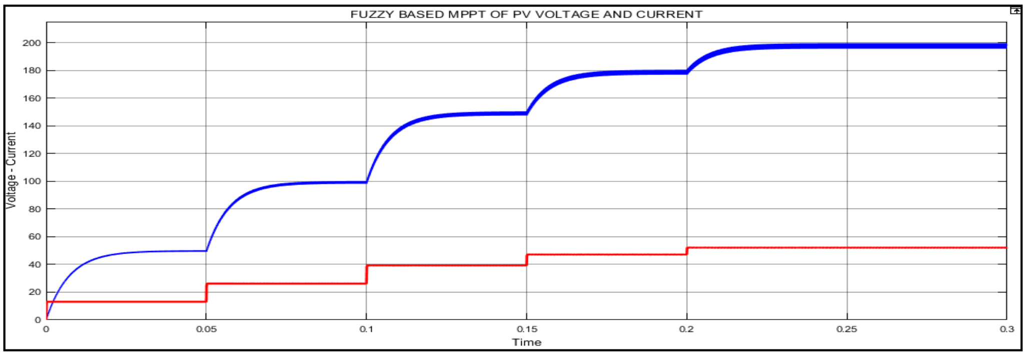


Figure 5: PV voltage and current of Fuzzy based MPPT

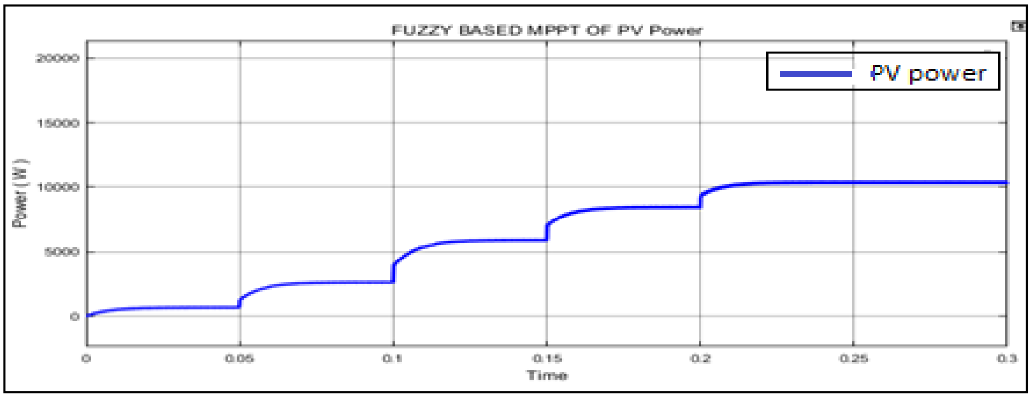
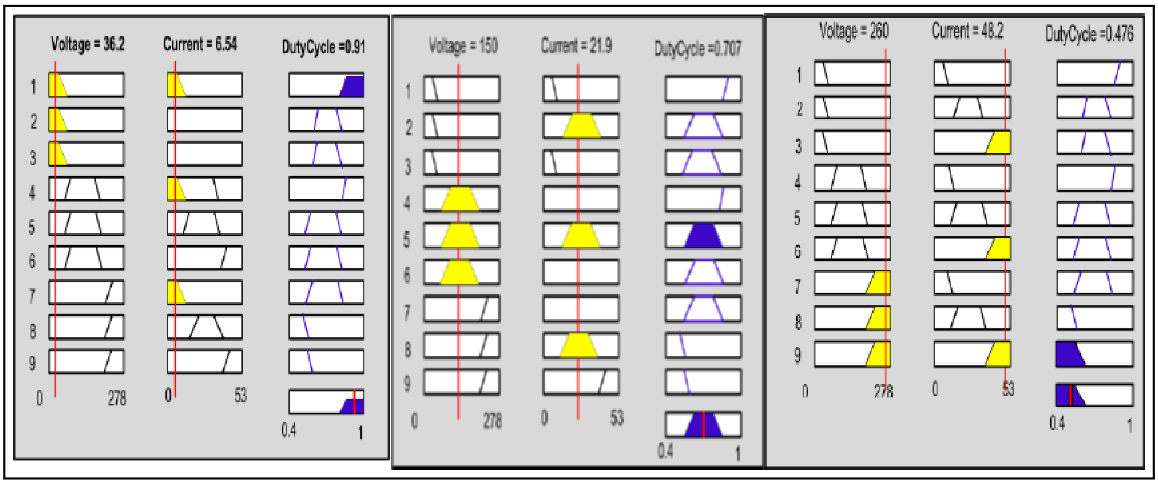


Figure 6: PV power generated using Fuzzy based MPPT

The total simulation results for the 10 kW solar PV systems may be shown in Figure 7. The PV system is connected to a typical DC/DC converter. In this study, two forms of maximum power point tracking (MPPT) approaches are used. Fuzzy MPPT strategies are compared to the incremental conductance method. In terms of the algorithm, the power curve has a slope of 0 at its greatest power point. That piece of peak grows and that section lowers at the same time. Instantaneous conductance and incremental conductance are used as a basis for tracking. When the maximum power point is reached, the reference voltage is equal to the peak voltage. Then PV array is made to operate at this point unless a change in current is noted due to some external changes. The reference voltage is increased or decreased in order to track the new MPP. With large increase in step faster tracking can be achieved but system may deviate from peak and oscillate around it. With this MPPT technique, the output power generated from PV system is 9662 W.

Another method used in this analysis is Fuzzy logic based MPPT technique where in PV voltage and PV current is used as two input variable and duty cycle is taken as output variable as shown in Figure 2 and 3. Three membership functions are used for PV voltage which is trapezoidal in shape. Similarly, PV current and duty cycle are represented using three membership functions. The fuzzy rule based is obtained for the fuzzy controller as shown in Table 1.

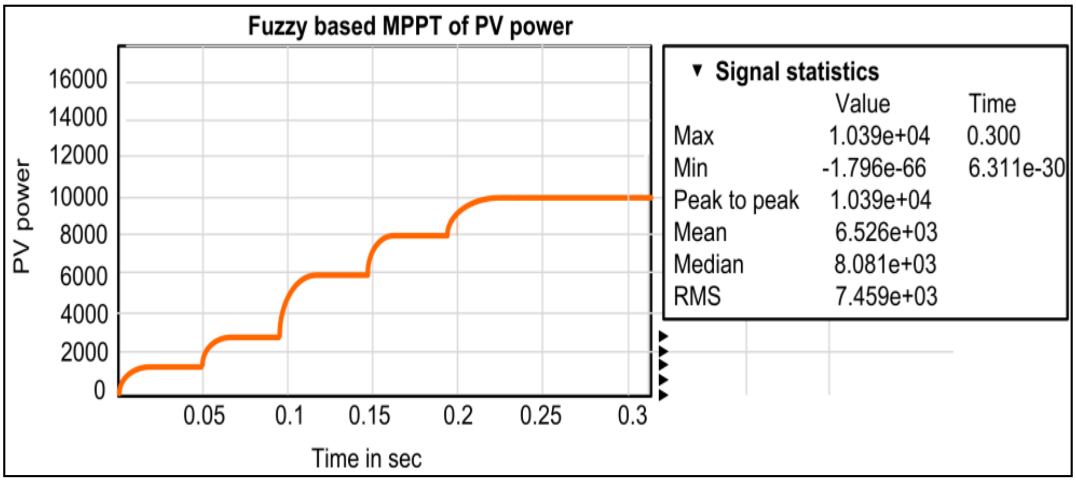


(a) (b) (c)

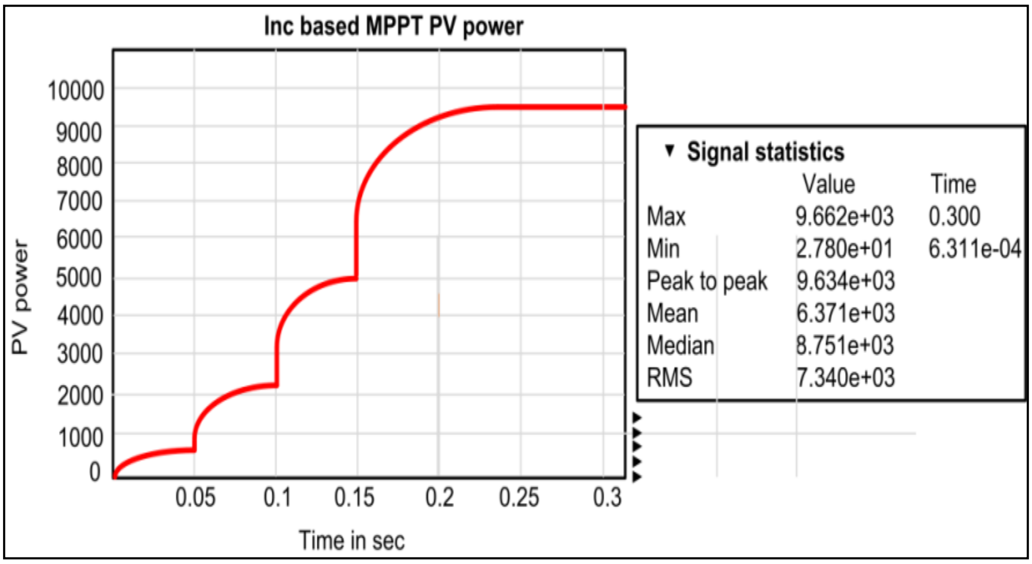
Figure 8 Fuzzy rules-based system for MPPT controller with a) low voltage, b) medium voltage and c) high voltage membership function

Result

Figure 8 is the pictorial representation of the intermediate result obtained during the simulation of the PV system. It is seen in figure 8a that at low voltage and low current, it gives high duty cycle as mentioned in the fuzzy rule base (first row and first column). Similarly Figure 8b at medium current and voltage, the duty cycle is set to medium (second row and second column of rule base). Similarly, when voltage and current both at high value, duty cycle is set to low (third row and third column of the rule base). The results obtained are shown in Figure 9. The output of fuzzy controller based MPPT is compared with that of the incremental conductance (IC) algorithm and tabulated in Table 2. It shows that maximum power can be extracted using fuzzy based MPPT controller compared to IC algorithm.



(a)



(b)

Figure 9: Power output from a) Fuzzy based MPPT controller and b) Incremental conductance based MPPT

Table 2: Comparison of output power between IC MPPT and FLC MPPT

Irradiance	Incremental Conductance	Fuzzy Logic
1000 W/m2	9662 W	10039 W

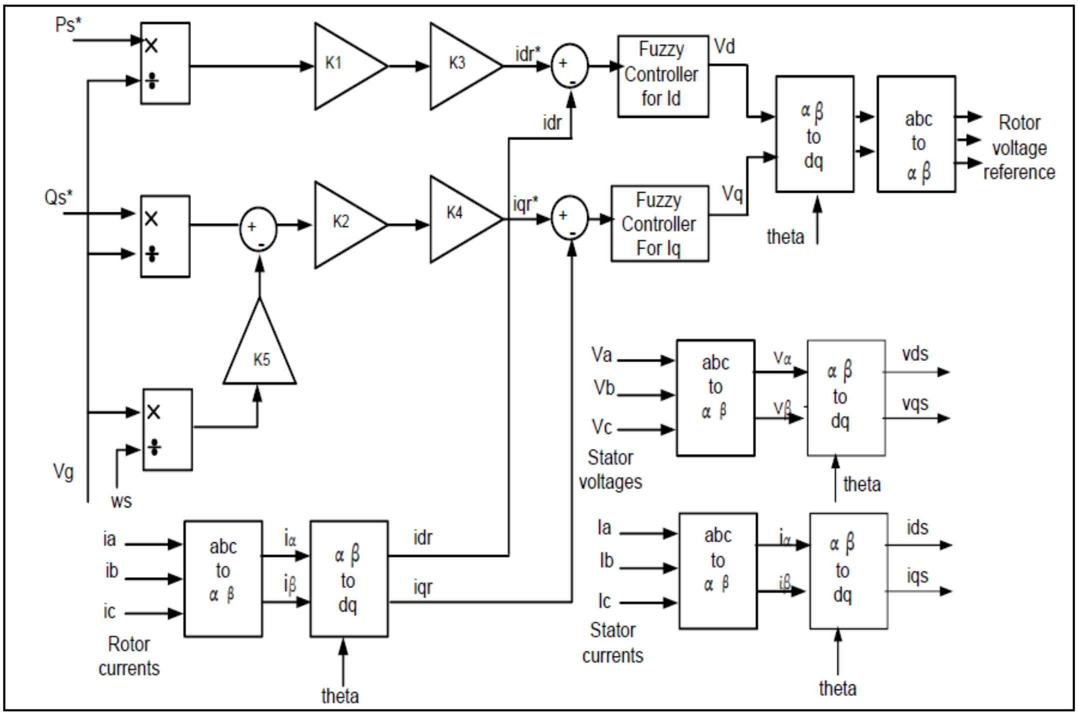


Figure 10: Calculation of the current references required for rotor converter

Table 3: DFIG based wind system description

Parameter	**Description**	**Parameter**	**Description**
Power output	10 kW	Stator Inductance	0.04 H
Frequency	50 Hz	Rotor resistance	10.7 Ω
Stator resistance	9.7 Ω	Rotor inductance	0.09 H
Stator current	20 A	Stator Voltage	1500 V
Rotor current	25 A	Rotor voltage	70 V

The specification of DFIG is presented as represented in Table 3. The FL controller has been developed for DFIG rotor current controller for improving the system power quality and is presented in Figure 11. The DFIG rotor currents are classified into two types namely direct axis current $I_d$and quadrature axis current I_q. Therefore, two separate fuzzy controllers are designed for I_d and I_q . They are represented in Figure 12 and Figure 13 respectively. The fuzzy input and output membership functions are developed by using trapezoidal function, and then the centroid method is used for defuzzification [18] [17]. The fuzzy controller developed for direct axis current regulation has one input and one output membership functions. Also, the fuzzy controller is developed for quadrature axis current regulation. It has one input and one output membership functions wherein quadrature axis current is taken as an input membership function and regulated quadrature axis current is taken as an output membership function [20][22].

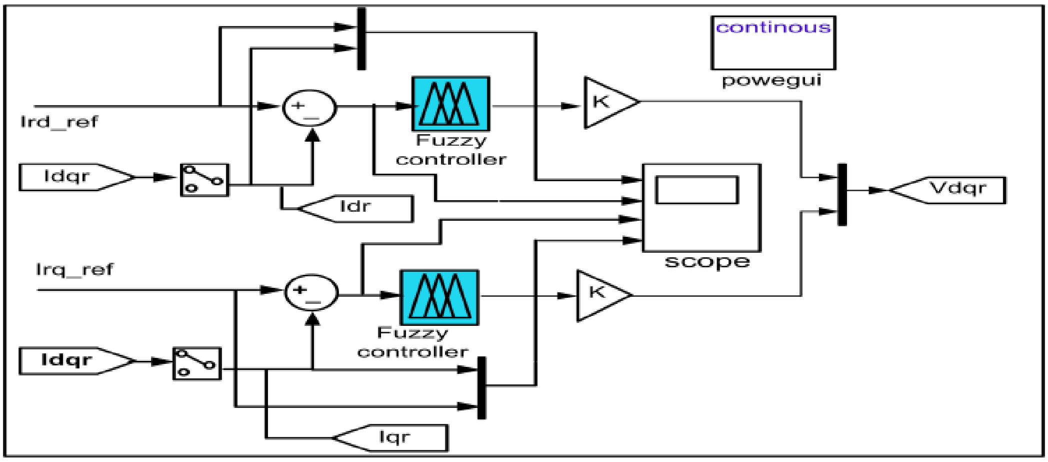


Figure 11: Fuzzy based Rotor Current controller

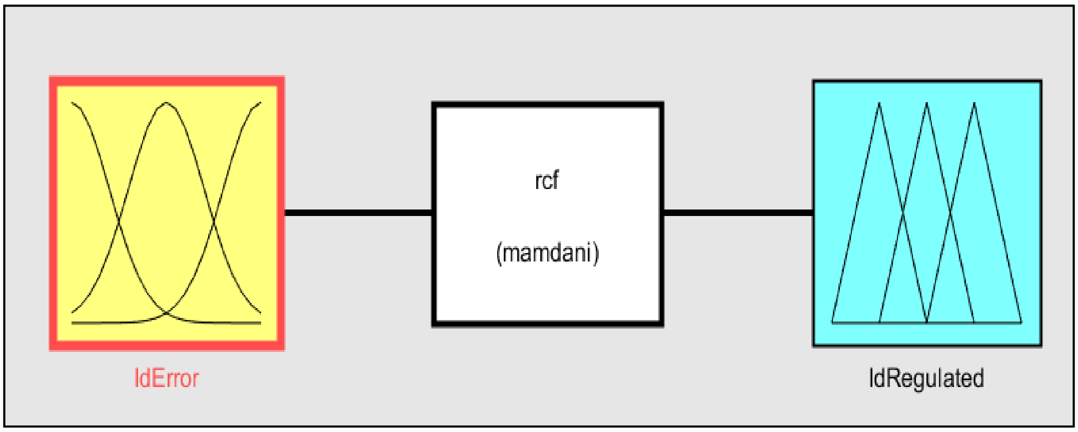


Figure 12: Design of Fuzzy Controller for I_d regulator

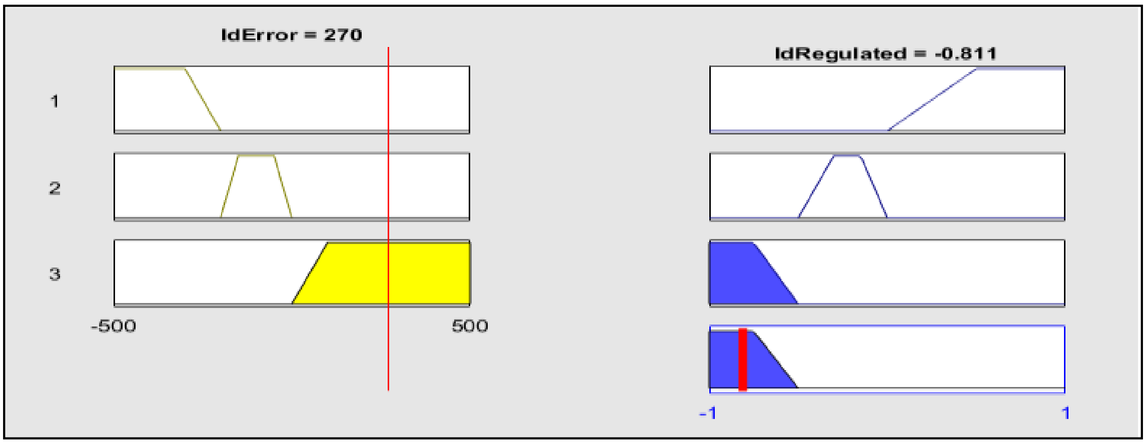


Figure 13: Fuzzy membership functions for DFIG controller

Conclusion

The PV system model is developed for 10 kW power generation and then the output generated is supplied to the grid. Two fuzzy controllers were used for the overall controlling and synchronization of the system with the grid. Fuzzy controllers are more flexible than PI controllers because of they have more parameters to obtain better control. These parameters are nothing but the types and membership functions parameters used in the fuzzification and defuzzification modules. A larger variety of working situations is covered, as well as greater natural language customization. To summarise, although Fuzzy controllers are simple to construct, they are difficult to fine tune. Fuzzy controllers are easy to understand in case of small number of linguistic variables because of their rule-bases. These controllers are completely dependent on human knowledge and expertise. Its effectiveness depends on type of kind of membership functions taken in the design, how set-up their parameter range etc.

Refrences

1. Dash, P.; Mishra, S.; Salama, M.; Liew, A. Classification of power system disturbances using a fuzzy expert system and a Fourier linear combiner. IEEE Trans. Power Deliv. 2000, 15, 472–477.
2. Bouali, C.; Schulte, H.; Mami, A. A High Performance Optimizing Method for Modeling Photovoltaic Cells and Modules Array Based on Discrete Symbiosis Organism Search. Energies 2019, 12, 2246.
3. Da Costa, L.C.; Thome, F.S.; Garcia, J.D.; Pereira, M.V.F. Reliability-Constrained Power System Expansion Planning: A Stochastic Risk-Averse Optimization Approach. IEEE Trans. Power Syst. 2021, 36, 97–106.
4. Elkholy, A.; El Ela, A.A. Optimal parameters estimation and modelling of photovoltaic modules using analytical method. Heliyon 2019, 5, e02137.
5. Haque, A.; Bharath, K.V.S.; Khan, M.A.; Khan, I.; Jaffery, Z.A. Fault diagnosis of Photovoltaic Modules. Energy Sci. Eng. 2019, 7, 622–644.
6. Khan, M.A.; Haque, A.; Kurukuru, V.B. Performance assessment of stand-alone transformerless inverters. Int. Trans. Electr. Energy Syst. 2020, 30, e12156.
7. Kumar, N.; Singh, B.; Panigrahi, B.K. Framework of Gradient Descent Least Squares Regression-Based NN Structure for Power Quality Improvement in PV-Integrated Low-Voltage Weak Grid System. IEEE Trans. Ind. Electron. 2019, 66, 9724–9733.
8. Kumar, R.; Singh, S.; Rodrigues, E.M.G. Solar photovoltaic modeling and simulation: As a renewable energy solution. Energy Rep.2018, 4, 701–712.
9. Kurukuru, V.S.B.; Blaabjerg, F.; Khan, M.A.; Haque, A. A Novel Fault Classification Approach for Photovoltaic Systems. Energies, 2020, 13, 308.
10. Li, F.; Huang, Y.;Wu, F.; Liu, Y.; Zhang, X. Research on clustering equivalent modeling of large-scale photovoltaic power plants. Chin. J. Electr. Eng. 2018, 4, 80–85.
11. Liu, C.-H.; Gu, J.-C.; Yang, M.-T. A Simplified LSTM Neural Networks for One Day-Ahead Solar Power Forecasting. IEEE Access 2021, 9, 17174–17195.
12. Liu, Y.; Zhang, N.;Wang, Y.; Yang, J.; Kang, C. Data-Driven Power Flow Linearization: A Regression Approach. IEEE Trans. Smart Grid 2019, 10, 2569–2580.
13. Ma, T.; Yang, H.; Lu, L. Solar photovoltaic system modeling and performance prediction. Renew. Sustain. Energy Rev. 2014, 36, 304–315.
14. Molzahn, D.K.; Dörfler, F.; Sandberg, H.; Low, S.H.; Chakrabarti, S.; Baldick, R.; Lavaei, J. A Survey of Distributed Optimization and Control Algorithms for Electric Power Systems. IEEE Trans. Smart Grid 2017, 8, 2941–2962.
15. Ongsakul,W.; Dieu, V.N. Artificial Intelligence in Power System Optimization; Informa UK Limited: London, UK, 2016.
16. Park, J.; Law, K.H. Bayesian Ascent: A Data-Driven Optimization Scheme for Real-Time Control with Application to Wind Farm Power Maximization. IEEE Trans. Control. Syst. Technol. 2016, 24, 1655–1668.
17. Radil, T.; Ramos, P.; Janeiro, F.; Serra, A. PQ Monitoring System for Real-Time Detection and Classification of Disturbances in a
18. Rodrigues, E.M.G.; Godina, R.; Marzband, M.; Pouresmaeil, E. Simulation and Comparison of Mathematical Models of PV Cells with Growing Levels of Complexity. Energies 2018, 11, 2902.
19. Saez-de-Ibarra, A.; Milo, A.; Gaztanaga, H.; Debusschere, V.; Bacha, S. Co-Optimization of Storage System Sizing and Control
20. Sahoo, S.; Dragicevic, T.; Blaabjerg, F. Cyber Security in Control of Grid-Tied Power Electronic Converters–Challenges and Vulnerabilities. IEEE J. Emerg. Sel. Top. Power Electron. 2020, 1, 1–15.

21. Sanchez-Garcia, R.; Fennelly, M.; Norris, S.; Wright, N.; Niblo, G.; Brodzki, J.; Bialek, J.W. Hierarchical Spectral Clustering of Power Grids. IEEE Trans. Power Syst. 2014, 29, 2229–2237.
22. Semero, Y.K.; Zhang, J.; Zheng, D. North China Electric Power University PV power forecasting using an integrated GA-PSOANFIS approach and Gaussian process regression based feature selection strategy. CSEE J. Power Energy Syst. 2018, 4, 210–218.
23. Single-Phase Power System. IEEE Trans. Instrum. Meas. 2008, 57, 1725–1733.
24. Strategy for Intelligent Photovoltaic Power Plants Market Integration. IEEE Trans. Sustain. Energy 2016, 7, 1749–1761.
25. Styvaktakis, E.; Bollen, M.; Gu, I.Y. Expert system for classification and analysis of power system events. IEEE Trans. Power Deliv. 2002, 17, 423–428.
26. Verastegui, F.; Lorca, A.; Olivares, D.E.; Negrete-Pincetic, M.; Gazmuri, P. An Adaptive Robust Optimization Model for Power Systems Planning with Operational Uncertainty. IEEE Trans. Power Syst. 2019, 34, 4606–4616.
27. Wang, Z.; Chen, Y.; Liu, F.; Xia, Y.; Zhang, X. Power System Security Under False Data Injection Attacks With Exploitation and Exploration Based on Reinforcement Learning. IEEE Access 2018, 6, 48785–48796.
28. Xiao, R.; Xiang, Y.;Wang, L.; Xie, K. Power System Reliability Evaluation Incorporating Dynamic Thermal Rating and Network Topology Optimization. IEEE Trans. Power Syst. 2018, 33, 6000–6012.
29. Yao, C.; Chen, M.; Hong, Y.-Y. Novel Adaptive Multi-Clustering Algorithm-Based Optimal ESS Sizing in Ship Power System Considering Uncertainty. IEEE Trans. Power Syst. 2018, 33, 307–316.
30. Zernichow, B.M. Usability of Visual Data Profiling in Data Cleaning and Transformation; University of Oslo: Basel, Switzerland, 2017.
31. Zhang, R.; Hredzak, B. Distributed Dynamic Clustering Algorithm for Formation of Heterogeneous Virtual Power Plants Based on Power Requirements. IEEE Trans. Smart Grid 2021, 12, 192–204.