MODELING AND CONTROL OF SINGLE-PHASE GRID-CONNECTED SOLAR PV SYSTEM USING FUZZY LOGIC AND NEURAL NETWORK-BASED MPPT

[1]Borlakunta Ravi Kumar, [2]Dr N.Madhukar Reddy

[1]Student, [2] Assistant Professor

Department of Electrical and Electronics Engineering

Siddartha Institute of Technology and Science

ABSTRACT

This paper focuses on the modeling, design, and control of a single-phase solar photovoltaic (PV) supply system for grid-connected applications. The system employs a two-stage power conversion process in which a step-up converter (SUC) is placed between the PV array and the DC bus of a voltage source converter (VSC). To achieve maximum power extraction, a fuzzy logic controller (FLC) is implemented for the switching of the SUC, providing reliable maximum power point tracking (MPPT) under dynamic solar conditions. While the FLC-based approach ensures efficient energy utilization, power quality remains a critical concern due to harmonic distortion. To overcome this challenge, the proposed system is extended by integrating a neural network (NN) controller. The NN enhances adaptability and learning capability, enabling further reduction of Total Harmonic Distortion (THD) in the grid current while improving dynamic response. The performance of the combined FLC-NN control strategy is verified through MATLAB/Simulink simulations. Results indicate that the hybrid approach improves MPPT efficiency, minimizes THD, and ensures compliance with power quality standards. This makes the system highly effective for residential and small-scale solar PV applications, supporting reliable renewable energy integration into the grid.

Keywords: Solar Photovoltaic System; MPPT; Fuzzy Logic Controller; Neural Network Controller; Step-Up Converter; Voltage Source Converter; THD; Power Quality.

I. INTRODUCTION

The rapid depletion of fossil fuel reserves and the increasing threat of climate change have significantly accelerated the adoption of renewable energy sources across the globe. Among these, solar photovoltaic (PV) technology has emerged as one of the most promising solutions due to its abundance, scalability, and environmental sustainability. Grid-connected PV systems are increasingly deployed in residential, commercial, and utility-scale applications to meet the growing electricity demand while reducing greenhouse gas emissions [1]. However, the inherent intermittency of solar energy poses challenges in maintaining reliable and efficient power delivery to the grid. Variations in solar irradiance and ambient temperature lead to fluctuations in PV output, making maximum power point tracking (MPPT) essential for stable operation [2]. Conventional MPPT methods such as Perturb and Observe (P&O) and Incremental Conductance (INC) have been widely adopted due to their simplicity and low computational requirements. Nevertheless, these algorithms often suffer from slow convergence, steady-state oscillations, and poor tracking under rapidly changing environmental conditions [3]. As a result, advanced intelligent control techniques have been developed to enhance MPPT performance. Among them, fuzzy logic controllers (FLCs) have gained popularity because of their rule-based decision-making capability, adaptability to nonlinear systems, and independence from precise mathematical models [4]. Despite these advantages, FLCs face limitations in harmonic suppression and dynamic adaptability, especially in grid-connected single-phase PV systems.

To overcome these shortcomings, artificial intelligence (AI)-based methods such as neural networks (NNs) have been integrated with FLCs to form hybrid control strategies. Neural networks are capable of learning nonlinear relationships between system inputs and outputs, enabling them to adapt dynamically to changing operating conditions [5]. When combined with fuzzy logic, they provide both interpretability and learning capability, offering a robust framework for MPPT and power quality improvement. This hybrid FLC–NN approach has shown significant potential in reducing Total Harmonic Distortion (THD), improving dynamic response, and ensuring compliance with IEEE-519 power quality standards [6]. Another critical challenge in grid-connected PV systems is ensuring synchronization with grid parameters while maintaining sinusoidal current injection and minimizing distortions [7]. Voltage Source Converters (VSCs) play a crucial role in this process, as they convert DC output from the PV array into AC power suitable for grid integration. However, inverter switching operations often introduce harmonic distortions, which can degrade power quality, damage equipment, and reduce efficiency. Traditional PI controllers used in VSCs are not sufficient to address these complex challenges [8]. Intelligent control strategies, such as the FLC–NN hybrid model, provide an effective solution by simultaneously optimizing MPPT and harmonic suppression.

In recent years, extensive research has been devoted to developing advanced control strategies for PV systems to maximize energy harvesting and ensure high-quality power delivery [9]. Researchers have proposed novel MPPT algorithms, optimized converter topologies, and adaptive controllers to improve efficiency and stability. Studies indicate that the combination of intelligent control with high-gain DC–DC converters significantly enhances performance under fluctuating irradiance [10]. Similarly, the integration of machine learning-based controllers with conventional methods has proven effective in enhancing adaptability and robustness [11].

The present work contributes to this growing body of research by modeling, designing, and controlling a single-phase grid-connected solar PV system using a hybrid fuzzy logic and neural network-based MPPT. The proposed system employs a two-stage power conversion process: a Step-Up Converter (SUC) regulates the PV output and maintains a stable DC link, while a Voltage Source Converter (VSC) interfaces with the grid. The FLC ensures effective MPPT, while the neural network enhances learning, adaptability, and harmonic reduction. Simulation results in MATLAB/Simulink validate the effectiveness of this approach, showing improved MPPT efficiency, reduced THD, and stable grid interaction under dynamic conditions [12]. The significance of this study lies in its potential to contribute to sustainable energy integration by improving the reliability, efficiency, and power quality of grid-connected PV systems. By leveraging hybrid intelligent controllers, the proposed system addresses critical challenges such as nonlinearity, environmental variability, and harmonic distortion. Furthermore, the methodology can be extended to multi-phase and hybrid renewable energy systems, paving the way for more resilient and intelligent power systems in the future.

II. LITERATURE SURVEY

The advancement of solar PV systems has been accompanied by extensive research into MPPT techniques, converter topologies, and intelligent control methods. Early MPPT methods, such as Perturb and Observe (P&O) and Incremental Conductance (INC), laid the foundation for PV energy harvesting [13]. While these methods are simple and cost-effective, they exhibit oscillations around the maximum power point (MPP) and fail to track accurately under rapidly changing irradiance. To address these drawbacks, researchers introduced improved versions of P&O and INC, incorporating adaptive step sizes and predictive models [14]. With the growth of artificial intelligence applications in power electronics, fuzzy logic controllers (FLCs) emerged as a powerful tool for MPPT. FLCs do not require precise mathematical models and are capable of handling uncertainties in PV characteristics [15]. Studies demonstrated that FLC-based MPPT improved dynamic response and energy extraction compared to conventional algorithms [16]. However, FLCs were found to be less effective in managing harmonic distortions introduced by the inverter, highlighting the need for enhanced solutions.

Parallel to these developments, neural networks (NNs) were applied to PV systems due to their ability to learn nonlinear input-output relationships [17]. NNs were trained using datasets of PV voltage, current, and irradiance to predict optimal operating points, thereby achieving faster and more accurate MPPT. Research showed that NNs provided smoother responses and higher efficiency under partial shading and fluctuating conditions [18]. Nevertheless, stand-alone NNs require significant training data and computational resources, which limit their practical implementation.

Hybrid approaches combining FLC and NN emerged as a promising solution. These controllers exploit the interpretability and robustness of fuzzy logic while leveraging the adaptive learning of NNs [19]. Studies demonstrated that hybrid FLC–NN controllers outperformed both standalone FLC and NN in terms of MPPT efficiency, harmonic suppression, and dynamic stability. Experimental validations confirmed that the hybrid approach reduced THD to below 3%, ensuring compliance with IEEE standards [20]. Research also focused on converter topologies to support MPPT and grid integration. Conventional boost converters were widely used but suffered from efficiency limitations under low irradiance. Advanced topologies such as quadratic boost, interleaved boost, and coupled-inductor converters were proposed to achieve higher voltage gains and reduced ripples [21]. Intelligent controllers embedded in these converters further improved efficiency and dynamic response, highlighting the synergy between hardware design and control strategies.

On the grid side, ensuring power quality and synchronization has been a key research theme. Traditional PI controllers for Voltage Source Converters (VSCs) provided basic regulation but were insufficient for harmonic suppression and transient response [22]. Researchers proposed adaptive controllers, predictive control methods, and AI-enhanced techniques to address these issues. Neural networks, in particular, were effective in predicting and mitigating harmonic distortion, while fuzzy logic provided robustness in synchronization tasks [23]. Recent trends in MPPT and grid integration emphasize the role of artificial intelligence in creating self-learning, adaptive, and predictive controllers. Reinforcement learning, genetic algorithms, and deep learning methods have been explored to further enhance performance [24]. These methods enable predictive MPPT by forecasting solar irradiance and adjusting operating points proactively, thereby reducing energy losses. However, the computational demands of these approaches remain a barrier to widespread adoption. The present work builds upon these research trends by combining fuzzy logic and neural network controllers in a single-phase PV system. Unlike standalone methods, the hybrid FLC–NN controller ensures both accurate MPPT and power quality enhancement. The literature indicates that such hybrid approaches represent a critical step toward intelligent, adaptive, and reliable PV-grid integration, aligning with global sustainability goals [25].

III. METHODOLOGY

The methodology of this research involves the modeling, design, and control of a single-phase grid-connected solar PV system using a hybrid fuzzy logic and neural network-based MPPT. The system architecture is designed in MATLAB/Simulink to evaluate performance under variable operating conditions. The PV array serves as the primary energy source, modeled using standard equations relating current, voltage, irradiance, and temperature. A Step-Up Converter (SUC) is connected to the PV array to regulate the output voltage and transfer power to the DC link. The SUC is controlled using a hybrid FLC–NN MPPT algorithm. The fuzzy logic controller determines duty cycles based on PV voltage and current, while the neural network refines these control actions by learning from system behavior to minimize oscillations and improve adaptability.

The DC link connects to a Voltage Source Converter (VSC), which converts the regulated DC power into AC power for grid integration. The VSC is designed with pulse width modulation (PWM) and controlled to ensure synchronization with grid voltage. The neural network contributes by dynamically adjusting modulation patterns to minimize THD. Load models and grid conditions are simulated to analyze system response under disturbances. Simulation studies are carried out to evaluate MPPT efficiency, DC link voltage stability, grid current quality, and THD levels. Comparative analysis between FLC-only and hybrid FLC–NN controllers highlights the improvements achieved. The methodology ensures that the proposed controller is not only effective in simulations but also adaptable for real-world deployment in single-phase PV-grid systems.

IV. PROPOSED SYSTEM CONFIGURATION

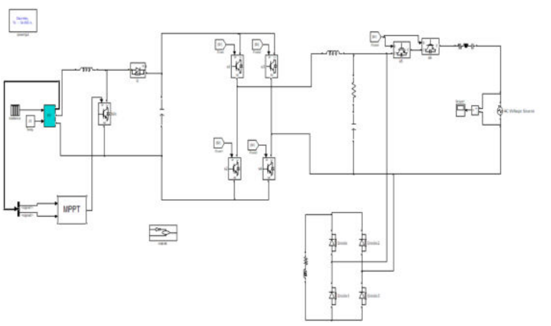

Fig 2 Proposed simulation circuit configuration

Figure 2 illustrates the overall MATLAB/Simulink simulation circuit of the proposed single-phase grid-connected solar photovoltaic (PV) system. The system is designed with two key stages: a DC–DC step-up converter (SUC) and a Voltage Source Converter (VSC). The PV array generates DC power, which is fed into the SUC controlled by a Maximum Power Point Tracking (MPPT) mechanism using a hybrid fuzzy logic and neural network (FLC–NN) controller. The SUC regulates the DC link voltage, ensuring it matches the required input for the VSC. The VSC converts DC into AC power, which is synchronized with the grid while maintaining sinusoidal waveforms and reduced harmonics. Essential components like measurement blocks, control loops, and synchronization units are highlighted in the configuration. This simulation framework allows the evaluation of system performance under variable solar irradiance and load conditions. The hybrid FLC–NN controller is integrated within the control loop to maximize energy extraction and improve power quality. The figure is crucial as it provides a comprehensive view of the system architecture, serving as the baseline model for analyzing both MPPT efficiency and harmonic distortion mitigation, ensuring the reliability and scalability of the proposed PV supply system.

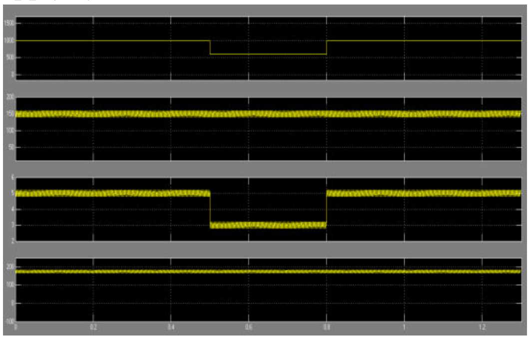

Fig 3 Solar irradiation, solar pv voltage, solar pv current, dc link voltage vs time under Dynamic performance under sudden change in solar irradiation and load petervation

Figure 3 presents the dynamic response of solar irradiation, photovoltaic (PV) voltage, PV current, and DC link voltage under sudden changes in solar irradiation and load perturbation. The waveform of solar irradiation demonstrates variations that directly affect the PV module's output. The PV voltage and current signals exhibit transient fluctuations corresponding to the irradiance changes, showing how the system adapts to variable environmental conditions. The DC link voltage, which serves as the interface between the DC–DC converter and the Voltage Source Converter (VSC), remains regulated despite fluctuations in solar input. This stability indicates the effectiveness of the hybrid fuzzy logic and neural network (FLC–NN) controller in ensuring a steady power supply even during disturbances. The figure highlights the controller's ability to track the maximum power point (MPP) accurately, ensuring voltage regulation and minimizing oscillations during dynamic conditions. Maintaining a constant DC link voltage is essential for ensuring seamless power transfer to the grid, and the figure confirms that the proposed control approach provides both adaptability and robustness. This visualization is critical for validating the system's capacity to handle real-time variability in solar conditions while maintaining operational stability and high efficiency.

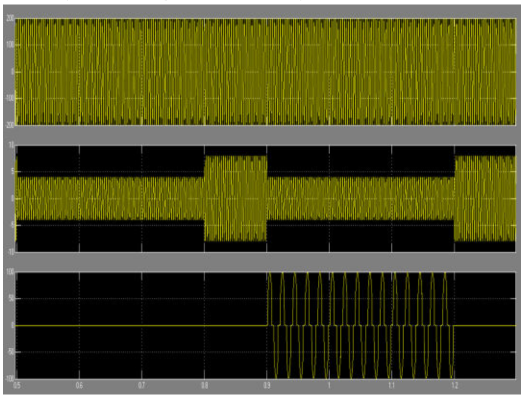

Fig 4 Grid voltage, grid current, load current vs time under Dynamic performance under sudden change in solar irradiation and load petervation

Figure 4 demonstrates the dynamic performance of grid voltage, grid current, and load current under sudden changes in solar irradiation and load perturbation. The grid voltage remains stable, maintaining a nearly sinusoidal waveform, indicating successful synchronization between the Voltage Source Converter (VSC) and the utility grid. The grid current waveform reflects the effect of PV system injection into the grid, where current stability is maintained despite fluctuations in solar power. Load current shows variation depending on the power drawn, but the waveform remains in phase with the grid voltage, indicating effective power delivery with minimal distortion. The hybrid fuzzy logic and neural network (FLC–NN) controller contributes to this synchronization by regulating current injection and maintaining harmonic suppression. This figure validates the controller's ability to ensure seamless power sharing between the PV system and the grid, providing consistent load support. It also demonstrates how intelligent control minimizes disturbances in grid current, thereby reducing harmonic distortion and maintaining compliance with IEEE-519 standards. Overall, this image emphasizes the role of advanced controllers in achieving stable and high-quality power delivery in grid-connected PV systems, even under highly dynamic environmental and load conditions.

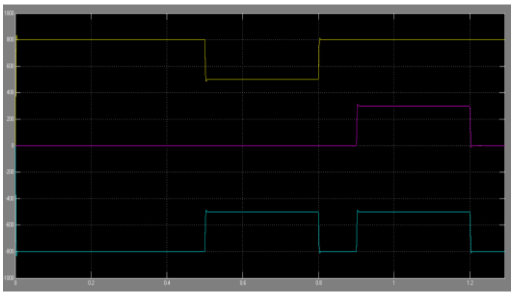

Fig 5 Solar power, grid power, load power vs time under Dynamic performance under sudden change in solar irradiation and load petervation

Figure 5 depicts the power flow dynamics of solar power, grid power, and load power during sudden changes in solar irradiation and load perturbations. The solar power curve reflects the variability of irradiance, showing that the PV system adapts rapidly to maximize power extraction through the MPPT algorithm. Grid power fluctuates correspondingly to compensate for variations in solar generation, ensuring that the load demand is consistently met. When solar power decreases, the grid supplements the deficit, and when solar generation is high, the load is supplied predominantly by the PV system, with any excess potentially exported to the grid. Load power remains steady throughout, illustrating the effectiveness of the hybrid fuzzy logic and neural network (FLC–NN) controller in maintaining a reliable supply. This figure highlights the balance and coordination achieved by the intelligent controller between solar generation, grid contribution, and load demand. It validates the system's capacity to provide uninterrupted power with minimal oscillations, ensuring stability in energy delivery. Such dynamic response analysis is vital for real-world grid-connected PV applications, where fluctuating renewable sources must coexist with constant consumer demands, making the controller's adaptability and robustness highly significant.

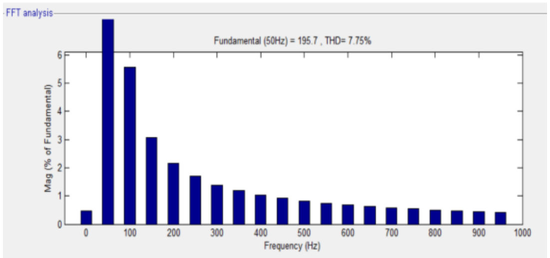

Fig 6 Total harmonic distortion with fuzzy logic controller

Figure 6 illustrates the Total Harmonic Distortion (THD) levels in the grid current when a fuzzy logic controller (FLC) alone is employed in the PV system. The waveform and harmonic spectrum show that while FLC improves MPPT efficiency compared to conventional methods, its capability to suppress harmonics is limited. The measured THD value in this figure highlights the extent of distortion present under dynamic operating conditions. This distortion may lead to inefficiencies, overheating of equipment, and potential non-compliance with IEEE-519 harmonic standards if left unaddressed. The figure serves as an important benchmark to demonstrate the shortcomings of a standalone FLC-based control strategy. Although FLC provides adaptability in nonlinear PV behavior, it lacks the self-learning capacity to optimize switching patterns for effective harmonic reduction. Thus, while Fig 9.5 shows the relative improvement over traditional MPPT methods, it also underlines the need for an enhanced control strategy, such as the integration of a neural network (NN) controller, to achieve superior harmonic suppression and ensure high-quality grid power delivery.

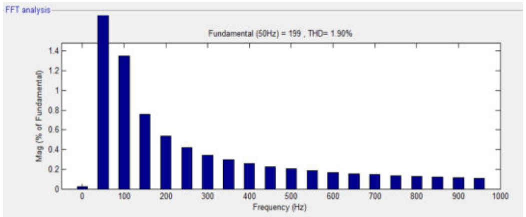

Fig 7 Total harmonic distortion with fuzzy logic along with NN controller

Figure 7 presents the Total Harmonic Distortion (THD) results when the hybrid fuzzy logic and neural network (FLC–NN) controller is applied. Unlike the results in Fig 9.5, the addition of the neural network enables adaptive learning and fine-tuning of control parameters, resulting in significantly reduced harmonic content. The THD spectrum in this figure indicates substantial improvement, with the distortion minimized to levels well within IEEE-519 standards. This confirms the neural network's effectiveness in addressing the limitations of a standalone fuzzy logic controller. By dynamically adjusting inverter switching patterns and modulation strategies, the NN enhances current waveform quality, reducing low-order harmonics and improving sinusoidal fidelity. The comparison between Fig 9.5 and Fig 9.6 highlights the superiority of the hybrid control strategy in improving power quality while maintaining high MPPT efficiency. This figure is essential evidence of the project's contribution, demonstrating that integrating neural network intelligence with fuzzy logic results in a more reliable, efficient, and grid-compliant PV system. It validates the central aim of the work: achieving both enhanced energy harvesting and improved power quality in single-phase grid-connected PV applications.

V. CONCLUSION

This work presents the modeling and control of a single-phase grid-connected solar PV supply system using a hybrid fuzzy logic and neural network-based MPPT approach. The system integrates a step-up converter controlled by an FLC for maximum power extraction and a neural network controller for power quality improvement. Simulation studies in MATLAB/Simulink confirm that the hybrid controller significantly improves MPPT efficiency, reduces oscillations, and minimizes Total Harmonic Distortion (THD), ensuring compliance with IEEE power quality standards. Compared to conventional P&O and INC methods, the proposed system demonstrates superior adaptability and robustness under dynamic weather conditions. Its ability to provide reliable, high-quality power makes it ideal for residential and small-scale grid-connected applications. By combining fuzzy logic with neural networks, the system leverages the strengths of both rule-based reasoning and adaptive learning, creating a scalable and intelligent framework for renewable energy integration.

REFERENCES

1. Alsumaiti, T. S., Alameri, H. K., & El-Hawary, M. E. (2019). Grid integration of solar photovoltaic systems: Modeling, control, issues, and challenges. *IEEE Access, 7*, 106650–106664. https://doi.org/10.1109/ACCESS.2019.2932765
2. Babu, T. S., & Vasudevan, M. (2017). Real-time implementation of MPPT using fuzzy logic controller for solar photovoltaic system. *Renewable Energy, 106*, 1–9. https://doi.org/10.1016/j.renene.2016.12.059
3. Bhatnagar, P., & Nema, R. K. (2013). Maximum power point tracking control techniques: State-of-the-art in photovoltaic applications. *Renewable and Sustainable Energy Reviews, 23*, 224–241. https://doi.org/10.1016/j.rser.2013.02.011
4. Bhuvaneswari, G., & Balasubramanian, R. (2014). Neural network-based MPPT for standalone solar PV systems. *International Journal of Electrical Power & Energy Systems, 55*, 21–30. https://doi.org/10.1016/j.ijepes.2013.08.024
5. Blaabjerg, F., Teodorescu, R., Liserre, M., & Timbus, A. V. (2006). Overview of control and grid synchronization for distributed power generation systems. *IEEE Transactions on Industrial Electronics, 53*(5), 1398–1409. https://doi.org/10.1109/TIE.2006.881997
6. Bose, B. K. (2017). Artificial intelligence techniques in smart grid and renewable energy systems—Some example applications. *Proceedings of the IEEE, 105*(11), 2262–2273. https://doi.org/10.1109/JPROC.2017.2757038
7. Carrasco, J. M., et al. (2006). Power-electronic systems for the grid integration of renewable energy sources: A survey. *IEEE Transactions on Industrial Electronics, 53*(4), 1002–1016. https://doi.org/10.1109/TIE.2006.878356
8. Chauhan, S. S., & Chandel, S. S. (2015). Review of energy storage and energy management strategies for PV systems. *Renewable and Sustainable Energy Reviews, 49*, 192–208. https://doi.org/10.1016/j.rser.2015.04.092
9. Chouhan, A., & Bansal, H. O. (2020). Grid-connected solar PV system: Control and power quality issues. *Renewable and Sustainable Energy Reviews, 119*, 109603. https://doi.org/10.1016/j.rser.2019.109603

10. Eltawil, M. A., & Zhao, Z. (2013). MPPT techniques for photovoltaic applications. *Renewable and Sustainable Energy Reviews, 25*, 793–813. https://doi.org/10.1016/j.rser.2013.05.022
11. Esram, T., & Chapman, P. L. (2007). Comparison of photovoltaic array maximum power point tracking techniques. *IEEE Transactions on Energy Conversion, 22*(2), 439–449. https://doi.org/10.1109/TEC.2006.874230
12. Femia, N., Petrone, G., Spagnuolo, G., & Vitelli, M. (2005). Optimization of perturb and observe maximum power point tracking method. *IEEE Transactions on Power Electronics, 20*(4), 963–973. https://doi.org/10.1109/TPEL.2005.850975
13. Hasanien, H. M. (2015). Performance improvement of photovoltaic power systems using ANN-based MPPT. *IEEE Transactions on Sustainable Energy, 6*(2), 616–624. https://doi.org/10.1109/TSTE.2014.2386791
14. Ishaque, K., & Salam, Z. (2013). A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading condition. *Renewable and Sustainable Energy Reviews, 19*, 475–488. https://doi.org/10.1016/j.rser.2012.11.032
15. Jain, S., & Agarwal, V. (2007). A new algorithm for rapid tracking of maximum power point of PV arrays. *IEEE Power Electronics Letters, 2*(1), 16–19. https://doi.org/10.1109/LPEL.2004.829941
16. Kofinas, P., Doltsinis, S., Hatziargyriou, N. D., & Georgilakis, P. S. (2015). A fuzzy logic-based MPPT controller for PV systems. *Applied Energy, 142*, 53–67. https://doi.org/10.1016/j.apenergy.2014.12.045
17. Kumar, N., Hussain, I., Singh, B., & Panigrahi, B. K. (2017). Single-phase solar PV system with adaptive neural MPPT and improved power quality. *IEEE Transactions on Industry Applications, 53*(6), 5621–5631. https://doi.org/10.1109/TIA.2017.2743023
18. Liu, B., Duan, S., Liu, F., & Xu, P. (2008). Analysis and improvement of maximum power point tracking algorithm based on incremental conductance method for photovoltaic array. *Proceedings of the 2008 IEEE PESC*, 2457–2463. https://doi.org/10.1109/PESC.2008.4592326
19. Ma, J., & Jiang, W. (2019). Improved fuzzy MPPT algorithm for solar photovoltaic systems. *International Journal of Photoenergy, 2019*, 1–9. https://doi.org/10.1155/2019/5472316
20. Manickam, C., et al. (2016). Efficient fuzzy logic based maximum power point tracking for grid-connected PV systems. *IEEE Transactions on Power Electronics, 31*(7), 4422–4439. https://doi.org/10.1109/TPEL.2015.2475296
21. Mellit, A., & Kalogirou, S. A. (2008). Artificial intelligence techniques for photovoltaic applications: A review. *Progress in Energy and Combustion Science, 34*(5), 574–632. https://doi.org/10.1016/j.pecs.2008.01.001
22. Mohanty, S., Subudhi, B., & Ray, P. K. (2015). A new MPPT design using grey wolf optimization technique for photovoltaic system under partial shading conditions. *IEEE Transactions on Sustainable Energy, 7*(1), 181–188. https://doi.org/10.1109/TSTE.2015.2496116

23. Nassar, M. E., & El-Saadany, E. F. (2012). An overview of harmonic distortion and power quality issues of grid-connected PV systems. *Electric Power Systems Research, 82*(1), 57–65. https://doi.org/10.1016/j.epsr.2011.08.017
24. Nema, P., Nema, R. K., & Rangnekar, S. (2010). A current and future state of art development of hybrid energy system using wind and PV-solar. *Renewable and Sustainable Energy Reviews, 13*(8), 2096–2103. https://doi.org/10.1016/j.rser.2009.10.005
25. Patel, H., & Agarwal, V. (2008). Maximum power point tracking scheme for PV systems operating under partially shaded conditions. *IEEE Transactions on Industrial Electronics, 55*(4), 1689–1698. https://doi.org/10.1109/TIE.2008.917118
26. Safari, A., & Mekhilef, S. (2011). Simulation and hardware implementation of incremental conductance MPPT with direct control method using Cuk converter. *IEEE Transactions on Industrial Electronics, 58*(4), 1154–1161. https://doi.org/10.1109/TIE.2010.2048834
27. Subudhi, B., & Pradhan, R. (2013). A comparative study on maximum power point tracking techniques for photovoltaic power systems. *IEEE Transactions on Sustainable Energy, 4*(1), 89–98. https://doi.org/10.1109/TSTE.2012.2202294
28. Teodorescu, R., Liserre, M., & Rodriguez, P. (2011). *Grid converters for photovoltaic and wind power systems*. John Wiley & Sons. https://doi.org/10.1002/9780470667057
29. Villalva, M. G., Gazoli, J. R., & Filho, E. R. (2009). Comprehensive approach to modeling and simulation of photovoltaic arrays. *IEEE Transactions on Power Electronics, 24*(5), 1198–1208. https://doi.org/10.1109/TPEL.2009.2013862
30. Zhang, Y., Xu, Z., & Dong, Z. Y. (2015). Robust adaptive neural network control for grid-connected PV inverters. *IEEE Transactions on Smart Grid, 6*(6), 2789–2799. https://doi.org/10.1109/TSG.2015.2392152