Pertanika J. Sci. & Technol. 32 (S1): 93 - 110 (2024)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Fuzzy Logic-based Power Optimizer for Solar Photovoltaic Power Systems

Revathy Subbiah Rajaram[1]*, Padaga Kumar Babu[2], Kirubakaran Victor[1], Raja Kandasamy[3], Ganeshan Pushpanathan[4], Vivek Sivakumar[5], Ramshankar Pushpanathan[6], Mohanavel Vinayagam[7] and Sachuthananthan Barathy[8]

[1]*Centre for Rural Energy, The Gandhigram Rural Institute - Deemed to be University, Gandhigram - 624302, Tamil Nadu, India*

[2]*Department of Mechanical Engineering, Geethanjali Institute of Science and Technology, Nellore - 524316, Andhra Pradesh, India*

[3]*Department of Mechanical Engineering, Anna University Regional Campus - Coimbatore, Coimbatore - 641046, Tamil Nadu, India*

[4]*Center for Augmented Intelligence and Design, Department of Mechanical Engineering, Sri Eshwar College of Engineering, Coimbatore - 641202, Tamil Nadu, India*

[5]*Department of Civil Engineering, GMR Institute of Technology, Razam, Andra Pradesh - 532127, India*

[6]*Department of Civil Engineering, College of Engineering Guindy, Anna University, Chennai - 600 025, Tamil Nadu, India*

[7]*Centre for Materials Engineering and Regenerative Medicine, Bharath Institute of Higher Education and Research, Chennai, 600073, Tamil Nadu, India*

[8]*Department of Mechanical Engineering, Sree Vidyanikethan Engineering College, Tirupati - 517102, Andhra Pradesh, India*

ABSTRACT

Solar photovoltaics has become the most popular renewable energy source due to its simplicity in installation and maintenance. However, the dependence on the availability of solar energy at the instant makes its operation non-linear. Various optimizing solutions are proposed to rule out this disadvantage. This paper dwells on a machine language approach to solve this problem. A maximal tracker for power points relies on fuzzy logic control. An embedded power optimizer is designed and tested under different environmental conditions through simulation. The results presented allow researchers to test various artificial intelligence techniques for renewable energy extraction processes.

Keywords: Fuzzy logic, machine language, MATLAB, photovoltaics, solar energy

ARTICLE INFO

Article history:
Received: 27 July 2023
Accepted: 17 October 2023
Published: 19 January 2024

DOI: https://doi.org/10.47836/pjst.32.S1.06

E-mail addresses:
revathysrajaram@gmail.com (Revathy Subbiah Rajaram)
kumarbabudrp@gmail.com (Padaga Kumar Babu)
kirbakaran@yahoo.com (Kirubakaran Victor)
rajagce@gmail.com (Raja Kandasamy)
ganeshan.p@sece.ac.in (Ganeshan Pushpanathan)
1717vivek@gmail.com (Vivek Sivakumar)
ramshankar1991@gmail.com (Ramshankar Pushpanathan)
mohanavel2k16@gmail.com (Mohanavel Vinayagam)
bsachu7@yahoo.co.in (Sachuthananthan Barathy)
* Corresponding author

ISSN: 0128-7680
e-ISSN: 2231-8526

INTRODUCTION

The solar photovoltaic technology has gained more importance in the recent years. The advantages of solar energy are manifold. The energy benefits include low or no transmission and distribution losses and high penetration levels (Raja et al., 2023). A short payback period and low electricity cost per watt-hour come under the economic profits (Yamunadevi et al., 2021). The benefits of solar energy in the environment are low carbon emission, reduced usage of land and water, improvement in public health, and a higher lifetime of about 25 years (Kaygusuz, 2009). The recent survey data from the Ministry of New and Renewable Energy, Government of India, shows a rapid increase in the installation of rooftop-based solar photovoltaic systems (Das et al., 2023). India, being a tropical country, is blessed with abundant solar potential. The government has set an ambitious target of having 175 GW of renewable energy capacity by 2022, including 98,298 MW of solar, 59,400MW of wind, 4385 MW of small hydropower, and 9880 MW from biomass (Padmanathan et al., 2019). Though the initiative received a warm welcome, the associated challenges in integrating renewable power into the existing grid are tricky (Azaharahmed et al., 2021). However, today's solar cells, like monocrystalline or polycrystalline, have a limited power conversion efficiency (Vinayagar et al., 2022).

The power produced by solar photovoltaic systems is affected by factors like mismatch losses caused by various factors like manufacturing differences, thermal variations, partial shading conditions, non-uniform degradation, and aging of the solar cells or modules (Rajeshwaran et al., 2018). The unidentical electrical characteristics of the PV cells/modules, inconsistency in the semiconductor materials used, and lack of precision cause manufacturing mismatch losses. Partial shading has been identified as a significant driving factor for mismatch losses (Saravanan et al., 2021). If only a fraction of cells is shaded, a problem arises as the exact amount of current must flow through cells connected in series. This reduction in current production by the non-shaded cells becomes an issue (Saravanan et al., 2021). Shading of only one cell in a module could reduce the module's power output by 86%, although the irradiance loss is only 3%.

The solar modules usually come with a lifetime warranty of about 20 years and are reported with a 1% yearly degradation. The aging process accelerates due to mechanical damages, hotspots, and uneven degradation (Radhaboy et al., 2019). Fractional power loss of up to 12% happens due to premature aging. The degradation rate due to aging in thin-film cells is 0.5%–0.7% per year, and the crystalline cells are 0.8% per year. There can be significant variations in temperature between modules depending on the differences in airflow over the modules (Raja et al., 2020). Modules centered in the array are generally not as affected by airflow as modules at the edge, which causes the centered modules to be hotter (Islam et al., 2018). Furthermore, the erratic weather patterns caused by global warming also affect the performance of solar modules, leading to inconsistent and unreliable power outputs (Revathy & Kirubakaran, 2020). Hence, including optimization components in the balance of the system is unavoidable.

Most optimization systems comprise a maximum power point tracker and other power electronics controllers like buck converters, boost converters, or buck-boost converters (Noman et al., 2017). The maximum power point tracker (MPPT) monitors the output generated by the solar array at a particular instant and makes optimization decisions (Vignesh Kumar et al., 2019). Usually, the power electronic controllers are used to maximize or minimize the solar array output voltage according to the load requirements. However, this maximum power point tracker makes the major decisions—does the optimization require a boost or reduction in voltage values? If so, at what rate? These questions are very crucial in the process of optimization, and this decides the system's overall performance and directly influences the profit made out of the power generation (Vignesh Kumar et al., 2019).

The highly effective maximum power point trackers measure and monitor the current and voltage outputs of the solar photovoltaic array to calculate the total power delivered at that instant. It then compares this estimated power value to the other power values at different operating points. By incessantly adjusting the operating parameters, it arrives at the best possible optimized value of power that can be delivered instantly. It also created a signal code based on the power electronics circuit's operation to provide the optimal output. The abovementioned process requires consistent operation at high speeds so the system supplies reliable power. Most earlier algorithms, like voltage-based control, current-based control, and hill-climbing algorithms, work fine under normal circumstances. Still, in case of frequent weather changes, they oscillate and fail at most operating points (Motahhir et al., 2018). Traditional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (IncCond), suffer from drawbacks like oscillations and slow convergence in dynamic conditions (Smith et al., 2023). Fuzzy logic controllers have emerged as a viable alternative due to their ability to adapt to changing needs and handle imprecise data (Lee et al., 2007). Hence, this process requires a method that can offer accuracy at high speeds and automatically adapt to the frequent changes in operating conditions.

The advantages of the fuzzy logic-based maximum power point trackers are multifold. Fuzzy logic controllers excel in handling solar PV systems' non-linear and uncertain nature. They can effectively track the maximum power point (MPP) even in partial shading, temperature fluctuations, and rapid irradiance changes (Gonzalez et al., 2023).

Fuzzy logic controllers adapt to varying operating conditions without requiring extensive parameter tuning. This adaptability is particularly useful in real-world applications where environmental factors constantly change (Smith et al., 2023). Fuzzy logic controllers exhibit smoother tracking than traditional algorithms, reducing oscillations around the MPP and minimizing stress on the PV system (Lee et al., 2007).

Despite their advantages, fuzzy logic-based MPPT controllers face specific challenges and areas for improvement. Implementing fuzzy logic controllers can be computationally intensive, which may limit their use in low-power embedded systems. Researchers are exploring optimizing their computational efficiency (Gonzalez et al., 2023). Some studies have proposed hybrid MPPT approaches combining fuzzy logic with other techniques like neural networks or genetic algorithms to improve tracking accuracy and speed (Lee et al., 2007). Investigating methods for automatically tuning the fuzzy logic controller's parameters in real-time is to enhance adaptability and performance in rapidly changing environments (Smith et al., 2023).

Recent research in the field of fuzzy logic-based MPPT controllers for solar PV systems has yielded promising results. Fuzzy logic controllers have been applied in multi-objective optimization scenarios, simultaneously considering factors like efficiency, tracking speed, and system stability (Lee et al., 2007). Integrating machine learning techniques with fuzzy logic controllers improves prediction accuracy and enhances the controller's adaptability (Smith et al., 2023). As researchers continue to address challenges and explore innovative approaches, the future of fuzzy logic-based MPPT controllers holds promise for further improving the efficiency and reliability of solar PV systems (Gonzalez et al., 2023; Lee et al., 2007).

Several machine language techniques are gaining popularity for their problem-solving skills, especially when there is a high level of non-linearity (Mlakić et al., 2018). Fuzzy logic, a popular machine language-based technique, combines human reasoning skills with the thinking process to resolve intricate non-linear problems (Patan et al., 2021). A fuzzy logic controller works in three steps: (1) fuzzification, (2) inference, and (3) defuzzification, as shown in Figure 1 (Karthika et al., 2014).

Fuzzification is the procedure of encoding the user-specified inputs into the machine-interpretable format, usually called fuzzy subsets (NG- -ve, ZE- 0, PE- +ve). The controller can only understand and handle these subsets (Bouselham et al., 2017).

The subsets thus arrived at are branded by membership functions; the choice of MFs and their respective ranges for preferred inlet and outlet variables influences the better

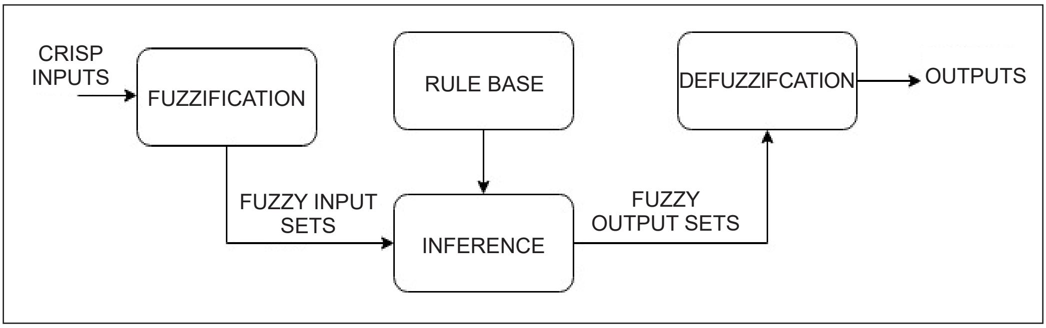

Figure1. Fuzzy controller block

performance of the controller. Defuzzification: The final step is where the fuzzy subsets are decoded to actual interpretable output variables (Saravana et al., 2014).

This paper discusses such a technique, which integrates machine learning with power electronics to optimize the performance of solar photovoltaic systems. The work involves designing a maximum power point tracker using a fuzzy logic-based controller. The output of this controller is applied to a conventional boost converter for better optimization.

MATERIALS AND METHODS

The proposed optimization technique involves the design of a solar photovoltaic array, a fuzzy logic controller, and a boost converter. All the scenarios are simulated using MATLAB/SIMULINK, and the performance is tested under different operating conditions.

Solar photovoltaic array with DC-DC converter: A solar photovoltaic array is designed in MATLAB SIMULINK and comprises 5 Canadian Solar CS5C -80M modules connected as a string. Under standard testing conditions, the array characteristics are a maximum array voltage of 110 V, a maximum array current of 4.97 A, and a maximum power of around 550 W.

Boost Converter: The (DC-DC converter) is designed for an optimum value of 100 V and 1 kHz (Revathy et al., 2022).

Fuzzy Logic Controller: The design of the fuzzy logic controller should align with the specific goals and requirements of the MPPT system and consider the characteristics of the PV system being controlled. It often involves balancing simplicity and accuracy to maximize energy harvesting from solar PV panels. The various stages involved in the design are explained below.

Input Selection: The design of a fuzzy controller involves many steps, where the first step consists of identifying the inputs. There are several choices in the case of inputs; weather parameters like irradiance and temperature can be considered if the required historical data is available. However, in most cases, the solar photovoltaic systems output current and voltage are preferred for more straightforward calculations (Kumar et al., 2019).

Output Selection: The primary output variable is the duty cycle or control signal for the DC-DC converter or inverter, which regulates the power flow between the PV panels and the load or battery.

Membership Function Selection: The next stage is the determination of membership functions for the fuzzy controller. Since the fuzzy controller does not interpret the real-time data, we convert them into fuzzy sets using a specific linguistic label called membership functions. Membership functions define how each input is mapped to fuzzy sets (e.g., power at an instant, change of power at another moment). The choice of membership functions should reflect the characteristics of the input data. Standard membership functions include triangular, trapezoidal, or Gaussian (Padmanathan et al., 2019).

Fuzzy Set Determination: Dedicated fuzzy sets or linguistic variables are selected for each input chosen. The fuzzy sets classify the input into different ranges for decision-making (for instance, negative, zero, and positive).

Fuzzy Rules Generation: The next stage involves creating a set of rules based on which the controller operates. Most of these rules are usually If-then-based conditions executed using basic Boolean operators like AND, OR, and NOT.

Rule Base Design: This stage involves designing a fuzzy inference system that utilizes the membership functions and the rules to arrive at optimal duty signal value in its machine language. This stage includes defining inference methods, such as Mamdani or Sugeno, to determine how the rules interact.

Defuzzification: The outputs of the inference system need to be translated into control signals understandable by the electronic circuits through defuzzification. Defuzzification is the opposite of fuzzification (Balasubramanian & Singaravelu, 2012)

Parameter Tuning: The membership functions and the rule weights must be fine-tuned to achieve the desired duty cycle through simulations in MATLAB.

Validation and Testing: To validate its efficiency, the FLC-based MPPT is tested with real-time data through simulation in the MATLAB platform, the solar PV system, and the DC-DC converter.

Figure 2 depicts the design aspects of the fuzzy controller.

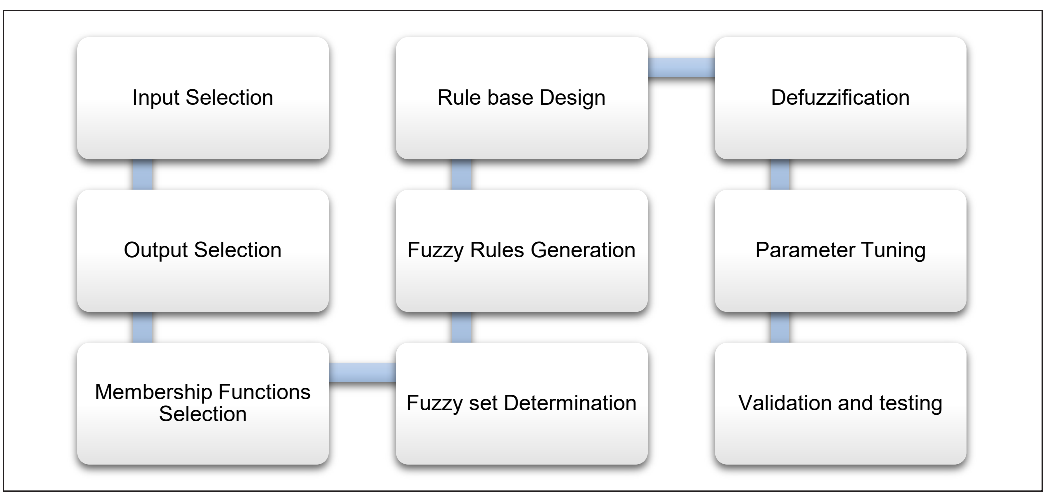

Figure 2. Fuzzy logic controller design

FUZZY LOGIC CONTROLLER DESIGN

A fuzzy controller works based on a distinctive rule base usually depicted in table form. The output parameters of the solar photovoltaic system, such as the voltage and current values, are considered input for the proposed controller. These values after acquisition are multiplied to calculate the power values at respective timestamps. The power error is calculated by subtracting the power at a particular instant from the power at the previous moment. Similarly, the change in error is calculated by subtracting the error in power at an instant k and the error at the last instant (k-1). Two factors, the error in Power E(k) (Equation 1) and the change in error CE(k) (Equation 2), are chosen as inlet factors for the fuzzy controller.

$$E(k) = P_{pv}(k) - P_{pv}(k-1) \tag{1}$$

$$CE(k) = E(k) - E(k-1) \tag{2}$$

The change in power from kth instant to k-1th instant is considered an error (Equation 1). The error and the change in error are considered the inlets of the fuzzy controller, and the duty cycle value D is regarded as the output value (Saravana et al., 2014). During fuzzification, the inlet and the outlet are broken into five fuzzy sets. The fuzzy sets are NS, NB, Z, PS, and PB. NS refers to Negative Small, NB to Negative Big, Z to zero, PS to Positive Small, and PB to Positive Big (Saravanan et al., 2022). Triangular membership functions are employed in both inlets and outlets for better results. The membership functions (MFs)for error, change of error, and duty ratio are given in Figures 3 to 5, respectively.

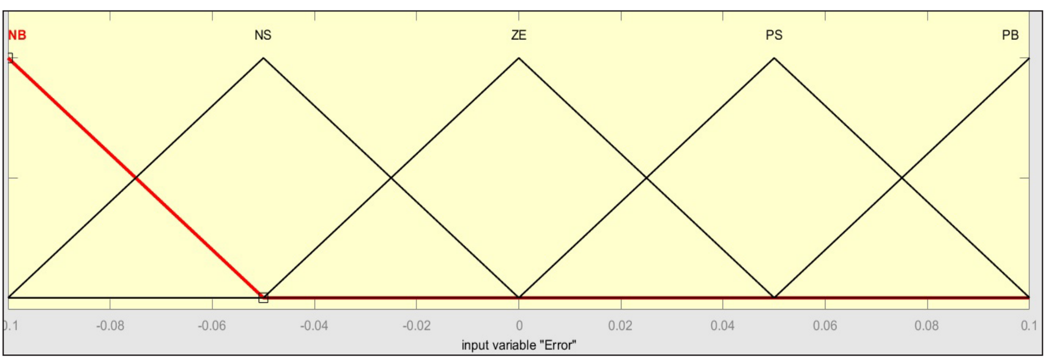

Figure 3. MF representing E(k)

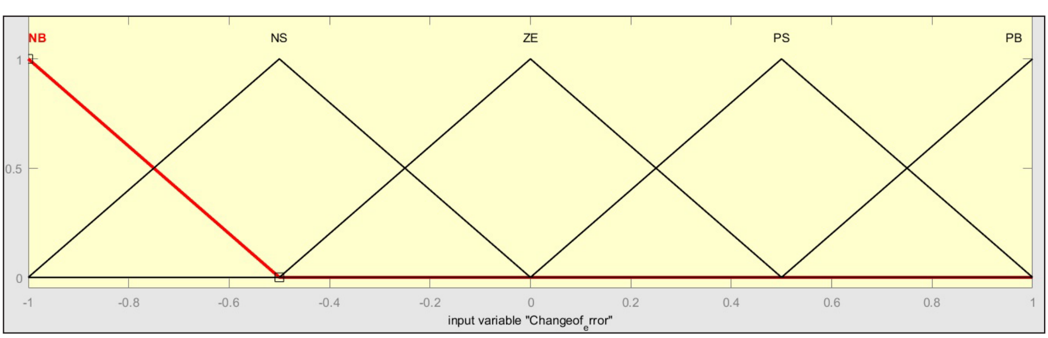

Figure 4. MF representing CE(k)

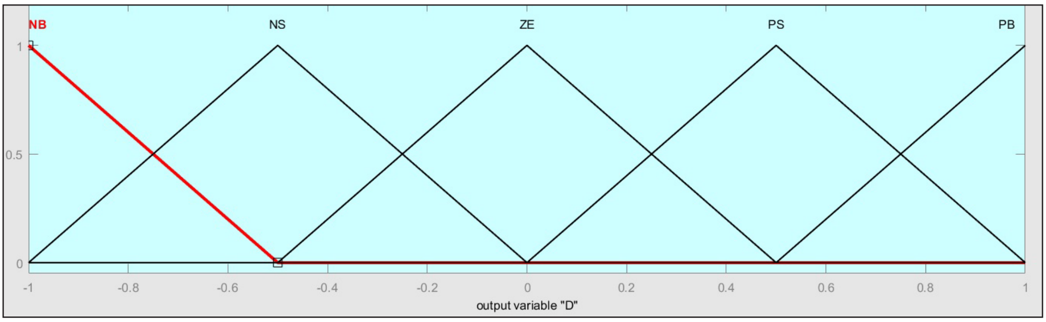

Figure 5. MF of the duty - D

The rules are framed with the fuzzy sets of the inputs and outputs. There are 25 rule sets for the FLC designed, and they are given in Table 1, which is easy to interpret. The first rule is interpreted as if the error and its change are NB; the duty ratio is NB.

The boost converter is controlled using these principles for the maximal power point. The rules in Table 1 are represented in a three-dimensional graph shown in Figure 6

The proposed fuzzy controller uses a Max-Min combination of the inference system called Mamdani. Mamdani Inference Systems are used in various applications, including control systems, decision support systems, and expert systems, where precise control and reasoning are required in uncertain or non-linear environments. The defuzzification is carried out through the

Table 1
Rules of fuzzy controller

CE \ E	NB	NS	Z	PS	PB
NB	NB	NB	NS	NS	Z
NS	NB	NS	NS	Z	PS
Z	NS	NS	Z	PS	PS
PS	NS	Z	PS	PS	PB
PB	Z	PS	PS	PB	PB

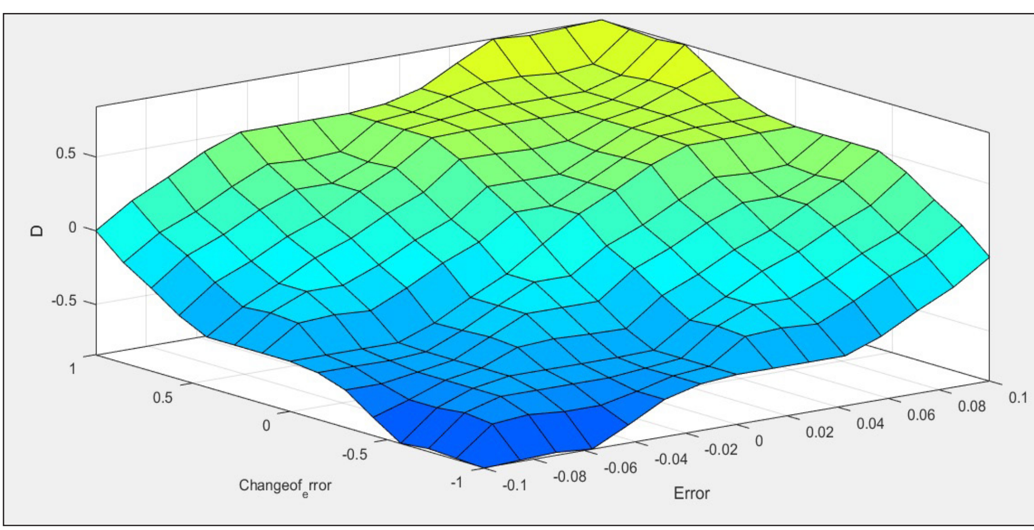

Figure 6. FLC rules

Centre of Arc method (COA), which involves the calculation of the center of gravity of the output variable Duty ratio, which is given by Equation 3 (Bendib et al., 2014).

$$\Delta D = \frac{\sum_{i=1}^{n} \mu(\Delta D_i) * \Delta D_i}{\sum_{i=1}^{n} \mu(\Delta D_i)} \tag{3}$$

The actual output D(k) is calculated by defuzzifying the change in duty ratio ΔD(k) and scaling it by a gain $S_{\Delta D}$ as in Equation 4 (Bendib et al., 2014).

$$D(k) = D(k-1) + S_{\Delta D} * \Delta D(k) \tag{4}$$

This duty ratio is input for the pulse width modulating generator, which generates the pulse D and regulates the boost converter's operation for optimized output power. The power optimization circuit driven by the fuzzy logic controller to extract maximum power is analyzed in MATLAB/SIMULINK for the proposed SPV array. The composition of the array includes 5 Canadian Solar CS5C -80M modules, all connected in series and to a DC-DC converter to optimize power. The proposed SIMULINK model is shown in Figure 7.

The fuzzy controller proposed involves current and voltage sensors at the initial level to derive the error and change in error values. The controller achieves good response time and reduced voltage fluctuations during the tracking process. Hence, the operational accuracy and speed of the fuzzy logic controller are undebatable. However, the only disadvantage is the design phase, where the designer must have exclusive knowledge of the detailed photo voltaic system.

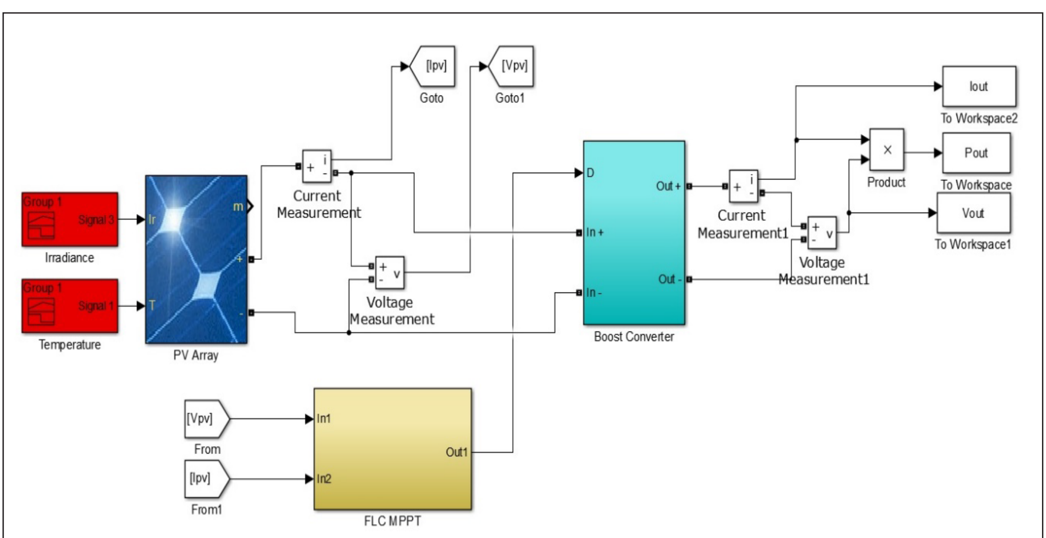

Figure 7. Power optimization of an SPV array with proposed MPPT in MATLAB/ SIMULINK

RESULTS AND DISCUSSION

The proposed maximum power point techniques are tested under various conditions. Testing Maximum Power Point Tracking (MPPT) techniques under multiple conditions is crucial for several reasons such as:

- Environmental conditions like varying solar irradiance (G) and module temperatures (T) reflect real-world scenarios. Testing under these conditions ensures that the MPPT algorithms perform optimally in the varying sunlight and temperature levels experienced by solar panels in different locations and climates.
- Solar panels are often installed in diverse environments with fluctuating weather patterns. MPPT algorithms need to adapt to these changes to ensure maximum energy harvesting.
- MPPT algorithms must be robust and reliable. Testing under different conditions helps identify potential weaknesses or vulnerabilities in the algorithms.
- Testing under standard conditions (i.e., STC) provides a baseline for validation, ensuring that the MPPT algorithms meet the expected performance levels.
- Understanding how MPPT algorithms behave under different conditions is essential since it aids in developing new algorithms or improving existing ones, fostering innovation in renewable energy technology.
- Understanding how MPPT functions under various conditions helps optimize the entire energy system in larger solar power installations.

The conditions and their description are given in Table 2.

According to the standard testing condition variables, the given solar photo voltaic array works at an irradiance level of 1000W/m^2 and an average temperature of 25^{o}C. The output power measured under different conditions is shown in Figures 7 to 10. The output at STC is used as a reference with other test conditions for better understanding. The maximum deliverable power the optimizers generate with the fuzzy controller under standard testing conditions is 0.488 kW.

The graph in Figure 9 depicts the dynamic performance of a photovoltaic array under rapidly changing weather conditions, simulated using SIMULINK. During a 50-second duration, the irradiance and temperature levels were intentionally varied three times,

Table 2
Test conditions

Test Conditions	Description
STC	Standard Testing Condition (G= 1000 W/m^2& T = 25^{o}C)
VWC	Rapidly varying weather condition G (W/m^2) = [700, 800, 900]; T(^{o}C) = [25, 30, 35]
PSC I	One module of the array is shaded partially
PSC II	Two modules are shaded partially.
PSC III	Three modules are shaded partially.

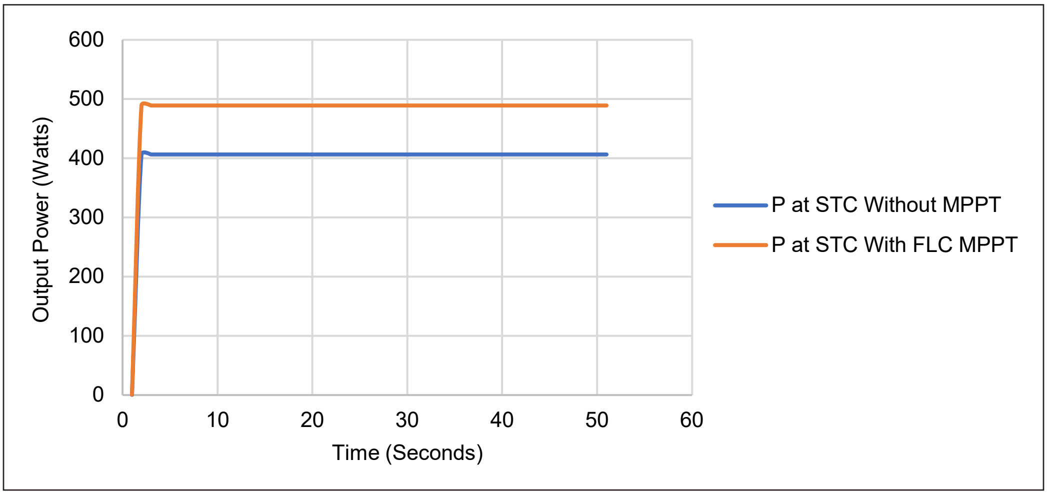

Figure 8. Output power of the power optimizer at STC

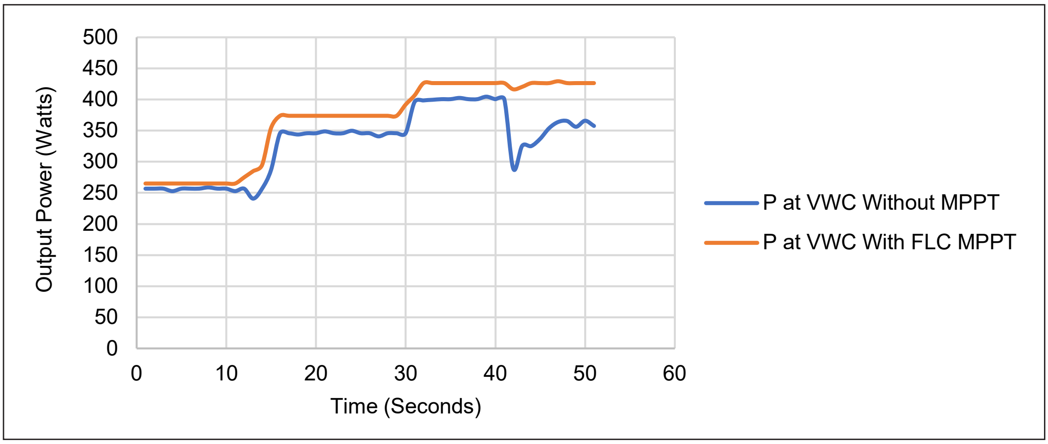

Figure 9. Output power of the power optimizers at VWC

showcasing the array's real-time response to these fluctuations. The graph illustrates a direct relationship between increased irradiance and higher power output, indicating the array's sensitivity to sunlight intensity. A Fuzzy Logic Control (FLC) Maximum Power Point Tracking (MPPT) system is in place, ensuring optimal power output. Even during sudden dips in irradiation, around the 40-second mark, the FLC MPPT system swiftly adapts, maintaining the array's power output at an optimal level. This graph provides valuable insights into the array's ability to efficiently harness solar energy under challenging and rapidly changing weather conditions, highlighting the effectiveness of the FLC MPPT system in maximizing energy harvest.

The graph in Figure 10 depicts a solar PV array's power-voltage (P-V) characteristics under both standard and partial shading conditions. Under standard conditions, the chart exhibits a smooth curve with a single peak representing the array's maximum power point (MPP), where the power output is optimized at a specific voltage. However, the graph shows a more intricate pattern with multiple peaks under partial shading conditions, simulated by varying irradiance levels on different modules. These peaks indicate local maximum power points, posing a challenge for most MPPT algorithms in correctly identifying the global MPP. Notably, the Fuzzy Logic Control (FLC) based MPPT algorithm stands out by accurately pinpointing the highest peak, representing the actual maximum power point of the solar PV array under partial shading conditions.

Figure 11 directly compares the output power of a solar array employing Fuzzy Logic Control (FLC) Maximum Power Point Tracking (MPPT) and the same array without MPPT. The maximum power point (MPP) is identified at 320 W. The FLC MPPT algorithm

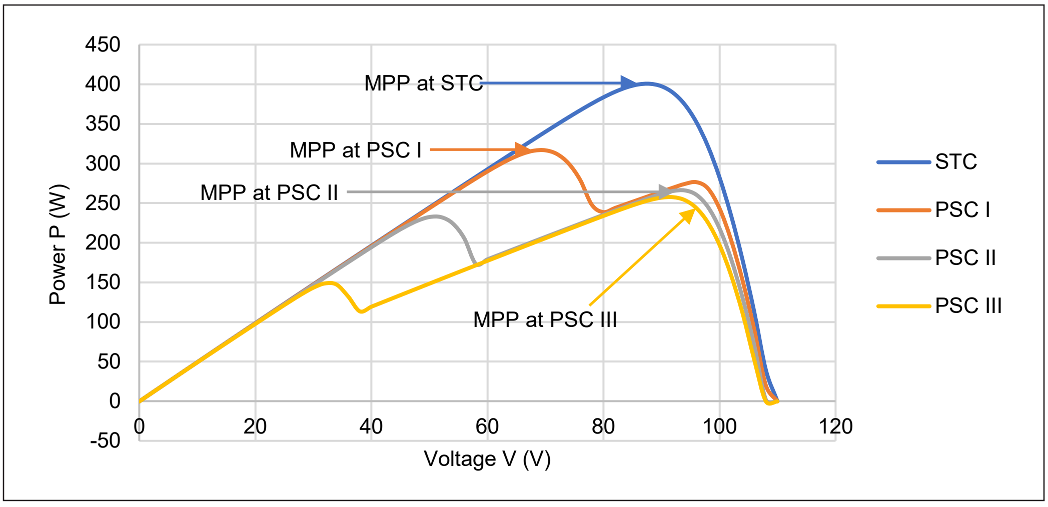

Figure 10. PV Curve under PSCs without optimization

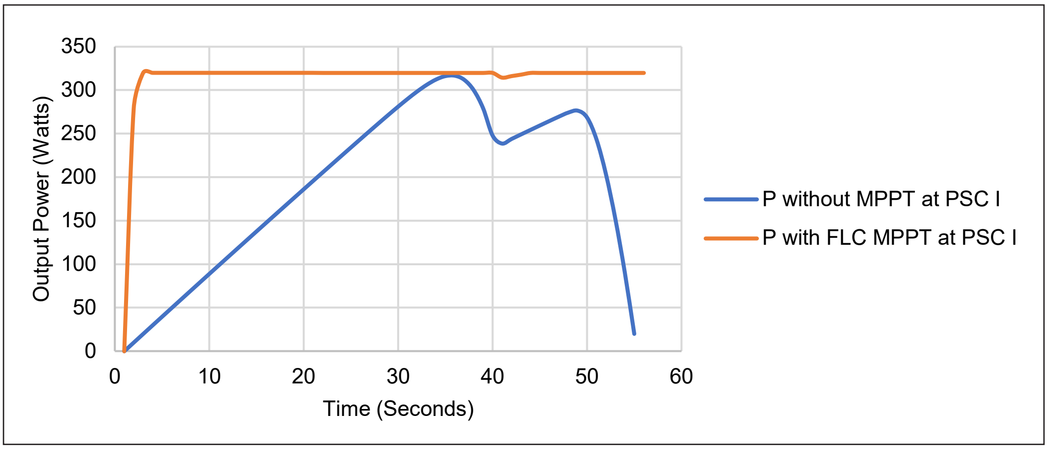

Figure 11. Output power of the optimizers under PSC I

optimizes the solar array's output to this value, ensuring efficient energy conversion. In contrast, the PV output without MPPT exhibits a less refined behavior, displaying two distinct peaks at 320 W and 275 W. This disparity illustrates the FLC MPPT's ability to pinpoint and maintain the MPP accurately, enhancing the solar array's performance and maximizing its power output.

Figure 12 displays the power characteristics of a solar array, revealing two distinct Maximum Power Points (MPPs) at 233 W and 266 W. Initially, the MPP is at 233 W, but with increased irradiance levels, it shifts to 266 W. The Fuzzy Logic Control (FLC) Maximum Power Point Tracking (MPPT) system efficiently optimizes the array's output to match this higher MPP, demonstrating its ability to adapt and maximize energy generation in response to changing light conditions.

In PSC III (Figure 13), initially, the MPP is identified at 150 W under specific irradiance conditions. As irradiance levels rise, the MPP significantly increases to 257 W. The Fuzzy Logic Control (FLC) Maximum Power Point Tracking (MPPT) system

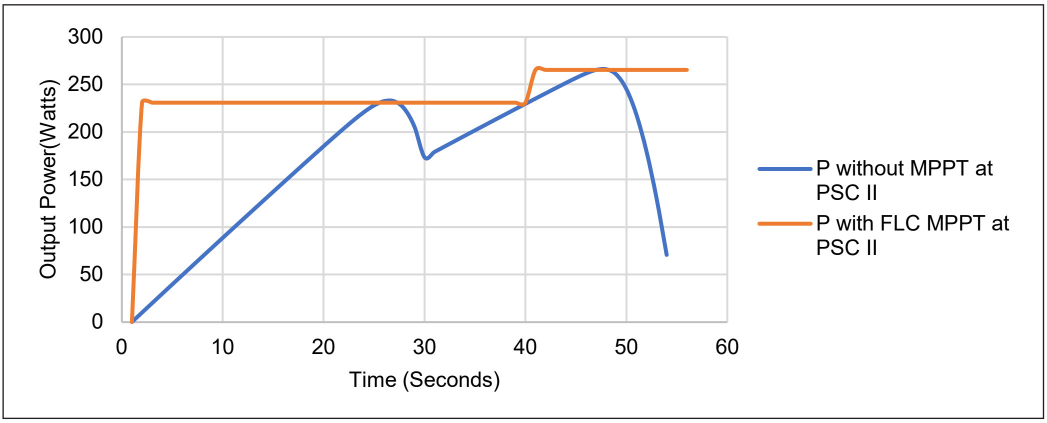

Figure 12. Output power of the optimizers under PSC II

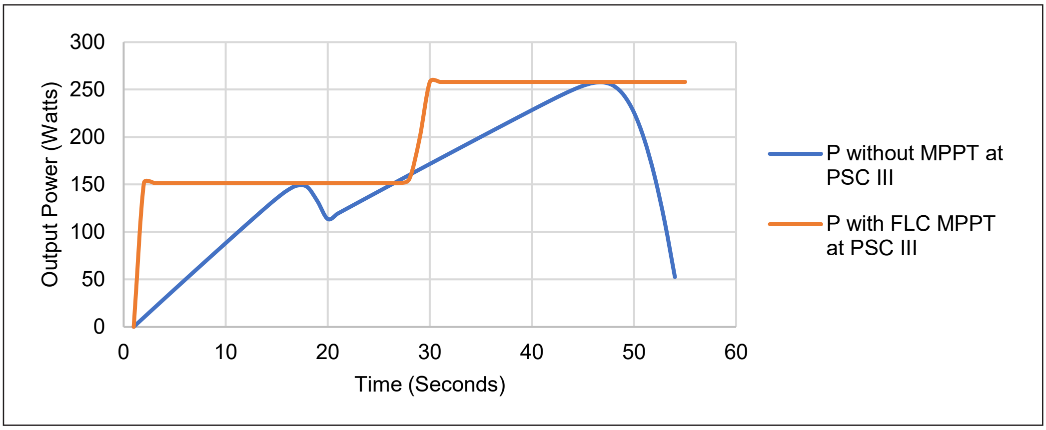

Figure 13. Output power of the optimizers under PSC III

is crucial in optimizing the array's output precisely to this higher MPP, showcasing its adaptability to changing light intensities and effectiveness in maximizing energy generation.

Table 3
Maximum power obtained through the proposed MPPT

Test Condition	Power (Watts)
STC	500
VWC	430
PSC I	320
PSC II	266
PSC III	257

Table 3 displays the maximum power the Fuzzy Logic Control (FLC) MPPT optimizer achieves across different testing conditions. While the power values decrease under specific conditions, the proposed MPPT demonstrates superior adaptability, ensuring better optimization in the given scenarios.

The power conversion efficiency of the photovoltaic array is given by Equation 5. P_{max} is the maximum power produced in Watts (W), G represents the irradiance levels in W/m^{2,} and A refers to the array area of the total array, which is 1.6864 m^2.

$$\eta = \frac{P_{max}}{GA} \times 100 \qquad (5)$$

The response time T_r of a Maximum Power Point Tracking (MPPT) system refers to the time it takes for the MPPT algorithm to detect a change in the operating conditions (such as variations in irradiance levels or temperature) and adjust the photovoltaic (PV) system to operate at the new maximum power point (MPP). In other words, it measures how quickly the MPPT algorithm can track and adapt to the optimal operating point as environmental conditions fluctuate. The response time for the proposed FLC-based MPPT can be observed in Figure 14.

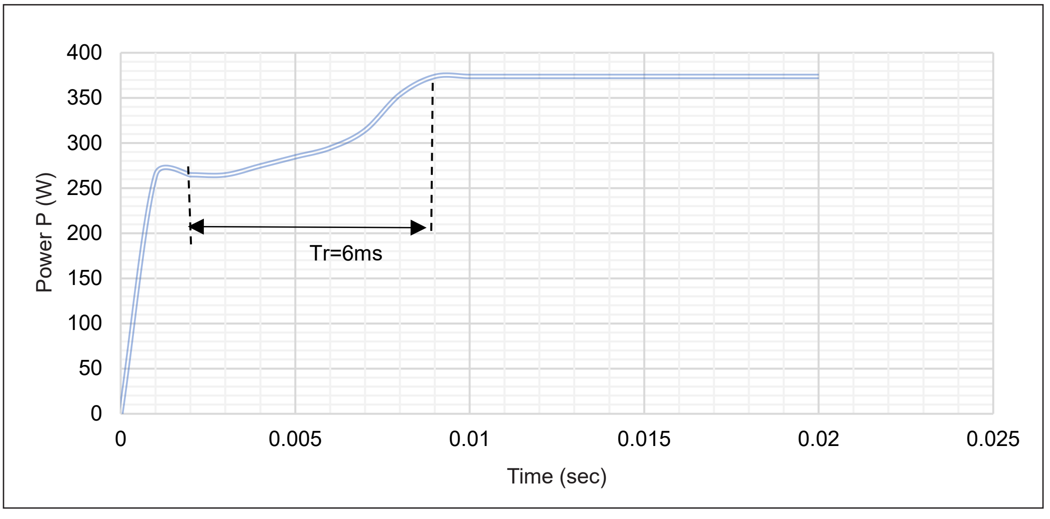

Figure 14. Response time, T_r

Table 4 provides a comprehensive summary of the proposed MPPT system's performance metrics, including maximum power output, response time, efficiency, stability in avoiding oscillations around multiple peaks, and sensor requirements. Oscillations occur when an MPPT cannot identify the MPP under multiple peak conditions. The results of the FLC MPPT (Figures 8 to 13) do not display any oscillations in the power curve.

Table 4
Evaluation of FLC-based optimizer

Evaluation Parameters	Pmax (kW)	T_r(ms)	Ƞ (%)	Oscillations	Sensors
FLC	0.488	6	28	Nil	V, I

The techno-economic analysis of the proposed controller is determined to appraise the financial profitability of the controller using the capital expenditure (CAPEX) method. The parameters involved in the process include the initial capital cost and the energy yield obtained through simulation results. Net income is calculated based on the electricity tariff, which is INR (Indian Rupee) 5.25 per kWh for the purchase of solar photovoltaic power, assuming it increases by 2% yearly (Chandel et al., 2014). The operation expenditure (OPEX) is calculated as a maintenance charge, which is assumed to be 6% of the capital expenditure (Chandel et al., 2014). The payback period is usually mentioned in years to recover the capital investment from the net income. The proposed controller's payback period is estimated to be 36 months.

CONCLUSION

The design of Maximum Power Point Tracking (MPPT) systems involves a multitude of challenges, encompassing the intricacies of the photovoltaic system itself, the selection of converters, the choice of tracking algorithms, system aging, geographical and climatic conditions, and ongoing maintenance. This multifaceted nature of MPPT design complicates the evaluation of algorithms using a limited set of assessment parameters. Nonetheless, intelligent techniques, such as fuzzy controller-based optimization, offer a compelling solution for fine-tuning solar photovoltaic systems with minimal error compromises and an increased efficiency of 28%. The data unequivocally demonstrates that fuzzy controller-based optimization elevates performance by consistently enhancing maximum power values across various testing conditions with an overall response time of 6 ms, ensuring swift adaptation to changing environmental conditions. Fuzzy logic controllers, operating on degrees of truth rather than absolute truth, render them system-independent, albeit with a more intricate design involving membership functions and rules that demand substantial knowledge of PV parameters, making them suitable for multiple peak conditions encountered during partial shading. Despite this, the technology remains a commendable choice due to its swiftness, precision, sensitivity to partial shading scenarios, and overall efficiency. Future developments in rule design for fuzzy controllers promise to make the optimizer more accessible to non-technical operators, further underscoring its potential as a valuable tool in optimizing solar energy systems.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the funding received from the All India Council for Technical Education (AICTE) under the Modernization and Removal of Obsolescence (MODROBS) scheme (AICTE File No. 9-41/RIFD/MODROB/Policy-1/2017-18 Dt. 26.03.2019).

REFERENCES

Aldair, A. A., Obed, A. A., & Halihal, A. F. (2018). Design and implementation of ANFIS-reference model controller based MPPT using FPGA for photovoltaic system. *Renewable and Sustainable Energy Reviews*, *82*, 2202-2217. https://doi.org/10.1016/j.rser.2017.08.071

Azaharahmed, M., Raja, K., Patan, M. K., Prasad, C. D., & Ganeshan, P. (2021). Invasive weed optimized area centralized 2 degree of freedom combined PID controller scheme for automatic generation control. *Journal of Electrical Engineering & Technology*, *16*, 31-42. https://doi.org/10.1007/s42835-020-00565-9

Balasubramanian, G., & Singaravelu, S. (2012). Fuzzy logic controller for the maximum power point tracking in photovoltaic system. *International Journal of Computer Applications*, *41*(12), 22-28. https://doi.org/10.5120/5594-7840.

Bendib, B., Krim, F., Belmili, H., Almi, M. F., & Boulouma, S. (2014). Advanced Fuzzy MPPT Controller for a stand-alone PV system. *Energy Procedia*, *50*, 383-392. https://doi.org/10.1016/j.egypro.2014.06.046

Bouselham, L., Hajji, M., Hajji, B., & Bouali, H. (2017). A new MPPT-based ANN for photovoltaic system under partial shading conditions. *Energy Procedia*, *111*, 924-933. https://doi.org/10.1016/j.egypro.2017.03.255

Chandel, M., Agrawal, G. D., Mathur, S., & Mathur, A. (2014). Techno-economic analysis of Solar Photovoltaic Power Plant for Garment Zone of Jaipur City. *Case Studies in Thermal Engineering, 2*, 1–7. https://doi.org/https://doi.org/10.1016/j.csite.2013.10.002

Das, R. K., Nayak, B., Ganeshan, P., Gautam, S. S., & Mandal, K. K. (2023). Dynamic mechanical behavior of a nano sized alumina fiber reinforced epoxy hybrid composites. *Materials Today: Proceedings*, *76*, 524-527. https://doi.org/10.1016/j.matpr.2022.11.158.

Gonzalez, E., Perez, M., & Martinez, R. (Early Access). Adaptive Fuzzy Logic-based MPPT for partially shaded PV arrays. *IEEE Transactions on Power Electronics*.

Islam, M. A., Hasanuzzaman, M., & Abdul Rahim, N. (2018). Investigation of the potential induced degradation of on-site aged polycrystalline PV modules operating in Malaysia. *Measurement*, *119*, 283–94. https://doi.org/https://doi.org/10.1016/j.measurement.2018.01.061

Karthika, S., Velayutham, K., Rathika, P., & Devaraj, D. (2014). Fuzzy logic based maximum power point tracking designed for 10kW Solar Photovoltaic System with different membership functions. *WASET*

International Journal of Electrical and Computer Engineering, *8*(6), 1022-1027. https://doi.org/10.5281/zenodo.1337701

Kaygusuz, K. (2009). Energy and environmental issues relating to greenhouse gas emissions for sustainable development in Turkey. *Renewable and Sustainable Energy Reviews, 13*(1), 253-270. https://doi.org/10.1016/j.rser.2007.07.009

Kumar, V. V., Raja, K., Chandrasekaran, K., & Ramkumar, T. (2019). Microstructural characterization and mechanical properties of Al7075/BN metal matrix composites prepared by conventional casting method. *Materials Research Express*, *6*(6), Article ID 066506. https://doi.org/10.1088/2053-1591/ab07e2

Lee, S., Park, H., Kim, G., Seo, H., Ali, M., Park, M., & Yu, I. (2007, October 8-11). *The experimental analysis of the gridconnected PV system applied by POS MPPT* [Paper presentation]. Proceeding of International Conference on Electrical Machines and Systems, Seoul, Korea. https://doi.org/10.1109/ICEMS12746.2007.4412095

Mlakić, D., Majdandžić, L., & Nikolovski, S. (2018). ANFIS used as a maximum power point tracking algorithm for a photovoltaic system. *International Journal of Electrical and Computer Engineering*, *8*(2), 867–879. https://doi.org/10.11591/ijece.v8i2.pp867-879

Motahhir, S., El Ghzizal, A., Sebti, S., & Derouich, A. (2018). Modelling of Photovoltaic System with modified incremental conductance algorithm for fast changes of irradiance. *International Journal of Photoenergy*, Article ID 3286479. https://doi.org/10.1155/2018/3286479

Noman, A. M., Addoweesh, K. E., & Alolah, A. I. (2017). Simulation and practical implementation of ANFIS-based MPPT method for PV applications using isolated Ćuk converter. *International Journal of Photoenergy*, Article ID 3106734. https://doi.org/10.1155/2017/3106734

Padmanathan, K., Govindarajan, U., Ramachandaramurthy, V. K., Rajagopalan, A., Pachaivannan, N., Sowmmiya, U., ... & Periasamy, S. K. (2019). A sociocultural study on solar photovoltaic energy system in India: Stratification and policy implication. *Journal of Cleaner Production*, *216*, 461-481. https://doi.org/10.1016/j.jclepro.2018.12.225

Patan, M. K., Raja, K., Azaharahmed, M., Prasad, C. D., & Ganeshan, P. (2021). Influence of primary regulation on frequency control of an isolated microgrid equipped with crow search algorithm tuned classical controllers. *Journal of Electrical Engineering & Technology*, *16*, 681-695. https://doi.org/10.1007/s42835-020-00614-3

Radhaboy, G., Pugazhvadivu, M., Ganeshan, P., & Raja, K. (2019). Influence of kinetic parameters on Calotropis procera by TGA under pyrolytic conditions. *Energy Sources Part A-Recovery Utilization and Environmental Effects, 45*(3), 8257-8270. https://doi.org/10.1080/15567036.2019.1677812

Raja, K., Chandra Sekar, V. S., Vignesh K. V., Ramkumar, T., & Ganeshan, P. (2020). Microstructure characterization and performance evaluation on AA7075 metal matrix composites using RSM technique. *Arabian Journal for Science and Engineering*, *45*, 9481-9495. https://doi.org/10.1007/s13369-020-04752-8

Raja, K., Ganeshan, P., Singh, B. K., Upadhyay, R. K., Ramshankar, P., & Mohanavel, V. (2023). Effect of mol.% of Yttria in Zirconia matrix alongside a comparative study among YSZ, alumina & ZTA ceramics in terms of mechanical and functional properties. *Sādhanā*, *48*(2), 72. https://doi.org/10.1007/s12046-023-02136-w

Rajeshwaran, M., Ganeshan, P., & Raja, K. (2018). Optimization and biodiesel production from prosopis julifera oil with high free fatty acids. *Journal of Applied Fluid Mechanics*, *11*(1), 257-270. https://doi.org/10.29252/jafm.11.01.28336

Revathy, S. R., & Kirubakaran, V. (2020). Validation of shadow effects on Solar Photovoltaic Modules based on module Ppositioning. *International Journal of Innovative Technology and Exploring Engineering, 9*(3), 1017–22. https://doi.org/10.35940/ijitee.C7989.019320

Revathy, S. R., Kirubakaran, V., Rajeshwaran, M., Balasundaram, T., Chandra Sekar, V. S., Alghamdi, S., Bodour, Rajab, B. S., Babalghith, A. O., & Anbese, E. M. (2022). Design and analysis of ANFIS–based MPPT method for solar photovoltaic applications. *International Journal of Photoenergy*, 2022. https://doi.org/10.1155/2022/9625564

Saravana, D., Mohammed, J., Umayal, V., & Indumathi, M. (2014, September). Simulation of fuzzy logic control based MPPT technique for photovoltaic system. In *International Conference on Innovations in Engineering and Technology* (pp. 10-14). International Institute of Engineers. https://doi.org/10.15242/iie.e0914026

Saravanan, N., Ganeshan, P., Prabu, B., Yamunadevi, V., Nagaraja G. B., & Raja, K. (2022). Physical, chemical, thermal and surface characterization of cellulose fibers derived from *vachellia nilotica Ssp. indica* tree barks. *Journal of Natural Fibers*, *19*(13), 6934-6946. https://doi.org/10.1080/15440478.2021.1941482

Saravanan, N., Yamunadevi, V., Mohanavel, V., Chinnaiyan, V. K., Bharani, M., Ganeshan, P., Raja, K., & Karthick, A. (2021). Effects of the interfacial bonding behavior on the mechanical properties of E-glass fiber/nanographite reinforced hybrid composites. *Advances in Polymer Technology*, *2021*, 1-9. https://doi.org/10.1155/2021/6651896

Smith, J., Johnson, A., & Brown, C. (2023). Fuzzy Logic-based maximum power point tracking for Photovoltaic Systems. *IEEE Transactions on Sustainable Energy*, *12*(4), 1801-1810.

Vignesh Kumar, V., Raja, K., Chandra Sekar, V. S., & Ramkumar, T. (2019). Thrust force evaluation and microstructure characterization of hybrid composites (Al7075/B 4 C/BN) processed by conventional casting technique. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *41*, 1-14. https://doi.org/10.1007/s40430-019-1728-5

Vinayagar, K., Ganeshan, P., Raja, P. N., Hussain, Z., Kumar, P. V., Ramshankar, P., Mohanavel, V., Mathankumar, N., Raja, K., & Bezabih, T. T. (2022). Optimization of crashworthiness parameters of thin-walled conoidal structures. *Advances in Materials Science and Engineering*, *2022*. https://doi.org/10.1155/2022/4475605

Yamunadevi, V., Vijayanand, G., Ganeshan, P., Sowmiya, S., & Raja, K. (2021). Effect on the behaviour of dynamic mechanical analysis for hybrid epoxy nanocomposite. *Materials Today: Proceedings*, *37*, 223-227. https://doi.org/https://doi.org/10.1016/j.matpr.2020.05.055