Support-centric PSO-based fuzzy MPPT tuning for photovoltaic systems under uniform conditions

Amel Smaili, El-Ghalia Boudissa, M'hamed Bounekhla
Laboratory of Electrical Systems and Control LABSET, Saad Dahlab University, Blida, Algeria

Article Info

Article history:

Received Apr 30, 2025
Revised Oct 4, 2025
Accepted Oct 17, 2025

Keywords:

Fuzzy logic control
Membership functions
Particle swarm optimization
Perturb and observe
Photovoltaic system
PSO-optimized FLC

ABSTRACT

Several conventional maximum power point tracking (MPPT) algorithms have been applied to harvest the optimal power of a photovoltaic (PV) system. However, the main drawbacks of these algorithms are their fluctuations around the maximum power point (MPP) and their dependence on climatic conditions variation. To overcome these issues, a fuzzy logic controller (FLC) is proposed, where the system performance depends strongly on the choice of membership functions (MFs). They are typically selected by trial and error, which may not always yield the best results. This paper seeks to enhance the efficiency of the traditional FLC method by using the particle swarm optimization (PSO) algorithm for optimizing the supports of the triangular MFs. The simulation was performed using MATLAB-Simulink environment using the "1Soltech 1STH-215-P" PV module and a single-ended primary-inductor converter (SEPIC) converter, under ideal environmental conditions of 25 °C and 1000 W/m². A comparison is established between PSO-optimized FLC and the standard FLC-based MPPT method, as well as with several other state-of-the-art approaches reported in related research. The simulation data present that the PSO-optimized FLC approach outperforms other algorithms.

Corresponding Author:

Amel Smaili
Laboratory of Electrical Systems and Control LABSET, Saad Dahlab University
Blida, Algeria
Email: smailiamel775@gmail.com

1. INTRODUCTION

The rise in global energy demand and the heavy pollution of the ecosystem are leading the world to adopt more sustainable energies. Solar energy technologies, photovoltaic (PV) systems, stand out for their abundance and environmental benefits, as they directly convert solar energy into electricity using PV panels [1]. However, the effective performance of these systems relies on many aspects, such as the chosen load [2]. To achieve their maximum efficiency regardless of these aspects, several maximum power point tracking (MPPT) control approaches such as perturb and observe (P&O) [3], [4], constant voltage tracing (CVT), incremental conductance algorithm (ICA) [5], [6], and curve fitting method [7], [8] have been implemented. Among these, Bhatnagar and Nema [8] presented the P&O approach. This method is widely used for its straightforward implementation and effectiveness. Still, it will suffer from oscillations around the maximum power point (MPP) due to the selected step size, leading to energy loss [9]. To address this issue, the fuzzy logic control (FLC) approach has been introduced. Previous studies, such as those by Samosir *et al.* [10] and Kandemir *et al.* [11], have proved the effectiveness of FLC in tracking the MPP. Samosir *et al.* [10] highlighted its capacity and efficiency to track the MPP. Kandemir *et al.* [11] conducted a comparative study, and they demonstrated that the tracking accuracy performance increased by 0.13% compared to the P&O method. Anwer *et al.* [12] applied FLC for the permanent magnet synchronous motor (PMSM) drive system.

They utilized the FLC to extract the maximum power from the PV modules that supply the PMSM drive system. The system was modeled in the MATLAB/Simulink environment. Despite this, the performance of FLC relies on certain membership functions' parameters, such as shape, number, cores, and support, which are generally chosen through experimentation. Therefore, an inaccurate selection of membership functions will prevent achieving optimal results.

Researchers have addressed this challenge by using metaheuristic methods [13], such as genetic algorithm (GA) [14], particle swarm optimization (PSO) [15], and ant colony optimization (ACO) [16]. Those methods will optimize the membership functions, leading to improved adaptability and efficiency of the MPPT, and better control of the overall decision-making process of the control system. Nikolic *et al.* [17] and Larbes *et al.* [18] applied the bee colony optimization and genetics algorithm, respectively, to tune the fuzzy membership functions, demonstrating improved FLC performance in MPPT applications. Building on this, the particle swarm optimization (PSO) algorithm offers another powerful optimization technique, providing significant improvements for optimizing membership functions in FLC.

As highlighted by Marini and Walczak [19], inspired by the behavior of certain group-living animals, such as fish and birds, the PSO algorithm utilizes a swarm of individuals to reach the optimal solution. They perform elementary tasks and interact with one another locally, and with their environment, all without central control. The global behavior of the group results from these local interactions and auto-organization. Even though the agents may be limited in their capabilities, their effectiveness in reaching the ultimate objective of problem-solving is guaranteed by their ability to share information and interact with each other [19]. Cheng *et al.* [20] followed a similar approach to this study, where they focused on optimizing a fuzzy-logic-based MPPT algorithm using the particle swarm optimization (PSO) technique. They applied a symmetrical FLC structure, which was later optimized into an asymmetrical FLC, achieving a maximum efficiency of 99.19%.

Pardeshi and Patil [21], adjusted the artificial neural network (ANN) framework using the PSO for photovoltaic solar systems. They conducted comparative simulations between the PSO-based ANN, FLC, and the P&O method using real-time data under different climatic conditions. The results reveal that their suggested approach achieved the greatest levels of efficiency, with a value of 99.6% in clear conditions. Kumar *et al.* [22] proposed a novel hybrid MPPT approach for solar PV systems that combines particle swarm optimization-trained machine learning with flying squirrel search optimization to enhance system efficiency. The method was tested in MATLAB/Simulink under various environmental conditions, including ideal ones. Their results, compared to several existing techniques from the literature, showed that the proposed approach improved efficiency by 0.72%.

In order to maximize the energy production of PV panels and improve their efficiency, this paper proposes to improve the FLC approach by leveraging PSO to optimize the membership function supports, with the aim of maximizing the energy production of PV panels and improving their efficiency. To examine the proposed approach and ascertain its effectiveness, the behavior of the 1Soltech 1STH-215-P” PV module was simulated in the MATLAB-Simulink environment under ideal environmental conditions of 25 °C and 1000 W/m². This enabled a comparative evaluation between the performance of conventional FLC and that of PSO-optimized FLC, where a notable improvement in efficiency was achieved.

2. METHOD

2.1. Exploring MPPT: “principle and design”

According to the V-I characteristics, there is one singular voltage value that aligns with the MPP. Any rise in load resistance leads the PV module to function at higher voltages than the MPP, resulting in a drop in the current and vice versa, as shown in Figure 1. This indicates that a direct connection between the PV panel and the load may prevent the PV module from operating at its MPP, and it is going to be forced to operate at voltages closer to the load impedance [23].

To reach the MPP, a matching stage DC-DC single-ended primary-inductor converter (SEPIC) converter with the parameters listed in Table 1 was added to link the PV module and the load, as illustrated in Figure 2. This ensures the match between the load resistance and the impedance seen by the PV module. An MPPT algorithm will be used to control the converter and to monitor the duty cycle D, optimizing its value with each change in environmental conditions.

2.2. MPPT-based fuzzy logic control

The FLC does not require a mathematical model. It is based on current–voltage input variables, which are read from the PV panel to determine the power output. The system consists of three main elements: fuzzification, fuzzy inference, and defuzzification, as shown in Figure 3.

2.2.1. Fuzzification

It requires identifying the input and the output variables to be fuzzified as a first step. For a PV system, voltage variation (ΔV), current variations (ΔI), power variations (ΔP), error variations, and errors ... can be used as input variables, and the duty cycle as an output variable. In this paper, the error variation (ΔE) and the error (E) are the inputs, whereas the duty cycle ratio variation (D) is the output of the fuzzy controller. Those variables are calculated by (1) and (2) [10]. The Mamdani method enables the variables' fuzzification.

$$E = \Delta P/\Delta V = (P(n) - P(n-1))/(V(n) - V(n-1) \tag{1}$$

$$\Delta E = E(n) - E(n-1) \tag{2}$$

With:
- "P(n)": The current power measured from the PV system;
- "P(n-1)": The power measured in the previous time step;
- "V(n)": The current voltage from the PV system;
- "V(n-1)": The voltage in the previous time step; and
- "E(n)": The error calculated at the current time step. "E(n-1)": "The error from the previous time step.

2.2.2. Inference system

To establish a link between the output and input variables, a set of rules must be defined based on experimentation and observation. In this paper, these rules are used to increase or decrease the duty cycle [10]. The complete set of rules is presented in Table 2 [24].

2.2.3. Defuzzification

It represents the reverse process of fuzzification. The operation is carried out using the fuzzy centroid method, which calculates the centroid after rule aggregation. The fuzzy MPPT control is implemented using the MPPT algorithm shown in Figure 4.

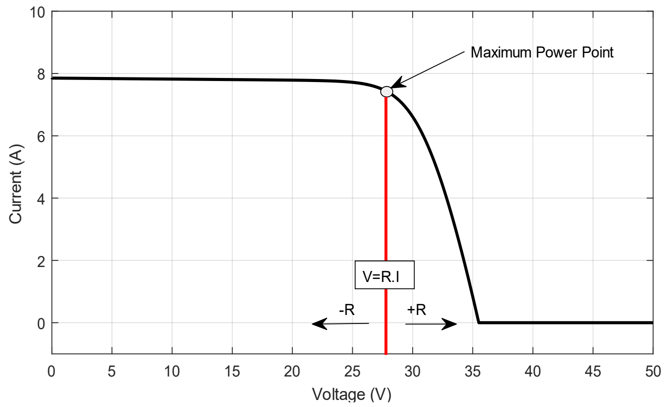


Figure 1. V-I characteristics

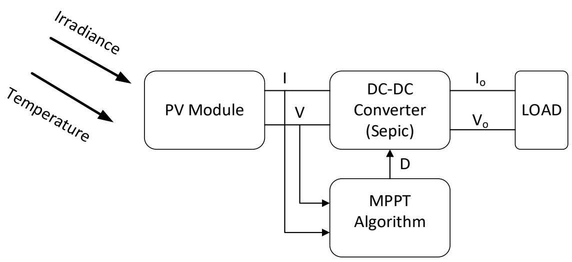


Figure 2. PV system block diagram

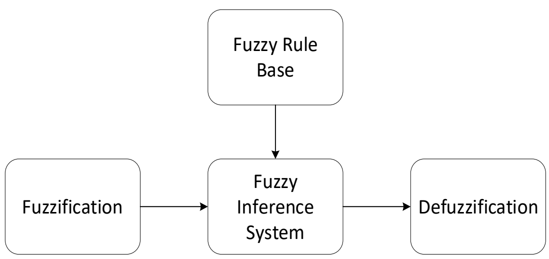


Figure 3. Structure of fuzzy logic controller

Table 1. Parameters of the SEPIC converter

Parameter	Value	Parameter	Value
C_in	5e-5	L1	100e-3
C1	5e-5	L2	400e-3
C2	10e-5	R	10

Table 2. Inference rules

ΔE/E	NS	NL	ZE	PL	PS
NS	PS	PS	PL	PS	PS
NL	PS	PL	PL	PL	PS
ZE	NL	NL	ZE	PL	PL
PL	NS	NL	NL	NL	NS
PS	NS	NS	NL	NS	NS

2.3. Fuzzy logic controller optimized by the PSO algorithm

As already mentioned within the first section, the PSO algorithm is an algorithm that reproduces the behavior observed in animal groups such as birds and fish [25]. It operates with 3 key components, which are:

- The particle: an individual entity such as a single bird.
- The swarm: refers to the population of particles moving together, akin to the collective movement of a flock [26].
- The solution: This represents the targeted outcome of the optimization process, in the same way as the search for a source of food for birds [26].

Each particle has its position and velocity, which guide its movement toward the optimal solution [25], [26]. Particles cooperate by exchanging the knowledge they have gathered during the exploration process. They maintain two important positions [26]:

- Personal Best (pbest) position: This represents the best position a particle has achieved based on its personal past experiences.
- Global Best (gbest) position: This signifies the best position discovered by any particle in the entire swarm, providing a shared target for all the particles.

By exchanging information, the particles update their positions and velocities iteratively and converge collectively toward the optimal solution [25]. The flowchart shown in Figure 5 will provide a more detailed overview of the PSO algorithm.

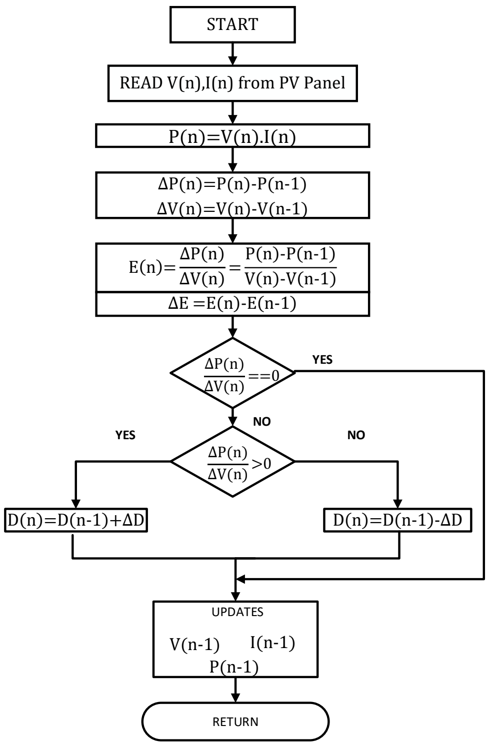


Figure 4. MPPT algorithm

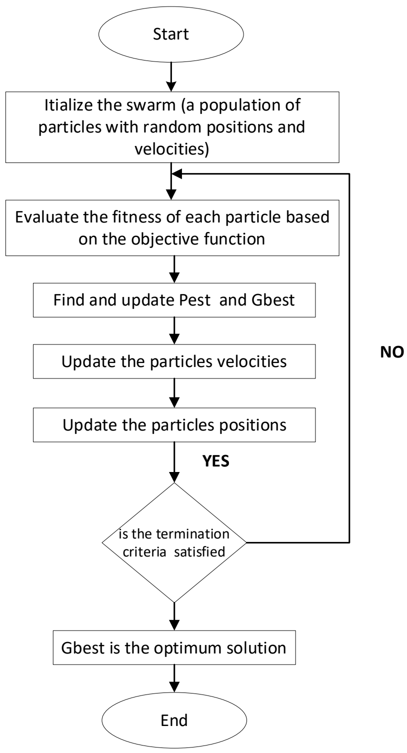


Figure 5. Particle swarm optimization algorithm

2.3.1. Optimization of membership functions using PSO

To improve the FLC and overcome the drawbacks experienced during the initial implementation, the support of the membership function for both inputs and outputs will be optimized. Each variable is described by 5 membership functions. By maintaining the peaks fixed and focusing on optimizing the supports of each membership function, 30 supports S1 to S30 have been optimized as illustrated in Figure 6.

a) Creation of the initial population

As presented in the flowchart depicted in Figure 5, the first step consists of creating a population. The maximum and minimum values for each parameter are defined, followed by the generation of a swarm (population) of 300 particles randomly. Each particle within the swarm will be represented by a vector of 30 elements, corresponding to the supports being optimized.

b) Fitness evaluation

This is a crucial step in the PSO algorithm, which will evaluate the efficiency of every generated particle in achieving the optimal solution. This evaluation will be performed by using the objective function, which is the mean squared error of the power as in (3).

$$fit = \frac{1}{n}\sum_{i=1}^{n}(P_{max} - P_{cc})^2 \quad (3)$$

Where "P_{max}", "P_{cc}", "n" represent maximum power, calculated power and the amount of data.

c) Update the pbest and gbest

The fitness particle values will be ranked from the best to the worst to determine the "pbest" position and the "gbest" position. If the newest fitness value is higher than the previous value, the particle updates its personal best "pbest". The particle with the highest performance in the group "best fitness value" takes on the status of the global best "gbest".

d) Update the velocity and position of particles

The velocity and the position will be updated by using (4) and (5), respectively.

$$v(t+1) = c_1 v(t) + c_2\big(pbest - x(t)\big)rand_1 + c_3\big(gbest - x(t)\big)rand_2 \quad (4)$$

$$x(t+1) = x(t) + v(t+1) \quad (5)$$

Where: i) "v(t+1)" and "v(t)" are the actual and the previous velocities; ii) "x(t+1)" and "x(t)" are the actual and the previous positions; and iii) "c_1" is the inertia weight, "c_2" is the cognitive coefficient and "c_3" is the social coefficient. "$rand_1$" and "$rand_2$" are two diagonal matrices of random elements that belong to the [0,1] interval. The PSO parameters used in this paper are presented in Table 3.

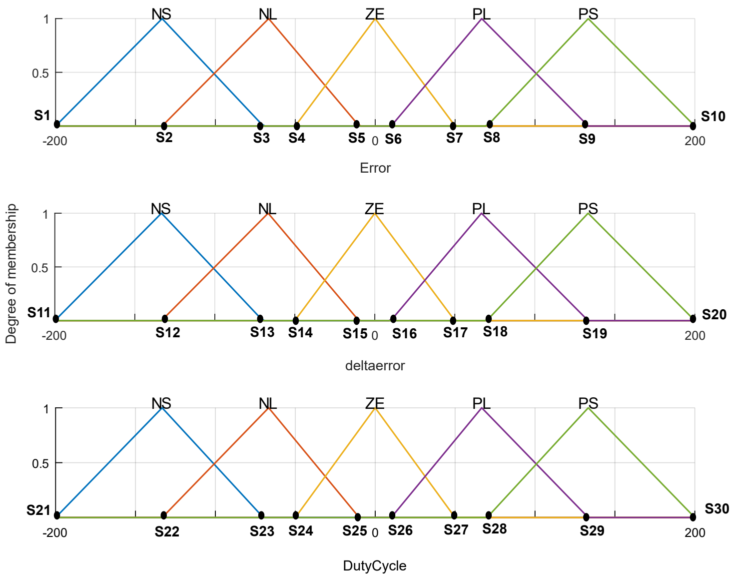


Figure 6. Membership functions support

Table 3. Control parameters vector for PSO

Algorithm	Control parameters vector	Value
PSO	Population size	300
	Inertia weight (C1)	1.5
	Acceleration constant (cognitive parameter) (C2)	2.5
	Acceleration constant (social parameter) (C3)	1.43

3. RESULTS AND DISCUSSIONS

This section presents the obtained results simulation using MATLAB/Simulink. The simulations were executed to assess the overall efficiency of the fuzzy MPPT algorithm and to analyze the impact of optimization using the PSO algorithm. An overview of the overall Simulink model of the PV system, which contains a PV array, the SEPIC converter, and the FLC block, can be viewed in Figure 7. Figure 8 depicts a detailed view of the elements composing the FLC block. To carry out the simulation. A “1Soltech 1STH-215-P” PV module was used under ideal environmental conditions of 25°C and 1000 W/m². Two different membership function configurations are simulated to evaluate the algorithm's effectiveness of their optimization and enhancing the system’s efficiency. The difference between the three configurations lies in the supports and the cores chosen for each membership function.

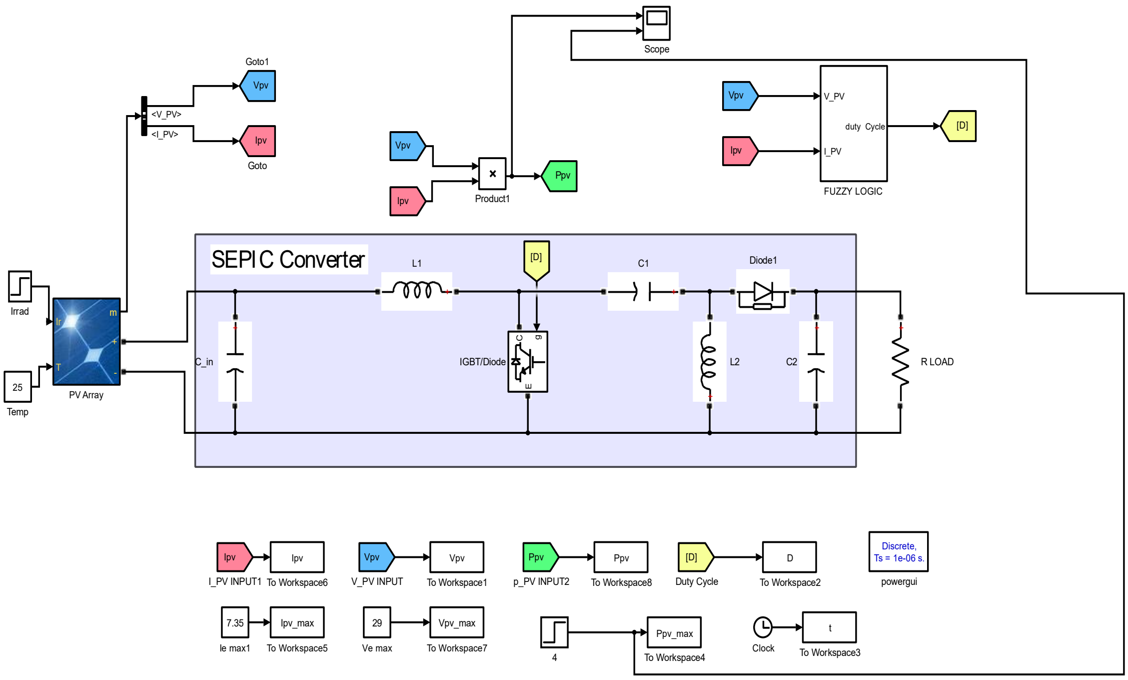


Figure 7. Simulink model of PV system

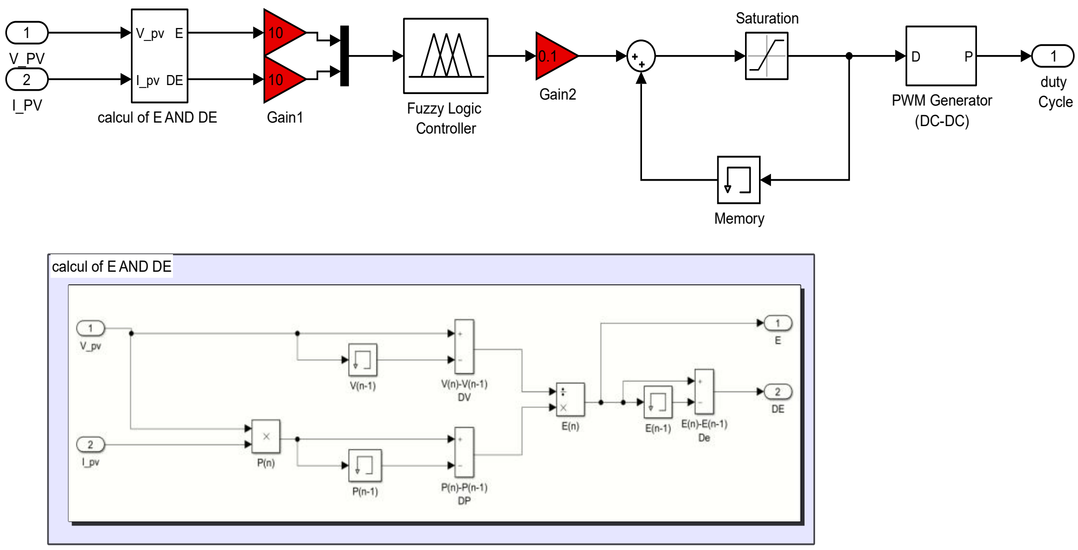


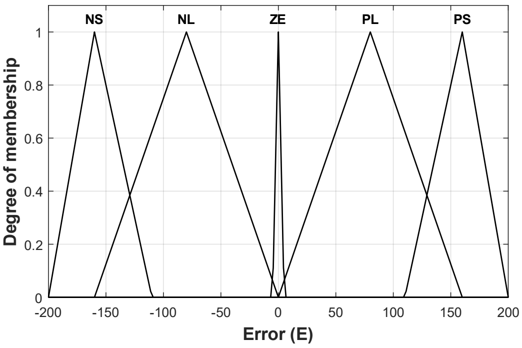
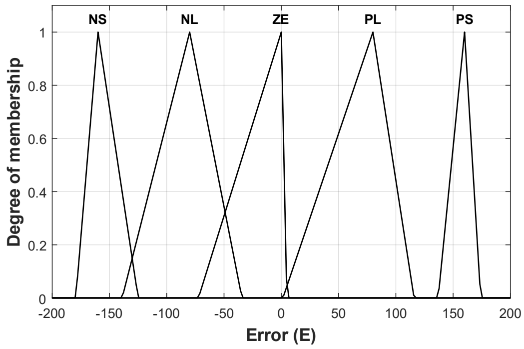
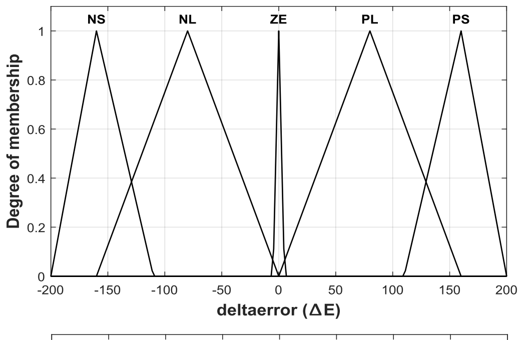
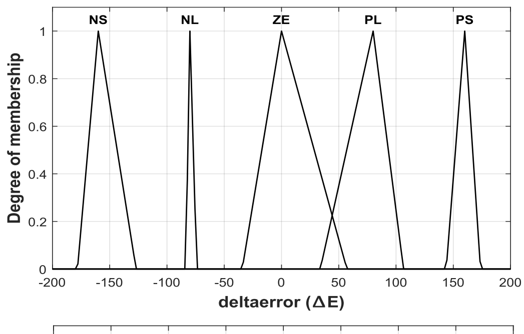
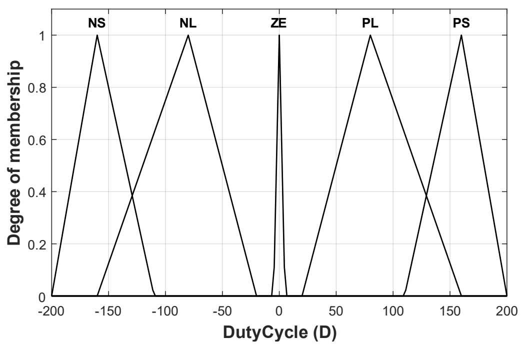
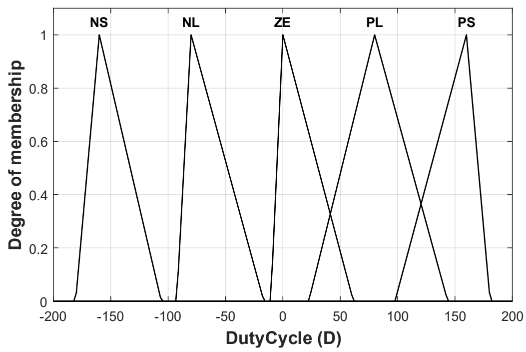
Figure 8. Fuzzy MPPT algorithm block

From the simulation data shown in Table 4, Figure 9, and Table 5, Figure 10 for configurations 1 and 2, respectively, it's clear that:

- For the 1st configuration, the system before optimization achieved a commendable efficiency of approximately 99.56%. However, the application of the PSO algorithm further improved this efficiency, reaching 99.63%. The Power Response highlights that after optimization, the fluctuations around the MPP are slightly reduced.
- For the 2nd configuration, we can clearly see that the efficiency before optimization is around 98.93%, which is satisfactory but not optimal. After optimizing the membership functions, the efficiency value was improved to around 99.67%, a highly favourable outcome.
- The fluctuations in the power response were significantly reduced after optimization.
- For both configurations, the PSO algorithm successfully optimized the membership functions, enabling the system to operate at a higher efficiency value compared to the results obtained before optimization.

In configuration 3, the fuzzy membership function was purposely set to be poorly configured to see if the optimization process could improve it. In consideration of the results presented in Table 6 and Figure 11, the initial system performed poorly, with an accuracy of around 1.8109%, confirming that it wasn't effective. After applying the optimization, the performance improved significantly to 99.7698 %, demonstrating the robustness and the corrective capacity of the proposed method. Table 7 presents a comparison between the proposed method applied to the different configurations and the existing works in the literature. As illustrated in Table 7, the FLC-PSO method developed in this study outperforms the configurations presented in the literature, achieving higher efficiency values across all tested cases.

Table 4. Inputs and output membership functions and efficiency before and after optimization for configuration 1

Parameters	Before optimization	After optimization
Input 1		
Input 2		
Output		
Efficiency	99.5550	99.6299

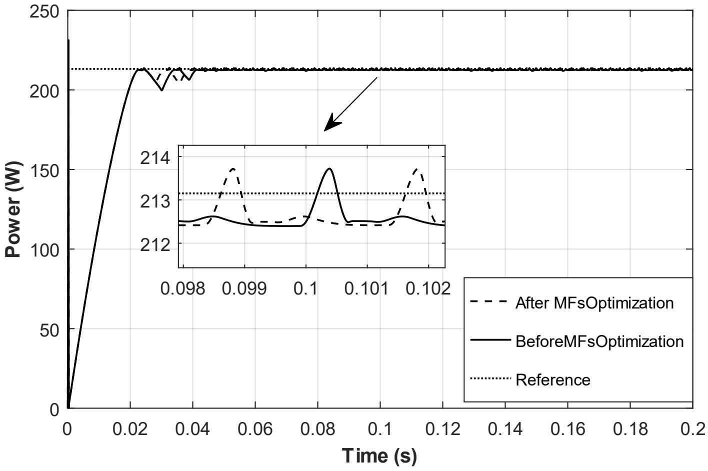
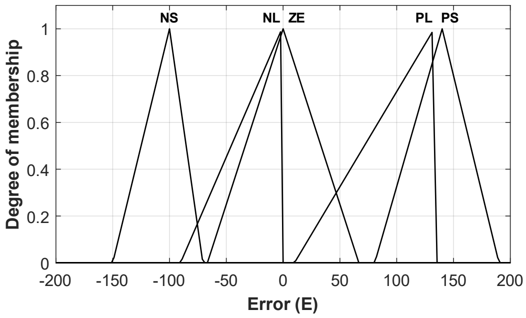
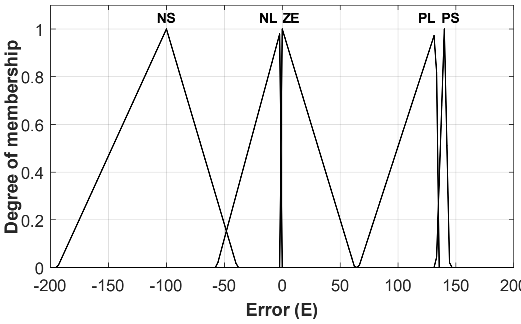
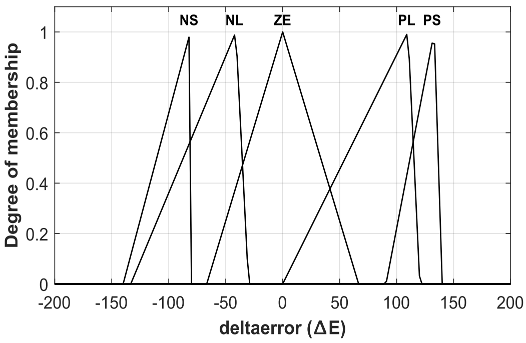
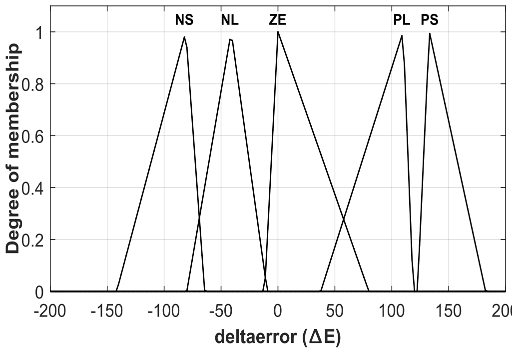
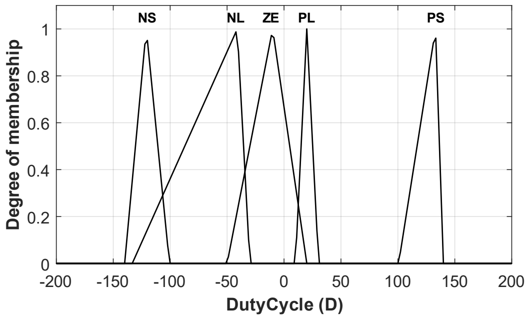
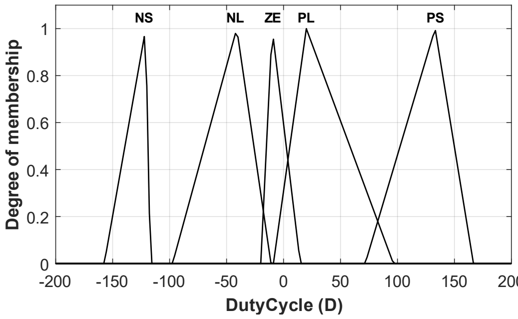


Figure 9. Power response comparison before and after optimization of membership functions with PSO for configuration 1

Table 5. Inputs and output membership functions and efficiency before and after optimization for configuration 2

Parameters	Before optimization	After optimization
Input 1		
Input 2		
Output		
Efficiency	98.9326	99.6729

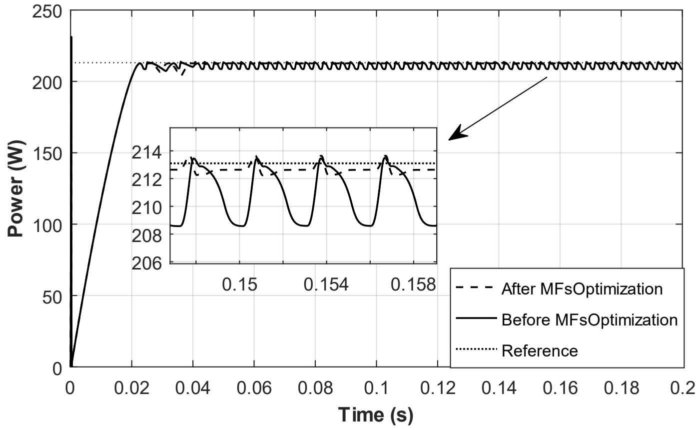
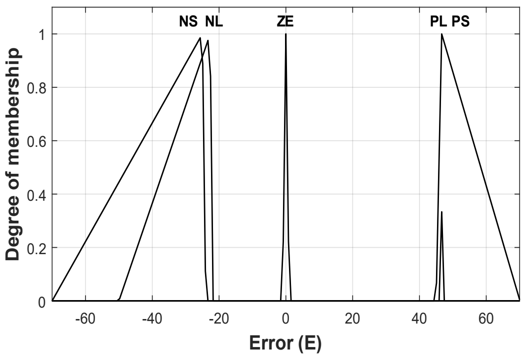
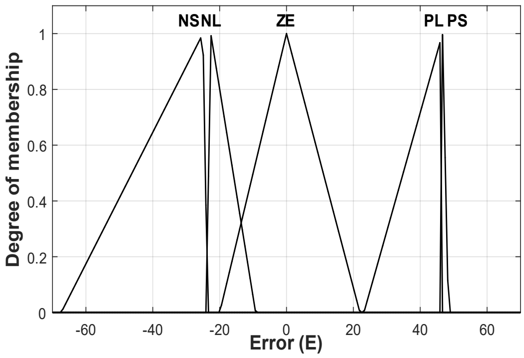
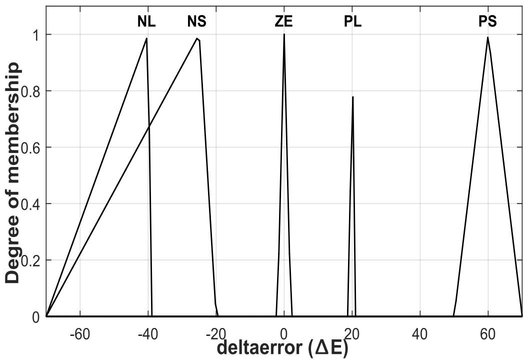
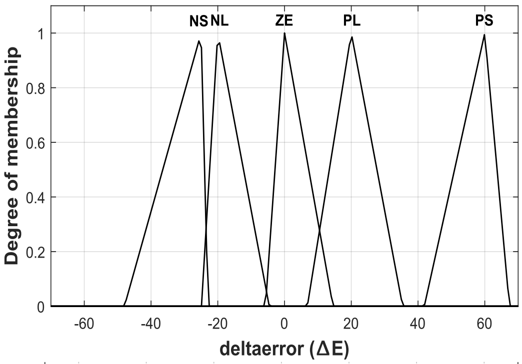
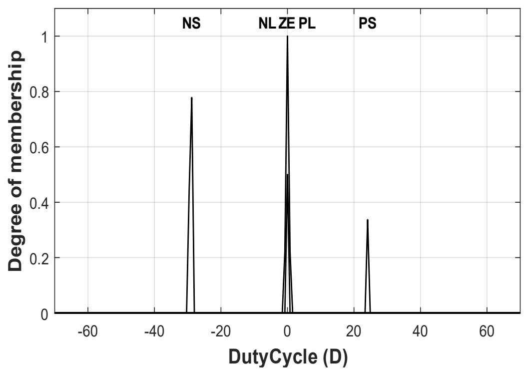
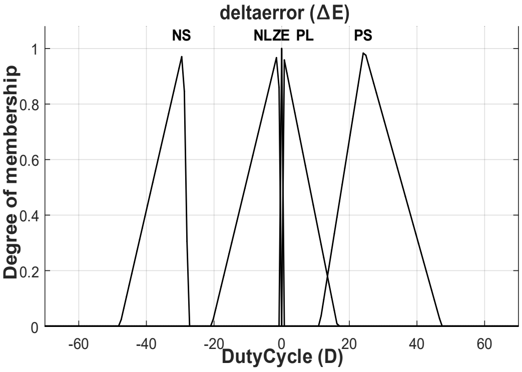


Figure 10. Power response comparison before and after optimization of membership functions with PSO for configuration 2

Table 6. Inputs and output membership functions and efficiency before and after optimization for configuration 3

Parameters	Before optimization	After optimization
Input 1		
Input 2		
Output		
Efficiency	1.8109	99.7698

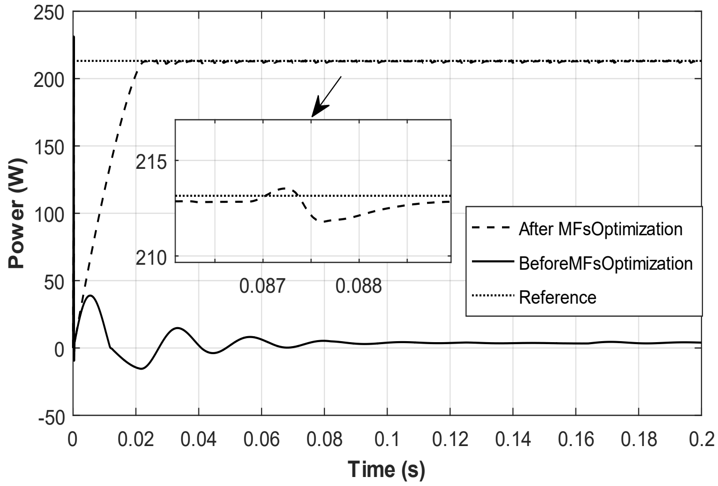


Figure 11. Power response comparison before and after optimization of membership functions with PSO for configuration 3

Table 7. Performance comparison between the proposed method and existing approaches

References	Method	Efficiency value
This paper	FLC-PSO C1	99.6299%
	FLC-PSO C2	99.6729%
	FLC-PSO C3	99.7698%
[20]	P&O (0.5 V)	99.16%
	P&O (3.5 V)	94.89%
	Symmetrical FLC	98.21%
	Asymmetrical FLC #1	98.26%
	Asymmetrical FLC #2	99.19%
[27]	P&O	84.99%
	FLC	95.65%
	PSO-based FLC	96.5%
[22]	PSO_ML-FSSO	99.601%

4. CONCLUSION

For the purpose of improving the effectiveness of the FLC method, an implementation of the PSO algorithm in conjunction with the FLC approach was suggested in this paper. A simulation in MATLAB Simulink was carried out using the "1Soltech 1STH-215-P" PV module, comparing the traditional FLC method with the PSO-optimized FLC. Three different membership function configurations were tested, where the supports of each membership function were optimized using the PSO algorithm. The results demonstrate that the PSO-optimized FLC method has substantially outperformed the traditional approach, providing closer adherence to the desired reference power value, regardless of the configuration used.

Configuration 3 highlights an important aspect of fuzzy system design: where initial membership functions are often selected based on experimentation, which can lead to poor system behavior. The result of this configuration demonstrates how the proposed optimization method can effectively refine the membership parameters and improve the efficiency from 1.8109% to 99.7698%, thereby improving performance without the need for expert intervention or manual tuning. Compared to recent MPPT techniques found in the literature, the proposed method has achieved superior performance in terms of tracking efficiency, making it effective and robust under the tested conditions.

FUNDING INFORMATION

The authors declare that no funding was received to support this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Amel Smaili	✓	✓	✓	✓	✓				✓	✓				
El-Ghalia Boudissa	✓				✓					✓		✓		
M'hamed Bounekhla	✓		✓			✓				✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [AS], upon reasonable request.

REFERENCES

[1] N. Kannan and D. Vakeesan, "Solar energy for future world: - A review," *Renewable and Sustainable Energy Reviews*, vol. 62, pp. 1092–1105, Sep. 2016, doi: 10.1016/j.rser.2016.05.022.

[2] M. Taherbaneh, A. H. Rezaie, H. Ghafoorifard, K. Rahimi, and M. B. Menhaj, "Maximizing output power of a solar panel via combination of sun tracking and maximum power point tracking by fuzzy controllers," *International Journal of Photoenergy*, vol. 2010, pp. 1–13, 2010, doi: 10.1155/2010/312580.

[3] A. Ghayth, Z. Yusupov, and M. Khaleel, "Performance enhancement of PV array utilizing perturb & observe algorithm," *International Journal of Electrical Engineering and Sustainability (IJEES)*, vol. 1, no. 2, pp. 29–37, 2023, [Online]. Available: https://ijees.org/index.php/ijees/index

[4] H. H. H. Mousa, A.-R. Youssef, and E. E. M. Mohamed, "State of the art perturb and observe MPPT algorithms based wind energy conversion systems: A technology review," *International Journal of Electrical Power & Energy Systems*, vol. 126, p. 106598, Mar. 2021, doi: 10.1016/j.ijepes.2020.106598..

[5] H. Hasan, A. Lubis, and T. Y. Arif, "Application and analysis of incremental conductance algorithm for a photovoltaic system with variable DC output voltage," in *2021 International Conference on Computer System, Information Technology, and Electrical Engineering (COSITE)*, IEEE, Oct. 2021, pp. 124–128. doi: 10.1109/COSITE52651.2021.9649621.

[6] V. K. P K and J. J J, "Implementation of incremental conductance MPPT algorithm for the performance enhancement of hybrid power generation systems," in *2023 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER)*, IEEE, Oct. 2023, pp. 96–100. doi: 10.1109/DISCOVER58830.2023.10316692.

[7] W. Xie and J. Hui, "MPPT for PV system based on a novel fuzzy control strategy," in *2010 International Conference on Digital Manufacturing & Automation*, IEEE, Dec. 2010, pp. 960–963. doi: 10.1109/ICDMA.2010.410.

[8] P. Bhatnagar and R. K. Nema, "Maximum power point tracking control techniques: State-of-the-art in photovoltaic applications," *Renewable and Sustainable Energy Reviews*, vol. 23, pp. 224–241, Jul. 2013, doi: 10.1016/j.rser.2013.02.011.

[9] D. Sera, T. Kerekes, R. Teodorescu, and F. Blaabjerg, "Improved MPPT method for rapidly changing environmental conditions," in *2006 IEEE International Symposium on Industrial Electronics*, IEEE, Jul. 2006, pp. 1420–1425. doi: 10.1109/ISIE.2006.295680.

[10] A. S. Samosir, H. Gusmedi, S. Purwiyanti, and E. Komalasari, "Modeling and simulation of fuzzy logic based maximum power point tracking (MPPT) for PV application," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 8, no. 3, p. 1315, Jun. 2018, doi: 10.11591/ijece.v8i3.pp1315-1323.

[11] E. Kandemir, N. S. Cetin, and S. Borekci, "A comparison of perturb & observe and fuzzy-logic based MPPT methods for uniform environment conditions," *Periodicals of Engineering and Natural Sciences (PEN)*, vol. 5, no. 1, Mar. 2017, doi: 10.21533/pen.v5i1.67.

[12] A. M. O. Anwer, F. A. Omar, and A. A. Kulaksiz, "Design of a fuzzy logic-based MPPT controller for a PV system employing sensorless control of MRAS-based PMSM," *International Journal of Control, Automation and Systems*, vol. 18, no. 11, pp. 2788–2797, Nov. 2020, doi: 10.1007/s12555-019-0512-8.

[13] V. Tomar, M. Bansal, and P. Singh, "Metaheuristic algorithms for optimization: a brief review," in *Engineering Proceedings*, Basel Switzerland: MDPI, Mar. 2024, p. 238. doi: 10.3390/engproc2023059238.

[14] B. Alhijawi and A. Awajan, "Genetic algorithms: theory, genetic operators, solutions, and applications," *Evolutionary Intelligence*, vol. 17, no. 3, pp. 1245–1256, Jun. 2024, doi: 10.1007/s12065-023-00822-6.

[15] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle swarm optimization: a comprehensive survey," *IEEE Access*, vol. 10, pp. 10031–10061, 2022, doi: 10.1109/ACCESS.2022.3142859.

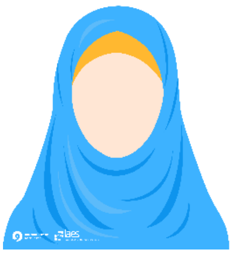
[16] N. Nayar, S. Gautam, P. Singh, and G. Mehta, "Ant colony optimization: a review of literature and application in feature selection," in *Inventive Computation and Information Technologies*, 2021, pp. 285–297. doi: 10.1007/978-981-33-4305-4_22.

[17] M. Nikolić, M. Šelmić, D. Macura, and J. Ćalić, "Bee colony optimization metaheuristic for fuzzy membership functions tuning," *Expert Systems with Applications*, vol. 158, p. 113601, Nov. 2020, doi: 10.1016/j.eswa.2020.113601.

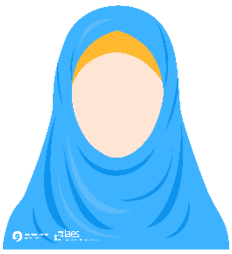
[18] C. Larbes, S. M. Aït Cheikh, T. Obeidi, and A. Zerguerras, "Genetic algorithms optimized fuzzy logic control for the maximum power point tracking in photovoltaic system," *Renewable Energy*, vol. 34, no. 10, pp. 2093–2100, Oct. 2009, doi: 10.1016/j.renene.2009.01.006.

[19] F. Marini and B. Walczak, “Particle swarm optimization (PSO). A tutorial,” *Chemometrics and Intelligent Laboratory Systems*, vol. 149, pp. 153–165, Dec. 2015, doi: 10.1016/j.chemolab.2015.08.020.
[20] P.-C. Cheng, B.-R. Peng, Y.-H. Liu, Y.-S. Cheng, and J.-W. Huang, “Optimization of a fuzzy-logic-control-based MPPT algorithm using the particle swarm optimization technique,” *Energies*, vol. 8, no. 6, pp. 5338–5360, Jun. 2015, doi: 10.3390/en8065338.
[21] N. M. Pardeshi and S. Patil, “PSO based artificial neural network with metaheuristic tuning for enhanced maximum power point prediction in photovoltaic systems solar PV array,” *International Journal of Scientific Development and Research (IJSDR)*, vol. 10, no. 3, pp. 3–8, 2025, [Online]. Available: https://ijsdr.org/papers/IJSDR2503202.pdf
[22] D. Kumar *et al.*, “A novel hybrid MPPT approach for solar PV systems using particle-swarm-optimization-trained machine learning and flying squirrel search optimization,” *Sustainability*, vol. 15, no. 6, p. 5575, Mar. 2023, doi: 10.3390/su15065575.
[23] R. T. Moyo, P. Y. Tabakov, and S. Moyo, “The efficacy of the maximum power transfer theorem in improving the efficiency of photovoltaic modules: a review,” in *Southern African Solar Energy Conference (SASEC 2019)*, 2020.
[24] S. Blaifi, S. Moulahoum, B. Taghezouit, and A. Saim, “An enhanced dynamic modeling of PV module using Levenberg-Marquardt algorithm,” *Renewable Energy*, vol. 135, pp. 745–760, May 2019, doi: 10.1016/j.renene.2018.12.054.
[25] D. Wang, D. Tan, and L. Liu, “Particle swarm optimization algorithm: an overview,” *Soft Computing*, vol. 22, no. 2, pp. 387–408, Jan. 2018, doi: 10.1007/s00500-016-2474-6.
[26] M. A. El-Shorbagy and A. E. Hassanien, “Particle swarm optimization from theory to applications,” *International Journal of Rough Sets and Data Analysis*, vol. 5, no. 2, pp. 1–24, Apr. 2018, doi: 10.4018/IJRSDA.2018040101.
[27] T. T. Jara, A. O. Salau, E. D. Markus, C. O. Omeje, and T. T. Tin, “Optimization of a fuzzy-based MPPT controller for a PV water pumping system through a PSO-based approach,” *Mathematical Modelling of Engineering Problems*, vol. 11, no. 9, pp. 2418–2424, Sep. 2024, doi: 10.18280/mmep.110914.

BIOGRAPHIES OF AUTHORS



Amel Smaili is a Ph.D. student at the University Saad Dahleb of Blida 1, Algeria. She is a member of the SET Laboratory, where her work focuses on advanced control techniques for photovoltaic energy systems. She earned her Master’s degree in Electronic Systems from the University of Science and Technology Houari Boumediene (USTHB), Algiers, graduating top of her class with honors. Her doctoral research centers on the development of maximum power point tracking (MPPT) control strategies based on metaheuristic algorithms. She can be contacted at email: smailiamel775@gmail.com.



El-Ghalia Boudissa is a lecturer at the University Saad Dahleb of Blida1, Algeria. She is a member of the ECME team, working on electrical machine control in the SET Laboratory. She received the electronic engineering degree from the University of Blida, Algeria in 1991, the master’s degree in control from the University of Tizi Ouzou, Algeria in 2000, and the Ph.D. degree in control from the University of Blida, Algeria in 2013. Her main research activities deal with non-linear systems, identification and optimization by metaheuristics with applications to induction machines, synchronous machines, automatic voltage regulators and photovoltaic systems. She can be contacted at email: boudissaelg@yahoo.fr.

M’hamed Bounekhla is a member of the ECME team working on electrical machine control in the SET laboratory at the University Saad Dahleb of Blida (USDB), Algeria. He received the electromechanical engineering degree from ENITA Bordj el Bahri, Algeria in 1979, the master’s degree in electrical machine from the national polytechnic school of Algiers (ENPA), Algeria in 1991, and the Ph.D. degree in electrical machine from the national polytechnic school of Algiers (ENPA), Algeria in 2004. His main research interests include nonlinear systems, optimization and identification with application to induction machines.He can be contacted at email: bounekhla.mhamed@yahoo.fr.