PSO-OPTIMIZED FUZZY LOGIC CONTROLLER FOR ROBUST VOLTAGE REGULATION IN PHOTOVOLTAIC CONVERTER

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ABSTRACT

The nonlinear characteristics of Photovoltaic (PV) systems and the switched-mode operation of the boost converter limit the performance of conventional control methods. This study addresses the development of a Particle Swarm Optimization (PSO) based Fuzzy Logic Controller (FLC) to achieve a stable output voltage in PV power conversion systems despite varying load and input voltage conditions. The parameters of the fuzzy set membership functions (MF), which directly affect controller performance, were dynamically optimized using the PSO algorithm. The proposed method was evaluated on a PV boost converter system modeled in MATLAB/Simulink under nominal operation, dynamic load, and input-voltage change scenarios. The controller's resistance to disturbances was analyzed under conditions of an approximately 32% drop in input voltage and a 43% change in load. The system's performance was analyzed against classical tuned FLC using critical metrics such as RMSE, MAE, rise time (t_r), and settling time (t_S). The simulation results obtained demonstrate that PSO-BMD outperforms the classical architecture in all scenarios. In particular, a 63% improvement in RMSE was achieved; the rise time was reduced from 0.323 seconds to 0.03 seconds, thereby increasing the system's dynamic response speed by approximately 10 times.

Keywords: Photovoltaic Systems, Boost Converter, Fuzzy Logic Controller, Particle Swarm Optimization.

1. INTRODUCTION

Global warming and the rapid depletion of fossil fuel reserves are driving the energy sector toward sustainable solutions that are at the heart of modern grids and have the potential to reduce the carbon footprint. In this context, renewable systems such as solar photovoltaics (PV) are emerging as key players in the fight against climate change due to their minimal freshwater consumption and carbon-free nature. Among these sources, PV systems stand out in the transition to sustainable energy due to their advantages, such as ease of installation, low maintenance costs, no fuel requirements, and silent operation [1]. The maximum power output of PV panels varies with factors such as solar irradiance, angle of incidence, and ambient temperature. In particular, the decrease in open-circuit voltage as panel temperature rises and the direct impact of changes in irradiance on the output current are key characteristics that necessitate system control [2].

The nonlinear nature of PV panels leads to instabilities and voltage fluctuations in the system. Regulating this variable behavior is critical for a stable energy supply; in this context, DC-DC boost converters are required to extract the maximum amount of solar energy from PV modules. DC-DC boost converters, in particular, are widely used due to their ability to boost low panel voltages and track power; the high-performance control of these units is indispensable for efficient energy conversion [3]. When combined with high-frequency switching operations and the variable characteristics of PV panels, boost converters generate highly nonlinear dynamics and voltage fluctuations that make system control difficult [4]. Although traditional PID controllers are preferred due to their low cost and simple structure, they have limitations when faced with nonlinear system dynamics and non-ideal operating conditions [5]. It has been observed that controllers designed using classical methods, such as the Ziegler-Nichols method, are unable to perform precise reference tracking over wide operating ranges and during sudden parameter changes (irradiation, temperature, etc.), leading to steady-state errors [6].

External disturbances, such as variations in system component parameters and sudden load changes, can degrade the performance of linear controllers and cause a loss of system stability [7]. Under complex operating conditions where traditional methods fall short, there is a need for intelligent control approaches that do not require a full mathematical model of the system and are robust against uncertainties [8].

Fuzzy Logic Controllers (FLC) solve complex control problems like human reasoning, using linguistic terms and rule bases based on expert experience [9]. In the management of complex processes, FLCs provide an effective control mechanism without requiring a precise mathematical model, thanks to their real-time adjustment capability and success in non-linear systems [10]. Especially in PV energy conversion systems, where environmental conditions exhibit high uncertainty and variability, the flexible structure offered by FLC is widely preferred in the literature [8].

The high performance expected from an FLC depends directly on the geometric structure of the designed membership functions (MFs) and the accuracy of the rule base [11]. Determining the boundary values of MFs using manual methods typically relies on time-consuming trial-error processes and does not always guarantee optimal performance [9]

To overcome complex design constraints and minimize total operational losses in the system, meta-heuristic optimization algorithms offer a powerful solution for identifying the most suitable circuit and controller parameters across large search spaces [12].

Daouadi et al. effectively used the Particle Swarm Optimization (PSO) algorithm to overcome the mathematical complexities encountered in determining FLC parameters and to handle challenging computational tasks, such as linear matrix inequalities (LMIs) [9].

The literature on MPPT algorithms and power electronics optimization aimed at improving PV system efficiency confirms the experimental success of the Evolutionary Algorithm (EA) in this field. It validates the performance of DC-DC converters in PV systems. Experimental results demonstrate that EA-MPPT reduces energy waste by 12% to 36% compared to P&O and PSO approaches. In comparison, the designed converter achieves an efficiency of 90% and low current ripple (7.3%), outperforming industrial standards [13].

Crivellari et al. implemented a robust design by employing a multi-objective optimization approach using the NSGA-II meta-heuristic, aiming to simultaneously optimize critical parameters such as energy losses, physical dimensions, weight, and efficiency under realistic environmental conditions [14].

This study presents a control architecture in which the MF parameters of a Fuzzy FLC are optimized using the PSO algorithm to achieve a stable output voltage and high efficiency in PV power conversion systems under varying atmospheric conditions. Due to the nonlinear nature of PV systems and the complex dynamics of boost converters, manually designing the MF intervals—which directly determine controller performance—cannot guarantee optimal results. The PSO-based approach developed to address this issue aims to improve the system's transient response by systematically determining the boundary values of the MFs. Simulation studies conducted in the MATLAB/Simulink environment were evaluated using critical performance metrics, including RMSE, ITAE, and settling time, and it was confirmed that the proposed method significantly improves system stability and error indices compared to classical FLC designs. The analyses are based on detailed simulations conducted under conditions of 1000 W/m² constant irradiance and 25°C temperature.

The study numerically demonstrates that the PSO-FLC offers a significant advantage in error metrics compared to the classical FLC. The settling-time data show that the system reaches the reference voltage much more quickly.

2. MATERIALS AND METHODS

The PV panel model used in the simulation was developed in MATLAB/Simulink. The technical data of a Lexman polycrystalline panel was used. The electrical behavior of the PV cell was analyzed using the single-diode equivalent circuit model. The PV panel parameters are listed in Table 1.

DC-DC boost converters are widely used in power electronics applications to obtain a higher-level, stable output voltage from a low-level, unregulated input voltage. The basic circuit of this converter is shown in Figure 1.

Table 1. PV panel parameters used in the simulation

Specifi	Symbol	Value
Maximum Power	**Pmax**	**79.92 W**
Open-Circuit Voltage	**Voc**	**22.1 V**
Short-Circuit Current	**Isc**	**4.8 A**
Maximum Power Point Voltage	**Vmp**	**18 V**
Maximum Power Point Current	**Imp**	**4.44 A**
Number of Cells (Parallel/Series)	**Ncell**	**36**

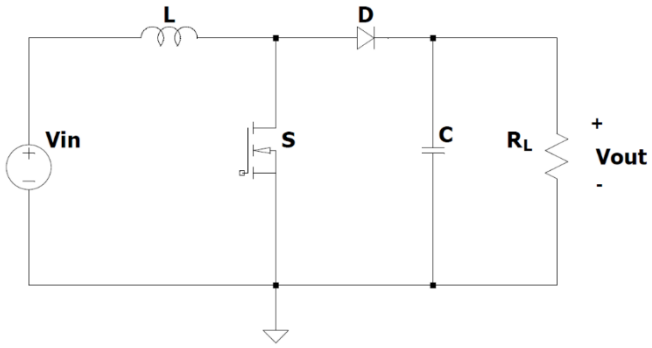


Figure 1. Boost Converter Circuit

In the control of PV-based boost converter systems, classical controllers suffer from performance limitations due to the system's inherent uncertainty and nonlinearity. To overcome these limitations, an FLC architecture has been selected, as it allows expert knowledge to be incorporated into the process without requiring mathematical modeling.

In this study, rather than using the Fuzzy Logic Toolbox, all controller stages (fuzzification, rule evaluation, and defuzzification) have been implemented using a proprietary algorithm within the MATLAB/Simulink environment. This approach has enabled the controller parameters (error MF limits) to be updated using an external optimization algorithm (PSO).

In the proposed controller, two input variables have been defined for the FLC. The first input is the error signal $e(k) = V_{ref} - V_{out}$. The second input is the error change, $de(k) = e(k) - e(k-1)$, which represents the time derivative of the error. Triangular MFs have been selected for their low computational cost and high speed. Unlike classical approaches, the corner points of the MFs for the error input, *e_params*, are dynamically calculated from data generated by the PSO algorithm. The triangular membership degrees μ have been coded based on the general formulation in Equation (1):

$$\mu(x) = max\left(0.1 - \frac{x-c}{w}\right) \quad (1)$$

where c represents the center point, whilst w represents the dynamically calculated width. The fact that the MFs have this flexible structure is critical for minimizing the system's margin of error. As a result of the optimization, the center points for the error input were determined as $e_{params} = [-28.77, -0.07, 64.10]$. Accordingly, the triangular MF obtained

for the error is shown in Figure 2. For the change in error, the range $de_{params} = [-5,0,5]$ has been defined to enable the system to respond to rapid oscillations, as shown in Figure 3. The MF is a singleton structure, as shown in Figure 4, and it is the PWM duty cycle ratio.

The success of FLC depends directly on the MFs' positions in the universal set. In this study, the PSO algorithm was used to optimize the center points (e_N, e_Z, e_P) of the triangular MFs associated with the error (e) input. Due to its high convergence rate and ability to operate without requiring derivative information, PSO is frequently preferred in the literature for the optimization of nonlinear systems.

In the study, the initial inertia coefficient w was set to 1 to preserve the global search capability, and it was updated at each iteration using a damping coefficient of $w_{damp} = 0.99$. The cognitive and social acceleration coefficients, c_1 and c_2, were set to 1.5 and 2.0, respectively, to facilitate convergence toward the optimal solution.

The cost function used to maximize controller performance accounts not only for the instantaneous error but also for the time-dependent weight of the error. To this end, the weighted Root Mean Square Error (RMSE) model presented in Equation (2) has been used:

$$J = \frac{1}{v_{ref}} \sqrt{\frac{1}{N} \sum_{k=1}^{N} \lambda(k) \cdot \left(V_{ref}(k) - V_{out}(k)\right)^2} + \beta \cdot |e_z| \qquad (2)$$

Here, λ(k) represents the time-weighted penalty coefficient. To focus on the system's steady-state stability rather than the oscillations at the start of the simulation, λ(t > 1) has been set to 20 to account for errors occurring after the first second. This high penalty coefficient necessitates the complete elimination of the offset error in the system.

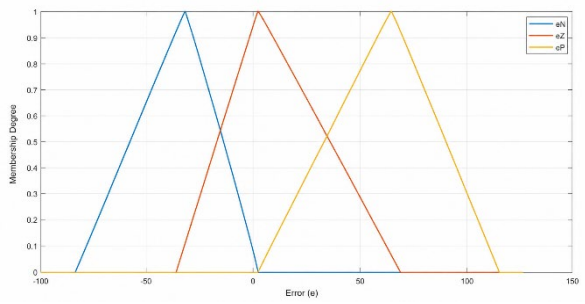


Figure 2. MFs for e

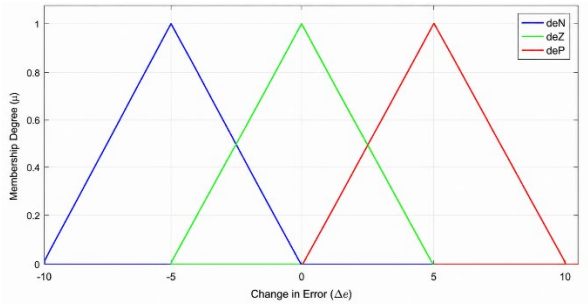


Figure 3. MFs for de

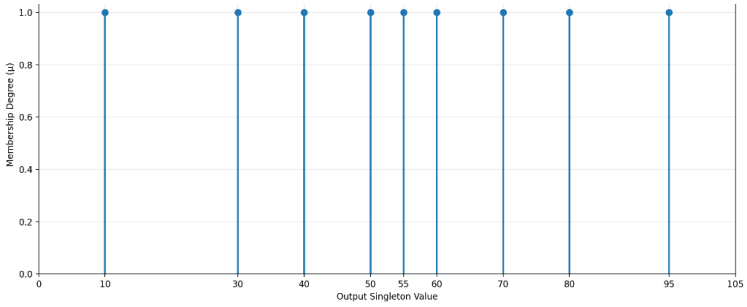


Figure 4. MFs for the duty ratio

Additionally, a penalty term with a coefficient of $\beta = 0.1$ has been included in the cost function to enhance the system's sensitivity at the nominal operating point and to fix the center of the "Zero" (e_z) MF at the reference point. Finally, the calculated RMSE value has been normalized to the system's reference voltage (42V) to achieve a scale consistent with the literature and to enhance the optimization's stability. As the process progressed with 20 particles and 15 iterations, the convergence curve shown in Figure 5 indicates that the *gbest* (global best) cost decreased until a stable structure was reached. The algorithm achieved a dramatic decrease in the cost metric (RMSE) within the first five iterations, then reached a plateau, stabilizing by the sixth iteration. This confirms that the selected population size of 20 particles and the acceleration factors achieve high efficiency in scanning the search space and avoiding local optima.

3. RESULTS AND DISCUSSION

The FLC performance optimized using the PSO algorithm was compared with that of the classical FLC structure. Simulations were conducted under three basic scenarios to assess not only the system's performance at nominal operating points but also its robustness against external disturbances. To measure the system's response under ideal conditions, solar irradiance was set to 1000 W/m², temperature to 25°C, and load resistance to R = 35 ohms. This scenario was used as the baseline to determine the controller's initial rise time and its accuracy in reaching the set point. The dynamic response for the nominal condition is as seen in Figure 6.

The controller was tested for load variation. The objective was to measure the controller's response to sudden changes in load demand in real-time applications. At the simulation time t = 1.5 seconds, the load resistance, which was initially 35 ohms, was suddenly reduced to R = 20 ohms (ΔR = 15 ohms). This test evaluated how quickly the controller could adjust its duty cycle to maintain the output voltage (42 V). This response is seen in Figure 7.

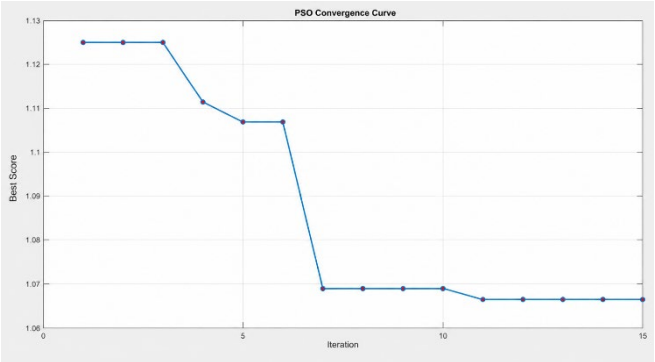


Figure 5. Convergence curve of the RMSE for the PSO algorithm as a function of iterations

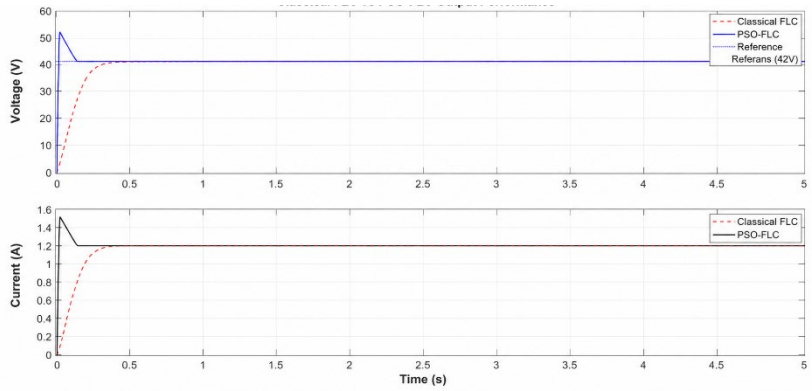


Figure 6. System response under nominal conditions (Vfixed-Rfixed)

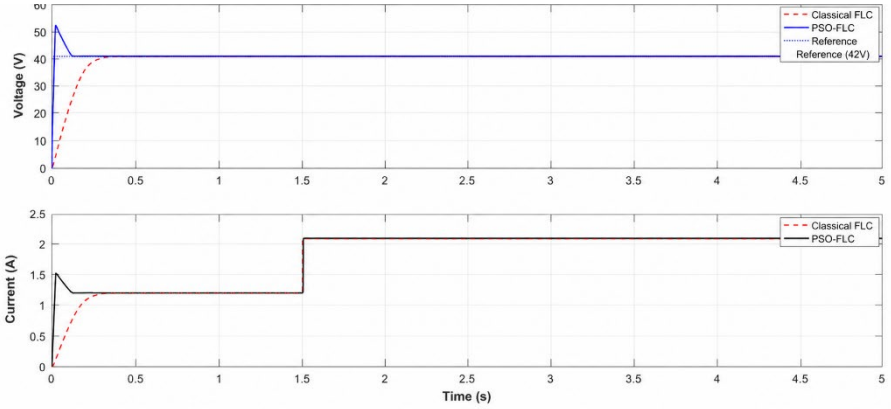


Figure 7. System response under dynamic load variations

The last scenario was designed to measure the controller's stability under conditions where PV panels produce fluctuating voltages due to environmental factors (such as cloud cover). A sudden fluctuation (voltage spike) of approximately $\Delta V = 7$ V was introduced in the system's input voltage (the open-circuit voltage Voc (V) was gradually reduced from 22.1 V to 15.1 V). Under this disruptive condition, the PSO-FLC's ability to dampen potential "offset" errors in the output voltage was analyzed. The response is shown in Figure 8.

To quantitatively validate the performance of the proposed PSO-FLC, the RMSE, Mean Absolute Error (MAE), Rise Time (t_r), and Settling Time (t_s) metrics were used. While the conventional controller produced an RMSE of 4.615 under nominal operating conditions, the PSO-optimized controller reduced it to 1.709, a 62.97% reduction.

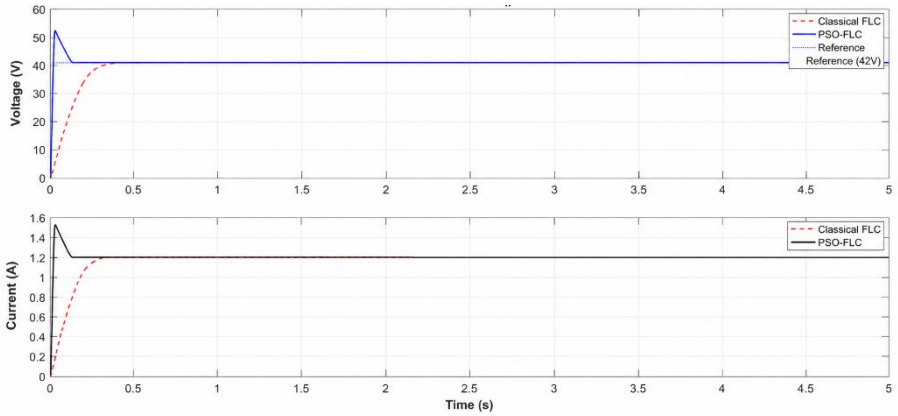


Figure 8. System response under input voltage variations

Similarly, in the input-voltage-variation scenario (Figure 8), the improvement in RMSE reached 64.14%. Upon examining the MAE metrics, it was found that PSO-FLC produced absolute errors that were 40% to 60% lower than those of the classical architecture. These numerical data demonstrate that PSO-based MF optimization minimizes the total error load during the system's reference tracking under all types of disturbances. All comparative data are presented in Table 2.

The performance evaluation results show that the proposed PSO-FLC approach outperforms the conventional FLC across all operating conditions. The steady-state error metrics show significant improvements in both RMSE and MAE. This shows that the proposed controller offers better voltage regulation and reduces the deviation from the reference signal.

Table 2. A comparative analysis of controller performance metrics

	RMSE			**MAE**			**Rise Time (s)**			**Settling Time (s)**		
Scenario	**Conv. FLC**	**PSO-FLC**	**% Impr.**	**Conv. FLC**	**PSO-FLC**	**% Impr.**	**Conv. FLC**	**PSO-FLC**	**% Impr.**	**Conv. FLC**	**PSO-FLC**	**% Impr.**
Nominal	4.62	1.71	62.97	0.86	0.49	42.94	0.32	0.03	90.71	0.53	0.23	57.22
Dynamic Load	4.62	1.72	62.75	0.86	0.53	38.56	0.32	0.03	90.71	0.53	0.23	57.03
Voltage Variation	4.62	1.66	64.14	0.84	0.31	62.94	0.32	0.03	91.02	0.53	0.22	59.12

4. CONCLUSION

This study proposes the design and analysis of an FLC parameterized using the PSO algorithm for output voltage regulation in PV systems. Unlike the trial-and-error methods used in traditional controller design processes, the controller's MF were mathematically determined using the PSO algorithm to optimize the system's dynamic response. The findings demonstrate that FLC performance depends on precise MF tuning. The PSO algorithm's ability to find the global optimum in this parametric space has reduced the burden of controller design and provided an optimization process free of human error.

Future work aims to integrate this optimization approach into real-time embedded systems and conduct comparative performance analyses with different meta-heuristic algorithms.

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