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Optimization of ANN-based DC voltage control using hybrid rain optimization algorithm for a transformerless high-gain boost converter

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ABSTRACT

This paper introduces an adaptive voltage regulation technique for a transformerless high-gain boost converter (HGBC) integrated within standalone photovoltaic systems. A neural network controller is trained and fine-tuned using the rain optimization algorithm (ROA) to achieve improved dynamic behavior under variable solar conditions. The proposed ROA-ANN framework continuously updates the duty cycle to ensure output voltage stability in real time. Validation was carried out using MATLAB–OrCAD co-simulation under multiple scenarios. Comparative results highlight superior performance of the ROA-ANN controller in terms of convergence speed, overshoot minimization, and steady-state response, outperforming conventional PID and ANN-based methods.

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1. INTRODUCTION

The increasing environmental and economic challenges associated with fossil fuel consumption have accelerated the global shift toward renewable energy systems [1]. Among these, solar photovoltaic (PV) technology has gained prominence due to its scalability, ease of deployment, and low environmental impact. Despite these benefits, fluctuations in solar irradiance introduce power variability that undermines voltage stability and overall system efficiency [2]. To mitigate such issues, advanced power conditioning and adaptive control techniques are required to ensure stable operation under changing environmental conditions [3].

In PV systems, DC-DC boost converters (BCs) are commonly employed to step up the inherently low voltage output of PV modules to levels appropriate for standalone or grid-connected use [4]. While traditional BCs perform adequately for moderate voltage requirements, their efficiency significantly declines at high voltage gain demands. This is primarily due to increased duty cycles and associated switching losses, which elevate stress on components and reduce overall performance [5].

To address these shortcomings, HGBCs have been introduced based on advanced configurations such as coupled inductors, switched capacitor networks, and voltage multiplier circuits [6], [7]. These topologies achieve elevated output voltages while operating at moderate duty cycles, thereby minimizing component stress. Nonetheless, maintaining voltage stability under dynamic operating conditions—particularly with fluctuating irradiance—continues to pose a significant control challenge that demands adaptive regulation strategies.

Proportional integral derivative (PID) controllers are widely utilized in power electronic applications due to their straightforward implementation and effective performance under stable conditions [8]. However, their static gain structure limits adaptability to rapidly changing inputs, often resulting in overshoot, prolonged settling times, and steady-state errors in nonlinear systems such as PV-powered HGBCs [9]. Additionally, PID controllers typically require manual tuning, making them less suitable for environments subject to frequent or unpredictable fluctuations.

To enhance control flexibility and precision, ANNs have emerged as a viable alternative to conventional methods. Due to their ability to capture complex nonlinear mappings between system variables, ANNs are well-suited for voltage regulation in power converter applications [10]. Prior research has demonstrated that ANN-based controllers can significantly improve both transient and steady-state behavior in HGBCs [11]. Nonetheless, their effectiveness heavily depends on the network's architecture and hyperparameter configuration, which directly influence training outcomes and control accuracy.

To overcome these limitations, researchers have employed metaheuristic algorithms to automatically fine-tune ANN parameters [12]. Among these, rain optimization algorithm (ROA) has demonstrated strong capabilities in avoiding local optima and achieving rapid convergence during training [13]. Inspired by the natural flow of raindrops across terrain surfaces, ROA has been effectively applied in optimizing neural networks for various engineering applications [14]. Recent studies indicate that combining ROA with ANN significantly enhances controller performance, particularly in terms of response time and output accuracy [15].

This paper proposes an ANN control strategy optimized using ROA to regulate the output voltage of a transformerless HGBC in PV-based applications. The objective is to enhance tracking accuracy, minimize overshoot, and achieve faster dynamic response under varying irradiance levels. ROA is employed to adjust the ANN's weights and biases during the training phase, resulting in a more robust and adaptive control system. The effectiveness of the proposed approach is verified through a co-simulation environment combining MATLAB and OrCAD, which enables accurate validation of both the control logic and hardware behavior. Performance is evaluated against conventional ANN and PID controllers to demonstrate the achieved improvements in realistic PV operating scenarios.

The rest of this paper is structured as follows: Section 2 presents the proposed methodology, covering converter modeling and ROA-ANN controller design. Section 3 provides simulation results and a comparative evaluation of controller performance across different scenarios. Section 4 summarizes the main findings and outlines directions for future research.

2. METHODOLOGY

This section presents the configuration of a standalone PV system employing a transformerless high-gain boost converter (HGBC) regulated by a ROA-optimized ANN controller. The control objective is to maintain a stable output voltage despite fluctuations in irradiance. The ROA-ANN controller computes the duty cycle in real time based on system feedback. The complete control structure is shown in Figure 1.

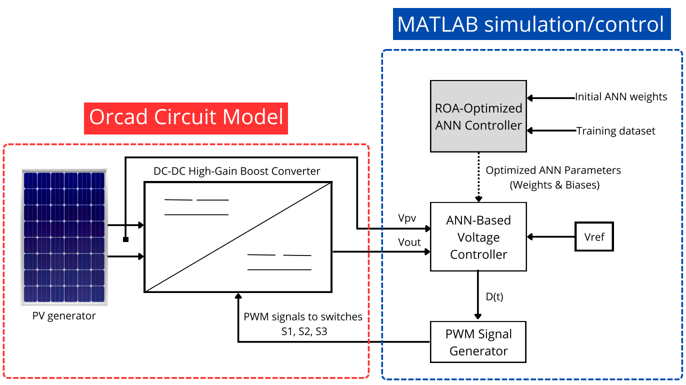

Figure 1. Synoptic diagram of the co-simulated PV-fed HGBC system

2.1. Model of the transformerless high-gain boost converter

High-gain DC-DC converters play a crucial role in PV applications by stepping up the inherently low voltage of PV sources to levels compatible with connected loads or inverters [16]. The transformerless HGBC considered in this study enhances voltage gain while reducing circuit complexity and power losses. Eliminating the need for bulky magnetic components such as transformers not only reduces the overall size and cost of the system but also improves its efficiency and reliability under fluctuating environmental conditions.

As illustrated in Figure 2, the HGBC topology comprises three inductors (L_1, L_2, L_3), two capacitors (C_1, C_o), two diodes (D_1, D_o), and three switching devices (S_1, S_2, S_3). The converter is designed to operate in continuous conduction mode (CCM), which facilitates consistent energy flow and stable DC output, even under variable irradiance conditions [17].

The converter operates in two distinct phases. During the first phase, when switches S_1, S_2, and S_3 are turned ON, inductor L_1 is energized directly from the PV source, while inductors L_2 and L_3 are charged via capacitor C_1. At this stage, diodes D_1 and D_o are reverse-biased, effectively isolating the load and maintaining the voltage level across C_o.

In the second phase, once the switches are turned OFF, inductor L_1 releases its stored energy to capacitor C_1 through diode D_1, while inductors L_2 and L_3 discharge through diode D_o to supply the output stage. This switching pattern enables high voltage gain at moderate duty cycles, which helps minimize conduction losses and extends the operational lifespan of the converter.

Applying the volt-second balance principle, the voltage gain of the converter is given by (1).

$$V_o = \frac{(1+D)}{(1-D)^2} V_{in} \tag{1}$$

Where D represents the duty cycle. This relationship demonstrates that the converter can attain substantial voltage amplification without requiring excessively high duty ratios, thereby reducing component stress and enhancing system reliability.

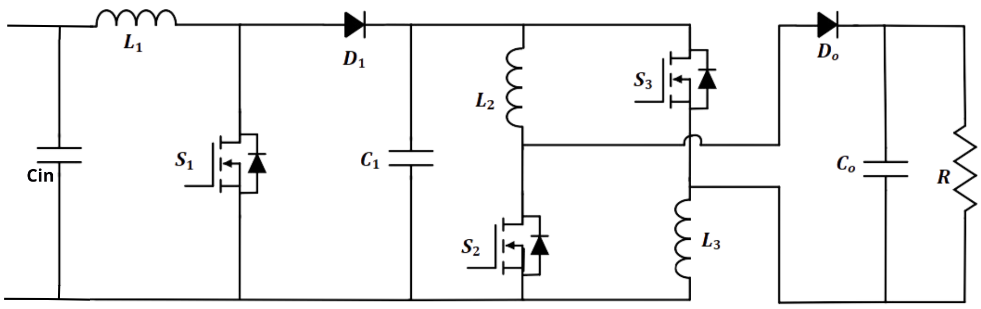

Figure 2. Topology of the proposed transformerless HGBC

2.2. Structure of the ROA-optimized ANN controller

To maintain stable output voltage from the transformerless HGBC under fluctuating environmental conditions, an ANN-based adaptive control approach is adopted. While conventional PID controllers offer simplicity and ease of deployment, their limited adaptability in nonlinear and time-varying systems makes them less effective under rapidly shifting irradiance conditions [18], [19]. In contrast, ANNs possess the capability to approximate complex nonlinear relationships and adjust dynamically to input variations, making them highly suitable for voltage regulation in PV applications.

The implemented ANN is structured as a feedforward network designed to generate the optimal duty cycle D for the HGBC. It processes four input signals: reference voltage (V_{ref}), output voltage (V_{out}), PV voltage (V_{pv}), and the voltage error defined as $e = V_{ref} - V_{out}$. These inputs enable the network to evaluate the system's real-time condition and make adaptive control decisions accordingly [20]. Sigmoid activation functions are employed in the hidden layers due to their ability to capture nonlinear relationships [21], while the output layer produces a normalized value of D that directly controls the switching of the converter.

The training dataset was obtained through MATLAB–OrCAD co-simulation by evaluating the system under various irradiance levels and voltage scenarios. A supervised learning approach was employed, utilizing the backpropagation algorithm to minimize the mean squared error (MSE) during the training process.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(D_i - \hat{D}_i\right)^2 \quad (2)$$

Where D_i and $\hat{D}_i$ represent the target and predicted duty cycles, respectively.

To enhance convergence performance and avoid entrapment in local optima, ROA is incorporated into the ANN training process [22], [23]. This algorithm is used to optimize critical hyperparameters—including learning rate, neuron allocation, and initial weight settings—that are typically chosen heuristically in standard ANN configurations. Inspired by the natural flow dynamics of raindrops, ROA facilitates a balanced search between global exploration and local exploitation within the solution space, as shown in Figure 3 [24].

Figure 4 illustrates the training performance of the conventional ANN compared to the ROA-optimized ANN. The ROA-enhanced model demonstrates faster convergence and achieves a lower final error. Its adaptive learning capability helps prevent stagnation during training and supports better generalization, which is particularly important in PV systems subject to significant environmental variability.

The progression of critical hyperparameters throughout the training process is depicted in Figure 5. ROA adaptively modifies the learning rate and adjusts the neuron count, contributing to enhanced training stability and improved performance [25]. In comparison, fixed hyperparameter settings in conventional ANN training can result in suboptimal convergence behavior or increased risk of overfitting.

The training workflow that incorporates ROA into the ANN optimization process is illustrated in Figure 6. ROA starts by initializing a population of candidate solutions and progressively refines them based on their mean squared error (MSE) performance. Through this iterative mechanism, the ANN controller is guided toward generating optimal duty cycle values suitable for dynamic PV operating conditions.

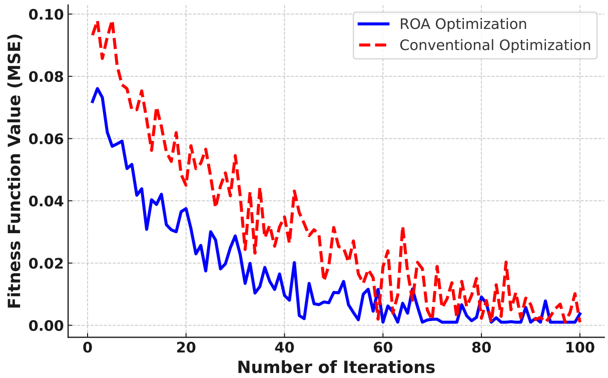

Figure 3. Convergence of ROA vs. conventional optimization during ANN training

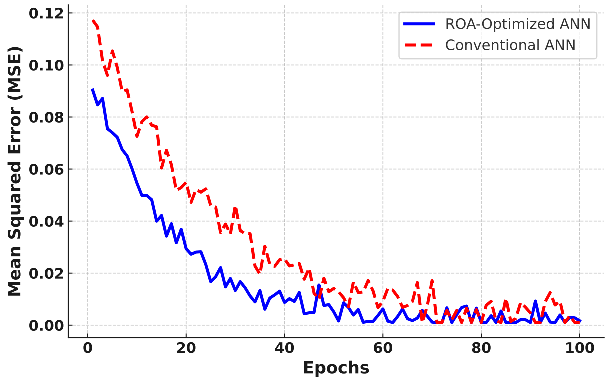

Figure 4. Training performance comparison between conventional ANN and ROA-optimized ANN

By integrating the learning ability of ANN with the adaptive search efficiency of ROA, the proposed control approach delivers precise tracking, rapid convergence, and strong robustness under fluctuating irradiance conditions. These attributes establish it as a reliable solution for advanced DC voltage regulation in PV-powered HGBC systems.

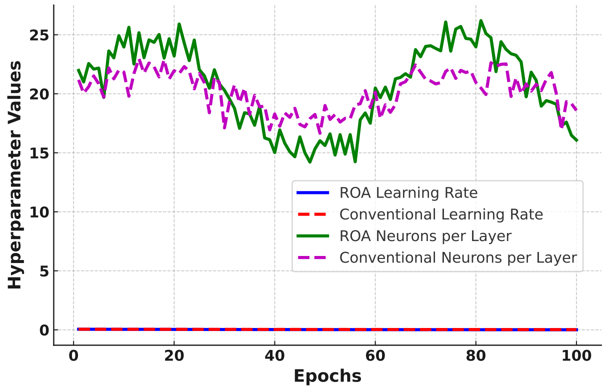

Figure 5. Evolution of learning rate and neurons per layer: ROA vs. conventional ANN

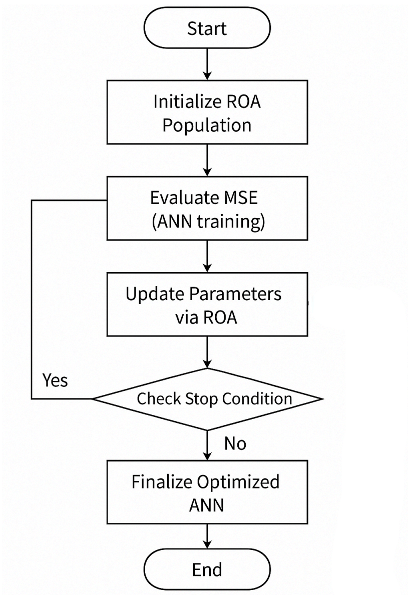

Figure 6. Workflow of ROA-integrated ANN training

3. RESULTS AND DISCUSSION

This section provides a detailed evaluation of the transformerless HGBC system managed by the ROA-optimized ANN controller. The performance assessment is carried out through a MATLAB–OrCAD co-simulation environment, enabling the observation of both control behavior and circuit-level dynamics. The analysis emphasizes output voltage regulation, transient response characteristics, and controller robustness across four operating scenarios representative of real-world PV variations.

The evaluated PV system is configured to supply 2.2 kW using a 4S-2P module arrangement, delivering 128 V at its maximum power point (MPP). This voltage is stepped up to 650 V by the HGBC, operating at a switching frequency of 100 kHz. Key system parameters are provided in Table 1, while the simulation scenarios used for performance evaluation are outlined in Table 2.

The performance of the ROA-ANN controller is compared against conventional ANN and PID controllers across the defined test scenarios. Four graphical results illustrate the dynamic responses under different conditions, followed by a comprehensive summary in Table 3, which quantifies key performance metrics for each control strategy.

Table 1. Standalone solar system parameters

Parameter		Value
PV array	Total power output (P_{PV})	2204.16 W
	Configuration	4S-2P
	Voltage at MPP (V_{mp})	128 V
	Current at MPP (I_{mp})	17.22 A
	Daily energy production	9.2 kWh/day
	Annual energy production	3365 kWh/year
High-gain boost converter	Input voltage (V_{in})	128 V
	Output voltage (V_{out})	650 V
	Switching frequency (f_s)	100 kHz

Table 2. Simulation scenarios for controller performance evaluation

Scenario	Irradiance (W/m^2)	Reference voltage (V)
S1: Constant irradiance	1000	650
S2: Constant irradiance, variable reference	1000	500, 550, 600, 650
S3: Variable irradiance	300, 500, 800, 1000	650
S4: Variable irradiance, variable reference	300–1000	500–650

Table 3. Controller performance summary across all scenarios

Performance metric	ROA-ANN	ANN	PID
Rise time (s)	< 0.1	0.6	> 1.5
Settling time (s)	< 0.3	0.7	> 1.5
Overshoot (%)	< 2	4–7	10–15
Tracking noise	Very low	Moderate	High
Response to ref. shift	Immediate	Acceptable	Overshoot + delay
Response to irradiance drop	Robust	Mild sag	Ripple + drift
Handling dual variation	Excellent	Acceptable	Unstable

Figure 7 shows the system's dynamic behavior under scenario S1, which represents standard test conditions with constant irradiance and reference voltage. The ROA-ANN controller exhibits a rapid transient response, achieving a rise time below 0.1 s and maintaining zero overshoot—highlighting its high regulation accuracy and system stability. This performance stems from the ROA's ability to continuously optimize the controller parameters in real time. In comparison, the conventional ANN requires approximately 0.6 s to stabilize due to its static training limitations. The PID controller performs poorly in this scenario, exhibiting a 12% overshoot and persistent oscillations beyond 1.5 s, mainly due to its fixed gain configuration and limited adaptability to the HGBC's nonlinear dynamics.

Scenario S2, illustrated in Figure 8, evaluates the controllers' ability to adapt to varying reference voltages. The ROA-ANN demonstrates precise tracking of each reference shift with minimal steady-state error and rapid convergence, emphasizing its strong generalization capability and responsiveness to dynamic inputs. While the conventional ANN maintains reasonable accuracy, it exhibits noticeable delays during significant transitions—such as from 500 V to 600 V—revealing the limitations of offline-trained architectures. The PID controller performs inadequately in this scenario, showing overshoots of up to 15% and extended settling times, indicative of its restricted adaptability under time-varying operating conditions.

Scenario S3, shown in Figure 9, examines system performance under varying irradiance levels with a fixed reference voltage. The ROA-ANN controller consistently delivers stable and accurate output across all irradiance conditions, including at low levels, demonstrating its robustness and adaptability to environmental disturbances. In contrast, the conventional ANN exhibits slight deviations at 300 W/m², attributed to limited exposure to low-irradiance cases during the training phase. The PID controller once again underperforms, showing ripple, voltage sag, and delayed response—issues that stem from its static control structure and inadequate handling of input variability.

In the final test scenario, S4, illustrated in Figure 10, both irradiance and reference voltage are varied simultaneously to assess controller performance under compounded disturbances. The ROA-ANN maintains fast, accurate, and stable tracking throughout, effectively handling the multivariable dynamics without introducing steady-state error. This highlights its capability to generalize and adapt in highly dynamic environments. The conventional ANN displays slower adaptation and increased output noise during concurrent transitions, particularly under low irradiance conditions. The PID controller fails to regulate the output reliably, exhibiting pronounced instability and large tracking errors, reaffirming its limitations in nonlinear systems subjected to simultaneous fluctuations.

Across all test scenarios, the ROA-ANN controller consistently outperforms conventional ANN and PID approaches in terms of rise time, settling response, noise attenuation, and tracking precision. Its resilience under both reference voltage shifts and irradiance fluctuations highlights the effectiveness of ROA-driven optimization in enhancing real-time control adaptability. These findings reinforce the suitability of ROA-ANN architectures for practical PV applications that demand fast and reliable voltage regulation under dynamic operating conditions.

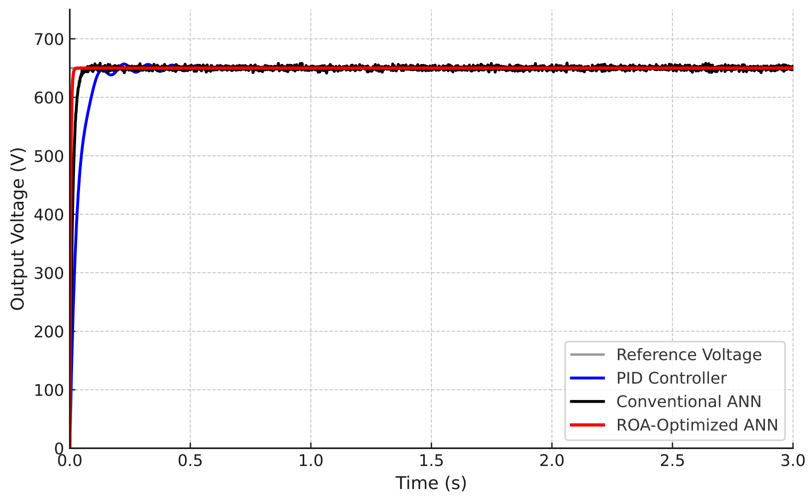

Figure 7. Constant irradiance and fixed reference voltage (S1)

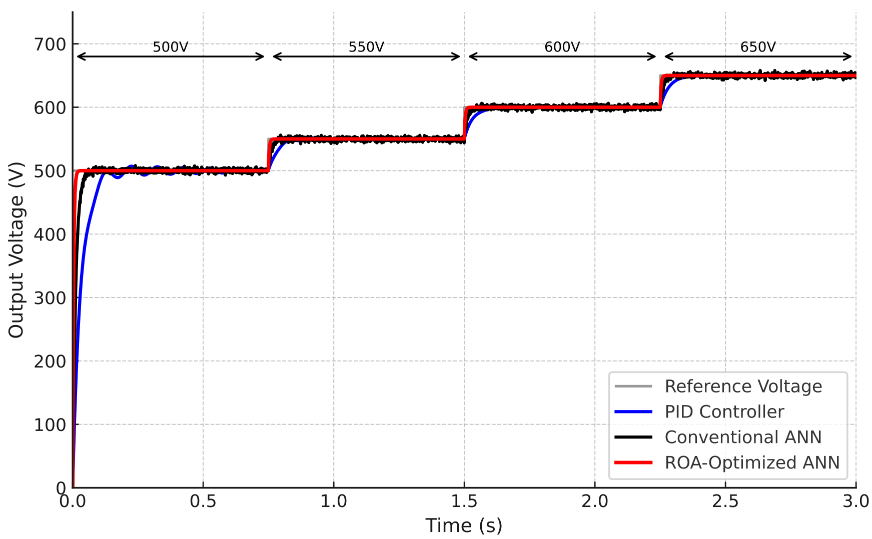

Figure 8. Constant irradiance and variable reference voltage (S2)

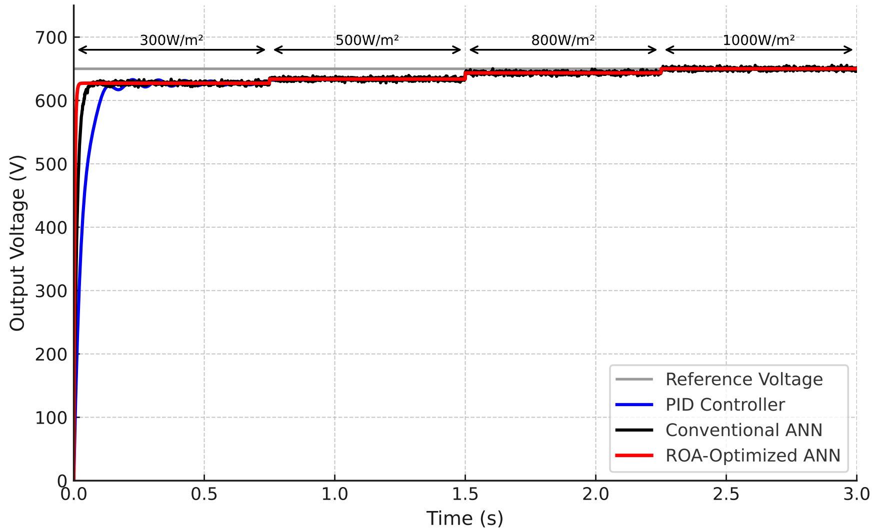

Figure 9. Variable irradiance and constant reference voltage (S3)

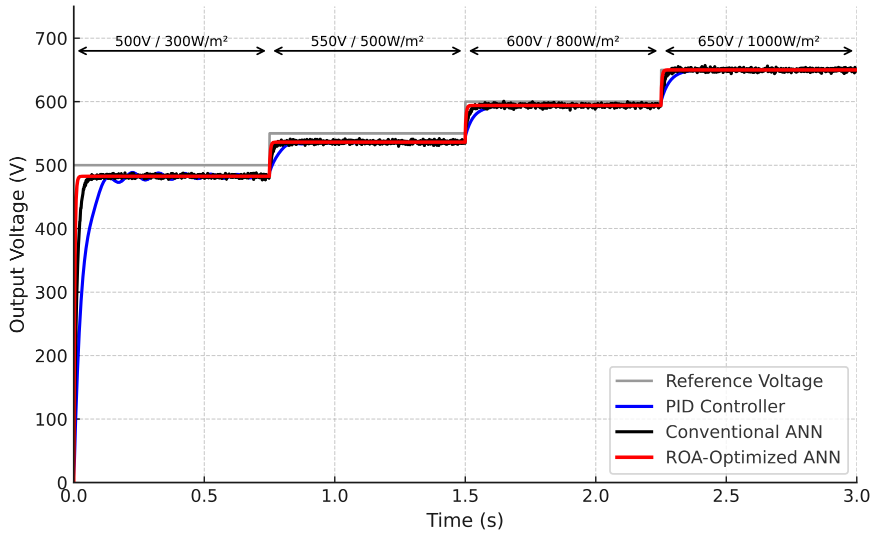

Figure 10. Variable irradiance and reference voltage (S4)

4. CONCLUSION

This study introduced a voltage regulation strategy based on an ROA-optimized ANN controller for transformerless high-gain boost converters in standalone PV systems. The controller's effectiveness was validated through MATLAB–OrCAD co-simulation under multiple test conditions involving varying irradiance and reference voltages. The results demonstrated that the ROA-ANN consistently outperformed both conventional ANN and PID controllers in terms of dynamic response, tracking precision, and overall robustness. These findings underscore the value of integrating metaheuristic optimization into neural network training for adaptive control in nonlinear power electronic applications. Future work will explore experimental validation and the extension of the proposed scheme to inverter-level control architectures.

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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
Mohcine Byar	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Abdelouahed Abounada		✓			✓		✓	✓	✓	✓	✓	✓	✓	✓

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 declare that there are no financial, personal, or professional conflicts of interest that could have influenced the findings, interpretations, or conclusions presented in this work. All contributions were made independently and according to ethical research standards.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author, [MB], upon reasonable request. All simulation models and co-simulation setups were developed by the authors and are not publicly archived due to ongoing related research.

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