



RESEARCH ARTICLE

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DESIGN OF MODIFIED LUO CONVERTER WITH ENHANCED MPPT ALGORITHM FOR PV SYSTEMS

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ABSTRACT

Photovoltaic (PV) systems are highly sensitive to partial shading conditions, which significantly reduce power extraction efficiency and introduce multiple local maxima in the power–voltage characteristics. This paper proposes a high-gain switched-inductor Modified Luo converter integrated with a Black Widow Optimized Artificial Neural Network (BWO-ANN) based Maximum Power Point Tracking (MPPT) technique for operation under near-zero partial shading conditions. The modified Luo converter enhances voltage gain and reduces current ripple through a switched-inductor configuration, operating in continuous conduction mode (CCM). The voltage conversion ratio is analytically derived using volt-second balance principles. The BWO algorithm optimally tunes ANN parameters to improve tracking speed and convergence accuracy under dynamic irradiance conditions. A high-frequency inverter and isolation transformer provide galvanic isolation between the PV source and DC bus/battery. MATLAB/Simulink validation demonstrates a converter efficiency of 97.79% and MPPT tracking efficiency of 98.96%, outperforming conventional P&O, PSO, and Hill-Climbing techniques. The proposed topology exhibits improved voltage gain, reduced ripple, fast convergence, and stable operation under varying environmental conditions.



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I. INTRODUCTION

The increasing demand for sustainable energy and the rapid depletion of fossil fuels have intensified global research on renewable energy resources [1],[2]. Among various renewable sources, photovoltaic (PV) systems have gained significant attention due to their clean operation, simple installation, modular configuration, and minimal maintenance requirements [3],[4]. However, PV systems inherently suffer from intermittency caused by variations in solar irradiance and temperature, which significantly affect their electrical characteristics and power output [5],[6]. Therefore, efficient Maximum Power Point Tracking (MPPT) techniques are essential to ensure optimal power extraction under dynamic environmental conditions [7],[8]. Conventional MPPT techniques such as Sliding Mode Control (SMC), Perturb and Observe (P&O), and Incremental Conductance (INC) methods have been widely implemented due to their simplicity and ease of realization [9-12]. Although these methods perform satisfactorily under uniform irradiance, they exhibit steady-state oscillations and slow tracking speed during rapidly changing atmospheric conditions [13],[14].

Furthermore, under partial shading conditions (PSC), multiple local maxima appear on the power–voltage (P–V) curve, making it difficult for classical methods to identify the global maximum power point (GMPP) [15],[16]. To overcome these challenges, meta-heuristic and intelligent optimization techniques such as Artificial Bee Colony (ABC), Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and hybrid optimization-based MPPT strategies have been proposed [17-20]. These approaches improve tracking accuracy under PSC but often suffer from increased computational burden and convergence delay [21],[22]. Recently, Artificial Neural Networks (ANN) have been introduced in MPPT applications due to their nonlinear mapping capability and adaptability to dynamic solar conditions [23],[24]. However, ANN performance strongly depends on optimal parameter tuning, and improper training may result in premature convergence or local trapping [25],[26].

In addition to MPPT challenges, the power conversion stage plays a crucial role in determining the overall efficiency of PV systems. Conventional boost converters provide limited voltage gain at high duty cycles and suffer from increased switching losses and voltage stress [27]. Advanced DC–DC topologies such as Cuk, SEPIC, and Luo converters have been developed to enhance voltage gain and reduce ripple content. Among them, Luo converters offer improved ripple performance and reduced electromagnetic interference; however, their voltage gain and efficiency can be further enhanced through structural modification. Therefore, this work proposes a switched-inductor Modified Luo converter integrated with a Black Widow Optimized Artificial Neural Network (BWO-ANN) based MPPT technique to achieve high voltage gain, reduced ripple, and improved tracking performance under near-zero partial shading conditions. The proposed approach enhances both power extraction efficiency and conversion performance, making it suitable for DC bus and battery-based renewable energy applications

II. MODELLING OF THE SYSTEM

In order to achieve efficient solar power utilization for DC bus and battery applications, coordinated optimization of power conversion and maximum power point tracking (MPPT) under varying environmental conditions is essential. The proposed system integrates an optimized MPPT algorithm with a Modified Luo converter, as illustrated in Figure 1. Due to fluctuations in solar irradiance and temperature, the output power of the photovoltaic (PV) array varies dynamically. To regulate and elevate the PV output voltage to the required DC bus or battery level, the PV output is interfaced with a high-gain Modified Luo converter.

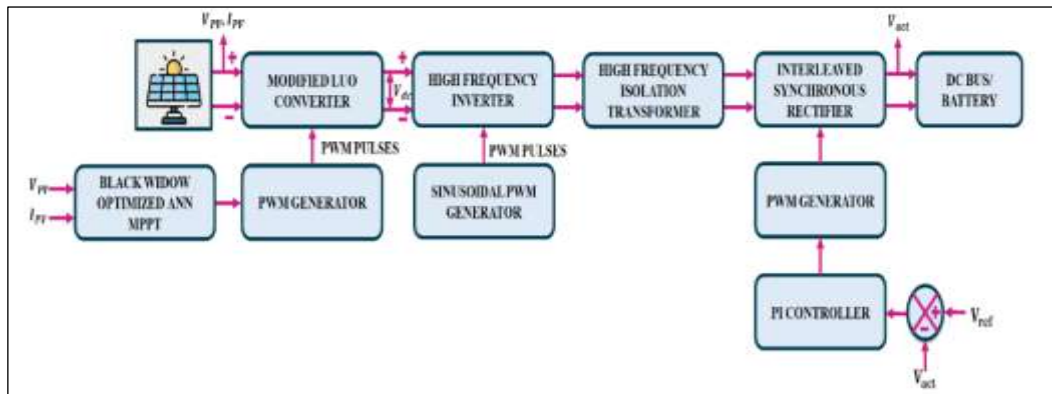


Figure 1: Block diagram of proposed work.
Source: Authors, (2026).

The instantaneous PV voltage and current are continuously sensed and supplied to the Black Widow Optimization-based Artificial Neural Network (BWO-ANN) MPPT controller. The controller determines the optimal duty cycle corresponding to the global maximum power point (GMPP) under near-zero partial shading conditions. The computed duty ratio is applied to a pulse-width modulation (PWM) generator, which produces the gating signals required for switching operation of the Modified Luo converter. The boosted DC output of the converter is subsequently applied to a high-frequency full-bridge inverter, which converts the regulated DC voltage into a high-frequency AC waveform.

This high-frequency AC signal is fed into an isolation transformer to provide galvanic isolation between the PV source and the DC bus/battery side. The isolation stage enhances operational safety, improves reliability, and protects sensitive components from electrical faults. The transformer output is then rectified using an interleaved synchronous rectifier to obtain regulated DC power. A proportional–integral (PI) controller is employed to regulate the rectifier output voltage and ensure stable DC bus/battery operation. The PWM unit generates the necessary gating pulses for the inverter and rectifier switches to maintain controlled energy transfer. Finally, the regulated DC output is delivered to the DC bus or battery for energy storage or direct utilization.

II.1 MODELLING OF PV SYSTEM

Figure 2 illustrates the equivalent electrical model of a photovoltaic (PV) cell. The PV cell operates based on the p–n junction principle, converting incident solar irradiation directly into electrical energy. To obtain the desired voltage and current levels, multiple PV cells are connected in series and parallel configurations to form a PV module or array.

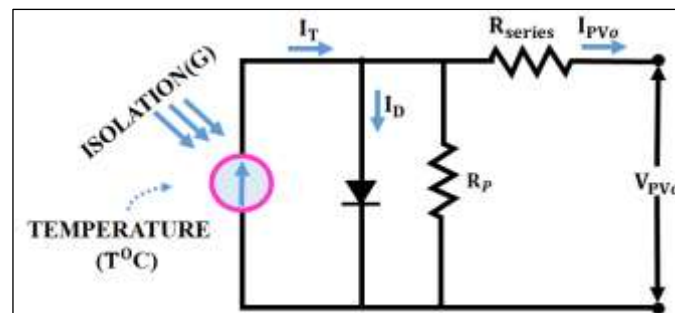


Figure 2: Equivalent diagram of PV system.
Source: Authors, (2026).

The single-diode equivalent circuit consists of a photo-generated current source I_{ph} , a diode representing the p-n junction characteristics, a series resistance R_s , and a shunt resistance R_{sh} . The series resistance accounts for internal ohmic losses, while the shunt resistance models leakage currents.

The output current of the PV module is expressed as

$$I_{PV} = I_{ph} - I_{sat} \left[\exp \left(\frac{q(V_{PV} + I_{PV}R_s)}{\eta k_B T} \right) - 1 \right] - \frac{V_{PV} + I_{PV}R_s}{R_{sh}} \quad (1)$$

where V_{PV} and I_{PV} denote the PV output voltage and current, respectively; I_{sat} represents the diode reverse saturation current; I_{ph} is the photo-generated current proportional to irradiance; R_s and R_{sh} are the series and shunt resistances; q is the electron charge (1.602×10^{-19} C); k_B is the Boltzmann constant (1.381×10^{-23} J/K); T denotes the cell operating temperature in Kelvin; and η is the diode ideality factor.

Due to variations in solar irradiance and temperature, the PV output voltage and current fluctuate continuously, resulting in a nonlinear power–voltage (P–V) characteristic. Therefore, a high-gain DC–DC converter is required to regulate and boost the PV output voltage to the desired DC bus or battery level. In this work, a Modified Luo converter is employed to achieve enhanced voltage gain, reduced ripple, and improved conversion efficiency, as discussed in the following section.

II.2 MODELLING OF MODIFIED LUO CONVERTER

The Luo converter is a voltage-lift type DC–DC converter widely used for step-up applications due to its reduced output ripple and improved electromagnetic compatibility compared to conventional boost converters. However, the classical Luo topology provides limited voltage gain at moderate duty ratios. To enhance the voltage conversion capability and efficiency, a switched-inductor (SI) cell is incorporated into the conventional Luo structure, forming the proposed Modified Luo converter, as shown in Figure 3.

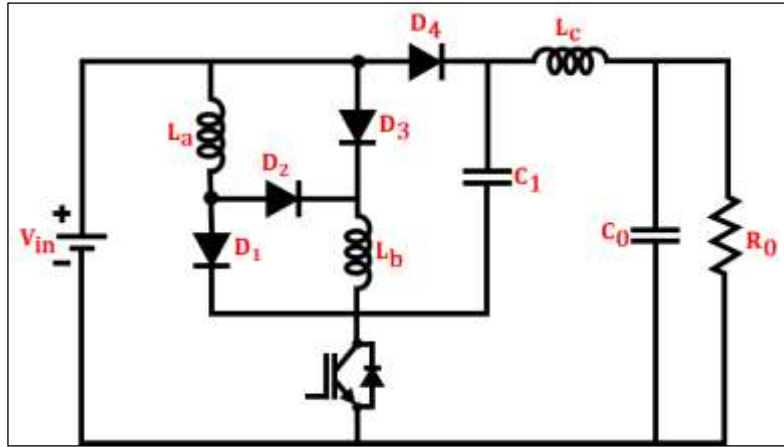


Figure 3: Circuit diagram of proposed Modified Luo converter.

Source: Authors, (2026).

The addition of the switched-inductor network increases the effective input voltage during the energy transfer interval, thereby improving voltage gain while maintaining reduced current ripple. The converter operates in two switching modes within one switching period T .

1) Mode 1: **SON**, D_2 OFF ($t_{on} = DT$)

When the main switch S is turned ON, diode D_2 is reverse biased, while diodes D_1 , D_3 , and D_4 are forward biased. During this interval:

Inductors L_a and L_b are connected in parallel and charged by the input source.

The output capacitor C_0 supplies energy to the load.

The inductor voltages during this interval are

$$V_{La} = V_{Lb} = V_{in} \quad (2)$$

Thus, both inductors store energy simultaneously.

2) Mode 2: **SOFF**, D_2 ON ($t_{off} = (1 - D)T$)

When the switch S is turned OFF, diode D_2 becomes forward biased, and diodes D_1 , D_3 , and D_4 are reverse biased. The inductors are now connected in series and transfer stored energy to the output.

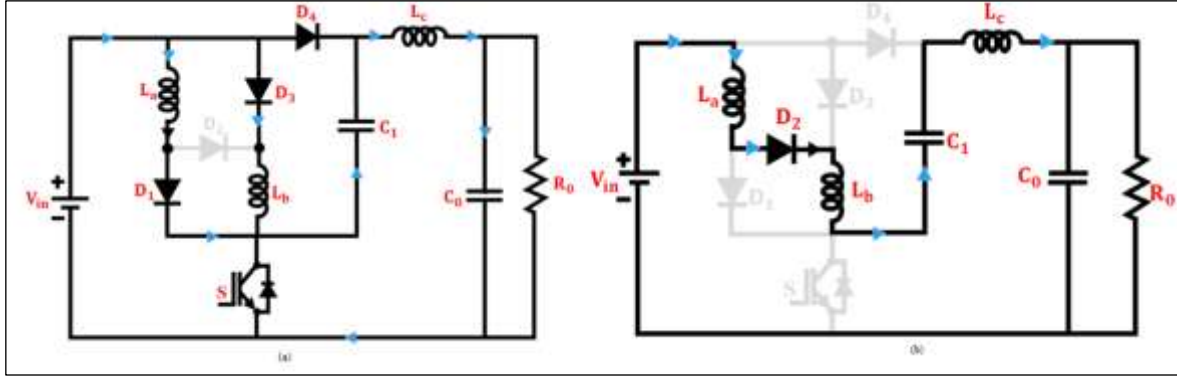


Figure 4: Modes of Operation of proposed Modified converter.
Source: Authors, (2026).

During this interval:

$$V_{La} + V_{Lb} = V_{in} + V_{in} - V_o \quad (3)$$

Since the switched inductors are symmetrical,

$$V_{La} = V_{Lb} = \frac{2V_{in} - V_o}{2} \quad (4)$$

3) Voltage Gain Derivation

Applying the volt-second balance principle over one switching period:

$$V_{La}(DT) + V_{La}((1-D)T) = 0$$

Substituting (2) and (4):

$$V_{in}DT + \frac{2V_{in} - V_o}{2}(1-D)T = 0$$

Simplifying,

$$V_{in}D = \frac{V_o - 2V_{in}}{2}(1-D) \quad (5)$$

Solving for voltage conversion ratio:

$$\frac{V_o}{V_{in}} = \frac{2}{1-D} \quad (6)$$

Thus, the proposed converter achieves a higher voltage gain compared to the conventional boost converter:

$$\text{Boost gain: } \frac{1}{1-D}$$

$$\text{Proposed gain: } \frac{2}{1-D}$$

4) Effect of Diode Voltage Drop

Considering diode forward voltage drop ΔV_D , the volt-second balance becomes

$$(V_{in} - \Delta V_D)DT + \frac{2V_{in} - V_o - 3\Delta V_D}{2}(1-D)T = 0 \quad (7)$$

The practical voltage gain is therefore

$$\frac{V_o}{V_{in}} = \frac{2}{1-D} - \frac{\Delta V_D}{V_{in}} \left(\frac{3-D}{1-D} \right) \quad (8)$$

This expression indicates that diode drops slightly reduce the theoretical gain, particularly at high duty ratios. While the converter ensures efficient voltage boosting, accurate maximum power point tracking remains essential for extracting maximum energy from the PV array under dynamic environmental conditions. Therefore, a Black Widow Optimization-based Artificial Neural Network (BWO-ANN) MPPT strategy is introduced in the following subsection.

II.3 MODELLING OF BLACK-WIDOW OPTIMIZED ANN BASED MPPT

The Black Widow Optimization (BWO) algorithm is a nature-inspired metaheuristic approach modeled on the hunting and mating behaviors of black widow spiders. The algorithm mimics their reproductive characteristics, including crossover, cannibalism, and mutation, to achieve improved convergence speed and high optimization accuracy.

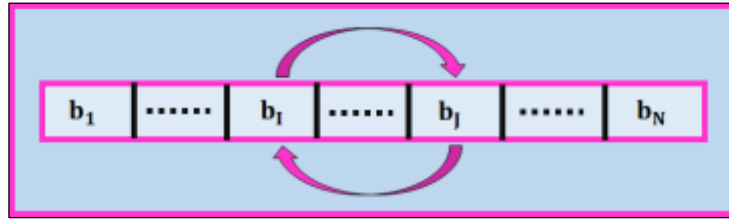


Figure 5: behaviour of mutation of individual spider.

Source: Authors, (2026).

The major phases of the BWO algorithm are described as follows.

Step 1: Population Initialization

Initially, a random population of spiders is generated. Each spider represents a candidate solution vector expressed as

$$\mathbf{b} = [b_1, b_2, \dots, b_{dim}]$$

where *dim* denotes the problem dimension and each element corresponds to a decision variable.

Step 2: Fitness Evaluation The fitness function evaluates the quality of each candidate solution. Individuals with superior fitness values are preserved, whereas weaker solutions are eliminated. Thus, the best solution is retained while the worst solution is discarded to ensure progressive improvement in solution quality.

Step 3: Crossover, Cannibalism, and Mutation Crossover is performed between two parent spiders $\mathbf{b}_1$ and $\mathbf{b}_2$ to produce offspring according to the crossover rate. The mathematical model governing the crossover operation is expressed as

$$\begin{aligned} y_1 &= \alpha \cdot \mathbf{b}_1 + (1 - \alpha) \cdot \mathbf{b}_2 \\ y_2 &= \alpha \cdot \mathbf{b}_2 + (1 - \alpha) \cdot \mathbf{b}_1 \end{aligned} \quad (9)$$

where $\alpha \in [0, 1]$ is a randomly generated coefficient array, $\mathbf{b}_1$ and $\mathbf{b}_2$ denote parent solutions, and y_1 and y_2 represent the generated offspring. Cannibalism is subsequently applied, where strong individuals eliminate weaker spiders, thereby preserving high-quality solutions within the population. This mechanism enhances selection pressure and accelerates convergence. Mutation is introduced to improve population diversity and exploration capability. As illustrated in Fig. 5, mutation involves swapping two randomly selected elements within the solution vector:

$$[b_1, \dots, b_i, \dots, b_j, \dots, b_n] \rightarrow [b_1, \dots, b_j, \dots, b_i, \dots, b_n]$$

This process facilitates effective exploration of the search space and prevents stagnation.⁷

Step 4: Population Update The population is updated iteratively by evaluating newly generated candidate solutions. The process continues until the maximum number of iterations is reached or the termination criterion is satisfied. Although BWO demonstrates strong optimization capability, it may experience premature convergence under certain conditions. To enhance global search performance, the β parameter is modified to evolve nonlinearly with iteration count, as defined by

$$\beta_i = 8 \times \left(\frac{2}{iter} \right)^2, \beta = [\beta_1, \beta_2, \dots, \beta_n] \quad (10)$$

where *iter* denotes the current iteration number.

Accordingly, the crossover equation is updated as

$$\begin{aligned} y_1 &= \alpha \cdot b_1 + (1 - \alpha) \cdot b_2 \\ y_2 &= \beta \cdot b_2 + (1 - \alpha) \cdot b_1 \end{aligned} \quad (11)$$

where b_1 and b_2 are parent solutions, and y_1 and y_2 are offspring. Experimental observations indicate that maintaining the β parameter at a constant value of 8 improves the global exploration ability of the algorithm.

II.4 PROPOSED BWO-ANN BASED MPPT

A novel BWO-ANN based Maximum Power Point Tracking (MPPT) technique is proposed to efficiently track the maximum power point (MPP) under varying environmental conditions. The process begins by initializing spider individuals, which represent the initial weight and bias parameters of the Artificial Neural Network (ANN) employed for MPPT. The ANN output is compared with the desired reference value, and the Root Mean Square Error (RMSE) is used as the performance metric.

During each iteration, the algorithm verifies whether the maximum number of iterations or the minimum error threshold has been achieved. If neither condition is satisfied, the BWO optimization procedures—crossover, cannibalism, and mutation—are applied to refine the ANN parameters. This iterative refinement enhances the learning capability and prediction accuracy of the ANN. Upon reaching the stopping criterion, the optimal ANN parameters are obtained. The optimized ANN model is then validated using a test dataset to compute the optimal MPPT value. The hybrid BWO–ANN framework thereby improves tracking accuracy, convergence speed, and robustness under dynamic solar conditions.

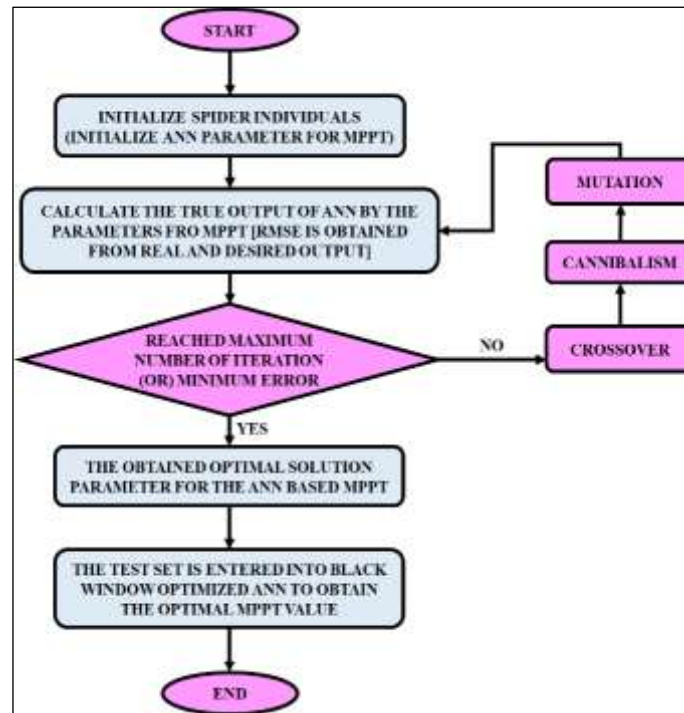


Figure 6: Flowchart of Proposed BWO-ANN based MPPT.

Source: Authors, (2026).

Subsequently, the DC output from the converter is processed through a high-frequency inverter to generate a high-frequency AC signal. An isolation transformer provides galvanic isolation between the PV source and load side, ensuring safe and reliable operation. The AC signal is then rectified using an interleaved synchronous rectifier to obtain regulated DC output. Finally, the rectified DC power is supplied to the DC bus or battery for storage or direct utilization without distortion.

III. RESULTS AND DISCUSSION

This section presents the simulation results obtained using MATLAB/Simulink for the proposed Modified Luo converter integrated with the BWO–ANN based MPPT technique. A comparative analysis with recently developed approaches is also carried out to validate the effectiveness of the proposed system. The system parameters employed in the simulation are summarized in Table 1.

Table 1: PV Panel.

Parameter	Specification
Rated Power	5 kW
Panels in Parallel	7
Panels in Series	3
Open Circuit Voltage	37.25 V
Short Circuit Current	8.95 A
Cells in Series per Panel	36

Source: Authors, (2026).

Table 2: Converter.

Parameter	Specification
Inductors (L_a , L_b , L_c)	4.7 mH
Switching Frequency	10 kHz
C_1	22 μ F
C_0	2200 μ F

Source: Authors, (2026).

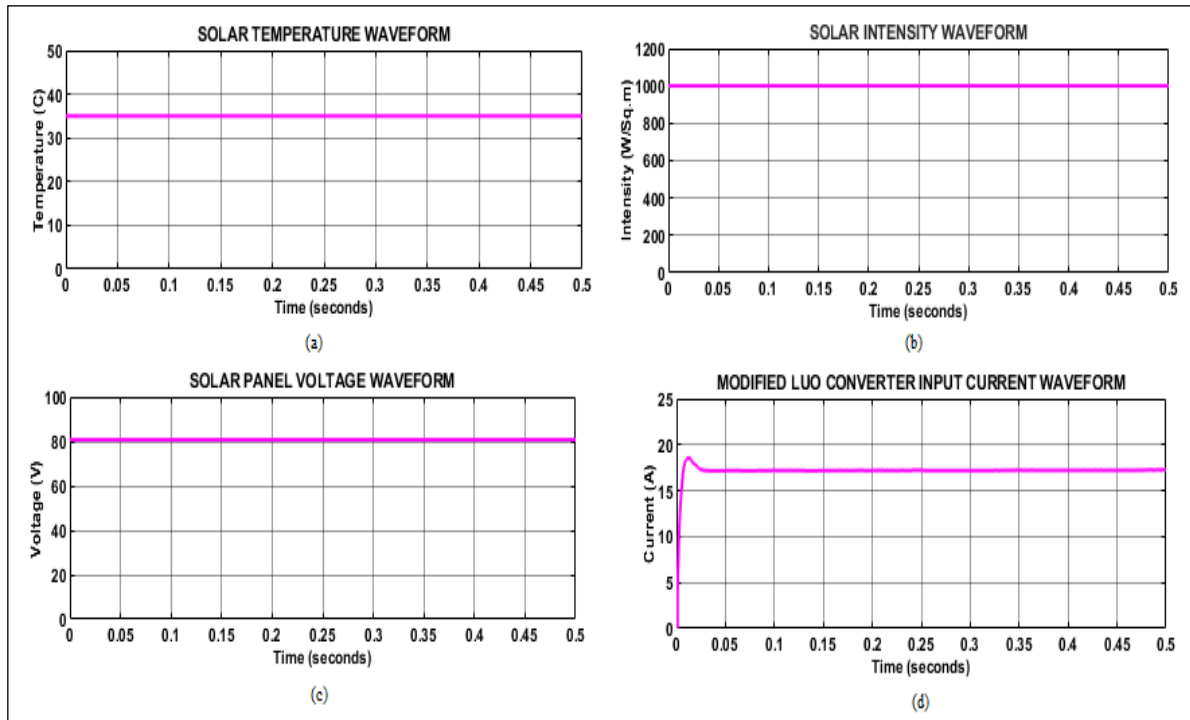


Figure 7: Solar panel Waveforms.

Source: Authors, (2026).

Figure 7 illustrates the solar panel characteristics under standard test conditions. The module temperature is maintained at 35°C, while the solar irradiance remains constant at 1000 W/m². The PV output voltage is regulated at approximately 80 V, and the corresponding output current is observed to be 17 A. These results confirm stable PV operation under uniform environmental conditions.

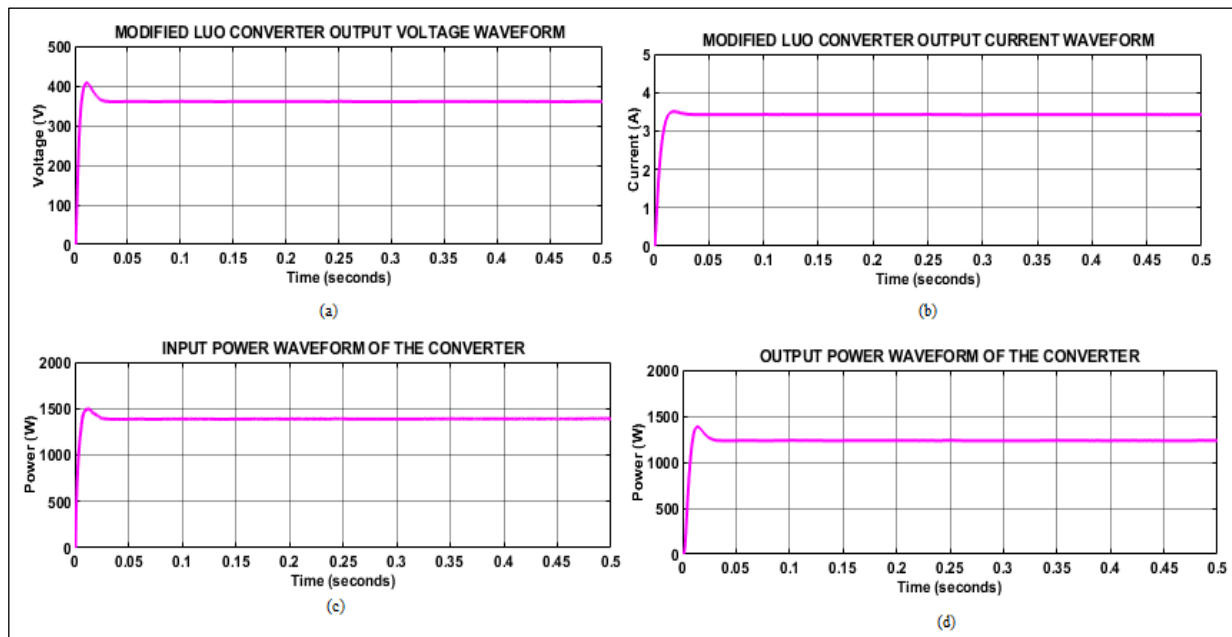


Figure 8: proposed Modified Luo converter waveforms.

Source: Authors, (2026).

The PV output is fed to the proposed Modified Luo converter to boost the voltage for DC bus/battery applications. As shown in Figure 8(a), the converter output voltage stabilizes at 380 V after minor transient oscillations. The output current, depicted in Figure 8(b), initially fluctuates but settles at 3.5 A after 0.05 s. The input power to the converter is maintained at 1360 W, whereas the output power stabilizes at 1330 W after 0.05 s, indicating efficient power transfer with minimal losses.

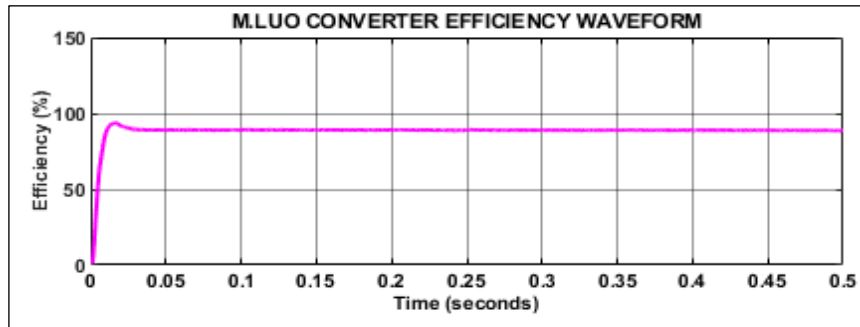


Figure 9: Converter Efficiency waveform.
Source: Authors, (2026).

The efficiency waveform shown in Figure 9 indicates that the proposed Modified Luo converter achieves a peak efficiency of 97.79%. This high efficiency validates the suitability of the converter for high-gain DC bus/battery applications.

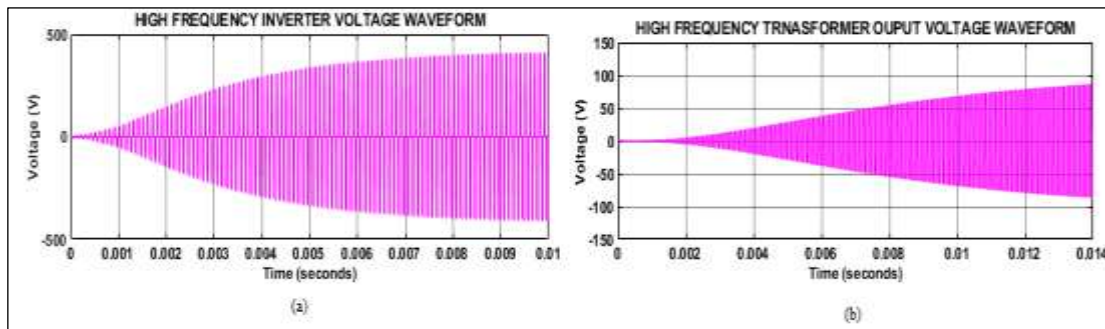


Figure 10: High frequency inverter and transformer output voltage waveform.
Source: Authors, (2026).

The high-frequency inverter voltage waveform (Figure 10(a)) exhibits initial oscillations up to 0.008 s and then stabilizes at 470 V. The transformer output voltage (Figure 10(b)) remains steady at 80 V with negligible distortion, confirming effective voltage transformation and isolation.

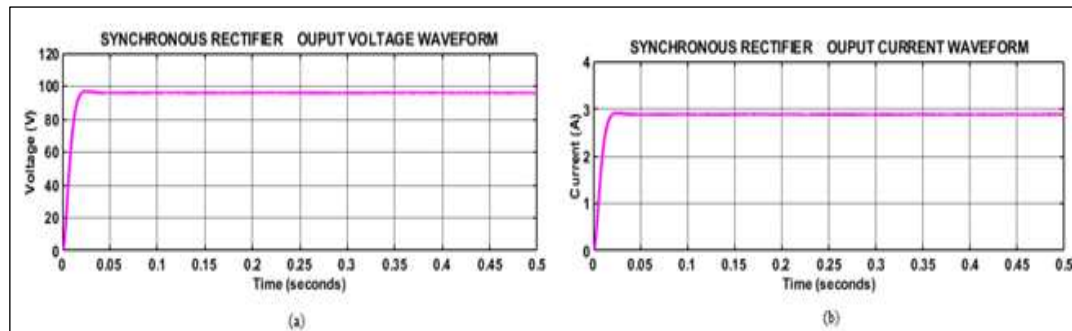


Figure 11: Synchronous rectifier 1 output voltage and current waveforms.
Source: Authors, (2026).

Figure 11(a) shows that the synchronous rectifier output voltage stabilizes at 97 V after 0.05 s. Similarly, the output current (Fig. 11(b)) reaches a steady value of 2.9 A without noticeable deviations. These results confirm reliable rectification and regulated DC output.

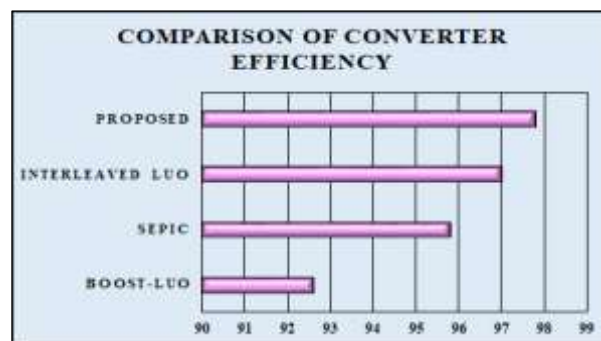


Figure 12: Comparison of converter efficiency.
Source: Authors, (2026).

The converter voltage conversion efficiency is compared with other recently developed converters for proving the importance of proposed High gain Modified Luo converter. From the Figure 12, it is analysed that compared to other converters as referred in [23–25], the proposed converter attains higher efficiency of 97.79% that improves the performance. Likewise, the tracking Efficiency of MPPT with various approaches are shown in Table 3, which signified that utilized BWO-ANN based MPPT approach attains maximized tracking efficiency of 98.96% when compared to the other topologies.

Table 3: Comparison of Tracking Efficiency.

MPPT Approaches	Tracking Efficiency (%)
P&O [26]	85.8
PSO [27]	96.96
Improved Hill climbing [28]	98.45
Proposed BWO-ANN	98.96

Source: Authors, (2026).

IV. CONCLUSION

This paper presents a novel BWO–ANN based MPPT integrated with a Modified Luo converter for enhanced photovoltaic energy extraction, particularly under low irradiance and near-zero partial shading conditions for DC bus/battery applications. The proposed BWO–ANN approach improves tracking accuracy, enhances convergence speed, and minimizes steady-state oscillations compared to conventional MPPT techniques. The Modified Luo converter delivers high voltage gain with reduced component losses and achieves a maximum efficiency of 97.79%. Furthermore, the incorporation of a high-frequency inverter and isolation transformer ensures safe and reliable operation by providing galvanic isolation between the PV source and DC bus/battery. Simulation results obtained from MATLAB/Simulink validate the effectiveness of the proposed system. Comparative analysis demonstrates superior converter efficiency (97.79%) and tracking efficiency (98.96%) compared to existing methods, thereby confirming the significance and improved performance of the developed system.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Sivaprasad Kollati.

Methodology: Sivaprasad Kollati, Satish Kumar Gudey.

Investigation: Sivaprasad Kollati.

Discussion of results: Sivaprasad Kollati, Satish Kumar Gudey.

Writing – Original Draft: Sivaprasad Kollati.

Writing – Review and Editing: Satish Kumar Gudey.

Resources: Sivaprasad Kollati, Satish Kumar Gudey.

Supervision: Sivaprasad Kollati.

Approval of the final text: Sivaprasad Kollati, Satish Kumar Gudey.

VI. REFERENCES

- [1] S. H. Hanzaei, S. A. Gorji, and M. Ektesabi, "A scheme-based review of MPPT techniques with respect to input variables including solar irradiance and PV arrays' temperature," IEEE Access, vol. 8, pp. 182229–182239, 2020, doi: 10.1109/ACCESS.2020.3022516.
- [2] U. Khan et al., "Heuristic algorithm based optimal power flow model incorporating stochastic renewable energy sources," IEEE Access, vol. 8, pp. 148622–148643, 2020, doi: 10.1109/ACCESS.2020.3015468.
- [3] C. González-Castaño, C. Restrepo, S. Kouro, and J. Rodriguez, "MPPT algorithm based on artificial bee colony for PV system," IEEE Access, vol. 9, pp. 43121–43133, 2021, doi: 10.1109/ACCESS.2021.3065525.
- [4] S. Ganesan et al., "Investigation on sizing of voltage source for a battery energy storage system in microgrid with renewable energy sources," IEEE Access, vol. 8, pp. 188861–188874, 2020, doi: 10.1109/ACCESS.2020.3031358.
- [5] K. Gupta et al., "Effect of various incremental conductance MPPT methods on the charging of battery load feed by solar panel," IEEE Access, vol. 9, pp. 90977–90988, 2021, doi: 10.1109/ACCESS.2021.3091174.
- [6] N. Ncir, N. El Akchioui, and A. El Fathi, "Enhancing photovoltaic system modeling and control under partial and complex shading conditions using a robust hybrid DE-FFNN MPPT strategy," Renewable Energy Focus, vol. 47, p. 100504, 2023, doi: 10.1016/j.ref.2023.100504.
- [7] J. Águila-León et al., "Optimizing photovoltaic systems: A meta-optimization approach with GWO-enhanced PSO algorithm for improving MPPT controllers," Renewable Energy, vol. 230, p. 120892, 2024, doi: 10.1016/j.renene.2024.120892.
- [8] M. H. EL-Banna et al., "On-grid optimal MPPT for fine-tuned inverter based PV system using golf optimizer considering partial shading effect," Alexandria Engineering Journal, vol. 103, pp. 180–196, 2024, doi: 10.1016/j.aej.2023.12.012.A
- [9] S. Ahmed et al., "Supertwisting sliding mode algorithm based nonlinear MPPT control for a solar PV system with artificial neural networks based reference generation," Energies, vol. 13, no. 14, p. 3695, 2020, doi: 10.3390/en13143695.
- [10] I. M. Ali et al., "An enhanced P&O MPPT algorithm with concise search area for grid-tied PV systems," IEEE Access, vol. 11, pp. 79408–79421, 2023, doi: 10.1109/ACCESS.2023.3297038.

- [11] L. Shang, H. Guo, and W. Zhu, "An improved MPPT control strategy based on incremental conductance algorithm," *Protection and Control of Modern Power Systems*, vol. 5, no. 2, pp. 1–8, 2020, doi: 10.1186/s41601-020-00159-1.
- [12] M. Dehghani et al., "Optimized fuzzy controller for MPPT of grid-connected PV systems in rapidly changing atmospheric conditions," *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 2, pp. 376–383, 2020, doi: 10.35833/MPCE.2019.000611.
- [13] P. Verma et al., "Meta-heuristic optimization techniques used for maximum power point tracking in solar PV system," *Electronics*, vol. 10, no. 19, p. 2419, 2021, doi: 10.3390/electronics10192419.
- [14] C. Hussaian Basha et al., "A novel design and implementation of hybrid MPPT controllers for solar PV systems under various partial shading conditions," *Scientific Reports*, vol. 14, p. 1609, 2024, doi: 10.1038/s41598-024-51609-3.
- [15] N. F. Ibrahim et al., "A new adaptive MPPT technique using an improved INC algorithm supported by fuzzy self-tuning controller for a grid-linked photovoltaic system," *PLoS ONE*, vol. 18, no. 11, p. e0293613, 2023, doi: 10.1371/journal.pone.0293613.
- [16] H. Meshael, A. Elkhateb, and R. Best, "Topologies and design characteristics of isolated high step-up DC–DC converters for photovoltaic systems," *Electronics*, vol. 12, no. 18, p. 3913, 2023, doi: 10.3390/electronics12183913.
- [17] M. Karthikeyan et al., "A hybridization of Cuk and boost converter using single switch with higher voltage gain compatibility," *Energies*, vol. 13, no. 9, p. 2312, 2020, doi: 10.3390/en13092312.
- [18] S. Kumar et al., "Improved control strategy for cuk converter assisted wind-driven SEIG for DC nanogrid," *IET Electric Power Applications*, vol. 14, no. 10, pp. 1906–1917, 2020, doi: 10.1049/iet-epa.2019.0875.
- [19] M. Vaigundamoorthi et al., "MPPT oscillations minimization in PV system by controlling non-linear dynamics in SEPIC DC-DC converter," *International Journal of Electrical and Computer Engineering*, vol. 10, no. 6, pp. 6268–6275, 2020, doi: 10.11591/ijece.v10i6.pp6268-6275.
- [20] R. Shenbagalakshmi, S. Vijayalakshmi, and K. Geetha, "Design and analysis of discrete PID controller for Luo converter," *International Journal of Power Electronics*, vol. 11, no. 3, pp. 283–298, 2020, doi: 10.1504/IJPELEC.2020.108087.
- [21] D. T. Prasad, R. Anandhakumar, and P. Balamurugan, "Intelligent MPPT control for SEPIC-Luo converter in grid tied photovoltaic system," *International Journal of Applied Engineering Research*, vol. 13, no. 1, pp. 102–112, 2024.
- [22] D. G. Jegha et al., "Optimally tuned interleaved Luo converter for PV array fed BLDC motor driven centrifugal pumps using whale optimization algorithm," *Electronics*, vol. 9, no. 9, p. 1445, 2020, doi: 10.3390/electronics9091445.
- [23] H. Gholizadeh et al., "Design and implementation of a single-switch step-up DC-DC converter based on cascaded boost and Luo converters," *Energies*, vol. 14, no. 12, p. 3584, 2021, doi: 10.3390/en14123584.
- [24] P. Kavitha and P. S. Karuvelam, "A highly efficient optimized PI controller fed SEPIC converter for hybrid renewable sources based microgrid system," *Microprocessors and Microsystems*, 2023, doi: 10.1016/j.micpro.2023.104797.
- [25] M. S. Endiz, "Performance analysis of P&O and PSO MPPT algorithms for PV systems under partial shading," *Konya Journal of Engineering Sciences*, vol. 12, no. 1, pp. 84–99, 2024.
- [26] E. W. Mukti et al., "Particle Swarm Optimization (PSO) based photovoltaic MPPT algorithm under the partial shading condition," *Jurnal Elektronika dan Telekomunikasi*, vol. 23, no. 2, pp. 99–107, 2023.
- [27] C. B. Nzoundja Fapi et al., "Real-time experimental assessment of Hill Climbing MPPT algorithm enhanced by estimating a duty cycle for PV system," *International Journal of Renewable Energy Research*, 2019.