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Optimizing Global MPPT in PV Systems: A Comparison of Modified TLBO and PSO Under Partial Shading

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ABSTRACT

Photovoltaic (PV) systems are essential for sustainable energy generation, yet their efficiency can be significantly compromised under partial shading conditions, leading to complex, multimodal P-V curves. MPPT methods often struggle in these scenarios, as they may converge on local maxima rather than identifying the global maximum power point (GMPP), thereby reducing energy harvest. This study introduces a Modified Teaching-Learning-Based Optimization (MTLBO) tailored for this context with adaptive strategies—such as multi-group initialization, an improved student phase, and hybrid learning mechanisms. The contribution is twofold. First, we conduct a methods-first characterization that compares ordinary TLBO (Teaching-Learning-Based Optimization) and MTLBO under function-evaluation–matched and seed-controlled protocol on canonical benchmark (Rosenbrock, Rastrigin, Griewank, Ackley), the objective is to select robust defaults and explain behavior using median, mean, dispersion, success ratios, and acceptance count metrics. Second, we fold the selected method into a multimodal operating condition induced by partial shading. Benchmark results show that MTLBO improves typical performance and reliability—achieving lower median final error than TLBO at the same computational budget. In application-level MPPT assessments, MTLBO proficiently tracks the GMPP and outperforms Incremental Conductance (INC) and Particle Swarm Optimization (PSO) in convergence speed, stability, and ripple reduction. These findings underscore the MTLBO method's potential to significantly enhance MPPT performance in PV systems subjected to partial shading.

1. INTRODUCTION

Photovoltaic (PV) systems have emerged as a vital, sustainable alternative to conventional fossil fuel-based power generation, offering a clean and abundant energy source. Despite their numerous advantages, PV systems face operational challenges that can impact their efficiency and energy output [1] they operating under partial shading develop multimodal P–V characteristics with several local maxima, a setting in which conventional maximum power point tracking (MPPT) like PO may settle at suboptimal peaks which cause a substantial energy losses, current flow limitation [2-4] causing substantial energy losses reaching up to 80% [5], in addition to reliability issues caused by hot spots.

Recent reviews document how partial shading complicates global tracking and motivate robust MPPT design under realistic disturbances [1]. In such regimes, improved PSO-type strategies and other metaheuristics have been proposed to accelerate convergence and avoid trapping at non-global peaks [6].

Within this landscape, Teaching–Learning-Based Optimization (TLBO) has gained significant attention due to its simplicity, parameter-lean, and efficiency across continuous problems. TLBO is a population-based optimization technique inspired by the teaching and learning process in a classroom environment, it organizes search into a teacher phase (pull toward the best-performing candidate relative to the mean) and a learner phase (pairwise collaborative refinement). Foundational studies established TLBO's effectiveness in constrained and large-scale settings and popularized it for engineering designs [7-10]. Despite its advantages, the classical TLBO algorithm has shown limitations, empirical MPPT reports in strongly multimodal regimes remain mixed: enabling diversity unconditionally can slow progress on near-smooth landscapes, whereas insufficient diversity risks premature convergence under complex shading. These observations motivate an approach that tightens evaluation protocols and activates diversity mechanisms only when justified by the landscape.

To address these challenges, various enhancements have been proposed to refine TLBO's performance by improving its exploration (global search) and exploitation (local search) capabilities [11, 12]. Still, Reproducibility guidance in evolutionary computation recommends explicit budgets, seed control, and artifact sharing to improve interpretability and reuse [13] which is a gap that recur in the literature, in fact comparisons among TLBO and its variants are not always performed under function-evaluation (FE)-matched, seed-controlled protocols; and diversity mechanisms in variants (grouping, rank-based sub-updates, ε-injection) are often enabled unconditionally.

We therefore propose a Modified TLBO (MTLBO) guided by two design principles. First, we strengthen teacher-guided intensification via multi-group initialization followed by selecting the better candidate. Second, we adopt landscape-aware diversity: mixed-group learning with periodic migration, rank-based student selection and class update, and a small ε-injection these are off by default and enabled only when multimodality is evident as under partial shading. The changes are minimal and implementation-friendly, preserving TLBO's simplicity while improving robustness.

The MTLBO characterization tests are done first. We compare TLBO and MTLBO under FE-matched, seed-controlled trials on a complementary suite of unconstrained benchmarks used widely in global optimization: Rosenbrock (curved valley; stresses intensification), Rastrigin and Ackley (pronounced multimodality), and Griewank (weakly coupled multimodality through a cosine product). Benchmark suites such as these are standard tools for probing the exploitation–exploration trade-off prior to system-specific testing [14, 15]. We report medians, means, dispersion, success ratios at fixed thresholds, and phase-acceptance counts (teacher versus learner). These diagnostics attribute progress to mechanism (intensification vs. diversity) rather than only end-point error. From them we extract practical rules: disable diversity and use moderate teacher extrapolation on near-smooth landscapes; enable grouping, rank-based updates, and a small ε-injection when multimodality dominates.

Finally, we embed the selected MTLBO configuration in an MPPT-oriented formulation suitable for partial shading: the decision variable is the duty ratio with practical bounds, the cost is defined as the converter output power with sampling/averaging details, and convergence is judged by improvement. application-level MPPT assessments are then done between MTLBO, incremental conductance (INC) and PSO method comparing convergence speed, stability, and ripple reduction under partial shading conditions [6]. This structure provides a rationale for method selection and an implementation-ready pathway for PV control.

The paper is outlined as fellow:

- Section 2 summarizes the studied PV system fundamental components and mathematical models.
- Section 3 gives a brief review about MPPT Algorithms for PV Systems under partial shading focusing on PSO.
- Section 4 develops the optimization methodology: TLBO fundamentals; the detailed MTLBO with equations and MPPT tailoring (decision variable, bounds, cost, sampling).
- Section 5 reports results and discussion: beginning with FE-matched, seed-controlled comparisons between TLBO and MTLBO on the four benchmark functions with acceptance-count diagnostics and sensitivity notes; followed by a detailed comparative simulation under multiple scenarios including partial shading conditions of MTLBO-MPPT versus PSO-MPPT.
- Section 6 concludes with practical limitations, and suggests potential directions for future research.

2. PV SYSTEM ARCHITECTURE

The photovoltaic (PV) system under examination features a standalone PV generator linked to a load through a DC-DC power stage and a digital controller that executes the selected MPPT routine, the controller proposes duty-cycle updates applied to the converter so that the operating point tracks the global maximum power point to optimize the extraction of available power from the PV generator amidst fluctuating environmental conditions. An illustrative diagram of this PV energy production system summarizing the main components and signal flow.

2.1 PV generator

The electrical behavior of a PV generator (Figure 1) can be represented by the single-diode model with series resistance R_s and shunt resistance R_{sh}. accounts for both the ideal photovoltaic effect and the non-ideal losses associated with practical PV cells (Figure 2). The mathematical expression governing the output current is [16]:

$$I = I_{ph} - I_0\left[exp\left\{\frac{q\cdot(v+I\cdot R)}{n\cdot k\cdot\cdot T}\right\} - 1\right] - \left(\frac{V+I\cdot R_S}{R_{sh}}\right) \quad (1)$$

where,

- *Iph:* Photogenerated current (depends on irradiance and temperature).
- I_S: Saturation current of the diode.
- q: Electron charge.
- V: Output voltage of the solar cell.
- R_S, R_{sh}: Series and shunt resistances, respectively.
- n: Ideality factor.
- $k = 1.38 \times 10^{-23}$ J/K (Boltzmann's constant).
- T: Cell temperature in Kelvin.

The PV generator typically aggregates modules in series (N_S) and in parallel (N_P) to meet the required voltage and current. The general structure of the PV system incorporating the MPPT algorithm is illustrated in Figure 1, while Figure 2 shows the bypass-diode configuration and the current flow that occurs when a PV cell is shaded.

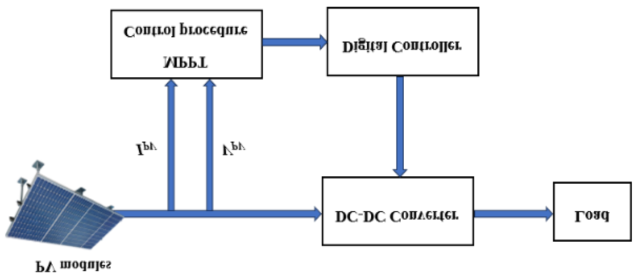


Figure 1. The general structure of the PV system with MPPT

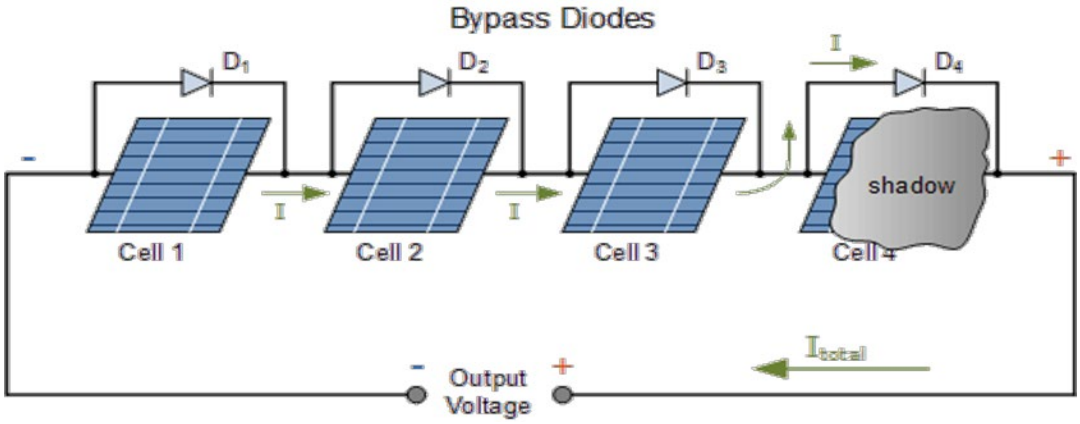


Figure 2. Bypass-diode configuration with current flow when the cell is shaded

2.2 Digital power stage and MPPT interface

The digital controller bridges the MPPT routine and the power stage. The control input is the duty ratio $d \in [d_{min}, d_{max}]$, applied to a DC-DC converter, in case of boost-type converter with non-idealities absorbed in an efficiency term $\eta\ (d, I)$. The relationships between the input and output voltages and is [17]:

$$\frac{V_{out}}{V_{in}} \approx \frac{I_{in}}{I_{out}} \approx \frac{1}{(1-D)} \tag{2}$$

where,

V_{out} is the output voltage, V_{in} is the input voltage, and the duty cycle D is defined as the fraction of the switching period during which the switch is in the "on" state.

At each sampled period Ts, the control updates the MPPT proposes dew, which is rate-limited. based on Vpv and Ipv, a short moving average can be used to attenuate switching ripple. These implementation details are consistent with the modelling adopted in our manuscript [17].

Software checks enforce operating bounds and protection rules: $d_{min} \leq d_{new} \leq d_{max}$; a maximum duty change $|d[k] - d[k-1]| \leq \Delta\ d_{max}$; voltage and current limits $V_{min} \leq Vpv \leq V_{max}$ and $0 \leq I_{pv} \leq I_{max}$; and optional derating under over-temperature.

These constraints mitigate hot-spot risk under partial shading and reduce component stress during transients [17, 18].

2.3 Shadowing on solar cells

The practical performance of a PV panel is significantly influenced by various factors such as manufacturing defects, cell degradation, high operating temperatures, and, partial shading. Among these, partial shading presents one of the most critical challenges, non-uniform irradiance across cells or substrings causes electrical mismatch: shaded elements limit the string current and may become reverse-biased. At array level, the *I–V* curve exhibits steps and the *P–V* curve presents multiple local maxima. This condition leads to:

• Reduction in power output: The overall module power drops.

• Hot spot formation: The shaded cell may dissipate excess power as heat, potentially damaging the module over time.

These multimodal characteristics motivate global MPPT strategies and careful controller design to avoid dwelling at non-global peaks [17, 18].

2.3.1 Bypass diodes for partial shading mitigation

To mitigate these effects posed by partial shading in PV systems, bypass diodes are installed in parallel with subsets of solar cells within a module. Bypass diodes conduct when the reverse voltage across a shaded substring exceeds the diode threshold, limiting reverse bias, prevent significant power losses and protects the affected cells from potential damage by reducing thermal stress. Their activation introduces the characteristic kinks in the *I–V* curve and multiple peaks in the *P–V* curve. The number and placement of bypass diodes influence both reliability and the difficulty of global tracking [17]. This mechanism is illustrated in Figure 2, where the bypass diode activates when a cell is shaded, ensuring that the remaining unshaded cells continue to function efficiently.

3. MPPT ALGORITHMS FOR PV SYSTEMS UNDER PARTIAL SHADING

Under partial shading conditions, the power-voltage *P-V* characteristics of PV arrays exhibit multiple peaks, including several local maxima, this complexity poses challenges for conventional MPPT methods, classical MPPT schemes- Perturb & Observe (P&O) and Incremental Conductance (INC)-adjust the operating point from local slope information, which makes them simple and inexpensive to implement. however, the *P–V* surface is multimodal: local rules may settle at non-global peaks and generate oscillations. Adaptive step sizes and basic filtering improve responsiveness versus ripple but do not fully resolve peak ambiguity in rapidly changing conditions. As a result, occasional scans or reset heuristics are often required to recover from mis-tracking.

Intelligent MPPT algorithms, employs population-based metaheuristics (e.g., GA, PSO, TLBO) to explore multiple candidate duty ratios in parallel, improving robustness on multimodal *P–V* landscapes. Hence improving both tracking accuracy and energy yield. [19, 20]. Theirs effectiveness depends on careful parameter Tuning, evaluation budget and on synchronizing population updates with converter timing and protection limits in real-time implementation [21, 22].

3.1 PSO-based MPPT

Particle Swarm Optimization (PSO) is a population-based search that iteratively updates a set of particles using social and cognitive feedback. For MPPT, each particle encodes a candidate duty ratio d and the objective is to minimize $f(d)$ =

$-P(d)$, where P (d)= $Vpv(d)\cdot Ipv(d)$ is measured at each period k which an integer multiple of the switching period Ts. Before actuation, proposed duty update is rate-limited and saturated.

Algorithm: The PSO-based MPPT algorithm operates through the following steps:

1. Initialization*:* Define population size n_{pop}, a swarm of particles is initialized with random positions x_i and velocities v_i, ($i = 1\ldots, n_{\text{pop}}$) where each particle represents a possible *P-V* combination, measure $f(d_i)$; set Best = *argmin f.*

2. Repeat at every MPPT update step (k):

- Evaluation: Each particle's fitness $f(x_i)$ is calculated based on its power output, then x_g best of the swarm is set.

- Update velocity and position:

The velocity update equation for each particle in the swarm is calculated as [21]:

$$v_i(k+1) = w \cdot v_i(k) + c_1 \cdot r_1 \cdot (x_i(k) - x_i(best)) + c_2 \cdot r_2 \cdot (x_g(k) - x_i(k)) \tag{3}$$

where,

vi(k) is the velocity the i-th particle at the k-t*h* iteration.

xi(*k*) is the position of the i-th particle at the k-th iteration.

xi(*best*) is the personal best position of the i-th particle.

xg (*k*) is the global best position of the swarm.

And w is the inertia weight. c_1, c_2 Are the cognitive and social scaling factors, respectively. r_1, r_2 Are random numbers in the range [0,1].

Then, the position update equation for each particle will be [22]:

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{4}$$

3. Evaluation*:* Apply rate limit, and compute $f = -P$ (using a short moving average if needed) and terminate when convergence corresponding to the GMPP or iteration budget reached; output x_g best of the swarm as the duty to apply.

PSO is less likely to get stuck in local maxima, making it more reliable for partial shading conditions. its limitations include computational complexity and multiple parameter selection [21].

4. TEACHING –LEARNING BASED METHODS FOR MPPT IN PV SYSTEMS

Maximum power point tracking (MPPT) in photovoltaic systems requires algorithms that are accurate, robust to partial shading, and lightweight for embedded implementation. Teaching–Learning-Based Optimization (TLBO) satisfies these design goals by maintaining a small population, using only generic operators, and requiring minimal hyper-parameter tuning. Below we recall the canonical TLBO and its MPPT interface; next section will introduce the proposed Modified TLBO (MTLBO).

TLBO is a population-based algorithm alternates two mechanisms inspired by classroom dynamics: a teacher phase that pulls the class towards the current best solution, and a learner phase that refines solutions via peer interactions [23, 24]. In the context of MPPT, the TLBO algorithm treats each candidate solution (operating point) as a "student" and seeks to optimize the solution iteratively by simulating a teaching phase and a learning phase. We consider a population of duty-ratio candidates $d_i \in [d_{\min}, d_{\max}]$ ($i = 1\ldots, n_{\text{pop}}$) and the MPPT objective $f(d) = -P(d)$, where $P = V_{pv} \bullet I_{pv}$ is the measured array power. At each MPPT update Tu, one proposed best candidate is calculated and after clipped and rate-limited to respect converter dynamics and protections [23].

Algorithm: The TLBO-based MPPT algorithm operates through the following steps

a. Initialization: Define population size n_{pop} , a population of learners xi is initialized, where each particle student represents a possible power-voltage combination, measure f (d_i); set Best = *argmin f.*

b. Repeat at every MPPT update step (*k*)

- Evaluation: Each student's fitness $f(x_i)$ is calculated based on its power output, then teacher (*T*) is set.

- Teacher Phase: The Update equation of each learner candidate x_i is [23]:

$$x_i(k+1) = x_i(k) + r_1 \cdot (T - F \cdot M) \tag{5}$$

where, *xi* (*k*) current position of the i-th candidate. *T*: Teacher (best candidate solution).

M: Mean position of the population. r_1: Random number in the range [0,1].

F: the teaching factor is having only two possible values (0, 1).

-Learner Phase: each pair of learners (*xi* (*k*), *xi* (*k*)) interact pairwise, the update equation of each learner i is:

$$x_i(k+1) = \begin{cases} x_i(k) + r_2 \cdot (x_j(k) - x_i(k)), & \text{if } f(x_j(k)) > f(x_i(k)) \\ x_i(k) + r_2 \cdot (x_j(k) - x_j(k)), & \text{if } f(x_j(k)) \le f(x_i(k)) \end{cases} \tag{6}$$

where, r_2 is a random number in the range [0,1] [24].

c. Evaluation: Apply rate limit, and compute $f = -P$ (using a short moving average if needed) and terminate when convergence corresponding to the GMPP or iteration budget reached; output x_g best of the population as the duty to apply.

Unlike the PSO, here there is no need for complex parameter tuning, such as inertia weights, also, the teaching factor F, has only two possible values (0, 1), which eliminates the need for fine-tuning algorithm-specific parameters and makes it easier to implement and tune.

however, studies under partial shading report that large population or dynamic tuning of the parameters may be needed in complex profiles [24]. On benign (near-smooth) landscapes, excessive diversity can slow convergence; conversely, on highly multimodal *P-V* surfaces, the method may prematurely settle near non-global peaks unless additional diversity is injected or teacher guidance is strengthened. These limitations can be exacerbated when measurement noise and converter dynamics blur the objective signal, motivating improvement [24-27]. Various benchmark test is given in simulation section to discuss the method and its enhancement.

4.1 Modified TLBO (MTLBO) for MPPT in PV systems

Enhanced MTLBO aim to address limitations by augmenting the standard TLBO algorithm with adaptive strategies-such as multi-group initialization, an improved student phase, (best-student selection), and mixed-group learning mechanisms, the objective is to effectively balances exploration (global search) and exploitation (local search) processes, preserve simplicity while improving robustness.

Algorithm: The MTLBO algorithm operates through the following steps:

a. Multi-Group Initialization

Define population size npop, a population of learners *xi* is initialized, where each particle student represents a possible power-voltage combination, then measure *f*(*d*) = −*P*(*d*), set Best = *argmin f* and set population teacher *T*.

a.1 Creation of Groups

The population is divided into m groups in MPPT context, since there are multiple peaks in the power-voltage curve, the proposed approach is to divide the population firstly into where *m* is the number of panels in series so if the initial population is npop there will be: $ng = n_{pop}/m$ learner in each group, and group learner will be now noted as x_i^g.

b. Repeat at Every MPPT Update Step (k)

Per-group Evaluation: within each group *gj* (*j=1….m*), each student's fitness $f(x_i^{gj})$ is calculated based on its power output, then best student in each group (S^g) is set. And also, global teacher *T* is set as the best from all groups with each group working independently to explore distinct solution regions. This increases the probability of identifying promising areas by starting from a diverse set of points, thereby reducing the risk of premature convergence.

b.1 Group Teaching Phase

Update each candidate x_i^g based on the S^g student:

$$x_i^g(k+1) = x_i^g(k) + r_{11}{}^g \cdot (S^g - F^g \cdot M^g) \quad g = 1 \dots m, i = 1 \dots . \frac{n}{m} \tag{7}$$

where, $x_i^g(k)$ current position of the i-th candidate. S^g : Est student (best candidate solution inside the group). M^g: Mean position of the group. $r_{11}{}^g$: Random number in the range [0,1].

F^g: the teaching factor inside group is has only two possible values (0, 1).

b.1.1 Group Member Adjustment

Ranking the students of each group by score, the top P_r^g percent (for example P_r^g gpercentage can be adjusted to 50 percent or 0.5) students noted x_{ir}^g of the group will remain in the same group to enter directly the group learning phase to learn from each other hence contributing to the exploitation (refining solutions in promising regions), while bottom P_r^g percent noted x_{inr} will join the global teacher *T* phase, this will guarantee that More student will join the Exploration resulting in faster convergence.

b.2 Mixed Group Learning Class Teaching Phase

Since the population is now divided to small groups and main class, there will be two sub-phases that will be executed in parallel:

b.2.1 Group Learning Phase

In this phase students will interact pairwise inside the region of the group.

For each group g and for each pair of students $(x_{ir}^g(k), x_{jr}^g(k))$:

$$x_{ir}^g(k+1) = \begin{cases} x_i^g(k) + r_{12}^g \cdot \left(x_{jr}^g(k) - x_{ir}^g(k)\right), & \text{if } f\left(x_i^g(k)\right) > f\left(x_j^g(k)\right) \\ x_i^g(k) + r_{12}^g \cdot \left(x_{jr}^g(k) - x_{ir}^g(k)\right), & \text{if } f\left(x_i^g(k)\right) \le f\left(X_j^g(k)\right), \\ g = 1 \dots m,\ i = 1 \dots (ng.P_r^g) \end{cases} \tag{8}$$

where, $f(x_i^g(k))$ is the Fitness function (power output for a given operating point). r_{12}^g: random number in the range [0,1].

b.2.2 Class Teaching Phase

The teacher (*T*) is determined as the best candidate solution in the population with the highest power output P_T.

The number of students that will join this class phase is: n (1-P_r^g), for each candidate student. $x_{i\,nr}$ will be updated based on the teacher *T*:

$$x_{i\,nr}\ (k+1) = x_{i\,nr}(k) + r_{21} \cdot (T - F \cdot M) \quad i = 1 \dots .. n\,(1\text{-}P_r^g) \tag{9}$$

where, $x_{i\,nr}(k)$current position of the i-th candidate.

T: global Teacher (best candidate solution).

M: Mean position of the population. and r_{21} random number in the range [0,1].

b.3 Class Learning Phase

In this step the students eliminated from the m groups will now interact pairwise to learn from each other contributing in turn to the exploitation.

For each pair of students is $\left(x_{i\,nr}(k), x_{j\,nr}(k)\right)$

$$x_{i\,nr}(k+1) = \begin{cases} x_{i\,nr}(k) + r_{22} \cdot \left(x_{j\,nr}(k) - x_{i\,nr}(k)\right), & \text{if } f\left(x_{j\,nr}(k)\right) > f(x_{i\,nr}(k)) \\ x_{i\,nr}(k) + r_{22} \cdot \left(x_{i\,nr}(k) - x_{j\,nr}(k)\right), & \text{if } f\left(x_{j\,nr}(k)\right) \le f(x_{i\,nr}(k)) \end{cases} i,j = \quad i,j = 1 \dots n\,(1 - P_r^g) \tag{10}$$

where, r_{22} random number in the range [0,1].

b.4 Group diversity

In order to keep exploitation since the number of group elements will decrease by group adjustment process a number of students noted e_p^g will be chosen randomly from the class to join once again the group:

$$e_p^g = ng\,(1 - P_r^g).\mu \tag{11}$$

where, *μ* chosen the range [0,1].

c. Evaluation Apply rate limit, and compute *f* = −*P* (using a short moving average if needed) by evaluating the power output for each candidate from the population *n* and the best students (S^g)inside each group. and terminate when convergence corresponding to the GMPP or iteration budget reached; output x_g best of the population.

Pseudocode

Inputs: bounds, n_{pop}, *m* (groups), P_r^g (top fraction), *μ* (re-group fraction), evaluation budget.

Calculate (n_g), define cost *f(d)* = −*P(d)* (short moving average optional).

1. Multi-Group Initialization: initialize learners; evaluate *f*; set Best Student and global teacher *T*, index learners x_i^g.

2. For each update (k):

2-1. Per-group evaluation: compute *f*; determine S^g (best in group); global teacher *T*.

2-2. Group Teaching Eq. (7) project to bounds.

2-2a. Group members adjustment: classify based on P_r^g.

2-3. Mixed execution (parallel): 2-3a and 2-3b.

2-3a. Group Learning Eq. (8): pairwise updates toward better peer; project.

2-3b. Class Teaching Eq. (9): update class using *M* and *T*; project.

2-4. Class Learning Eq. (10): pairwise updates within class; project.

2-5. Re-grouping Eq. (11): return μ fraction of class to groups to sustain exploitation.

3. Evaluation / Convergence: duty rate-limit; compute *f*; if GM/budget satisfied → STOP; else loop to 2-1.

5. SIMULATION RESULTS

5.1 Evaluation MTLBO versus TLBO

In this sub-section we conduct a methods-first characterization that compares ordinary TLBO and MTLBO under function-evaluation–matched and seed-controlled protocols using simple benchmark that minimize workload while remaining rigorous composed of the following 4 functions: Rosenbrock for mainly Valley/conditioning and precision, Rastrigin with Strong multimodality and exploration stress, Griewank with Weak multimodality and coupling, Ackley characterized by Flat outer region and multimodal. The objective is to select robust defaults and explain behavior using median, mean, dispersion, success ratios at fixed thresholds, and acceptance counts in the teacher and learner phases.

Protocol: the benchmarking protocol is

• Functions dimension: D = 10.

• Function-evaluation budget: FE = 100,000 (identical for both TLBO and MTLB s and all functions). Realized as 2 × N × G with Population N = 50 and generation G = 1000.

• Identical initialization.

• Runs: 10 independent runs per function per algorithm.

• Boundary handling: clamping to the function given domain; no resampling.

• Acceptance: strict improvement only; keep incumbent on ties.

Evaluation criteria: with final objective at FE = 100000, the adopted metrics are:

• Best: minimum final objective across the 10 runs for an algorithm on a function.

• Mean: arithmetic average of final objectives over 10 runs.

• Std: standard deviation of final objectives over 10 runs.

• Median (optional): report if distributions are skewed.

• Success Rate (reliability) at thresholds ($\leq 10^{-3}$, $\leq 10^{-2}$).

• Teacher/Learner acceptance (diagnostic).

Under the proposed protocol and chosen metrics the evaluation results are summarized in what fellow:

The comparative Tables 1 to 3 show that: for Rosenbrock, MTLBO's has lower mean reflects heavy-tailed outcomes under TLBO which attains a lower median and higher success rate. For Rastrigin and Griewank the reading shows that MTLBO decisively outperforms TLBO in accuracy and reliability; near-zero medians indicate consistent deep convergence, the acceptance profile (more teacher-phase, fewer learner-phase updates) is consistent with stronger guidance. while for Ackley results show that both TLBO and MTLBO reach machine precision; the task does not distinguish them at this budget. This is confirmed by the comparative convergence curves given by the following Figure 3.

Table 1. Final objective and success rates

Metric	Rosenbrock		Rastrigin		Griewank		Ackley	
	TLBO	**MTLBO**	**TLBO**	**MTLBO**	**TLBO**	**MTLBO**	**TLBO**	**MTLBO**
Best	2.63e-04	3.59e-04	0.00e+00	0.00e+00	0.00e+00	0.00e+00	3.99e-15	3.99e-15
Mean	2.08e-03	1.73e-03	1.29e+00	9.95e-02	1.97e-03	1.07e-09	3.99e-15	3.99e-15
Std	2.54e-03	1.08e-03	1.33e+00	3.14e-01	6.23e-03	3.15e-09	0.00e+00	0.00e+00
Median	7.28e-04	1.54e-03	9.95e-01	0.00e+00	1.11e-16	5.55e-17	3.99e-15	3.99e-15
SRat1e-2	1.00	1.00	0.40	0.90	0.90	1.000	1.00	1.00
SRat1e-3	0.60	0.20	0.40	0.90	0.90	1.000	1.00	1.00

Table 2. Relative change

Metric	Rosenbrock	Rastrigin	Griewank	Ackley
Mean (%)	-16.78	-92.31	-100	0
Median (%)	111.86	-100	-50	0

Table 3. Acceptance diagnostics (accepts/run; mean ± std)

Metric	Rosenbrock		Rastrigin		Griewank		Ackley	
	TLBO	**MTLBO**	**TLBO**	**MTLBO**	**TLBO**	**MTLBO**	**TLBO**	**MTLBO**
Teacher	4584 ± 1161	4803 ± 1244	370 ± 379	962 ± 570	804 ± 510	1280 ± 680	3693 ± 356	3567 ± 71
Learner	13265 ± 1793	14407 ± 1650	13250 ± 4177	11898 ± 2552	12333 ± 3174	10854 ± 4294	6251 ± 961	4439 ± 34

5.2 PV-System with MTLBO

In the next sub-section, we provide the simulation results under MATLAB of a photovoltaic (PV) system composed of five PV modules (ET Solar Industry ET-P654200WW, 200W each), a DC-DC Boost converter, and a resistive load (100 Ω). The performance of the proposed MTLB) algorithm for MPPT is compared with the PSO-based MPPT and the Incremental Conductance (INC-COND) MPPT under different operating conditions. The main characteristics of the PV panel, Boost converter, PSO and MPPT algorithms are summarized in Tables 4, 5, 6, and 7. The partial shading condition is translated by different irradiance levels for each panel hence expected multiples maximum points in the P-V curve, in addition, the temperature is considered to be constant (25°C). The simulation scheme is illustrated in Figure 4, and the model validations are given by Figure 5.

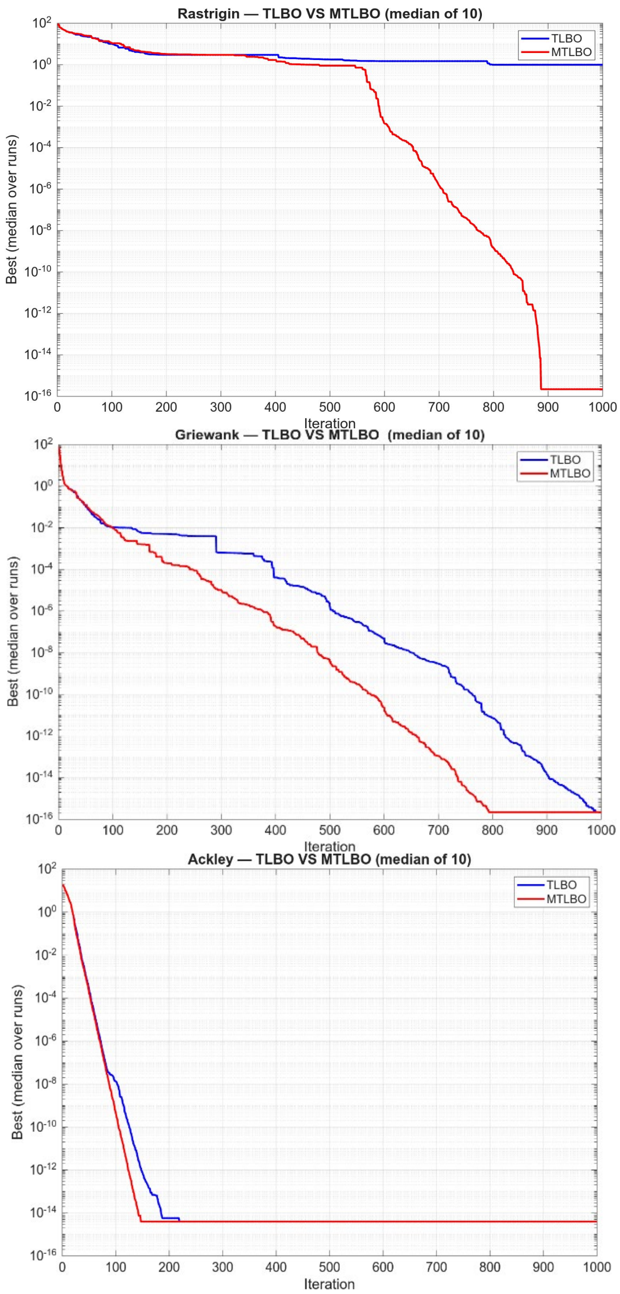


Figure 3. Comparative convergence curves for the 4 function tests (Rosenbrock, Rastrigin, Griewank, Ackley)

Table 4. PV array parameters

Parameter	Value	Parameter	Value
Maximum Power (W)	200.26	Light-generated current IL (A)	7.877
Cells per module *Ncell*	54	I_0 (A)	$2.35.10^{-10}$
Voc (V)	32.72	R_{sh} (ohms)	201.19
Isc (A)	7.86	R_S (ohms)	0.1956
Vmp (V)	27.21	*T* coefficient of *Voc* (%/deg.C)	-0.357
Imp (A)	7.36	T coefficient of Isc (%/deg.C)	0.05

Table 5. Boost converter parameters

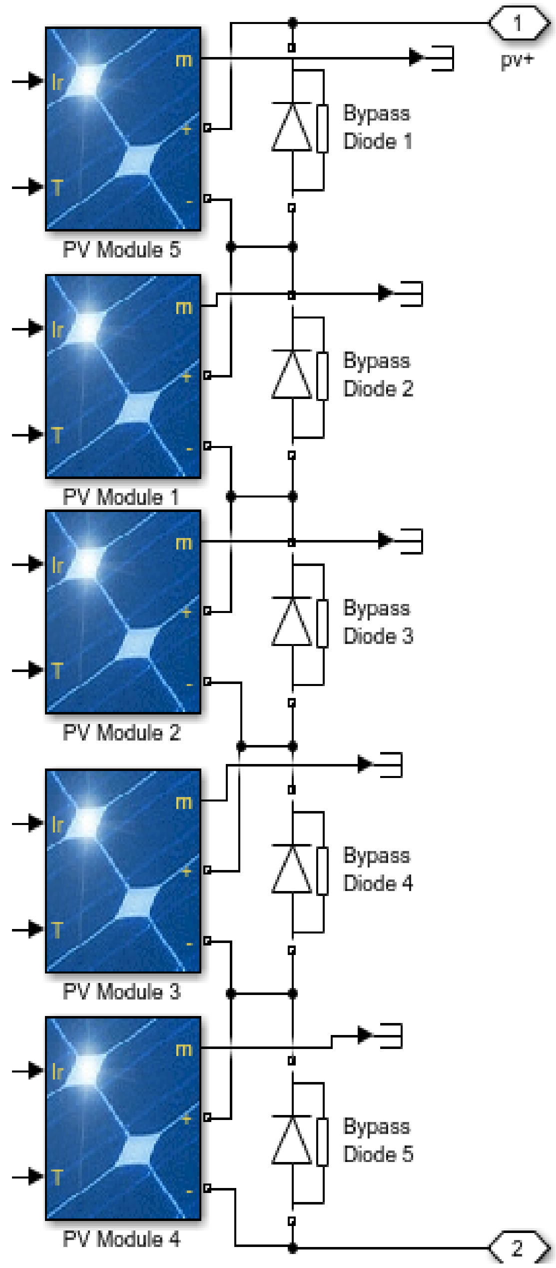
Parameter	Value	Parameter	Value
Inductance *H*	5.10^{-3}	Internal Inductance Resistance (H)	3.10^{-3}
Capacitance *F*	22.10^{-6}	Switching Frequency (Hz)	1.10^{4}

Table 6. PSO parameters

Parameter	Value	Parameter	Value
Swarm Size *n*	30	Inertia Weight ω	0.4
Cognitive Coefficient C_1	1.5	Social Coefficient C_2	1.8

Table 7. MTLBO parameters

Parameter	Value	Parameter	Value
Population Size (n)	60	Number of Group *m*	5
r_{1ij} (Random)	[0,1]	Teaching Factor F	[0,1]
P_r^g adjustment factor	0.5	μ Factor	0.2



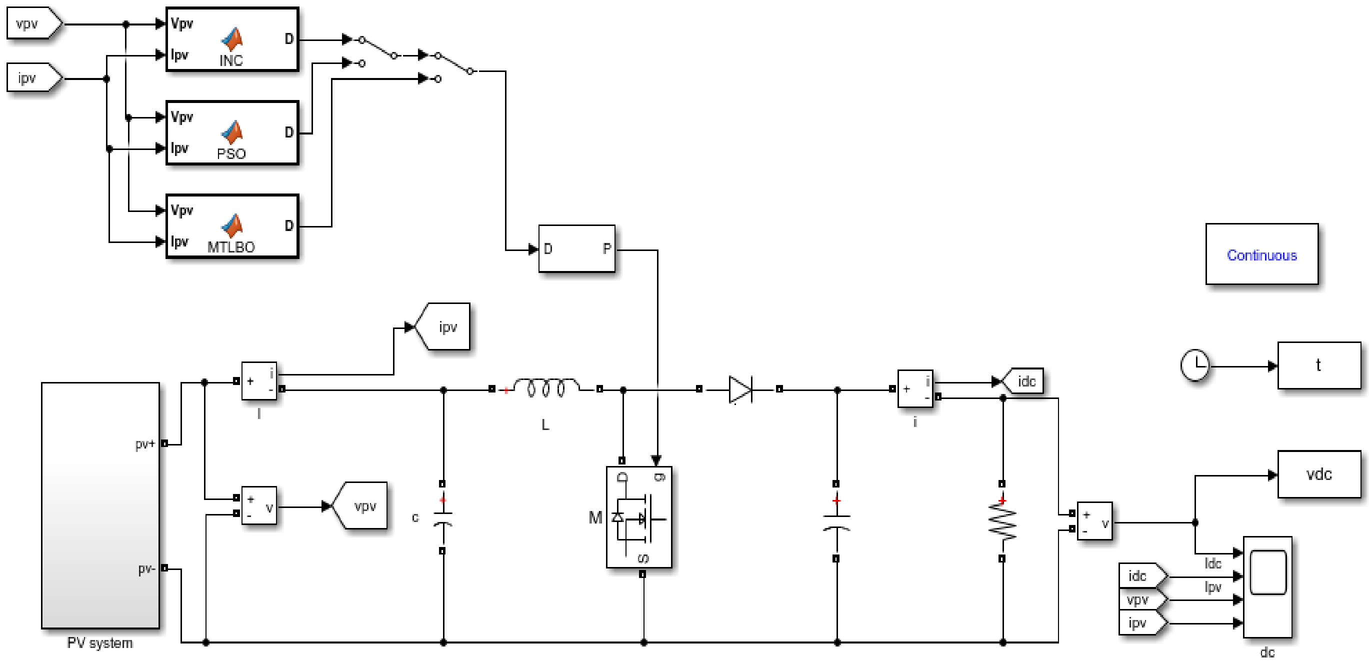


Figure 4. PV array simulation

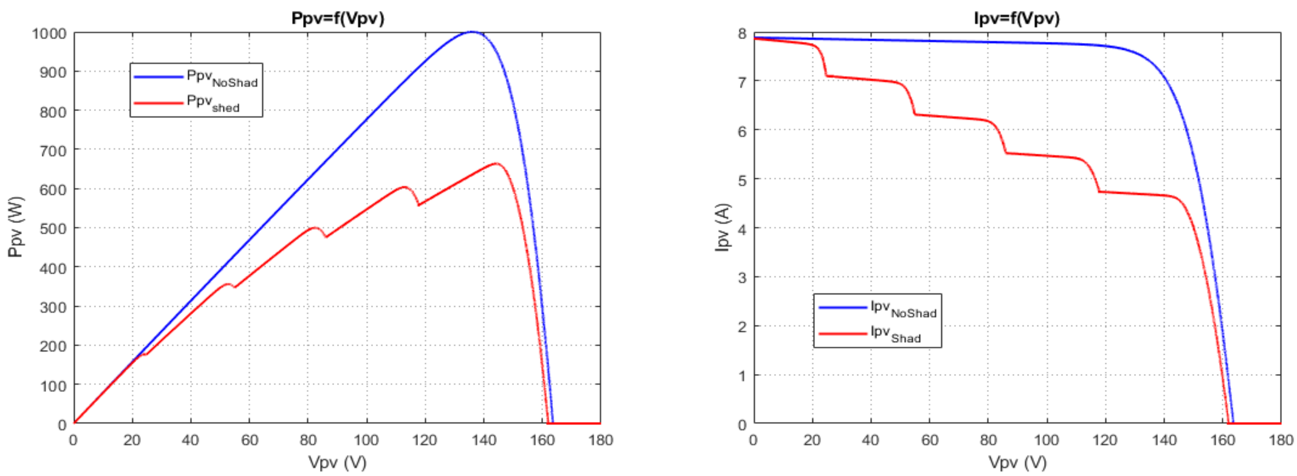


Figure 5. (P-V) and (I-V) curves of the PV modules under max and partial irradiance conditions

Table 8. MPP characteristics of the studied PV system under different shading conditions

Point	MPP (No Shading)	GMPP	MPP2	MPP3	MPP4	MPP5
P_{pv} (W)	1000	663	603	499	355	176
I_{pv} (A)	7.35	4.6	5.3	6.1	6.7	7.3
V_{pv} (V)	136	144	113	82	53	24

Figure 5 depict the P-V and I-V characteristics of the PV model under both uniform and partial shading conditions. The shading scenario is simulated using STEPED irradiance levels for each module: 1000 W/m², 900 W/m², 800 W/m², 700 W/m², and 600 W/m². These variations create multiple peaks in the power curve, corresponding to different maximum power points (MPPs). The MPPs identified during the simulation are summarized in Table 8.

5.2.1 Scenario 1: Variable irradiance and temperature profiles (no partial shading)

The test profile consists of initial fixed irradiance (1000W/m²) and temperature (25°C), representing the General MPP, followed by varying irradiance and temperature levels, it is uniformly applied to all five modules, resulting in a rapidly changing MPP compared to the static partial shading test. as shown in Figure 6.

The performance of the previously studied system (comprising five PV panels, a DC-DC converter, and a load) is evaluated under a random irradiance and temperature profile using three MPPT algorithms: MTLBO, PSO, and INC-COND. The corresponding results are presented in Figures 7 and 8.

The simulation results reveal that the MTLBO method exhibits behavior akin to the PSO algorithm, effectively tracking the MPP. Both MTLBO and PSO outperform the INC-COND algorithm, which demonstrates significant fluctuations under rapidly changing conditions. Notably, the

MTLBO algorithm achieves superior convergence speed, as evidenced by the PV module power output results on the DC-DC boost converter output side.

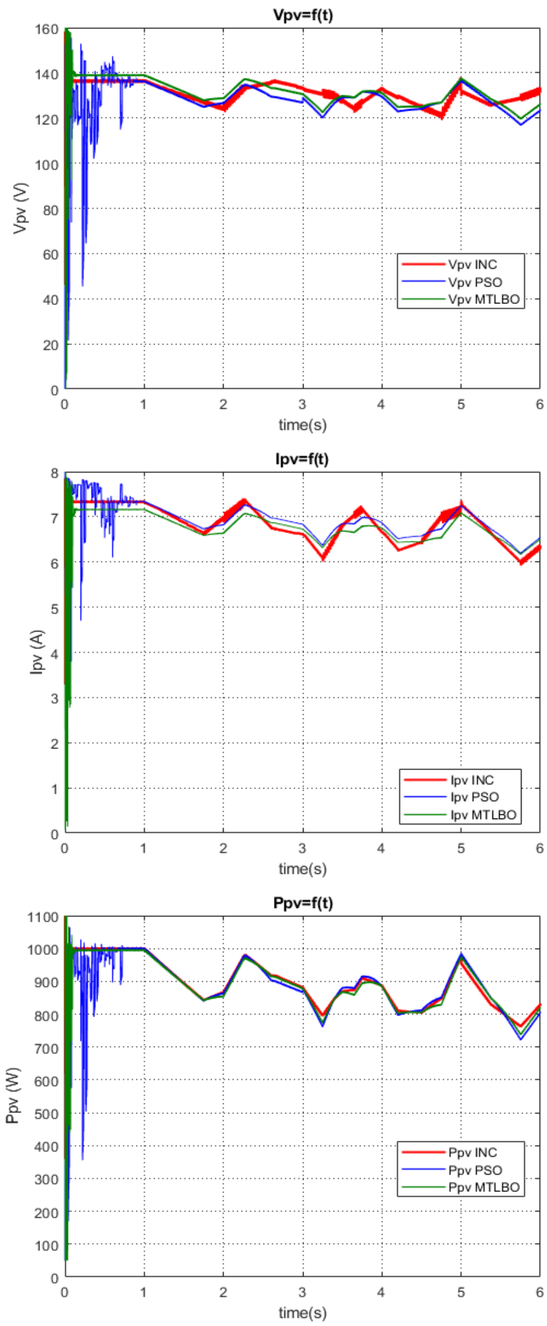
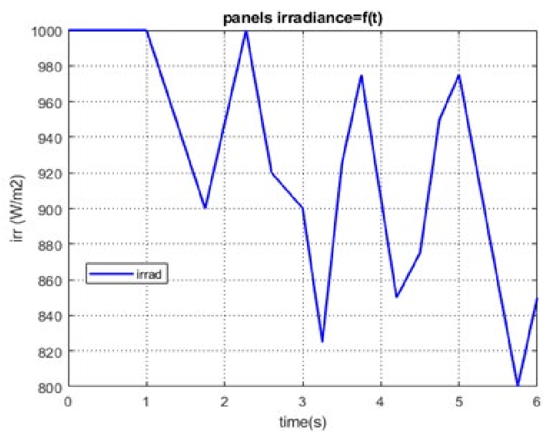


Figure 6. Irradiance and temperature profiles



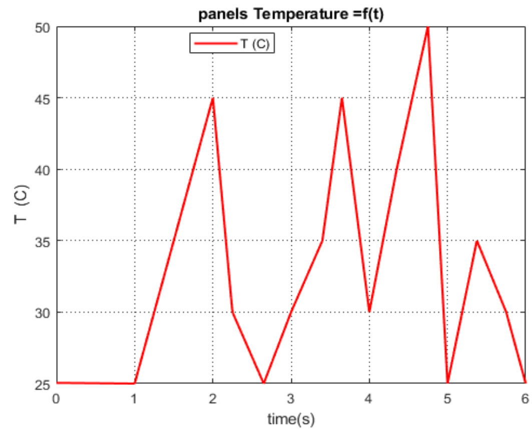


Figure 7. PV modules output voltage, current, and power

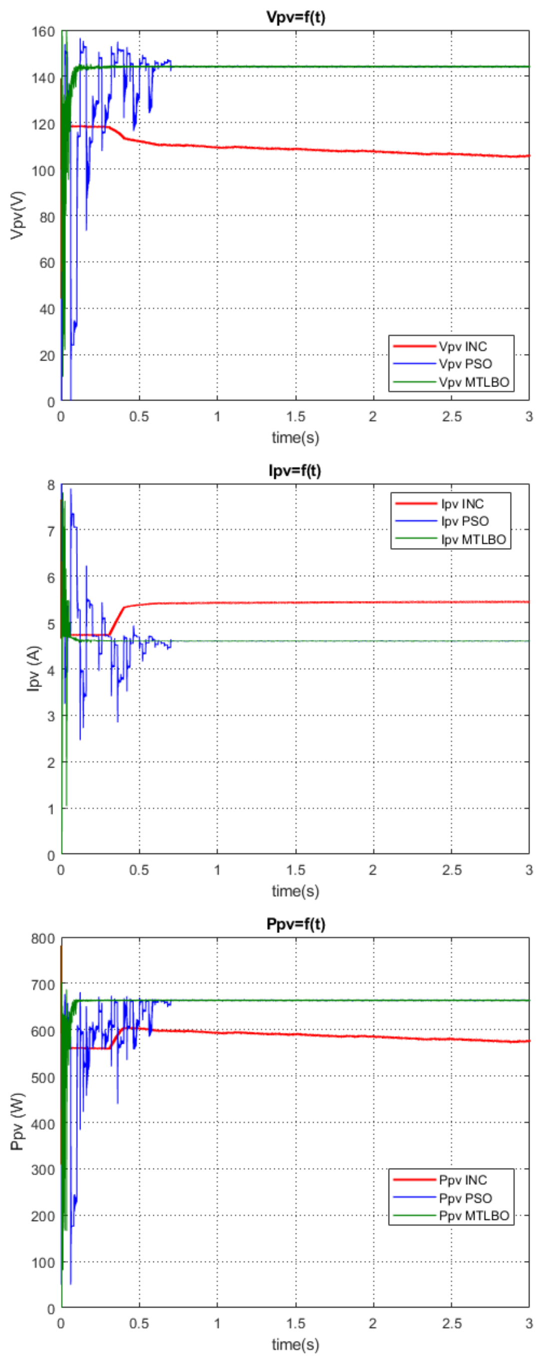


Figure 8. Boost converter output voltage and current

5.2.2 Scenario 2: Partial shading condition

To assess the system's performance under non-uniform irradiance, a partial shading scenario is simulated, where each one of the five PV panel operates at a different irradiance level: 1000 W/m², 900 W/m², 800 W/m², 700 W/m², and 600 W/m², the temperature remains constant at 25°C.

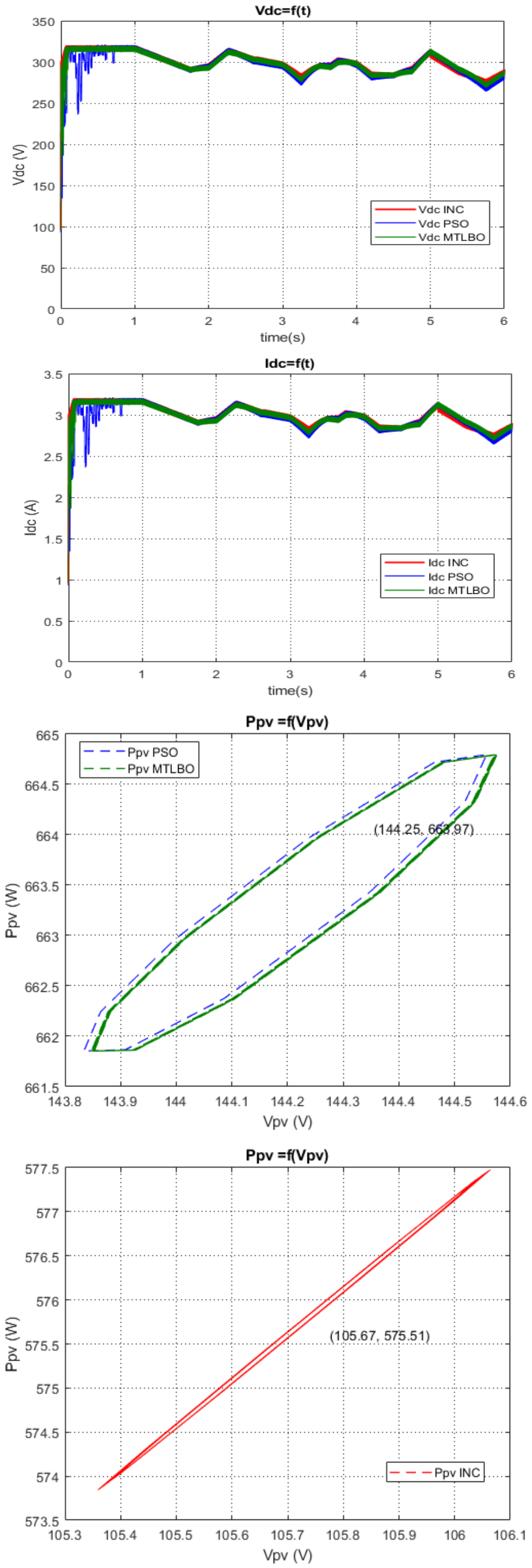
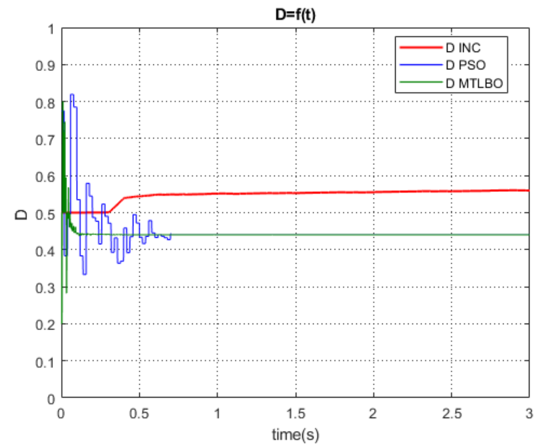


Figure 9. PV modules output voltage, current, and power



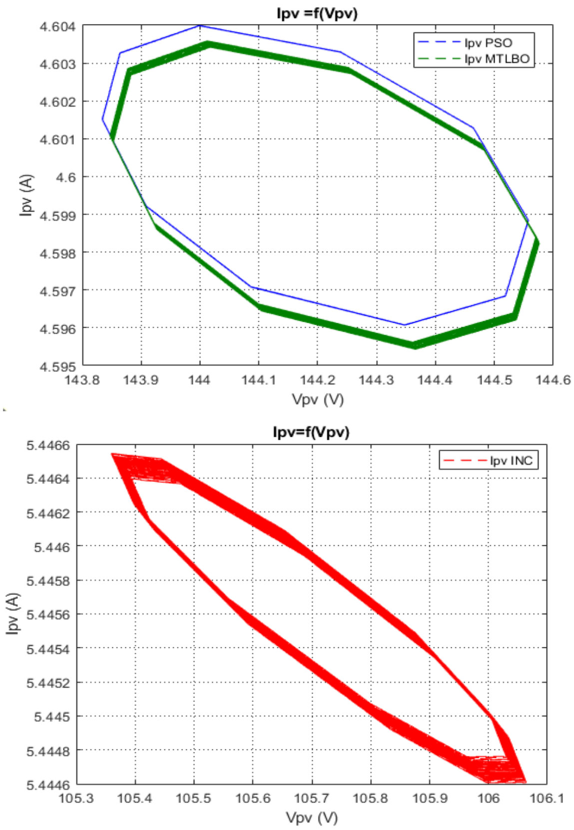


Figure 10. steady-state P-V and P-I curves

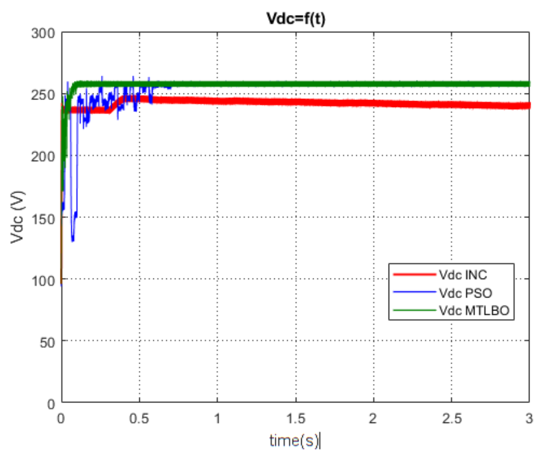


Figure 11. Duty cycle (D) of the boost converter

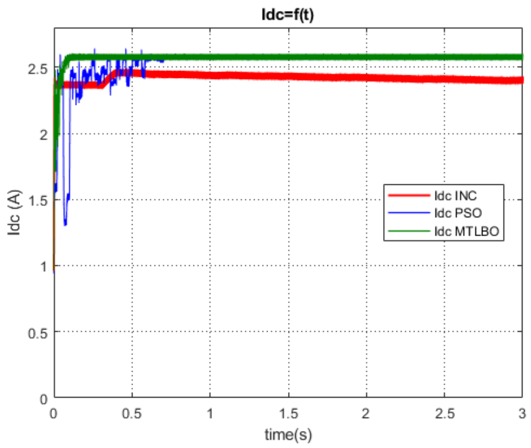


Figure 12. Boost converter output voltage and current

The simulation results are presented in Figures 9, 10, 11, and 12.

The simulation results demonstrate that the Modified Teaching-Learning-Based Optimization (MTLBO) algorithm effectively tracks the GMPP at 663 W (see Table 8), outperforming the Incremental Conductance (INC-COND) algorithm, which struggles under partial shading conditions. This confirms the efficacy of MTLBO in accurately identifying and maintaining operation at the GMPP.

A significant improvement in convergence speed is observed with the MTLBO method, as evidenced by the power output results. The steady-state power-voltage (P-V) and power-current (P-I) curves (Figure 10) illustrate that MTLBO achieves smoother and more stable MPP tracking compared to PSO algorithm, this stability is crucial for maintaining consistent energy harvesting from the PV system, and its translates to a more stable output voltage from the boost converter (Figure 11) enhancing the overall efficiency and reliability of the power electronic components.

The MTLBO algorithm's ability to effectively navigate the complexities introduced by partial shading underscores its potential as a superior alternative for MPPT in PV systems.

6. CONCLUSION

This study presented a Modified Teaching–Learning-Based Optimization (MTLBO) algorithm developed to enhance the performance and reliability of photovoltaic (PV) systems under partial shading conditions. The algorithm integrates adaptive mechanisms such as multi-group initialization, a best-student phase, and mixed-group learning to strengthen its optimization behavior.

A comprehensive characterization procedure was conducted, comparing ordinary TLBO and MTLBO under a function-evaluation–matched and seed-controlled protocol on canonical benchmark functions to analyze the behavioral differences between both algorithms. Subsequently, the proposed MTLBO was evaluated against the PSO algorithm in real operating scenarios, demonstrating superior convergence speed, tracking precision, and robustness under varying irradiance patterns. These refinements effectively balance exploration and exploitation within the search process, enabling the algorithm to accurately and rapidly track the GMPP while minimizing power oscillations, thereby improving both dynamic response and steady-state stability of PV systems.

Furthermore, the parameter-free structure of MTLBO simplifies implementation and deployment, making it highly suitable for real-time applications. Future work should focus on experimental validation under real-world operating conditions and on the integration of MTLBO with hybrid or intelligent control strategies to further enhance global tracking performance and energy yield in modern PV installations.

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