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Original Article

Comparative Performance Evaluation of P&O, Grey Wolf Optimization, and Teaching–Learning-Based Optimization Algorithms for MPPT in Photovoltaic Systems

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Abstract

Photovoltaic (PV) systems have gained importance as one of the major renewable energy technologies because of its clean and sustainable characteristics; however, PV nonlinear current-voltage and power-voltage characteristics are a significant factor in limiting the maximum available power determined by the amount of available power under different environmental and load conditions. Maximum Power Point Tracking (MPPT) algorithms are one of the most important performance enhancements to help make PV energy conversion systems more efficient and reliable. Conventional MPPT techniques such as Perturb and Observe (P&O) have been widely used due to their simple and easy implementation in terms of control strategies, however, they exhibit steady-state oscillations, slow convergence, and poor dynamic performance under fast changing conditions of irradiation and load. To overcome these limitations, validation of intelligent and bio-inspired optimization and MPPT algorithms have attracted a great deal of interest. This paper includes a comprehensive comparative analysis of three MPPT techniques that are: conventional P&O algorithm, Grey Wolf Optimization algorithm (GWO), and Teaching-Learning-Based Optimization algorithm (TLBO). A detailed model of PV system coupled with dc-dc boost converter is built in Matlab/Simulink and the algorithms are tested with a constant irradiation and variable load and with simultaneous irradiation and load variation. Performance criteria like tracking performance, speed of convergence, steady state oscillations and robustness under dynamic conditions are analyzed. Based on the simulation results it is proven that both GWO and TLBO clearly outperforms the conventional P&O algorithm. Amongst all the optimization-based approaches, TLBO provides good performance with near-instantaneous convergence, minimum oscillations and consistent tracking efficiency is close to 100% for all the tested scenarios. The results prove that TLBO-based MPPT offers solid and computationally efficient solution for real world applications of PV systems especially in those with frequent and random operating condition variation environment.

Keywords: *Photovoltaic System, Maximum Power Point Tracking, Grey Wolf Optimization, Teaching–Learning-Based Optimization, Perturb and Observe.*

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1. Introduction

The world energy realm is in a radical change as a result of the fast-depletion of fossil fuel resources, increasing energy demand, and the fears of climate change and environmental sustainability S. Mohanty et al. [1]. Renewable sources of energy have become a mainstay of modern electricity supply applications, and solar photovoltaic (PV) technology has been one of the world's most promising solutions because of its abundance, scalability, and negligible environmental impact B. Subudhi et al. [2]. The decreasing cost of PV modules and the development of power electronics interfaces have led to the rapid establishment of solar energy systems both to grid connected as well as standalone applications. Despite these advantages, the efficiency of PV systems received strong criticism in terms of nonlinear electrical characteristics and high dependence on environmental factors due to solar irradiation and temperature G. Rashmi and M. M. Linda [3].

PV array has a unique power voltage (P-V) characteristic that has a single maximum power point (MPP) under uniform irradiation condition. Running the PV system outside of this point means that major power dissipations can arise V. M. Tehrani et al. [4]. Furthermore, changes in irradiation, temperature and load impedance constantly move the MPP and it is necessary to use an effective Maximum Power Point Tracking (MPPT) algorithm to allow optimal energy extraction at any time. MPPT controllers change the duty cycle of the operating PV arrays by controlling the point of the operation of a PV array DC-DC convert, in real time to track M. Tebaa et al. [5].

Traditional methods such as Incremental Conductance (INC) and Perturb and Observe (P&O) have been widely used among the MPPT approaches presented in the literature because of the simplicity and low computation burden and ease of implementation. However, these approaches have certain disadvantages F. Abdelmalek et al. [6]. Especially the P&O algorithm causes steady state oscillations around the MPP, and hence power losses. Its performance is deteriorated greatly in the presence of rapidly changing irradiation and load conditions, since the system has a challenging task finding the difference between the power variations due to perturbation and those due to changing environment J. Aguila-Leon et al. [7].

In order to overcome these limitations, intelligent and optimization-based MPPT techniques have received more and more attention. Metaheuristic algorithms based on the behaviors of nature, such as Particle Swarm Optimization, Genetic Algorithms, Grey Wolf Optimization (GWO) and Teaching-Learning-Based Optimization (TLBO) have proven to be better tracking performance under complex and dynamic operating conditions. These algorithms are able to perform global search which leads to not getting trapped in local optima and quickly approaching the global MPP N. Cintury et al. [8].

Grey Wolf Optimization is influenced by the leader hierarchy and hunting strategy of grey wolves in nature. It utilizes cooperative search behavior and social hierarchy in order to meet fast convergence seek and high tracking accuracy. Teaching-Learning-Based Optimization, on the other hand, has its motivation in the pedagogical interaction between teachers and learners in a classroom environment. TLBO is especially interesting in MPPT applications because of its parameter-less nature, simplicity of the algorithm and exploration versus exploitation N. S. Alsharafa et al. [9].

Although some studies have been conducted separately to investigate these algorithms, comparative evaluation of P&O, GWO, and TLBO is still limited to allow a detailed evaluation of the three algorithms in the same system configurations and operating conditions. This paper attempts to fill this gap by offering a comprehensive performance comparison of these three MPPT techniques in constant and variable irradiation and load cases. The study offers useful information on their dynamic behaviors, efficiency and applicability to practical PV applications.

2. Literature Review

Extensive research has been made on MPPT techniques since they can improve the efficiency of photovoltaic systems. Early MPPT techniques like Perturb and Observe and Incremental Conductance are still popular because of their simple nature with low cost of implementation M. Wang and B. Gao [10]. However, there are numerous studies that report the usage of these techniques suffer from steady state oscillations as well as poor performance under rapidly varying environmental conditions. Researchers have tried to enhance the conventional methods of MPPT through introductions of adaptive step sizes and hybrid control schemes, but they have somewhat improved the inherent limitations of the conventional methods S. E. Babaa et al. [11].

Intelligent control techniques such as fuzzy logic controllers and artificial neural networks have been investigated in order to overcome the drawbacks of the classical MPPT techniques A. Gupta et al. [12]. These approaches provide better dynamic response and lessened oscillations but typically require a lot of training data and expert knowledge as well as complex tuning procedures. Moreover, their performance can deteriorate if they are operated under conditions that are very different from those used in the training data B. Schürmann et al. [13].

Metaheuristic optimization algorithms have provided the powerful alternative in MPPT applications. Particle Swarm Optimization and Genetic Algorithms have been proved to have better global search capability and convergence time E. Malarvizhi et al. [14]. However, these algorithms are sensitive to a careful selection of the algorithmic parameters and sometime rather prone to premature convergence or can be rather slow with algorithmic complexity Grey Wolf Optimization P. Aguilera et al. [15] has attracted attention because of its simple structure, rate of convergence and robustness in condition of partial shading and variable irradiation levels. Several experiments have established that GWO-based MPPT performed better than conventional techniques taking into consideration that the tracking accuracy and power stability D. J. K. Kishore et al. [16]. Teaching-Learning-Based Optimization has been extensively exploited in optimization problems in engineering due to its parameter less nature and efficient convergence nature K. L. Wang, et al. [17]. In recent years, TLBO has been applied successfully for MPPT in PV systems, which has an excellent performance in dynamic operating conditions. According to the comparative methods, TLBO has faster convergence and less steady-state oscillations than those of the other metaheuristic algorithms K.-H. Chao and M.-C. Wu [18].

Despite these enhancements, the need remains for a common comparative framework that is able to assess conventional methods of and optimization-based MPPT techniques in a common system configuration and realistic operating situations. This paper contributes to the literature by making a detailed comparative analysis of P&O, GWO and TLBO MPPT algorithms. Abbreviations and Symbols Used in the Study are presented in Table 1.

Table 1. Abbreviations and Symbols Used in the Study

Abbreviation	Full Form / Description (with SI Units)
PV	Photovoltaic
MPPT	Maximum Power Point Tracking
P&O	Perturb and Observe Algorithm
GWO	Grey Wolf Optimization
TLBO	Teaching-Learning-Based Optimization
V_{pv}	Photovoltaic output voltage (V)
I_{pv}	Photovoltaic output current (A)
P_{pv}	Photovoltaic output power (W)
V_{mp}	Voltage at maximum power point (V)
I_{mp}	Current at maximum power point (A)
P_{mp}	Maximum power (W)
V_{oc}	Open-circuit voltage (V)
I_{sc}	Short-circuit current (A)
D	Duty cycle
R_S,R_{sh}	Series and shunt Resistance
Dmin, Dmax	Minimum and Maximum values of dutycycle
η	Efficiency
k	Iteration index
T	Temparature(K)
Di^{new}	New value or updated value of duty cycle

3. Methodology

The photovoltaic system, which is under consideration in this study comprises of a PV system array, a DC-DC boost converter and a variable load. The MPPT controller adjusts the boost converter duty cycle to ensure its operation on the maximum power point C. Ratsame and T. Tanitteerapan [19]. Functional block diagram of MPPT controlled PV system, as shown in Fig 1.

The PV cell output current can be given by:

$$I = I_{ph} - I_0\left[\exp\left(\frac{q(V+IR_s)}{nkT}\right) - 1\right] - \frac{V+IR_s}{R_{sh}} \quad \text{......... (1)}$$

The PV output Power is given as

$$P = V \times I \quad \text{.. (2)}$$

The duty cycle (D) of the boost converter is related to the input and output voltages of the boost converter as:

$$V_o = \frac{V_{in}}{1-D} \quad \text{...... (3)}$$

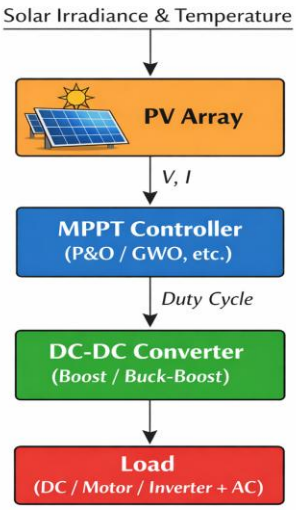

Figure 1. Functional block diagram of the MPPT controller-based PV system

In P&O method, the duty cycle is increased or decreased and corresponding change in power is measured to know the direction of tracking M. A. Aredes et al. [20], the detailed flow chart is presented in Fig. 2.

In GWO-based MPPT the duty cycle is optimized by the hierarchical hunting behavior of grey wolves with the best solutions directing the search process Moh. Z. Efendi et al. [21]. The Grey Wolf Optimization (GWO) based Maximum Power Point Tracking (MPPT) algorithm is a bio-inspired optimization algorithm, which mimics the leadership structure and cooperative hunting behavior of the grey wolves in nature. In a PV system, T. Nagadurga et al. [22] the search agents (wolves) are the candidate duty cycle of the DC-DC boost converter, while the fitness of each agent is measured using the extracted PV powerG. Jipeng et al. [23]. The algorithm divides the population into four hierarchical levels: alpha (α), beta (β), delta (δ), and omega (ω) and the alpha wolf correspond to the best solution (maximum power point). During the optimization process L. Guanghua et al. [24], the wolves are iterating updates in positions by surrounding and moving close to the prey, corresponding as the global maximum power point on the power voltage curve of the PV system. This cooperative hunting scheme which allows the exploration and exploitation to be well balanced, so as to make the GWO converge quickly, and avoid the local maxima due to nonlinear PV characteristics and even the partial shading effects. Compared with traditional MPPT methods S. J. Yaqoob et al. [25] R. Bisht et al. [26], GWO shows better dynamic response, little steady state oscillation and higher robustness when variable irradiance and load condition are employed. Its relatively straightforward mathematical structure and relatively few parameter tuning requirements render GWO as a MPPT solution for real time photovoltaic energy conversion systems a practical and efficiently working method. The detailed flow is presented in Fig. 3. The objective function is shown below

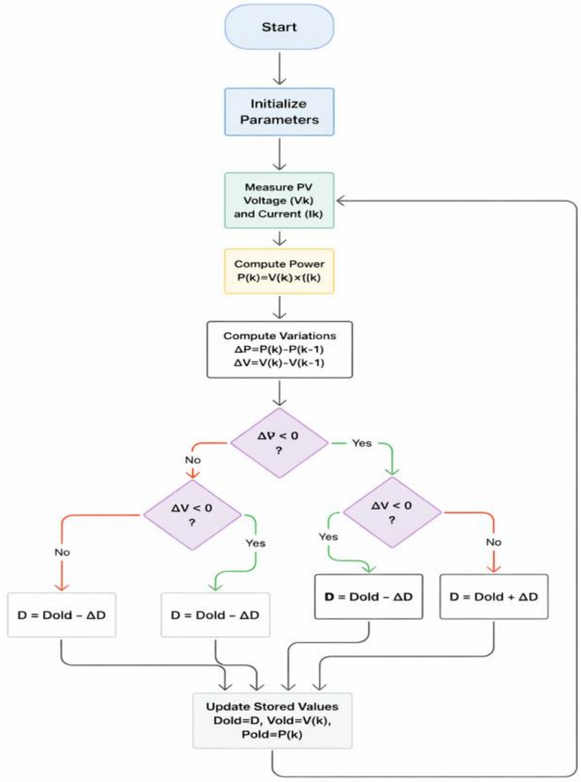

Figure 2. P&O MPPT Flow chart

$$\max_D f(D) = P_{PV}(D) = V_{PV}(D) \times I_{PV}(D) \quad \ldots \quad (4)$$

In TLBO-based MPPT H. Rezk and A. Fathy [27], duty cycle adjustment is performed in teacher and learner phases, which allows the converging of the duty cycle very fast without being tuned by specific parameters in algorithm H. Singh et al. [28]. The Teaching-Learning-Based Optimization (TLBO) is a population based intelligent optimization technique that is inspired by the process of knowledge transfer of a classroom environment. In case of photovoltaic (PV) systems TLBO A. Ariprihartа et al. [29] is effectively used for Maximum Power Point Tracking (MPPT), based on the optimizing of the duty-cycle of the DC-DC boost converter. Each learner in the population is equivalent to one candidate duty cycle and the quality of the learners is compared based on the PV output power by each learner. The TLBO algorithm is divided into two sequential phases, i.e., the teacher phase and the learner phase Venkata Anjani Kumar Gaddam and Manubolu Damodar Reddy

[30]. In the teacher phase, the learner that performs the best (teacher) attempts to push the mean performance of the population towards the global maximum power point, by leading other learners. In case of the learner phase, when learners are interacting with each other in order to enhance the individual knowledge levels of learners by pairwise learning. This dual-phase learning mechanism achieves a good balance between the exploration/exploitation of the PV operating space.

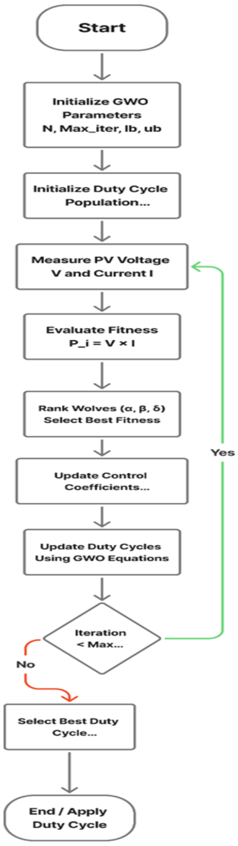

Figure 3. GWO MPPT Flowchart

A major plus point of TLBO is its parameter-less feature because TLBO algorithm isn't dependent on algorithm-specific tuning parameters like inertia weights or acceleration coefficients. As a result, TLBO has the advantage of fast convergence, little steady-state oscillations and high tracking accuracy under drastically varying irradiance and load condition, which therefore makes it a robust and computationally-efficient MPPT solution to be applied to practical photovoltaic applications. The detailed Flowchart is presented in Fig. 4. The objective function for GWO and TLBO given below

$$D(t+1) = clip(D(t+1), Dmin, Dmax) \ldots\ldots (5)$$

$$D_i^{new} = clip(D_i^{new}, Dmin, Dmax) \ldots\ldots\ldots\ldots\ldots (6)$$

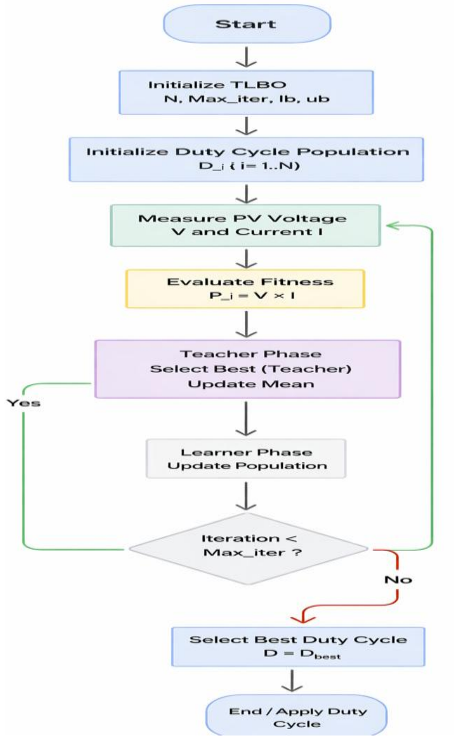

Figure 4. TLBO MPPT Flowchart

4.Results and Discussion

In this work the proposed system is implemented on Matlab/Simulink to assess the performance of the three MPPT algorithms under different operating conditions on a test case as presented in Fig. 5. PV panel specifications as shown in fig 6 and the table 2 represents the parameters used in the test model

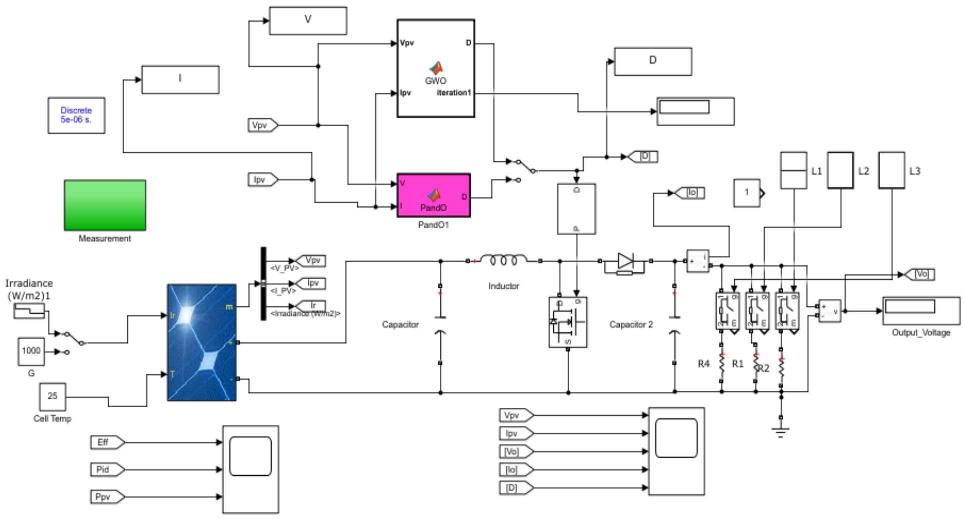

Figure 5. PV MPPT Test Case

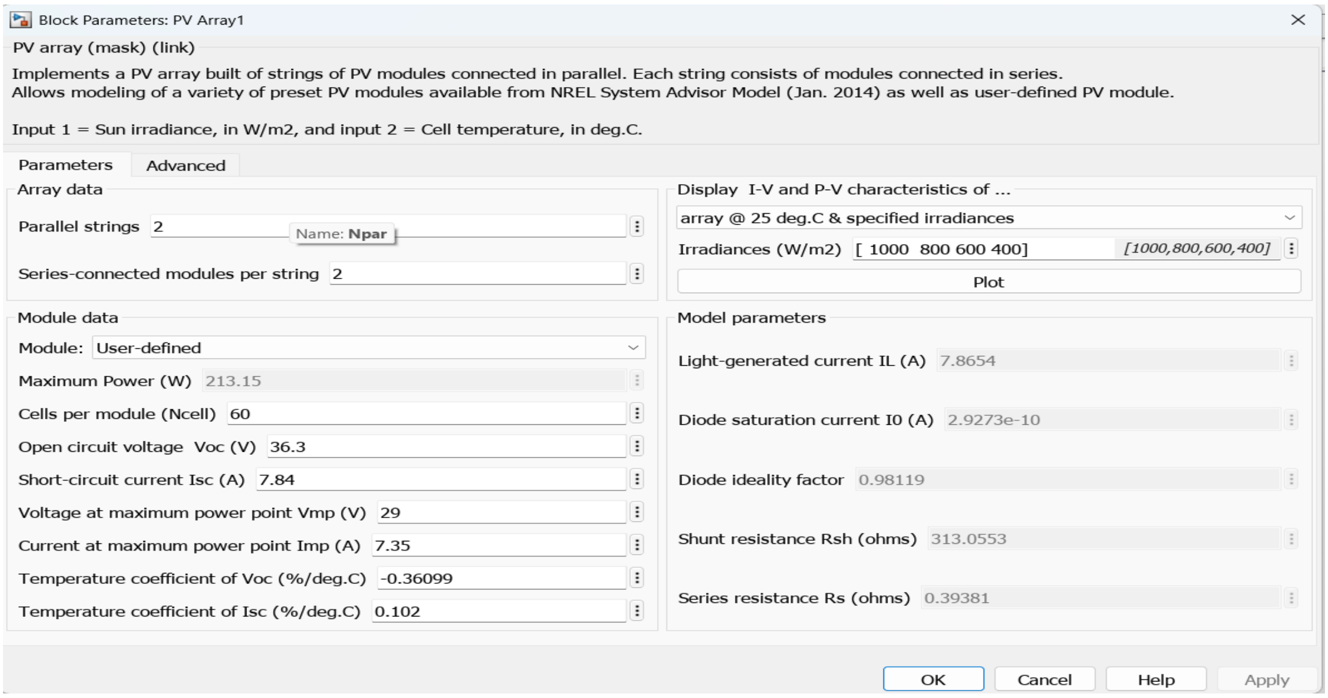

Figure 6. PV Panel specifications used in the test case

Table 2. PV System and Converter Parameters Used in Simulation

Parameter	Value
Inductor (L)	2 mH
Capacitor (C1, C2)	100 μF
Load (L1, L2, L3)	50 Ω
Parameter	Value

The irradiance is gradually varied throughout the simulation to assess MPPT performance under realistic variations in sunlight. The profile of irradiance utilized is presented in Table 3.Initially P & O MPPT is implemented on the above test case. The performance evaluation is shown below.

The performance of meditation of PV system using P&O MPPT under variable load condition at fixed irradiation has been shown in the Fig. 7. From 0 to 0.3 sec, 0.3 to 0.6 sec and 0.6 to 1 sec connected load are load1, load2 and load3 respectively. The rapid increase in efficiency curve from startup indicated in the upper plot, and near unity, shows good tracking of the maximum power point. Increased ripple-Transient response of the P&O algorithm makes the ripple small dips around load transitions. The lower plot shows that the actual PV power follows the ideal power with some small oscillations on load change, hence having stable and reliable MPPT working.

Table 3. Timining of Irradiation

Time (s)	Irradiance (W/m²)
0 – 0.2	1000
0.2 – 0.4	800
0.4 – 0.6	600
0.6 – 0.8	400

The Fig. 8 presents the performance of a PV system using P&O MPPT under variable load and variable irradiation. From 0 to 0.3 sec, 0.3 to 0.6 sec and 0.6 to 1 sec connected load are load1, load2 and load3 respectively. The above plot shows that the efficiency curve first rises and stays high, with noticeable dipping in case of sudden changes in irradiation and load, one can see that there are transient tracking errors. The lower plot shows that the actual PV power is quite close to the ideal power but there are more oscillations and short deviations when the variation is rapid. This behavior reflects poorly dynamic response of the P&O algorithm to fast changing operating conditions.

The performance in the GWO based MPPT is shown to be significantly improved. It converges faster to MPP and has lower steady state oscillations as compared to P&O. During load alterations, GWO adjusts fast to the new running point with high efficiency. However, a short initialization phase and small chattering of power are observed in the case of startup.

The Fig. 9 shows the performance of the PV system using Grey Wolf Optimization (GWO) based MPPT under the variable load and constant irradiation. The top one (efficiency curve) shows rapid increase from startup and quickly level clearly towards unity, thus fast convergence to maximum power point. The bottom is used to show the actual PV power compares well with the ideal power with little oscillation. Small transients during load changes are rapidly damped, and show the better tracking accuracy and performance of the dynamic response of the GWO algorithm.

The Fig. 10 shows the dynamic behaviour of PV under variable load and changing irradiance situation adopting Grey wolf Optimizer (GWO) based MPPT technique. First, during the transient phase there are oscillations and low efficiency in the system. As GWO gets closer the efficiency rises rapidly and fixes close to 100%, which indicates good maximum power point tracking. Small changes in efficiency are associated with sudden changes in load and irrigation. The bottom plot indicates that the PV output power tracks with the ideal load power closely under different operating levels, which proves the fast response, high tracking accuracy as well as robust performance of the GWO algorithm under dynamic conditions.

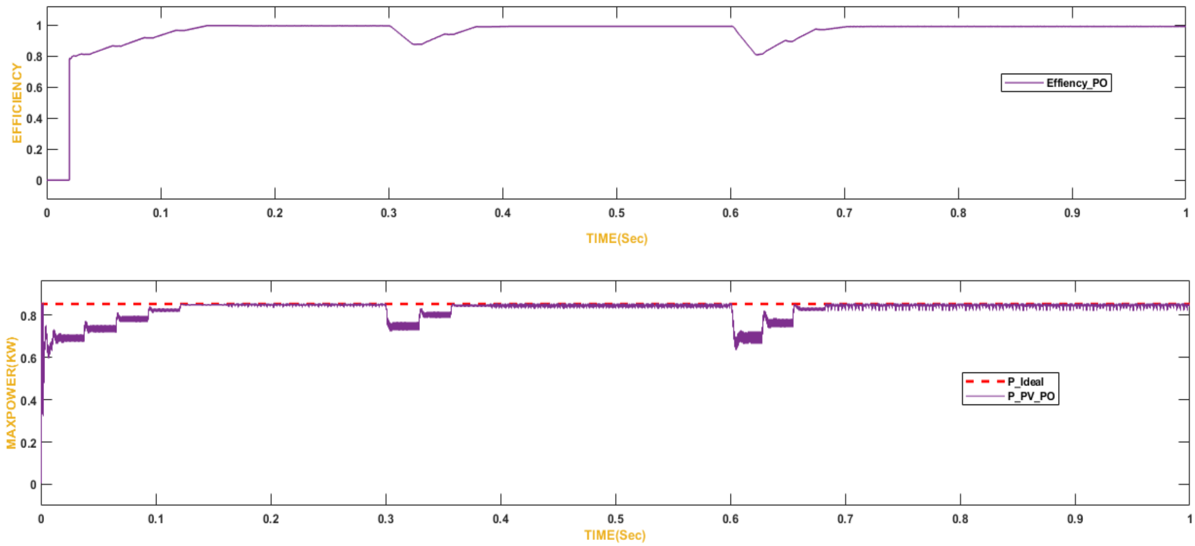

Figure 7. PV system with P&O MPPT for Variable Load with Constant Irradiation

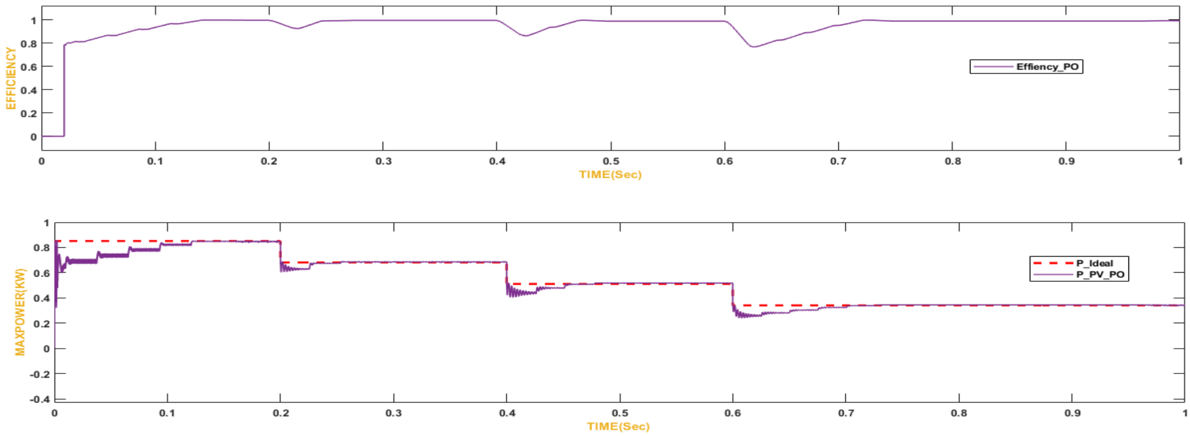

Figure 8. PV system with P&O MPPT for variable load with variable irradiation

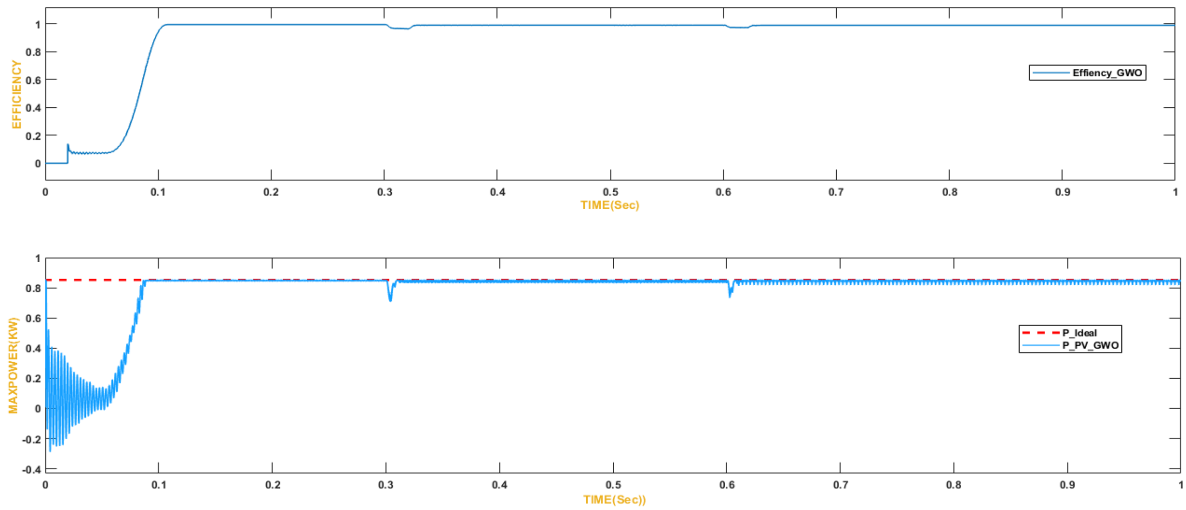

Figure 9. PV system with GWO for Variable Load with Constant Irradiation

The TLBO-based MPPT proves to be better than both P&O and GWO all the time. It is nearly instantaneously convergent with very little oscillations, and retains the efficiency of the tracking close to 100% for all scenarios tested. Under simultaneous variation of irradiation and load TLBO is extremely robust in the sense that the duty cycle is quickly adjusted according to the new MPP without too large lost power. The lack of algorithm specific parameters is another step to make it even more reliable and easy to implement. The Fig. 11 represents the TLBO analysis of the variable load at constant irradiation PV system. The top graph validates the efficiency of tracking having stayed close to 100% with slight transient dips (0.3s and 0.6s) where the algorithm is quickly reacting to the changing load. Correspondingly, the bottom graph shows the extracted power P_{TLBO} being able to track the ideal power curve PIDEAL with minimal oscillation. This shows that TLBO is highly successful in maintaining Maximum Power Point (MPP) whereby variations in the electrical load do not cause significant derailments in energy extraction efficacy.

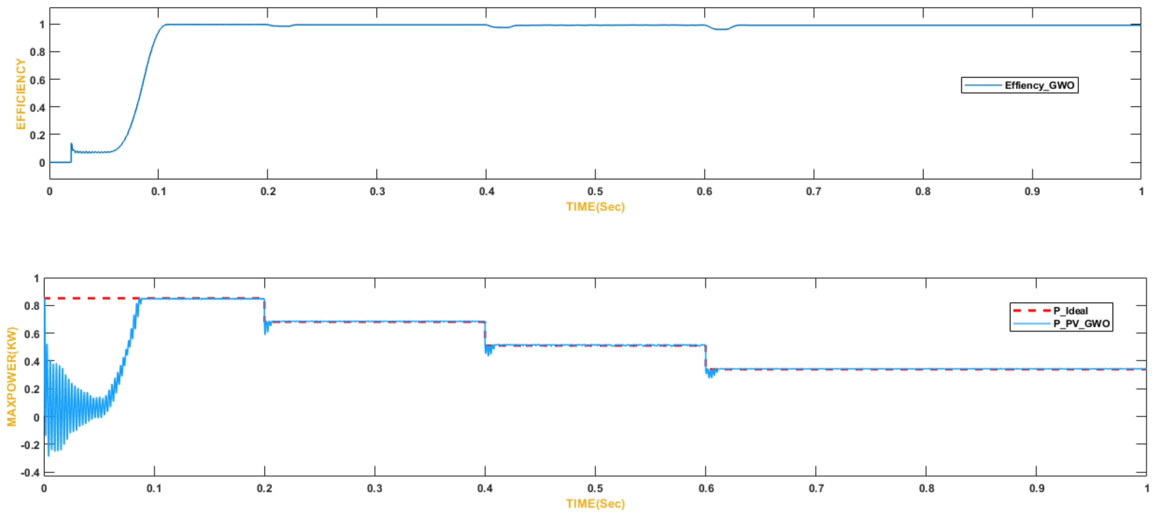

Figure 10. Variable load with variable irradiation PV system with GWO

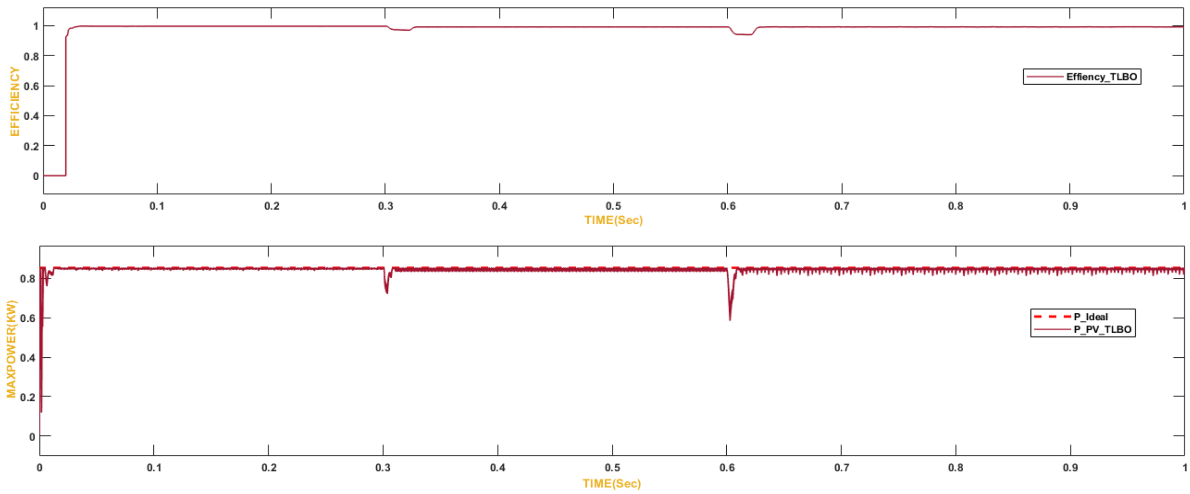

Figure 11. Variable load at constant irradiation PV system with TLBO analysis.

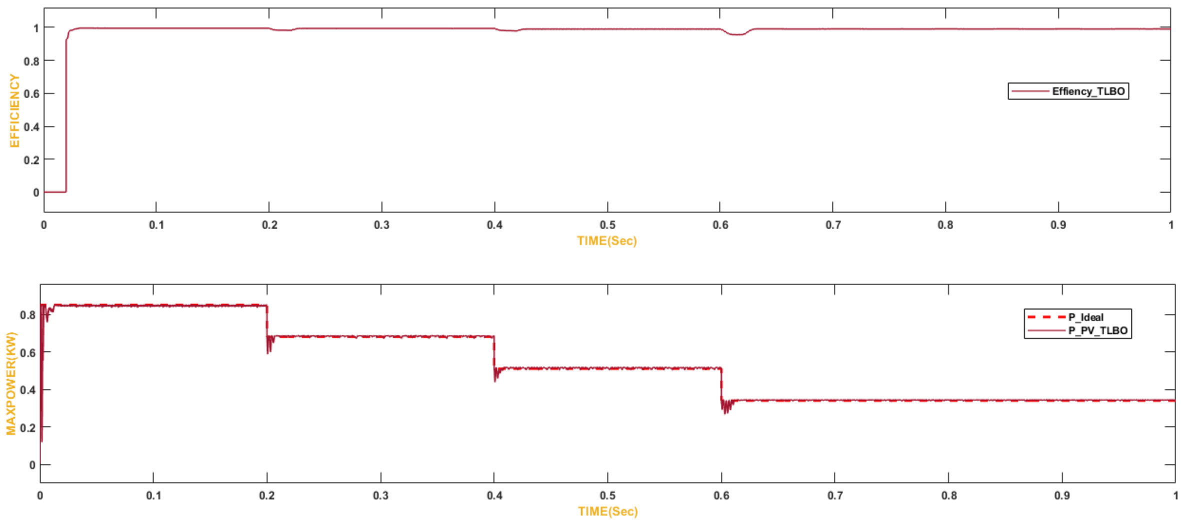

Figure 12. Variable load at variable irradiation PV system with TLBO analysis

The Fig. 12 shows the performance of photovoltaic system in Teaching Learning Based Optimization (TLBO) algorithm with variable irradiation conditions and variable loads. The top graph shows that the efficiency of tracking is extremely high returning to near 100% after transient fluctuations that occur at: 0.2s, 0.4s, and 0.6s. In the bottom graph, the stepped reduction in maximum power PIDEAL indicates the change in the irradiation from the environment, but the tracked power PTLBO matches these new values almost perfectly. This brings to light the robustness of TLBO in engineering applications due to maintenance of the Maximum Power Point (MPP) with very little steady state oscillation even if the Moi system experiences changing conditions of the atmosphere and load demand simultaneously

Comparative result clearly shows that although optimization-based MPPT techniques require a little more computational effort than conventional method, the performance gain of efficiency, stability and robustness are large. TLBO in particular is an ideal compromise between performance and implementation simplicity. The Fig. 13 shows the comparative analysis of performances of three Maximum Power Point Tracking (MPPT) techniques (P&O MPPT, GWO and TLBO) under constant irradiation and dynamic load conditions. The TLBO algorithm (red) shows the best performance, that is, the algorithm converges to the ideal power PIDEAL almost instantly and with a consistent efficiency of about 100%, also during the load disturbances. In comparison, the P&O algorithm (purple) exhibits severe efficiency degradation and slow recovery times after load steps, while the GWO algorithm (blue) has a slow initialization stage, as well as a high frequency power chattering during the first 0.1s of operation. Ultimately, it is the metaheuristic TLBO approach that can be effectively applied in research issues since they can break the steady-state oscillations that can be encountered in gradient approach to the slow convergence problem that can be called early-stage bio-inspired algorithms, to ensure for the maximum energy harvesting regardless of load side variations

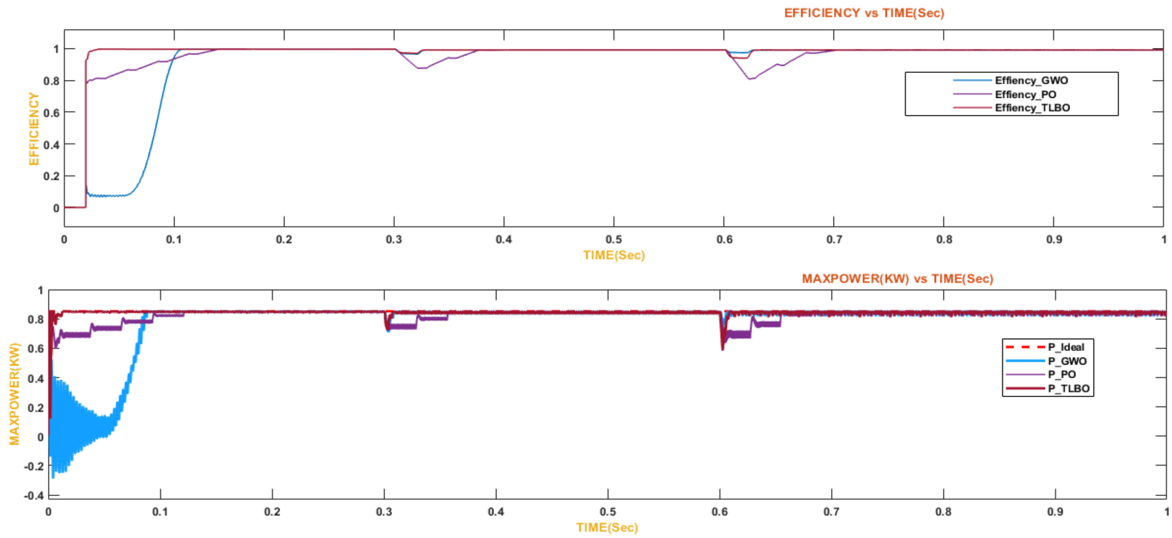

Figure 13. Variable load at constant irradiation PV system with P&O MPPT, GWO AND TLBO algorithms

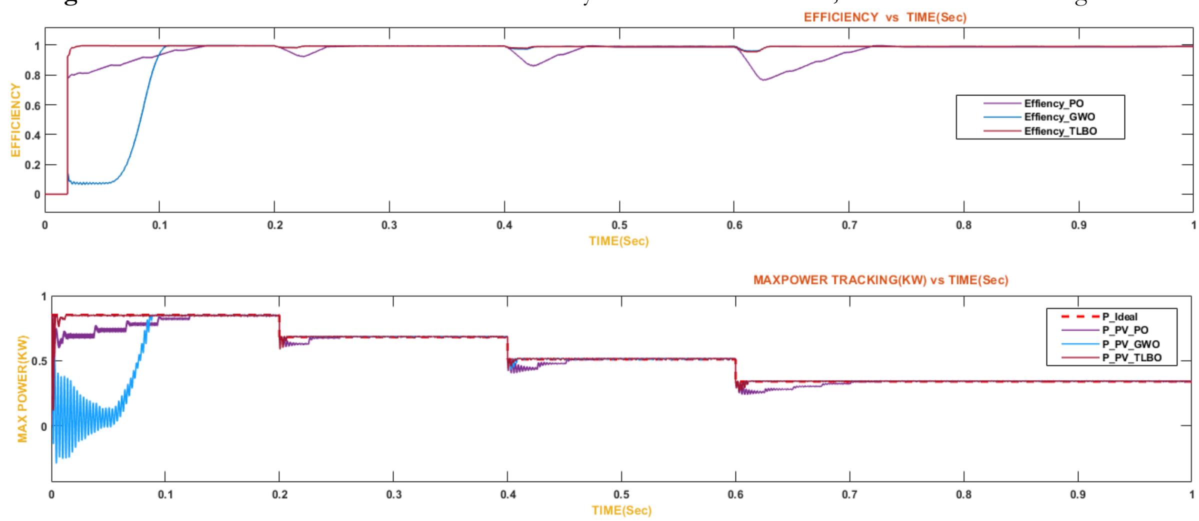

Figure 14. Variable load with variable irradiation PV system with P&O MPPT, GWO AND TLBO algorithms

The Fig. 14 represents the comparative study evaluates the performance of three Maximum Power Point Tracking (MPPT) algorithms are P&O MPPT, GWO and TLBO integrated into a PV system subjected to simultaneous variations in irradiation and load impedance. The top and bottom plots that showed the TLBO algorithm (red) shows superior robustness as it shows near-instantaneous convergence and that it is at approximately 98.6% efficiency during all transient steps. On the other hand, the P&O algorithm (purple) shows considerable efficiency loss and slow recovery in the transition of the load and irradiation. While the

GWO algorithm (blue) achieves high steady state accuracy this suffers from both a long initialization period and strong power chattering at high frequencies at startup clean comparison table of major MPPT techniques focusing specifically on the key metrics, such as efficiency and tracking speed, presented in Table 4

Table4. Comparison of various MPPT algorithms with time and efficiency

MPPT Algorithms	MPPT Tracking Time(s)	Efficiency (%)
P&O	0.13	95.5
GWO	0.09	97.9
TLBO	0.02	98.6

5. Conclusion:

This paper gave a detailed comparative performance evaluation of three MPPT techniques namely Perturb and Observe, Grey wolf optimization and Teaching-Learning Based Optimization for photovoltaic system under dynamic load and irradiance conditions. Simulation result shows that the conventional P&O MPPT has steady state oscillation, slow convergence and poor performance under varying operating conditions. In the contrary, optimization-based techniques improve substantially the tracking performance and increased efficiency for the system. Grey Wolf Optimization As a result, Grey Wolf Optimization will improve the convergence speed and also minimize the fluctuations of power, making it a feasible solution as an alternative to classical MPPT methods. However, Teaching-Learning-Based Optimization proves the best among the three. TLBO has few parameter tuning requirements and achieves near-perfect tracking efficiency, fast convergence and low oscillations. Its robustness in the case of simultaneous load and irradiation variations makes it very appropriate for the PV world. The outcomes of this investigation demonstrate the possible use of TLBO based MPPT as a dependable and effective solution for contemporary Photovoltaic systems. Future work may include focusing on experimental validation, and real-time implementation on the embedded implementation, as well as work on hybrid optimization method to further improve the system performance in partially shaded conditions and grid connected scenario.

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