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An Improved Teaching Learning Based Optimization Algorithm for Simulating the Maximum Power Point Tracking Controller in Photovoltaic System

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ABSTRACT

The usage of photovoltaic system as a source of energy becomes one of the most important and essential issue nowadays. Each PV module has its own specific characteristics and its own maximum power point (MPP). This maximum power point varies according to the change in temperature and solar irradiation. Therefore, it is important to use a maximum power point tracker (MPPT) in the PV system; to guarantee a maximum output power from solar module under varying conditions. There are many algorithms used to perform controller function that are conventional and meta-heuristic methodologies, in this paper a proposed meta-heuristic algorithm based on an improved teaching-learning based optimization algorithm (ITLBO) is presented and investigated to track the MPP extracted from the PV system under variable operating conditions. The proposed algorithm gives the available maximum power under non-uniform solar irradiation. The obtained results are compared with those obtained via the conventional perturb and observe (P&O), particle swarm optimization (PSO) and TLBO algorithms. The proposed ITLBO results are more accurate and give fast convergence output power.

1-INTRODUCTION

Because of using the traditional sources of the energy for many years has led to the increase of the pollution in the world. Renewable energy sources are used as alternative resources of energy as it is much clean, inexhaustible, free to harvest and environmentally friendly. The solar energy is one of the most promising renewable energy resources as it is the most abundant, sustainable and clean resource. However, despite all the merits of solar systems they suffer from having low efficiency in practice [1]. Photovoltaic system recognized to be in the forefront in renewable electric power generation. It can generate direct current electricity without environmental impact and pollution when exposed to solar radiation. Each photovoltaic array has its own maximum power point (MPP), which varies with solar irradiation and temperature so the usage of maximum power point tracker (MPPT) algorithms is essential to produce the MPP from a solar array [2]. One of the most popular algorithms of MPPT is perturb and observe (P&O) due to its simplicity in implementation compared to the others. However, in

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shadow conditions P&O failed in catching the global maximum power point (GMPP) because of existing local minimum points. The effect of shadow in power-voltage characteristics has been studied in [3]. Many artificial intelligence based MPPT techniques are discussed in [4]. Additionally, artificial neural networks (ANN) are used in mapping between a partial shading conditions and optimum power [5]. Genetic algorithm (GA) simulating model has been built to solve MPP problem in shadow conditions in [6, 7]. In addition, PID and Fuzzy logic controllers were used in MPPT under varying conditions in [8].

In this paper, a new optimization approach based on an improved teaching learning based optimization algorithm (ITLBO) is used to maximize the output power of photovoltaic under partial shadow conditions. The proposed modification is given in learner phase to improve the performance of students by adding the effect of best student and the effect of teacher on the student. The proposed ITLBO is compared with P&O, particle swarm optimization (PSO) and conventional TLBO algorithms. The obtained results encourage the usage of the proposed ITLBO in simulating the MPPT, as it requires less time in convergence to the MPP. The paper is organized as follows: section 2 shows the modeling of PV system, section 3 presents the maximum power point tracking algorithms, section 4 presents the proposed algorithm, simulation results are given in section 5 and finally section 6 concludes the findings.

2-Modeling of PV system

2.1. Model of PV cell

The PV cell model is modelled by an equivalent electrical circuit composed of a current source, I_{ph} , one diode, series resistance, R_s, and shunt resistance, R_{sh}. As the PV generator is a nonlinear device and is usually described by its equivalent circuit, voltage-current curve and voltage-power characteristic as shown in Fig 1.

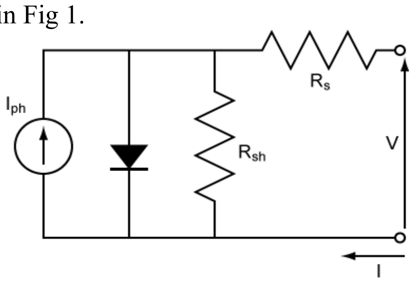


Fig. 1 equivalent circuit of PV cell

There are various mathematical models of PV cell were developed to represent this nonlinear behavior like four parameter model as in [9]. In this paper, the mathematical model can be obtained via the equivalent circuit as follows [10]:

$$I_{ph} = \frac{G}{1000} * (I_{scr} + K_i (T - 298)) \quad (1)$$

Where I_{scr} is the cell short circuit current at reference temperature (t= 25 ºC), K_i is the cell short current temperature coefficient and G is the solar radiation (W/m^2). The cell saturation current is dependent on the temperature; therefore the output current is also dependent on the temperature and solar radiation as shown in the following equations.

$$I_{or} = \frac{I_{scr}}{[\exp(\frac{qV_{oc}}{KAT}) - 1]} \quad (2)$$

$$I_{os} = I_{or} * (\frac{T}{T_r})^3 * \exp[\frac{q * E_g}{AK} * (\frac{1}{T_r} - \frac{1}{T})] \quad (3)$$

Where I_{or} is the cell reverse saturation current, V_{oc} is the open circuit voltage of PV cell. T is temperature in kelvin, $T_r$is the reference temperature in kelvin. A is ideal factor, E_g is the energy band gap and I_{os} is the saturation current. Then the output current I_{pv} of PV cell can be written as follows:

$$I_{pv} = I_{ph} - I_{os} * [\exp(\frac{q}{AKT}(V + I_{pv} * R_s)) - 1] - \frac{V + I_{pv} * R_s}{R_{sh}} \quad (4)$$

2.2. PV module model

A solar cell is the building block of solar panel; PV module is formed by connecting solar cells in series. The output current equation becomes as follows:

$$I_{pv} = I_{ph} - I_{os} * [\exp(\frac{q}{N_s AKT}(V + I_{pv} * N_s * R_s)) - 1] - \frac{V + I_{pv} * N_s * R_s}{N_s * R_{sh}} \quad (5)$$

In practical implementation PV array is used to generate large output power. The PV array is composed from N_s series modules and N_p parallel modules and output current is calculated by [11]

$$I_{pv} = I_{ph} - I_{os} * [\exp(\frac{q}{N_s AKT}(V + I_{pv} * \frac{N_s}{N_p} * R_s)) - 1] - \frac{V + I_{pv} * \frac{N_s}{N_p} * R_s}{\frac{N_s}{N_p} * R_{sh}} \quad (6)$$

The voltage-current and the voltage-power characteristics of the PV system under normal condition (STC) and under varying ambient temperature and solar radiation are shown in Fig. 2.

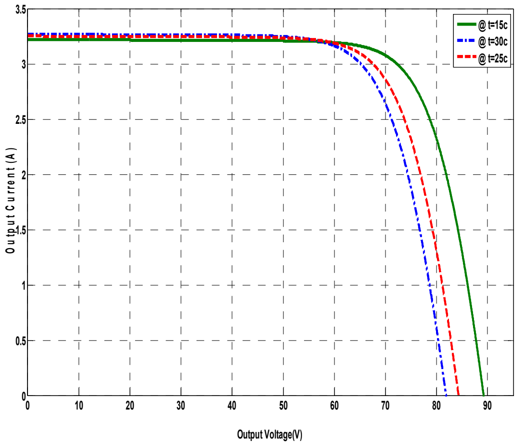


Fig. 2 (a) The voltage-current characteristics at different temperatures and G =1000W/m^2.

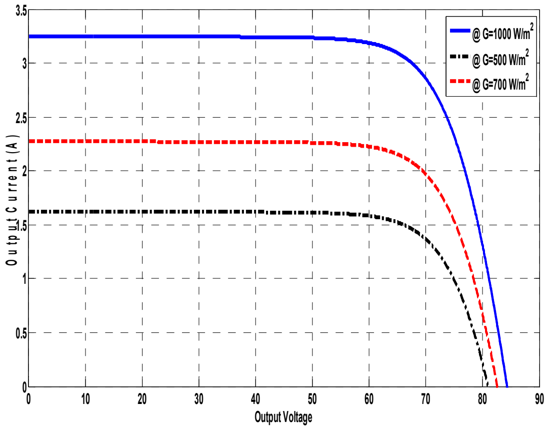


Fig. 2(b) The voltage-current characteristics at different solar radiations and T=25c.

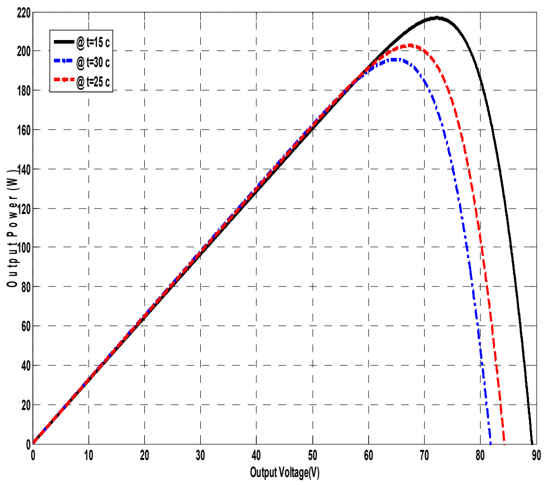


Fig. 2(c)The voltage-power characteristics at different temperatures and G =1000W/m^2.

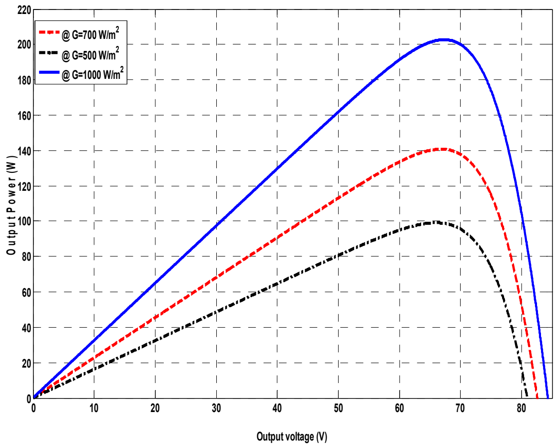


Fig. 2 (d) The voltage-power characteristics at different solar radiation and T = 25c.

2.3. Shaded PV module

As mentioned in the previous section; the value of the PV output current depends on the amount of solar radiation striking the module surface. This means that the PV output current is proportional to the amount of light that is falling on its surface. In case of light reduction due to shadow of the surrounding buildings, clouds or increasing dust on PV surface, the output voltage will reduce by ΔV [12]

$$\Delta V = \frac{V}{n} + I * R_p \quad (7)$$

Where n is the number of cells in PV module, ΔV is the drop in the voltage due to one shaded cell in the module. This change in the output values of PV module leads to a change in its characteristics as in Fig. 3.

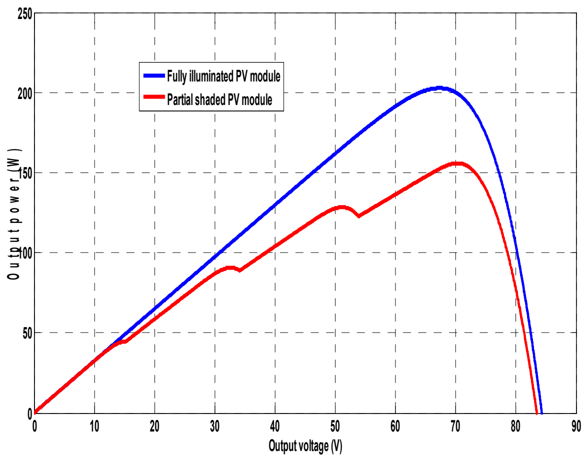


Fig. 3 The voltage-power characteristics in case of fully illuminated and partially shaded PV.

Non-uniform solar radiation causes high power consumption that produces a hot spot [13]. To prevent this phenomenon and protect the shaded module from damage a bypass diode is connected in parallel with the module. The goal of this diode is to prevent the reverse current to flow in the model by providing an alternative path and making all cells in forward bias and so improving the performance of PV model. The result of using a bypass diode is to make the module V-P characteristic becomes more complicated, it has more peaks but without bypass diode, it has one peak value as shown in Fig. 4.

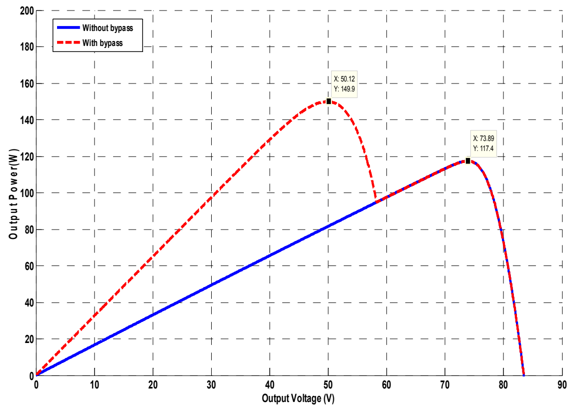


Fig. 4 The power-voltage characteristics in case of using bypass diode

3-The MPPT algorithms

The tracking of maximum power point in the PV system is an essential process in the system to obtain the maximum possible power under different operating conditions. There are many algorithms for MPPT simulation, P&O, Fuzzy logic controller [14] and neural network. The meta-heuristic optimization algorithms are also presented for MPPT design such as Artificial Bee Colony (ABC), Modified ABC [12] and PSO [13].

3.1. Perturb and Observe (P&O) algorithm

P&O is the most popular algorithm in simulating the MPPT because of ease of implementation. A perturbation occurs in the voltage value (called P&O) or in the duty value of power converter (called hill climbing) [11]. In hill climbing, the duty value is increasing or decreasing with perturbation value. Then measure the corresponding output power and compare it with the previous value. If the power increased the change in the duty will occur in the same direction else the change will occur in the reverse direction as shown in the flow chart of Fig 5. Where D represents the duty cycle value and ΔD is the perturbation value.

In the shading conditions, this algorithm fails to reach the global power point but falls in the local minimum point. According to the value of increment, the convergence time changes with small increments the algorithm will take a long time but reach to maximum point in normal condition. However, with large increments, it takes less time but possibly do not reach the global power.

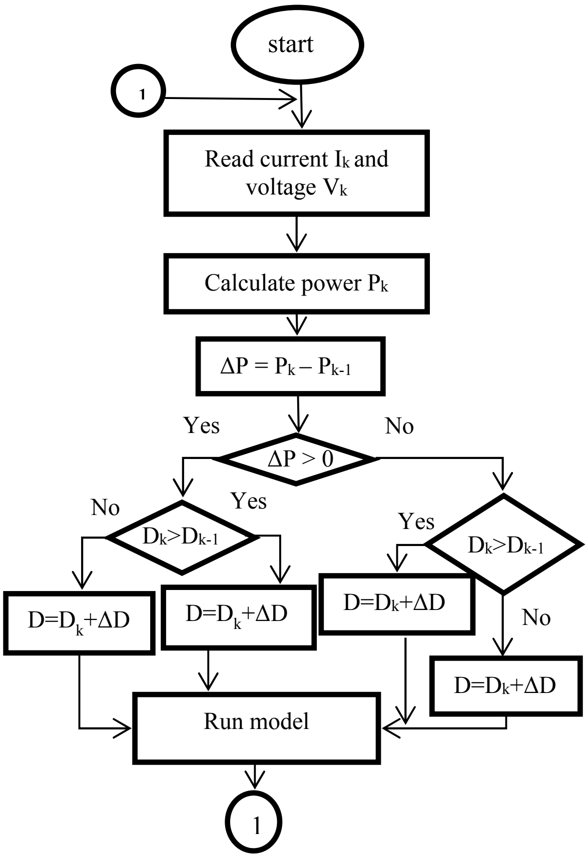


Fig5. P&O flow chart

3.2. *Particle Swarm Optimization (PSO)*

PSO is a population-based algorithm, which uses properties of a swarm like a flock of bird to search about the best solution. Where each particle in the swarm represents a candidate solution, each swarm has its own best neighbour P_{best} and one global best solution g_{best}. According to the values of P_{best} and

g_{best}; every particle adjusts its position by the following equations [13]

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (8)$$

Where x_i^t is the current position, x_i^{t+1} is the desired position and v_i^{t+1} is the velocity given by,

$$v_i^{t+1} = w * v_i^t + c_1 r_1 (p_{best,i} - x_i^t) + c_2 r_2 (g_{best} - x_i^t)$$
$$i = 1, 2, ...N \quad (9)$$

Where w is the inertia weight, r_1, r_2 are uniformly distributed random variables within [0, 1], $c_1 and c_2$, are acceleration coefficients [1, 2]. Fig. 6 shows the movement of particles in the optimization process and the PSO flow chart is in Fig. 7.

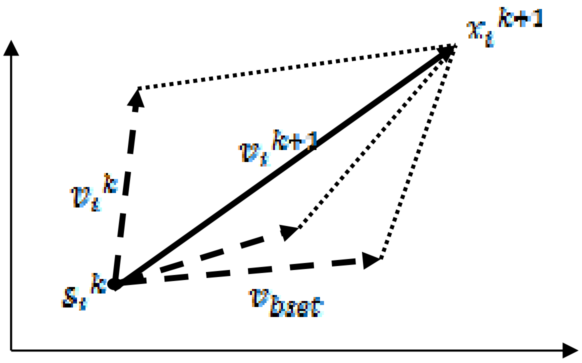


Fig. 6 The movement of particle

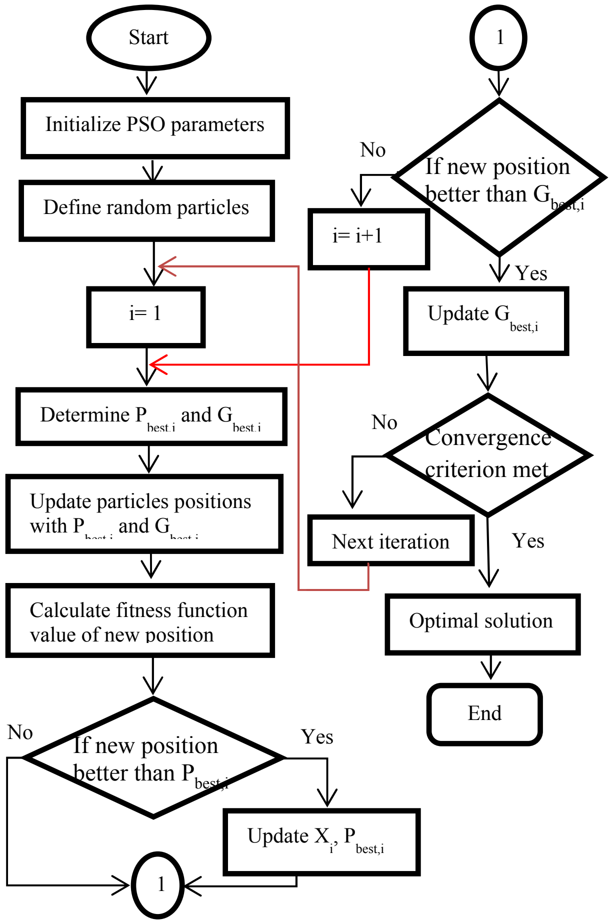


Fig.7 PSO flow chart

3.3. *Teaching Learning Based Optimization Technique (TLBO)*

TLBO is a population-based algorithm that simulates the learning process in the classroom. There are group of students (learners) and one teacher, this teacher tries to improve the performance of all students; a good teacher produces better students in their results and marks or grades. The searching process is divided into two phases, teacher phase and learner phase [15].

- **The teacher phase**

In this phase, the learning process is based on the teacher, T_i. He tries to move the mean value of students, M_i, towards its own level so the new desired mean, M_{new}, will be the teacher value.

The difference between the desired mean and old mean value is used to update the existing value of the student (X_i) by the following equation:

$$diff\_mean_i = r_i * (M_{new} - T_f * M_i) \quad (10)$$

Where r_i is a random number [0, 1] and T_f is the teaching factor [1 or 2] calculated with

$$T_f = round[1 + rand(0,1)\{2-1\}] \quad (11)$$

Then the updating in the learner value is calculated by the following equation

$$X_{new,i} = X_{old,i} + diff\_mean_i \quad (12)$$

- **The learner phase**

The learning process is performed through interaction between the students to increase their knowledge.

Every student may learn a new information in case of the others have more information than him. The updating process is done by selecting two random students and comparing between their results as follows:

$$X_{new,i} = X_{old,i} + r_i * (X_i - X_j) \quad (13)$$

$$X_{new,i} = X_{old,i} + r_i * (X_j - X_i) \text{ if } f(X_j) > f(X_i) \quad (14)$$

The updated value is accepted if it gives a better result than the old value. The following flow chart in Fig. 8 shows the operation and implementation steps of TLBO algorithm.

4-The Proposed Improved Teaching Learning Based Optimization algorithm (MTLBO)

In the conventional TLBO algorithm, the learners gain the new knowledge from the teacher in teacher phase or by the interaction with other learners in learner phase. This concept leads to slow convergence in the optimization problem [16]. In nature the discussion between teacher and learners, especially the first learner that is the second best after teacher in the teacher phase can help in improving the performance of learners. However, in the learner phase, the teacher cannot exist with learners for a long time. On the other hand, the best learner already exists with other learners so its effect will help in the learning process. Considering this option to enhance the performance of learners and reach fast convergence response in MPPT.
In the teacher phase the effect of discussion with this learner in course session can be considered and the updating equation becomes

$$X_{new,i} = F * X_{old,i} + diff\_mean_i \quad (15)$$

Where $F = T_i / best_i$

In the learner phase; the best learner takes the role of the teacher and is considered as a second teacher with the other learners in addition to the effect of teacher in the learners. The modification equations becomes as follows.

Select two random learners X_i and X_j where $i \neq j$

$$X_{new,i} = X_{old,i} + r_i * (X_i - X_j) + w * (best_i - X_j)$$
$$\text{if } f(X_i) > f(X_j) \quad (16)$$

$$X_{new,i} = X_{old,i} + r_i * (X_j - X_i) + w * (best_i - X_i)$$
$$\text{if } f(X_j) > f(X_i) \quad (17)$$

Where w is the weight value to indicate the range of teacher effect in the learners

$$w = teacher / X_i \quad (18)$$

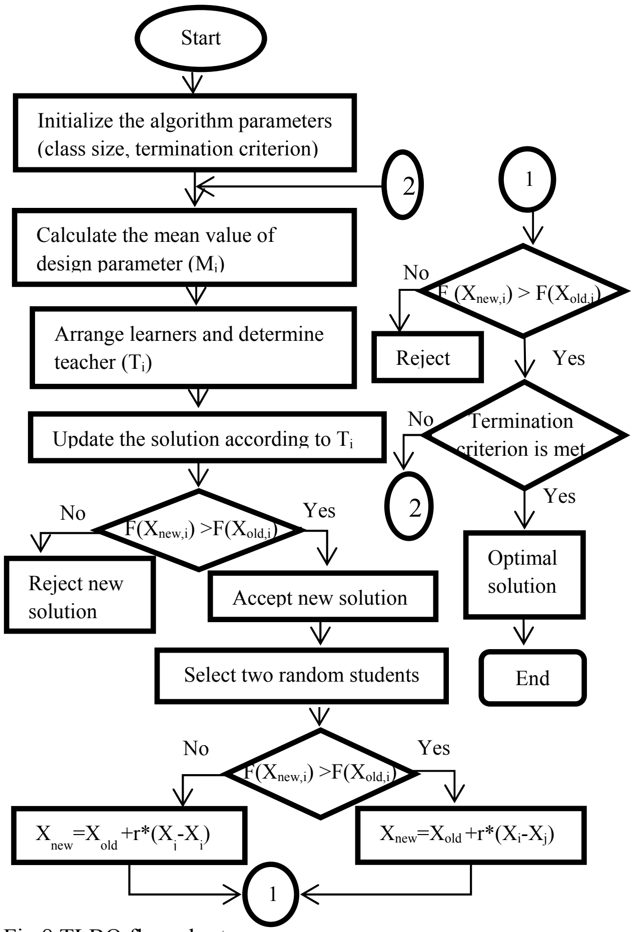


Fig.8 TLBO flow chart

5- Simulation results

The analysis is used LA361K51S PV module that has electrical specifications as given in Table 1 [17]. Fig 9 shows Matlab Simulink model of PV system that consists of four PV modules in series, boost converter block and MPPT block. MPPT block is the main block of the proposed model that determines the maximum operating power point of PV system and determines the gate signal to the boost converter. First; a fully illuminated PV array is studied; Table 2 shows the MPP, the corresponding duty cycle, the algorithm convergence time, the voltage at MPP and the current at MPP obtained via the algorithms under study.

Table 1 Electrical characteristics data of PV module [17]

Characteristics	Specification
Maximum power (W)	51
I_{sc} (A)	3.25
V_{oc} (V)	21.2
I_{MPP} (A)	3.02
V_{MPP} (V)	16.9

From Table 2, one can say that the proposed ITLBO gives the best power with minimum convergence time. The responses of each algorithm in STC operation conditions are shown in Fig. 10.

Table 2 Comparison between the algorithms under STC (G=1000 W/m^2 and T= 25 ^{o}C).

In order to ensure the reliability and efficiency of the proposed ITLBO, different shadow patterns are studied. Table 3 shows the obtained results under non-uniform solar irradiation and constant temperature using four algorithms where each module from the four used modules is exposed to different levels of shadow where the solar radiation striking each module's surface is G_1, G_2, G_3 and G_4 respectively. From table 3, one can say that the proposed ITLBO gives the highest value of MPP and the fastest response compared to the other algorithms. Fig.11and Fig.12 show the voltage-power characteristics for the shadow pattern under study.

Fig. 13 shows the responses of the four algorithms under study. Finally, it is derived that the proposed ITLBO is efficient, reliable, less convergence time in catching the global maximum power extracted from the PV array under fully illuminated array and under shadow patterns.

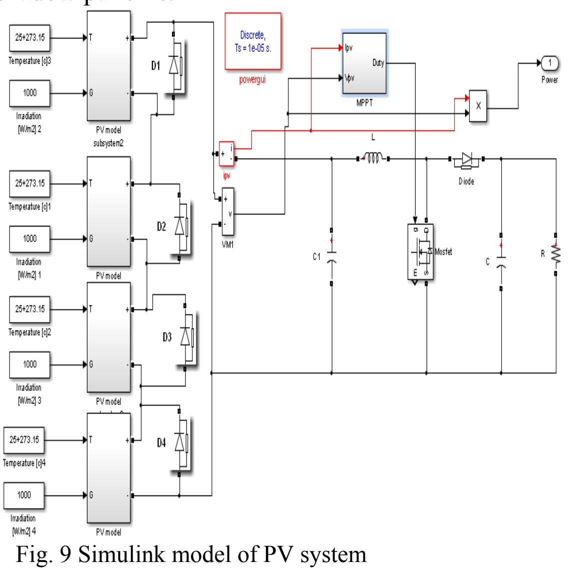


Fig. 9 Simulink model of PV system

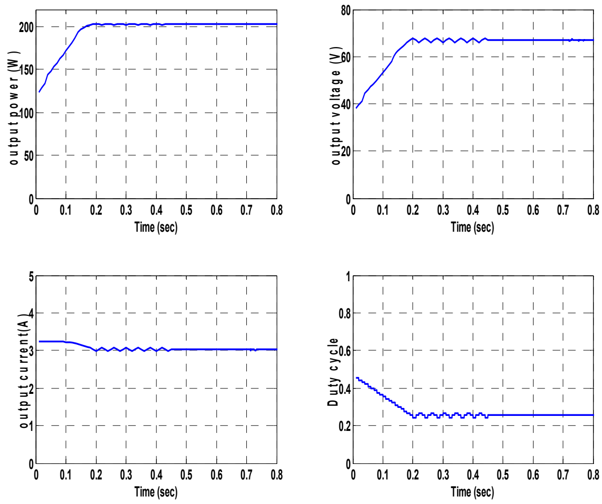


Fig. 10 (a) The output results of P&O algorithm

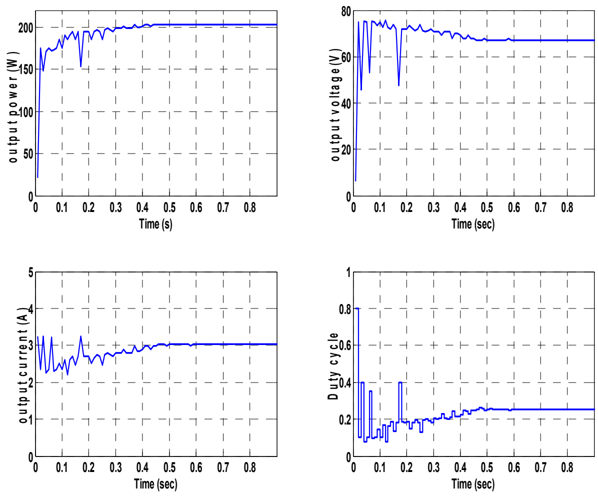
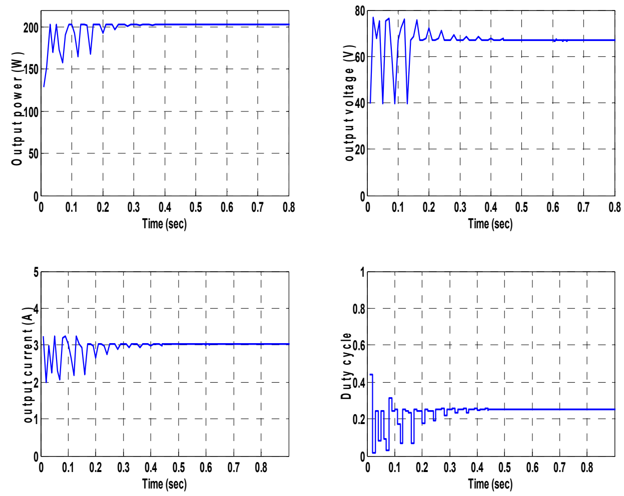


Fig. 10 (b) PSO output result



. Fig.10(c) TLBO algorithm output results

Table 2 Comparison between the algorithms under STC (G=1000 W/m^2 and T= 25 ^{o}C)

Parameter	P&O	PSO	TLBO	ITLBO
Maximum power (W)	202.6864484864	202.6864484958	202.6864484496	202.6864484496
Duty @ MPP	0.2549	0.2508	0.2531	0.2508
Convergence time (Sec.)	0.42	0.44	0.28	0.13
Voltage @ MPP (V)	66.931586995911	66.9315870327289	66.9315868503460	66.931586850346
Current @ MPP (A)	3.0282630008287	3.02826299930294	3.02826300686519	3.028263006865

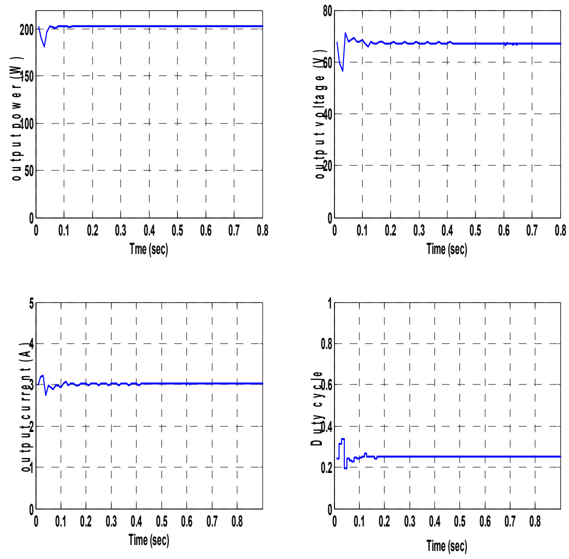


Fig 10 (d) ITLBO output result

6-Conclusion

This paper presents MPPT controller based on a proposed improved teaching learning based optimization (ITLBO) algorithm to extract the MPP from the PV array either in fully illuminated operation or in shadow pattern operation. The proposed algorithm is based on modification in the learner phase to improve the performance of students by adding the effect of best student and the effect of teacher on the student to speed up reaching to the maximum power point of photovoltaic array under non-uniform solar irradiation. The proposed technique gives the optimum duty cycle value to the boost converter which leads to good results where photovoltaic system operating at maximum power point with fast and accurate tracking, when compared with perturb and observe algorithm (P&O), particle swarm optimization algorithm (PSO) and teaching learning based optimization technique (TLBO). Different shadow patterns are studied and the obtained results encourage the usage of the proposed solution algorithm, ITLBO, in simulating the MPPT as it gives the solution closest to the original MPP with minimum convergence time.

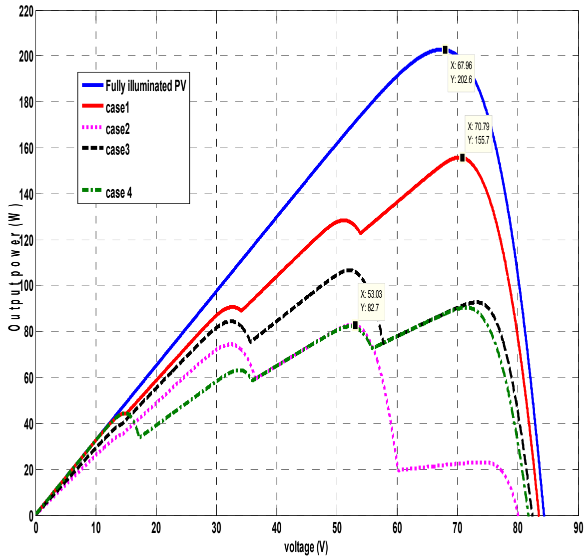


Fig 11 V-P curves of cases from 1 to 4

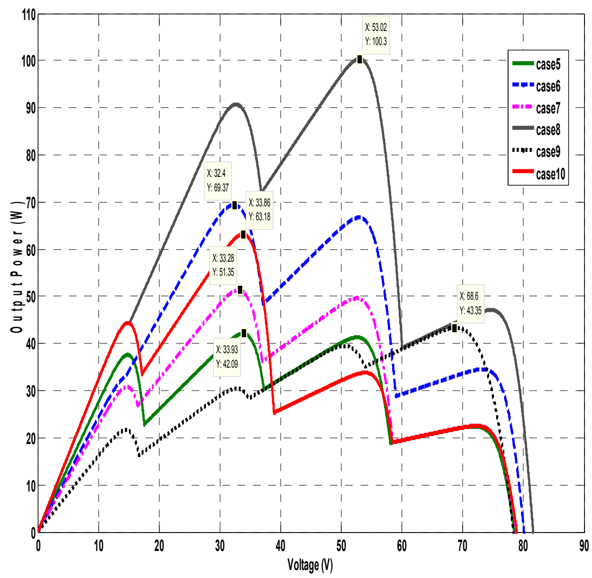


Fig 12 V-P curves of cases 5 to 10

Table 3 Comparison between the algorithms at different shadow patterns

Case Study	Parameter	P&O	PSO	TLBO	ITLBO
G=[1000, 900, 800, 700]	Maximum power (W)	98.548915	155.310342097	155.2765024221	155.2765024221
	Duty @ MPP	0.3610	0.0238	0.0112	0.0112
	Convergence time (Sec.)	0.01	0.17	0.09	0.05
	Voltage @ MPP (V)	37.927650	71.265573516	71.29329591118	71.29329591118
	Current @ MPP (A)	2.5983395	2.179317929	2.17799584712	2.17799584712
G=[800, 650, 100, 500]	Maximum power (W)	68.33773	82.70260746	82.711739052529	82.716763584646
	Duty @ MPP	0.1349	0.077	0.03347	0.0152
	Convergence time (Sec.)	0.01	0.13	0.13	0.09
	Voltage @ MPP (V)	42.13479	52.0887464368	52.10897583248	52.12043874320
	Current @ MPP (A)	1.6218835	1.5877250485	1.587283912822	1.5870312219009
G=[650, 850, 400, 900]	Maximum power (W)	81.11138447	106.467010651	106.467010651	106.4670106516
	Duty @ MPP	0.383	0.1338	0.195	0.1017
	Convergence time (Sec.)	0.01	0.19	0.17	0.04
	Voltage @ MPP (V)	34.47775358	52.4819858752	52.4819858752	52.4819858752
	Current @ MPP (A)	2.352571615	2.02863913924	2.028639139242	2.02863913924
G=[500, 600, 1000, 400]	Maximum power (W)	55.321854352	82.1009680467	82.106876351	82.110071511
	Duty @ MPP	0.339	0.0874	0.047	0.0100
	Convergence time (Sec.)	0.03	0.14	0.21	0.13
	Voltage @ MPP (V)	28.4844616	51.9002271363	51.9203872704	51.93181743881
	Current @ MPP (A)	1.94217658	1.58189997571	1.581399536242	1.581112997022
G=[400, 100, 850, 250]	Maximum power (W)	36.895556	41.803743950	41.8059879232	41.806319288572
	Duty @ MPP	0.5512	0.1711	0.1728	0.1509
	Convergence time (Sec.)	0.1	0.21	0.21	0.09
	Voltage @ MPP (V)	15.5718133	32.9997358728	33.0033530204	33.00388810802
	Current @ MPP (A)	2.36938086	1.266790258898	1.2667194117	1.266708914772
G=[350, 400, 700, 750]	Maximum power (W)	51.7620084	55.32828135	69.0362809885	69.03628098852
	Duty @ MPP	0.1417	0.0225	0.394	0.302
	Convergence time (Sec.)	0.07	0.17	0.12	0.05
	Voltage @ MPP (V)	36.7752349	42.661684259	31.49541073983	31.49541073983
	Current @ MPP (A)	1.40752352	1.2969080408	2.191947314445	2.191947314445
G=[700, 300, 500, 100]	Maximum power (W)	30.515594	47.77125462683	50.5921210621	50.5921894088
	Duty @ MPP	0.53	0.1011	0.2993	0.2099
	Convergence time (Sec.)	0.03	0.25	0.25	0.21
	Voltage @ MPP (V)	14.1828340	35.2270637971	31.758244630	31.75831233356
	Current @ MPP (A)	2.151586478	1.3560952710	1.59303896205	1.59303771804
G=[900, 200, 600, 1000]	Maximum power (W)	85.70593726	97.144916524	97.144916524	97.224695379172
	Duty @ MPP	0.4313	0.1858	0.1431	0.1003
	Convergence time (Sec.)	0.03	0.1	0.05	0.04
	Voltage @ MPP (V)	29.54178916	50 157242938	50.1572429385	50.2042702921
	Current @ MPP (A)	2.901176254	1.9368073449	1.9368073449	1.936582183416
G=[250, 500, 300, 200]	Maximum power (W)	21.55687456	30.0267194439	30.0383098483	30.0383098483
	Duty @ MPP	0.4313	0.0874	0.0601	0.0542
	Convergence time (Sec.)	0.02	0.13	0.13	0.09
	Voltage @ MPP (V)	14.91275540	31.512069249	31.531216303	31.5312163030
	Current @ MPP (A)	1.445532632	0.95286409809	0.9526530648	0.9526530648
G=[100, 1000, 200 600]	Maximum power (W)	55.3216984	61.80305726673	61.845663408	61.845663408988
	Duty @ MPP	0.3674	0.2199	0.2627	0.2138
	Convergence time (Sec.)	0.03	0.26	0.12	0.08
	Voltage @ MPP (V)	28.48442199	35.077412011	35.0600275945	35.06002759454
	Current @ MPP (A)	1.942173810	1.76190470512	1.76399574796	1.763993574796

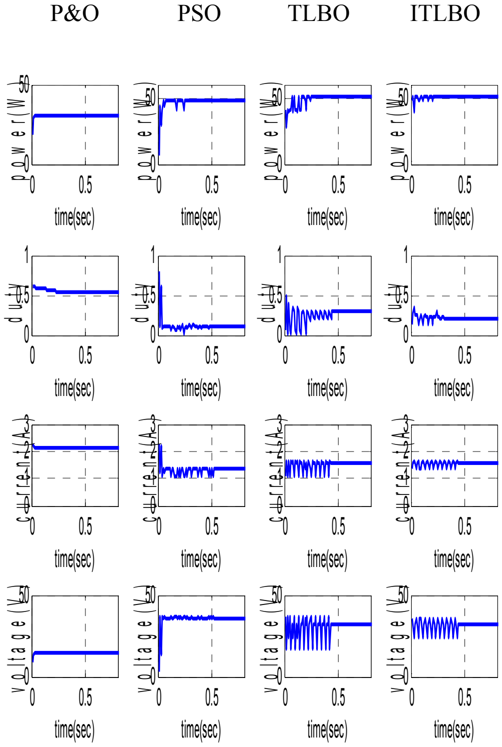


Fig 13 Responses of case number 7 of the algorithms under study.

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