ICIC Express Letters ICIC International ©2016 ISSN 1881-803X
Volume **10**, Number **11**, November **2016** pp. **2703–2710**

AN ADAPTIVE TLBO ALGORITHM FOR MAXIMUM POWER POINT TRACKING IN A PHOTOVOLTAIC MODULE ARRAY

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Received April 2016; accepted July 2016

Abstract. *This paper presents an adaptive teaching-learning-based optimization (ATLBO) algorithm as a reliable and efficient way of global maximum power point tracking (GMPPT) for photovoltaic module arrays (PVMAs) under a variety of shaded conditions. This is done by the introduction of an adaptive teaching factor taking account of the past learning experience of an MPP tracker. A combined use of a smart tracking and a partial self-learning mechanism can not only speed up a tracking process, but also improve the steady-state tracking performance. Tracking performances are simulated on various testing cases using MATLAB, and the presented adaptive algorithm is validated to outperform a typical counterpart in terms of dynamic and steady-state tracking performance.*

Keywords: Photovoltaic module array (PVMA), Partial shading, Maximum power point tracking (MPPT), Adaptive teaching-learning-based optimization (ATLBO) algorithm

1. **Introduction.** Over recent years, there have been a great volume of publications on the issue of MPP tracking under shaded conditions. So far, the most frequently employed as well as representative tracking algorithms cover differential evolution (DE) [1], ant colony optimization (ACO) [2], artificial bee colony algorithms (ABC) [3], etc. DE algorithm is performed in a similar way as a genetic algorithm. A real number coding is performed on a specific population, and a global search for the optimum is conducted via differential evolution and exponential crossover strategy. In [4], DE is applied to a PVMA, and MPP tracking performance is simulated but without experimental validation. Furthermore, as suggested by Storn in [5], individual mutation strategy requires an expression containing 5 terms, which slows down a tracking process and requires careful comparison in the progress of binary coding using a microcontroller. In contrast, ACO refers to a probabilistic algorithm seeking out an optimal route. As ants forage, pheromone is released to attract and guide others as a way to avoid a time-consuming random search, and an optimal foraging route is found accordingly. As explicitly pointed out in [6], ACO prevents an MPP tracker from being trapped at a local MPP, since the conversion between the pheromone density and the route travelled becomes a random number. However, ACO is experimentally found to give rise to a long tracking process, when applied to MPPT in a PVMA, for the reason that the updated pheromone density is an exponential expression. In regards to ABC, once scout bees have found a food source, waggle dance is employed as a way to communicate the location of nectar to others for more food collection. Nonetheless, a major disadvantage in ABC is that the quality of search performance cannot be well maintained due to a random foraging process, and the number of bees demonstrates an effect on the dynamic and steady-state tracking performance when foraging, as presented in [7]. Moreover, when applied to MPPT in PVMAs, statistical comparison on the tracking performance between ABC and a particle swarm

optimization (PSO) algorithm indicates that it takes ABC 5-6 seconds to track the MPP, meaning that there is still room for tracking performance improvement.

In the literature, smart algorithms have been successfully integrated into conventional algorithms to address the issue of MPP tracking in PVMAs, say, PSO and P&O in [8] and PSO and a genetic algorithm (GA) in [9]. Although this move is able to locate the wanted global MPP, a major problem is a slow dynamic response. For this sake, an adaptive algorithm is presented herein as an improved version of the teaching-learning-based optimization (TLBO) algorithm [10]. Without constraints on optimization population, it is an easy-to-implement algorithm, has excellent adaptability, and requires a small number of design parameters. Underlain by [11], a tracking mechanism is developed in an effort to improve the global MPP tracking performance. Consequently, the presented adaptive algorithm is validated to outperform the existing MPP tracking algorithms in the literature, particularly when dealing with the multiple peak problem on a P-V characteristic curve of a PVMA. In this paper, Section 2 describes briefly the implementation procedure of the typical and proposed adaptive TLBO algorithms to track the actual maximum power points when applied to multipeaked output characteristic curves of PVMAs. Then, the characterizations of PVMAs are illustrated in Section 3. In Section 4, some simulation results are made to demonstrate the effectiveness of the proposed adaptive TLBO algorithm. In Section 5, conclusions are given.

2. The Typical and Proposed Adaptive TLBO Algorithms.

Firstly proposed by Rao and Patel in 2011 [12], a typical teaching-learning-based optimization algorithm was developed as a solution to a complicated constrained optimization problem. Simply speaking, it simulates an interactive teaching and learning process between students and teachers, such that the overall performance of a class can be improved. During the process, all the students and the teacher serve as the particles and the one with the best fitness value.

2.1. Typical TLBO algorithm.

A typical TLBO algorithm is stated as follows.

1) Specify the number of students N_p, the number of iterations E, teaching step r_i and learning factor T_F.
2) Initialize a class, and randomly specify the learning ability of each student X.
3) Substitute the initial ability into the objective function for the assessment of each student's grade.
4) One of the best students is selected as the teacher $X_{teacher}$, the difference between two means (*Different_Mean)* is given by

$$Different\_Mean_i = r_i(X_{teacher} - T_F \times M); \quad i = 1, 2, \ldots, E \tag{1}$$

and each student's grade is updated as

$$X_{k,new} = X_{k,old} + Different\_Mean_i; \quad k = 1, 2, \ldots, N_P \tag{2}$$

where M is the mean value of all the students' grades.

5) Suppose that 2 randomly selected students, X_P and X_Q, learn from each other. More precisely, it is that the one with poor performance, as a mentee, learns from the other as a mentor, and both are updated as

$$X'_{k,new} = X_{k,new} + \begin{cases} r_i(X_{k,P} - X_{Q(\neq k)}) & \text{if } X_P > X_Q \\ r_i(X_{Q(\neq k)} - X_{k,P}) & \text{if } X_P < X_Q \end{cases} \tag{3}$$

$$i = 1, 2, \ldots, E; \quad k = 1, 2, \ldots, N_P$$

6) A tracking task terminates once the desired global optimum solution is found or the maximum number of iterations is reached.

Table 1 gives the values of all the parameters involved in a typical TLBO algorithm, and nomenclature is given as follows.

N_p: The total number of the students involved.

E: The number of iterations, i.e. the number of teaching/learning among students.

M: The mean value of all the students' grades.

r_i: The teaching step, a random parameter with various characteristics between 0 and 1.

T_F: Teaching factor, a random parameter = 1 or 2, representing the teacher's teaching ability to students.

Table 1. Parameter settings involved in a typical TLBO algorithm

N_p	4
E	40
r_i	a random number between 0 and 1
T_F	1 or 2

As explicitly stated above, T_F is specified as either 1 or 2 in a typical TLBO algorithm. Consequently, a major problem is that the learning ability variation among students cannot be reflected by a fixed-valued T_F. This move may lead to a poor performance with regard to students' learning. For this sake, an adaptive T_F is presented here as a way to improve the performance of a typical TLBO algorithm.

2.2. **Proposed adaptive TLBO algorithm.** An adaptive TLBO algorithm is presented herein as a modified version of the typical one discussed in the preceding section, and Steps 4-5 are modified as follows.

Modification 1: T_F is made adaptive as

$$T_F = \frac{X}{X_{teacher}} \tag{4}$$

Modification 2: during a learning process, a student learns from another student who can benefit the mentee the most.

Modification 3: taking account of the prior learning experience, each student's learning status is made adaptive, and is updated as

$$X''_{i,k,new} = X'_{i,k,new} + r_i\left(X'_{i,k,new} - X'_{i-1,k,new}\right); \quad i = 1, 2, \ldots, E; \quad k = 1, 2, \ldots, N_P \tag{5}$$

In Equation (1), T_F decreases with *Different_Mean* if $X_{teacher}$ and M are kept constant during a teaching/learning process. However, in a PVMA tracking event, a large tracking step is expected when the operation point is distant from the MPP, and vice versa. Accordingly, when applied to a PVMA tracking task, X_1, X'_1 and $X_{teacher}$ are replaced with the power P_1, P'_1 and the tracked maximum power $P_{teacher}$ up to now, respectively, in Modification 1, and T_F in Equation (4) is rewritten as

$$T_{F1} = \frac{P_1}{P_{teacher}} \tag{6}$$

$$T_{F2} = \frac{P'_1}{P_{teacher}} \tag{7}$$

The tracking mechanism is illustrated with Figure 1. To begin with, the operation point stays distant from the MPP, the current grade of a student is symbolized as X_1, and then the PVMA output power is represented as P_1. Equations (6) and (1) give a low value of T_{F1} and a high value of *Different_Mean*, respectively, meaning that the MPP tracker makes a huge step toward the MPP. Since the operation point now stays closer to the MPP, the current grade of the student is symbolized as X'_1, and then the PVMA output power is represented as P'_1 accordingly. The condition $P'_1 > P_1$ gives rise to a higher value

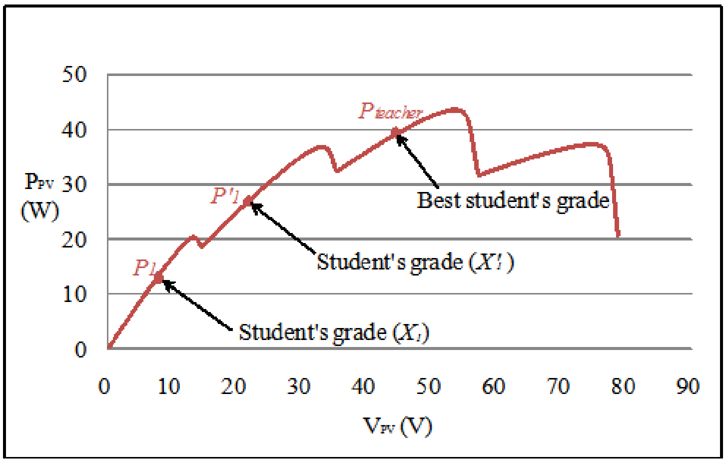

FIGURE 1. An illustration of the adaptive tracking mechanism via the tuning parameter T_F

of T_{F2} and a low value of *Different_Mean* as compared with the previous case, meaning that the tracker now makes a smaller step toward the MPP in an adaptive manner. As stated in Modifications 2 and 3, a student with a current learning ability $X''_{i,k,new}$ takes into consideration his/her previous learning ability $X'_{i-1,k,new}$, when autonomously leaning from the mentor. This move can speed up the learning/teaching process, and an MPP tracker becomes able to converge toward the global, rather than a local, MPP efficiently and reliably.

3. **Characterization of PVMA.** In most cases, PVMA is configured in a way that meets the specified output power requirement. However, the P-V characteristic curves of a PVMA distort, even with multiple peaks, due to the dust, stain on the module surface, or even the shadow cast by high-rise buildings. In this study, tracking performance tests are conducted on various array configurations, built with a SANYO HIP 2717 PV module [13] as the building block, under shadeless and partially shaded conditions. Respectively illustrated in Figure 2 is a family of simulated P-V characteristic curves for a 4-series-1-parallel array with the number of 30% shaded modules as a parameter. An observation in Figure 1 reveals that the shading effect not only results in multiple peaks on the P-V curves, but also represses the maximum output power as the number of the shaded modules increases.

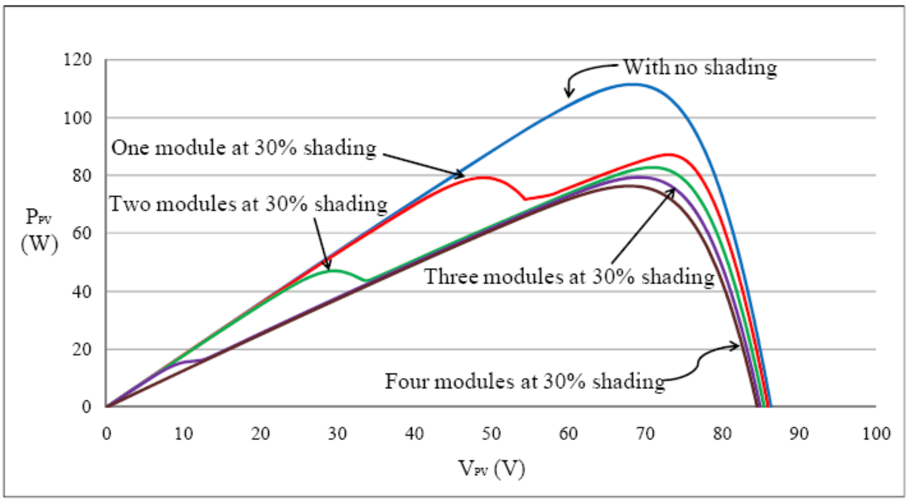

FIGURE 2. A family of P-V characteristic curves for a 4-series-1-parallel PVMA with the number of 30% shaded modules as a parameter

4. **Simulated Tracking Performance Comparison.** Table 2 gives 4 array configurations as the testing cases. All the configurations are built with a SANYO HIP 2717 PV module as the building block. Comparisons on simulated MPP tracking performance using MATLAB are made between a typical TLBO algorithm and the presented adaptive counterpart.

Table 2. Tracking case description

Case	Shading conditions	Number of peaks in the P-V curve
1	2-series-1-parallel: 0% shading+40% shading	Double peaks
2	3-series-1-parallel: 0% shading+30% shading+70% shading	Triple peaks
3	4-series-1-parallel: 0% shading+30% shading+50% shading+70% shading	Quadruple peaks
4	2-series-2-parallel: (30% shading+ 0% shading)// (0% shading+ 50% shading)	Double peaks

Illustrated in Figure 3 is a simulated P-V characteristic curve for Case 1. As listed in Table 2, Case 1 is a 2-series-1-parallel array configuration with a 40% shaded module. There exist 2 peaks on the simulated curve, where the global MPP stands on the right. As can be found in Figure 4, both algorithms can as expected track the global MPP, while the adaptive counterpart requires a smaller number of iterations.

Presented in Figure 5 is a simulated P-V characteristic curve for Case 2. It is a 3-series-1-parallel array configuration, and the global MPP appears in the center. As illustrated in Figure 6, both algorithms can track the global MPP as in Case 1, while the typical

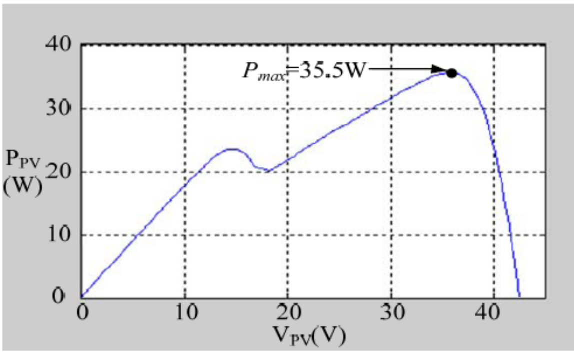

Figure 3. A simulated P-V characteristic curve for Case 1

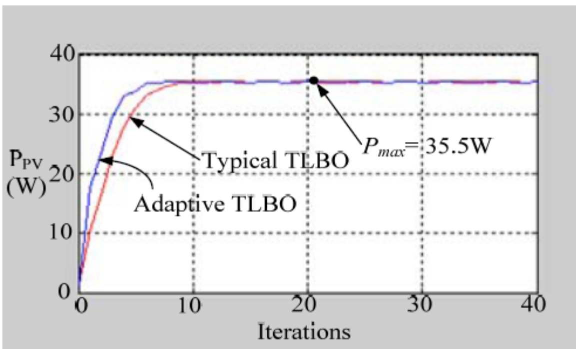

Figure 4. Tracking performance comparison between the presented adaptive TLBO algorithm and a typical counterpart in Case 1

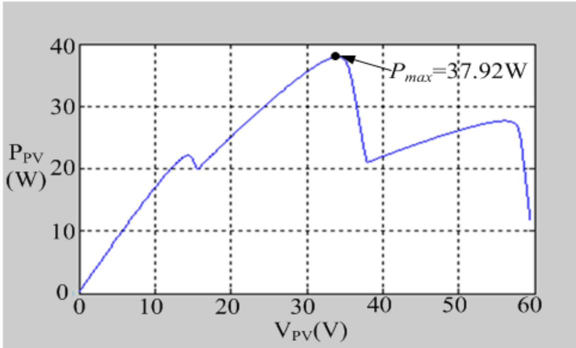

FIGURE 5. A simulated P-V characteristic curve for Case 2

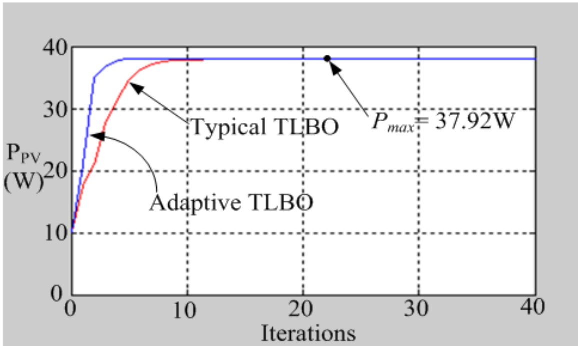

FIGURE 6. Tracking performance comparison between the presented adaptive TLBO algorithm and a typical counterpart in Case 2

TLBO algorithm requires a greater number of iterations as the number of PV modules connected in series increases, and a significant tracking performance superiority is seen in this case using the proposed algorithm.

Exhibited in Figure 7 is a simulated P-V characteristic curve for Case 3. The number of peaks on the P-V curve is found to increase with that of PV modules connected in series. Furthermore, the four peaks on the curve result from the four inconsistently shaded modules. As compared in Figure 8, the presented adaptive counterpart outperforms a typical TLBO algorithm to a great extent, although they both successfully track the global MPP in the end.

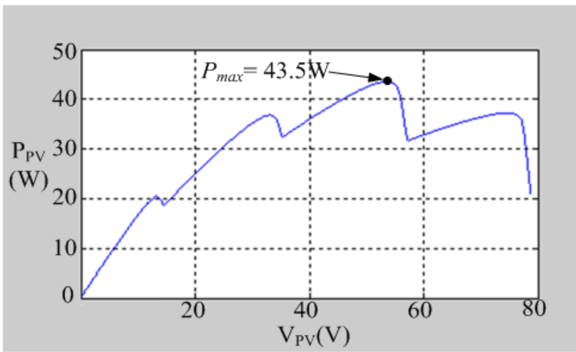

FIGURE 7. A simulated P-V characteristic curve for Case 3

Demonstrated in Figure 9 is a simulated P-V characteristic curve for Case 4. It is a 2-series-2-parallel array configuration built with inconsistently shaded modules. There are two peaks on the P-V curve, and the global MPP stands on the right side. A tracking performance comparison is illustrated in Figure 10, and the adaptive counterpart is found again to outperform a typical one, as in the previous cases.

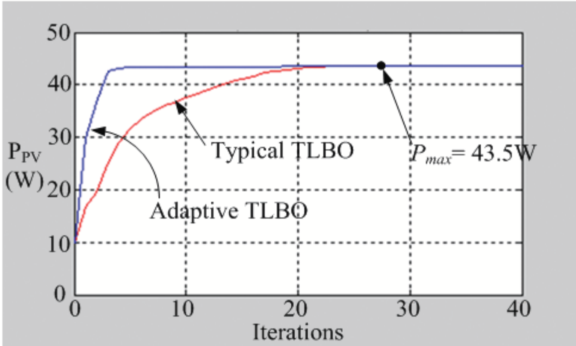

Figure 8. Tracking performance comparison between the presented adaptive TLBO algorithm and a typical counterpart in Case 3

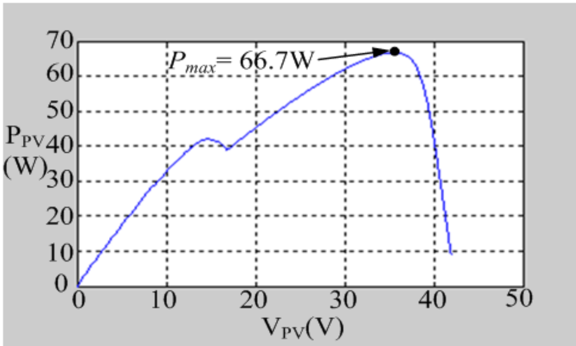

Figure 9. A simulated P-V characteristic curve for Case 4

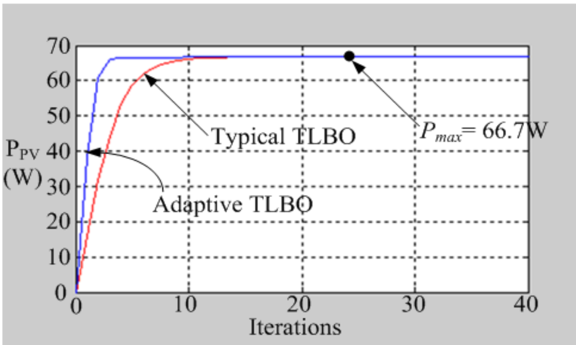

Figure 10. Tracking performance comparison between the presented adaptive TLBO algorithm and a typical counterpart in Case 4

Table 3. Simulated tracking performance comparison between this proposal and a typical TLBO counterpart

Case	Number of peaks in the P-V curve	Average iteration times	
		Typical TLBO	Adaptive TLBO
1	Double peaks	12.7	10.1
2	Triple peaks	14.2	5.5
3	Quadruple peaks	23.5	15.7
4	Double peaks	13.2	5.6

In this work, simulated MPP tracking performances are compared between a typical TLBO algorithm and the presented adaptive counterpart. There are 4 testing cases, each with 40 simulations, and Table 3 gives the average number of iterations for comparison purposes. The adaptive algorithm shows a clear tracking performance advantage over a typical one.

5. **Conclusions.** This work presents an adaptive TLBO algorithm as a way to improve the global MPP tracking performance for the operation of a PVMA. This is done simply by the introduction of an adaptive teaching factor. In addition, taking account of past learning experience, a student is permitted to learn autonomously from another student as a mentor. In this manner, the performance of an MPP tracker can be improved to a great extent. Tracking performance simulations are conducted on four array configurations built with partially shaded modules, and the proposal is validated to outperform a typical TLBO algorithm considerably in terms of the number of iterations required, particularly when dealing with the multi-peak problem on a P-V characteristic curve. In the future, some experimental results will be made to demonstrate the effectiveness of the proposed MPPT method based on modified TLBO algorithm for practical photovoltaic system.

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