

A Modified Particle Swarm Optimization Based Maximum Power Point Tracking for Photovoltaic Converter System

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ABSTRACT

This paper presents a control method suitable for photovoltaic (PV) systems which ensure that power generated is maximized for various conditions. Due to partial shading conditions in PV, the power-voltage characteristics exhibit multiple local peaks; one such phenomenon is the global peak. These conditions make it very challenging for maximum power point tracking (MPPT) to locate the global maximum power point. Many tracking algorithms have been proposed for this purpose. In this paper, a modified particle swarm optimization (PSO)-based MPPT technique is proposed. Unlike the conventional PSO-based MPPT methods, the proposed method accelerates convergence of the PSO algorithm by consistently decreasing the weighting factor, the cognitive and social parameters thus reducing the steps of iterations and improving the tracking response time. The advantage of the proposed method is that it requires fewer search steps (converges to the desired solution in a reasonable time) compared to other methods. It requires only the idea of series cells so that it is system independent. The study is supported by numerical and experimental results.

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Introduction

In the past decade, the photovoltaic (PV) system has gained wide popularity as a renewable-energy source due to the possibility of the depletion of conventional energy sources as well as the high cost of conventional energy sources and their negative effects on the environment. An essential feature of all PV systems is the efficacy of its maximum power point tracking (MPPT). This aspect has drawn immense attention from photovoltaic researchers and industry experts as the most economical means to enhance the photovoltaic system efficacy.

Several MPPT techniques have been proposed [1 - 10]. These methods differ in their accuracy, speed or complexity. Hossain *et al* [4], Eltawil *et al* [5] and David *et al* [6] reviewed and discussed various techniques. For the partially-shaded condition where the shaded cell in a PV module causes a decrease in power, the conventional MPPT technique becomes invalid due to the PV characteristics becoming more complicated and also displaying multiple MPP. This effect of partial shading has been analyzed by many researchers [7, 8]. In [10], a global stage was employed to locate the regions of the local MPP, while a perturb-and-observe algorithm was employed at the local stage to find the global MPP. Adaptive P&O MPPT was proposed in [11].

Particle swarm optimization (PSO) has high potential for MPPT due to its simple structure, easy implementation and fast computation capability. Since PSO is based on search optimization in principle, it should be able to locate the MPP for any type of PV curve regardless of environmental variations. The direct control structure was adopted by some researchers where

Excellent dynamic tracking speeds under severe partial-shading conditions were able to be handled using the method. Furthermore, the steady state oscillations were found to be exceptionally low. For instance, to track the global point in a constant bus voltage application, the conventional PSO was employed in [12]. An analytical expression of the objective functions based on PV current, irradiance and temperature was formulated in order to track the MPP.

The current-based PSO method was proposed by Miyatake *et al* [13], where the series inductor current of the boost converter is used as the reference signal to generate the PWM signals for the switching converter. A repulsive term in the velocity equation of the PSO was also introduced. Miyatake *et al* [13] proposed an adaptive perceptive PSO (APPSO)-based MPPT algorithm. Ishaque *et al* [14] presented an improved PSO-based MPPT algorithm for PV systems and discussed the advantages of using PSO in conjunction with the direct duty cycle control in detail. However, no system design guidelines and practical design considerations are provided in these papers. Miyatake *et al* [15] attempted to approach the global MPP using the PSO algorithm. The authors tried to realize centralized MPPT control of the modular (multi-module) PV system. The MPPT algorithms have good performance under various partial-shading conditions; however, these methods are only suitable for systems that consist of multiple converters. However, the use of one central high-power single-stage electronic converter is very common in the PV system due to the economic reasons and the relative

simplicity of the overall system. It is not only valid for the centralized PV inverter system, but can also be applied to other topologies. Thus, this study uses the same topology with a modified PSO to track global MPPs quickly and consistently on the multi-peak characteristic curves of a PV module during partial shading.

For a particle swarm optimization problem, there is need for a better global search in starting phase to help the algorithm converge to an area quickly; there is need for a stronger local search to get high precision value. Thus, the contribution and the advantages of this paper is the use of modified particle swarm optimisation (PSO)-based MPPT technique for PV systems. Unlike the conventional PSO-based MPPT methods, the proposed method accelerates convergence of the PSO algorithm by consistently decreasing the weighting factor and the cognitive and social parameters thus reducing the steps of iterations and improved the tracking time response. It requires fewer search steps or iterations (converges to the desired solution in a reasonable time) compared to [16]. The method requires only the idea of series cells; thus, it is system independent. The study is supported by numerical simulation and experimental results.

Materials and Method

In the proposed method, the parameter selection is very important in demonstrating the application of PSO in tracking the MPP; thus, the position of the particle is designated as the duty cycle of the power converter, while the fitness value evaluation function was chosen as the extracted power P_{PV} for the entire PV system.

For the initialization step of the PSO, the particles could be either established in the random range or placed in the stationary position. In this case, it makes more sense to initialize the particles around a definite point if there are data available regarding the position of the global MPP in the search range. Thus, the searching spaces of the particles that cover (d_{min}, d_{max}) are initialised on a definite point, where d_{min} and d_{max} are the duty cycle minimum and maximum values of the DC-DC converter used, respectively.

The main purpose of this proposed method is to extract the optimal power P_{PV} of the PV system; therefore, the objective function can be formulated as shown in Eq. 1 [17].

$$P(d_i^t) > P(d_i^{t-1}) \quad (1)$$

where P is the PV power, d is the duty cycle, i is number of particle, t is the number of iteration.

As illustrated in figure 1, the fitness value which is designated as the generated power is then evaluated. The pulse width modulation acts according to the particle position i that denotes the duty cycle state; then the PV voltage V_{PV} and current I_{PV} can be measured to calculate the fitness value P_{PV} of particle

i , which can then be used. However, to obtain the right sampling time, it should be noted that the power converter's settling time has to be less than the evaluation time interspaces between subsequent particles.

In this study, in order to update the individual and global best values, consistent decreases of the weighting factor and cognitive and social parameters reducing the steps of iterations were adopted for the PSO equations. The means that greater step sizes are used to increase the particle search velocity during the initial search because the distance to the global optimum is relatively large initially. However, even though it is not always that there is need to increase the particle search velocity at the initial search, but it also depends on the choice of another important factor which the initial generation solution to be considered. This prevents an excessively small step size from making local optimum traps unavoidable, and the weighting factor, ω , decreases gradually as the number of iterations increases because the particles are now approaching the MPP; the decrease in ω causes the steps in the particle movements to reduce, enabling the particles to track the MPP more accurately.

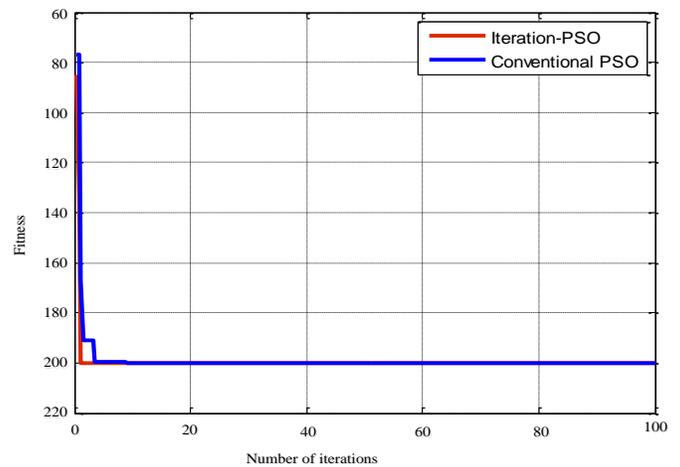


Figure 1. Convergence Characteristics of PSO and modified PSO based Optimization.

Furthermore, to maintain the particle acceleration in the same direction in which it was originally moving, the first term $\omega(t) V_i(t)$ in Eq. 2 is employed so that the converging demeanor of the PSO is controlled. For a PSO problem, there is need for a better global search in starting phase to help the algorithm converge to an area quickly and then the need for a stronger local search to get high precision value [18]. Suitable selection of ω provides a balance between global exploration and local exploitation which eliminates the need of V_{max} and also reduces the total number of iterations [19]. Therefore, it is paramount to keep ω as a variable value and not constant. In this paper, the inertia weight ω is set to a larger value and slowly reduce it for

better exploration (changes from range $\omega_{max} = (1.0)$ to $\omega_{min} = (0.1)$) according to iterations and the velocity constants c_{1max} and c_{1min} are set to 1.2 and 1 while c_{2max} and c_{2min} are set to 1.6 and 1 respectively. r_1 and r_2 are random numbers between (0, 1) as in Eq. 2.

$$\omega(t) = \omega_{max} - \beta t, \text{ where } \beta = \frac{1}{t_{max}}(\omega_{max} - \omega_{min}) \quad (2)$$

The minimum and maximum bounds of ω are denoted by ω_{min} and ω_{max} . While the maximum allowed number of iterations is denoted by t_{max} . Likewise, the social and cognitive terms can be remodelled. Also, the search ability of PSO can be affected by the values of c_1 and c_2 which changes the particle direction. Selecting c_1 greater than c_2 sampling with respect to the bearing of p_{best} would be biased, while selecting c_1 less than c_2 in the reverse case sampling in respect to the bearing of g_{best} will be much preferred [20]. For these reasons, these two terms are defined as continuously increasing and continuously decreasing functions, as in Eqs. 3 and 4 respectively:

$$c_1(t) = c_{1,max} - x_1 t, \text{ where } x_1 = \frac{1}{t_{max}}(c_{1,max} - c_{1,min}) \quad (3)$$

$$c_2(t) = c_{2,max} - x_2 t, \text{ where } x_2 = \frac{1}{t_{max}}(c_{2,max} - c_{2,min}) \quad (4)$$

Two convergence criteria are employed in this study. The proposed MPSO-based MPPT method will terminate and yield the g_{best} solution if the maximum number of iterations is attained or if all the particles' velocities become smaller than a certain threshold. Basically, PSO algorithms are utilized to solve the optimization difficulty, so that the optimum result is time invariant. However, in this case, the fitness value (which is the global MPP) sometimes varies or depends on environmental factors as well as loading states. To search for the new global MPP again in these cases, the particles must be reinitialised. Considering the change in irradiance and shading pattern to be detected here, the following constraint is employed. The particles will be reinitialised whenever the following condition is satisfied as in Eq. 5:

$$\frac{|P_{pv,new} - P_{pv,old}|}{P_{pv,old}} \geq \Delta P(\%) \quad (5)$$

where $P_{pv,new}$ is the new PV power, $P_{pv,old}$ is the PV power at the global MPP of the last operating point and $\Delta P(\%)$ is the normalised power tolerance. Its value is set to 10% or selected as 0.1. Thus, if the normalized power mismatch is larger than 0.1, the samples will be dispersed on the PV curve; otherwise they remain on the MPP. Figure 2 depicts the comprehensive flowchart of the proposed system.

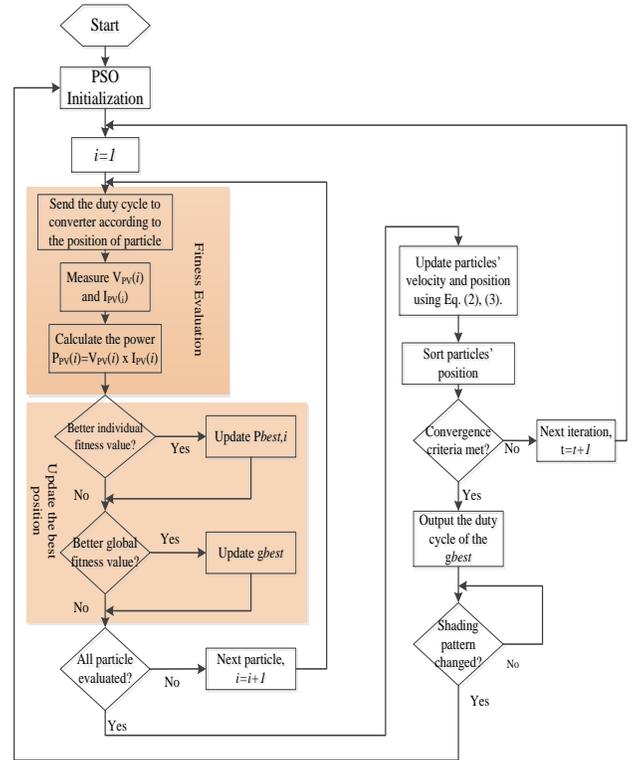


Figure 2. Flowchart of the proposed Modified PSO-Based MPPT algorithm

As shown in Figure 3, in the first pattern, there are two local MPPs, and the global MPP occurs at the leftmost one on the PV curve. In the second pattern, there are two local maximum points, and the global MPP does not occur at the rightmost or leftmost of the PV curve but occurs in-between. In the third pattern, there are two local maximum points, and the global MPP occurs at the rightmost one on the PV curve (i.e. close to the open-circuited voltage on the PV curve).

In order to begin the optimisation process, the search spaces of the particles that cover $[d_{min} d_{max}]$ are initialised on the definite point, where d_{min} and d_{max} are the duty cycle minimum and maximum values (as shown in Figure 4, where the triangular, circular and square points represent *duty cycle 1*, *duty cycle 2* and *duty cycle 3*) to be transmitted to the DC-DC converter respectively. The duty cycles are computed using Equation (2) which serves as the $p_{best, i}$ in the first iteration. As described earlier, consistently decreasing weighting factors with reduced iteration steps was adopted for the PSO equation. The advantage of this is that greater step sizes are used to increase the particle search velocity during the initial search because the distance to the global optimum is relatively large. Even though it is not always that there is need to increase the particle search velocity

at the initial search, but it also depends on the choice of another important factor which the initial generation solution to be considered This prevents an excessively small step size from making local optimum traps unavoidable. Thus, the particle tracking will be faster because they are approaching the global MPP. The decrease in the weighting factor causes the steps in the particle movements to reduce, enabling the particles to track the global MPP more accurately (i.e. points A, B and C).

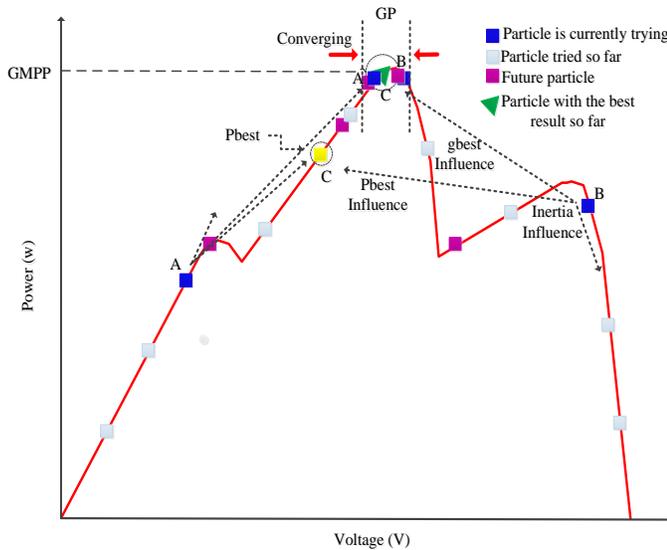


Figure 3. P-V characteristic of the PV shading condition

Results and Discussion

To demonstrate the effectiveness of the proposed MPSO-based MPPT technique, simulations and experiments are performed. The simulation model parameters of the PV module are shown in Table 1. The simulation is performed using MATLAB, Simulink model. According to the design principle, the specified parameters of the complete MPSO-based MPPT algorithm is shown in Table 2. The PV module characteristic curves are simulated by arbitrarily setting the irradiation of the series-connected PV cells under the effect of uniform and partial-shading conditions. The PV module temperature is taken to be constant at 25 °C during the simulation. Unshaded PV modules are considered entirely radiated at 1000 W/m². Irradiation on the shaded PV modules is considered constant and changes from 0 to 1000 W/m². The MPSO-based MPPT algorithms are tested and verified for different shading patterns and the simulation results are presented with a comparison.

Table 1. Simulation Parameters of ICO-SPC 100W PV [21]

Parameter	Value
Maximum Power (P_{max})	100 W
Voltage at P_{max} (V_{max})	17.3
Current at P_{max} (I_{max})	5.79
Open Circuit Voltage (V_{oc})	20.76
Short Circuit Current (I_{sc})	6.87

Table 2. Simulation Parameter Setting of the MPSO-based MPPT

Parameter	Value	Parameter	Value
Number of particles	3	ω_{min}	0.1
Minimum duty cycle	0.02	$C_{1, min}$	1
Maximum duty cycle	0.98	$C_{1, max}$	1.2
Sampling time	0.1s	$C_{2, min}$	1
Maximum iteration	3	$C_{2, max}$	1.6
ω_{max}	1.0		

Simulation under Uniform Irradiance Conditions

In the case of uniform irradiance, under normal operating conditions, there is only one MPP, which occurs at 200 W under ideal case. Figures 4 and 5 present the power, voltage and current waveforms of the proposed method in comparison to incremental conductance and conventional PSO MPPT method while figure 6 is the switching duty cycle waveform of the PSO-based MPPT method. As can be seen from the voltage plot, V_{pv} closely tracks the voltage at maximum power V_{mppt} when the controller is activated. It is also easy to see that the modified PSO method has higher accuracy and better response time in comparison with the other two algorithms. This is because the modified PSO method employed consistently-adjusted weighting factor, cognitive and social learning factor which enable it to track true MPPs at a 99.98% success rate under various irradiance conditions. This demonstrates that the controllers function properly. It takes a few iterations for the controller to reach the MPP. Note that a modified PSO cycle is the time required for the three particles to locate the MPP. During the first iteration, the three particles follow the initial values; after that, the reference values are calculated based on Eqs. 3 and 4 for the remaining iterations before reaching the MPP.

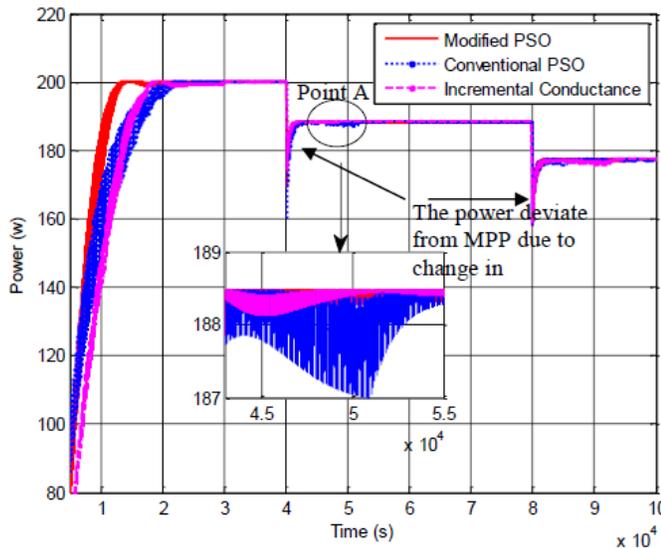


Figure 7. Power waveforms for dynamic response time under change in irradiance condition.

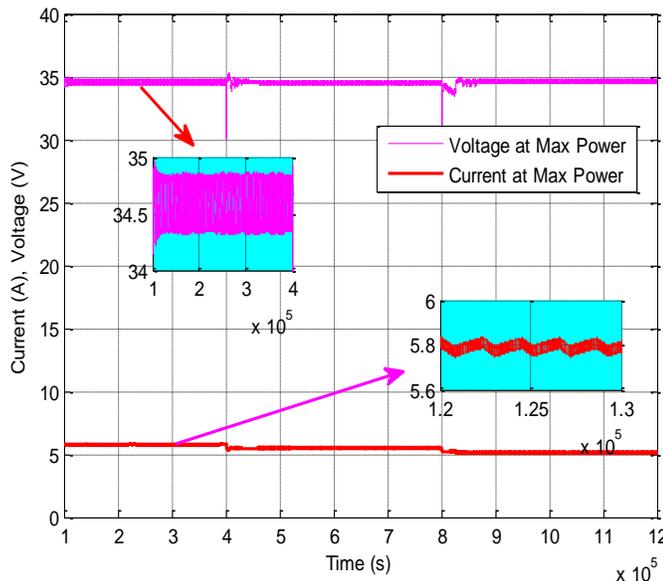


Figure 8. Voltage and current waveforms of the proposed method for change in irradiance condition.

Simulation under Changing Load Conditions

To test the performance of the proposed controller, a comprehensive simulation under step load change with constant irradiance and temperature were tested as in figure 9. This is the situation where the load changes suddenly from one value of load resistance to another. This is particularly interesting because it is

a typical problem for power electronics, where the power supply is supposed to compensate quickly for the load variation. Figures 10 and 11 show the performance of the proposed controller under step load change condition. Figure 10 shows the simulation result under step load change with constant irradiance and temperature. The irradiance and temperature were fixed to 1000 W/m^2 and $25 \text{ }^\circ\text{C}$ respectively. At 10 ms, a step load change occurs, the load resistance changes from $25 \text{ } \Omega$ to $20 \text{ } \Omega$ and in second scenario from $20 \text{ } \Omega$ to $25 \text{ } \Omega$. As a result of this change, it is shown that the proposed method tracked the maximum power of 99.98 W . The drop in the output power went down by 65 W and it took about less than 1 ms for it to settle down at the maximum power point again. It is noted that the PV voltage, V_{mpp} and current, I_{mpp} were tracked exactly on the MPP voltage and current of 17.3 V and 5.79 A provided by the manufacturer as shown in Figure 12 and 13 respectively. Figure 14 shows the switching duty cycle of the proposed method under changing load conditions. From this result, we can say that the controller is able to track the output power during steady-state condition with reference power of the PV module in case of sudden change in load. Clearly, the proposed controller is able to perform satisfactorily well with excellent disturbance rejection and fast response.

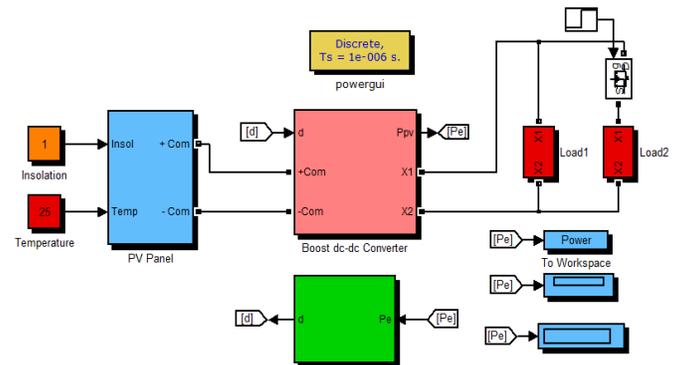


Figure 9. MATLAB/Simulink configuration of the proposed PV system under varying load.

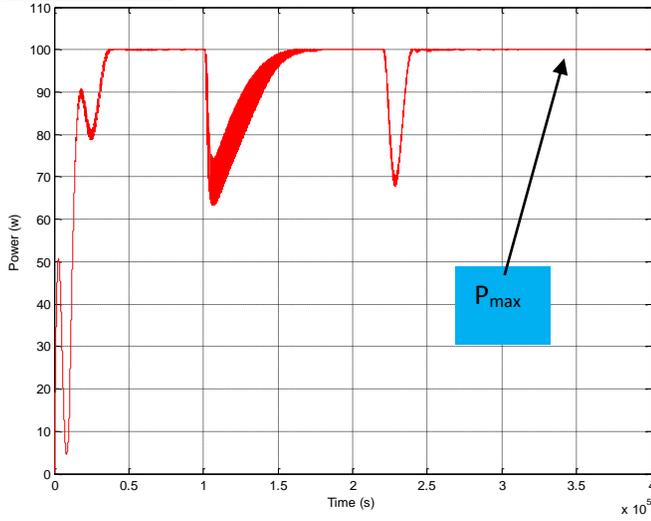


Figure 10. PV power tracked by proposed method under varying load conditions.

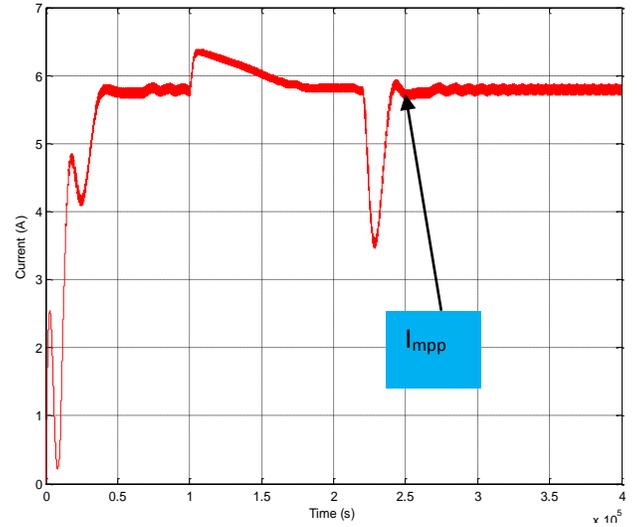


Fig. 13 PV current at maximum power of the proposed MPSO-based MPPT under varying load conditions.

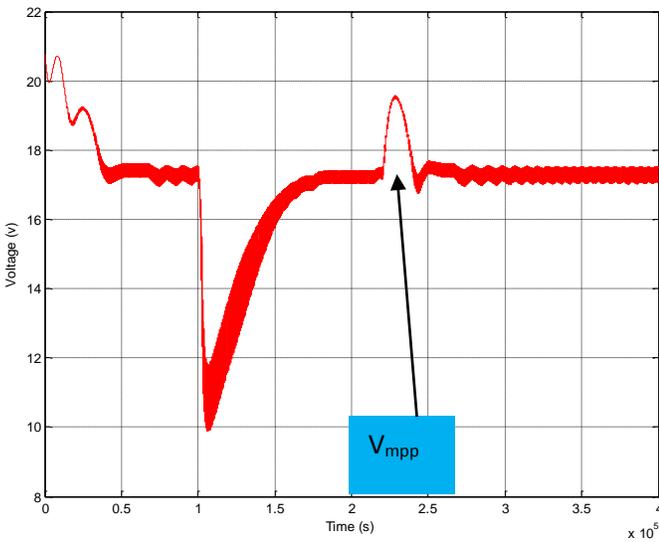


Figure 11. PV voltage at maximum power of the proposed MPSO-based MPPT under varying load conditions.

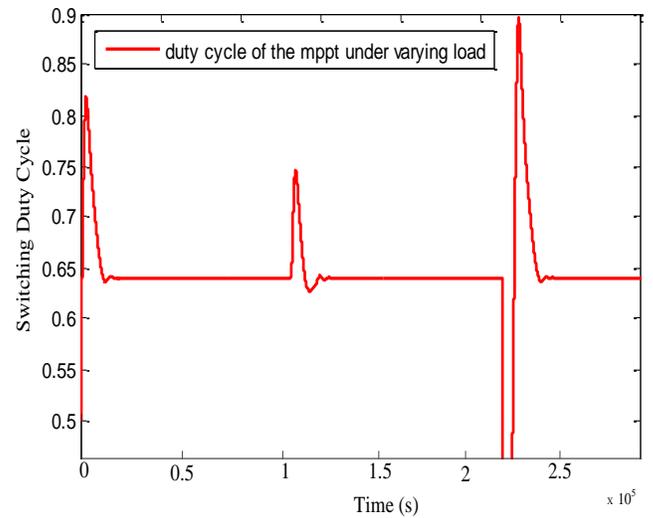


Fig. 14 Switching duty cycle of the proposed method under changing load conditions.

Tracking Efficiency of the MPPT Algorithm

The accuracy of the tracker in tracking the MPPT and the efficiency of the technique also helps in determining the method to be used by the user. Some techniques provide accurate results, whereas some are not able to track the MPPT efficiently, thus decreasing the efficiency of the tracker. The efficiency can be calculated by the following formula given in Eq. 6 [22].

$$\eta_{MPPT} = \frac{P_{pv}}{P_{MPPT}} \times 100\% \quad (6)$$



The accuracy of the tracker to make the P_{PV} closer to P_{MPPT} determines the efficiency of the system. The closer the P_{PV} is to P_{MPPT} , the more accurate is the technique. It is particularly difficult to estimate the exact accuracy of a technique without implementation of the same.

Performance Evaluation and Comparison

It is very difficult to analyze, through simulations, the amount of energy obtainable from a PV system while taking into account the effect of partial shading. The challenge lies in simulating the rapidly changing shading as well as its shape in such a way that the simulation vividly reflects the actual behaviour of a PV system. Hence, the most reliable means to evaluate the effectiveness of the proposed method is by having real-time measurements of generating power for some hours. Then the performance of the proposed algorithm is compared with other established MPPT schemes for the same conditions, namely, i) the incremental conductance algorithm (INC), and ii) the MPPT based on the conventional PSO search method. A similar study was carried out in [23]. Figure 8 shows the experimental set-up of the proposed method.

Taking into account the actual sun power, the same clear day was chosen for conducting the experiment. The weather data for the day was taken between 8:00 am to 6:00 pm. In addition, the experiments were carried out in the month of March as the weather is clear and more stable in Skudai Malaysia during this period. Figure 14 shows the irradiance and temperature profile. Figure 15 shows the experimental power waveforms of the proposed methods under partial conditions. It should be noted that there was a difference in the power extracted by three different MPPT algorithms. This was mainly due to the nature of the MPPT algorithm capability. The incremental conductance and conventional PSO methods showed lower generated power compared with that of the proposed method under partial-shading conditions; hence, the power generated was comparatively higher than other tracking methods.

Conclusion

In this paper, a modified PSO-based MPPT method for tracking MPP was presented. The proposed method accelerates convergence of the PSO algorithm by consistently decreasing the weighting factor and the cognitive and social parameters thus reducing the steps of iterations and improved the tracking time response. The advantage of the proposed method is that it requires fewer search steps (converges to the desired solution in a reasonable time) compared to other methods. The method requires only the idea of series cells; thus, it is system independent. It has been demonstrated that the proposed method for tracking MPP is highly robust to variations in solar irradiation and high tracking efficiency. The proposed method has been verified by numerical simulations and experimentally tested under shading conditions. The results show good performance in

terms of speed of convergence and also guaranteed convergence to global MPP with faster time response compared to the other methods.

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