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Maximum power point tracking of partially shaded solar photovoltaic arrays

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ABSTRACT

The paper presents the simulation and hardware implementation of maximum power point (MPP) tracking of a partially shaded solar photovoltaic (PV) array using a variant of Particle Swarm Optimization known as Adaptive Perceptive Particle Swarm Optimization (APPSO). Under partially shaded conditions, the photovoltaic (PV) array characteristics get more complex with multiple maxima in the power–voltage characteristic. The paper presents an algorithmic technique to accurately track the maximum power point (MPP) of a PV array using an APPSO. The APPSO algorithm has also been validated in the current work. The proposed technique uses only one pair of sensors to control multiple PV arrays. This result in lower cost and higher accuracy of 97.7% compared to earlier obtained accuracy of 96.41% using Particle Swarm Optimization. The proposed tracking technique has been mapped onto a MSP430FG4618 microcontroller for tracking and control purposes. The whole system based on the proposed has been realized on a standard two stage power electronic system configuration.

1. Introduction

Solar photovoltaic systems (SPV) are being increasingly employed in grid connected, hybrid and stand-alone systems. However, a major challenge in using a PV source is to tackle its nonlinear output characteristics, which vary with temperature and solar insolation. The characteristics get more complicated if the entire array does not receive uniform solar insolation, as in partially shaded conditions, due to passing by clouds, neighboring buildings, towers, trees and telephone poles, resulting in multiple peaks in the P–V characteristics. The presence of multiple peaks reduces the effectiveness of the existing maximum power point tracking (MPPT) schemes, due to their inability to effectively discriminate between the local and global maxima in the *P–V* characteristics [1–3]. It is pertinent to track and find the optimal operating voltage of PV arrays in order to increase the efficiency of PV generators.

Over the years, several researchers have studied the characteristics of partially shaded PV modules and the external factors that affect them [4–6]. Walker has proposed a MATLAB based model of a PV module in [4] to simulate its characteristics for studying the effect of temperature, insolation and load variation on available power. Alonso-Gracia et al. have experimentally obtained the *I–V* characteristics of PV module and the constituent cells to study the effect of partial shading in [5]. Kawamura et al. proposed a computer simulation model in [6] to investigate the relation between the output lowering due to shaded PV cells and the change of *I–V* characteristics. However, the *I–V* and *P–V* characteristics of a single module considered in [4–6] do not predict the presence of multiple steps and peaks, which are common in *P–V* characteristics of large PV arrays that receive non-uniform insolation.

Few researchers have studied the effects of fluctuations of PV power on the utility and connected systems. Kern et al. have studied the consequences of shading of PV due to passing by clouds on the PV power generation in [7]. Giraud et al. used an artificial neural network (ANN) based model in [8] to investigate the effects of passing by clouds on a grid connected PV system with battery storage. It is customary to select a proper size of PV array in such systems [9]. Otherwise, a large change in PV power because of insolation variation caused by shading may lead to instability.

Various maximum power point tracking methods have been proposed and used to extract maximum power from PV arrays under varying atmospheric conditions [10–16]. However, most of the schemes available in literature are suitable under ideal conditions under uniform illumination and are not able to track the maximum power point under partially shaded conditions, where more than one maximum peak are obtained in the PV array characteristics depending upon the series–parallel connections of the series strings of the array experiencing different levels of solar insolation.

Several researchers have attempted in the global MPPT realization by evolving different algorithms. However, most of them [17–20] use lengthy calculations, on-line sensed data or special circuit configurations. Miyatake et al. attempted to approach the global MPP using Particle Swarm Optimization algorithm [21]. However, the conventional particle swarm optimization suffers from some drawbacks. In a standard PSO,

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the farther the particle is from the best position based on its own experience and its neighbor, the larger a change in velocity is to be made in order to return to that best position. The acceleration limits the trajectory of particle oscillation. The smaller the acceleration, the smoother the trajectory of the particle is. However, too small an acceleration can lead to slow convergence, whereas too large an acceleration drives the particles towards infinity. The updated velocity is limited by the maximum velocity to prevent particles from moving too fast in space [22]. Kaekawkamnerdpong and Bentley proposed a Perceptive Particle Swarm Optimization (PPSO) algorithm in [22] with the objective of further closely approaching the global optimum in the search space. However, the perception radius, number of sample points and the number of sampling directions are kept constant in PPSO. This has a serious drawback. If the number of sample points per direction and the number of sampling directions are kept sufficiently low, then the algorithm runs quite fast, but we may miss the global optimum position. On the other hand, increasing the number of sampling points per direction and the number of sampling directions, we may reach the global optimum very closely, but we shall have to pay considerably for the computation time of the algorithm. The authors in their previous work [23] have established a variant of Particle Swarm Optimization known as Adaptive Perceptive Particle Swarm Optimization, using which the global optimum can be approached more closely.

The paper presents the simulation and hardware implementation of maximum power point (MPP) tracking of a partially shaded solar photovoltaic (PV) array using a variant of Particle Swarm Optimization known as an Adaptive Perceptive Particle Swarm Optimization (APPSO). The authors aim to realize a power tracking scheme that can find the global MPP to maximize the generated power from the PV source. It should be applicable to large scale PV system, resulting from series–parallel combination of solar cells. The proposed tracking technique has been mapped onto a MSP430FG4618 microcontroller for tracking and control purposes. The whole system based on the proposed has been realized on a standard two stage power electronic system configuration.

The whole paper is organized as follows. Section 2 focuses on the power output of a partially shaded PV array. Section 3 presents the APPSO algorithm and its validation. Section 4 presents the application of an APPSO to MPP tracking of a solar PV array and its simulation results. Section 5 presents the two stage power electronic system configuration for MPPT.

2. Power output of partially shaded PV array

Fig. 1 shows M series–parallel connected PV modules and their power–voltage characteristics. Each module consists of an n series connected PV cells. The PV array 1 in Fig. 1(a) is totally illuminated by solar radiation. The graph is Fig. 1(c) clearly indicates that there exists only one maximum in the power–voltage (P–V) characteristics of PV array 1 under totally illuminated condition. However, the PV array 2 shown in Fig. 1(b) is partially illuminated by solar radiation. If the modules with different optimal current, caused by uneven solar insolation are connected in series–parallel, local maximum power points (MPPs) often appear in the power vs. voltage (P–V) characteristics. This is due to the fact that the optimal current of each PV module is nearly proportional to the insolation falling on it. Hence, corresponding to n series connections, there exists n maxima in the P–V characteristics of P–V array 2 under partially shaded condition as shown in Fig. 1(c). Under these conditions, the conventional MPPT controller may track to a local MPP instead of a global MPP. Hence, the generated power may reduce and the PV system efficiency will decrease.

We have ignored the effect of protection diodes across the modules, which are sometimes used for protecting the solar modules from lightning discharge. The voltage across the modules, even under the partially shaded conditions is not expected to be affected by the presence of protection diodes under reverse bias conditions. Sometimes, bypass diodes are used across the cells/modules to avoid hotspot breakdown. However, the effects of these bypass diodes can be neglected when the cells/modules are partially shaded with the level of illumination not less than 20% for all practical purposes.

3. Adaptive perceptive particle swarm optimization

The proposed adaptive perceptive particle swarm optimization algorithm is relatively similar to the perceptive swarm optimization algorithm [22] and the conventional particle swarm optimization algorithm. In conventional PSO, for an n-dimensional optimization problem, an n-dimensional search space is considered. However, in PPSO and in the proposed APPSO, the algorithm operates in $(n+1)$ dimensional search space. The added dimension represents the underlying performance of particles at their positions in an n-dimensional space. As in the PPSO algorithm, in an APPSO also, the particles fly around $(n+1)$ dimensional search space. In effect, the particles fly over a physical fitness landscape observing its crests and trough from a far. Particles observe the search space within their perception ranges by sampling a fixed number of directions to observe and sampling a finite number of points along those directions. The particles attempt to observe the search space for landscape at several sampled distances from its position, in each direction. If the sampled point is within the landscape, the particle perceives the height of the landscape at that point. The particles can observe neighboring particles in their perception range. The particle randomly chooses the neighboring particles, which will influence the particle to move towards them. The position of the chosen neighbor will be used as the local best position of the particle. However, unlike the PPSO algorithm, in an APPSO algorithm, if the local best position of the particle at the current iteration does improve the performance of the particle, then its personal best position is updated in the next iteration. Apart from that, the spacing between the sample points along any direction within the perception radius is minimized and/or the number of sampling directions is increased and/or the perception radius is minimized. This encourages more social interaction of the particles. Conversely, if the local best position of the particle at the current iteration deteriorates the performance of the particle, the spacing between the sample points along any direction within the perception radius is minimized and/or the number of sampling directions and/or perception radius is increased. The basic idea behind such modification is to explore the landscape more exhaustively near the local maxima, so that the global maximum is very closely reached which means that the results will be more optimized in an APPSO than in case of PPSO. The presence of neighboring particles influences the calculation of new velocity for the next iteration in the same way as the local social interaction in the conventional particle swarm optimization. As in PPSO, in an APPSO also the fitness function is the average of the height of the landscape observed from all observation directions minus distance between the particle and the point of observation in the landscape. A detailed discussion of an APPSO is given in [23].

3.1. Validation of the APPSO algorithm

The performance of the conventional PSO algorithm is compared with the APPSO algorithm applied on the same problems. The fitness function for the experiment with the conventional PSO algorithm is

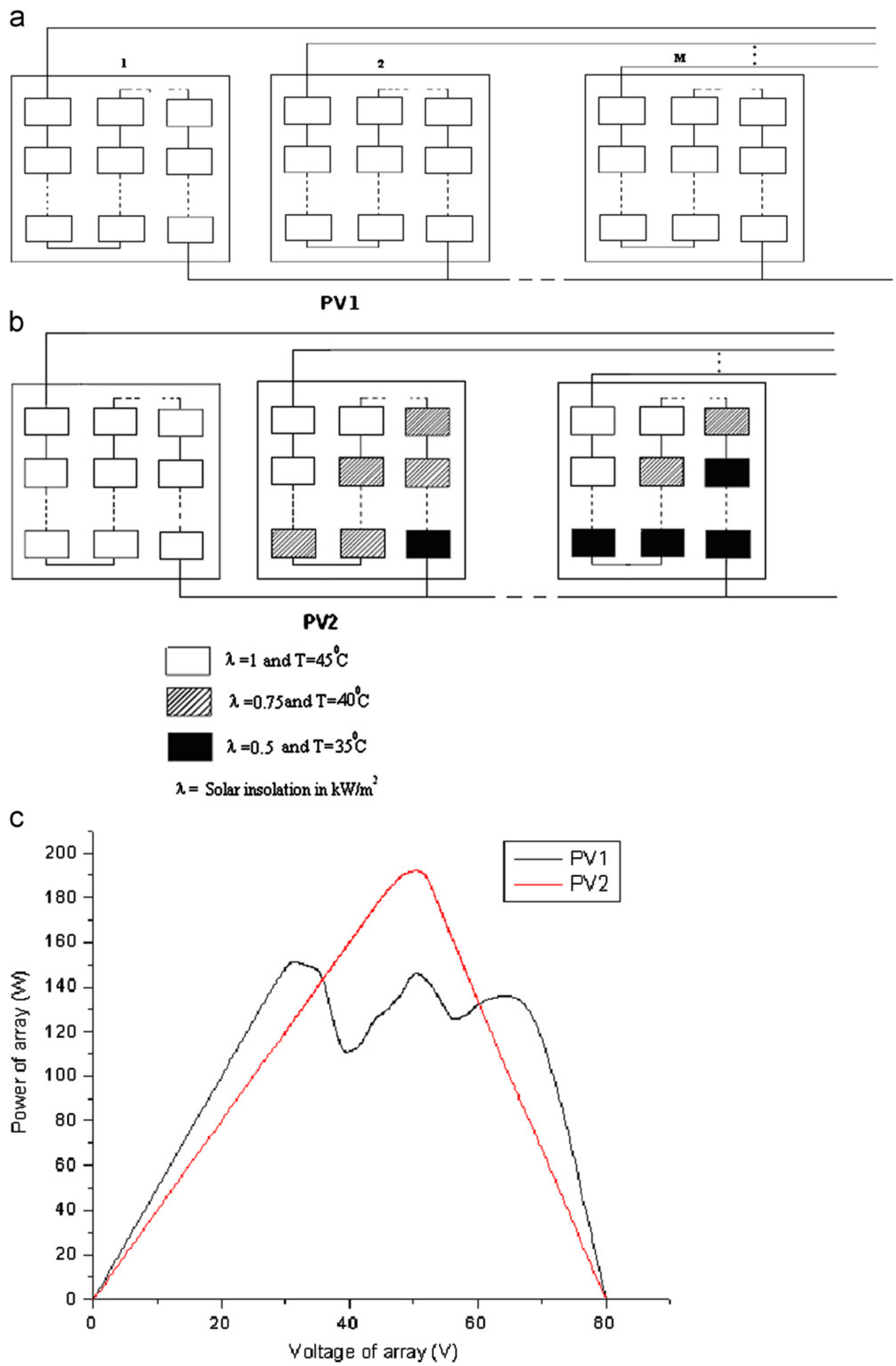

Fig. 1. (a) PV array configuration of module PV1 (under total illumination). (b) PV array configuration of module PV2 (under partial shading). (c) Power – vs. – voltage characteristics of modules PV1 and PV2.

the function to optimize, while the fitness function for the APPSO algorithm experiment is the average of the height of the landscape observed from all observation directions minus the distance between the particle and observed landscape. The reason for having different fitness functions for each algorithm is that the APPSO algorithm has no communication and no knowledge of the function to optimize available to the swarm. Apart from the fitness function, both algorithms are experimented on the same settings. The performance of the algorithms has been compared using MATLAB simulations. The performance of each algorithm is presented in terms of the optimization errors, which is the minimum distance between the maxima of the landscape and the final personal best position of each algorithm over all runs.

The functions used in the experiments are the following:

$$f_1(x) = 20e^{-x^2/20} \tag{1}$$

$$f_2(x) = 18e^{-(x+10)^2/10} + 20e^{-(x-10)^2} \tag{2}$$

$$\begin{aligned} f_3(x) = {} & 16e^{-(x+19)^2/0.25} - 16e^{-(x+18)^2/0.25} + 4e^{-(x+17)^2/0.25} \\ & -4e^{-(x+16)^2/0.25} + 6e^{-(x+15)^2/0.25} - 6e^{-(x+14)^2/0.25} \\ & +8e^{-(x+13)^2/0.25} - 8e^{-(x+12)^2/0.25} + 18e^{-(x+11)^2/0.25} \\ & +20e^{(x-19)^2/0.01} \end{aligned} \tag{3}$$

The first function, shown in Fig. 2a, is a simple function optimization problem, where there is one optimum with symmetrical slopes of moderate gradient. Using this function, the first experiment aims to investigate the performance of the PPSO algorithm on a simple task. In Fig. 2b, the second function consists of two optima. The local optimum peak expands in a larger area compared to the steeper global optimum peak; thus it is easier to find the local one. The second experiment uses this function to examine the ability of PPSO to find the global optimal solution, when a local optimal solution is nearby. The third and last function, shown in Fig. 2c, has several local optimum peaks on one side and a global optimum spike at the other side, and is used in the third experiment.

In the experiments, the number of particles is varied to investigate the effect of changing in the number of particles. Each optimization problem is experimented in one, two and three dimensions. The parameter settings for the experiments on both algorithms are described as follows. The maximum velocity is set as 7.0 units. The inertia weight is a random number between 0.5 and 1.0. The acceleration constants are set at 1.494. Each experiment was run 20 times in order to obtain a reliable result. The algorithms terminate when they reach the maximum

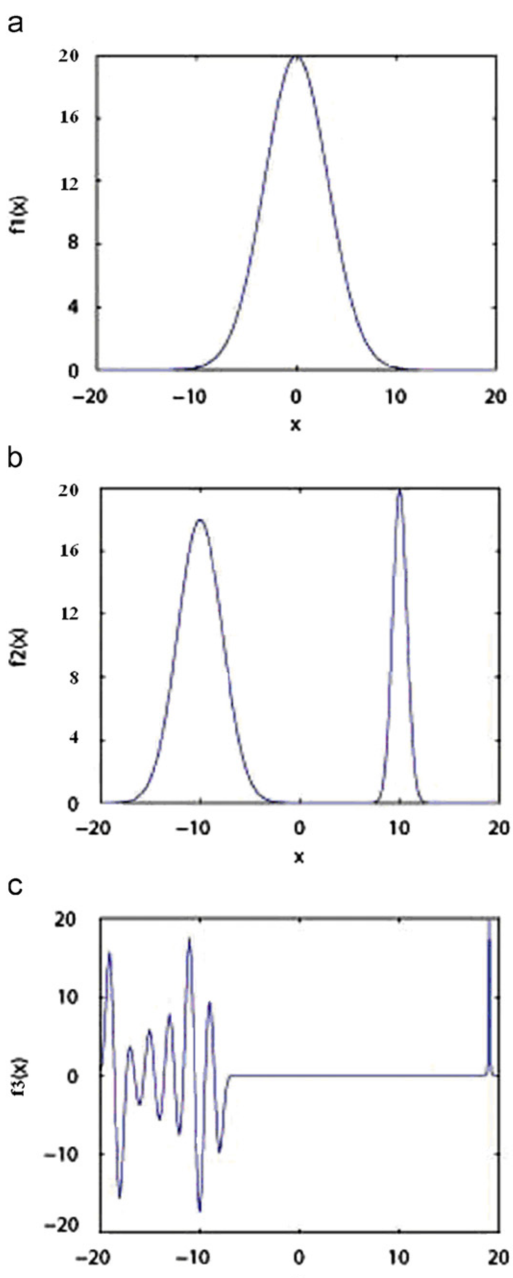

Fig. 2. Three functions in one dimension used in the experiments.

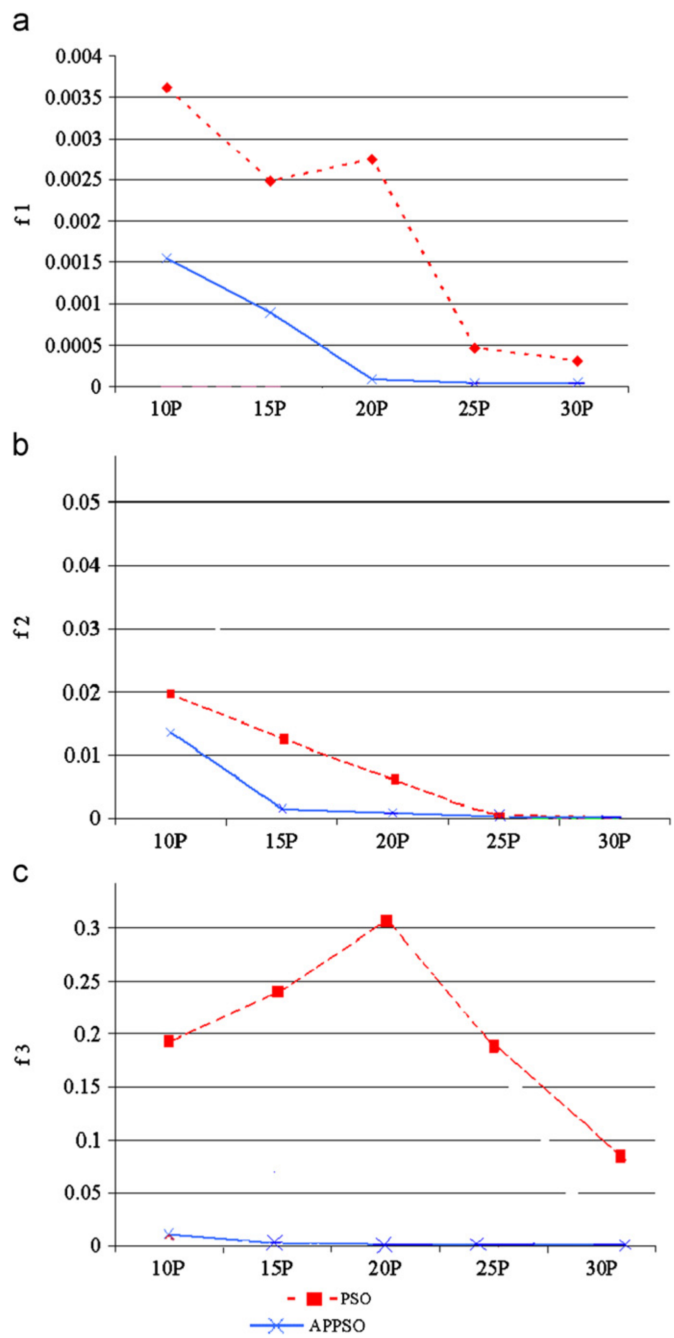

Fig. 3. Performance comparison of PSO and an APPSO in terms of optimization error. *X* axes show the number of particles and *Y* axes show the optimization error.

iteration of 50,000 or when all particles move less than a distance of 0.4 units.

For the experiment on an APPSO algorithm, the particles operate in $n+1$ dimension when the function to optimize is an n-dimension. Apart from parameter settings based on the conventional PSO algorithm, the parameters for an APPSO algorithm are the minimum number of observation directions set as 3, the inner perception radius of 3.0 units, the outer radius of 12.0 units and minimum sample points per direction set as 3. The results shown are representative of the other results obtained from the experiments. Fig. 3 illustrates the comparison between four algorithms in terms of the optimization error. The number of particles in the swarm has been varied in the different sets of experiments for the three aforementioned functions and the optimization error has been plotted in the Y-axis against the number of particles in the X-axis. Compared to the PSO algorithm, an APPSO algorithm resulted in good performance in terms of an optimization error.

The results show that the greater the number of particles in the swarm, the more the PPSO algorithm finds a good solution; however, this is at the expense of greater computation time. In contrast, having fewer particles might suffer from greater optimization error, but it requires less time.

4. Application of the APPSO to MPPT tracking of PV array

In case of constant bus voltage applications, only one current sensor is sufficient for tracking the maximum power from several individual PV modules. It is called multidimensional MPPT control. The terminal voltage of the individual PV systems are grouped and represented in the form of an N-dimensional row vector indicating the position vector of the particles $\vec{x}^k$ as

$$\vec{x}^k = [V_1{}^k, V_2{}^k, \ldots, V_N{}^k] \tag{4}$$

where N is the size of the row vector and indicates the number of PV strings.

The velocity vector $\vec{v}$ can be represented as

$$\vec{v}^k = [V_1{}^k - V_1{}^{k-1}, V_2{}^k - V_2{}^{k-1}, \ldots, V_N{}^k - V_N{}^{k-1}] \tag{5}$$

The landscape function is the generated power that is spanning over $N+1$ dimensional search space. The output vector changes and measures the power$P(\vec{x}^k)$.

$$P(\vec{x}^k) = V_1{}^k I_1 + V_2{}^k I_2 + \cdots + V_N{}^k I_N \tag{6}$$

where I_1, I_2, …, I_N refers to the string currents in the strings with terminal voltages $V_1{}^k, V_2{}^k, \ldots, V_N{}^k$, respectively.

For obtaining the currents, the circuit model of a PV cell is considered. The circuit model of a PV cell is shown in Fig. 4. The shunt resistance is ignored for the sake of simplicity which is good enough for fairly accurate models.

The current equations which describe the I–V characteristics of the module are

$$I = I_L - I_0(e^{q(V+IR_S)/nkT} - 1) \tag{7}$$

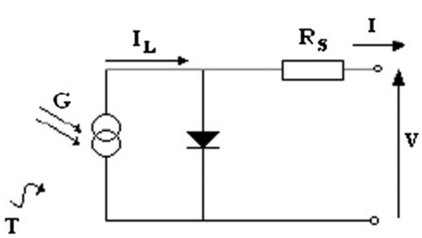

Fig. 4. Circuit model of a PV cell.

Table 1
Initialization of particle velocities.

Agent	V_1 [V]	V_2 [V]
1	$0.2V_{OC}$	$0.3V_{OC}$
2	$0.5V_{OC}$	$0.4V_{OC}$
3	$0.6V_{OC}$	$0.1V_{OC}$
4	$0.8V_{OC}$	$0.7V_{OC}$
5	$0.9V_{OC}$	$0.4V_{OC}$

$$I_L = I_{L(T_1)}(1 + K_0(T - T_1)) \tag{8}$$

$$I_{L(T_1)} = G.I_{SC(T_{1,nom})}/G_{(nom)} \tag{9}$$

$$K_0 = (I_{SC(T_2)} - I_{SC(T_1)})/(T_2 - T_1) \tag{10}$$

$$I_0 = I_{0(T_1)}(T/T_1)^{3/n} e^{-(qV_g/nk).(1/T - 1/T_1)} \tag{11}$$

$$I_{0(T_1)} = I_{SC(T_1)}/(e^{qV_{OC(T_1)}/nkT_1 - 1}) \tag{12}$$

$$R_S = -dV/dI_{V_{OC}} - 1/X_V \tag{13}$$

$$X_V = I_{0(T_1)}(q/nkT_1)e^{qV_{OC(T_1)}/nkT_1} \tag{14}$$

In the above set of equations, I represents the current at the output of a PV cell and V represents its terminal voltage. I_L represents the photocurrent. A series resistance R_S has been included, but not the shunt resistance. The photocurrent I_L is directly proportional to the irradiance G. The temperature dependence of the diode saturation current I_0 and photocurrent I_L has been incorporated in the model to make the model more accurate. T refers to the temperature and the nominal temperature T_1 has been chosen to be 25 °C. K_0 refers to the temperature coefficient of short circuit current. V_{OC} and I_{SC} refer to the open circuit voltage and short circuit current, respectively. The ideality factor n assumes a value between 1 and 2.

4.1. Simulation and results

For simulation, we consider two strings of PV modules. Module PV1 is totally illuminated by solar radiation. However, module PV2 is partly under shade. Hence, in the context of the present problem, the number of modules M is set to 2. The number of particles N is set to 5. The circuit parameters have been taken same as in [22].

The particle velocities are initialized randomly as shown in Table 1:
where V_{OC} refers to the open circuit voltage of an array.

Using the 8 variations of an APPSO given in [23], as well as PSO and GA, we have got the results of maximum power point tracking as shown in Table 2:

The optimal value of power has been calculated analytically using circuit parameters as in [21]. This has been calculated to be 391 W. An analysis of Table 2 reveals that an APPSO3 yields the maximum power point (382 W) that is closest to the global optimal maximum power point (391 W). Moreover we see that while using PSO, the global optimal MPP of 377 W is reached with 96.41% accuracy, the MPP can be reached with 97.7% accuracy using an APPSO algorithm.

5. Two stage power electronic system configuration for MPPT

Based on the proposed technique, a two stage power electronic system architecture has been proposed as shown in Fig. 5.

The system comprises of a boost type dc–dc converter and an inverter to feed the power generated by PV array to the grid and

Table 2
Results of maximum power point tracking obtained using different techniques.

Algorithm	PV1 voltage		PV1 current (A)	PV2 voltage		PV2 current (A)	Power		Efficiency (%)
	Optimal (V)	MPPT (V)		Optimal (V)	MPPT (V)		Optimal (W)	MPPT (W)	
APPSO1	45	45.7	4.13	45	46.8	4.06	391	379	96.93
APPSO2		45.8	4.12		46.9	4.04		378	96.67
APPSO3		45.9	4.16		46.3	4.12		382	97.70
APPSO4		45.4	4.18		46.3	4.11		381	97.44
APPSO5		45.5	4.14		46.5	4.09		379	96.93
APPSO6		45.6	4.13		46.9	4.06		378	96.67
APPSO7		45.5	4.14		46.2	4.08		377	96.41
APPSO8		45.7	4.16		46.9	4.06		381	97.44
PSO		46.1	4.06		47.1	4.03		377	96.41
GA		46.2	4.01		46.9	4.07		376	96.16

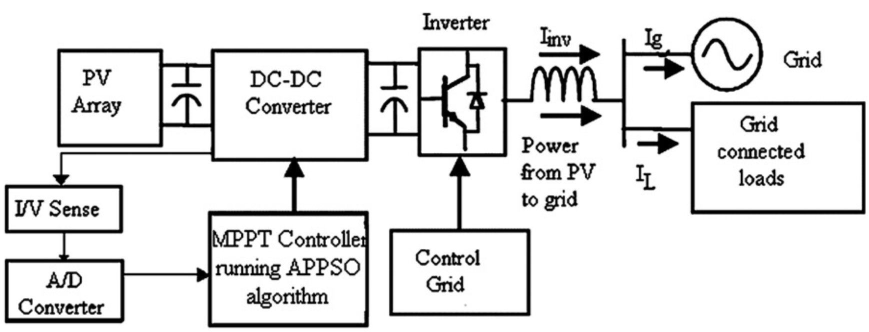

Fig. 5. System configuration for grid connected PV-based system.

grid connected loads. The system configuration shown in Fig. 5 is standard power system architecture available in standard literatures. This also elucidates that the APPSO algorithm can be mapped onto the standard power system architecture. We used MSP430FG4618 to implement the MPPT algorithm. The MSP430 incorporates a 16-bit RISC CPU, peripherals, and a flexible clock system that interconnect using a von Neumann common memory address bus (MAB) and memory data bus (MDB). In the present application, a square wave of varying duty cycle has been generated using the microcontroller. This square wave drives the dc–dc buck converter. At regular intervals, we performed the MPPT algorithm and according to that the duty cycle of the output is varied. In our case, the required interval was 10 s. The interrupt capability of the timer has been used. The timer is initially started and continues with the generation of square wave. After specified interval CPU is interrupted by the timer and corresponding interrupt service routine (ISR) is invoked. The ISR is actually the MPPT algorithm based on an APPSO. After execution of the routine, new duty cycle is established and the system operates with the modified duty cycle. The DC–DC converter can be realized on the TMS320F280X DC–DC buck converter. For converting the analog current being sensed into the digital form to be understood by the microcontroller, an A/D converter ADS1208 has been used.

6. Conclusion

A novel MPPT algorithm using an APPSO technique was proposed to control several PV arrays with one pair of voltage and current sensors. The developed algorithm is simple and also reduces cost in the data acquisition system. The proposed technique indicates that the MPP can be tracked with greater accuracy using an APPSO algorithm than that is possible with the PSO algorithm. The proposed technique has been mapped onto a two stage standard power electronic system configuration. Further works are going on.

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