

An Application of Vector Based Swarm Optimization for Designing MPPT Controller of a Stand-Alone PV System

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Abstract: In this paper, the Vector Based Swarm Optimization method is used for designing an optimal controller for the maximum power point tracker of a stand-alone PV System. The proposed algorithm is executed on vectors in a multi-dimension vector space. These vectors by appropriated orientation converge to a global optimum while the algorithm progresses. The Remarkable point of the VBSO algorithm is the fact that using completely random coefficients increases the algorithm performance. The generated energy by PV is delivered to a boost converter feeding a resistive load. The duty cycle of the converter's switch is determined by a controller in order to minimize the dP/dV of the PV.

Keywords: Boost Regulator, Maximum Power Point Tracker, Photovoltaic Systems, VBSO, Vector Based Swarm Optimization.

1 Introduction

Renewable Energies are one of the most interesting fields in engineering. Photovoltaic Cells (abbreviated as PV Cells) are the leading technology in clean electricity generation. However low conversion rate and costly manufacturing process of these cell cause financial limits for widespread use of them. Accordingly it is favorable to use the maximum power generation capacity of PV based systems. Systems that force PV cells to work in the most efficient condition are known as "Maximum Power Point Tracking" (MPPT) systems [1, 2]. The simple principle governing all MPPT systems is to tune PV cell's output current and voltage such that their product reaches its maximum value. The point in which the product of the PV cell's voltage and current maximizes is known as the "Maximum Power Point" or MPP. Various number of MPPT methods have been developed in recent years. Methods based on lookup-table are most commonly used [3]. Other famous methods are: perturb and observe (P&O) method [3, 4], sliding mode control [5], incremental conductance method [3, 6], and artificial intelligence

methods [7-13] including artificial neural network [7-9], reinforcement learning [10, 11], multilayer perceptron neural network [12] and fuzzy systems [13]. The obvious disadvantage of P&O method is the oscillation of PV cell's operation point around the MPP at the steady state. More over the P&O and incremental conductance methods cannot perform well when the atmospheric conditions change fast [3]. In this paper the proposed optimization method and two other methods (Genetic Algorithm and DARLA) are used for tuning a PID controller of a boost voltage regulator to drive PV cell operating point to the maximum power point. However PID controllers are traditional but they are very simple to implement. Next section gives a short description of the VBSO method. Section 3 gives a brief review over DARLA optimization method. Section 4 includes a discussion about simulation model and parameter values. In Section 5 results of the proposed method are compared with other methods (Genetic Algorithm and DARLA) to show the superiority of the proposed method, and the last section comprises the conclusion.

2 Vector Based Swarm Optimization

The general trend of VBSO [14] Algorithm is described here:

1) Initialize with a population of random vectors:

An initial N_{pop} number (Number of population) of D dimensional vectors is produced randomly according to Eq. (1). The result is called population parents of the first iteration.

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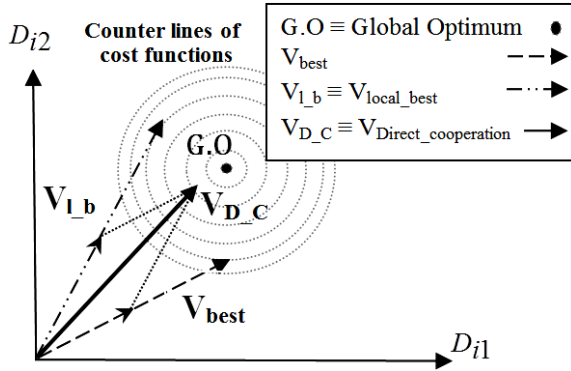


Fig. 1 The direct cooperation of V_{best} and V_{local_best} .

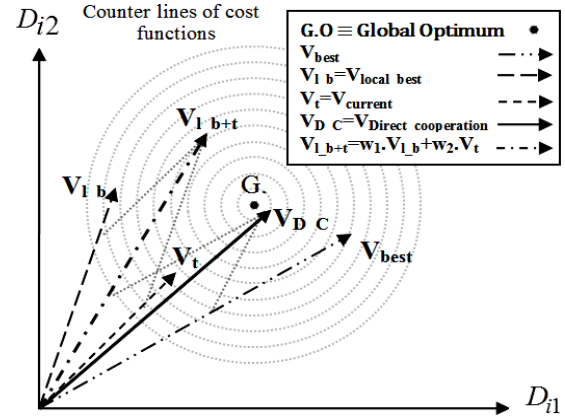


Fig. 2 The direct cooperation of V_{best} , V_{local_best} and $V_{current}$.

$$V_{i,j}[0] = v_j^{low} + rand.(v_j^{up} - v_j^{low}) \quad (1)$$

where: $i \in [1, N_{pop}]$ represents the i -th population vector $j \in [1, D]$ represents the j -th dimension of V_i vector, $V_{i,j}[0]$ represents the value of the j -th dimension of the i -th vector from initial population, $rand$ is a uniformly distributed random value in the interval $(0, 1)$, v_j^{low} and v_j^{up} are lower and upper limits of the j -th dimension, respectively.

2) Calculate the fitness of each vector:

3) Generate a new population of vectors based on their fitness values. The population's children are obtained by making some changes in their parents' population.

4) If convergence condition or end condition is not satisfied, the algorithm iterates from step 2. The mechanism of VBSO Algorithm for reproducing new vectors is as follows.

2.1 Participation

(Cooperative Effect or Cooperation)

This operation is done by a suitable combination or summation of multiple vectors from problem search space, which is divided into two sections:

- 1) Vectors' Direct Cooperation
- 2) Vectors' Differential Cooperation.

2.1.1 Vectors' Direct Cooperation

$V_{Direct_cooperation}$ is the direct cooperation vector and can be built from an appropriate combination of cooperative vectors: $V_{current}$, V_{ave} , V_{best} , V_{local_best} and V_{rand} , where $V_{current}$ is the current solution vector, V_{ave} is the average of solution vectors, V_{best} is the best solution vector till the current iteration, V_{local_best} is the best vector in the neighborhood of the i -th vector and V_{rand} is a random vector. The direct cooperation aims to determining the direct cooperation vector by employing these five vectors. Direct cooperation vector can be formulated as following:

$$V_{Direct_cooperation}[k] = w_1 \cdot V_{current}[k] + w_2 \cdot V_{ave}[k] + \dots + w_3 \cdot V_{best}[k] + w_4 \cdot V_{local_best}[k] + w_5 \cdot V_{rand}[k] \quad (2)$$

In the above equation, k shows the k -th iteration. w_1 , w_2 , w_3 , w_4 and w_5 are cooperative weighting coefficients in the interval $[0, 1]$. These weights should be selected such that each dimension of $V_{Direct_cooperation}$ places in the valid area $V_{i,j} \in [v_j^{low}, v_j^{up}]$. All five coefficients w_1 , w_2 , w_3 , w_4 and w_5 must not be zero simultaneously. For example, Fig. 1 shows a two-dimensional problem of the k -th iteration, in which direct cooperation of two vectors, V_{best} and V_{local_best} produce the direct cooperation vector. (Assuming $w_1 = 0$, $w_2 = 0$ and $w_5 = 0$). As seen in Fig. 1, $V_{Direct_cooperation}$ can be determined as close to the Global Optimum as needed by adding enough percentage of V_{best} and V_{local_best} . Another example, Fig. 2 shows the direct cooperation of three vectors, V_{best} , V_{local_best} and $V_{current}$ to obtain $V_{Direct_cooperation}$ ($w_2 = 0$ and $w_5 = 0$). The share each cooperation vector has in $V_{Direct_cooperation}$, determined by w_1 , w_2 , w_3 , w_4 and w_5 is very important. These coefficients based on the problem type and dimensions can take different values in $[0, 1]$ under a relation like $w_1 + w_2 + w_3 + w_4 + w_5 = 2$.

2.1.2 Vector Difference Cooperation

Differential cooperation vector is built by combining differential vectors: $(V_{ave} - V_{current})$, $(V_{best} - V_{current})$, $(V_{local_best} - V_{current})$, $(V_{rand} - V_{current})$. Differential Cooperation Vector is used in small-scale search and orients $V_{current}$ to other cooperation vectors. Differential cooperation vector can be formulated as following:

$$V_{Difference_cooperation}[k] = w_6 \cdot (V_{ave}[k] - V_{current}[k]) + w_7 \cdot (V_{best}[k] - V_{current}[k]) + \dots + w_8 \cdot (V_{local_best}[k] - V_{current}[k]) + w_9 \cdot (V_{rand}[k] - V_{current}[k]) \quad (3)$$

In Eq. (3) w_6 , w_7 , w_8 and w_9 are the Differential cooperation weights under an acceptable relation like $w_6 + w_7 + w_8 + w_9 = 2$ in $(0, 1)$. Contrary to the direct cooperation, all of these coefficients can be zero simultaneously. For example, Figs. 3 to 6 show 4 states of two-vector and three-vector the differential cooperation. Generally, there are 16 states and one of them is $w_6 = w_7 = w_8 = w_9 = 0$ and $V_{Difference_cooperation}$ is zero.

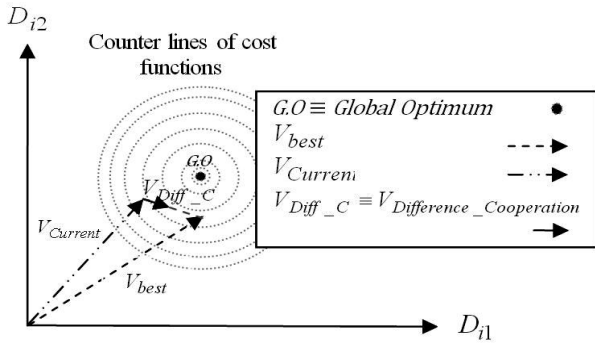


Fig. 3 The differential cooperation of $V_{current}$ and V_{best} .

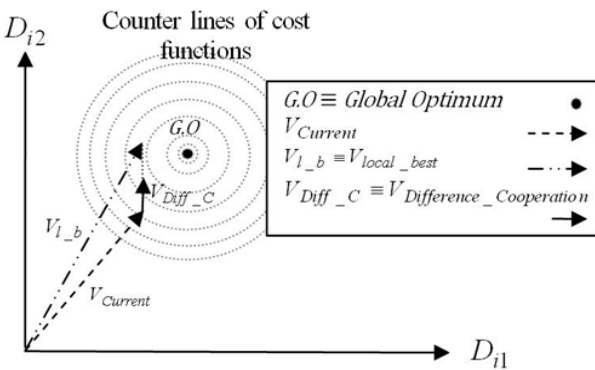


Fig. 4 Differential cooperation of $V_{current}$ and V_{local_best} .

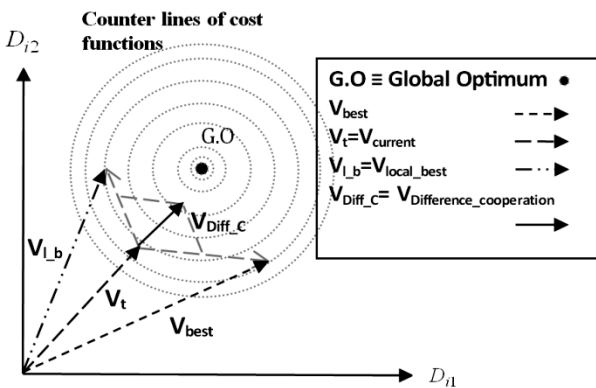


Fig. 5 The differential cooperation of $V_{current}$, V_{best} and V_{local_best} .

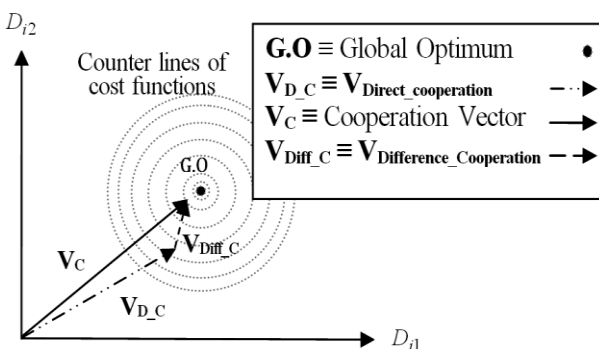


Fig. 6: Cooperation Vector V_c by Differential Cooperation Vector V_{Diff_c} and Direct Cooperation Vector V_{D_c} .

The differential cooperation aims to investigate around the direct cooperation vector to avoid local optimums. The differential cooperation vector is transferred to the location of the direct cooperation vector:

$$V_{Cooperation}[k] = V_{Direct_cooperation}[k] + V_{Difference_cooperation}[k] \quad (4)$$

where $V_{Cooperation}[k]$ is the cooperation vector in the k th iteration.

2.2 Mutation

Mutation is done In VBSO by transferring origin of the search space to a point far enough from the current position according to a specific or random probability distribution. The proposed displacement is determined as a random number multiplied by $0.1(v_j^{up} - v_j^{low})$ for each dimension j . For the sake of convergence the mutation rate is decreased dynamically to zero during the algorithm process. Accordingly the j th row of the mutation vector can be written as:

$$V_{mutation\ j}[k] = \frac{d}{10} rand [v_j^{up} - v_j^{low}] \quad (5)$$

where “*rand*” is a pseudo-uniform random number in (0, 1) and d is a number equal to 1 at the beginning of algorithm process and decreases dynamically to zero while algorithm iterates. Offspring vectors $V_{off}[k]$ results by mutation are as the following (Fig. 7):

$$V_{off}[k] = V_{Cooperation}[k] + V_{mutation}[k] \quad (6)$$

2.3 Boundary Check (Conformity)

After reproducing new vectors, it has to be checked whether they are inside the problem space or not (boundary check or conformity). Several strategies are possible:

- 1) If $V_{ij} > v_j^{up}$ then the value of V_{ij} will replace the v_j^{up} and if $V_{ij} < v_j^{low}$ it will be limited to v_j^{low} .
- 2) Any vector component outside of search space is replaced by its corresponding parents' component.
- 3) Any component of the V_{ij} which is not in the allowable interval, is replaced by the corresponding one of the V_{best} of the previous step.

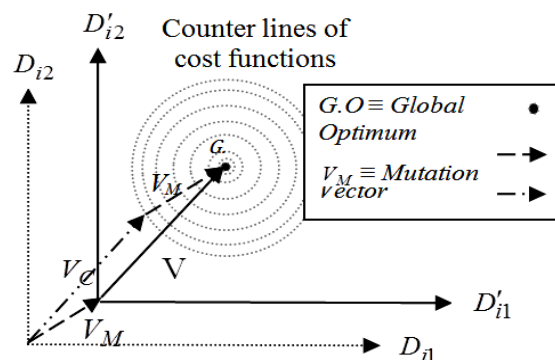


Fig. 7 Offspring vector V by mutation on the cooperative vector.

2.4 Selection

Three selection methods are proposed in the VBSO Algorithm:

- 1) Children of the new generation are used as the parents of the next generation.
- 2) A N_{pop} population is selected from parents and offspring based on their fitness as the next population.
- 3) Parent vectors of the next generation $V[k+1]$ are generated from the participation of current vector $V[k]$ and offspring vector $V_{off}[k]$ formulated as $V[k+1] = aV[k] + bV_{off}[k]$ where a is random and $a + b = 1$. The overall VBSO flowchart is expressed in Fig. 8.

3 Discrete Action Reinforcement Learning Automata

Reinforcement learning automata (RLA) method was first presented by Howell, Frost, Gordon and Wu in 1997. In this paper, the discrete action reinforcement learning automata algorithm is used [15-19]. The algorithm steps are:

1. Select a set of decision variables randomly according to their cumulative distribution functions.
2. Supply the selected set to the test function.
3. Calculate output of the objective function and calculate the cost function.
4. Calculate the reinforcement signal according to the cost function.
5. Change probability density functions using reinforcement signal.
6. Find cumulative distribution functions by integrating density functions and return to step 1.

Initial probability density functions are defined as [15, 17-19]:

$$f_i^{(0)}(d) = \begin{cases} \frac{1}{N_i} & d = 1, 2, \dots, N_i \\ 0 & \text{other} \end{cases} \quad (7)$$

$$i = 1, 2, \dots, n$$

where n is the number of decision variables and N_i is the number of intervals of the i -th decision variable. When the algorithm starts, a new set of decision variables is selected in each step according to probability density functions and fed to the objective function. This selection is done by using the cumulative probability of each variable according to Eq. (8): [15, 17-19].

$$C_i^{(k)}(d) = \sum_{q=1}^d f_i^{(k)}(q), d = 1, 2, \dots, N_i \quad (8)$$

where $C_i^{(k)}(d)$ is the cumulative probability of the i -th decision variable in the k -th iteration. These CDFs are used for random selection of decision variables which are applied to the objective function. The objective function is in the form of a weighted combination of performance indexes, like Eq. (9) [15, 17 - 19].

$$J(k) = G_1 P_1(Y) + G_2 P_2(Y) + \dots + G_m P_m(Y) \quad (9)$$

where G_i , P_i and $Y = [y_1, y_2, \dots, y_l]$ are weights, performance indexes and output vectors, respectively.

The DARLA structure is designed to minimize the objective function. In each iteration, when the objective

function value is calculated, it will be compared with the objective value of previous iterations, and then the reinforcement signal is calculated accordingly [15, 17-19]. The reinforcement signal is calculated according to Eq. (10) [15, 17-19]:

$$\beta(J) = \min \left\{ 1, \max \left\{ 0, \frac{J_{\text{mean}} - J}{J_{\text{mean}} - J_{\text{min}}} \right\} \right\} \quad (10)$$

where J_{mean} and J_{min} are the average and minimum of previous objective values respectively. The range of β variation is between 0 and 1. Objective values that are larger than the mean of previous objective values cause a zero reinforcing (0) while objective values that are smaller than the mean, lead to a reinforcing value equal to one (1) [15, 17-19]. After calculating reinforcement signal, probability density functions are manipulated using β and the Power Function Q (Eq. (11)):

$$Q(d, r) = \lambda 2^{-(d-r)^2} \quad (11)$$

Probability density functions are updated by Eq. (12). Where α is the normalizing coefficient and is defined as Eq. (13) [15, 17-19].

$$f_i^{(k+1)}(d) = \alpha_i^{(k)} \left(f_i^{(k)} + \beta(k) Q(d, \tilde{d}_i) \right) \quad (12)$$

$$d = 1, 2, \dots, N_i; \quad i = 1, 2, \dots, n$$

$$\alpha_i^{(k)} = \frac{1}{\sum_{q=1}^{N_i} f_i^{(k)}(q) + \beta(k) Q(d, \tilde{d}_i)} \quad (13)$$

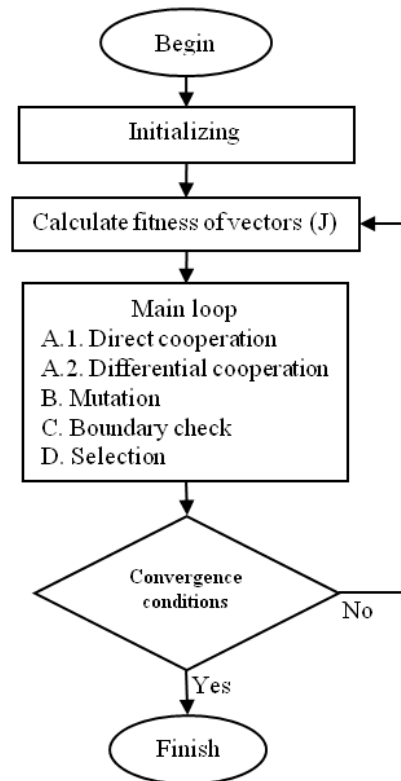


Fig. 8 VBSO Algorithm flowchart.

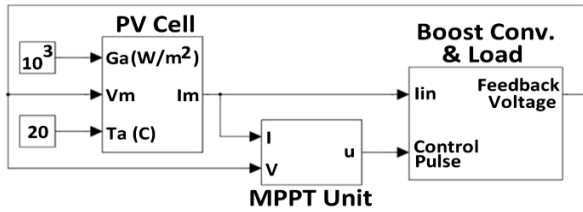


Fig. 9 Simulation model.

After changing probability density functions, the algorithm iterates. DARLA has a repetitive structure and a criterion is needed for terminating the algorithm, in this paper, "repeating algorithm for a certain number of iterations" is used as the terminating condition [15, 17 - 19].

4 The MPPT Model and Simulation [20, 21]

As Fig. 9 illustrates, the model used for simulation purpose consists of three main sections:

- 1) The photovoltaic cell model
- 2) MPPT Unit
- 3) Boost Converter and Load [10].

The first part stands for the simulation of PV cell behavior, in this model, PV cell parameters are determined as follows:

- Number of cells in parallel in the module = 1
- Number of cells in series in the module = 72
- Open circuit voltage of the module: 9.7 V
- Short circuit current of the module: 0.91 A
- Maximum power of the module: 6.7 W
- Isc temperature coefficient: $0.0022 \text{ A} \cdot (\text{°C})^{-1}$
- Cell temperature coefficient: 0.03
- Voc irradiation coefficient: 6.37
- Voc temperature coefficient: $-0.1368 \text{ V} \cdot (\text{°C})^{-1}$
- Idealizing factor: 1.64
- Reference temperature: 25 °C
- Ambient temperature: 20 °C
- Environment radiation = $1000 \text{ W} \cdot \text{m}^{-2}$
- Reference and Ambient Irradiance: $1000 \text{ W} \cdot \text{m}^{-2}$

Detailed model of PV cells can be found in [1] page 107 or in [2] pages 54 to 63.

The PV cell model is shown in Fig. 10. Also, the MPPT unit is shown in Fig. 11. The MPPT unit calculates the derivative term dP/dV (i.e. variation of power relative to PV cell voltage) and applies it as an error signal to a PID controller. The PID controller intrinsically tries to diminish the error signal so it will generate the control signal v in such a way that the input e approaches zero. The control signal v is modulated as the 200 Hz PWM signal [20, 21] u which will be fed to the gate of the boost converter's switch. While the Power-Voltage diagram of PV cells has usually just one peak, diminishing e is possible and leads to the maximum value of solar power generated by the PV cell, so the control system is stable [10].

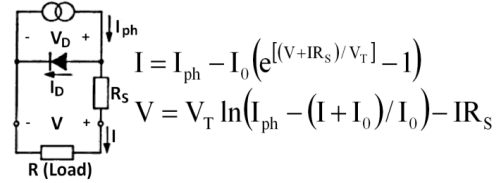


Fig. 10 PV cell model.

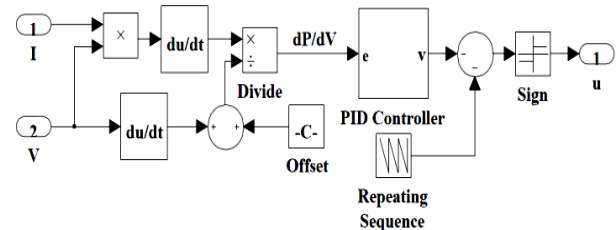


Fig. 11 MPPT unit.

Eq. (14) is used as the cost function in all optimization methods:

$$J = 10^6 \int_0^{T_f} te^2 dt \quad (14)$$

The optimization method finds PID coefficients (K_P , K_I and K_D) such that the above cost function is minimized. Fig. 12 shows the diagram of the boost converter [20, 21]. The current source on the left side of Fig. 12 reproduces PV-cell current and the resistor R on the right side is the load. Parameters of this converter are [10] $C = 1056 \mu\text{F}$, $L = 250 \mu\text{H}$ and $R = 25 \Omega$.

Accordingly considering u as the PWM pulse width, V_R and I_R as the resistor's voltage and current other parameters as in Fig. 10 [21]:

$$V_R = \frac{u}{1-u} V_m, I_R = \frac{V_R}{R} \quad (15)$$

Neglecting boost converter dissipations:

$$V_m I_m = V_R I_R = \frac{V_R^2}{R} = \frac{1}{R} \left(\frac{u}{1-u} V_m \right)^2 \quad (16)$$

$$\Rightarrow I_m = \frac{1}{R} \left(\frac{u}{1-u} \right)^2 V_m$$

So it is possible to change the operating point of the PV array by the PWM pulse width u . The model is run for simulating three situations:

First: The solar panel faces a light source with constant radiation of $1000 \text{ W} \cdot \text{m}^{-2}$.

Second: The solar panel is facing a light source with constant radiation of $1000 \text{ W} \cdot \text{m}^{-2}$ and in a short time, the radiation decreases to $500 \text{ W} \cdot \text{m}^{-2}$.

Third: The solar panel is facing a light source with constant radiation of $500 \text{ W} \cdot \text{m}^{-2}$ and in a short time, the radiation increases to $1000 \text{ W} \cdot \text{m}^{-2}$.

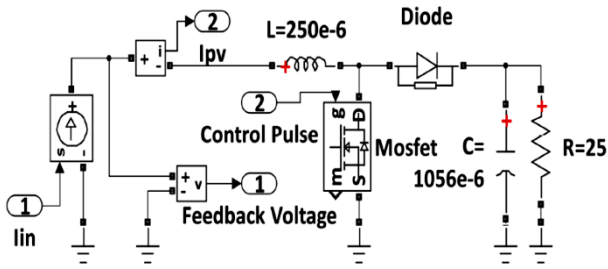


Fig. 12 Boost converter.

5 Results

The simulation is done by three methods: Genetic Algorithm, DARLA and VBSO. Variables' ranges are regarded as: $0 < KP < 10^4$, $0 < KI < 2 \times 10^6$, $0 < KD < 2 \times 10^3$.

Algorithm properties are: Genetic Algorithm: Population = 20, selection = uniform pdf, elite count = 2, %crossover = 80, crossover type = scattered, migration dir. = forward, %Migration = 20, generations = 100. DARLA: Iterations = 1000, divisions = 50. VBSO: Iterations = 20, population=50. Table 1 and Figs. 13 to 16 compare the results.

Table 1 Comparison between GA, DARLA and VBSO for 3 Situations.

Situation n	Method	PID Gain Values			Cost Value J_{min}
		KP	KI	KD	
1	GA	9468.537	718521.261	90.4401	1.2072
	DARLA	8300	750000	90	1.1995
	VBSO	6279.848	1444707.293	203.906	0.9236
2	GA	9517.474	720249.674	89.1769	0.7154
	DARLA	8000	736000	104	0.6951
	VBSO	5812.792	1500237.618	195.871	0.5549
3	GA	9518.157	720354.862	201.807	0.7374
	DARLA	7900	740000	108	0.7172
	VBSO	5815.492	1517956.247	198.489	0.5469

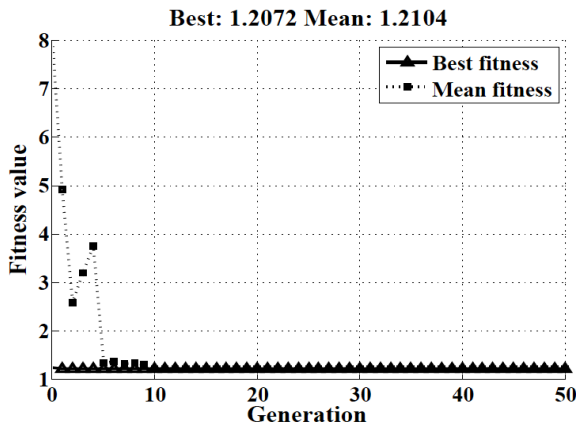


Fig. 13 An instance of GA progress.

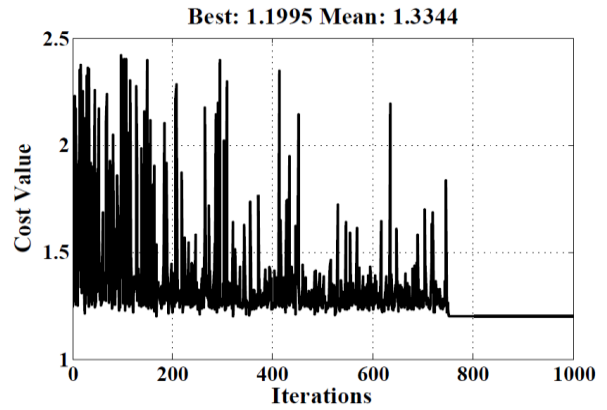


Fig. 14 An instance DARLA progress.

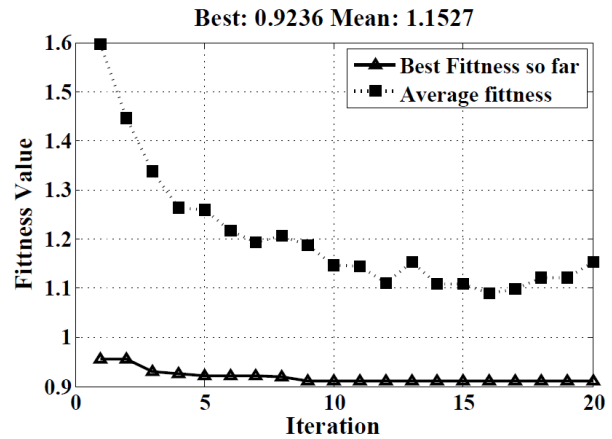


Fig. 15 An instance VBSO progress.

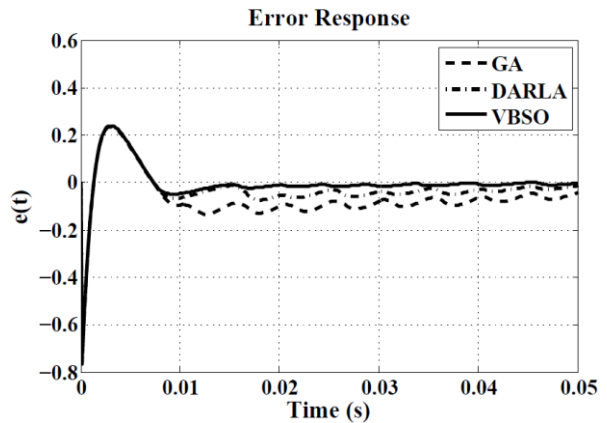


Fig. 16: Error signal comparison

The model simulates the situation in which the solar panel faces a light source with constant radiation of 1000 W.m^{-2} . Fig. 16 compares the error response relative to various tunings of the PID controller for the first situation.

6 Conclusion

In this paper, an optimal MPPT controller for a stand-alone PV system has been designed. The optimal design was done by three different optimization methods for the purpose of comparison. These methods

were: Genetic Algorithm, Discrete Action Reinforcement Learning, and Vector Based Swarm Optimization (abbreviated as: GA, DARLA, and VBSO). All these methods are heuristic and were supposed to tune the PID controller used in the MPPT controller according to a unique fitness function. GA is a well-known heuristic optimization method mentioned here as a reference method. Simulation results show the superiority of VBSO and DARLA; however VBSO acts much better in tuning the PID controller.

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