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Cuckoo Search Algorithm Applied for Maximum Power Point Determination of Bifacial PV Using Different PV Cell Models

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Abstract. This paper proposes an application of a novel nature-inspired algorithm called Cuckoo Search Algorithm (CSA) in the determination of the maximum power point in a bifacial photovoltaic (PV). The optimisation algorithm mimics the behaviour of the cuckoo birds, especially their very strange reproduction strategy. The Cuckoo Search in general is a minimisation search algorithm and suits fine with the objective function of this investigation, which is the absolute value of the power difference of the calculated and catalogue value for given metrological conditions. For the calculated output power three different photovoltaic cell presentations are used: ideal single, real single-diode and double-diode PV cell presentation. The determination of the maximum power point is performed using the different photovoltaic cell circuits and for different solar irradiation at constant temperature. The aim of this work is to compare the results gained using the three PV cell models using the cuckoo search optimisation algorithm.

Key words. Bifacial photovoltaic, ideal single-diode PV cell model, real single-diode model, double-diode model, cuckoo search algorithm.

1. Introduction

The increased need for electricity and the strategy for application of green, clean and renewable energy sources for production of electricity encouraged the governments, the power companies and investors to orient the electricity production towards renewable energy sources. The photovoltaics are one of those sources that have been installed in the world following an exponential rate during the years. The same applies in North Macedonia with a trend more bifacial photovoltaics (PV) to be in installed in the coming years. During the past several years, by the companies dealing with design and installation of PV system, it was found out that during the design process it is very important to know the maximum power point (MPPT) of a given PV system for different weather conditions. This is especially important in the case of the design and configuration of the individual elements of the PV system. In order to achieve this goal, there is a need for a large number of calculations of the MPPT for different solar irradiations at different seasons and temperatures. In addition to this the increasing demand for electricity has motivated engineers to develop more efficient photovoltaic (PV) technologies, resulting in the emergence of bifacial PV cells. These cells offer enhanced electricity generation per unit area, leading to a significant increase in the construction of bifacial PV power plants in the world, as well as in North Macedonia over the past two years. Furthermore, some existing power plants are in the process of upgrading their infrastructure by replacing monofacial modules with bifacial ones. Bifacial PV modules are highly efficient, capable of absorbing light and generating power from both their front and rear surfaces. This dual-sided absorption translates to a greater power output per unit area compared to conventional monofacial modules. Therefore, beside the atmospheric conditions the bifaciality of the PVs has to be taken into consideration. Actually, the bifaciality of the PVs at some weather conditions can cause significant increase of the output power if it is not taken into consideration during the design process of a given PV plant. In order to tackle this problem a good and reliable optimization algorithm for determining the maximum power at given weather conditions should be used in which all the necessary conditions and different combinations can be taken into account.

The gradient based optimization techniques have suffered a lot in their practical application, due to their difficulty of generating automatically objective functions and their derivatives for highly non-linear engineering problems. In the mid of the twentieth century, a lot of computer scientists have done a lot of work and investigation towards implementation of the nature-based algorithms and their application in optimization processes. That is the way how a birth was given to a subclass of gradient free methods called genetic algorithms (GA) [1]. Since then, a lot of other algorithms have been developed that have been inspired by nature, for example particle swarm optimization (PSO) [2], ant and bee colony, differential evolution (DE) [3] and, more recently, the cuckoo search algorithm (CSA) [4]. These are heuristic techniques that perform their search by using a large population of possible solutions at each iteration (generation). In each iteration, for each member of the population, the objective function is evaluated and a fitness value is assigned to it. For each algorithm, a set of rules is then used to move the population towards the optimum solution. Although this results in a global search without the need to calculate objective function gradients, the large number of objective function evaluations means the computational efficiency of these procedures is often inferior to classical gradient-based methods.

In this paper the cuckoo search optimization algorithm is applied in the optimization process. In the text that follows a brief introduction to the algorithm is presented. Followed by a presentation of the objective function, as well as the parameters of the bifacial module that is under investigation. The maximum power point is calculated using the following three different presentations of the photovoltaic cell: ideal single-diode, real single-diode and double-diode and PV cell model. A comparative analysis of the optimisation data for different solar irradiation and PV cell models is performed.

2. Introduction of Cuckoo Search Algorithm

The Cuckoo Search is a metaheuristic search algorithm proposed by Yang and Deb (2010) [4]. Inspired by the cuckoo bird's breeding strategy, the algorithm models how cuckoos lay eggs in the nests of other birds [5]. Host birds may discover these foreign eggs and either discard them or abandon the nest. This has led to the evolution of cuckoo eggs that mimic those of the host.

The cuckoo search algorithm (CSA), that is graphically presented in Fig. 1, is based on three idealised rules:

- Each cuckoo lays one egg at a time and deposits it in a randomly chosen nest. The selection of this nest often involves a random process, such as Levy flights, which allows for both local and more explorative searches.
- The best nests, those containing high-quality eggs (solutions with good objective function values), are carried over to the next generation.
- The number of host nests is fixed, and a host bird discovers a cuckoo's egg with a probability $p_s \in (0, 1)$. This probability p_s influences the balance between exploration and exploitation. A higher p_s encourages exploration by leading to more new nests being created, while a lower p_s favours exploitation by allowing the algorithm to focus on refining existing solutions. If the host discovers the egg, it may discard it or abandon the nest and build a new one elsewhere.

In the algorithm, each egg represents a potential solution to the optimization problem. While each cuckoo lays one egg at a time, a host nest can contain multiple eggs, representing different potential solutions. The algorithm's core function is to generate new and potentially better solutions to replace poorer ones. The quality of a solution (egg) is evaluated using a problem-specific objective function. Furthermore, the last rule is approximated by an additional parameter, p_s called the switching probability. This parameter determines when the worst of the n host nests is replaced by a new, randomly generated nest. Essentially, this parameter balances two key components of the Cuckoo Search (CS) process: exploration and exploitation. Exploration enables the algorithm to discover promising local solutions within the search space, while exploitation allows it to refine those solutions and converge towards the global optimum, which is likely located near one of the better local solutions. A good metaheuristic algorithm must rapidly converge to the global optimum of the objective function. A flowchart of the CSA-MPPT program, used for the determination of the maximum power point of a given PV cell model at certain metrological is presented in Fig. 1.

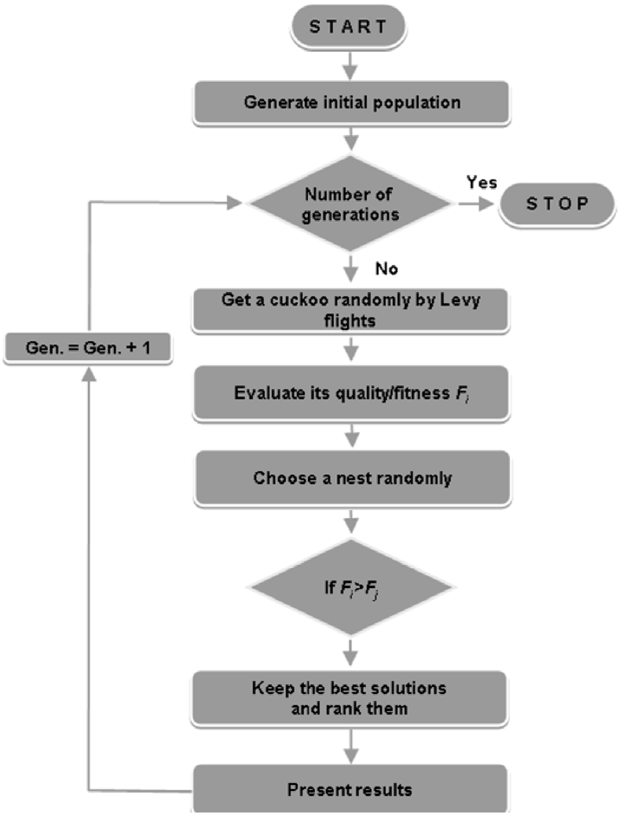

Fig. 1. Cuckoo search algorithm main steps

3. Bifacial PV cell models

This section briefly introduces the parameters and characteristics of the analysed module. The investigated module is a bifacial, monocrystalline, p-type module manufactured using PERC technology. Table 1 presents the module's characteristics under standard test conditions (Irradiance 1000 W/m², Cell Temperature 25 °C, Air Mass AM1.5). The data in Tables 1 and 2 is presented in reference [6]. Table 2 shows the characteristics of the module, if bifaciality of 10% is implemented.

Table 1. Standard parameters of the analysed module given by the producer

Parameters	**Unit**	**Values**
Peak power	(Wp)	540
Maximum voltage per MPP	(V)	41.64
Maximum current per MPP	(A)	12.97
Open circuit voltage	(V)	49.60
Short circuit current	(A)	13.86
Efficiency	(%)	20.9
Area of the module	(m^2)	2.58

$I_D =$

Table 2. Parameters of the analysed module given by the producer with included bifaciality of 10%

Parameters	Unit	Values
Peak power	(Wp)	578
Maximum voltage per MPP T	(V)	41.65
Maximum current per MPPT	(A)	13.88
Open circuit voltage	(V)	49.93
Short circuit current	(A)	14.93
N_s	(# of cells)	60
K_I	(%/˚C)	0.00543
K_V	(%/˚C)	-0.136
G_{STC}	(W/m^2)	1000

A. Ideal single-diode PV cell model

The ideal solar cell circuit consists of a single diode (D) connected in parallel with light-generated current sources for the front I_{PVf} and rear I_{PVr} sides of the cell, as shown in Fig. 2. The output current (I) from Fig. 2 can be determined as: $I = I_{PVf} + I_{PVr} - I_D$.

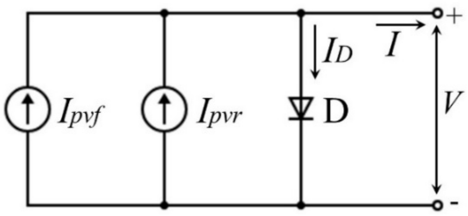

Fig. 2. Ideal single-diode PV cell model

In practice the diode D is investigated as an ideal one and therefore the current through it is taken to be equal to zero, so finally the output current has the following form:

$$I = I_{PVf} + I_{PVr} - I_D \quad (1)$$

where: I_{PVf} and I_{PVr} are the cell light generated currents at the front and rear side of the PV cell, respectively; I_D is the reverse saturation current of the diode D and it is defined by the material properties of the PV cell. In equation (1) the front and rear cell light generated current can be determined using the following equations given by [7] and [8]:

$I_{PV,}$

I_{PVr}

where: where: I_{PV_STC} is the light generated current at standard test conditions (STC), $\Delta T = T - T_{STC}$ (T_{STC}=25 ˚C); G_f and G_r are the surface irradiance of the cell on the front and on the rear side, respectively and G_{STC} (1000 W/m^2) is the irradiance at STC. K_I is the short-circuit current coefficient, normally provided by the manufacturer. In this investigation the rear side irradiance is taken to be 10% of the front irradiance whatever it is for a certain optimization process. In equation (1) the reverse saturation current of the diode D can be determined using the following equation defined in [8]:

The constant K_v is the open circuit voltage coefficient and it is available from the datasheet given by the producer. The same applies for the short circuit current at standard test conditions $I_{(SC\_STC)}$.

B. Real single-diode PV cell model

The real solar cell circuit presentation consists of a single diode (D) connected in parallel with a light generated current sources for the front (I_{PVf}) and the rear (I_{PVr}) side of the cell, a parallel connected resistance R_p and in series connected resistance R_s, as it is shown in Fig. 3. The series resistance arises from the bulk resistance of the semiconductor material, the bulk resistance of the metal electrodes, and the contact resistance between the semiconductor and metal. Careful design of the top contact and emitter resistance can control the series resistance [9]. A low series resistance is crucial for optimal solar cell efficiency, as a higher value reduces the short-circuit current [10]. The shunt resistance R_p is due to the leakage across the p–n junction, impurities and crystal defects. The value of shunt resistance should be low. This low value of shunt resistance causes reduction in open circuit voltage. Up to now in literature a large number of papers is dealing with the determination of the cell parameters including R_s and the calculation approaches can be divided in three groups: analytical [11-12], numerical iterative procedure [13], [14] and experimental approach in which the cell resistances are determined based on measured I-V characteristics of investigated PV cells [15]. In this work a different approach is introduced, where at the beginning the value of the series resistance is determined by a simple approach [16] and then in the optimization process this value as allowed to change between a lower and upper limit for a fine tuning of the value. This is done due to the fact that the first part of the value of the resistance is depends on the intensity of the solar irradiation [17]. With this approach the robust and time-consuming calculations are eliminated. Both series and shunt resistance losses decrease the efficiency and fill factor of the solar cell [18]. The output current I can be determined based on the presented circuit in Fig. 3, as:

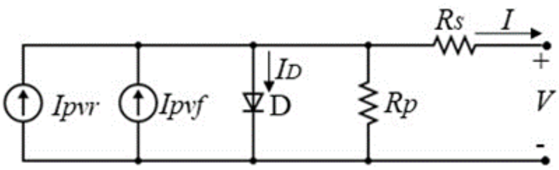

Fig. 3. Real single-diode PV cell model

$$I = I_{PVf} + I_{PVr} - I_D\left[exp\left(\frac{V_{mp}+I_{mp}R_s}{aV_{T1}}\right) - 1\right] - \left(\frac{V_{mp}+I_{mp}R_s}{R_p}\right)$$
(5)

where all the parameters are presented previously. Additionally, in this model the parallel connected resistance R_p can be determined using equation (6).

$$\boldsymbol{R_p} = \frac{\boldsymbol{V_{mp}+I_{mp}\cdot R_s}}{\left\{(\boldsymbol{I_{PVf}+I_{PVr}})-\boldsymbol{I_D}\left[\mathbf{exp}\left(\frac{(\boldsymbol{V_{mp}+I_{mp}\cdot R_s})}{\boldsymbol{V_T}}\right)+\mathbf{exp}\left(\frac{(\boldsymbol{V_{mp}+I_{mp}\cdot R_s})}{(\boldsymbol{p}-1)\boldsymbol{V_T}}\right)+\mathbf{2}\right]-\boldsymbol{P_{max,E}/V_{mp}}\right\}} \quad (6)$$

C. Double-diode PV cell model

The double-diode electrical model of solar PV is known to be more accurate than its single diode model counterpart since it takes into account the effect of recombination. The double-diode model [8] is presented in Fig. 4.

Using this model greater accuracy can be achieved in comparison with the one diode model, although in the case of the two-diode model it requires a computation of eight parameters: I_{PVf}, I_{PVr}, I_{D1}, I_{D2}, R_p, R_s, a_1 and a_2.

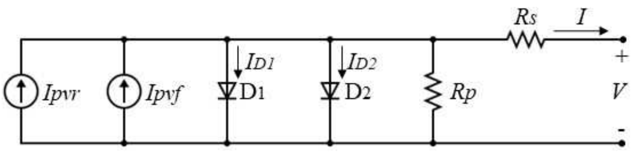

Fig. 4. Two-diode PV cell model

The PV current can be described as a function of temperature and irradiance:

$$I = I_{PVf} + I_{PVr} - I_{D1}\left[exp\left(\frac{V_{mp}+I_{mp}R_s}{a_1 V_{T1}}\right) - 1\right] - I_{D2}\left[exp\left(\frac{V_{mp}+I_{mp}R_s}{a_2 V_{T2}}\right) - 1\right] - \left(\frac{V_{mp}+I_{mp}R_s}{R_p}\right) \quad (7)$$

All the parameters in equation (7) are previously explained in the single diode model, while the coefficients a_1 and a_2 are the ideality factors of the first and second diode, consequently. In accordance to Shockley's diffusion theory, the diffusion current, a_1 must be unity. The value of a_2, however, is flexible. Based on extensive simulation carried out [8], it is found that if $a_2 \geq 1.2$, the best match between the proposed model and practical I–V curve is observed. Since (a_1+a_2) /p=1 and a_1=1, follows that the variable p can be $p \geq 2.2$. To maintain the same form as in equation (4), both the reverse saturation currents I_{D1} and I_{D2} are set to be equal in magnitude and can be determined using the following equation:

$$I_{D1} = I_{D2} = I_D = \frac{\left(I_{SC_{STC}} + K_I \Delta T\right)}{exp\left[\left(\frac{V_{OC,STC} + K_V \Delta T}{\frac{(a_1+a_2)}{p} V_T}\right)\right] - 1} \quad (8)$$

Therefore, equation (7) can be simplified and defined as:

$$I = I_{PVf} + I_{PVr} - I_D\left[exp\left(\frac{V_{mp}+I_{mp}R_s}{V_T}\right) + exp\left(\frac{V_{mp}+I_{mp}R_s}{(p-1)V_T}\right) + 2\right] - \left(\frac{V_{mp}+I_{mp}R_s}{R_p}\right) \quad (9)$$

The presented mathematical models of the investigate PV cell presentations are afterwards implemented in the multi-verse optimisation algorithm and a number of results are derived. The results from the optimization process are presented in the following section.

4. Cuckoo search optimisation results

The purpose of this investigation is to define the maximum power point (MPP) for a given location at different weather conditions. Therefore, for the defined optimization process first of all it is necessary to define the objective function and the optimization parameters. In this investigation the objective function it is defined to be the difference between the calculated maximum power using CS algorithm ($P_{mppt,CSA}$) and the maximum power ($P_{mppt,catalog}$) experimentally determined value given by the producer for certain conditions.

$$\boldsymbol{Objective\ function} = \Delta\boldsymbol{P} = \boldsymbol{P_{mppt,CSA}} - \boldsymbol{P_{mppt,catalog}} \quad (\mathbf{10})$$

The maximum output power determined by using CS algorithm for the PV module can be calculated by using the following equation:

$$\boldsymbol{P_{mppt,CSA}} = \boldsymbol{V_{mpp}} \cdot \boldsymbol{I_{mpp}} \quad (11)$$

In a similar manner the maximum power determined by the producer using the catalogue data is determined.

Since the CSA is a minimisation algorithm the aim of the optimization process is to minimise the power difference of the two powers as much as possible. Next step is to define the variable parameters that will be changed during the optimization process. Since the output current will be calculated the output voltage at maximum power conditions is defined as a variable. As it was mentioned in the description of the single and double diode models the series resistance R_s is also defined as a variable parameter. Each variable parameter is varied between its lower and upper bound that are defined by the user and their values are presented in Table 3.

Table 3. Optimiptimization parameters and their optimization bounds

Variables	**Description**	**Lower boundary**	**Upper boundary**
V_{mppt} (V)	Voltage at MPPT	36	42
R_s (Ω)	PV cell series resistance	0.1	0.3

For the purpose of this research work a number of CSA searches were realised. First a large number of optimisations were realised for the different PV cell models at different solar irradiations at constant temperature. The search was also performed for different values of the number of nests starting from 10 up to 1000, where on the other hand the number of iterations was altered from 10 to 500. The objective function value, as well as the values of the optimization parameters gained from the best CSA search for each PV cell model and different solar irradiations are presented in the following text. For the realization of this search 500 nests were used during the 100 iterations.

A. Ideal single-diode PV cell model

In the optimisation of the ideal single-diode PV cell model only the output voltage is defined as a variable since this is an ideal model and there is no series resistance R_s. The optimization results for the ideal single diode PV cell model at irradiation of 1000 W/m^2 are presented in Table 4, while the comparative optimization results for all the analysed solar radiations are presented in Table 5.

Table 4. Optimization Data at 1000 W/m^2

Variables	Unit	Catalogue data	CSA solution
V_{mppt}	(V)	41.65	37.9356
I	(A)	13.88	15.239
ΔP	(W)	/	$4.6\cdot 10^{-7}$
P_{mppt}	(W)	578.102	581.976

Table 5. Optimization Data for Other Solar Irradiations

Parameter	Unit	Values		
		200 W/m^2	600 W/m^2	1000 W/m^2
V_{mppt}	(V)	36.8621	37.6762	37.9356
I	(A)	2.996	8.32	15.239
ΔP	(W)	$2.1\cdot 10^{-7}$	$3.4\cdot 10^{-7}$	$4.6\cdot 10^{-7}$
$P_{mppt,\ CSA}$	(W)	110.44	313.467	581.976
$P_{mppt,\ catalog}$	(W)	110.44	313.467	578.102

The objective function value change during the iterations of the CSA search for a solar radiation of 1000 W/m^2 is presented in Fig. 5.

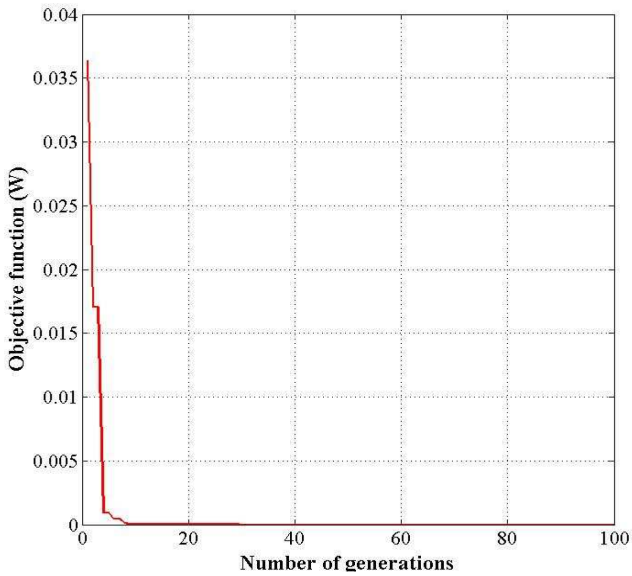

Fig. 5. Objective function change during the CSA search for ideal single-diode model at 1000 W/m^2

B. Real Single-Diode PV Cell Model

The optimization results for the real single-diode PV cell model at irradiation of 1000 W/m^2 are presented in Table 6, while the comparative optimization results for all the analysed solar radiations are presented in Table 7. The objective function value change during the iterations of the CSA search for a solar radiation of 1000 W/m^2 is presented in Fig. 6.

Table 6. Optimisation Data at 1000 W/m^2

Variables	Unit	Catalogue data	CSA solution
V_{mppt}	(V)	41.65	41.6502
R_s	(Ω)	/	0.20786
I	(A)	13.88	13.88
ΔP	(W)	/	$1.3\cdot 10^{-9}$
P_{mppt}	(W)	578.102	578.102

Table 7. Optimisation Data for Other Solar Irradiations

Parameter	Unit	Values		
		200 W/m^2	600 W/m^2	1000 W/m^2
V_{mppt}	(V)	40.1598	41.2998	41.6502
R_s	(Ω)	0.20698	0.20554	0.20786
I	(A)	2.75	7.59	13.88
ΔP	(W)	$1.1\cdot 10^{-9}$	$2.1\cdot 10^{-9}$	$1.3\cdot 10^{-9}$
$P_{mppt,\ CSA}$	(W)	110.44	313.467	578.102
$P_{mppt,\ catalog}$	(W)	110.44	313.467	578.102

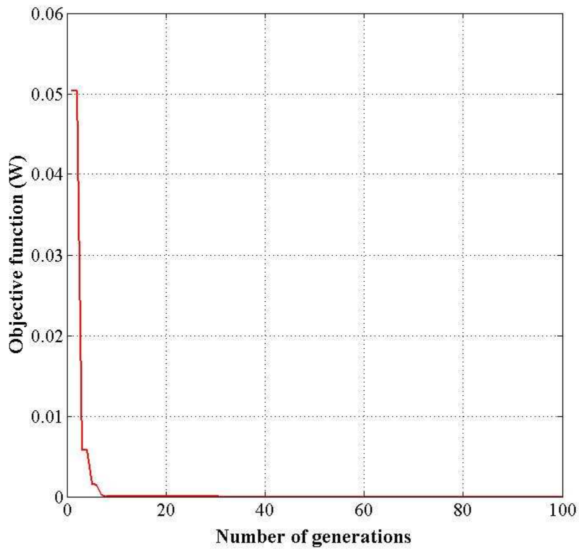

Fig. 6. Objective function change during the CSA search for real single-diode model at 1000 W/m^2

C. Double-Diode PV Cell Model

The optimization results for the double-diode PV cell model at irradiation of 1000 W/m^2 are presented in Table 8, while the comparative optimization results for all the analysed solar radiations are presented in Table 9.

Table 8. Optimisation Data at 1000 W/m^2

Variables	Unit	Catalogue data	CSA solution
V_{mppt}	(V)	41.65	41.6502
R_s	(Ω)	/	0.2191
I	(A)	13.88	13.88
ΔP	(W)	/	$1.2108\cdot 10^{-14}$
P_{mppt}	(W)	578.102	578.102

Table 9. Optimisation Data for Other Solar Irradiations

Parameter	Unit	Values		
		200 W/m^2	600 W/m^2	1000 W/m^2
V_{mppt}	(V)	40.1598	41.2998	41.6502
R_s	(Ω)	0.21072	0.20976	0.2191
I	(A)	2.75	7.59	13.88
ΔP	(W)	$1.42\cdot 10^{-14}$	$2.22\cdot 10^{-14}$	$1.211\cdot 10^{-14}$
$P_{mppt,\ CSA}$	(W)	110.44	313.467	578.102
$P_{mppt,\ catalog}$	(W)	110.44	313.467	578.102

The objective function value change during the iterations of the CSA search for a solar radiation of 1000 W/m^2 is presented in Fig. 7.

Based on the presented results it can be concluded that the objective function reaches very small values which means that the calculated maximum power is very close to the experimentally determined maximum power by the producer for given metrological conditions. These results show that the used optimisation algorithm is quite suitable for the determination of maximum power point for the analysed bifacial photovoltaic module, as well as for any other PV module.

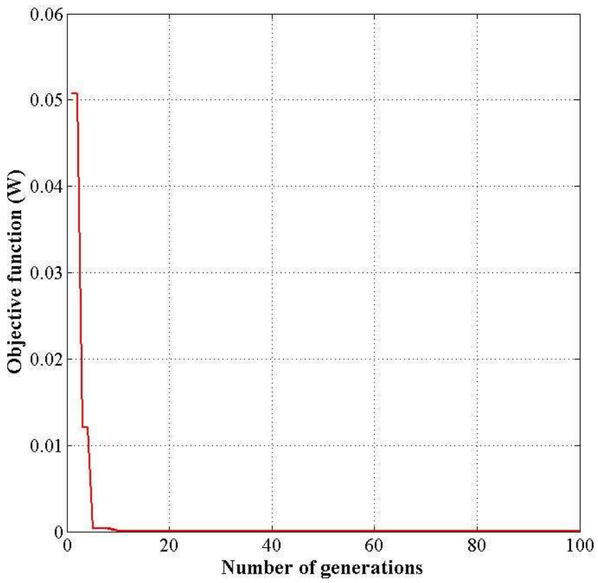

Fig. 7. Objective function change during the CSA search for double-diode model at 1000 W/m^2

If only the value of the objective function is analysed it can be noticed that the CSA optimisation always reaches a similar optimal solution where the difference of the values of the objective functions is between the 7th and 14th decimal point based on the investigated PV cell models for different solar irradiations. On the other hand, if the values of the optimised parameters are analysed it can be concluded that the real single-diode and double-diode models give more realistic and useful results, as well as very close to the catalogue data. Those two models together with the three-diode model will be used in further research work towards the determination of the MPPT for given new PV plant. The determination of the MPPT for a new PV plant at a certain location for different metrological conditions is very important for the dimensioning of the inverter, cables and other electrical equipment. The intention is to use this algorithm in the design process and not in the exploitation process of the PV where other methods are used. This optimisation and analysis procedure is especially important in case when extreme metrological conditions at given location are reached.

5. Conclusion

In this research work an implementation of a swarm-based optimization algorithm named cuckoo search algorithm to determine the maximum power point of a bifacial PV module is realised. Based on the presented results it can be concluded that the CSA is quite appropriate for determining the maximum power point of a bifacial photovoltaic module for different weather conditions. The algorithm gives reliable and good optimization results. The determination of the maximum power point using CSA was applied on three different PV cell models: ideal single-diode model, real single-diode model and double-diode model. All the used models gave quite good optimisation results regarding the objective function, but regarding the optimisation parameters the real single-diode and the double-diode model gave much more realistic and useful results. As a future work it is foreseen the application of a three-diode PV cell model to be used. Comparative analysis of this method with other nature-based algorithms is also planned to be done in our future work.

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