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Parameter extraction of photovoltaic models by honey badger algorithm and wild horse optimizer

Bal porsuğu algoritması ve vahşi at optimize edici ile fotovoltaik modellerin parametre çıkarımı

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Parameter Extraction of Photovoltaic Models by Honey Badger Algorithm and Wild Horse Optimizer

Highlights

- *PV parameter estimation has been made with honey badger algorithm (HBA) and wild horse optimizer (WHO)*
- *PV cells and modules are modeled with single and double diode models and real measurement data are used to test the problem.*
- *Objective function values are calculated between 9.9318E-04 and 1.7011E-03 with HBA and between 9.8602E-04 and 1.7298E-03 with WHO.*

Graphical Abstract

In this article, the topic of PV parameter extraction has been studied and this optimization problem has been solved with HBA and WHO.

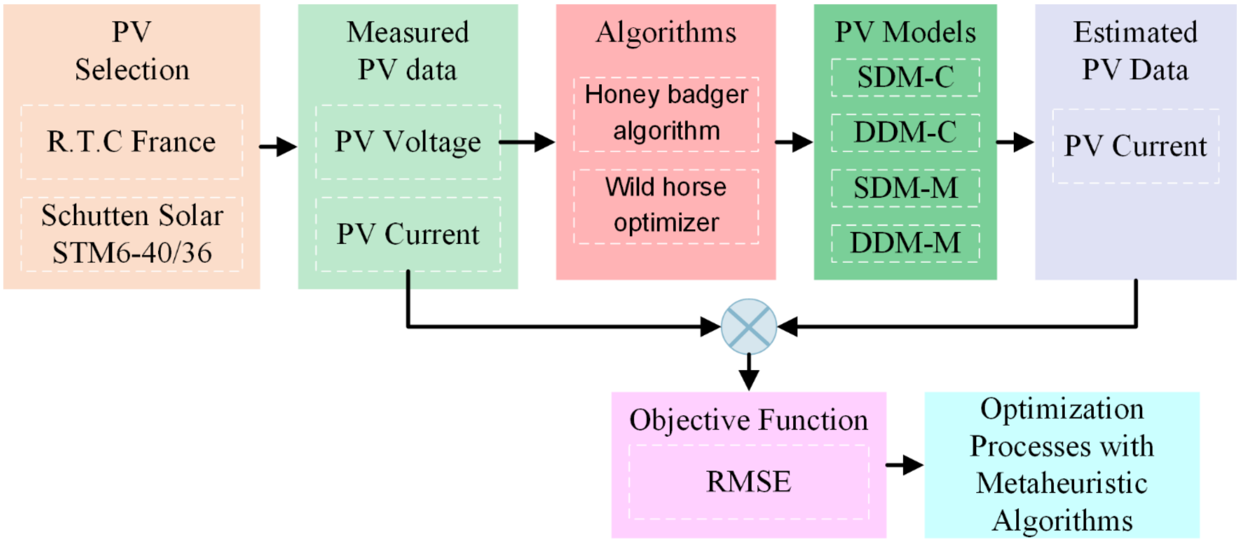

Figure. Optimization process for PV parameter extraction with HBA and WHO

Aim

In this study, it is aimed to extract PV parameters and obtain optimal parameters with HBA and WHO.

Design & Methodology

PV cells and modules are modeled with single and double diode models. The root mean square error was chosen as the objective function and the results of HBA and WHO were compared with the evaluation metrics in terms of computational accuracy and computational time.

Originality

HBA and WHO were used together and compared for the first time in this study.

Findings

When the algorithms are compared in terms of computational accuracy and computational time; it has been observed that both WHO and HBA, with WHO in the first place, produce successful, stable and fast results in PV parameter extraction.

Conclusion

As a result; It has been seen that HBA and WHO are effective and successful in PV parameter extraction and can be used in the solution of such engineering problems with their competitive structure compared to the literature.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Parameter Extraction of Photovoltaic Models by Honey Badger algorithm and Wild Horse Optimizer

(This study was presented at ECRES 2022 conference.)

Araştırma Makalesi / Research Article

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ABSTRACT

Analyzing the processes ranging from the determination of the installation configuration of the photovoltaic (PV) systems to the operation at the maximum power, from the technical and economic feasibility study to the positive contribution to the region where the production is planned are just possible with the accurate and efficient simulation models of the PV systems. PV parameter extraction, which is a topic frequently discussed recently, is crucial for the detailed modeling of PV cells and modules and simulating the behavior of these systems. For this reason, the current study examined PV parameter extraction and solved this optimization problem with the honey badger algorithm (HBA) and wild horse optimizer (WHO). PV cells and modules were modeled with the single diode model (SDM) and double diode model (DDM) and tested with actual measurement data. The root-mean-square error (RMSE) was chosen as the objective function, and the results were compared with the evaluation metrics for computational accuracy and time. Based on four PV model results, RMSE values were calculated between 9.9318E-04 to 1.7011E-03 for HBA and between 9.8602E-04 and 1.7298E-03 for WHO. As a result, even though both algorithms produce successful, stable, and fast results in PV parameter extraction, the WHO yielded better results.

Keywords: Double diode PV model, honey badger algorithm, PV parameter extraction, single diode model, wild horse optimizer.

Bal Porsuğu Algoritması ve Vahşi At Optimize Edici ile Fotovoltaik Modellerin Parametre Çıkarımı

ÖZ

Fotovoltaik (FV) sistemlerin kurulum konfigürasyonunun belirlenmesinden, maksimum güç noktasında çalıştırılmasına, teknik ve ekonomik fizibilite çalışmasından üretim yapması planlanan bölgeye sağlayacağı pozitif katkısına kadar olan süreçlerin analizinin yapılması FV sistemlerin doğru ve verimli simülasyon modellerine bağlıdır. FV hücrelerin ve modüllerin detaylı modellenmesi ve bu sistemlerin davranışının taklit edilebilmesi için FV parametre çıkarımı son derece önemli olup son zamanlarda sıklıkla çalışılan bir konudur. Bu sebeple bu çalışmada, FV parametre çıkarımı konusunda çalışılmış ve bu optimizasyon problemi bal porsuğu algoritması (BPA) ve vahşi at optimize edici (VAO) ile çözülmüştür. FV hücre ve modüller tek diyotlu model (TDM) ve çift diyotlu model (ÇDM) ile modellenmiştir. Bu modellerin test edilmesinde ise gerçek ölçüm verileri kullanılmıştır. Amaç fonksiyonu olarak hata kareler ortalamasının karekökü (RMSE) seçilmiş ve sonuçlar, hesaplama doğruluğu ve zamanı açılarından değerlendirme metrikleri ile karşılaştırılmıştır. Dört FV modelin sonuçlarına göre; BPA 9,9318E-04 ile 1,7011E-03 aralığında ve VAO ise 9,8602E-04 ile 1,7298E-03 aralığında RMSE değerleri hesaplanmıştır. Sonuç olarak her iki algoritma da PV parametre çıkarımında başarılı, kararlı ve hızlı sonuçlar vermesine rağmen VAO daha iyi sonuçlar vermiştir.

Anahtar Kelimeler: Çift diyotlu FV model, bal porsuğu algoritması, FV parametre çıkarımı, tek diyotlu FV model, vahşi at optimize edici.

1. INTRODUCTION

PV systems attract the attention of researchers in theory and investors in practice because of their ability to transform solar energy directly into electrical energy and their application in many fields [1-2]. PV systems operating in severe ambient conditions are affected by many factors such as extreme temperatures, dust, pollution, rain, and snow. These factors, causing various malfunctions, shorten the life of the PV modules and reduce the entire system's efficiency [3-4]. PV systems need to be modeled in detail in order to design PV systems or to ensure that existing systems work at optimum efficiency levels [5-6]. The model should also contain the effects of environmental factors for an optimum PV system design. Modeling of a PV system starts with the PV cells, the smallest unit of the PV system, and then the modules and arrays are handled, respectively. However, the information obtained from the PV manufacturer data sheets alone is insufficient for modeling PV cells, modules, and arrays. Therefore, it is necessary to create electrically equivalent circuit models

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to PV models and extract unknown parameters [7]. Equivalent circuit equations are non-linear due to the diodes in the electrical equivalent circuits of PV cells. The larger the number of diodes, the greater the variety of parameters to be determined and the system complexity. The most dominant elements of PV cells are diodes. Therefore, the circuit models of PV systems get their names according to the number of diodes. The most common circuit models are the single diode model, the double diode model, and the three diode model (TDM). In addition, in the literature, PV circuit models are named according to the unknown parameter counts in the equivalent circuit. SDM, DDM, and TDM are also called the 5-parameter model, the 7-parameter model, and the 9-parameter model, respectively. Accurate, fast, and reliable estimation of the parameters of PV models is the primary goal of an optimal operation [8-9].

The PV cell has a nonlinear mathematical infrastructure. Solving the equations and getting optimal parameters for PV systems is an optimization problem. A review of valuable literature studies showed that analytical, deterministic, and meta-heuristic methods generally served in PV parameter extraction. Meta-heuristic algorithms are popular among these methods. Many researchers work on them because they have chief advantages, such as not having problem constraints, ease of use, being usable in multidimensional optimization problems, and producing fast and reliable results [10]. Garip et al. used henon chaotic based whale optimization algorithms (HBOA) to estimate the parameters of the SDM model of three commercial modules PWP-201 (36 cells), STM-40/36 (36 cells), and STP6-120/36 (36 cells) and compared HBOA with the classical whale optimization algorithm. HBOA variants produced a smaller RMSE than the classical whale optimization algorithm [11]. Rizk et al. used the emended heap-based optimizer (EHBO) to find the parameters of the SDM model of three commercial modules PWP-201, KC200GT (36 cells), and Shell solar PowerMax Ultra 85-P (54 cells). They compared the proposed algorithm with particle swarm optimizer, interior search algorithm, artificial ecosystem optimizer, equilibrium optimizer, and heap-based optimizer algorithms. The RMSE value of EHBO was 2.4170E-03 and produced better results than other algorithms [12]. Wang et al. used the enhanced ant lion optimizer (EALO) to estimate the SDM and DDM parameters in the commercial model of RTC France and the SDM parameters in the PWP-201 commercial model. RTC France-SDM results were compared with artificial bee colony optimization (ABC), chaos pattern search, generalized oppositional teaching learning based optimization algorithm (GOTLBO), artificial bee swarm optimization, and hybrid bee pollinator flower pollination algorithm (FPA). EALO, hybrid BPFPA, and ABC algorithms gave better results than others by their RMSE values. RTC France-DDM results were compared with pattern search, harmony search-based algorithms, simulated annealing algorithm, ABC, artificial bee swarm optimization, GOTLBO, and hybrid FPA. The best RMSE value was 9.8247E-03 produced by the EALO. In the PWP-201-SDM results, the best RMSE value from the proposed algorithm was 2.4248E-03 [13]. Yeşilbudak used the african vulture optimization algorithm to determine the SDM and DDM parameters in the commercial RTC France and the SDM parameters in the PWP-201 commercial model. The proposed algorithm, compared with many algorithms in the cell and module model, worked successfully [14]. Ndi et al. determined the optimal parameters of the DDM and SDM equivalent circuit models in RTC France using the balance optimizer algorithm and found the RMSE values 9.8553E-04 and 9.8603E-04 for DDM and SDM, respectively. The proposed algorithm gave successful results in parameter extraction [15]. Pourmousa et al. found DDM and SDM parameters in the RTC France commercial cell model and SDM parameters in the STM6-40 commercial module with an improved Lozi map-based chaotic optimization algorithm. The RMSE values of DDM, SDM, and PV modules were 8.8257E-04, 9.8602E-04, and 1.6932E-02, respectively [16]. Long et al. used the enhanced adaptive butterfly optimization algorithm to find the DDM, SDM equivalent circuit models in the RTC France model, and the SDM parameters in the PWP-201 commercial module. The RMSE values of the DDM cell, SDM cell, and PV module were found at 9.8607E-04, 9.8602E-04, and 2.4252E-03, respectively [17].

The literature review has revealed that many algorithms, methods, and techniques for optimum PV parameter extraction were available, but no single algorithm or method could solve all problems. Therefore, unknown SDM and DDM parameters in PV models (modules and cells) were estimated using HBA and WHO algorithms, and their performances were compared using evaluation metrics. The current study employing HBA and WHO for optimizing PV parameter extraction might remarkably contribute to the literature for future studies.

This article comprises five parts. After the introduction, Section 2 covers the PV parameter extraction problem. Section 3 explains the optimization algorithms and mathematical background, which are the tools for solving this problem. The results and discussion sections are in Section 4, while Section 5 covers the conclusion part.

2. DEFINITION OF PROBLEM

It is possible to come across different circuit models while expressing the current-voltage relationship of PV systems [18]. In this study, PV parameter extraction, which is the main topic of this study, was carried out through four models: single diode cell (SDM-C), double diode cell (DDM-C), single diode module (SDM-M), and double diode module (DDM-M). In this direction, the current study covered the equivalent circuit models and mathematical infrastructure of the PV cell and module in the following subsections and defined the objective function for the unknown parameter identification.

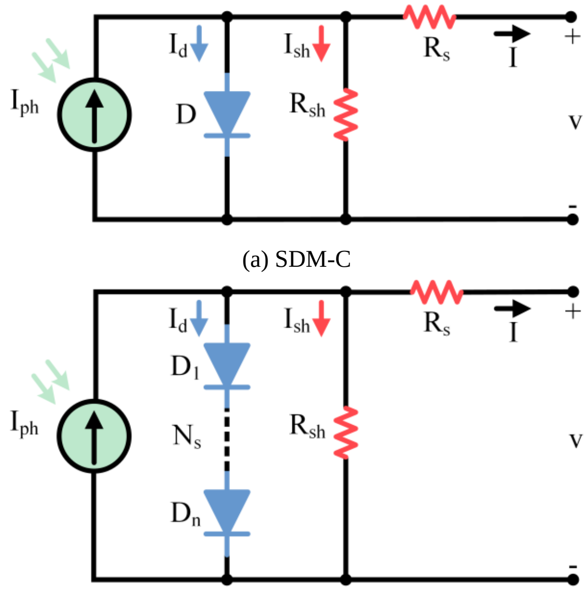
2.1. Single Diode Model (SDM)

The single diode cell consisted of one diode, parallel and series resistors, and a photo/generated current source. Figure 1(a) shows the equivalent circuit model of the SDM-C model. While Equation 1 shows the general representation of the output current (I_{SDM}) of the SDM equivalent circuit, Equation 2 shows the output current (I_{SDM-C}) of the SDM-C [19]-[22]. In these equations, I_{ph} is the photo/generated current, V is the output voltage of the cell, I_o is the reverse saturation current, R_s and R_{sh} are the series and parallel resistance, respectively, T is the operating temperature, α is the diode ideality factor, q is the electron charge ($1.60217646x10^{-19}C$) and k is the Boltzmann constant ($1{,}3806503x10^{-23}J/K$). Figure 1(b) shows the equivalent circuit model of the SDM-M. No parallel cells were available in this study. Equation 3 shows the output current (I_{SDM-M}) of SDM-M [21]-[24]. In SDM-M, N_s refers to cells connected in series. There were five parameters to be estimated in the SDM-C and SDM-M models, namely I_{ph}, I_o, α, R_s, and R_{sh}.

$$I_{SDM} = I_{ph} - I_d - I_{sh} \tag{1}$$

$$I_{SDM-C} = I_{ph} - I_o\left[e^{\frac{q(V+IR_S)}{\alpha kT}} - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{2}$$

$$I_{SDM-M} = I_{ph} - I_o\left[e^{\frac{q(V+IR_SN_S)}{\alpha kTN_S}} - 1\right] - \frac{V+IR_SN_S}{R_{sh}N_S} \tag{3}$$



(a) SDM-C

(b) SDM-M

Figure 1. SDM equivalent circuits of PV cell and module

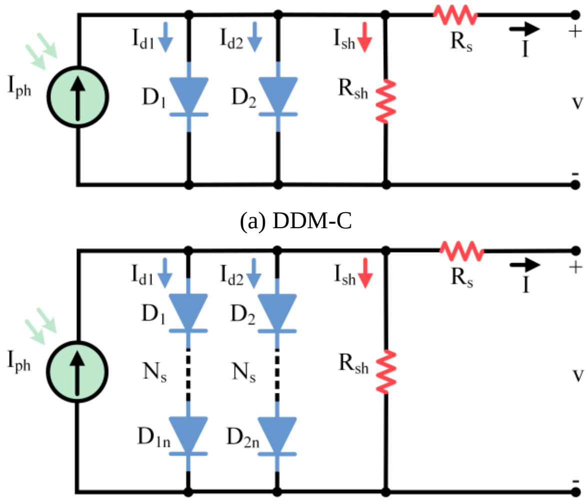
2.2. Double Diode Model (DDM)

DDM-C consisted of two diodes, parallel and series resistors, and a photo/generated current source. Figure 2(a) shows the equivalent circuit model of DDM-C. The common representations of the output current (I_{DDM}) of DDM and the output current (I_{DDM-C}) of DDM-C are in Equations 4 and 5, respectively [20]-[23]. In these equations, I_{d1} and I_{d2} are the diode currents, α_1 and α_2 are ideality factors of the 1st and the 2nd diodes, and I_{o1} and I_{o2} are the reverse saturation currents. Figure 2(b) shows the equivalent circuit DDM-M. The study assumed that all cells in the PV module were series-connected. This module's output current (I_{DDM-M}) is in Equation 6 [25]. Seven parameters were defined in cell and module models: I_{ph}, I_{o1}, I_{o2}, α_1, α_2, R_s, and R_{sh}.

$$I_{DDM} = I_{ph} - I_{d1} - I_{d2} - I_{sh} \tag{4}$$

$$I_{DDM-C} = I_{ph} - I_{o1}\left[e^{\frac{q(V+IR_S)}{\alpha_1 kT}} - 1\right] - I_{o2}\left[e^{\frac{q(V+IR_S)}{\alpha_2 kT}} - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{5}$$

$$I_{DDM-M} = I_{ph} - I_{o1}\left[e^{\frac{q(V+IR_SN_S)}{\alpha_1 kTN_S}} - 1\right] - I_{o2}\left[e^{\frac{q(V+IR_SN_S)}{\alpha_2 kTN_S}} - 1\right] - \frac{V+IR_SN_S}{R_{sh}N_S} \tag{6}$$



(a) DDM-C

(b) DDM-M

Figure 2. DDM equivalent circuits of PV cell and module

2.3. Objective Function

The present work has solved the PV parameter extraction problem by transforming it into an optimization problem. As with all optimization problems, the objective function must be specified for analyzing and evaluating the selected algorithms. The parameter extraction optimization is usually performed according to the error between the calculated and measured currents. Therefore, parameter extraction is a minimization problem. Most previous studies have selected RMSE as an objective function (fitness function) to solve this problem. To compare the study results with the literature, the RMSE given in Equation 7 was chosen as the objective function. Equation 8 shows the decision variables of the objective function: I_{ph}, I_o, α, R_s, and R_{sh} for SDM-C and SDM-M; I_{ph}, I_{o1}, I_{o2}, α_1, α_2, R_s, and R_{sh} for DDM-C and DDM-M.

$$RMSE = \sqrt{\frac{1}{K}\sum_{k=1}^{K} f(x)^2} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}(I_{measured} - I_{calculated})^2} \quad (7)$$

$$x = \begin{cases} I_{ph}, I_o, \alpha, R_s, R_{sh} & SDM-C \text{ and } SDM-M \\ I_{ph}, I_{o1}, I_{o2}, \alpha_1, \alpha_2, R_s, R_{sh} & DDM-C \text{ and } DDM-M \end{cases} \quad (8)$$

3. OPTIMIZATION ALGORITHMS

Two metaheuristic algorithms, HBA and WHO, were preferred to find a solution to the optimal PV parameter extraction problem. The source of inspiration, solution steps, and mathematical design and equations of the algorithms are in the subsections.

3.1. Honey Badger Algorithm (HBA)

Proposed and published in 2022 by Hassim et al., HBA was inspired by the foraging behavior of honey badgers. The HBA algorithm has two basic steps. The first step is the digging phase. This step imitates the honey badger's smell sense to approach its prey and dig to hunt it. The second stage is the honey phase. During the honey phase, the honey badger follows the honeyguide birds to reach the beehive location. There is teamwork between the honeyguide bird and the honey badger–which is unskilled at finding beehives. Equation 9 shows the processes and mathematical background of the HBA algorithm, including initialization, density definition, updating density factor, escaping from the local optimum, and updating the agent positions. Algorithm 1 presents the pseudocode of the HBA. Figure 3 also shows the flowchart of the algorithm. After defining the initial parameters, random locations of the candidate solutions, namely honey badgers, are assigned. The fitness of the positions of each honey badger is evaluated. Hunting continues until the stopping criterion is met.

Algorithm 1. Pseudo-code of HBA

Determination of T_{HBA}, N_{HBA}, C, β
Initialize the honey badger population with random location
Asses the fitness of each honey badger position x_i using objective function and designate to f_i, $i \in [1, 2, \ldots N]$
Record best honey badger position x_{prey} and designate fitness to f_{prey}
while t $\leq T_{HBA}$ **do**
  Modify the decreasing factor α
  for $i = 1$ to N_{HBA} **do**
    Calculation the intensity I_i
    if $r < 0.5$ **then**
      Modify the position x_{new} using digging phase equation in Eq. (9)
    else
      Modify the position x_{new} using honey phase equation in Eq. (9)
    end if
    Asses new position and assign to f_{new}
    if $f_{new} \leq f_i$ **then**
      Set $x_i = x_{new}$ and $f_{prey} = f_{new}$
    end if
    if $f_{new} \leq f_{prey}$ **then**
      Set $x_{prey} = x_{new}$ and $f_{prey} = f_{new}$
    end if
  end for
end while stop criteria satisfied
return x_{prey}

$$HBA = \begin{cases} \textit{Initialization phase} & \begin{cases} x_i = [x_i^1, x_i^2, x_i^3, \cdots, x_i^D] \\ x_i = lb_i + r_1 \times (ub_i - lb_i) \end{cases} \\ \textit{Defining intensity} & \begin{cases} I_i = r_2 \times \frac{S}{4\pi d_i^2} \\ S = (x_i - x_{i+1})^2 \\ d_i = x_{prey} - x_i \end{cases} \\ \textit{Update density factor} & \alpha = C \times exp\left(\frac{-t}{T_{HBA}}\right) \\ \textit{Escaping from local optimum} & F = \begin{cases} 1 & r_6 \leq 0.5 \\ -1 & r_6 > 0.5 \end{cases} \\ \textit{Updating the agents' positions} & \begin{array}{ll} \textit{Digging phase} & \begin{cases} x_{new} = x_{prey} + F \times \beta \times I \times x_{prey} + \cdots \\ \cdots F \times r_3 \times \alpha \times d_i \times |cos(2\pi r_4) \times (1 - cos(2\pi r_5))| \end{cases} \\ \textit{Honey phase} & x_{new} = x_{prey} + F \times r_7 \times \alpha \times d_i \end{array} \end{cases} \quad (9)$$

Where, x_i is honey badger position, lb_i is the lower bound, ub_i is the upper bound, D is the dimension, I_i is smell intensity of prey, $r_1, r_2, r_3, r_4, r_5, r_6, r_7$ are random numbers between [0,1], S is source strength, d_i is prey distance and i is the badger, α is the density factor, C is the constant number ($C \geq 1$, default 2), x_{prey} is the position of the prey, β is the constant number ($\beta \geq 1$, default 6), x_{new} is the new position of the honey badger, F is the flag, and T_{HBA} and t are the maximum numbers of iterations and current iteration, respectively, [26].

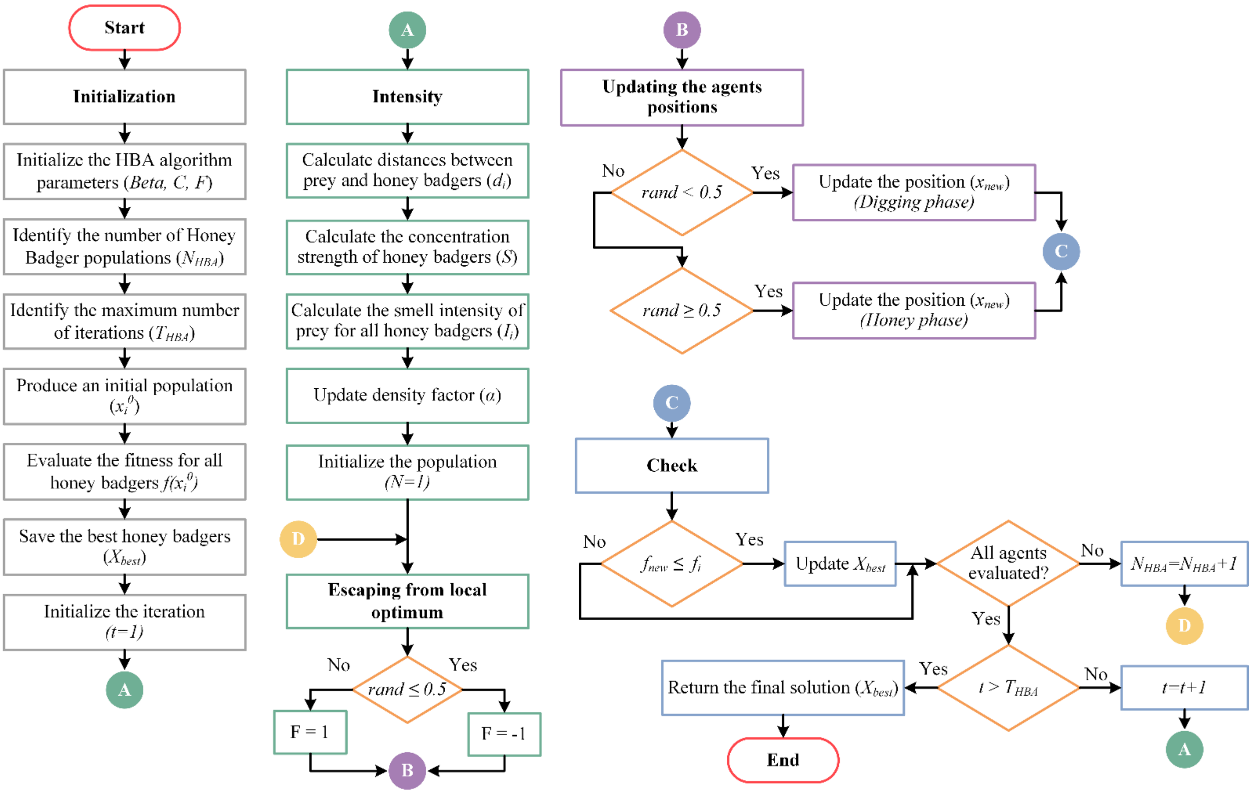


Figure 3. Flowchart of HBA algorithm

3.2. Wild Horse Optimizer (WHO)

Recommended and published by Naruei et al. in 2021, WHO was inspired by non-terrestrial horses. These horses are usually in a herd consisting of several mares, foals, and a stallion led by the most dominant mare. WHO simulates these horses' behaviors and group dominance, leadership, grazing, and mating characteristics within the group. Equation 10 shows the WHO algorithm processes and their mathematical backgrounds, including population formation, grazing, mating, group leadership, and leader selection. After defining the initial parameters, the random initial positions of the candidate solutions, horses, are determined. The compatibility of each wild horse is evaluated according to its objective function. Solution seeking process continues until the stopping criterion is met. Algorithm 2 shows the pseudocode of the WHO, while Figure 4 shows the flowchart of the algorithm.

$$WHO = \begin{cases} Creating an initial population & \begin{cases} \vec{x} = \{\vec{x_1}, \vec{x_2}, \vec{x_3}, \cdots, \vec{x_n}\} \\ G = [N_{WHO} \times PS] \end{cases} \\ Grazing behaviour & \begin{cases} \overline{X^j}_{i,G} = 2Z\cos(2\pi RZ) \times \left(Stallion^j - X^j{}_{i,G}\right) + Stallion^j \\ P = \vec{R}_1 < TDR \\ IDX = (P = 0) \\ Z = R_2 \Theta IDX + \vec{R}_3 \Theta (IDX) \\ TDR = 1 - t \times \left(\frac{1}{t_{max}}\right) \end{cases} \\ Horse mating behaviour & \begin{cases} X^P{}_{G,K} = Crossover\left(X^q{}_{G,i}, X^z{}_{G,j}\right) \\ i \neq j = k, p = q = end \\ Crossover = Mean \end{cases} \\ Group leadership & \begin{cases} \overline{Stallion_{Gi}} = \begin{cases} 2Z\cos(2\pi RZ) \times (WH - Stallion_{Gi}) + WH & R_3 > 0.5 \\ 2Z\cos(2\pi RZ) \times (WH - Stallion_{Gi}) - WH & R_3 \leq 0.5 \end{cases} \\ Stallion_{Gi} = \begin{cases} X_{G,i} & if cost(X_{G,i}) < cost(Stallion_{Gi}) \\ Stallion_{Gi} & if cost(X_{G,i}) > cost(Stallion_{Gi}) \end{cases} \end{cases} \end{cases} \tag{10}$$

Where, x is horse population, N_{WHO} is the number of populations, G is the number of groups, PS is the percentage of stallions, $X^j{}_{i,G}$ is group members' current position, π is pi-number, R is the uniform number inside [−2, 2], $Stallion^j$ position of stallion, Z is an adaptive mechanism, $\overline{X^j}_{i,G}$ is the group members' new position, P

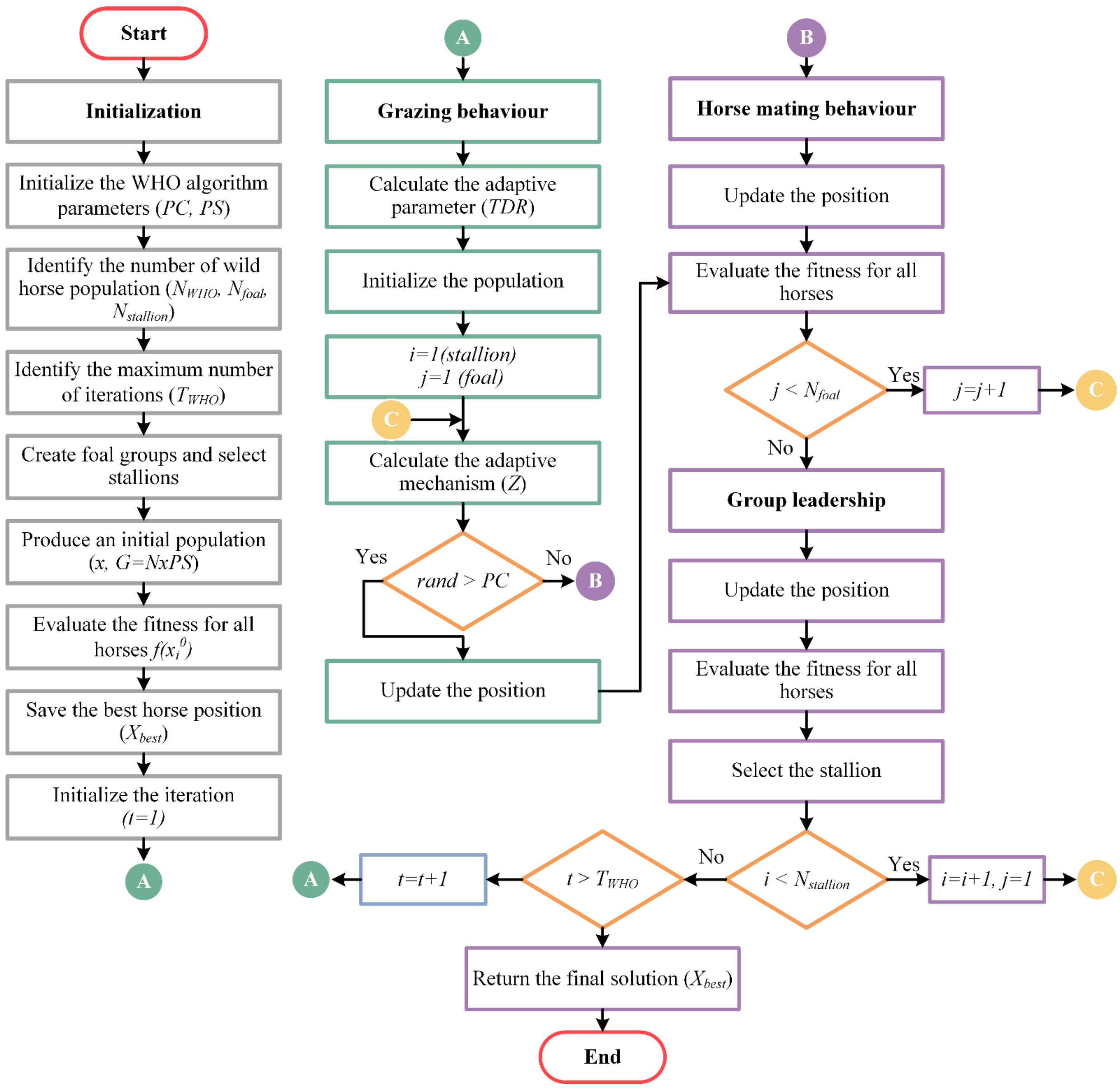


Figure 4. Flowchart of WHO algorithm

is a vector, $\vec{R}_1$, R_2, and $\vec{R}_3$ are random vectors, IDX are indexes of the random vectors, TDR is the adaptive parameter, t is current iteration, T_{WHO} is the maximum number of iterations, WH is the position of a suitable area (the water hole), ${X^z}_{G,j}$ is the position of the horse z in group j, $\overline{Stallion}_{Gi}$ is following position of the leader of the i group (stallion position), ${X^P}_{G,K}$ is the position of horse p from group k, ${X^q}_{G,i}$ is the position of the foal in group i, $Stallion_{Gi}$ is the current position of the leader of the group [27].

4. RESULTS AND DISCUSSION

In this part, the optimization problem of parameter extraction was solved using HBA and WHO, and the results were analyzed in detail. The control parameter values of the algorithms are given in Table 1. For the solution of the parameter extraction optimization problem, the number of agents is generally taken as 50 and the number of iterations as 10000 in the literature. Therefore, in this study the HBO and WHO algorithms were run in 10000 iterations over 50 populations. After 30 independent studies, 300000 functions were evaluated. There were two control parameters in the HBA and three in the user-adjusted WHO. These control parameters are based on the values reported in the original article. β and C were 6 and 2 in the HBA algorithm, respectively. In WHO, percent cross (PC), percent stallion (PS), and crossover parameters were taken as 0.13, 0.2, and $Mean$, respectively. RTC France [28] and Schutten Solar STM6-40/36 [29] panel data served to test the optimization performance of HBA and WHO. Table 2 shows the upper and lower limits of the decision variables in the objective function. Parameter extraction results and comparison of optimization results according to evaluation metrics are in the subtitles.

Algorithm 2. Pseudo-code of WHO

Determination of $N_{WHO}, T_{WHO}, PC, PS,$
$N_{stallion} = PS \times N_{WHO}, N_{foal} = N_{WHO} - N_{stallion}$
Compute the fitness of all horses
Create foal groups and select stallions
Discover best horse as the optimum
while t $\leq T_{WHO}$ **do**
    Calculate TDR by Eq. (10)
    for i= 1 to $N_{stallion}$ **do**
        Calculate Z by Eq. (10)
          for i= 1 to N_{foal} **do**
           if $rand > PC$
           Modify the position of the all foals by Eq. (10)
           else
           Modify the position of the all foals by Eq. (10)
           end if
          end for
           if $rand > 0.5$
            Modify the position $\overline{Stallion_{G_i}}$ by Eq. (10)
           else
            Modify the position $\overline{Stallion_{G_i}}$ by Eq. (10)
            end if
            if $cost(Stallion_{G_i}) < cost(stallion)$
              Stallion=$\overline{Stallion_{G_i}}$
            end if
            Classify foals of groups by cost
            Choose foal with lowest cost
            if $cost(foal) < cost(Stallion)$
              Exchange foal and stallion position Eq. (10)
            end if
    end for
    Modify optimum
end while

Table 1. Control parameter values of algorithms

Algorithm	Control Parameter	Value
HBA	β	6
	C	2
WHO	PC	0.13
	PS	0.2
	Crossover	$Mean$

4.1. Results of SDM-C and SDM-M

Table 3 shows the results of the decision variables of the problem and the objective function for the SDM-C and SDM-M. The most successful algorithm for single diode cells and single diode modules was HBA because this algorithm produced the smallest RMSE value between these two models. The RMSE result produced with the WHO was 4.97117E-10%, which was higher than HBA. Figure 5 shows the P-V and I-V curves obtained from the voltage and current results and the results of the HBA and WHO. The curves in Figure 5(a) belong to SDM-C, and the curves in Figure 5(b) belong to SDM-M. The comparison of SDM-C and SDM-M shows that measured and simulation data overlap successfully, and both algorithms are successful in parameter estimation.

4.2. Results of DDM-C and DDM-M

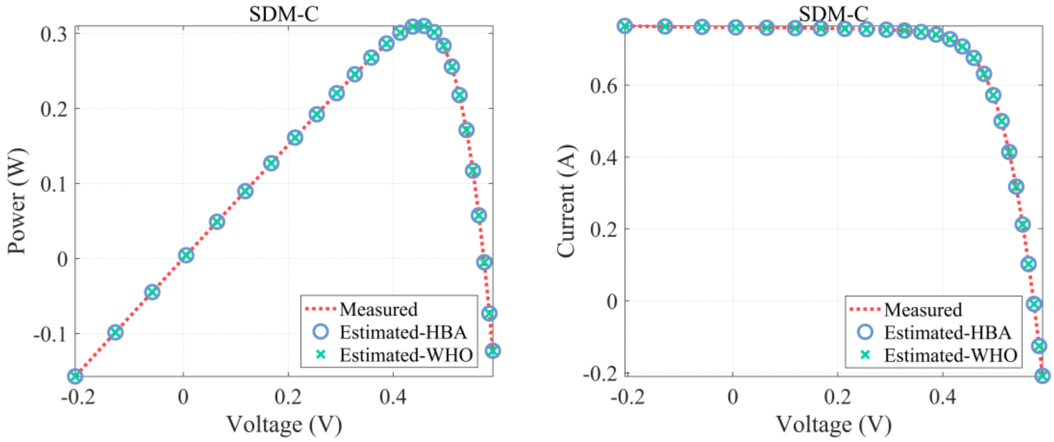
Table 4 shows the PV parameter extraction results of the DDM-C and DDM-M. For DDM-C, WHO yielded the smallest RMSE, and the RMSE result of HBA was 1.08896 percent greater than WHO. As in SDM-C and SDM-M, the HBA was the most successful algorithm in DDM-M. Figure 6 shows the P-V and I-V curves obtained from the voltage and current results and also the results of the HBA and WHO. As in SDM, the measured data and simulation data matched perfectly, and both algorithms were successful in parameter extraction.

Table 2. Lower and upper limits of PV models

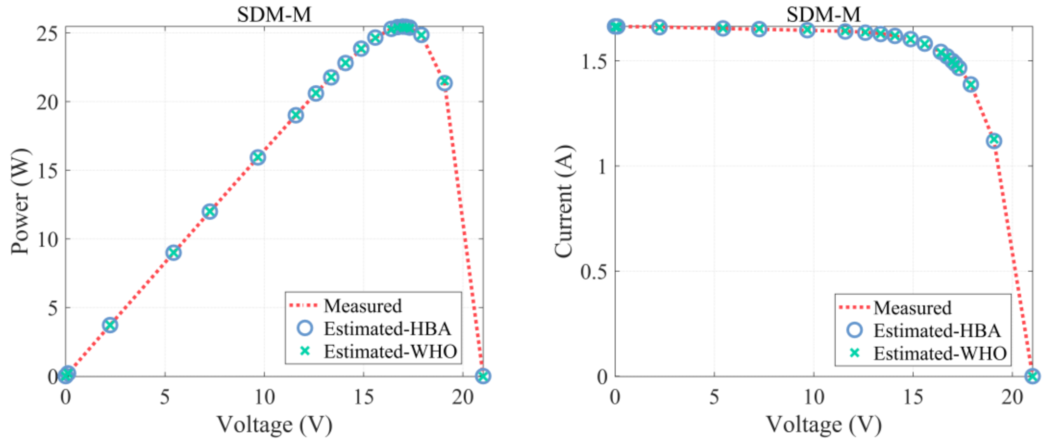
Model	Parameter	Limit		Model	Parameter	Limit		Unit
		Upper	Lower			Upper	Lower	
SDM-C DDM-C	I_{ph}	1	0	SDM-M DDM-M	I_{ph}	2	0	A
	I_o	1	0		I_{o1}, I_{o2}	50	0	μA
	R_{sh}	100	0		R_{sh}	1000	0	Ω
	R_s	0.5	0		R_s	0.36	0	Ω
	α	2	1		α_1, α_2	60	1	-

Table 3. Parameter extraction results of SDM-C and SDM-M

Model	Alg.	I_{ph} (A)	I_o (μA)	R_{sh} (Ω)	R_s (Ω)	α	$RMSE$	Rank
SDM-C	HBA	0.76078	0.32302	53.71853	0.03638	1.48119	9.8602E-04 0.000986021877891178933	**1**
	WHO	0.76078	0.32302	53.71857	0.03638	1.48119	9.8602E-04 0.000986021877896669101	2
SDM-M	HBA	1.66390	1.73866	15.92831	0.00427	1.52030	1.7298E-03 0.001729813709949546660	**1**
	WHO	1.66155	5.50511	23.55866	0.00000	1.65853	3.3299E-03 0.003329850937087186660	2



(a) SDM-C



(b) SDM-M

Figure 5. P-V and I-V curves for SDM-C and SDM-M

Table 4. Parameter extraction results of DDM-C and DDM-M

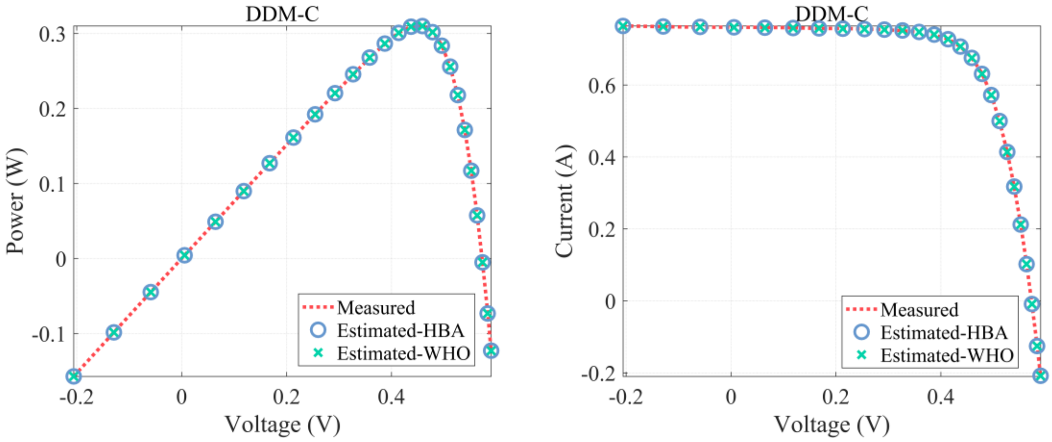
Model	Alg.	I_{ph} (A)	I_{o1} (μA)	I_{o2} (μA)	R_{sh} (Ω)	R_s (Ω)	α_1	α_2	$RMSE$	Rank
DDM-C	HBA	0.76079	0.10014	1.00000	57.65219	0.03727	1.39050	1.82558	9.9318E-04 0.00099318377796803734	2
	WHO	0.76078	0.22574	0.75136	55.49025	0.03674	1.45093	2.00000	9.8248E-04 0.00098248491200868542	**1**
DDM-M	HBA	1.66382	4.62062	0.00060	17.95595	0.00899	1.71338	1.00000	1.7011E-03 0.00170114625497150680	**1**
	WHO	1.66390	0.00000	1.73866	15.92829	0.00427	60.00000	1.52030	1.7298E-03 0.00172981370994071620	2

In order to fully reveal the performances of the HBA and WHO algorithms, the RMSE results of the algorithms used in parameter extraction in the literature were compared with the RMSE results of the HBA and WHO of this study. This comparison is given in Table 5.

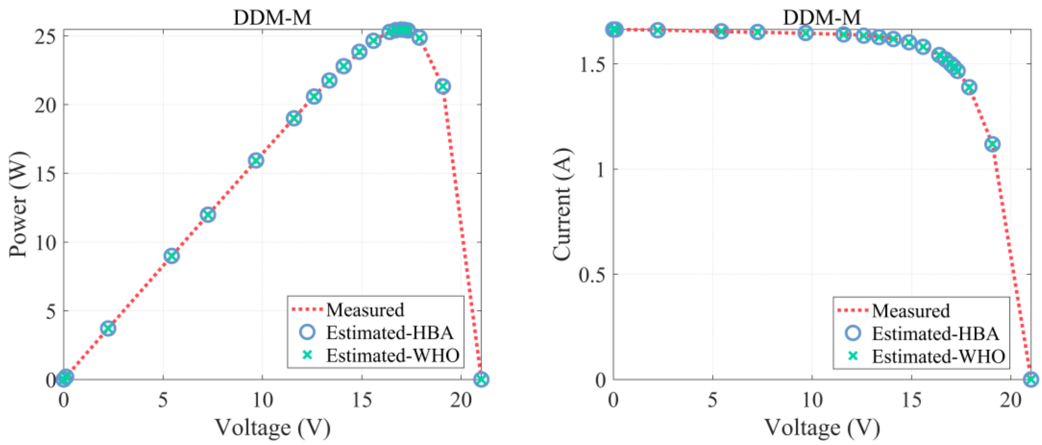
When Table 5 is examined, the RMSE results produced by the HBA and WHO algorithms are within the range reported in the literature. Therefore, these two algorithms can be used successfully in parameter extraction problem.

4.3. Results of Parameter Extraction Based on Evaluation Metrics

After independently running HBA and WHO algorithms 30 times, the results were recorded. The recorded objective function results and calculation times were analyzed using evaluation metrics. Table 6 shows the standard deviation (SD), the minimum, average, and maximum results of the objective function. WHO produced the lowest minimum values in SDM-C, DDM-C, and SDM-M. WHO algorithm had the lowest mean and maximum RMSE in all models, and HBA produced the highest objective function value. The smallest SD in all models belonged to the WHO algorithm.



(a) DDM-C



(b) DDM-M

Figure 6. P-V and I-V curves for DDM-C and DDM-M

Table 5. RMSE comparison results of PV models and algorithms

Algorithm	SDM-C	SDM-M	DDM-C	DDM-M
HBA	9.8602E-04	1.7298E-03	9.9318E-04	1.7011E-03
WHO	9.8602E-04	3.3299E-03	9.8248E-04	1.7298E-03
Equilibrium optimizer [15]	9.8603E-04	-	9.8553E-04	-
Adaptive harris hawks optimization [30]	9.8933E-04	-	9.9486E-04	-
Improved chaotic optimization algorithm [16]	9.8602E-04	1.6932E-02	9.8257E-04	-
Cat swarm optimization [31]	9.8602E-04	-	9.8252E-04	-
Complex evolution algorithm [32]	9.8602E-04	1.7298E-03	9.8248E-04	
Artificial ecosystem-based optimization algorithm [35]	9.8602E-04	1.7298E-03	9.8602E-04	1.7298E-03
Flexible particle swarm optimization [33]	9.8602E-04	1.6743E-02	9.8253E-04	
Artificial bee colony optimization [34]	9.8629E-04	-	9.8619E-04	-
Runge kutta optimizer [35]	1.0062E-03	1.7330E-03	9.8631E-04	1.8393E-03
Grey wolf optimizer [35]	3.6574E-03	3.1076E-01	2.5667E-03	5.0353E-03
Weighted mean of vectors optimization algorithm [35]	9.8602E-04	1.7298E-03	9.8248E-04	1.6949E-03
Artificial hummingbird algorithm [35]	9.8602E-04	1.7298E-03	9.8375E-04	1.7091E-03
Reptile search algorithm [35]	3.7211E-02	1.7714E-02	5.6100E-02	6.8145E-03
Grey wolf optimizer with dimension learning [36]	9.8602E-04	-	9.8248E-04	-

In addition, both algorithms showed a determined approach to providing successful solutions. Table 7 shows the results of the evaluation metrics for calculation times. HBA had the lowest minimum, average, and maximum calculation time. HBA had the lowest SD in the SDM-C, DDM-C, and DDM-M models, while WHO had the lowest SD in the SDM-M model. However, the calculation time alone is not a sufficient criterion. Although it varies according to the purpose of the problem, the algorithm performances should be evaluated together with the computational accuracy and computational time.

4.4. Convergence Curves

Figure 7 shows the process of producing solutions to the parameter extraction optimization problem of the HBA and WHO algorithms for the four models. The convergence curves showed that the results obtained by statistical methods and evaluation metrics converged.

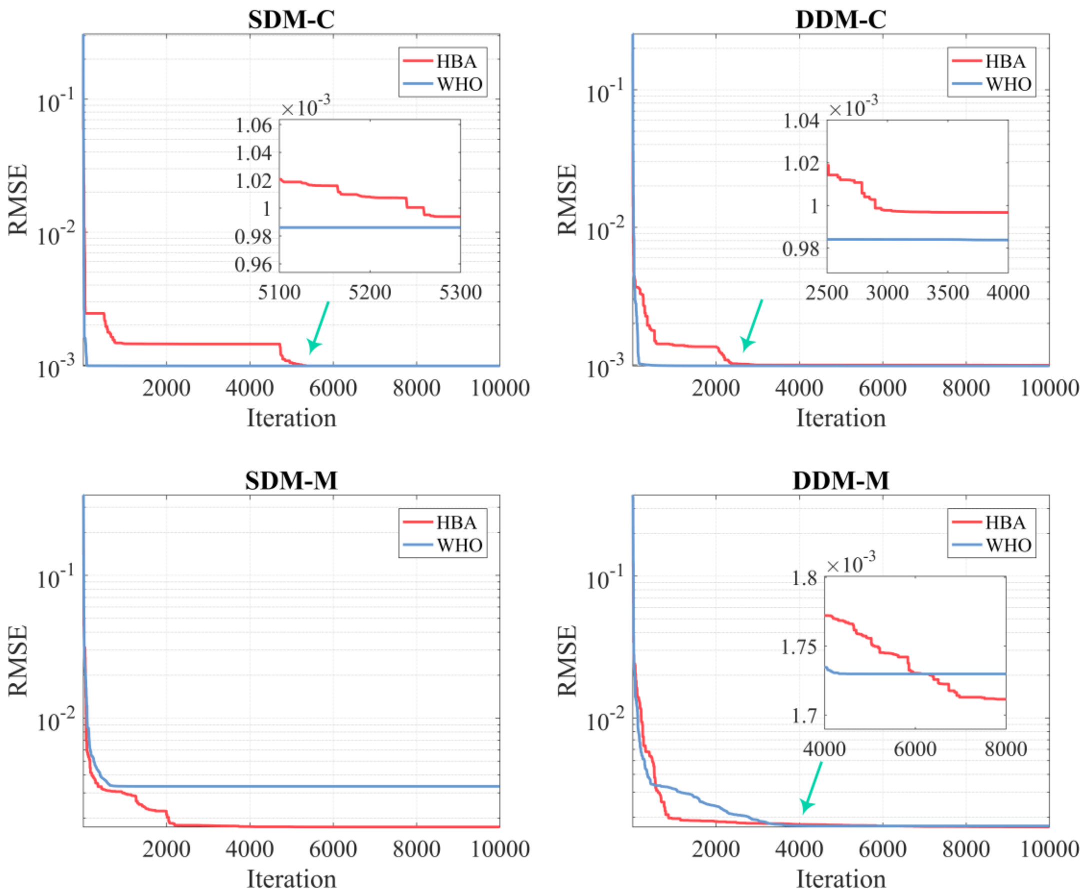


Figure 7. Convergence curves

Table 6. RMSE values for 30 runs

Model	Alg.	Minimum	Average	Maximum	SD	SD Rank
SDM-C	HBA	9.8602E-04 0.00098602187789165793	6.3480E-03 0.00634804181783911110	4.6014E-02 0.04601356782948297400	1.3538E-02 0.01353793060590704900	2
	WHO	9.8602E-04 0.000986021877891**5**1698	1.1403E-03 0.00**1**14032872604427630	2.4480E-03 0.0**0**114032872604427630	**3.1383E-04** **0.00031383106734804580**	**1**
DDM-C	HBA	9.8264E-04 0.00098264011744690649	3.8184E-03 0.00381841049961808300	4.6014E-02 0.04601356782948298100	9.9143E-03 0.00991429450862335060	2
	WHO	9.8248E-04 0.000982**4**8488734911437	1.0875E-03 0.00**1**08754751229876580	1.4385E-03 0.0**0**143847589736776350	**1.8936E-04** **0.00018935544657424784**	**1**
SDM-M	HBA	1.7298E-03 0.00172981370994070080	5.4262E-02 0.05426210555185624600	3.1076E-01 0.31075740938424645000	1.1667E-01 0.11667187601222467000	2
	WHO	1.7298E-03 0.0017298137099406**6**390	9.0574E-03 0.0**0**905739476217793520	1.5548E-01 0.**1**5548108439011429000	**2.8222E-02** **0.02822202932953198800**	**1**
DDM-M	HBA	1.7011E-03 0.0017**0**114625497150680	3.4372E-02 0.03437157918835451900	3.1076E-01 0.31075740938424645000	9.3710E-02 0.09371039366414607400	2
	WHO	1.7298E-03 0.00172980864681144640	2.8868E-03 0.0**0**288684546378478780	5.3604E-03 0.**0**0536036853218376480	**1.2361E-03** **0.00123612186837523560**	**1**

Table 7. Computational time values for 30 runs

Model	Alg.	Minimum	Average	Maximum	SD	SD Rank
SDM-C	HBA	1.4859E+01	1.6572E+01	1.9783E+01	**1.3490E+00**	**1**
	WHO	2.7135E+01	2.9517E+01	3.3453E+01	1.7139E+00	2
DDM-C	HBA	1.7345E+01	1.8065E+01	1.9282E+01	**6.0430E-01**	**1**
	WHO	2.5676E+01	2.7602E+01	3.0571E+01	1.4302E+00	2
SDM-M	HBA	1.3643E+01	1.5229E+01	1.9042E+01	1.6866E+00	2
	WHO	2.3984E+01	2.5047E+01	2.6649E+01	**6.4504E-01**	**1**
DDM-M	HBA	1.5566E+01	1.6636E+01	1.9505E+01	**9.6358E-01**	**1**
	WHO	2.6425E+01	2.9744E+01	3.9331E+01	3.5869E+00	2

5. CONCLUSION

Correct parameter extraction and working with optimum parameters are critical issues in PV systems. Besides, the maximum power point directly affects the monitoring performance, especially in converters connected to PV panels. Therefore, the current study used HBA and WHO algorithms to solve the parameter extraction optimization problem. The RMSE results for the four models, including SDM-C, SDM-M, DDM-C, and DDM-M, were 9.8602E-04, 1.7298E-03, 9.9318E-04, 1.7011E-03 for HBA, respectively. For WHO, they were 9.8602E-04, 3.3299E-03, 9.8248E-04 and 1.7298E-03, respectively. In addition, the algorithm performances were determined with evaluation metrics over RMSE. In computational accuracy and time, both algorithms–especially WHO–were effective and successful in PV parameter extraction and such engineering problem solutions.

In the next stages, the authors of this study plan to study MPPT efficiency in a real-time PV system with the data obtained from this study. The compatibility of the modeled PV system according to the data calculated by parameter estimation will be compared with the data obtained from a real PV system. Another work planned for the future, a hybrid algorithm can be designed by combining HBA and WHO algorithm to obtain more stable parameter values.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Kezban KOÇ: Writing-Original Draft, Review, Editing, Methodology, Conceptualization.

Mehmet DEMİRTAŞ: Supervision, Methodology, Writing-Original Draft, Review, Editing, Conceptualization, Validation.

İpek ÇETİNBAŞ: Conceptualization, Software, Methodology, Writing-Original Draft, Review, Editing, Formal analysis, Visualization.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

NOMENCLATURE

α	density factor	r_5	random numbers between [0,1]
ABC	artificial bee colony optimization	r_6	random numbers between [0,1]
C	constant number ($C \geq 1$, default 2)	r_7	random numbers between [0,1]
DDM	double diode model	R	uniform number
DDM-C	double diode model based on PV cell	$\vec{R}_1$	random vectors between [0,1]
DDM-M	double diode model based on PV module	$\vec{R}_2$	random vectors between [0,1]
D	dimension of HBA	$\vec{R}_3$	random vectors between [0,1]
d_i	prey distance and i is the badger	RMSE	root mean square error
EHBO	emended heap-based optimizer	N_s	number of series cells
F	flag	R_s	series resistance
FPA	flower pollination algorithm	R_{sh}	shunt resistance
G	number of groups	S	source strength of HBA
GOTLBO	generalized oppositional teaching learning based optimization algorithm	$Stallion^j$	position of stallion
HBA	honey badger algorithm	SDM	single diode model
IDX	indexes of the random vectors	SDM-C	single diode model based on PV cell
I_i	smell intensity of prey	SDM-M	single diode model based on PV module
I_{d1}	first diode current	$\overline{Stallion_{Gi}}$	next position of the leader of the i group
I_{d2}	second diode current	$Stallion_{Gi}$	current position of the leader

I_{DDM}	output current of DDM	T	operating temperature
I_{DDM-C}	output current of DDM-C	TDM	three diode model
I_{DDM-M}	output current of DDM-M	TDR	adaptive parameter
I_o	diode reverse saturation current	T_{HBA}	maximum number of iterations of HBA
I_{o1}	first diode reverse saturation current	T_{WHO}	maximum number of iterations of WHO
I_{o2}	second diode reverse saturation current	ub_i	upper bound of HBA
I_{ph}	photo-generated current	V	output voltage of the PV cell
I_{SDM}	output current of SDM	WHO	wild horse optimizer
I_{SDM-C}	output current of SDM-C	WH	position of the water hole
I_{SDM-M}	output current of SDM-M	Z	adaptive mechanism
I_{sh}	shunt resistor current	x	horse population
k	boltzmann constant	x_i	honey badger position
lb_i	lower bound of HBA	x_{prey}	position of the prey
N_{HBA}	number of populations of HBA	x_{new}	new position of the honey badger
N_{WHO}	number of populations of WHO	${X^j}_{i,G}$	group members' current position
PS	percentage of stallions	$\overline{X^j}_{i,G}$	group members' new position
PV	photovoltaic	${X^z}_{G,j}$	is the position of the horse z in group j
P	a vector	${X^P}_{G,K}$	position of horse p from group k
q	electron charge	${X^q}_{G,i}$	position of the foal in group i
r_1	random numbers between [0,1]	α	diode ideality factor
r_2	random numbers between [0,1]	α_1	first diode ideality factor
r_3	random numbers between [0,1]	α_2	second diode ideality factor
r_4	random numbers between [0,1]	β	constant number ($\beta \geq 1$, default 6)

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