Gazi Üniversitesi
Fen Bilimleri Dergisi
PART C: TASARIM VE TEKNOLOJİ

Gazi University
Journal of Science
PART C: DESIGN AND TECHNOLOGY

GU J Sci, Part C, 12(4): 945-959 (2024)

Parameter Extraction of Photovoltaic Cell and Module with Four-Diode Model Using Flood Algorithm

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Article Info

Research article
Received: 13/11/2024
Revision: 29/11/2024
Accepted: 05/12/2024

Keywords

Flood Algorithm
Four-Diode Model
Friedman Test
Parameter Extraction
Photovoltaic
Wilcoxon Signed-Rank Test

Makale Bilgisi

Araştırma makalesi
Başvuru: 13/11/2024
Düzeltme: 29/11/2024
Kabul: 05/12/2024

Anahtar Kelimeler

Taşkın Algoritması
Dört Diyotlu Model
Friedman Testi
Parametre Çıkarımı
Fotovoltaik
Wilcoxon İşaretli Sıra Testi

Graphical/Tabular Abstract (Grafik Özet)

In this study, the PV parameter extraction problem has been studied. The eleven unknown parameters of the four-diode model have been extracted using the FLA, PLO, MGO, WO, and ECO algorithms. The results have been evaluated using evaluation metrics and statistical tests. / Bu çalışmada, FV parametre çıkarımı problemi üzerinde çalışılmıştır. Dört diyotlu modelin bilinmeyen on bir parametresi FLA, PLO, MGO, WO ve ECO algoritmaları ile çıkartılmıştır. Sonuçlar, değerlendirme metrikleri ve istatistiksel testler ile değerlendirilmiştir.

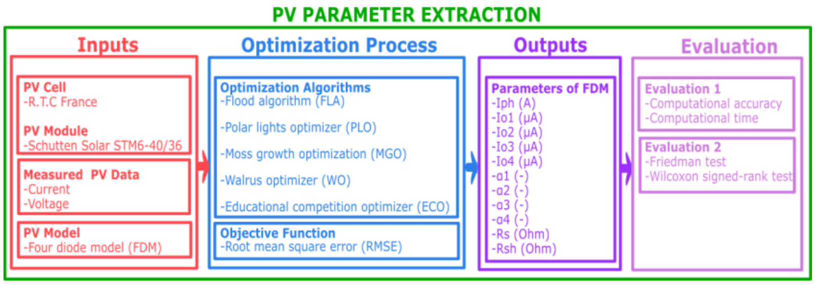

***Figure A**: PV parameter extraction process / **Şekil A**:. FV parametre çıkarımı süreci*

Highlights (Önemli noktalar)

- *The PV parameter extraction of the four-diode model has been performed. / Dört diyotlu modelin PV parametre çıkarımı yapılmıştır.*
- *For the first time, the FLA, PLO, MGO, WO, and ECO algorithms have been used to solve this problem in this study. / Bu problemin çözümü için FLA, PLO, MGO, WO ve ECO algoritmaları ilk defa bu çalışmada kullanılmıştır.*
- *The success of the FLA algorithm in PV parameter extraction has been statistically proven. / FLA algoritmasının PV parametre çıkarımında ki başarısı istatistiksel olarak kanıtlanmıştır.*

***Aim (Amaç):** This study aims to extract the unknown parameters of a PV cell and module. / Bu çalışma bir FV hücrenin ve modülün bilinmeyen parametrelerini çıkarmayı amaçlamaktadır.*

***Originality (Özgünlük):** When examining literature, it can be observed that single, double, and triple diode models are widely used, while four-diode model is included in very few studies. Motivated by this, this article focuses on PV parameter extraction for four-diode model using metaheuristic algorithms. FLA, PLO, MGO, WO, and ECO have been used for the first time to solve the defined problem and successful results have been obtained. / Literatür incelendiğinde, tek, çift ve üçlü diyot modellerinin yaygın olarak kullanıldığı, dört diyotlu modelin ise çok az çalışmada yer aldığı görülmektedir. Bu noktadan yola çıkılarak bu makale, meta sezgisel algoritmalar kullanılarak dört diyotlu model için PV parametre çıkarımına odaklanmaktadır. Tanımlanan problemin çözümünde FLA, PLO, MGO, WO ve ECO ilk kez kullanılmış ve başarılı sonuçlar elde edilmiştir.*

***Results (Bulgular):** The smallest minimum RMSE was obtained with FLA, calculated as 9.8251385E-04 with FDM-C and 1.6884311E-03 with FDM-M. / En küçük minimum RMSE FLA ile elde edilmiş olup FDM-C ile 9.8251385E-04 ve FDM-M ile 1.6884311E-03 olarak hesaplanmıştır.*

***Conclusion (Sonuç):** According to evaluation metrics and statistical tests, FLA produced significantly better results than the other algorithms and outperformed them in pairwise comparisons. In conclusion, FLA has proven to be a successful and promising algorithm for PV parameter extraction, with its success statistically validated. / Değerlendirme metrikleri ve istatistiksel testlere göre; FLA diğer algoritmalardan daha önemli sonuçlar ürettiği ve ikili karşılaştırmalar neticesinde de diğer algoritmalardan daha başarılı olduğu görülmüştür. Sonuç olarak, FLA'nın FV parametre çıkarımında başarılı ve umut vaat eden bir algoritma olduğu görülmüş ve başarısı istatistiksel olarak kanıtlanmıştır.*

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DOI: 10.29109/gujsc.1584147

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Abstract

Photovoltaic (PV) cells exhibit a nonlinear characteristic. Before modeling these cells, obtaining accurate parameters is essential. During the modeling phase, using these parameters is crucial for accurately characterizing and reflecting the behavior of PV structures. Therefore, this article focuses on PV parameter extraction. A PV cell and module were selected and modeled using the four-diode model (FDM). This problem, consisting of eleven unknown parameters related to the FDM, was solved with the flood algorithm (FLA). To compare the algorithm's performance on the same problem, the polar lights optimizer (PLO), moss growth optimization (MGO), walrus optimizer (WO), and educational competition optimizer (ECO) were also employed. These five metaheuristic algorithms were used for the first time in this study, both for solving the PV parameter extraction problem and with the FDM. The objective function aimed at obtaining the smallest root mean square error (RMSE) was evaluated and compared through evaluation metrics, computational accuracy, computational time, and statistical methods. The smallest minimum RMSE was obtained with FLA, calculated as 9.8251385E-04 with FDM-C and 1.6884311E-03 with FDM-M. To statistically demonstrate and reinforce FLA's success over other algorithms, the Friedman test and Wilcoxon signed-rank test were utilized. According to these tests, FLA produced significantly better results than the other algorithms and outperformed them in pairwise comparisons. In conclusion, FLA has proven to be a successful and promising algorithm for PV parameter extraction, with its success statistically validated.

Taşkın Algoritması Kullanılarak Dört Diyotlu Model ile Fotovoltaik Hücre ve Modülün Parametre Çıkarımı

Makale Bilgisi

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Öz

Fotovoltaik (FV) hücreler doğrusal olmayan karakteristiğe sahiptir. Bu hücrelerin modellenmesinin öncesinde doğru parametrelerin elde edilmesi gereklidir. Modellenme aşamasında ise bu parametrelerin kullanımı FV yapıların davranışlarının doğru karakterize edilebilmesi ve yansıtılabilmesi açısından çok önemlidir. Bu sebeple bu makalede, FV parametre çıkarımı çalışılmıştır. Bir FV hücre ve modül seçilmiş ve dört diyotlu model (FDM) ile modellenmiştir. FDM'ye ilişkin bilinmeyen on bir parametreden oluşan bu problem taşkın algoritması (FLA) ile çözülmüştür. Aynı problemin çözümünde algoritmanın karşılaştırılması için, kutup ışıkları optimizasyonu (PLO), yosun büyüme optimizasyonu (MGO), mors optimizasyonu (WO) ve eğitim rekabeti optimizasyonu (ECO) kullanılmıştır. Bu beş meta sezgisel algoritma, hem FV parametre çıkarımı probleminin çözümü için hem de FDM ile ilk defa bu çalışmada kullanılmıştır. En küçük kök ortalama kare hatası (RMSE) elde edilmenin amaçlandığı amaç fonksiyonu; değerlendirme metrikleri, hesaplama doğruluğu, hesaplama zamanı ve istatistiksel metotlar ile değerlendirilmiş ve karşılaştırılmıştır. En küçük minimum RMSE FLA ile elde edilmiş olup FDM-C ile 9.8251385E-04 ve FDM-M ile 1.6884311E-03 olarak hesaplanmıştır. FLA'nın diğer algoritmalara göre başarısını istatistiksel olarak kanıtlamak ve pekiştirmek için statistical tests kullanılmıştır. Bu testlere göre; FLA diğer algoritmalardan daha önemli sonuçlar ürettiği ve ikili karşılaştırmalar neticesinde de diğer algoritmalardan daha başarılı olduğu görülmüştür. Sonuç olarak, FLA'nın FV parametre çıkarımında başarılı ve umut vaat eden bir algoritma olduğu görülmüş ve başarısı istatistiksel olarak kanıtlanmıştır.

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1. INTRODUCTION (GİRİŞ)

According to the International Energy Agency data, PV and wind energy systems have doubled in both capacity increase and their share in electricity generation between 2018 and 2023. This significant development is expected to reflect as a cost reduction by 2030 [1]. Among renewable energy sources, PV systems play a key role in the clean energy transition due to their low cost. With their modular technological structure, they have a wide range of applications, from small residential-type installations to large-scale, gigawatt-level power plant applications [2], [3]. PV systems can convert sunlight directly into electrical energy without moving parts. These systems are a sustainable energy source through their various applications. Additionally, they stand out for their environmentally friendly approach and advantages [4]-[6].

Maximizing the benefit obtained from PV systems requires focusing on PV cells. The accurate characterization of the behavior of these cells is related to obtaining electrical models and extracting the fundamental parameters that form these models with the highest possible accuracy. Correctly modeling the current-voltage characteristics of PV cells, which have a nonlinear characteristic, forms the basis for many topics, including PV cell design, fault detection, energy forecasting, and maximum power point tracking. Furthermore, it directly affects the design and capacities of other components in PV systems, playing a decisive role in the operation and optimal energy management of the systems [7]-[9].

In PV parameter extraction studies, PV cells and modules are modeled as single diode, double diode, three diode, and four-diode models. Various approaches are used to improve computational accuracy and reduce computation time in obtaining the parameters of these models. Analytical and numerical/iterative methods [10], deterministic methods [11], modified deterministic methods [12], numerical/iterative and deterministic methods [13], metaheuristic algorithms and advanced / improved / enhanced bio-inspired techniques [14]-[25], and hybrid and adaptive methods [26]-[34] are among the many methods used. A total of 25 articles corresponding to these categories have been reviewed. The summary of this literature review is provided in Table 1, with column headings for algorithm/method, PV cell/module, PV model, and objective function. In studies where RMSE is used as the objective function for different algorithms and methods, PV cells and modules have been modeled as single diode model based cell (SDM-C), single diode model based module (SDM-M), double diode model based cell (DDM-C), double diode model based module (DDM-M), three diode model based cell (TDM-C), three diode model based module (TDM-M), four-diode model based cell (FDM-C), and four-diode model based module (FDM-M).

Table 1. Literature review (Literatür incelemesi)

Algorithm/Method	PV Cell/Module	PV Model								Objective Function (RMSE)
		SDM		DDM		TDM		FDM		
		C	M	C	M	C	M	C	M	
Analytical and numerical/iterative methods [10]	SP70		☑							☑
Lambert W-function [11]	SP40, SP70, KC200GT		☑							☑
Modified newton–raphson method [12]	RTC France, CHL285P, PWP210	☑	☑							☑
Iterative method and the Lambert W function [13]	SQ80, KC200GT, ST40		☑							☑
Weighted leader search algorithm [14]	R.T.C France, PVM 752, STM6-40/36, LSM 20, PWP201, STP6-120/36, KC200GT, ESP-160 PPW	☑	☑	☑	☑	☑	☑			☑
INFO algorithm [15]	RTC France, Photowatt-PW201, STM6-40/36, STP6-120/36	☑	☑	☑	☑					☑
Artificial hummingbird algorithm [16]	RTC France	☑		☑		☑				☑
Puffer fish inspired optimization technique [17]	RTC France							☑		☑
Ranking teaching–learning-based optimization algorithm [18]	R.T.C France, STM6-40/36, STP6-120/36	☑	☑	☑	☑					☑
Diversity improvement-oriented differential evolution [19]	PW201, STM6-40/36, STP6-120/36	☑	☑	☑		☑				☑

Multi-strategy gaining-sharing knowledge-based algorithm [20]	RTC France, PW201, STM6-40/36, STP6-120/36	☑	☑	☑	☑						☑
Manta ray foraging optimization with dynamic fitness distance balance [21]	STP6–120/36, PWP201, XKD-50W, XHYG-10W						☑				☑
Developed JAYA algorithm [22]	RTC France, PWP201	☑	☑	☑		☑					☑
Multi-strategy-based tree seed algorithm [23]	RTC France, PWP201, STM6-40/36	☑	☑	☑	☑						☑
Enhanced snake optimization algorithm [24]	RTC France, PWP201, STM6-40/36	☑	☑	☑	☑						☑
Fractional order kepler optimization algorithm [25]	RTC France, KC-200, Ultra-Power-85, SP-70	☑	☑	☑	☑						☑
Hybrid white shark optimizer and artificial rabbits optimization [26]	R.T.C France, PVM 752, STM6-40/36, LSM 20, PWP 201, STP6-120/36, STE 4/100, KC200GT	☑	☑	☑	☑						☑
Hybrid particle swarm optimization and dingo optimizer [27]	RTC France							☑			☑
Enhanced chaotic JAYA algorithm [28]	R.T.C France, STM6-40/36, STP6-120/36	☑	☑	☑	☑						☑
Hybrid analytical/iterative method [29]	R.T.C France, PVM 752, PWP201	☑	☑								☑
Micro adaptive fuzzy cuckoo search optimization [30]	PWP201, STM6-40/36		☑		☑		☑		☑		☑
Improved grey wolf optimization [31]	RTC France							☑			☑
Fitness-guided particle swarm optimization with adaptive newton-raphson [32]	RTC France, SM55, KC200GT							☑	☑		☑
Multiagent system based cuckoo search optimization with lambert W-function [33]	R.T.C France, PWP201	☑	☑								☑
Lambert w-function and newton-raphson method collaborated with spider wasp optimizer [34]	R.T.C France, PWP201, KC200GT, STM6-40/36	☑	☑	☑	☑	☑	☑				☑

In addition to various methods, different metaheuristic algorithms have been used for PV parameter extraction. The solution of a problem with different metaheuristic algorithms can be explained using the no free lunch theorem. According to this theorem, no algorithm can solve all problems. Furthermore, the success of algorithms in problem-solving is not standard and may be either good or bad depending on the problem. There is no such thing as the best algorithm [35]. This is because each metaheuristic algorithm has its strengths and weaknesses. As a result, different success levels appear in different problems [36]. Additionally, when examining Table 1, it can be observed that SDM, DDM, and TDM are widely used, while FDM is included in very few studies in the literature. Motivated by this, this article focuses on PV parameter extraction for FDM using metaheuristic algorithms.

This article presents PV parameter extraction. The extraction of the eleven unknown parameters of a PV cell and module, modeled as FDM-C and FDM-M, was obtained using FLA. This problem was also solved using the PLO, MGO, WO, and ECO algorithms. These five metaheuristic algorithms were used for the first time in this study to solve the parameter extraction problem. The objective function, aimed at obtaining the smallest RMSE, was compared using evaluation metrics and statistical methods.

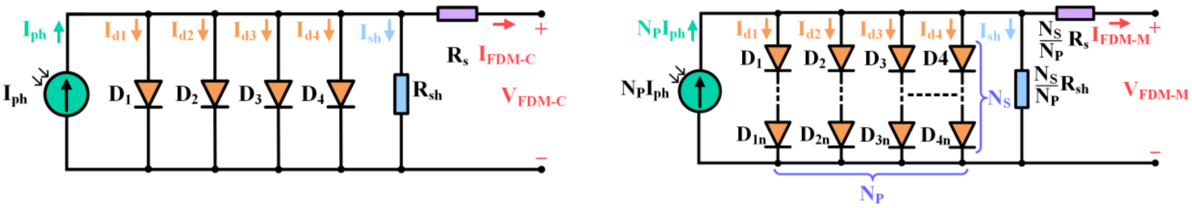
This article consists of five sections. Following the introduction, the second section defines the problem and objective function. The third section presents the FLA algorithm, the solution method for the problem, in detail. Additionally, the PLO, MGO, WO, and ECO algorithms are summarized. The fourth section examines the parameter extraction results in detail, and the fifth section presents the conclusions.

2. DEFINITION OF THE PROBLEM
(PROBLEMİN TANIMLANMASI)

The problem of this article is PV parameter extraction for FDM. This section is presented under two subheadings: FDM of PV cell and module, and objective function.

2.1. Four-Diode Model (FDM) of PV Cell and Module (PV Hücre ve Modülün Dört Diyotlu Modeli (FDM))

FDM is a detailed approach for modeling PV cells and modules. Despite its high computational demand, parameter sensitivity, and complex implementation, it allows the nonlinear nature and behavior of PV to be reflected with higher accuracy under various conditions compared to single, double, and three-diode models. The electrical circuit of a PV cell and module with FDM is shown in Figure 1(a) and (b). It consists of a photo-generated source (I_{ph}), four diodes connected in parallel (D_1, D_2, D_3, D_4), a parallel/shunt resistance (R_{sh}), and a series resistance (R_s). The diffusion current is represented by the first diode, recombination in the depletion region by the second diode, recombination in other regions by the third diode, and leakage currents due to structural imperfections by the fourth diode. The general current representation for FDM, obtained by subtracting the diode currents and shunt current from the photo-generated current, is given for FDM-C and FDM-M in Equation (1) [9], [30], [37]-[38].



a) FDM-C b) FDM-M

Figure 1. Electrical circuit of PV cell and module with FDM (FDM ile FV hücre ve modülün elektriksel devresi)

$$I_{FDM}=\begin{cases} I_{FDM}=I_{ph}-I_{d1}-I_{d2}-I_{d3}-I_{d4}-I_{sh} \\ I_{FDM-C}=\left[\begin{aligned} & I_{ph}-I_{o1}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_1 V_t}\right)}-1\right]-I_{o2}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_2 V_t}\right)}-1\right]-\cdots \\ & I_{o3}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_3 V_t}\right)}-1\right]-I_{o4}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_4 V_t}\right)}-1\right]-\frac{V_{FDM-C}+R_s I_{FDM-C}}{R_{sh}} \end{aligned}\right. \\ I_{FDM-M}=\left[\begin{aligned} & I_{ph}-I_{o1}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_1 V_t N_s}\right)}-1\right]-I_{o2}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_2 V_t N_s}\right)}-1\right]-\cdots \\ & I_{o3}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_3 V_t N_s}\right)}-1\right]-I_{o4}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_4 V_t N_s}\right)}-1\right]-\cdots \\ & \frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{R_{sh} N_s} \end{aligned}\right. \end{cases} \quad (1)$$

Where, I_{FDM} is the output current of FDM, I_{ph} is the photo-generated current, I_{d1} is the 1st diode current, I_{d2} is the 2nd diode current, I_{d3} is the 3rd diode current, I_{d4} is the 4th diode current, I_{sh} shunt resistance current, I_{o1} is the 1st diode reverse saturation current, V_{FDM-C} are the output voltage of PV cell, R_s is the series resistance, I_{FDM-C} are the output current of PV cell, α_1 is the 1st diode ideality factor, V_t is the junction thermal voltage, I_{o2} is the 2nd diode reverse saturation current, α_2 is the 2nd diode ideality factor, I_{o3} is the 3rd diode reverse saturation current, α_3 is the 3rd diode ideality factor, I_{o4} is the 4th diode reverse saturation current, α_4 is the 4th diode ideality factor, R_{sh} is the shunt resistance, V_{FDM-M} are the output voltage of PV module, N_s is the number of series-connected PV cells, and I_{FDM-M} are the output current of PV module.

2.2. Objective Function (Amaç Fonksiyonu)

The objective function of the PV parameter extraction problem to be solved with FLA, PLO, MGO, WO, and ECO algorithms is RMSE. To achieve this, the difference between the estimated and measured currents of the PV cell or module is minimized. The general representation of the function showing the difference between the estimated and measured current for FDM, the current function for FDM-C, the current function for FDM-M, and the decision variables of these functions are given in Equation (2). The RMSE used as the objective function is given in Equation (3) [15].

$$f_{FDM}(x) = \begin{cases} f_{FDM}(x) = (I_{estimated}) - (I_{measured}) \\ f_{FDM-C}(x) = \begin{matrix} \left(I_{ph} - I_{o1}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_1 V_t}\right)} - 1\right] - I_{o2}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_2 V_t}\right)} - 1\right] - \cdots \right. \\ \left. I_{o3}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_3 V_t}\right)} - 1\right] - I_{o4}\left[e^{\left(\frac{V_{FDM-C}+R_s I_{FDM-C}}{\alpha_4 V_t}\right)} - 1\right] - \frac{V_{FDM-C}+R_s I_{FDM-C}}{R_{sh}}\right) - \left(I_{FDM-C_{measured}}\right) \end{matrix} \\ f_{FDM-M}(x) = \begin{matrix} \left(I_{ph} - I_{o1}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_1 V_t N_s}\right)} - 1\right] - I_{o2}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_2 V_t N_s}\right)} - 1\right] - \cdots \right. \\ I_{o3}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_3 V_t N_s}\right)} - 1\right] - I_{o4}\left[e^{\left(\frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{\alpha_4 V_t N_s}\right)} - 1\right] - \cdots \\ \left. \frac{V_{FDM-M}+N_s R_s I_{FDM-M}}{R_{sh} N_s}\right) - \left(I_{FDM-M_{measured}}\right) \end{matrix} \end{cases} \tag{2}$$

$$x = \begin{cases} x_{FDM-C} = I_{ph}, I_{o1}, I_{o2}, I_{o3}, I_{o4}, \alpha_1, \alpha_2, \alpha_3, \alpha_4, R_s, R_{sh} \\ x_{FDM-M} = I_{ph}, I_{o1}, I_{o2}, I_{o3}, I_{o4}, \alpha_1, \alpha_2, \alpha_3, \alpha_4, R_s, R_{sh} \end{cases}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[f_{FDM}(x)]^2} \tag{3}$$

Where, $f(x)$ is the current function, x is the decision variable, $f_{FDM}(x)$ is the current function of FDM, $I_{estimated}$ is the estimated current, $I_{measured}$ is the measured current, $f_{FDM-C}(x)$ is the current function of FDM-C, $I_{FDM-C_{measured}}$ is the measured current of FDM-C, $f_{FDM-M}(x)$ is the current function of FDM-M, $I_{FDM-M_{measured}}$ is the measured current of FDM-M, x_{FDM-C} is the decision variables of FDM-C, x_{FDM-M} is the decision variables of FDM-M, and $RMSE$ is the root mean square error.

3. FLOOD ALGORITHM (FLA) AND BRIEF SUMMARY OF PLO, MGO, WO, AND ECO ALGORITHMS (TAŞKIN ALGORİTMASI (FLA) VE PLO, MGO, WO VE ECO ALGORİTMALARININ KISA ÖZETİ)

The PV parameter extraction problem has been solved using the FLA, PLO, MGO, WO, and ECO algorithms, and the details are provided in the subsections.

3.1. Flood Algorithm (FLA) (Taşkın Algoritması (FLA))

FLA is a metaheuristic algorithm inspired by natural flood events in river basins and the movement of water masses during these events. The movement of water in natural flood events, the behavior of water in response to slopes, and changes in the flow velocity and levels of water have all been addressed and mathematically modeled. FLA operates in two phases: regular movement and flooding, and the flowchart and pseudocode of FLA are shown in Figure 2 and Algorithm 1, respectively. Here, the water mass corresponds to the population of the algorithm, which searches for the best solution. The movement of the water mass in the direction of the slope corresponds to moving toward a better solution. Flooding corresponds to increasing population diversity.

3.1.1. Phase I: regular movement (Faz I: düzenli hareket)

This phase involves the modeling of three stages. In the first stage, the population search represents the natural movement of water toward the slope or a better point for the defined problem size. In the second stage, the population representing the water flow is modeled. In the final stage, the soil impermeability coefficient and its effect on the flood are examined. The general movement inspired by the natural movement of the water mass is given in Equation (4). Floods can occur as the flow of water in the river increases. The flow of water is modeled with the water depletion coefficient in Equation (5). Floods are not planned events and occur based on many factors. This random situation is reflected by the random ($rand$) parameter and the motion of the water masses is given in Equation (6). Another factor affecting the flood is the water permeability, which expresses the relationship between water and soil and reduces the risk of flooding. The soil permeability coefficient is given in Equation (7). There is an inverse relationship between this value and water flooding. A high soil permeability coefficient reduces the probability of water flooding, while the opposite increases the likelihood of flooding. As a result, the motion of the water masses or the position of the new swarm is determined by the rule given in Equation (8).

$$S_i^{new} = \begin{matrix} S_{best} + rand \times (S_j - S_i) \\ j = 1{:}D \end{matrix} \tag{4}$$

$$Pk = (1.2/t) \times \left[\sqrt{T_{FLA} \times t^2 + 1} + \left((1/(T_{FLA}/4) \times t) \times \ln\left(\sqrt{T_{FLA} \times t^2 + 1} + (T_{FLA}/4)\right)\right)\right]^{-2/3} \tag{5}$$

$$S_i^{new} = S_i + \left((Pk)^{randn}/t\right) \times (rand \times (S_{max} - S_{min}) + S_{min}) \quad (6)$$

$$Pe_i = ((f(S_i) - f_{min})/(f_{max} - f_{min}))^2 \quad (7)$$

$$S_i^{new} = \begin{cases} Equation\ 6 & if\ rand > rand + Pe_i \\ Equation\ 4 & if\ rand \le rand + Pe_i \end{cases} \quad (8)$$

Where, S_i^{new} is the motion of the water masses or ith position of new swarm, S_{best} is the slope of the water path, $rand$ is the random values between 0 and 1, S_j is the jth randomly member of the population, S_i is the ith randomly member of the population, D is the size of the problem, Pk is the water depletion coefficient, T_{FLA} is the maximum number of iterations, t is the current iteration, $randn$ is the normally distributed random number, S_{max} is the upper bound of the decision variable/s, S_{min} is the lower bound of the decision variable/s, f_{max} is the best value of the objective function, and f_{min} is the worst value of the objective function.

3.1.2. Phase II: flooding (Faz II: taşkın)

In real life, water can be added to the water basin by rain or melting snow, and some water can evaporate by evaporation. It is assumed that the probability of water being added or evaporating is equal, as expressed in Equation (9). The poor solutions will be displaced by the newly added particles, and the position of the new solutions is given in Equation (10).

$$Pt = |\sin(rand/t)| \quad (9)$$

$$S_e^{new} = \begin{matrix} S_{best} + rand \times (rand \times (S_{max} - S_{min}) + S_{min}) \\ e = 1{:}\, N_e \end{matrix} \quad (10)$$

Where, Pt is the probability of occurrence of increase or decrease of water mass and N_e is the number of water particles [39].

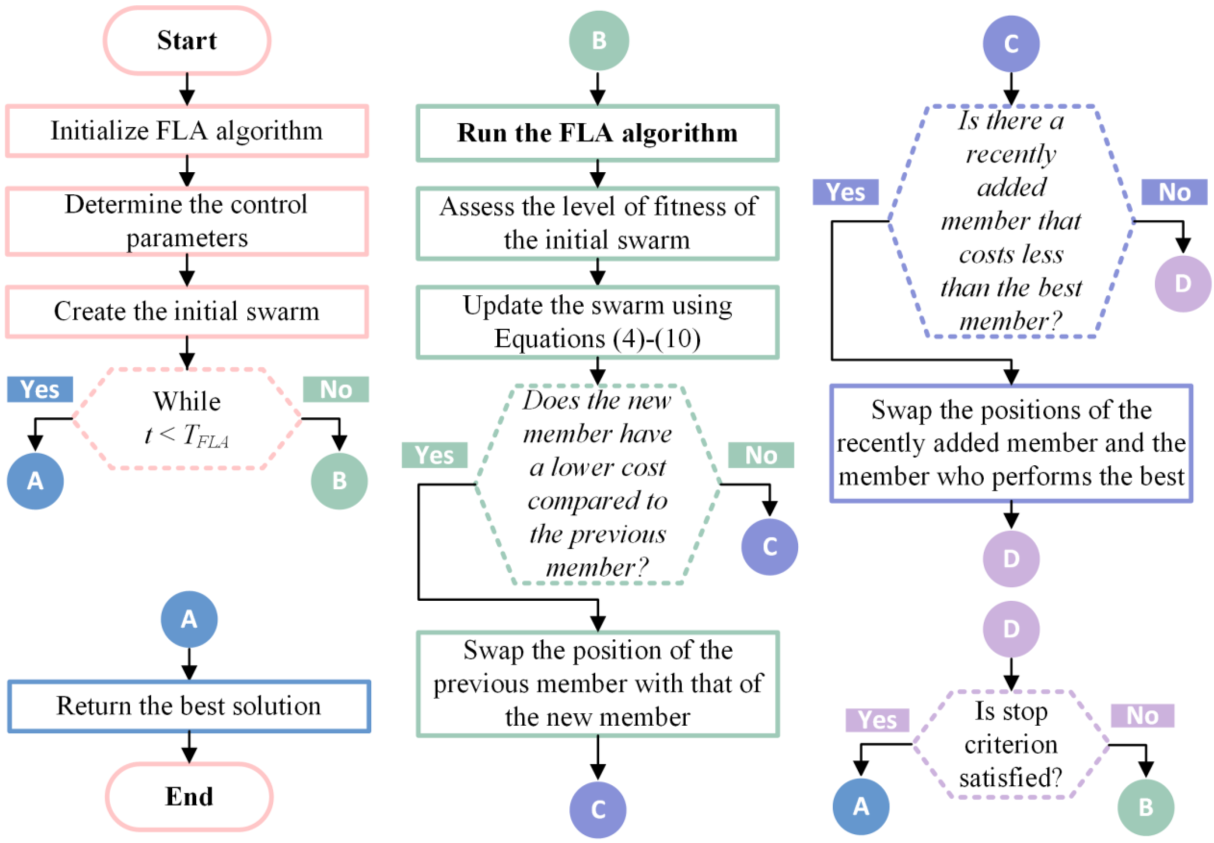


Figure 2. Flowchart of FLA (FLA'nın akış diyagramı)

Algorithm 1. Pseudocode of FLA (FLA'nın sözde kodu)

Phase	Step	FLA algorithm
Initialization		Parameter settings: N_e, N_{FLA}, t, T_{FLA}
Process	1	To create the accidental initial swarm/population N_{FLA} $(i = 1, \cdots, N_{FLA})$
	2	$S_i = S_{min} + rand \times (S_{max} - S_{min})$
	3	To evaluate the fitness of initial random swarm
	4	**while** $t = 0 \leq T_{FLA}$ **do**
	5	To arrange the generations $t = t + 1$
	6	**for** $i = 1$ in N_{FLA} **do**
	7	$Pe_i = ((f(S_i) - f_{min})/(f_{max} - f_{min}))^2$
	8	**if** $rand > rand + Pe_i$ **then**
	9	$S_i^{new} = S_i + ((Pk)^{randn}/t) \times (rand \times (S_{max} - S_{min}) + S_{min})$
	10	**else**
	11	$S_i^{new} = S_{best} + rand \times (S_j - S_i)$
	12	**end if**
	13	**if** $f(S_i^{new}) < f(S_i)$ **then**
	14	$S_i = S_i^{new}$ and $f(S_{best}) = f(S_i)$
	15	**end if**
	16	**if** $f(S_i) < f(S_{best})$ **then**
	17	$S_{best} = S_i$ and $f(S_{best}) = f(S_i)$
	18	**end if**
	19	**end for**
	20	**if** $rand < P_t, Pt = \lvert\sin(rand/t)\rvert$ **then**
	21	**for** e= 1 in N_e **do**
	22	$S_e^{new} = S_{best} + rand \times (rand \times (S_{max} - S_{min}) + S_{min})$
	23	**if** $f(S_e^{new}) < f(S_{best})$ **then**
	24	$S_{best} = S_e^{new}$ and $f(S_{best}) = f(S_e^{new})$
	25	**end if**
	26	**end for**
	27	**end if**
	28	**end while**
Output		Return the optimum solution S_{best} that has been optimized by FLA

3.2. Brief Summury Of PLO, MGO, WO, And ECO Algorithms (PLO, MGO, WO ve ECO Algoritmalarının Kısa Özeti)

In addition to FLA, the PLO, MGO, WO, and ECO algorithms were also used in solving this problem. These algorithms are summarized in Table 2 with the column headings algorithm, inspiration source, control/key parameter, and value. As seen in the table, these five algorithms have different operating scenarios and mathematical infrastructures due to their inspiration sources. FLA is inspired by water dynamics and flood behavior, PLO by aurora phenomena and light movement, MGO by growth and expansion patterns of moss, WO by social behavior and foraging of walruses, and ECO by competitive learning in educational settings. FLA, MGO, and ECO have one, PLO has two, and WO has three control/key parameters, which influence the performance of the algorithms [39]-[43].

Table 2. Inspiration and control parameters of FLA, PLO, MGO, WO, and ECO algorithms (FLA, PLO, MGO, WO ve ECO algoritmalarının ilham ve kontrol parametreleri)

Algorithm	Inspiration Source	Control/Key Parameter	Value
Flood algorithm (FLA) [39]	Water dynamics and flood behavior	N_e	5
Polar lights optimizer (PLO) [40]	Aurora phenomena and light movement	m	100
		α	[1,1.5]
Moss growth optimization (MGO) [41]	Growth and expansion patterns of moss	w	2
Walrus optimizer (WO) [42]	Social behavior and foraging of walruses	N_{WO}	50
		T_{WO}	10000
		p	0.4
Educational competition optimizer (ECO) [43]	Competitive learning in educational settings	N_{ECO}	50

4. RESULTS OF PV PARAMETER EXTRACTION AND EVALUATION (FV PARAMETRE ÇIKARIMI SONUÇLARI VE DEĞERLENDİRME)

In this section, the PV parameter extraction results for FDM-C and FDM-M using the FLA, PLO, MGO, WO, and ECO algorithms and their performance in solving this problem are presented. This section is provided under the subheadings of inputs, results, computational accuracy and computational time, statistical tests, and convergence curves.

4.1. Inputs (Girdiler)

MATLAB software has been used for the simulation of this article. The code has been written as an m-file. The specifications of the computer on which the algorithms were run are as follows: Intel(R) Core(TM) i7-4790 CPU@3.60GHz, 24GB RAM. The number of particles for all algorithms is 50. One run consists of 10,000 iterations, and a total of 30 runs were performed. For the PV parameter extraction problem, one PV cell and one PV module have been selected. The real current and voltage data of RTC France [44] have been used for the PV cell, and the real current and voltage data of Schutten Solar STM6-40/36 [45] have been used for the PV module. The short-circuit current, open-circuit voltage, current, and voltage at the maximum power point of the RTC France photovoltaic (PV) cell are 0.7603 A, 0.5728 V, 0.6894 A, and 0.4507 V, respectively. The Schutten Solar STM6-40/36 PV module consists of 36 series-connected cells. The short-circuit current, open-circuit voltage, current, and voltage at the maximum power point of this module are 1.663 A, 21.02 V, 1.50 A, and 16.98 V, respectively. There are eleven parameters to be extracted for FDM-C and FDM-M. The lower and upper bounds of decision variables for FDM-C and FDM-M are provided in Table 3.

Table 3. Lower and upper bounds of decision variables for FDM-C and FDM-M (FDM-C ve FDM-M için karar değişkenlerinin alt ve üst sınırları)

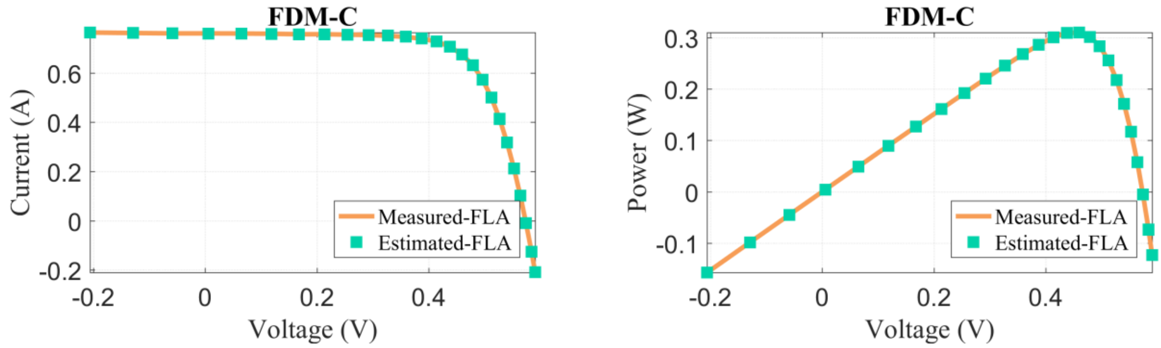
PV Model	Lower Bound					Upper Bound				
	I_{ph} (A)	$I_{o1}, I_{o2}, I_{o3}, I_{o4}$ (μA)	$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ (-)	R_s (Ω)	R_{sh} (Ω)	I_{ph} (A)	$I_{o1}, I_{o2}, I_{o3}, I_{o4}$ (μA)	$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ (-)	R_s (Ω)	R_{sh} (Ω)
FDM-C	0	0	1	0	0	1	10	2	1	1000
FDM-M	0	0	1	0	0	2	50	60	0.36	1000

4.2. Results Of PV Parameter Extraction (FV Parametre Çıkarımı Sonuçları)

RTC France PV cell has been modeled with FDM. Then, its eleven parameters were estimated using the metaheuristic algorithms FLA, PLO, MGO, WO, and ECO. The PV parameter extraction results of FDM-C in the 30th run is provided in Table 4. The RMSE results are ranked from smallest to largest. When comparing the results of the algorithms, the smallest RMSE of 9.8259271E-04 was obtained by the FLA algorithm. FLA is followed by the MGO, WO, PLO, and ECO algorithms. The I-V and P-V curves plotted using the measured data of the RTC France PV cell and the estimated data by FLA are shown in Figure 3. When examining the graphs, it can be observed that the measured data and estimated data match and align successfully. This demonstrates the success of FLA in PV parameter extraction.

Table 4. PV parameter extraction results of FDM-C in the 30th run (FDM-C'nin 30. çalışmasında ki FV parametre çıkarımı sonuçları)

Parameter	FLA	PLO	MGO	WO	ECO
I_{ph} (A)	0.7607786	0.7618875	0.7620525	0.7607443	0.7644102
I_{o1} (μA)	0.2367755	0.0000000	0.4379903	0.8278776	0.0028874
I_{o2} (μA)	0.1753640	2.2315195	0.0001060	3.4578557	9.9999343
I_{o3} (μA)	0.4295003	5.1182996	0.0000000	0.0165228	0.0000000
I_{o4} (μA)	0.0514301	0.0771697	2.5467624	0.0208131	4.5437976
α_1 (-)	1.4549103	1.9999474	1.5388396	1.6145120	2.0000000
α_2 (-)	2.0000000	1.9725127	1.7562160	1.9989313	2.0000000
α_3 (-)	2.0000000	1.9644260	1.9972460	1.9986554	1.9964226
α_4 (-)	2.0000000	1.4314299	1.9527657	1.9402148	2.0000000
R_s (Ω)	0.0366915	0.0264810	0.0315264	0.0278392	0.0142843
R_{sh} (Ω)	55.2848811	999.9861154	904.8492791	1000.0000000	999.9999986
RMSE	**9.8259271E-04**	5.3341190E-03	3.4425204E-03	4.1260695E-03	8.7908497E-03
RMSE Rank	**1**	4	2	3	5



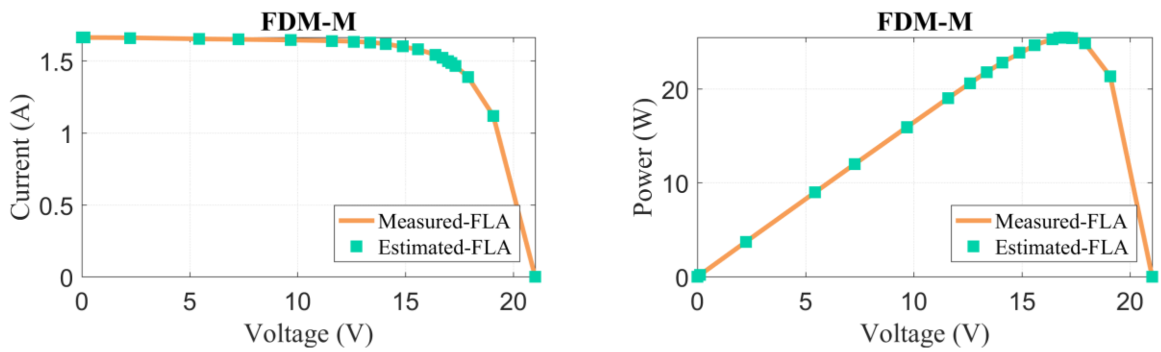
a) I-V b) P-V

Figure 3. Measured data and estimated results by the FLA algorithm for FDM-C (FDM-C için ölçülen veriler ve FLA algoritması tarafından tahmin edilen sonuçlar)

Schutten Solar STM6-40/36 PV module has been modeled with FDM. The unknown parameters were estimated using five algorithms. The PV parameter extraction results of FDM-M in the 30th run is provided in Table 5. When comparing the results, as in FDM-C, the smallest RMSE was obtained by the FLA algorithm. FLA, with an RMSE value of 1.7298036E-03, is followed by WO, PLO, ECO, and MGO. The I-V and P-V curves plotted using the measured data of the PV module and the estimated data by FLA are shown in Figure 4. When examining the graphs, it can be observed that the measured data and estimated data successfully align. This further reinforces the success of FLA in PV parameter extraction.

Table 5. PV parameter extraction results of FDM-M in the 30th run (FDM-M'nin 30. çalışmasında ki FV parametre çıkarımı sonuçları)

Parameter	FLA	PLO	MGO	WO	ECO
I_{ph} (A)	1.6639045	1.6603123	1.5678745	1.6567446	1.6700870
I_{o1} (μA)	50.0000000	37.2997289	4.8006234	47.1939470	43.3733815
I_{o2} (μA)	1.7384783	12.4044569	0.7767664	7.2122661	21.0710384
I_{o3} (μA)	50.0000000	49.9997600	3.1665514	48.5210498	31.3869353
I_{o4} (μA)	0.0000006	18.8837222	7.4204936	3.0396871	49.5251575
α_1 (-)	60.0000000	54.9375789	57.0870319	14.6349084	47.6637244
α_2 (-)	1.5202937	1.7717246	1.4398523	1.6940785	1.8569793
α_3 (-)	60.0000000	57.4100491	46.0022475	29.2704550	3.4923193
α_4 (-)	60.0000000	56.9073724	48.3385472	28.3250795	58.8497972
R_s (Ω)	0.0042740	0.0000007	0.0000000	0.0000001	0.0000015
R_{sh} (Ω)	15.9451344	999.5697608	996.4024267	67.8580756	772.1200189
RMSE	**1.7298036E-03**	9.5790451E-03	6.2579367E-02	4.4530579E-03	1.8810481E-02
RMSE Rank	**1**	3	5	2	4



a) I-V b) P-V

Figure 4. Measured data and estimated results by the FLA algorithm for FDM-M (FDM-M için ölçülen veriler ve FLA algoritması tarafından tahmin edilen sonuçlar)

4.3. Computational Accuracy And Computational Time (Hesaplama Doğruluğu ve Hesaplama Zamanı)

With the FLA, PLO, MGO, WO, and ECO metaheuristic algorithms, the eleven unknown parameters of FDM-C and FDM-M have been estimated. Among these algorithms, FLA has been the most successful algorithm with the smallest RMSE value. In addition, the results of 30 runs for FLA and the other four algorithms have been examined in terms of computational accuracy and computational time. The average, maximum, minimum, and standard deviation of RMSE results for each algorithm over 30 runs have been calculated. These values were considered as evaluation metrics and used in the comparison of the algorithms. The results of computational accuracy are presented in Table 6. When examining the mean rank and total rank obtained for FDM-C and FDM-M, it is observed that FLA achieved the smallest average and smallest minimum RMSE in all 30 runs. It can be seen that FLA was stable while obtaining these results.

Table 6. Results of computational accuracy (Hesaplama doğruluğunun sonuçları)

Model	Algorithm	Average	Rank	Maximum	Rank	Minimum	Rank	Standard Deviation	Rank
FDM-C	FLA	3.5935746E-03	1	1.9545185E-02	4	9.8251385E-04	1	4.0925274E-03	4
	PLO	5.3270909E-03	4	6.8654356E-03	1	2.9804325E-03	5	8.4791828E-04	1
	MGO	1.2313673E-02	5	8.1558691E-02	5	1.9179928E-03	4	1.4768313E-02	5
	WO	5.1329891E-03	3	7.7100840E-03	2	1.1112930E-03	3	1.6308073E-03	2
	ECO	3.6185213E-03	2	8.7908497E-03	3	9.8282486E-04	2	2.9561315E-03	3
FDM-M	FLA	2.0424885E-03	1	5.3526331E-03	1	1.6884311E-03	1	8.3286997E-04	1
	PLO	5.7040859E-03	3	9.5790451E-03	3	4.3762803E-03	5	1.0998252E-03	3
	MGO	5.8146164E-02	5	1.9412997E-01	5	2.3186272E-03	3	5.2869327E-02	5
	WO	4.3529314E-03	2	5.4001772E-03	2	1.7443232E-03	2	9.4028259E-04	2
	ECO	7.6413890E-03	4	1.8810481E-02	4	3.2180135E-03	4	3.8708561E-03	4
Model	**Algorithm**	**Mean Rank**	**Total Rank**	**Mean Rank**	**Total Rank**	**Mean Rank**	**Total Rank**	**Mean Rank**	**Total Rank**
FDM-C and FDM-M	FLA	1.000	**1**	2.500	3	1.000	**1**	2.500	3
	PLO	3.500	4	2.000	**1**	5.000	5	2.000	**1**
	MGO	5.000	5	5.000	5	3.500	4	5.000	5
	WO	2.500	2	2.000	2	2.500	2	2.000	2
	ECO	3.000	3	3.500	4	3.000	3	3.500	4

Results of computational time in seconds are provided in Table 7. FLA is slower than the other algorithms in terms of computational time. This situation requires evaluating both computational accuracy and computational time together. When examining the mean rank and total rank obtained for FDM-C and FDM-M, the algorithm with the best speed in terms of average, maximum, and minimum is MGO. However, in terms of computational accuracy, it ranks last in both average and maximum, and fourth in minimum. In terms of standard deviation, ECO is ranked first. In computational accuracy, the most stable results were produced by FLA, which ranked fourth in stability. Detailed modeling studies are conducted for PV systems, and based on feasibility studies, a decision is made regarding whether the system is feasible or not. Since the initial investment cost is high and the system is planned for approximately 25 years, it is not a correct choice to only reference computational time; computational accuracy should be considered as the reference.

Table 7. Results of computational time in seconds (Saniye olarak hesaplama zamanının sonuçları)

Model	Algorithm	Average	Rank	Maximum	Rank	Minimum	Rank	Standard Deviation	Rank
FDM-C	FLA	7.5228295E+01	4	8.8241180E+01	3	6.8833375E+01	5	4.4631682E+00	3
	PLO	8.1867098E+01	5	1.2522939E+02	5	6.3543348E+01	3	1.1831198E+01	5
	MGO	4.2401781E+01	1	5.1080383E+01	2	3.9898257E+01	1	3.0551056E+00	2
	WO	7.3454392E+01	3	1.0920248E+02	4	6.4644150E+01	4	9.1429877E+00	4
	ECO	4.2528322E+01	2	4.8869973E+01	1	4.0571758E+01	2	1.8302202E+00	1
FDM-M	FLA	1.0383685E+02	5	1.7047343E+02	5	5.9285478E+01	5	2.6327109E+01	5
	PLO	7.1289870E+01	3	1.0583865E+02	3	5.5181437E+01	4	1.0679184E+01	2
	MGO	6.3604604E+01	2	9.6735429E+01	2	3.9857680E+01	1	1.3012154E+01	4
	WO	6.1961489E+01	1	7.4850672E+01	1	4.9918176E+01	3	6.4269138E+00	1
	ECO	7.4966452E+01	4	1.0916227E+02	4	4.6934324E+01	2	1.2364525E+01	3
Model	**Algorithm**	**Mean Rank**	**Total Rank**	**Mean Rank**	**Total Rank**	**Mean Rank**	**Total Rank**	**Mean Rank**	**Total Rank**
FDM-C and FDM-M	FLA	4.500	5	4.000	4	5.000	5	4.000	5
	PLO	4.000	4	4.000	5	3.500	3	3.500	4
	MGO	1.500	**1**	2.000	**1**	1.000	**1**	3.000	3
	WO	2.000	2	2.500	2	3.500	4	2.500	2
	ECO	3.000	3	2.500	3	2.000	2	2.000	**1**

4.4. Friedman And Wilcoxon Statistical Tests
(Friedman Ve Wilcoxon İstatistiksel Testleri)

Among the FLA, PLO, MGO, WO, and ECO algorithms, FLA has achieved successful results in PV parameter extraction. These results were evaluated using two statistical tests, namely the Friedman test and the Wilcoxon signed-rank test. The first statistical test is the Friedman test. It is a test that tells whether there is a significant difference between the results computed by the algorithms in solving the PV parameter extraction problem for 30 runs and ranks the algorithms. For a 0.05 significance level, the p-value is examined, and if this value is less than 0.05, it indicates a significant difference between the algorithms. The results of the Friedman test are provided in Table 8. The p-value for FDM-C was calculated as 8.5587363E-07, and for FDM-M it was 8.9032486E-19, showing a significant difference between the algorithms. In both models, the smallest mean rank, or the best results, were obtained with FLA. The results of the mean and total ranking of algorithms are presented in Table 9. Based on the ranking of the results obtained in these two models, the Friedman test proves that the most successful results were produced by FLA among the five algorithms.

Table 8. Results of Friedman test (Friedman testinin sonuçları)

Model	Algorithm	Mean Rank	Rank	P-value	Conclusion
FDM-C	FLA	2.000	**1**	8.5587363E-07	P-value < 0.05 There is significant difference among the performance of algorithms at 5% level of significance.
	PLO	3.167	4		
	MGO	4.233	5		
	WO	3.100	3		
	ECO	2.500	2		
FDM-M	FLA	1.033	**1**	8.9032486E-19	P-value < 0.05 There is significant difference among the performance of algorithms at 5% level of significance.
	PLO	3.333	3		
	MGO	4.600	5		
	WO	2.300	2		
	ECO	3.733	4		

Table 9. Results of ranking of algorithms (Algoritmaların sıralanmasının sonuçları)

Model	FLA	PLO	MGO	WO	ECO
FDM-C	1	4	5	3	2
FDM-M	1	3	5	2	4
Mean Rank	1.000	3.500	5.000	2.500	3.000
Total Rank	**1**	4	5	2	3

The second statistical test is the Wilcoxon signed-rank test. According to the Friedman test, FLA is the most successful algorithm among the five. With the Wilcoxon signed-rank test, FLA was compared pairwise with the other four algorithms. As in the Friedman test, the p-value for a 0.05 significance level was examined. The results of the Wilcoxon signed-rank test are presented in Table 10. A total of 8 comparisons were made, with 4 in FDM-C and 4 in FDM-M. In 7 of these 8 cases, it is evident that the results found by FLA are better than those of the other algorithms, as the p-value is less than 0.05. The results of the mean and total ranking of algorithms are provided in Table 11. According to the pairwise comparison of the results obtained in these two models, the algorithm closest to FLA in performance is ECO, followed by WO, PLO, and MGO.

Table 10. Results of Wilcoxon signed-rank test (Wilcoxon işaretli sıra testinin sonuçları)

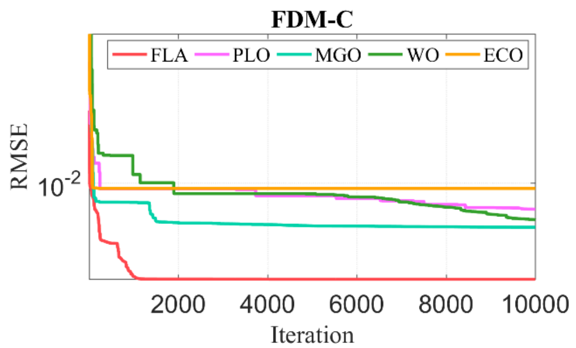
Model	FLA vs Compared Algorithm	P-value	Rank	H	Zval	Ranksum	IS/ IS NOT
FDM-C	PLO	4.0329776E-03	3	1	-2.8755707	720	IS
	MGO	2.8789721E-06	1	1	-4.6792706	598	IS
	WO	3.5011674E-03	2	1	-2.9199240	717	IS
	ECO	8.4999697E-02	4	0	-1.7223856	798	IS NOT
FDM-M	PLO	9.9186286E-11	2	1	-6.4681861	477	IS
	MGO	8.9934060E-11	1	1	-6.4829705	476	IS
	WO	1.6947245E-09	4	1	-6.0246534	507	IS
	ECO	1.3288512E-10	3	1	-6.4238328	480	IS

Table 11. Results of ranking of algorithms
(Algoritmaların sıralanmasının sonuçları)

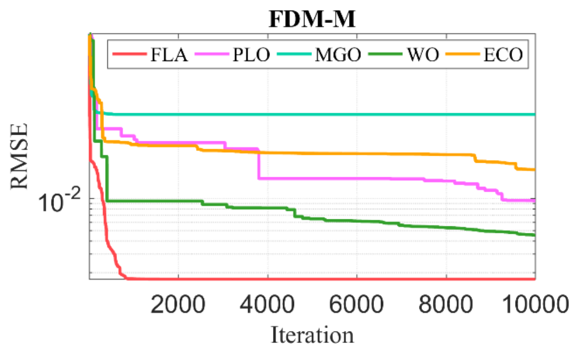
Model	PLO	MGO	WO	ECO
FDM-C	3	1	2	4
FDM-M	2	1	4	3
Mean Rank	2.500	1.000	3.000	3.500
Total Rank	2	1	3	4

4.5. Convergence Curves (Yakınsama Eğrileri)

For 10,000 iterations, the solution finding process of FLA, PLO, MGO, WO, and ECO algorithms in PV parameter extraction can be shown with convergence curves in the 30th run. The convergence curves for FDM-C are shown in Figure 5(a), and for FDM-M in Figure 5(b). As seen in the figures, the lowest RMSE value was obtained with the FLA algorithm compared to the other algorithms.



a) FDM-C



b) FDM-M

Figure 5. Convergence curves in the 30th run (30. çalışmadaki yakınsama eğrileri)

5. CONCLUSION (SONUÇLAR)

The correct modeling of PV systems with the right parameters is required to accurately express their response to changing meteorological conditions. Accurately defining the current-voltage characteristics with the correct parameters is crucial for predicting and planning the performance of FV systems in real-world applications. In this article, PV parameter extraction of a PV cell and module was performed using FDM. The eleven unknown parameters of FDM were obtained using the meta-heuristic algorithms FLA, PLO, MGO, WO, and ECO. These five algorithms were used for both solving the parameter extraction problem and for the first time in this study with FDM. RMSE was selected as the objective function. The RMSE was evaluated using assessment metrics, computational accuracy, computational time, and statistical methods. The smallest minimum RMSE was obtained with FLA, calculated as 9.8251385E-04 for FDM-C and 1.6884311E-03 for FDM-M. To statistically prove and reinforce the success of FLA over the other algorithms, the Friedman test and Wilcoxon signed-rank test were used. According to these tests, FLA produced more significant results than the other algorithms, and, based on pairwise comparisons, it was shown to be more successful than the others. As a result, FLA was found to be a successful and promising algorithm for PV parameter extraction for FDM, and this was statistically proven.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan ederler.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

***İpek ÇETİNBAŞ*:** She performed the simulation studies, analyzed the results, and carried out the writing process.

Benzetim çalışmalarını gerçekleştirmiş, sonuçlarını analiz etmiş ve yazım işlemini gerçekleştirmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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