Publisher: Engineering College, Al Muthanna University
Open Access
DOI:10.52113/3/eng/mjet/2026-14-03-/73-83, Vol. (14), Issue (3), (2026)
Muthanna Journal of Engineering and Technology
MJET
Submitted 08 April 2026, Accepted in revised form 15 June 2026, Published online 17 June 2026

Towards Renewable Energy in Iraq: Accurate Photovoltaic Parameter Estimation Using Metaheuristic Algorithms

Qusay Shihab Hamad

University of Information Technology and Communications (UoITC), Baghdad, Iraq

Corresponding Author E-mail: qusay.phd@gmail.com

Abstract

Nowadays there is a global transition to renewable energy because of the urgent need to combat climate change and enhance energy sustainability. For Iraq, which has been facing frequent power shortages and the negative consequences of climate change, such as water shortages and desertification, the investment in renewable energy is no longer optional. Iraq has a high potential for using solar energy due to its high solar radiation levels and long days of sunlight. Solar photovoltaic (PV) systems offer a clean and reliable alternative to diesel generators, but their effectiveness relies largely on exact approximation of nonlinear internal parameters. In this work, three recent metaheuristic algorithms (MAs): FATA (an efficient optimization approach based on geophysics), Moss Growth Optimization (MGO), and Polar Lights Optimizer (PLO), are applied for parameter estimation of single-diode, double-diode, and modified PV models. Results showed that the FATA consistently outperformed MGO and PLO, obtaining the lowest average fitness over 30 independent runs, which means improved accuracy in PV parameter extraction. The achieved results demonstrate how MAs can be a significant tool for enhancing the performance of PV systems.

Keywords: *Solar energy systems, Metaheuristic Algorithm, Photovoltaic parameter estimation, Renewable energy in Iraq, SDG 7, artificial intelligence and applications*

1. Introduction

Unfortunately, the Iraqi energy industry is going through tremendous difficulties, due to the fact that more than 98% of its electrical power is generated from traditional fuels, which resulted in a shortage of electricity in the country. However, Iraq has great and largely untapped solar power potential: more than 3,000 hours of sunshine annually. If low irradiation is considered the lowest ones in Iraqi cities, then they receive about 60% more solar energy than the most productive ones in Germany [1][2][3][4][5][6]. To support the use of renewable energy and to cut down on the emission of greenhouse gases, Iraq signed the Paris Agreement in 2015 and made the country a promising place for large-scale renewable energy projects, specifically solar energy, because of its high natural light levels and vast open areas.

Recently, photovoltaic (PV) models have become essential to provide a sustainable and clean source of energy. While hardware design is important, precise electrical modeling of PV cells is equally critical and vital for improving performance and efficiency. The famous types are the single-diode model (SDM), double-diode model (DDM), and the PV module model (MM) [7]. There are complicated problems in these models such as the photogenerated current, diode saturation

currents, series and shunt resistances, and diode ideality factors. This is considered a nonlinear optimization problem, generally comprising many local optima and complicated interdependencies among parameters, which makes classical analytical and numerical methods inefficient [8].
One of the good ways of finding the best parameters of PV systems is using metaheuristic algorithms (MAs). Recently MAs have been successfully applied due to their flexibility, low dependency on the problem structure, and ability to balance exploration (global search) and exploitation (local refinement) [9][10][11]. Recent studies have introduced various novel MAs for this purpose. For example, the QLESCA optimizer has achieved an excellent efficiency in PV parameter selection [9]. in another study at [12] The author used a Nutcracker optimization algorithm and achieved higher accuracy and lower computing cost compared to previous approaches. The same as at [7], the authors enhanced the Prairie Dog algorithm to deal with PV model extraction accuracy, while the RIME optimizer at [13] achieved quick convergence and excellent parameter estimation.
Although many optimizers in the literature have been used for PV parameter estimation, challenges remain in achieving optimal parameters with robustness across different PV models. These obstacles led to a research gap where further evaluation of novel MAs is necessary to ensure reliable PV modeling under different scenarios. To address this gap, this paper investigates three recent and competitive algorithms for PV parameter estimation:

- FATA (An efficient optimization method based on geophysics) [14]
- MGO (The Moss Growth Optimization: Concepts and performance) [15]
- PLO (Polar Lights Optimizer: Algorithm and applications in image segmentation and feature selection) [16]

The conventional tools for PV parameter estimation have been the Genetic Algorithms (GA) and the Particle Swarm Optimization (PSO). The paper turns the attention to the newest generation of metaheuristics, as these classic approaches have been well studied in the literature. To our knowledge, these particular optimizers (FATA, MGO, PLO) haven't yet been used in these PV models. When we test them we can investigate new and very efficient options with more sophisticated search mechanisms that are capable of addressing the typical drawbacks of earlier algorithms. This paper makes contributions as follows:

1. Three recent MAs (FATA, MGO, and PLO) are used to estimate the parameters of SDM, DDM, and MM respectively.
2. The performance of these three MAs is evaluated in 30 independent runs, where performance is measured by the average fitness values, standard deviation, and the convergence curve.
3. The outcomes show the effectiveness of the application of these MAs to enhance an effective PV system.

The rest of this paper is organized as follows: Section 2 presents the problem formulation of the photovoltaic system. Section 3 discusses an analysis of the experimental findings and the performance of the MAs. Finally, Section 4 presents the conclusions of this study and suggests new directions for further research.

2. Problem Formulation

To achieve good results from the modeling of photovoltaic systems, it should depend on identifying parameters that align with experimental current and voltage characteristics. In our work, we examine three more popular models; these models are SDM, DDM, and MM. Parameter estimations are defined as an optimization problem and need to be solved by good metaheuristic optimization algorithms. The five unknown parameters in the SDM include the diode ideality factor (n), series resistance (R_s), shunt resistance (R_{sh}), photogenerated current (I_{ph}), and diode saturation current (I_{sd}). While the DD model incorporates diffusion and recombination diodes, requiring seven parameters, these parameters are I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, and n_2. The SDM structure is applied at the module level within the MM. Figure 1 illustrates the circuit representations of these three models, while Table 1 provides a summary of the ranges for each parameter. For more details of photovoltaic systems, refer to this paper [17]. Given the nonlinear and multimodal characteristics of this problem, metaheuristic algorithms are particularly effective for accurate parameter estimation.

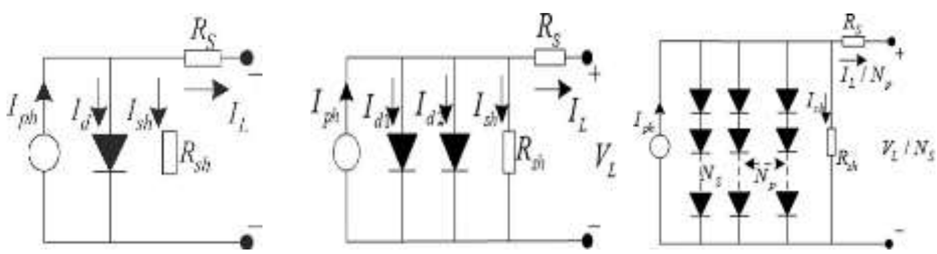
(a) (b) (c)

Fig.1: The schematic diagram (a) SDM, (b) DDM, and (c) MM

Table 1: The parameter values for PV models.

Parameter	SD/DD		PV module	
	Lower bound	Upper bound	Lower bound	Upper bound
I_{ph} *(A)*	0	1	0	2
I_{sd}, I_{sd1}, I_{sd2} *(μA)*	0	1	0	50
R_s *(Ω)*	0	0.5	0	2
R_{sh}*(Ω)*	0	100	0	2000
n, n_1, n_2	1	2	1	50

3. Performance Evaluation and Discussion

In this study, we compared the performance of the three metaheuristic optimization algorithms and discovered which one is more suitable. To ensure maximum technical accuracy, all experiments and simulations were conducted using the MATLAB 2025a software environment. Parameter estimation tests were conducted for the three types of photovoltaic models, and these types are SDM, DDM, and MM. There are three optimizers: FATA, MGO, and PLO. The full details of the setting and parameters of these optimizers have been clarified in Table 2. Since these algorithms are stochastic in nature, and to ensure a fair comparison, each experiment was performed independently 30 times with a termination condition of 500 fitness evaluations. The flowchart of these three-optimization algorithm has been clarified at figures 2,3, and 4.

3.1 Optimization Framework and Execution Steps

To provide a clear operational view of how the comparative analysis is executed, the step-by-step workflow of the optimization framework for all three metaheuristic algorithms (FATA, MGO, and PLO) is structured as follows:

Step 1 (Start): Start running the execution framework.

Step 2 (Data Loading): Input the parameters for the photovoltaic model and experimental data for a particular solar cell type (SDM, DDM or MM).

Step 3 (Initialization): Initialize the parameters of the baseline experiments by using 30 search agents and 500 maximum fitness evaluations.

Step 4 (Optimization Loop): run the main part of the metaheuristic updater. For each run, use the particular search operator from FATA, MGO, or PLO to change the location of the agents in the search space.

Step 5 (Fitness Evaluation): Compute the objective function (RMSE) for the current agent positions.

Step 6 (Termination Check): Check for 500 fitness evaluations limit.
If NO, go back to Step 4;
If you responded “yes,” move on to the next step.

Step 7 (Statistical Evaluation): Repeat the whole process 30 times independently for the selected algorithm, calculating the average fitness values and standard deviations at the end of each set.

Step 8 (Output): Output the optimal estimated PV internal parameters and save the PV statistical data.

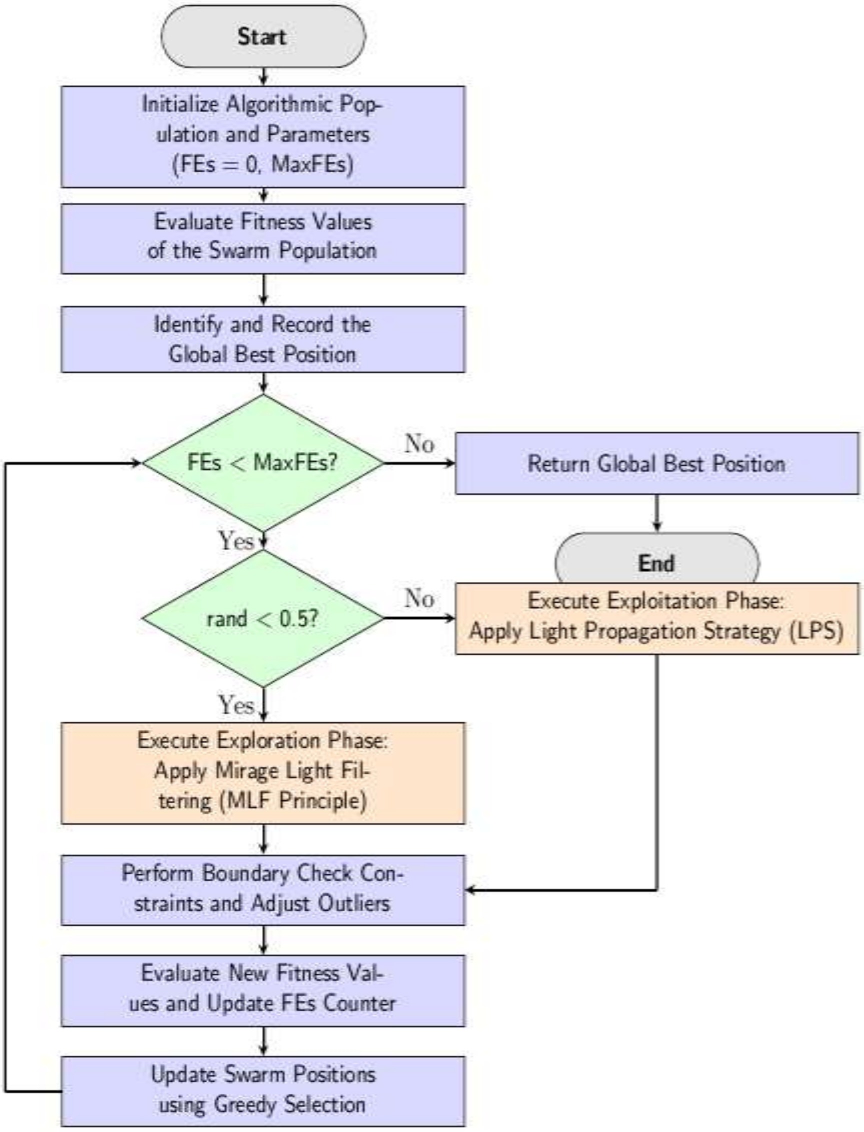

Fig.2 The Flowchart of FATA

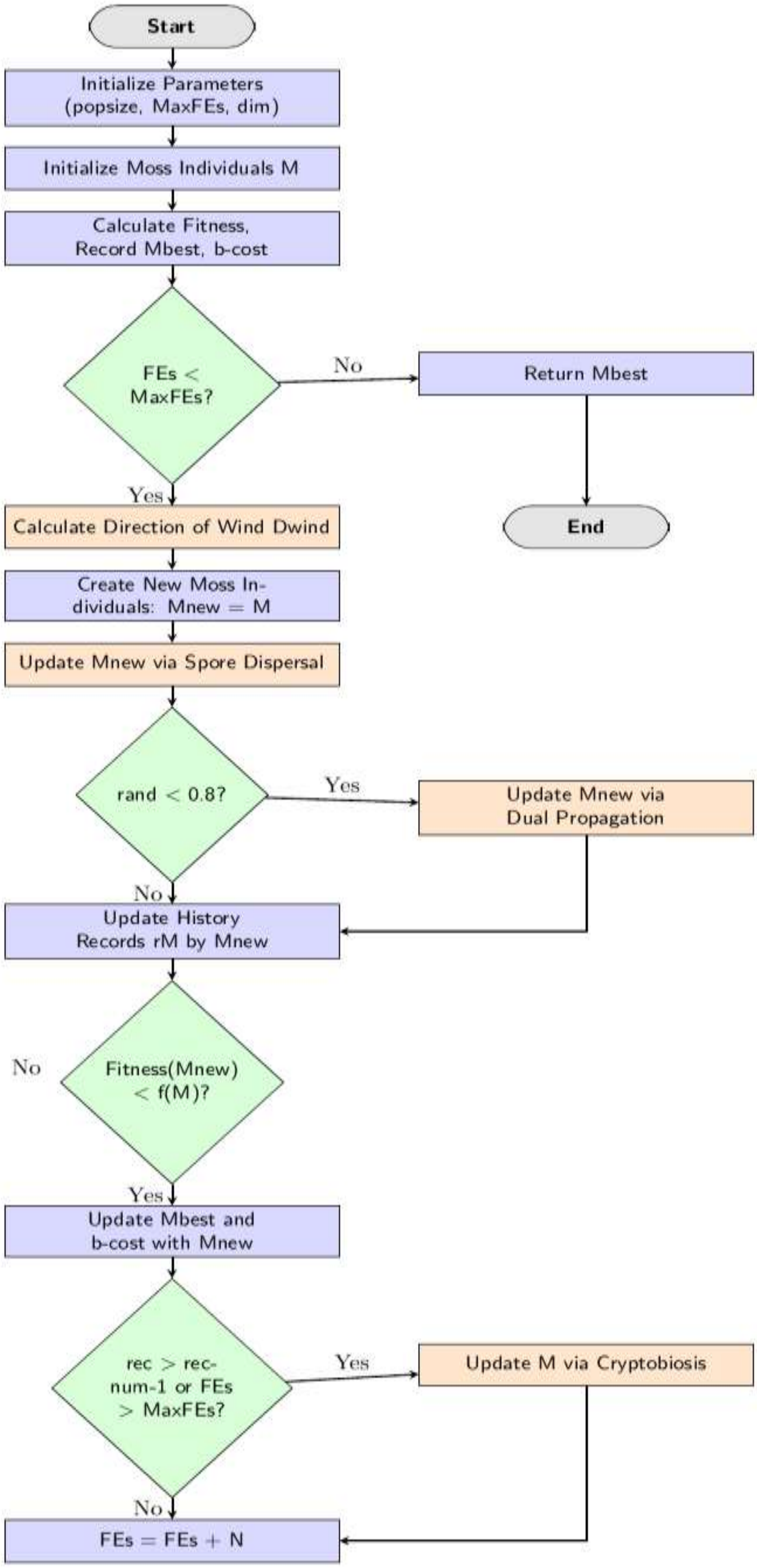

Fig.3 The Flowchart of MGO

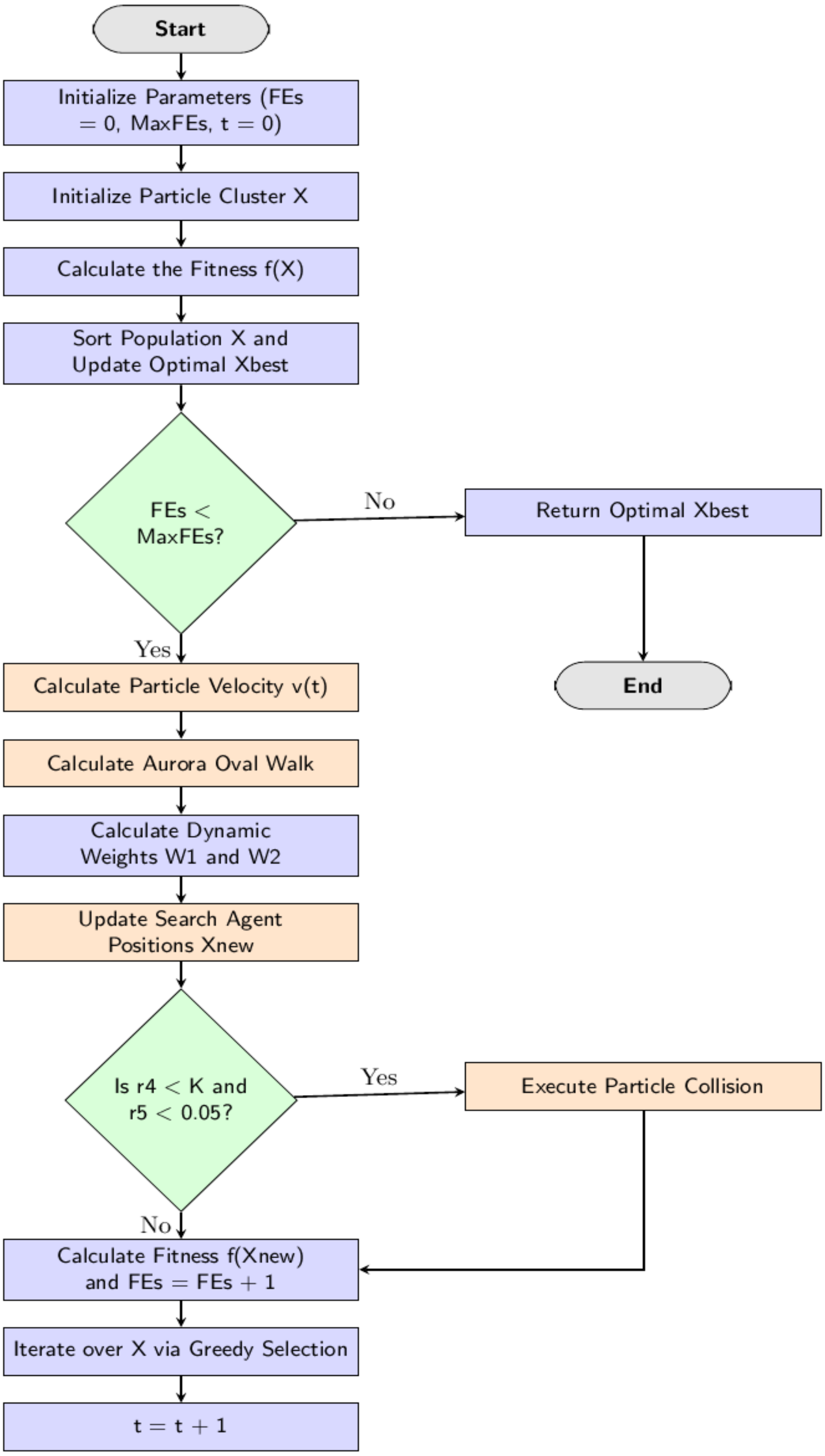

Fig.4 The Flowchart of PLO

3.2 Results and Discussion

The average fitness values and standard deviations of the three algorithms are given in Table 3. However, the results clearly show that the average fitness value obtained by FATA were the lowest in all three PV models. In particular, for the SD and DD models, FATA displayed better results compared with MGO and PLO. Although the latter is more complex model of

PV module with all the algorithms showing higher error because of higher non-linearity, the FATA algorithm had the best results.
Standard deviation analysis showed that the value of FATA algorithm is lower than that of other algorithms, which means that the algorithm is robust and stable. However, MGO algorithm had the slightly high difference in the 3rd one (PV module) and its average error was also higher than FATA, which limits its overall competitiveness. On the other hand, the PLO showed good performance in the first two models (SD and DD) but was less reliable in the third (PV module) model, with huge variability.
From these findings, it is totally clear that FATA algorithm has an excellent ability to find best PV parameters, which led to the good balance between exploration and exploitation. That makes it ideal for this type of task. Then the MGO algorithm scored second overall, show good robustness but less accuracy compared to FATA. And at the end rank, the PLO algorithm showed good performance in only the second problem (double diode); it suffered instability, especially in the PV module model.

Table 2: Algorithms parameters settings

Algorithm	Population size	Fitness evaluations	Other parameters
FATA [14]	30	500	Artificial Reflectance Factor (*ARF*)=0.2
MGO [15]	30	500	Weight Factor (*W*) = 2, Record Number (rec_num) = 10, Dispersal Rate (*D1*) = 0.2
PLO [16]	30	500	beta in Levy Flight = 1.5

All the control parameters were set to their default values, as recommended by the original authors of each algorithm, as listed in Table 2. We did not fine-tune and change these internal settings. This way we're able to make a full, unbiased comparison, and can judge each optimizer on its own without having to add their own "fancy" filters. All algorithms were evaluated on 30 separate runs using the same number of search agents (N = 30) and fitness evaluations (500).

Table 3: The average of fitness value and standard deviation of the three optimization algorithms

Algorithms	FATA		MGO		**PLO**	
	Avg.	**Std.**	**Avg.**	**Std.**	**Avg.**	**Std.**
Single diode	0.037	0.017	0.071	0.033	0.107	0.052
Double diode	0.038	0.020	0.087	0.043	0.081	0.045
Photovoltaic module	0.078	0.100	0.133	0.090	0.513	0.247

Table 4: Optimized parameters for a SDM.

optimizer	I_{ph} (A)	$I_{sd,}$(μA)	R_s (Ω)	R_{sh}(Ω)	n
FATA	0.7470	0.0000	0.0184	51.3884	1.5191
MGO	0.7583	0.0000	0.0403	44.9843	1.5394
PLO	0.7757	0.0000	0.0296	57.0267	1.6164

Table 5: Optimized parameters for a DDM.

Algorithm	I_{ph} (A)	I_{sd1}(μA)	R_s (Ω)	R_{sh}(Ω)	n_1	I_{sd2}(μA)	n_2
FATA	0.7612	0.0000	0.0289	52.7488	1.6237	0.0000	1.6252
MGO	0.7329	0.0000	0.0327	56.5258	1.6403	0.0000	1.6305
PLO	0.7628	0.0000	0.0258	56.8170	1.7150	0.0000	1.8673

Table 6: Comparison between algorithms regarding the optimal parameters on the MM

Algorithm	I_{ph} (A)	$I_{sd,}$(μA)	R_s (Ω)	R_{sh}(Ω)	n

FATA	1.0369	0.0000	1.0562	921.0289	48.1294
MGO	0.0010	0.0000	0.0011	1.0322	0.0471
PLO	0.0010	0.0000	0.0010	1.1059	0.0408

The three optimizers have curves, which are plotted together in Figures 2 to 4, showing where they meet. FATA is shown in red, MGO in blue and PLO in green in these figures. Specifically, the convergence behaviour for the SDM is illustrated in Fig. 5, for the DDM in Fig. 6 and for the MM in Fig. 7. By examining these figures one could easily see that the convergence performance of the FATA algorithm is best; it is able to start improving its fitness values in the evaluations continuously while the MGO and PLO algorithms are not so successful at balancing the exploration/exploitation aspect.

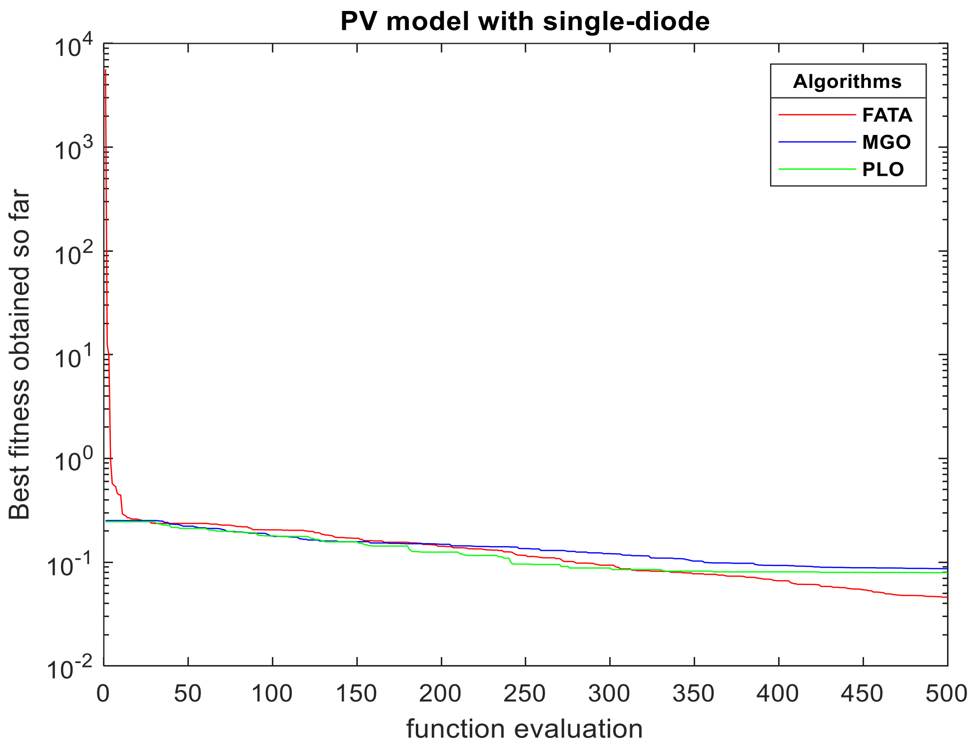

Fig. 5: Convergence curve of the average fitness value for the SDM.

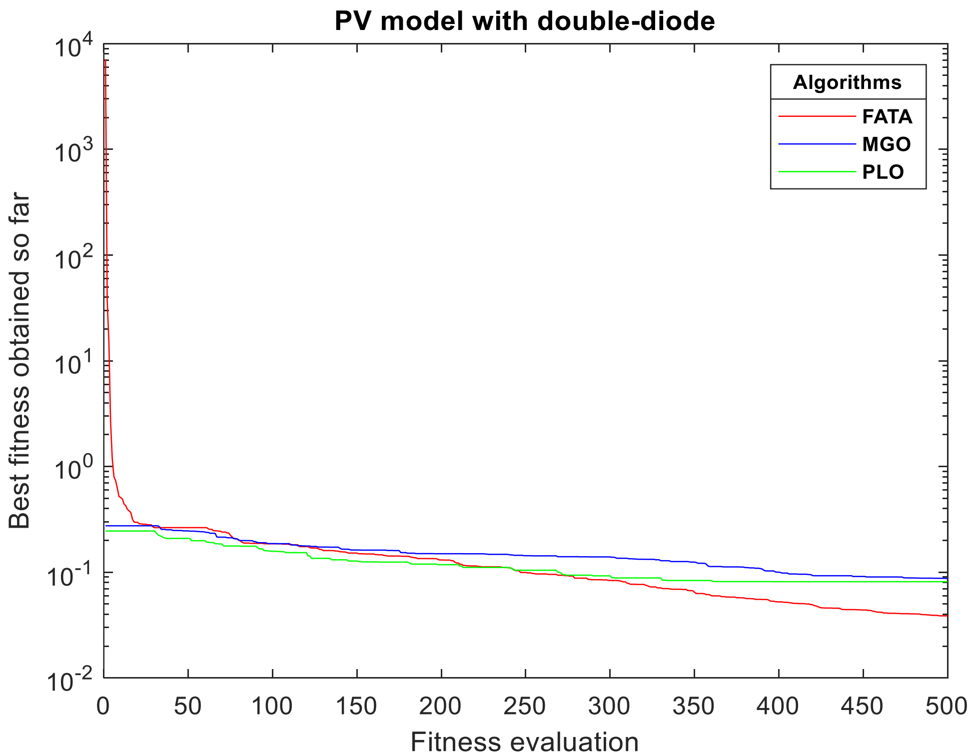

Fig. 6: Convergence curve of the average fitness value for the DDM.

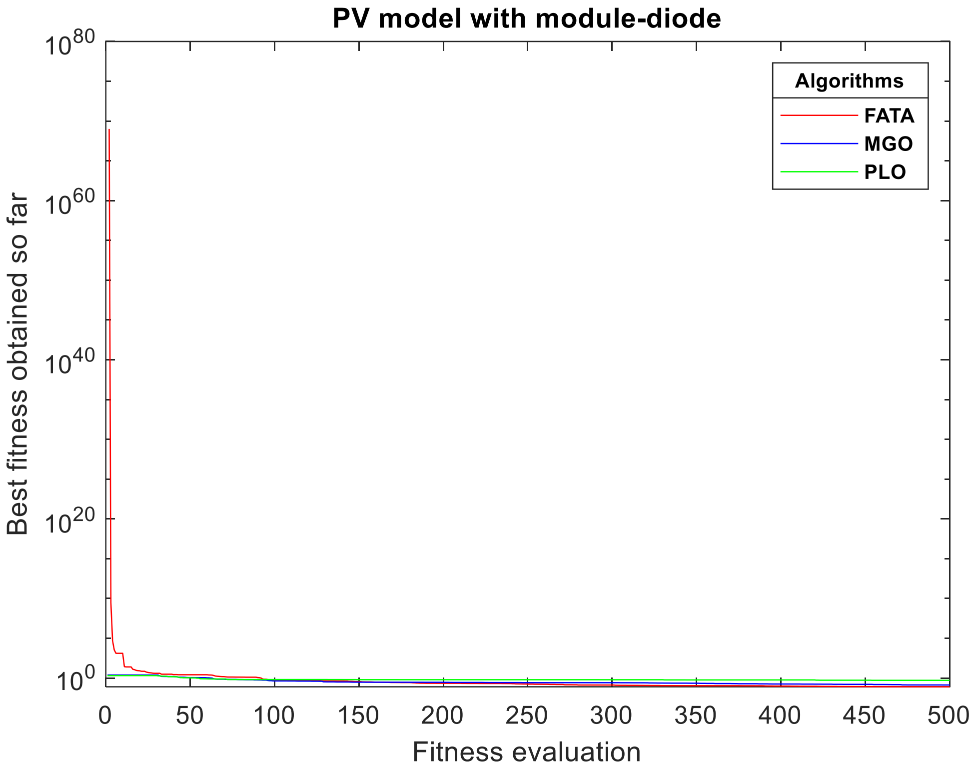

Fig. 7: The Convergence curve of the average fitness value for the PV MM.

4. Computational Efficiency and Execution Time Analysis

In the real world, solar PV data monitoring isn't just about accuracy. The speed is as important. Real time monitoring devices can't be used if the parameters can't be calculated quickly, within the time frame of the algorithm. Therefore, we measured the exact time it takes for each of these three approaches to be carried out. Table 7 shows the time, in seconds, required for FATA, MGO and PLO to complete their search.

Table 7: Time consumed by each algorithm (Second)

Algorithms	FATA	MGO	**PLO**
Single diode	0.4199	0.4535	0.4468
Double diode	0.4401	0.4529	0.4719
Photovoltaic module	0.4626	0.4619	0.4794

The recorded numbers tell the very clear story. FATA is extremely quick! For a single diode model FATA requires only 0.4199 seconds for the absolute best parameters. MGO is not as good as 0.4535 seconds and PLO is 0.4468 seconds. FATA gets the win this time. This is very similar for the double diode data too. The solar module test is slightly different. Each single algorithm slows down a little bit because of a full module having more complex mathematical equations. It's normal. Despite this added challenge FATA remains a very competitive speed, placing 0.4626 seconds.
How does that make a difference at sub-second speeds? They are important, because today's power grid evolves rapidly. Clouds drift by and dust falls on the window glass. FATA takes less than half a second to update, meaning it can be easily executed by a local industrial microcontroller all day long. It can monitor changes in real time without any system hardware delays.

5. Statistical Significance Analysis

A Wilcoxon rank-sum test was performed to ensure the superiority of FATA's accuracy is mathematically reliable. This test aims to determine the difference in performance between 30 independent runs at 5% significance level. FATA was compared directly to MGO and PLO, and was used as the base algorithm. The p-value resulting is presented in Table 8.

All p-values in Table 8 are relatively small compared to 0.05. This indicates that the difference in performance between FATA and the other two algorithms is statistically significant at the 100% level. The low counts, particularly in the full PV module test (3E-11) are sufficient evidence that FATA proves to be the best under identical conditions consistently.

Table 8: Statistical test P value (Wilcoxon sum rank test)

Algorithms	MGO	**PLO**
Single diode	1.64E-05	4.8E-07
Double diode	1.53E-05	0.00032
Photovoltaic module	3.81E-07	3E-11

6. Practical Engineering Implications for the Iraqi Environment

Understandably, the internal parameter values derived by our models are physical parameters for local maintenance engineers in the context of Iraq's challenging environment. Numbers are more than numbers! For example, excessive dust buildup physically prevents the solar radiation. This blockage results in a readily measurable decrease in the estimated photo-generated current (I_{ph}). Concurrently, during hot summer, the direct effect of summer heat induces deterioration of the panel materials resulting in the increment of internal series resistance (R_s) of the cells. This accuracy in the parameters extracted using the FATA algorithm enables operators at local power stations to make a mathematical diagnosis of the condition of their solar arrays. These can be monitored over time. This information enables them to know exactly when to bring in physical cleaning or maintenance for the panels based on weather problems. Additionally, the running of FATA is extremely fast and this process of diagnosis can be carried out, say, at any time of the day. In cases where the complete solar string is not only failing but dirty too, engineers should ideally be able to detect this easily, without having to individually test all solar panels in the farm. This provides both time savings and maintenance cost reductions.

7. Conclusions and future directions

Three recent metaheuristic algorithms: FATA, MGO, and PLO are tested in this work to accurately estimate the parameters of PV models, such as SDM, DDM and MM models. They have been tested across 30 independent runs and their average fitness and SD is used for performance evaluation. The findings revealed that the performance of FATA was optimum. The PLO's methodology came in the last place while the MGO was the one that came on second position.

Some directions that could be taken in the future are:

1. Optimize these FATA/MGO/PLOs together with other metaheuristic optimizers or machine learning techniques to improve their convergence rate and quality.
2. Increasing the number of large PV farms tested for various conditions.
3. Investigating how these might be applied for solving other energy optimization problems like wind turbine modelling or smart grid scheduling.
4. Testing the FATA optimizer with a limited amount of partial shade and under extreme temperature tests and a hardware-in-the-loop setup to test its performance under the conditions of real Iraqi dust and dust and temperature waves.

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