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Photovoltaic Model Parameters Estimation Via the Fully Informed Search Algorithm

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ABSTRACT

Effective parameter estimation for photovoltaic (PV) systems holds significant importance for both researchers and industry professionals. An accurate understanding of PV models, achieved through modeling and simulation, plays a pivotal role in optimizing the design, control, testing, and forecasting of PV system performance. Developing a precise and robust parameter identification method significantly contributes to enhancing the modeling, control, and optimization of photovoltaic systems. In this context, our research contribution introduces a novel version of Rao metaheuristic algorithm named the Fully Informed Search Algorithm (FISA). Which demonstrate acceptable performance to solving optimization problems in several applied fields. While, maintaining the simplicity and non-parametric nature of the original algorithm. The proposed algorithm holds promise for various industrial applications, particularly in optimizing complex systems such as photovoltaic (PV) systems. For which, we used it to efficiently identifying the parameters of the single-diode model (SDM). Thus, we demonstrate its effectiveness through the application in two distinct case studies within our simulation research. in the end, we compared the results of FISA algorithm to seven other well-known algorithms, the obtained results indicate the superiority of the proposed algorithm in term of the stability of the system, a faster convergence and higher accuracy.

1. Introduction

Since the end of 2019, the COVID-19's global pandemic has highlighted the energy issue and unbalanced the energy markets, which pushes the researchers to show their agility to build adapted responses and help to construct a solid society ready to face similar issues. COVID-19 has also a considerable affect on the industry. Renewable energy sources (RESs) could protect the humanity in the face of future and current catastrophe due to its preferential access to electricity networks and its lower costs [1]. Consequently, the exploration and harnessing of eco-friendly power sources has emerged as an imperative subject to avoid the crises consequences. Particularly noteworthy, photovoltaic (PV) setups have attained widespread adoption due to its abundant reserves, emission-free nature, and the consistent decrease in costs over successive years, etc. To ensure the effective integration and utilization of PV systems across diverse industrial applications, it becomes critical to have detailed information and rigorous modelling of its basic components. Regrettably, the essential data required to model the fundamental constituent (i.e., solar cell or module) of a complete PV system remains elusive, where almost all manufacturers did not provides the complete necessary information in its data sheets.

Noting that various equivalents circuits model (ECM), including single diode (SDM), double diode (DDM) and triple (TDM), are utilized to study the behaviour of the PV module/array. Among these models, the SDM is consedred to be the easiest one to be implemented, in real application, with the lowest complexity [2]. However, the primary challenge is solving the nonlinear equation offered by the SDM model and identifying its ungiven parameters. Considering the non-linearity of the model, deterministic methods are streamlined through specific approximations. Recently, optimization algorithms have been broadly studied and have garnered popularity among researchers for solving the parameter estimation problem [3]–[12].

One of the first and popular applied meta-heuristic optimization algorithms to extract the unknown PV cell parameters is the particle swarm optimization [13]. Since then, enormous methods have been applied to estimate the SDM and other models parameters. The authors in [14] prove that the introduction of random reselection mechanisms to the PSO, to obtain a hybrid algorithm, gives more robustness and the convergence accuracy against the original algorithm. In Nguyen et al. [15], the PV estimation issue has been addressed using the artificial ecosystem optimization (AEO). This algorithm is based on three mechanisms of ecosystem, first the production which preserves the balance between exploration and exploitation, where the consumption step is applied to examine the search space. Finally, the decomposition mechanism helps to boost the exploitation phase. In [16], the authors proposed a modified Stochastic Fractal Search (MSFS) algorithm to estimate values of PV modules variables for a best modelling. The main modification are applied to the diffusion process and the update processes to enhance the basic algorithm. Ismaeel et al. [17], applied a gradient based optimizer (GBO) to evaluate the unknown PV parameters. Another recent work [18], use a symmetric chaotic (SC) generator to improve the performances of the GBO method. The proposed SC-GBO is examined on different of PV modules, and it outperforms several techniques. In [19] a recent optimization technique, called DOLADE was introduced to tackle the parameters identification problem of solar PV modules. The proposed DOLADE combines the dynamic opposite learning strategy with the differential evolution method to enhance the performance of the JADE algorithm. In Wang et al. [20] the Rao-1 algorithm has been suggested to extract the PV parameters for the DDM. Other variants have been presented to boost the accuracy and effectiveness of Rao-1 algorithm. The authors in [21] exploited the features of using a chaotic map with the basic algorithm to propose a novel version namely LCROA; while the CLRao-1 algorithm [22] introduce three mutually equation based on quantum and Levy flight strategy to improve the standard Rao-1.

While the majority of the methods mentioned above and other algorithms including HHO [23]–[27], IGWO [28]–[31], RUN [32]–[35], GTO [36]–[39], CPA [40]–[44] and CDO [45]–[48] have demonstrated impressive performance in extracting PV parameters, there remains a necessity to create novel optimization algorithms [49],[50].

In summary, PV systems and other renewable energy sources are essential for creating resilient and sustainable energy systems by reducing greenhouse gas emissions, enhancing energy security, fostering economic development, and promoting environmental stewardship [51]. Their widespread adoption is crucial in global efforts to combat climate change and build a more resilient future. In this paper, we deal with the problem of parameters estimation of the PV. The main contribution is to introduces a new metaphor optimization based on Rao's algorithms [52], called FIS (fully informed search) Algorithm [53]. Which demonstrate acceptable performance to solving optimization problems in parameters estimation of the PV. And that indicate the superiority of the proposed algorithm in term of the stability of the system, a faster convergence and higher accuracy.

The remaining sections of this paper are structured as follows: Section 2 elucidates the Photovoltaic models and objective function employed in this study. The introduced algorithm is delineated in Section 3. Section 4 delves into the discussion of simulation results. Lastly, Section 5 draws the conclusion.

2. Photovoltaic models and objective function

2.1. Single diode model

The SDM, which is the most ECM commonly used and the easiest one to be implemented, and the PV module designed with N_s cells linked in a series configuration and/or N_p cells connected in parallel are mathematically expressed by (1) and (2) respectively:

$$I_{pv} = I_L - I_s \left[\exp\left(\frac{q(V_{pv} + I_{pv}R_s)}{nkT} \right) - 1 \right] - \frac{V_{pv} + I_{pv}R_s}{R_p} \tag{1}$$

$$I_{pv} = N_p I_L - N_p I_s \left[\exp\left(\frac{q(V_{pv} + (N_s/N_p)R_s I_{pv})}{nN_s kT} \right) - 1 \right] - \frac{V_{pv} + (N_s/N_p)I_{pv}R_s}{(N_s/N_p)R_p} \tag{2}$$

where:

I_{pv} output current

I_L photo-generated current

V_{pv} output voltage

T: cell temperature

k: Boltzman's constant ($1.380653 \times 10^{-23} J/K$),

q: electron's charge ($1.60217646 \times 10^{-19} C$)

n: diode ideality factor,

I_s: reverse saturation current.

R_p: parallel resistance

R_s: series resistance

These physical parameters collectively describe the electrical characteristics of a PV cell and are essential for modeling its behavior under various operating conditions.The(SDM) provides a simplified yet comprehensive framework for analyzing and optimizing PV.

Note that the previous models comprises five parameters which, have not been provided and should be identified, i.e., n, I_s, I_L, R_s and R_p. The SDM equivalent circuit is as shown in Fig. 1.

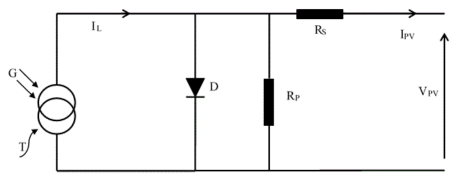

Fig. 1. Equivalents circuits model of SDM

2.2. Objective function

Almost all optimization algorithms require and should use an objective function (to be minimized or maximized) during the updating step. In this paper the difference between the computed data (calculated) and the observed data (measured) was established as an objective function. The global difference is calculated by the Root Mean Square Error (RMSE) as follows:

$$RMSE(x) = \sqrt{\frac{1}{M}\sum_{i=1}^{M} f\left(V_{mes},\ I_{mes},\ x\right)^2} \tag{3}$$

which M is the total measured points, the function f defined in (4) present the error function, x is the solution vector, I_{mes} and V_{mes} are the measured current and voltage, respectively.

$$f\left(V_{mes},\ I_{mes},\ x\right) = I_L - I_s\left[\exp\left(\frac{q(V_{mes}+I_{mes}R_s)}{nkT}\right) - 1\right] - \frac{V_{mes}+I_{mes}R_s}{R_p} - I_{pv} \tag{4}$$

3. Fully informed search (FIS) algorithm

The FIS is a simple and recent metaphor less algorithm [53] base on another simple algorithm proposed by Rao [52]. Rao algorithms, that do not include any specific or complex parameters, updates the current solutions to converge toward the global solution using three different formula, i.e., (5), (6) and (7) generating respectively three simple algorithm called Rao-1, Rao-2 and Rao-3. the Rao-1 is defined as:

$$Y_{i,j}^{new} = Y_{i,j}^{t} + \rho_{1,j} \times (Y_{b,j}^{t} - Y_{w,j}^{t}) \tag{5}$$

the Rao-2 is defined as:

$$\begin{cases} if\ f(Y_i^t) < f(Y_k^t) \\ Y_{i,j}^{new} = Y_{i,j}^{t} + \rho_{1,j} \times (Y_{b,j}^{t} - Y_{w,j}^{t}) + \rho_{2,j} \times (|Y_{i,j}^{t}| - |Y_{k,j}^{t}|) \\ else \\ Y_{i,j}^{new} = Y_{i,j}^{t} + \rho_{1,j} \times (Y_{b,j}^{t} - Y_{w,j}^{t}) + \rho_{2,j} \times (|Y_{k,j}^{t}| - |Y_{i,j}^{t}|) \end{cases} \tag{6}$$

the Rao-3 is defined as:

$$\begin{cases} if\ f(Y_i^t) < f(Y_k^t) \\ Y_{i,j}^{new} = Y_{i,j}^{t} + \rho_{1,j} \times (Y_{b,j}^{t} - |Y_{w,j}^{t}|) + \rho_{2,j} \times (|Y_{i,j}^{t}| - Y_{k,j}^{t}) \\ else \\ Y_{i,j}^{new} = Y_{i,j}^{t} + \rho_{1,j} \times (Y_{b,j}^{t} - |Y_{w,j}^{t}|) + \rho_{2,j} \times (|Y_{k,j}^{t}| - Y_{i,j}^{t}) \end{cases} \tag{7}$$

where $j \in$ [1 Dim] is the j^{th} dimension (Dim) of the i^{th} solution (noted by $Y_{i,j}^{t}$) throught the current iteration t. $\rho_{1,j}$ and $\rho_{2,j}$ are two random numbers selected from the interval $[0,\ 1]$. The best, worst and a random solutions are denoted by $Y_{b,j}^{t}$, $Y_{w,j}^{t}$ and $Y_{k,j}^{t}$, respectively. Lastly, (8) is utilized to ascertain the value of the i^{th} solution in the next iteration.

$$\begin{cases} Y_i^{t+1} = Y_i^{new},\ if\ f(Y_i^{new}) < f(Y_i^t) \\ Y_i^{t+1} = Y_i^{t},\ else \end{cases} \tag{8}$$

By keeping the simplicity of the previous techniques, FIS algorithm introduces a new formula to move the current solutions toward the best solution as given in (9).

$$Y_{i,j}^{new} = Y_{i,j}^{t} + \rho_{1,j} \times (MY_{b,j}^{t} - Y_{i,j}^{t}) + \rho_{2,j} \times (Y_{i,j}^{t} - MY_{w,j}^{t}) \tag{9}$$

For each iteration, the new introduced variables MY_b^t is presented as

$$MY_b^t = \frac{Y_b^t + \sum_{l \in Bi} Y_l^t}{length(Bi) + 1} \tag{10}$$

For each iteration, the new introduced variables MY_w^t is presented as

$$MY_w^t = \frac{Y_w^t + \sum_{l \in Wi} Y_l^t}{length(Wi) + 1} \tag{11}$$

where Wi and Bi are the set of population variables that have a worst and better fitness than the i^{th} variable in iteration t, respectively, and the enumeration of the members in the set is denoted by $length(.)$.
To clarify the designed algorithm, the block diagram of the proposed algorithm is presented in Fig. 2.

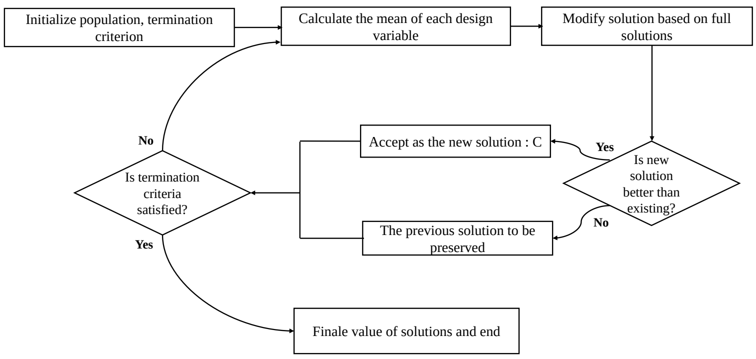

Fig. 2. The bloc diagram of the FISA algorithm

4. Numerical results

In this particular section, the FIS algorithm is executed within the MATLAB environment to estimate the parameters of SDM. This involves utilizing actual experimental data from two sources: a Poly-solar 320W-72P panel module, and a polycrystalline PV array that consists of three CLS-220P module types, as indicated in the work by Haddad et al [1]. The specific ranges chosen for each variable are illustrated in Table 1. The outcomes achieved through the implementation of the FIS approach are evaluated against the results of seven alternative algorithms, namely Rao-1 [20], HHO [23], IGWO [28], RUN [32], GTO [36], CPA [40] and CDO method [45]. All these techniques are programmed using a uniform number of iterations (MaxIt) and an identical population size (PopSize) set at 1000 and 30, respectively. Additionally, to ensure reliability in the comparison, each method is executed independently 30 times.

Table 1. Unknown PV parameters' range for the two studied cases

	Poly-solar 320W-72P		CLS-220P	
Parameter	**Min**	**Max**	**Min**	**Max**
I_L $[A]$	0	10	0	10
I_s $[\mu A]$	0	1	0	100
n	1	2	1	2
R_s $[\Omega]$	0	0.1	0	0.1
R_p $[\Omega]$	0	50000	0	50000

4.1. Case study (i): Poly-solar 320W-72P

First, a thorough examination is conducted for the obtained outcomes from the Poly-solar 320W-72P PV module. Fig. 3. illustrates the graphical representation of the I-V characteristics for both the simulated curve, employing the extracted parameters, and the experimental curve. Clearly, the optimized variables, upon integration into the PV model (as outlined in (1)), show a remarkable precision in replicating the real PV characteristic.

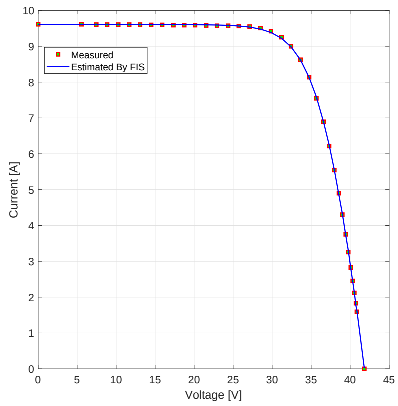

Fig. 3. Experimental and simulated curves for Poly-solar 320W-72P module

Table 2 offers the gained parameters, along with their corresponding RMSE values, comprising both the FIS algorithm and its competing methods. Notably, the lowest RMSE value $(2,5727764 \times 10^{-2})$ with a Std of $6,37109 \times 10^{-4}$ was achieved by the FIS algorithm which confirms the high accuracy and stability of the proposed algorithm.

Table 2. Estimated parameters of Poly-solar 320W-72P at the best RMSE

Parameters	I_L $[A]$	I_s $[A]$	**n**	R_s $[\Omega]$	R_p $[\Omega]$	**RMSE**	**Std**
FISA	9,60508	1,8298E-07	1,18484	4,5640E-03	20464,28	2,5727764E-02	6,37109E-04
HHO	9,60493	1,8185E-07	1,18442	4,5650E-03	17634,65	2,5730486E-02	2,58656E-02
IGWO	9,60594	1,9314E-07	1,18845	4,5505E-03	38975,06	2,5746217E-02	9,83990E-04
Rao1	9,60478	1,9419E-07	1,18874	4,5373E-03	50000,00	2,5816131E-02	1,04709E-03
RUN	9,60753	1,7996E-07	1,18371	4,5594E-03	100,68	2,5850208E-02	7,53345E-03
GTO	9,58741	2,7469E-07	1,21214	4,3545E-03	20937,45	3,3536324E-02	1,52667E-01
CPA	9,64967	2,8585E-08	1,07361	5,0159E-03	4,68	3,8383140E-02	3,65357E-01
CDO	9,61922	1,0000E-06	1,30979	4,1697E-03	20641,76	6,0737492E-02	5,25619E-02

Furthermore, the convergence graphs of FIS technique in comparison with those of HHO, IGWO, Rao1, RUN, GTO, CPA and CDO are drawn in Fig. 4. Upon observing this graphical representation, the proposed algorithm showcases an accelerated convergence rate towards the the best RMSE with a minimal number of iterations.

4.2. Case study (ii): CLS-220P module

The results derived from the analysis of a photovoltaic (PV) array (three CLS-220P polycrystalline modules), constitute the focus of this second case study. In this regard, identified parameters, RMSE and Std attained through the utilization of distinct techniques, including the applied FIS method are tabulated in Table 3. In the context of this table, it is evident that the best RMSE was acquired by the proposed FIS method, while the least favorable RMSE value was gained by the CDO algorithm. Also, Table 3 shows that the FIS technique proves its superiority in terms of both stability and accuracy when compared to its counterparts.

Additionally, the illustrated parameters in this table are used to plot (as depicted in Fig. 5) the I-V curve alongside the actual experimental curve for this case study.

Moreover, a display of the convergence curves produced by various algorithms is presented in Fig. 6. Obviously, This representation further confirms the computational efficiency and precision

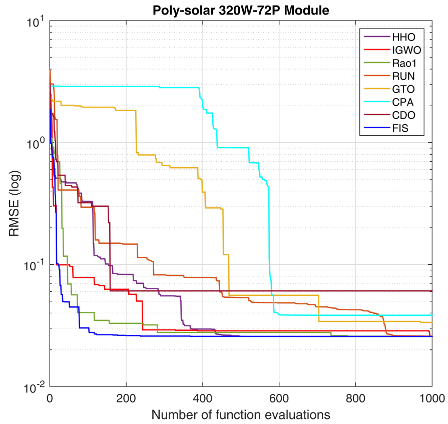

Fig. 4. Convergence graphs for Poly-solar 320W-72P module

Table 3. Estimated parameters of CLS-220P array at the best RMSE

Parameters	I_L $[A]$	I_s $[A]$	**n**	R_s $[\Omega]$	R_p $[\Omega]$	**RMSE**	**Std**
FISA	7,26125	8,8828E-08	1,18003	9,9328E-03	39819,65	2,1078827E-02	3,20551E-03
RUN	7,26277	2,1637E-07	1,24030	9,5564E-03	49998,91	2,3958763E-02	2,25800E-02
IGWO	7,26603	2,1498E-07	1,23987	9,6127E-03	7135,06	2,4761645E-02	8,64107E-03
Rao1	7,25403	2,6397E-07	1,25425	9,5126E-03	32098,25	3,4199762E-02	9,07210E-03
HHO	7,27454	5,8354E-07	1,31585	9,2775E-03	49686,26	3,7871432E-02	1,75464E-02
CPA	7,28469	3,5362E-06	1,47730	8,0784E-03	30708,81	5,7373468E-02	3,87291E-01
GTO	7,23763	1,7703E-06	1,41110	8,4457E-03	35591,81	5,9339053E-02	6,02164E-01
CDO	7,34312	8,8424E-05	1,88946	5,0639E-03	29523,00	1,1939979E-01	2,42783E-02

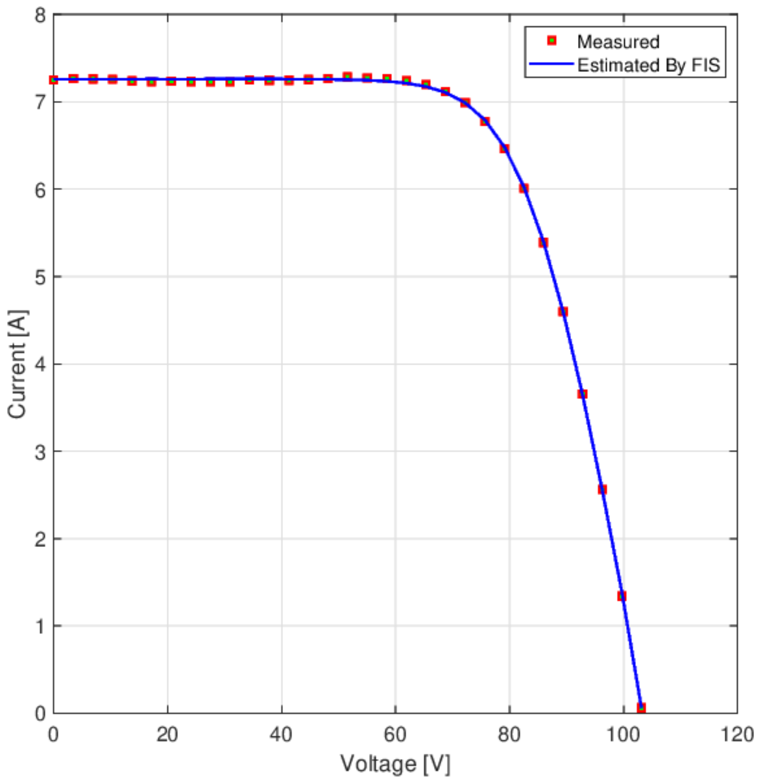

Fig. 5. Experimental and simulated curves for CLS-220P module

exhibited by the FIS algorithm.

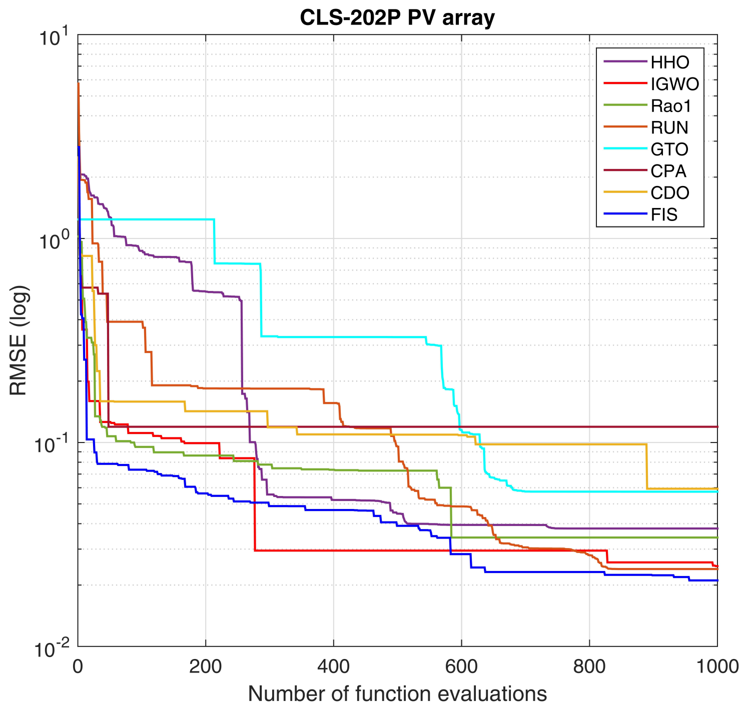

Fig. 6. Convergence graphs for CLS-220P module

5. Conclusion

The purpose of this paper is to examine the performance of the newly proposed FIS algorithm in estimating the unknown parameters for SDM. The algorithm is built upon Rao's approach, known for its simplicity and lack of specific or complex parameters. The paper is structured into four sections, encompassing the introduction, ECM of PV cells/modules, the illustration of the proposed method, and its validation using two modules: the Poly-solar 320W-72P panel module, along with a polycrystalline PV array comprising three CLS-220P modules. The accomplished results demonstrate the accuracy of parameters extraction using the FIS algorithm. The used algorithm succeeded in minimizing the fitness function to $2,5727764 \times 10^{-2}$ when applied for the Poly-solar 320W-72P component and it reaches $2,1078827 \times 10^{-2}$ as to CLS-220P PV array. Also, the experiments clearly affirms the superiority of the FIS method over seven recently introduced parameter identification approaches in both accuracy and stability. Besides, with the high matching of I–V characteristic with real data, FIS technique usable as an efficiency tool for optimizing the PV SDM parameters for various applications such as the MPPT.

In future work, we will study the implementation and tests a real PV photovoltaic systems, we also like to use the FISA algorithm to estimate the parameters of the adaptive P-type iterative learning control for robot manipulator systems.

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