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Identification study of solar cell/module using recent optimization techniques

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ABSTRACT

This paper proposes the application of a novel metaphor-free population optimization based on the mathematics of the Runge Kutta method (RUN) for parameter extraction of a double-diode model of the unknown solar cell and photovoltaic (PV) module parameters. The RUN optimizer is employed to determine the seven unknown parameters of the two-diode model. Fitting the experimental data is the main objective of the extracted unknown parameters to develop a generic PV model. Consequently, the root means squared error (RMSE) between the measured and estimated data is considered as the primary objective function. The suggested objective function achieves the closeness degree between the estimated and experimental data. For getting the generic model, applications of the proposed RUN are carried out on two different commercial PV cells. To assess the proposed algorithm, a comprehensive comparison study is employed and compared with several well-matured optimization algorithms reported in the literature. Numerical simulations prove the high precision and fast response of the proposed RUN algorithm for solving multiple PV models. Added to that, the RUN can be considered as a good alternative optimization method for solving power systems optimization problems.

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1. INTRODUCTION

The increased demand for electrical energy while decreasing CO_2 emission associated with electricity generation requires green renewable energy sources (GRERs). As a source of green energy, photovoltaic (PV) can generate electricity from sunlight using semiconductor materials. Globally, there is a massive increase in solar photovoltaic capacities in comparison with those of wind energy as per the REN21 latest published report in 2021 [1]. The Egyptian government pays a concentration towards the exploitation of available GRERs and PV especially. One of the most significant constructed PV projects in the world was at Benban, Aswan, Egypt, which has an installed capacity of 1.8 GW [2].

Due to this high potential spread, accurate modeling of PVs has a high impact on their performance under varied environmental conditions and shading. To express the non-linearity relationship between current-voltage (I-V) and power-voltage (P-V) of the PV cell, equivalent circuit models will be required. As per the literature, the single and double diode equivalent circuit models are used in parameter extraction of PV cells, which can be reviewed in [3]. However, its simplicity and reduced number of estimated parameters of the single diode equivalent circuit model, its precision diminishes at low irradiation levels with temperature variation [4], [5]. The estimated parameters in the single diode model are the photogenerated current, the reverse saturation currents, the series and shunt resistances, and the ideality factor. The double diode equivalent circuit model is composed of seven parameters, five of them the same as five parameters of the single diode in addition to two parameters, which are the reverse saturation current and the ideality factor of the additional diode.

As per the literature review, the parameter extraction techniques of the PV equivalent circuit model can be classified into three categories, namely analytical, numerical (deterministic and stochastic), and hybrid techniques [6], [7]. The analytical methods utilize the power-voltage and current-voltage data curves with the aids of selected data points from the manufacturer datasheets (the open-circuit voltage V_oc, the maximum output power P_m, the short circuit current I_sc, the maximum output current I_m, the maximum output voltage V_m) to constitute the mathematical parameter estimation problem [8]–[13]. These methods require some mathematical approximations (simplification) to reduce the number of extracted parameters. Although the used approximation provides ease of implementation and less computational effort, however, it has a significant impact on the solution accuracy. In study [14], it was approved that these approaches are less accurate than numerical approaches. To overcome modeling imprecision that may arise if there are inaccurate selected data from datasheets, the measured data of I-V are the same as used in numerical (iterative) techniques. The parameter extraction techniques can be categorized into two categories: deterministic and stochastic (heuristic and meta-heuristic) techniques. The deterministic techniques such as Newton-Raphson [15], linear identification [16], or the Levenberg-Marquardt (LM) algorithm [17] can be used for parameter extraction of PV equivalent circuit parameters. The main drawback of these conventional methods is local optimum trapping due to its sensitivity to the initial solution. As an alternative to the deterministic techniques, the naturally inspired (meta-heuristic) are extensively used in the last decade. In literatures, there are a lot of these methods such as, biogeography-based heterogeneous cuckoo search (BHCS) [18], pattern search (PS) [19], firefly algorithm (FA) [20], ant lion optimizer (ALO) [21], Jaya algorithm [22], salp swarm algorithm (SSA) [23], elephant herd optimizer [24], enhanced sine cosine algorithm (ISCA) [25], hybridized interior search algorithm (HISA) [26], an artificial bee colony-differential evolution (ABC-DE) [27], improved adaptive Nelder-Mead simplex (NMS) hybridized with the artificial bee colony (ABC) metaheuristic, algorithm of hybrid adaptive and Nelder-Mead simplex (EHA-NMS) [28], mutative-scale parallel chaos optimization algorithm (MPCOA) [29], classified perturbation mutation based particle swarm optimization (CPMPSO) [30], heterogeneous comprehensive learning particle swarm optimizer (HCLPSO) [31], and improved shuffled complex evolution (ISCE) [32]. A forensic based optimization algorithm was developed in [33] for finding the optimal parameters of solar cell modules. Another optimizer called turbulent flow of water optimizer in [34] was developed to optimize the parameters of three solar cell models. An assessment study based on the elephant herd optimization, which developed with different versions [35], is compared with closed loop particle swarm optimizer in [36]. The An interval branch and bound global optimization algorithm (IBBGO) that is referred to, interval branch/bound global optimizer, was integrated to find the optimal parameters of three PV models [37].

All these meta-heuristic optimization algorithms aim at minimizing the objective/cost function while balancing between exploration and exploitation phases. At the same time, meta-heuristic optimization algorithms cannot provide robust search capability towards optimal solutions [38]. To overcome these challenges, a novel metaphor-free population optimization based on the mathematics of the Runge Kutta method (RUN) is presented [39]. RUN optimizer balances between exploration and exploitation phases in dynamic behavior. Moreover, the RUN optimization algorithm has a competitive convergence speed as well as an enhanced solution quality to avoid local optimal solutions.

It is cleared that many meta-heuristic optimization algorithms are used for parameter extraction of the equivalent circuit of the PV model. Nevertheless, most of these algorithms have several control parameters that require tuning to achieve better performance for an optimization problem. The RUN algorithm has fewer control parameters due to its specific property which depends on the main logic of the Runge Kutta technique. This advantage motivates the authors of the presented article to use it in parameter estimation of the double diode model of PV cell/module. The main contribution of this research can be summarized as: i) develop RUN optimization algorithm for PV parameter extraction based on double diode model, ii) assessment of the extracted parameter using RUN with the recent optimization algorithms, iii) recommending the best method and best equivalent circuit model to be used for PV cell/module, and iv) the proposed RUN has the best convergence rates compared with the competitive methods.

This paper will be organized as follows: After this section, problem formulation will be introduced in section 2. Section 3 will develop the RUN optimization algorithm for use in parameter extraction of a PV cell/module. Application of the proposed algorithm to different commercial cell/module and test results will be emphasized in section 4. Section 5 will conclude the results drawn from this research.

2. PROBLEM FORMULATION

2.1. Electrical models

Mathematical modeling of PV cell/module equivalent circuits will be illustrated. The equivalent circuit models emulate the non-linear (I-V) and (P-V) relationships of the PV cell. This model is considered as the simplest equivalent circuit model. It has five parameters which are the photogenerated current I_{ph}, series and shunt resistances R_s, R_{sh}, the ideality factor n and the reverse saturation current I_{RS} as shown in Figure 1(a). The load current I of solar cells can be represented by (1):

$$I = I_{ph} - I_{RS-1}\left[\exp\left(\frac{V + IR_s}{n\,V_t} - 1\right)\right] - \frac{(V + IR_s)}{R_{sh}} \quad (1)$$

In this model, the recombination of generated charge carriers was neglected. Moreover, its precision diminishes at low irradiation levels with temperature variation [4]–[6]. The recombination effect was modeled in the double diode model that is presented in Figure 1(b), the load current I of solar cells can be represented by (2):

$$I = I_{ph} - I_{RS-1}\left[exp\left(\frac{V + IR_s}{n_1 V_t} - 1\right)\right] - I_{RS-2}\left[exp\left(\frac{V + IR_s}{n_2 V_t} - 1\right)\right] - \frac{(V + IR_s)}{R_{sh}} \quad (2)$$

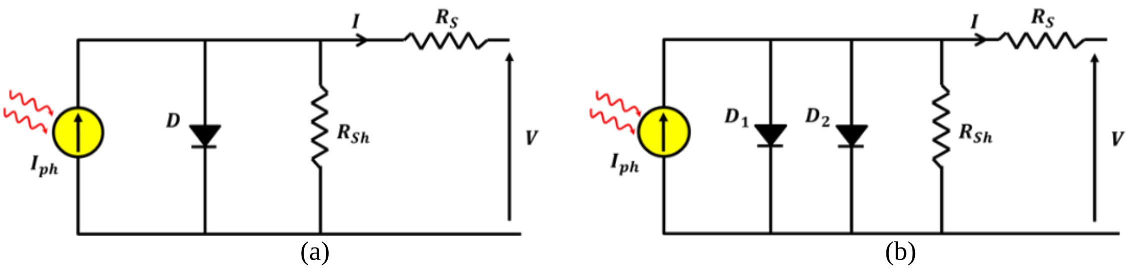

Figure 1. Diode equivalent circuit models, (a) single and (b) double

2.2. Mathematical representation of parameter extraction problem

The parameter extraction problem is considered an optimization problem. The main objective of the estimation problem is to minimize the variance between the experimental data and simulated results so that the optimal values of these unknown model parameters can be extracted. The objective function is defined as the overall root mean square error (RMSE). For N-measurements, the objective function is formulated as [38] as in (3):

$$RMSE(x) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[f(V_k, I_k, x) - I_k]^2} \quad (3)$$

where, $x = \{I_{ph}, I_{RS-1}, I_{RS-2}, R_S, R_{sh}, n_1, n_2\}$ and the $f(V_k, I_k, x)$ is used for current calculation from (2).

3. RUNGE KUTTA OPTIMIZER (RUN)

The Runge Kutta-based optimization (RUN) is a novel optimization algorithm proposed in [39]. The RUN is developed based on the mathematics of the Runge Kutta method. It is inspired by the logic of slope variations computed by the Runge Kutta method as a promising and logical searching mechanism for global optimization. In RUN, three distinctive phases are simulated. These phases are active exploration and exploitation phases for exploring the promising regions in the feature space and constructive toward the global best solution. Moreover, in the last phase, an enhanced solution quality mechanism is employed to avoid the local optimal solutions and increase convergence speed. Figure 2 demonstrates the phases of the proposed RUN algorithm. The phases of the suggested RUN optimizer are discussed in detail in the following sub-sections.

Algorithm 1. The pseudo-code of RUN

```
Stage 1. Initialization
Initialize a, b
Generate the RUN population X_n (n = 1, 2, …, N)
Calculate the objective function of each member of the population
Determine the solutions x_w, x_b, and x_best
Stage 2. RUN operators
  for i= 1: Maxi
     for n = 1 : N
        for l = 1 : D
          Calculate position x_{n+1,l} using Eq. 4
        end for
        Enhance the solution quality
         if rand < 0.5
          Calculate position x_new2 using Eq. 7
            if f(x_n) < f(x_new2)
            if rand< w
                 Calculate position x_new3 using Eq. 9
              end
            end
         end
      Update positions x_w and x_b
     end for
     Update position x_best
    i=i+1
  end
Stage 3. return x_best
```

Figure 2. Pseudo-code of the proposed algorithm (RUN)

3.1. Updating solutions stage

In the updating solutions stage, the RUN uses a search mechanism (SM) based on the runge kutta method to update the position of the current solution at each iteration, which is defined as (4):

$$\begin{aligned}
&if\ \ rand < 0.5\\
&\text{(Exploration phase)}\\
&\quad x_{n+1} = (x_c + r.SF.g.x_c) + SF.SM + \mu.randn.(x_m - x_c)\\
&else\\
&\text{(Exploitation phase)}\\
&\quad x_{n+1} = (x_m + r.SF.g.x_m) + SF.SM + \mu.randn.(x_{r1} - x_{r2})\\
&end
\end{aligned} \tag{4}$$

where, r is an integer number, which is 1 or-1. g is a random number in the range [0, 2]. SF is an adaptive factor. Where, μ is a random number. The formula of SM is defined in [34]. The formula of SF is as (5):

$$SF = 2.(0.5 - rand)\times f \tag{5}$$

where, $f = a \times exp\left(-b \times rand \times \left(\frac{i}{Maxi}\right)\right)$, *Maxi* stands for the largest number of iterations. The formula of x_c and x_m are as (6):

$$\begin{aligned}
x_c &= \varphi \times x_n + (1 - \varphi) \times x_{r1}\\
x_m &= \varphi \times x_{best} + (1 - \varphi) \times x_{lbest}
\end{aligned} \tag{6}$$

where, φ is a random number in the range of (0,1). x_{best} is the best-so-far solution. x_{lbest} is the best position obtained at each iteration.

3.2. Enhanced solution quality stage

In the RUN algorithm, enhanced solution quality (ESQ) is employed to increase the quality of solutions and to avoid local optima in each iteration. The following scheme is executed to create the solution (x_{new2}) by using the ESQ (7), (8):

$$\begin{aligned}
&if\ \ rand < 0.5 \\
&if\ \ w < 1 \\
&x_{new2} = x_{new1} + r.w.|(x_{new1} - x_{avg}) + randn| \\
&else \\
&x_{new2} = (x_{new1} - x_{avg}) + r.w.|(u.x_{new1} - x_{avg}) + randn| \\
&end
\end{aligned} \tag{7}$$

$$\begin{aligned}
&w = rand(0, 2).exp\left(-c\left(\frac{i}{Maxi}\right)\right), x_{avg} = \frac{x_{r1}+x_{r2}+x_{r3}}{3}, \\
&x_{new1} = \beta \times x_{avg} + (1-\beta) \times x_{best}
\end{aligned} \tag{8}$$

where, β is a random number in the range of [0, 1]. c is a random number, which is equal to $5\times rand$ in this study. r is an integer number, which is 1, 0, or-1. x_{best} is the best solution explored so far. The solution calculated in this part (x_{new2}) may not have better fitness than that of the current solution (i.e., $f(x_{new2}) > f(x_n)$). To have another chance for creating a good solution, another new solution (x_{new3}) is generated, which is defined as in (9),

$$\begin{aligned}
&\text{if rand} < w \\
&x_{new3} = (x_{new2} - rand.x_{new2}) + SF.(rand.x_{RK} + (v.x_b - x_{new2})) \\
&end
\end{aligned} \tag{9}$$

where v is a random number with a value of $2 \times rand$.

4. SIMULATION AND RESULT

To assess the proposed algorithm, a comprehensive study is employed compared with several previous optimization algorithms. Numerical simulations on different commercial PV cells/modules will be illustrated below. To evaluate the performance of the proposed algorithm, A set of standard data for a commercial silicon solar cell (made by R.T.C. company from France) with a diameter of 57 mm, at a temperature of 33 °C, and 1 sun (1,000 W/m^2) [40]. The PhotowattPWP201 PV commercial module with 36 polycrystalline silicon cells connected in series, operating under an irradiance of 1,000 W/m^2 and temperature of 45 °C [41]. Table 1 summarizes the datasheets of the selected commercial PV cell/module to be tested in this work. The boundary constraints of the extracted parameters are given in Table 2. The proposed RUN-based model and the other comparative algorithms are executed by the authors via the matrix laboratory (MATLAB) 2017a platform using an Intel ® core TM i5-7200U CPU, 2.50 GHz, 8 GB RAM Laptop. Accuracy examination of the proposed optimization RUN algorithm for parameters identification will be additionally accomplished by the current calculation based on the values estimated for the two models considered for comparison with that taken from the experimental measurements. The error concerning each of the measured values was evaluated by relative error (RE) and individual absolute error (IAE), calculated as given in (10) and (11), respectively.

$$RE = (I_{Measured} - I_{Estimated})/I_{Measured} \tag{10}$$

$$IAE = |I_{Measured} - I_{Estimated}| \tag{11}$$

Table 1. Datasheets of selected cell/module for study

Company	Cell type	V_{oc} [V]	I_{sc} [A]	V_m [V]	I_m [A]	P_m [W]	Reference temp. [°C]	# of cells / module
France solar	NA	0.5728	0.76	0.45	0.691	11.315	33	1
Photowatt	Polycrystalline	16.778	1.03	12.60	0.898	0.311	45	36

Table 2. Boundary constraints of the extracted parameters

Model		Parameters				
France solar		I_{ph} [A]	$I_{RS1,2}[\mu A]$	R_S [Ω]	R_{sh} [Ω]	$n_{1,2}$
	Min	0	0	0	0	1
	Max	1	1	0.5	100	2
Photowatt 201	Min	0	0	0	0	1
	Max	2	10	0.5	3000	2

4.1. RTC. france solar cell

For RTC solar cell model, the optimal parameters attained using different optimization techniques are presented in Table 3. The solar cell parameters estimated using the RUN algorithm have the lowest RMSE value. Figure 3 demonstrates that the estimated I-V and P-V characteristics using RUN are identical compared to the measurement as well as the datasheet. Table 4 spots the light on the coincidence between both the measured and estimated values for voltage and current. The results of MPP are highlighted in green in Table 4 and illustrated in Figure 3. As can be concluded from Figure 4, RUN has the lowest RMSE value (0.0009829) in comparison with sunflower optimization (SFO), which has the highest value (0.002). On the other hand, RUN has the lowest execution time of (9.95 s) in comparison with SFO, which has the highest execution time of (44.402 s).

Table 3. Optimum parameter settings using different optimization techniques for RTC France solar cell

	RCGA	CSA	SSA	PSO	SFO	GW-CS	RUN
I_{ph} (A)	0.7606	0.7608	0.7604	0.76077	0.76275	0.76002	0.76077
$I_{RS-1}(\mu A)$	0.3743	0.6489	0.3165	0.6680	0.2452	0.2272	0.22266
$I_{RS-2}(\mu A)$	0.0731	0.2199	0.1728	0.2389	0.8324	0.2553	0.67737
R_S (Ω)	0.0357	0.0367	0.0369	0.0366	0.0339	0.0359	0.03674
$R_{sh}(\Omega)$	60.823	54.946	59.7711	55.691	51.165	67.0574	55.4973
n_1	1.4968	1.9454	1.69629	2.000	1.4768	1.4632	1.45006
n_2	1.9607	1.4493	1.43602	1.4559	1.7895	1.6630	1.96604
RMSE	0.0010	0.000985	0.00103	0.00098	0.002	0.00110	0.0009829
Duration [s]	13.655	11.524	10.1512	10.567	44.402	14.131	9.95

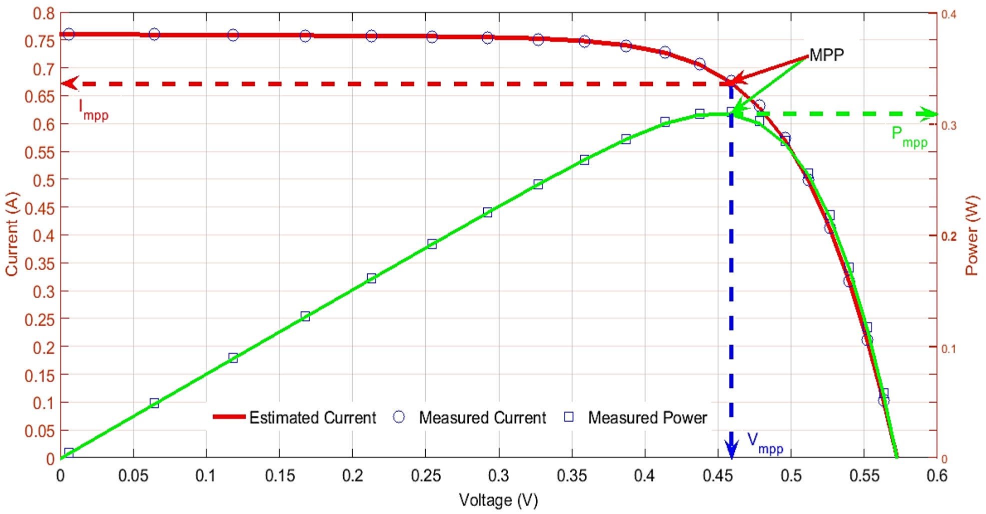

Figure 3. The coincidence between measured and estimated results in V-I and V-P curves of RTC-solar cell

Table 4. The relative error for each measurement using a RUN-based two diode model

Measured Voltage	Measured current	Estimated current	IAE	RE	Measured Voltage	Measured current	Estimate d current	IAE	RE
-0.2057	0.764	0.7640	0.0000	0.0000	0.4373	0.728	0.7399	0.0014	0.0019
-0.1291	0.762	0.7626	0.0006	0.0008	0.4590	0.7065	0.7271	0.0009	0.0012
-0.0588	0.7605	0.7613	0.0008	0.0011	0.4137	0.6755	0.7066	0.0001	0.0001
0.0057	0.7605	0.7602	0.0003	0.0004	0.4784	0.632	0.6748	0.0007	0.0010
0.0646	0.7600	0.7591	0.0009	0.0012	0.4960	0.573	0.6302	0.0018	0.0029
0.1185	0.7590	0.7581	0.0009	0.0012	0.5119	0.499	0.5711	0.0019	0.0033
0.1678	0.7570	0.7572	0.0002	0.0002	0.5265	0.413	0.4982	0.0008	0.0017
0.2132	0.7570	0.7562	0.0008	0.0010	0.5398	0.3165	0.4118	0.0012	0.0030
0.2545	0.7555	0.7552	0.0003	0.0004	0.5521	0.212	0.3150	0.0015	0.0046
0.2924	0.7540	0.7537	0.0003	0.0004	0.5633	0.1035	0.2095	0.0025	0.0119
0.3269	0.7505	0.7514	0.0009	0.0012	0.5736	-0.01	0.0997	0.0038	0.0368
0.3585	0.7465	0.7473	0.0008	0.0010	0.5833	-0.123	-0.0126	0.0026	-0.2618
0.3873	0.7385	0.7640	0.0000	0.0000	0.5900	-0.21	-0.1280	0.0050	-0.0408

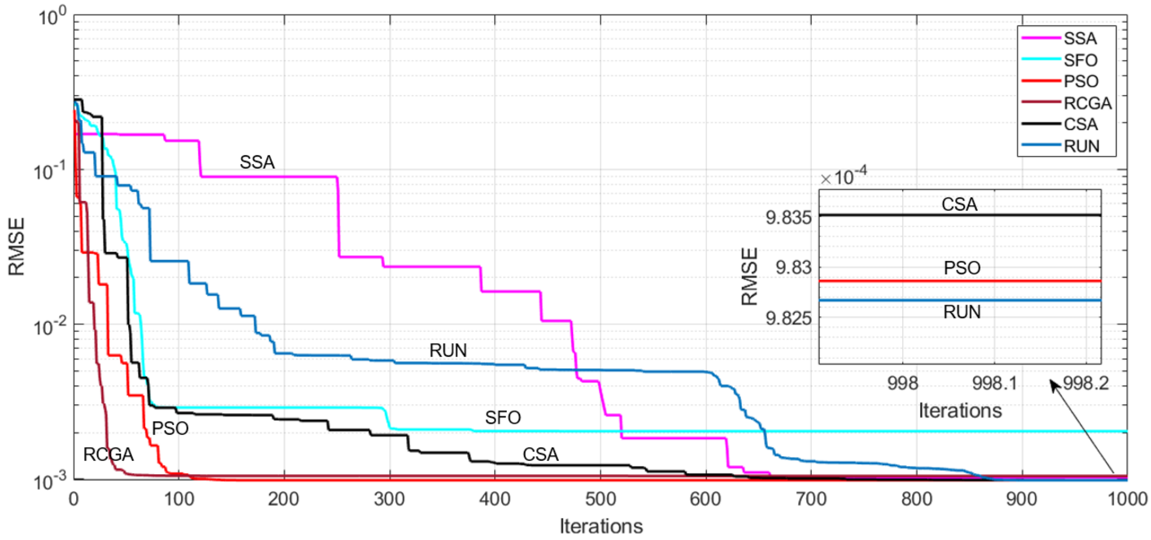

Figure 4. The objective function of the competitive estimation algorithms

4.2. Photo watt PWP201

In the Photowatt PWP201 module, from the obtained results in Tables 5 and 6, the RUN has the lowest RMSE value (0.003139) among the competitive optimization algorithms. The maximum power point (MPP) is highlighted in green in Table 6 and illustrated clearly in Figure 5. The RMSE for all optimization techniques are plotted in Figure 6. Generally speaking, RUN has the lowest RMSE value (0.003139) compared to all the applied optimization techniques. The crow search algorithm (CSA) comes in the first class in terms of execution time with (10.2910 s) in comparison with the SFO with (46.7350 s), which has the highest value of elapsed time.

Table 5. Optimum parameter settings using competitive optimization algorithms for Photowatt-PWP201

	RCGA	CSA	SSA	PSO	SFO	GW-CS	RUN
I_{ph} (A)	1.0252	1.0258	1.02867	1.0258	1.01883	1.02574	1.0270
$I_{RS-1}(\mu A)$	5.1463	9.8979	7.59250	3.8226	0.2769	0.2527	1.4074
$I_{RS-2}(\mu A)$	2.4599	3.8944	7.53697	5.0705	0.9499	6.01257	5.5321
R_S (Ω)	0.0321	0.0322	0.02864	0.03175	0.03724	0.03191	0.0321
$R_{sh}(\Omega)$	1000	1001	629.437	1000	351.092	248.962	100.3905
n_1	1.3982	1.877	1.48011	1.7271	1.32756	1.89869	1.9920
n_2	1.767	1.3723	1.61563	1.4007	1.23380	1.41230	1.4034
RMSE	0.0035	0.0035	0.00491	0.00349	0.00734	0.00347	0.003139
Duration[s]	12.0730	10.2910	19.5530	10.4660	46.7350	11.4380	11.25

Note: RCGA= real coded genatic algorithm, SSA = introduced in the introduction, PSO is particle swarm optimization, GW-CS = gray wolf cuckoo search algorithm

Table 6. The relative error for each measurement using a RUN-based two diode model

Measured voltage	Measured current	Estimated current	IAE	RE	Measured Voltage	Measured current	Estimated current	IAE	RE
1.9426	1.0345	1.0272	0.0073	0.0070	12.6490	0.9120	0.9227	0.0028	0.0030
0.1248	1.0315	1.0266	0.0049	0.0047	13.1231	0.8725	0.9117	0.0003	0.0003
1.8093	1.0300	1.0261	0.0039	0.0038	14.2221	0.7265	0.8715	0.0010	0.0012
3.3511	1.0260	1.0256	0.0004	0.0004	14.6995	0.6345	0.7264	0.0001	0.0002
4.7622	1.0220	1.0249	0.0029	0.0029	15.1346	0.5345	0.6352	0.0007	0.0010
6.0538	1.0180	1.0239	0.0059	0.0058	15.5311	0.4275	0.5349	0.0004	0.0007
7.2364	1.0155	1.0222	0.0067	0.0066	15.8929	0.3185	0.4285	0.0010	0.0024
8.3189	1.0140	1.0189	0.0049	0.0049	16.2229	0.2085	0.3188	0.0003	0.0010
9.3097	1.0100	1.0131	0.0031	0.0031	16.5241	0.1010	0.2083	0.0002	0.0009
10.2163	1.0035	1.0029	0.0006	0.0006	16.7987	-0.0080	0.0989	0.0021	0.0204
11.0449	0.9880	0.9862	0.0018	0.0018	17.0499	-0.1110	-0.0076	0.0004	-0.0472
11.8018	0.9630	0.9603	0.0027	0.0028	17.2793	-0.2090	-0.1106	0.0004	-0.0034
12.4929	0.9255	1.0272	0.0073	0.0070	17.4885	-0.3030	-0.2091	0.0001	-0.0005

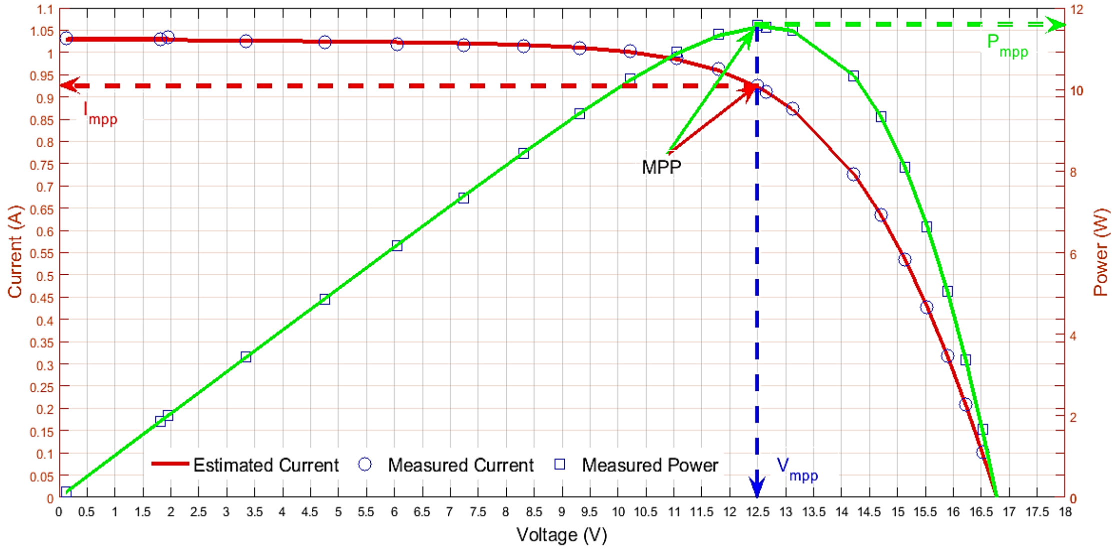

Figure 5. The coincidence between measured and estimated results in V-I and V-P curves of PWP201

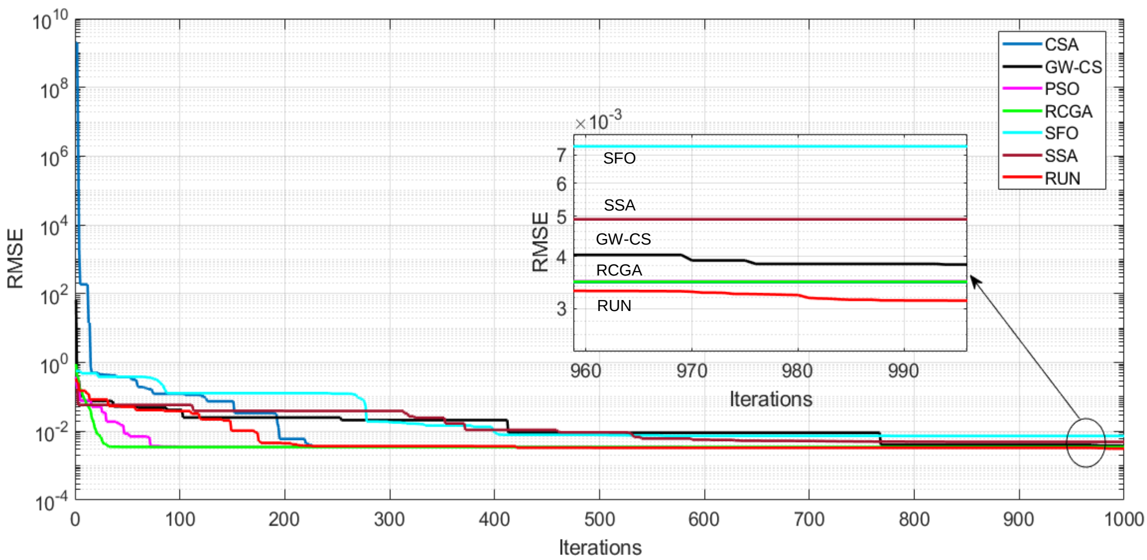

Figure 6. The convergence rates of objective function decline using competitive algorithms

5. CONCLUSION

This manuscript presents a new physical implementation of modern inspired optimization algorithms called RUN for PV cells/modules parameter estimation. To validate and verify the main findings, the proposed algorithm was implemented and tested on two commercial cells/modules. Moreover, a comprehension comparison of the latest meta-heuristic optimization algorithms was illustrated. The attained theoretical and experimental results are coincident, which proves the superiority of RUN in the field of parameter estimation for PV cells/modules. The results signify the effectiveness and reliability of the proposed RUN in estimating the accurate double diode model of two practical PV cells/modules. The RUN realizes steady convergence rates than other competitive algorithms. Finally, the main findings of this article will pave the way for the authors as well as the researchers to evaluate the impact of the estimated parameters in emulating PV equivalent circuits under various real operating conditions.

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