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Article

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Research paper

Extraction of uncertain parameters of single-diode model of a photovoltaic panel using simulated annealing optimization

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ABSTRACT

In this article, our goal is to improve the estimation of the parameters of solar photovoltaic models, we propose a method based on Simulated Annealing (SA) Optimization, the proposed algorithm takes into account the uncertainties of measurements. This algorithm consists of three steps such as the extraction of the parameters in a conventional manner, then the determination of the uncertainties of each parameter, finally the determination of the instantaneous parameters taking into account the results of the first two steps. For the validation of the proposed theoretical developments, the algorithm is applied to four different PV parameter estimation problems. The results obtained are compared with well-established algorithms to confirm its effectiveness. These comparisons have shown that the proposed method exhibits largely effective performances than existing methods in the literature.

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1. Introduction

The use of renewable energy sources such as wind, sun, biomass, etc. receives increasing interest. For the creation of electricity, solar photovoltaic systems are widely used around the world. However, the use of photovoltaic systems depends on meteorological and environmental factors, such as variations in temperature and overall irradiance. Therefore, there is a need for optimization of the photovoltaic system. This can be achieved by using a precise analytical model based on the measurement data of (current (I), voltage (V)). In the literature, the simple diode model is most used. The objective is the parameters extraction of the model to analytically fitting of the experimental measurements. Therefore, the accuracy of parameter values is essential to the study of solar photovoltaic systems. Consequently, the method used for the determination of the parameters plays a primordial role in the resolution of this problem.

Over the years, several methods are used for extracting solar cell parameters. Three main groups of methods are introduced. First, analytical methods are characterized by their simplicity and rapidity of calculation. However generally, they lack precision since they are based on several hypotheses. We can cite some works such that, the conductance method (Chegaar et al., 2004), the five-point and the modified methods (Kennerud, 1969),..., etc. Secondly, deterministic methods, these methods are very sensitive to the initial values in addition they are demanding at the level of differentiability and convexity such that

Newton method (Lun et al., 2013), Newton–Raphson method (Easwarakhanthan et al., 1986a), non-linear algorithm method (Cabestany and Castaier, 1983). Finally, to circumvent the weaknesses of the previous two methods, the meta-heuristic methods were considered as a promising solution for the extraction of PV model parameters. Because these methods do not have strict requirements and are easy to implement.

Most meta-heuristic methods are inspired by the phenomena of nature. They do not need to satisfy the conditions of convexity or differentiability of objective functions. Because of these advantages, different meta-heuristic methods have been applied to solve PV parameter estimation problems. Such as particle swarm optimization (PSO) (Abdul Hamid et al., 0000), simulated annealing algorithm (SA) (El-Naggar et al., 2012), genetic algorithm (GA) (Patel et al., 2013), pattern search (PS) (AlHajri et al., 2012), biogeography based optimization (BBO) (Niu et al., 2014), Artificial bee colony (ABC) (Oliva et al., 2014), chaotic asexual reproduction (CAR) (Yuan et al., 2015), adaptive differential evolution (ADE) (Chellaswamy and Ramesh, 2016), symbiotic organic search (SOS) (Xiong et al., 2018), improved shuffled complex evolution (ISCE) (Gao et al., 2018b), hybrid firefly algorithm and pattern search (HFAPS) (Beigia and Maroosi, 2018), multi learning backtracking search (MLBTS) (Yu et al., 2018), firefly algorithm (FA) (Louzazni et al., 2018), ant lion optimization (ALO) (Kanimozhi Harish Kumar, 2018), particle swarm optimization/ adaptive mutation strategy (PSOAMS) (Merchaoui et al., 2018), improved cuckoo search algorithm (ImCSA) (Kang, 2018), improved teaching learning based optimization (ITLBO) (Li et al., 2019), hybridizing cuckoo search / biogeography based optimization (BHCS) (Chena and Yu, 2019), JAYA algorithm (Yu et al., 2017,

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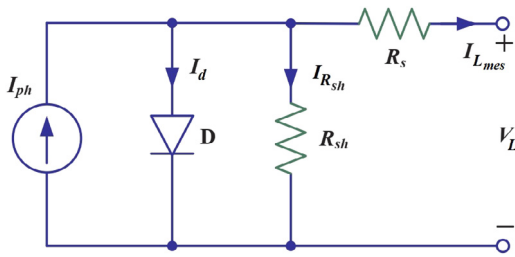


Fig. 1. Equivalent circuits of single diode model.

2019) and three point based approach (TPBA) (Chin and Salam, 2019).

Although these meta-heuristic methods have yielded satisfactory results compared to analytical or deterministic methods, their accuracy and reliability still need to be improved. In addition, the performance of the algorithms can be affected in the case of the wrong choice of their algorithmic parameters. In addition, the problem of the presence of measurement uncertainty has not been taken into account in the work involving meta-heuristic methods. Although the treatment of measurement uncertainties can be considered as an important parameter for the design of the mathematical model.

In this paper, the measurement uncertainty parameter will be considered to perform the parameter extraction procedure of a single-diode model using SA. The extraction procedure consists of three steps. First, the SA algorithm is used to extract the parameters without taking into account the uncertainty. Then, in order to minimize the search interval of the parameters, we look for the uncertainty of each parameter taking into account the result of the first step, so we will obtain more precise search intervals. Finally, the values of the parameters are estimated at each iteration taking into account the results of the first two steps. For the validation of the theoretical developments proposed in this article, it applies to four different PV parameter estimation problems. A test of statistical study will be used (Wilcoxon test). The results obtained are compared with well-established algorithms to confirm its effectiveness. It should be noted that the performance of the proposed technique is much higher than the existing work in the literature.

2. Preliminary

Before proceeding to the parameter extraction phase, it is essential to have a mathematical model that accurately represents the electrical characteristics of the solar cell. Although many equivalent circuit models have been developed and proposed over the past four decades to describe the behaviour of solar cells. in this article, we are interested in the 5 parameters model. the equivalent circuit of the single diode model illustrated by Fig. 1, the photovoltaic system under illumination is modelled as a photocurrent source, a diode and two parasitic resistors such as

3. Problem formulation and main results

In this paper, our goal is to extract the parameters of the equivalent circuit shown in Fig. 1.

3.1. The classic metaheuristic extraction solar cell parameters method

The equivalent circuit can be represented in the form of an analytical equation such as:

$$\hat{I}_L = I_{ph} - I_d - I_{sh} \quad (1)$$

where \hat{I}_L denotes the estimated output current, I_{ph} denotes the photo generated current. I_{sh} is the shunt resistor current. I_d represents the diode current. The terms I_{sh} and I_d of Eq. (1) are expressed as follows:

$$I_d = I_{sd} \left[\exp\left(\frac{V_L + R_s I_{L_{mes}}}{nV_t}\right) - 1 \right] \quad (2a)$$

$$I_{sh} = \frac{V_L + R_s I_{L_{mes}}}{R_{sh}} \quad (2b)$$

$$V_t = \frac{kT}{q} \quad (2c)$$

where I_{sd} denotes the saturation current, V_L denotes the output voltage, $I_{L_{mes}}$ denotes the measured output current, R_s denotes the series resistance, n denotes the diode ideal factor and R_{sh} the shunt resistance. V_t denotes the thermal voltage of the diode such that k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), q is the electron charge ($1.60217646 \times 10^{-19}$ C) and T is the cell temperature (K).

It is observed from Eqs. (1)–(2) that if we know the values of I_{ph} , I_{sd} , R_s , R_{sh} , and n , then the $I - V$ characteristic of this model can be constructed. Therefore, accurate extraction of these five unknown parameters is the core of this study. Over the years, several methods have been used to solve the problem of solar cell parameters extraction. In this paper, the estimation problem is formulated as a nonlinear optimization problem. The SA algorithm is used to estimate the parameters by minimizing a preselected objective function.

$$F = \min_{X \in [l_b, u_b]} \sqrt{\frac{1}{N} \sum_{i=1}^N (f(V_L(i), I_{L_{mes}}(i), X))^2} \quad (3)$$

where

$$f(V_L, I_{L_{mes}}, X) = I_{L_{mes}} - \hat{I}_L = I_{L_{mes}} - (I_{ph} - I_{sd} \left[\exp\left(\frac{V_L + R_s I_{L_{mes}}}{nV_t}\right) - 1 \right] - \frac{V_L + R_s I_{L_{mes}}}{R_{sh}}) = 0 \quad (4)$$

where $X = [I_{ph}, I_{sd}, R_s, R_{sh}, n]$ represent the vector of unknown parameters, N is the number of data points, l_b and u_b are the lower and upper bounds on parameter vector X .

The objective function must be minimized with respect to the parameter set. Theoretically, the objective function should be zero when the exact values of the parameters are obtained. But this objective is practically impossible since there is always some unforeseen with respect to the operator such as “noise, unknown inputs, etc ...”. In addition, the smaller the objective function, the better the solution.

3.2. Proposal of extraction of the uncertainties of the parameters

Accessing an objective value of reality without error is simply impossible. This leads us to conclude that any experimental measure is tainted with error. The error is part of the measurement operation. In this case, the analysis of experimental results becomes more difficult to achieve. In order to improve the performance of this analysis, we will introduce the notion of uncertainty. Consequently, the correct way to state the result of the measurement is to give the best estimate of the quantity and the range within which you are confident the quantity lies. Based on these notions, we can write the following form:

$$I_{L_{mes}} = \hat{I}_L \pm \delta I_L \quad (5)$$

δI_L represent the measurement uncertainty of I_L . Taking into account equation (5), the expression of I_L can be bounded by the following range:

$$I_{1_{mes}} = I_{L_{mes}} - \Delta I_L \leq I_{L_{mes}} \leq I_{L_{mes}} + \Delta I_L = I_{2_{mes}} \quad (6)$$

where ΔI_L is the measurement uncertainty norm of I_L such that $\Delta I_L = \sqrt{\sum_{i=1}^N (I_{L_{mes}}(i) - \hat{I}_L(i))^2}$. Now, we suppose that the expressions I_1 and I_2 can be expressed as equations that depend on the uncertainties ΔI_{ph} , ΔI_{sd} , Δn , ΔR_s and ΔR_{sh} such that

$$\hat{I}_1 = (\hat{I}_{ph} - \Delta I_{ph}) - (\hat{I}_{sd} - \Delta I_{sd}) \left[\exp\left(\frac{V_L + (\hat{R}_s - \Delta R_s) I_{L_{mes}}}{(\hat{n} - \Delta n) V_t}\right) - 1 \right] - \frac{V_L + (\hat{R}_s - \Delta R_s) I_{L_{mes}}}{(\hat{R}_{sh} - \Delta R_{sh})} \quad (7a)$$

$$\hat{I}_2 = (\hat{I}_{ph} + \Delta I_{ph}) - (\hat{I}_{sd} + \Delta I_{sd}) \left[\exp\left(\frac{V_L + (\hat{R}_s + \Delta R_s) I_{L_{mes}}}{(\hat{n} + \Delta n) V_t}\right) - 1 \right] - \frac{V_L + (\hat{R}_s + \Delta R_s) I_{L_{mes}}}{(\hat{R}_{sh} + \Delta R_{sh})} \quad (7b)$$

where \hat{I}_{ph} , \hat{I}_{sd} , \hat{R}_s , \hat{n} and \hat{R}_{sh} are the estimated of parameters I_{ph} , I_{sd} , R_s , n and R_{sh} respectively, these estimations are determined previously using the optimization problem (4).

We note that the uncertainties ΔI_{ph} , ΔI_{sd} , Δn , ΔR_s and ΔR_{sh} are bounded by the interval $[0, \Delta I_L]$. Now, our objective is to estimate the uncertainties. In this context, we consider the following objective function:

$$f_1(V_L, I_{L_{mes}}, \hat{X}, \Delta X) = \min_{\Delta X \in [0, \Delta I_L]} \sqrt{\frac{1}{N} \sum_{i=1}^N \left((I_{1_{mes}}(i) - \hat{I}_1(i))^2 + (I_{2_{mes}}(i) - \hat{I}_2(i))^2 \right)} \quad (8)$$

At this level of paper, an estimate of the parameters and their uncertainties were obtained. As a consequence, a new search interval of the unknown parameters can be obtained, such that:

$$\hat{X} - \widehat{\Delta X} \leq X \leq \hat{X} + \widehat{\Delta X} \quad (9)$$

where $\hat{X} = [\hat{I}_{ph}, \hat{I}_{sd}, \hat{R}_s, \hat{R}_{sh}, \hat{n}]$ denotes the estimated of unknown parameters vector, $\widehat{\Delta X} = [\widehat{\Delta I_{ph}}, \widehat{\Delta I_{sd}}, \widehat{\Delta R_s}, \widehat{\Delta R_{sh}}, \widehat{\Delta n}]$ denotes the estimated of uncertainties parameters vector.

3.3. Instant solar cell parameter extraction proposal

Now, we will propose a new concept that is used to extract the instantaneous values of each unknown parameters. To do this, we will consider the new parameters limitation interval described in (9) and the overall flow of the proposed algorithm is depicted in Fig. 2. In addition, we will consider a new optimization problem such that:

$$f_2(V_L, I_{L_{mes}}, X) = \min_{X \in [\hat{X} - \widehat{\Delta X}, \hat{X} + \widehat{\Delta X}]} \sqrt{\frac{1}{N} \left(I_{L_{mes}}(i) - \hat{I}_L(i) \right)^2} \quad (10)$$

4. Simulated annealing

Simulated annealing (SA) is a probabilistic technique for approaching the global optimum of a given function (El-Naggar et al., 2012). The approach is inspired by the annealing technique in metallurgy, this technique controls the heating and cooling of a material in order to increase the size of its crystals and reduce their defects. These two parameters affect the thermodynamic free energy and the temperature of the material to be studied. the principle consists to generate series of repetitive configurations from an initial solution and initial temperature which will decrease throughout the process until reaching a state of equilibrium (global minimum). This is often done by the following procedure Fig. 3 :

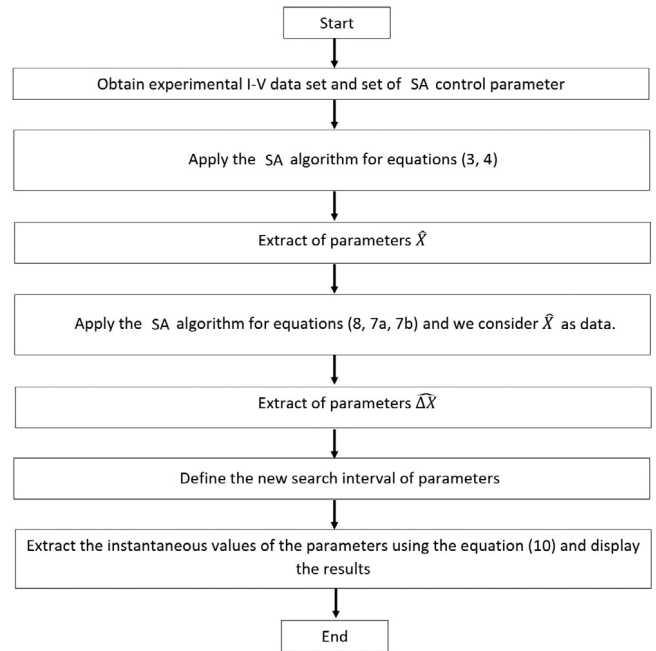


Fig. 2. Overall flowchart of proposed algorithm.

Initialize the system configuration.

Randomize $x(0)$.

Initialize T with a large value.

Repeat:

a. **Repeat:**

i. Apply random perturbations to the state $x = x + \Delta x$.

ii. Evaluate $\Delta E(x) = E(x + \Delta x) - E(x)$:

if $\Delta E(x) < 0$, keep the new state;

otherwise, accept the new state with probability $P = e^{-\frac{\Delta E}{T}}$.

until the number of accepted transitions is below a threshold level.

b. Set $T = T - \Delta T$.

until T is small enough.

Fig. 3. Simulated annealing algorithm.

5. Results and discussions

In this work, the SA is applied to estimate the uncertain parameters of the single-diode models of solar cell and solar module cited in Easwarakhanthan et al. (1986b) and Tong and Pora (2016) such that:

The measurements are performed on a silicon solar cell RTC France under the following conditions 1 sun (1000 W/m²) at 33 °C and a solar module (Photowatt-PWP 201) in which 36 polycrystalline silicon cells are connected in series under 1 sun (1000 W/m²) at 45 °C (Easwarakhanthan et al., 1986b). The second measurement series consider the two solar modules such that the mono-crystalline STM6-40/36 at 51 °C and polycrystalline STP6-120/36 at 55 °C and Both solar modules contain 36 cells in series under 1 sun (1000 W/m²) (Tong and Pora, 2016). For reasonable comparison, the search range of each parameter is given in Table 1. Additionally, the proposed algorithm was compared with six recent algorithms: (TPBA, 2019) (Chin and Salam, 2019), (BHCS, 2019) (Chena and Yu, 2019), (ITLBO, 2019) (Li et al., 2019), (ImCSA, 2018) (Kang, 2018), (ISCE, 2018) (Gao et al., 2018b), and (HFAPS, 2018) (Beigia and Maroosi, 2018). For the proposed algorithm, we consider that the maximum number of function evaluations (MaxNFE = 2500), the number of iterations is equal to 125, the function tolerance equal to $1e^{-10}$ (we used the algorithm proposed in Corte (2011)) and 30 independent

Table 1
The boundaries of extracted parameters.

| Parameters | R.T.C. France solar cell | | Parameters | Photowatt-PWP201 module | | STM6-40/36 module | | STP6-120/36 module | |
|-----------------------|--------------------------|-------|------------------------|-------------------------|-------|-------------------|-------|--------------------|-------|
| Ranges | I_b | u_b | Ranges | I_b | u_b | I_b | u_b | I_b | u_b |
| I_{ph} (A) | 0 | 1 | I_{phm} (A) | 0 | 2 | 0 | 2 | 0 | 8 |
| I_{sd} (μA) | 0 | 1 | I_{sdm} (μA) | 0 | 50 | 0 | 50 | 0 | 50 |
| n | 1 | 2 | n_m | 1 | 50 | 1 | 60 | 1 | 50 |
| R_s (Ω) | 0 | 0.5 | R_{sm} (Ω) | 0 | 2 | 0 | 0.36 | 0 | 0.36 |
| R_{sh} (Ω) | 0 | 100 | R_{shm} (Ω) | 0 | 2000 | 0 | 1000 | 0 | 1500 |

Table 2
Parameter extraction with classical method.

| Algorithm | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|-----------|--------------|--------------|-------|--------------------|-----------------------|-----------|
| SA | 0.76073 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0.0029835 |

Table 3
Uncertainties extraction of solar cell.

| Algorithm | ΔI_{ph} | ΔI_{sd} | Δn | ΔR_s | ΔR_{sh} | RMSE 1 | RMSE 2 |
|-----------|-----------------|-----------------|------------|--------------|-----------------|-----------|-----------|
| SA | 0.015213 | 0 | 0 | 0 | 0 | 0.0029839 | 0.0029839 |

Table 4
The new operating intervals of the solar cell parameters.

| | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) |
|-----|--------------|--------------|-------|--------------------|-----------------------|
| Min | 0.74552 | 9.9414e-07 | 1.602 | 0.030966 | 100 |
| Max | 0.77594 | 9.9414e-07 | 1.602 | 0.030966 | 100 |

executions were performed to study the statistical performance of the proposed algorithm.

5.1. Extraction of parameters of the silicon solar cell RTC France

Our objective is the extraction of the silicon RTC France solar cell parameters using the development proposed in this article. The extraction procedure is composed of three steps such that: The first step consists of extracting parameters using the classical method (without consideration of measurement uncertainties). Then, based on the results obtained in the first step, the extraction of the uncertainties of the parameters will be the objective of the second stage. Finally, the third step will be dedicated to the extraction of these parameters in an instantaneous way.

Step 1: Extraction of solar cell parameters with the classical method. The objective function must be minimized using Eqs. (3) and (4), to obtain an optimal set of parameters to characterize the solar cell. Table 2 presents the extracted parameters from the experimental data of a silicon solar cell. We note that the RMSE is equal to 0.0029835. So we can conclude that those results are satisfactory.

Step 2: Extraction of the uncertainties of the parameters. After estimating the parameters using the classical method, we now proceed to the extraction of uncertainties of measurement specific to each parameter. Taking into account Table 2, Eq. (7) and the operating intervals of the uncertainties of parameters $[0, \Delta I_L]$ such that $\Delta I_L = \sqrt{\sum_{i=1}^N (I_{Lmes}(i) - \hat{I}_L(i))^2} = 0.015213$. On the basis of objective function (8) and the SA algorithm, we obtain the following values of the uncertainties Table 3 with RMSE 1 and RMSE 2 represent the Root Mean Square Error between (I_{1mes}, \hat{I}_1) and (I_{2mes}, \hat{I}_2) respectively:

Based on the results given in Table 3, we can define the new operating intervals for the parameters of the solar cell such that Table 4:

Table 5
Uncertain parameter extraction of Silicon solar cell RTC.

| Iterations | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|------------|--------------|--------------|-------|--------------------|-----------------------|------------|
| 1 | 0.76218 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 2 | 0.76094 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 3 | 0.76015 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 4 | 0.76079 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 5 | 0.76089 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 6 | 0.76045 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 7 | 0.759 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 8 | 0.75963 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 9 | 0.75899 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 10 | 0.75889 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 11 | 0.75791 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 12 | 0.75855 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 13 | 0.75876 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 14 | 0.7623 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 15 | 0.76258 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 16 | 0.76437 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 17 | 0.7658 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 18 | 0.76517 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 19 | 0.76228 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 20 | 0.76051 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 5.5511e-17 |
| 21 | 0.75856 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 22 | 0.75847 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 2.7756e-17 |
| 23 | 0.76019 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 4.1633e-17 |
| 24 | 0.76003 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 8.6736e-18 |
| 25 | 0.75294 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 0 |
| 26 | 0.7687 | 9.9414e-07 | 1.602 | 0.030966 | 100 | 2.7756e-17 |

Step 3: Instant solar cell parameter extraction proposal. We will now proceed to the extraction of the parameters in an instantaneous way taking into account their uncertainties. To do this, we will consider the new parameters limit interval Table 4 and the objective function described in (10). We thus obtain the following values of the parameters Table 5:

Table 5 represent the values of the parameters estimated for each iteration, we note that the values of the parameters I_{ph} change almost every iteration, which can be explained by the presence of disturbances affecting the light source. On the other hand, the other parameters are practically constant throughout the simulation.

5.1.1. Comparison among various parameter estimation algorithms

The proposed algorithm will be compared to other recent and well-established work in the literature. According to Table 6, we note that the performance of the work proposed in this article is much higher than that of other works.

Remark 1. For the representation of the $\hat{I}_L - V$ curve, it suffices to replace the values (I_{ph} , I_{sd} , n , R_s and R_{sh}) of Table 5 and the experimental data I and V in the Eqs. (1) and (2) for the modelling of the silicon solar cell RTC France. The RMSE of the proposed approach is given by the data of \hat{I}_L and I.

5.1.2. Statistical study

In order to obtain a higher level of confidence in the results of the statistical comparison, 30 independent runs were implemented to extract the cell parameters of the Silicon solar cell

Table 6
Comparison of proposed algorithm with other algorithms for the Silicon solar cell RTC.

| Algorithm | I_{ph} (A) | I_{sd} (μ A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|----------------------------------|--------------|---------------------|-------------|--------------------|-----------------------|--------------|
| Proposed | See Table 5 | See Table 5 | See Table 5 | See Table 5 | See Table 5 | 1.5727e–17 |
| TPBA (Chin and Salam, 2019) | 0.76072 | 0.31911 | 1.47986 | 0.03629 | 54.19241 | 8.1291e–04 |
| BHCS (Chena and Yu, 2019) | 0.76078 | 0.32302 | 1.48118 | 0.03638 | 53.71852 | 9.86022e–04 |
| ITLBO (Li et al., 2019) | 0.7608 | 0.3230 | 1.4812 | 0.0364 | 53.7185 | 9.8602e–04 |
| ImCSA (Kang, 2018) | 0.760776 | 0.323021 | 1.481718 | 0.036377 | 53.718524 | 9.8602e–04 |
| ISCE (Gao et al., 2018b) | 0.76077553 | 0.32302083 | 1.48118360 | 0.03637709 | 53.71852771 | 9.860219e–04 |
| HFAPS (Beigia and Maroosi, 2018) | 0.760777 | 0.322622 | 1.48106 | 0.0363819 | 53.6784 | 9.8602e–04 |

Table 7
The statistical study of the proposed algorithm.

| Algorithm | RMSE | | | | Proposed Vs |
|-----------|--------------|--------------|--------------|-------------|-------------|
| | Min | Mean | Max | Std | |
| Proposed | 1.135e–17 | 1.7815e–17 | 2.8982e–17 | 5.0636e–18 | |
| TPBA | NA | NA | NA | NA | NA |
| BHCS | 9.82485e–04 | 9.83800e–04 | 9.86865e–04 | 1.53897e–06 | † |
| ITLBO | 9.8602e–04 | 9.8602e–04 | 9.8602e–04 | 2.19e–17 | † |
| ImCSA | 9.8249e–4 | 9.8258e–4 | 9.8396e–4 | 2.8197e–7 | † |
| ISCE | 9.860219e–04 | 9.860219e–04 | 9.860219e–04 | 3.98e–17 | † |
| HFAPS | NA | NA | NA | NA | NA |

Table 8
Parameter extraction of solar module Photowatt-PWP 201 with classical method.

| Algorithm | I_{ph} | I_{sd} | n | R_s | R_{sh} | RMSE |
|-----------|----------|------------|--------|--------|----------|-----------|
| SA | 1.0285 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0.0026174 |

Table 9
Parameter extraction of solar module mono-crystalline STM6-40/36 with classical method.

| Algorithm | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|-----------|--------------|--------------|--------|--------------------|-----------------------|----------|
| SA | 1.6609 | 5.8968e–06 | 59.977 | 0.00049449 | 963.87 | 0.003399 |

Table 10
Parameter extraction of solar module polycrystalline STP6-120/36 with classical method.

| Algorithm | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|-----------|--------------|--------------|--------|--------------------|-----------------------|----------|
| SA | 7.5699 | 1.8297e–08 | 34.288 | 0.22641 | 63.411 | 0.060761 |

Table 11
Uncertainties extraction of solar module Photowatt-PWP 201.

| Algorithm | ΔI_{ph} | ΔI_{sd} | Δn | ΔR_s | ΔR_{sh} | RMSE 1 | RMSE 2 |
|-----------|-----------------|-----------------|------------|--------------|-----------------|-----------|-----------|
| SA | 0.013087 | 0 | 0 | 0 | 0 | 0.0026174 | 0.0026174 |

Table 12
Uncertainties extraction of solar module mono-crystalline STM6-40/36.

| Algorithm | ΔI_{ph} | ΔI_{sd} | Δn | ΔR_s | ΔR_{sh} | RMSE 1 | RMSE 2 |
|-----------|-----------------|-----------------|------------|--------------|-----------------|-----------|-----------|
| SA | 0.015201 | 0 | 0 | 0 | 0 | 0.0033992 | 0.0033992 |

Table 13
Uncertainties extraction of solar module polycrystalline STP6-120/36.

| Algorithm | ΔI_{ph} | ΔI_{sd} | Δn | ΔR_s | ΔR_{sh} | RMSE 1 | RMSE 2 |
|-----------|-----------------|-----------------|------------|--------------|-----------------|----------|----------|
| SA | 0.29766 | 0 | 0 | 0 | 0 | 0.060761 | 0.060761 |

RTC. The significant difference between two approaches can be measured by nonparametric statistical analysis. In this article, we consider the Wilcoxon rank-sum test, as it is a reliable and robust statistical analysis tool. The Wilcoxon rank-sum test at a confidence level of 0.05 is used to distinguish the significant difference between the proposed method and the other methods compared in the same case. The test results are shown in Table 7. The † symbol indicates that the proposed method is statistically better

Table 14
Uncertain parameters extraction of solar module (Photowatt-PWP 201).

| Iterations | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|------------|--------------|--------------|--------|--------------------|-----------------------|------------|
| 1 | 1.0323 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 2 | 1.0319 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 3 | 1.0289 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 4 | 1.026 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 5 | 1.0234 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 6 | 1.0229 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 7 | 1.0249 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 8 | 1.0268 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 9 | 1.0304 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 10 | 1.0315 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 11 | 1.0321 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 12 | 1.0319 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 13 | 1.0297 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 14 | 1.0302 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 15 | 1.0281 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 16 | 1.0269 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 17 | 1.0272 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 0 |
| 18 | 1.0263 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 19 | 1.0275 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.1102e–16 |
| 20 | 1.0285 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 2.7756e–17 |
| 21 | 1.0321 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 8.3267e–17 |
| 22 | 1.0279 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 6.9389e–18 |
| 23 | 1.028 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 1.3878e–17 |
| 24 | 1.0291 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 8.3267e–17 |
| 25 | 1.0278 | 4.9614e–06 | 49.991 | 1.1638 | 1632.5 | 5.5511e–17 |

than that of its competitor. The results show that the proposed method significantly improves the methods of competition.

5.2. Extraction of parameters of solar modules photowatt-PWP 201, mono-crystalline STM6-40/36 and polycrystalline STP6-120/36

Step 1: Extraction of solar modules parameters without uncertainties. Our goal is to extract the parameters of the Solar modules photowatt-PWP 201, mono-crystalline STM6-40/36 and polycrystalline STP6-120/36 for the single-diode model. The proposed extraction procedure consists of three steps. The first step is to extract the parameters using the SA algorithm without taking into account measurement uncertainties. Tables 8–10 presents the extracted parameters from the experimental. So we can conclude that those results are satisfactory based on the RMSE given by those tables.

Step 2: Extraction of the uncertainties of the parameters. Tables 8–10, Eq. (7) and the operating intervals of the uncertainties

Table 15
Uncertain parameters extraction of solar module (mono-crystalline STM6-40/36).

| Iterations | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|------------|--------------|--------------|--------|--------------------|-----------------------|------------|
| 1 | 1.663 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 2 | 1.6631 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 3 | 1.6633 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 4 | 1.6588 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 5 | 1.658 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 6 | 1.6569 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 7 | 1.6579 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 8 | 1.6599 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 9 | 1.66 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 10 | 1.6599 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 11 | 1.6546 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 12 | 1.6615 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 13 | 1.6633 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 14 | 1.6668 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 15 | 1.665 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 16 | 1.664 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 17 | 1.6635 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 18 | 1.6633 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |
| 19 | 1.6536 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 2.2204e-16 |
| 20 | 1.6615 | 5.8968e-06 | 59.977 | 0.00049449 | 963.87 | 0 |

Table 16
Uncertain parameters extraction of solar module (polycrystalline STP6-120/36).

| Iterations | I_{ph} (A) | I_{sd} (A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|------------|--------------|--------------|--------|--------------------|-----------------------|------------|
| 1 | 7.5067 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 2 | 7.6207 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 3 | 7.6025 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 4 | 7.6336 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 5 | 7.6229 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 8.8818e-16 |
| 6 | 7.6123 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 7 | 7.6259 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 8 | 7.6181 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 9 | 7.6013 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 8.8818e-16 |
| 10 | 7.5895 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 11 | 7.5592 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 12 | 7.5363 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 13 | 7.5222 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 14 | 7.5014 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 15 | 7.496 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 16 | 7.4402 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 17 | 7.4651 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 18 | 7.5335 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 19 | 7.5381 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 20 | 7.5902 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 8.8818e-16 |
| 21 | 7.6286 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |
| 22 | 7.6584 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 8.8818e-16 |
| 23 | 7.6631 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 4.4409e-16 |
| 24 | 7.534 | 1.8297e-08 | 34.288 | 0.22641 | 63.411 | 0 |

of parameters $[0, \Delta I_L]$ such that $\Delta I_L = 0.013087$ for solar module (Photowatt-PWP 201), $\Delta I_L = 0.015201$ for solar module (mono-crystalline STM6-40/36) and $\Delta I_L = 0.29766$ for solar module (polycrystalline STP6-120/36). On the basis of objective function (8) and the SA algorithm, we obtain the following values of the uncertainties Tables 11–13:

Step 3: Instant solar module parameter extraction proposal.

Based on the previous Tables. 8–13, the uncertainties parameters for each solar module are considered as follows: Table 14 represent the uncertainties parameters of solar module (Photowatt-PWP 201), Table 15 represent the uncertainties parameters of solar module (mono-crystalline STM6-40/36) and Table 16 represent the uncertainties parameters of solar module (polycrystalline STP6-120/36).

In Tables 14–16, we note that the results presented are very satisfactory since the instantaneous RMSE in these tables are practically null.

5.2.1. Comparison among various parameter estimation algorithms

Tables 17–19 show that the performances of the proposed approach in this article are vastly superior to other works.

Remark 2. For the representation of the $\hat{I}_L - V$ curve, we follow the same procedure described in Remark 1.

5.2.2. Statistical study

To carry out a statistical comparison, 30 independent runs were carried out to extract the parameters of Solar modules photowatt-PWP 201, STM6-40/36 mono-crystalline and STP6-120/36 polycrystalline. The results of Tables 20–22 show that the proposed method considerably improves competition methods.

6. Conclusion

In this paper, we proposed a method to estimate single-diode PV model parameters. The proposed algorithm takes into account the problem of measurement uncertainties. More precisely, the proposed algorithm determines the instantaneous values of the parameters taking into account the measurement uncertainties of each parameter. We applied SA to solve four different parameter estimation problems, including the single-diode model and the PV array modules. On the basis of the experimental results, we conclude that the proposed method presents much better performances to well-established algorithms such as TPBA, ITLBO, ImCSA, ISCE and HFAPS. These results confirm that the proposed algorithm is a valuable tool for estimating PV parameters. For future work, it will be interesting to apply this approach to solve other optimization problems in the field of energy.

Table 17
Comparison of proposed algorithm with other algorithms the solar module (Photowatt-PWP 201).

| Algorithm | I_{ph} (A) | I_{sd} (μ A) | n | R_s | R_{sh} (Ω) | RMSE (Ω) |
|----------------------------------|--------------|---------------------|--------------|--------------|-----------------------|-------------------|
| Proposed method | See Table 10 | See Table 10 | See Table 10 | See Table 10 | See Table 10 | 6.8284e-17 |
| TPBA (Chin and Salam, 2019) | 1.03353 | 2.12479 | 1.30017 | 0.03471 | 19.37196 | 2.422747e-3 |
| ITLBO (Li et al., 2019) | 1.0305 | 3.4823 | 48.6428 | 1.2013 | 981.9823 | 2.4251e-3 |
| ImCSA (Kang, 2018) | 1.030514 | 3.482263 | 48.660397 | 1.201271 | 981.982233 | 2.425e-3 |
| ISCE (Gao et al., 2018b) | 1.0305143 | 3.48226304 | 48.642835 | 1.201271 | 981.98228038 | 2.425075e-3 |
| HFAPS (Beigia and Maroosi, 2018) | 1.0305 | 3.4842 | 48.6449 | 1.2013 | 984.2813 | 2.4251e-3 |

Table 18
Comparison of proposed algorithm with other algorithms for the mono-crystalline STM6-40/36 solar module.

| Algorithm | I_{ph} (A) | I_{sd} (μ A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|-----------------------------|--------------|---------------------|--------------|--------------------|-----------------------|----------------|
| Proposed method | See Table 15 | See Table 15 | See Table 15 | See Table 15 | See Table 15 | 4.9651e-17 |
| TPBA (Chin and Salam, 2019) | 1.6632 | 2.7698 | 1.5656 | 0.004186 | 16.7328 | 1.774e-03 |
| BHCS (Chena and Yu, 2019) | 1.66390 | 1.73866 | 1.52030 | 0.00427 | 15.92829 | 1.72981e-03 |
| ITLBO (Li et al., 2019) | 1.6639 | 1.7387 | 1.5203 | 0.0043 | 15.9283 | 1.7298e-03 |
| ImCSA (Kang, 2018) | 1.663971 | 2.0000 | 1.533499 | 0.002913631 | 15.840511 | 1.79436329e-03 |
| ISCE (Gao et al., 2018b) | 1.66390478 | 1.73865691 | 1.52030292 | 0.00427377125 | 15.92829413 | 1.72981371e-03 |

Table 19
Comparison of proposed algorithm with other algorithms for the polycrystalline STP6-120/36 solar module.

| Algorithm | I_{ph} (A) | I_{sd} (μ A) | n | R_s (Ω) | R_{sh} (Ω) | RMSE |
|-----------------------------|--------------|---------------------|--------------|--------------------|-----------------------|----------------|
| Proposed method | See Table 16 | See Table 16 | See Table 16 | See Table 16 | See Table 16 | 3.7376e–16 |
| TPBA (Chin and Salam, 2019) | 7.4830 | 0.8868 | 1.1872 | 0.0053819 | 10.5309 | 1.4091e–02 |
| BHCS (Chena and Yu, 2019) | 7.47253 | 2.33499 | 1.26010 | 0.00459 | 22.21990 | 1.66006e–02 |
| ITLBO (Li et al., 2019) | 7.4725 | 2.3350 | 1.2601 | 0.0046 | 22.2199 | 1.6601e–02 |
| ImCSA (Kang, 2018) | 7.482778 | 1.00 | 1.197729 | 0.005386970 | 10.00 | 1.5865799e–02 |
| ISCE (Gao et al., 2018b) | 7.47252992 | 2.33499500 | 1.26010348 | 0.00459463460 | 22.21990556 | 1.66006031e–02 |

Table 20
The statistical study of solar module (Photowatt-PWP 201).

| Algorithm | RMSE | | | | Proposed Vs |
|-----------|-------------|-------------|-------------|-------------|-------------|
| | Min | Mean | Max | Std | |
| Proposed | 1.135e–17 | 1.7815e–17 | 2.8982e–17 | 5.0636e–18 | |
| TPBA | NA | NA | NA | NA | NA |
| BHCS | NA | NA | NA | NA | † |
| ITLBO | 2.4251e–3 | 2.4251e–3 | 2.4251e–3 | 1.27e–17 | † |
| ImCSA | 2.425075e–3 | 2.425075e–3 | 2.425091e–3 | 2.915426e–3 | † |
| ISCE | 2.425075e–3 | 2.425075e–3 | 2.425075e–3 | 2.47e–17 | † |
| HFAPS | NA | NA | NA | NA | NA |

Table 21
The statistical study of mono-crystalline STM6-40/36 solar module.

| Algorithm | RMSE | | | | Proposed Vs |
|-----------|---------------|---------------|---------------|----------------|-------------|
| | Min | Mean | Max | Std | |
| Proposed | 1.135e–17 | 1.7815e–17 | 2.8982e–17 | 5.0636e–18 | |
| TPBA | NA | NA | NA | NA | NA |
| BHCS | 1.72981e–3 | 1.83648e–3 | 3.32985e–3 | 4.05942e–4 | † |
| ITLBO | 1.7298e–3 | 1.7298e–3 | 1.7298e–3 | 4.75e–18 | † |
| ImCSA | 1.79436329e–3 | 1.79436329e–3 | 1.79436329e–3 | 2.11238634e–14 | † |
| ISCE | 1.729814e–3 | 1.729814e–3 | 1.729814e–3 | 2.30e–17 | † |
| HFAPS | NA | NA | NA | NA | NA |

Table 22
Statistical study of solar module (polycrystalline STP6-120/36).

| Algorithm | RMSE | | | | Proposed Vs |
|-----------|--------------|--------------|--------------|---------------|-------------|
| | Min | Mean | Max | Std | |
| Proposed | 2.2963e–10 | 2.812e–08 | 8.7303e–08 | 2.8947e–08 | |
| TPBA | NA | NA | NA | NA | NA |
| BHCS | 1.66006e–02 | 2.43602e–02 | 1.34824e–01 | 2.60620e–02 | † |
| ITLBO | 1.6601e–02 | 1.6601e–02 | 1.6601e–02 | 7.22e–17 | † |
| ImCSA | 1.5865799e–2 | 1.5865799e–2 | 1.5865799e–2 | 4.6901709e–15 | † |
| ISCE | 1.660060e–02 | 1.660060e–02 | 1.660060e–02 | 8.74e–14 | † |

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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