Article


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Abstract: A recent optimization algorithm, the Rime Optimization Algorithm (RIME), was developed to efficiently utilize the physical phenomenon of rime-ice growth. It simulates the hard-rime and soft-rime processes, constructing the mechanisms of hard-rime puncture and soft-rime search. In this study, an enhanced version, termed Modified RIME (MRIME), is introduced, integrating a Polynomial Differential Learning Operator (PDLO). The incorporation of PDLO introduces non-linearities to the RIME algorithm, enhancing its adaptability, convergence speed, and global search capability compared to the conventional RIME approach. The proposed MRIME algorithm is designed to identify photovoltaic (PV) module characteristics by considering diverse equivalent circuits, including the One-Diode Model (ONE-DM) and Two-Diode Model (TWO-DM), to determine the unspecified parameters of the PV. The MRIME approach is compared to the conventional RIME method using two commercial PV modules, namely the STM6-40/36 module and R.T.C. France cell. The simulation results are juxtaposed with those from contemporary algorithms based on published research. The outcomes related to recent algorithms are also compared with those of the MRIME algorithm in relation to various existing studies. The simulation results indicate that the MRIME algorithm demonstrates substantial improvement rates for the STM6-40/36 module and R.T.C. France cell, achieving 1.16% and 18.45% improvement for the ONE-DM, respectively. For the TWO-DM, it shows significant improvement rates for the two modules, reaching 1.14% and 50.42%, respectively. The MRIME algorithm, in comparison to previously published results, establishes substantial superiority and robustness.

Keywords: RIME optimizer; polynomial differential learning operator; single-diode model; double-diode model; parameter PV cell extraction

1. Introduction

A myriad of countries have noticed an ongoing rise in their energy demand due to their quickly growing populations and aggregate industries. Furthermore, the primary disadvantages of conventional fossil fuel supplies are environmental contamination and fuel shortages. These factors have led scientists to discover a new energy source that may save energy without harming the environment. As a result, scientists have considered using alternate sources of energy that are renewable, such as solar, wind, hydroelectricity, and geothermal power, to produce large amounts of energy without contributing to environmental degradation. Solar PV is one of the sources of clean energy that has attracted a lot of attention in recent decades because of its many benefits, including low maintenance costs, low operating costs, high power density, and low computational costs [1]. PV
cells are arranged in both parallel and series to form the PV panel. The panel output is influenced by the manufacturing process as well as external factors such as light intensity and temperature [2].

Several electrical models have been investigated in the scientific literature, among which are the one-diode model (ONE-DM) [3] and the two-diode model (TWO-DM) [4]. The main challenge is to resolve the nonlinear formula associated with these models and determine the unknown parameters; many approaches of different kinds have been described in the scientific literature [5]. A myriad of approaches to precisely determine the assessment of parameters for PV models could be broadly divided into two categories: analytical techniques and metaheuristics inspired by nature. Examples of analytical techniques are the Lambert W function [6] and the Newton–Raphson method [7]. Nature-inspired metaheuristics (NiMHs) can effectively handle optimization and evaluation problems, since they function like a black box, without imposing any restrictions on the issue formulation. Because of this, NiMH has some advantages over alternative strategies. NiMH finds use in a wide range of industries. Consequently, in order to overcome the parametric problems related to solar PV cell models, academics have recently employed a range of NiMHs [8].

Ridha et al. [9] established an upgraded augmented mutation Harris Hawk Optimizer (AMHHO) to assess the parameters associated with the PV system ground accurately in order to create a more reliable and efficient model. In order to accurately assess the solar cell ground modelling variables, the convergence process of the algorithm can be accelerated by using the proposed method. Chen [10] integrated the adversarial-based exploration method and chaotic drift strategy into the Harris Hawk Optimizer (HHO). In order to boost global convergence and local mining capabilities, the moth flame method (MFO) was demonstrated in [11], to identify the parameters of PV modules. This led to outstanding outcomes in the ONE-DM and TWO-DM PV models.

An Improved Sine Cosine Algorithm called ISCA was proposed by Chen et al. [12] to evaluate the unknown parameters for the ONE-DM and TWO-DM. Wu [13] proposed a method for parameter evaluation based on the improved ant-lion optimizer (IALO). IALO achieved favorable results using the photovoltaic model. Liu et al. [14] employed the upgraded Harris Hawk algorithm (CCNHHO) to ascertain the parameters of the solar model. Merchaoui proposed the adaptive variational Particle Swarm Optimization (PSO) approach for identifying the unknown parameters of different photovoltaic models and maximizing the ideal parameters for solar models under diverse conditions [15,16]. Jiao et al. [17] used orthogonal learning (OL) and generalized opposition-based learning (GOBL) approaches to accurately and efficiently evaluate the characteristics of PV modules’ solar cells. Abbassi et al. [18] proposed an improved algorithm based on the salp swarm method that makes use of an opposition-based learning strategy to tackle the parameter estimation issue encountered by solar cells. Ridha et al. [19] provided a thorough analysis based on multi-objective optimization and multi-criteria approaches on independent PV systems in order to help select the optimal design solutions. The metaheuristic technique and its variants have several drawbacks, even if its execution is faster and with higher solution quality. Furthermore, the approach is a somewhat specialized, and its excellent performance is restricted to particular kinds of optimization problems, which limits its use cases.

Studying PV systems is crucial due to their pivotal role as ideal companions for both renewable and traditional energy sources in hybrid energy systems. These systems are widely adopted globally because of their reliability and stability in energy production from individual sources; such systems include PV/Grid [20], PV energy forecasting [21], PV/STATCOM [22], PV/Voltage regulators [23], and microgrid management [24]. Additionally, a variety of maximum power point tracking (MPPT) methodologies have been developed to optimize the operation of solar PV arrays for maximum power output [25]. In Ref. [26], a global MPPT-based variable vortex search (VVS) methodology was presented for photovoltaic (PV) generation systems. In this study, several modern heuristic
algorithms were utilized and statistically analyzed via the Monte Carlo method under partial shading conditions (PSCs). In Ref. [27], several techniques were contrasted and adopted for MPPT, including Perturb and Observe (P&O), cuckoo search, Jaya, Salp swarm, Emperor Penguin optimization, Grey Wolf optimization, and artificial Bee colony and Ant colony optimization algorithms, while a Chimp Optimization algorithm (ChOA) was utilized and simulated for the same purpose via MATLAB 2017b /SIMULINK in Ref. [28].

Recently, the Rime Optimization Algorithm (RIME) method was introduced by H. Su et al. [29]. By inspiring the natural development of soft and hard rime particles, Rime agents experience Soft-Rime Search (SRS) and Hard-Rime Puncture (HRP) phases to simulate environmental conditions. Parameters such as adhesion degree and attachment coefficient impact particle distance, thereby influencing condensation probability and optimizing the process. Also, fitness values act as guides for information exchange between agents. In recent times, novel domains have surfaced in the utilization of fractional differential systems, particularly leveraging their inherent advantages in viscoelasticity [30–33]. This paper proposes a Modified RIME (MRIME) incorporating a Polynomial Differential Learning Operator (PDLO). The proposed incorporation of PDLO with the presented MRIME algorithm introduces diversity in the population by combining information from two randomly selected individuals to update the position of the current individual. The randomness introduced by the permutation helps in exploring the search space effectively. The proposed MRIME algorithm is designed to identify PV module characteristics by considering diverse equivalent circuits, including the ONE-DM and TWO-DM, to determine the unspecified parameters of the PV. To showcase the effectiveness of the MRIME algorithm, it undergoes testing against more advanced algorithms in the context of the PV ONE-DM and TWO-DM. The experimental study illustrates the excellent outcomes achieved by the proposed MRIME algorithm. In summary, the key contributions of this paper are as follows:

- An enhanced MRIME algorithm is proposed by incorporating the PDLO to enhance its searching diversity.
- The proposed MRIME algorithm is implemented on two commercial PV systems of the STM6-40/36 module and R.T.C. France cell.
- The MRIME algorithm exhibits considerable advantages and robustness for both PV models compared to the conventional RIME algorithm and previously reported outcomes.
- Tests of the MRIME algorithm’s efficacy on the PV ONE-DM and TWO-DM reveal a very good correlation between simulated and actual data.

The remaining structure of this paper is as follows: Section 2 presents the problem definition, considering the ONE-DM and TWO-DM frameworks. Section 3 thoroughly describes the proposed MRIME technique. Experimental findings are examined in detail in Section 4, confirming the effectiveness of the MRIME technique. Section 5 presents the conclusions for this work.

2. Problem Formulation of Solar PV Parameter Extraction

This section covers the ONE-DM and TWO-DM for mathematical simulation of PV modules [22]. Following that, the objective function will be highlighted in order to address the problem of parameter estimation for the aforementioned PV models.

2.1. ONE-DM

The ONE-DM, represented in Figure 1 [34], is simple to create when the solar cell is thought of as an inner parallel circuit. The entire output current of the circuit is indicated by the symbol (I), which may be expressed using the following formula [35]:

\[ I = I_{ph} - I_{sh} - I_{d} \]  

(1)
where $I_{ph}$ stands for the photocurrent, $I_s$ is the shunt resistor current, and $I_d$ is the diode current.

**Figure 1.** Demonstration of ONE-DM circuit.

The shunt resistor current ($I_s$) may be expressed using the following formula [36]:

$$I_s = \frac{I \cdot R_s + V}{R_{Ss}},$$

where $V$ denotes the output voltage, and $R_s$ and $R_{Ss}$ stand for the series and shunt resistances. The diode current is represented mathematically by $I_d$, which may be computed [37] by applying Equation (3).

$$I_d = I_{S1} \left[ \exp \left( \frac{I \cdot R_s + V}{\eta_1 V_{th}} \right) - 1 \right],$$

where $I_{S1}$ denotes the diode reverse saturation current and $\eta_1$ indicates the ideal factor for the diode. The junction thermal voltage ($V_{th}$) [38] is determined by Equation (4).

$$V_{th} = \frac{K_B T}{q_c},$$

where $T$ signifies the temperature defined in Kelvin, $q_c$ denotes the electron charge of $1.60217646 \times 10^{-19}$ C, and $K_B$ indicates the Boltzmann’s value ($1.380655 \times 10^{-23}$ J/K). Finally, by combining the aforementioned formulations, Equation (5) explains the link between various parameters with the output current [39].

$$I = I_{ph} - I_{S1} \times \left[ \exp \left( \frac{I \cdot R_s + V}{\eta_1 V_{th}} \right) - 1 \right] - \frac{V}{R_{Ss}} \cdot \frac{I \cdot R_s}{R_{sh}},$$

Five variables ($R_s$, $R_{Ss}$, $I_{S1}$, $I_{ph}$ and $\eta_1$) need to be extracted in the ONE-DM, as can be determined in Equation (7).

### 2.2. TWO-DM

The loss of composite currents throughout the ONE-DM is addressed by the development of the TWO-DM. Consequently, the computation of the overall current flow in the equivalent circuit displayed in Figure 2 is indicated by Equation (6).

$$I = I_{ph} - I_{Ss} - I_{S1} - I_{d2}.$$
By integrating the aforementioned formulations, Equation (7) establishes a correlation between the current flowing through the output, the output voltage, and multiple other variables in the TWO-DM [38]:

\[
I = I_{ph} - I_{S1} \left[ \exp \left( \frac{I \cdot R_s + V}{\eta_1 \cdot V_{dern}} \right) - 1 \right] - I_{S2} \left[ \exp \left( \frac{I \cdot R_s + V}{\eta_2 \cdot V_{dern}} \right) - 1 \right] - \frac{V}{R_{sh}} - \frac{I \cdot R_s}{R_{sh}},
\]

where \( I_{S1} \) and \( I_{S2} \) denote the first and second diode reverse saturation currents, while \( \eta_1 \) and \( \eta_2 \) indicate the ideal factor for the two diodes.

Seven variables \((I_{S1}, R_{sh}, R_s, I_{S2}, I_{ph}, \eta_1, \eta_2)\) need to be extracted in the TWO-DM, as can be determined using Equation (7).

2.3. PV Module Development

The PV module model has a more intricate design; it is primarily made up of several solar cells coupled in parallel or series. The current flowing in the PV module model’s equivalent circuit can be addressed by observing Equation (8).

\[
I = N_p \left( I_{ph} - I_{S1} \left[ \frac{1}{\eta_1 \cdot V_{dern} \cdot N_s} \left( (V + I \cdot R_s \cdot N_s) / N_p \right) \right] - 1 \right) - I_{S2} \left[ \frac{1}{\eta_2 \cdot V_{dern} \cdot N_s} \left( (V + I \cdot R_s \cdot N_s) / N_p \right) \right] - 1 - \frac{(V + I \cdot R_s \cdot N_s) / N_p}{N_p \cdot N_s \cdot R_{sh}},
\]

where the numbers of solar cells in parallel and series are indicated by \( N_p \) and \( N_s \) respectively.

2.4. Objective Model

To establish objective functions that are suitable for a number of computational methods, it must first be possible to quantify the output voltage and current that is produced in each of the models [41–43]. As a result, the function’s target may be to find the disparity between the current that is generated in the model that has been developed and the experimental current. The present research aims to decrease the RMSE, which is defined as follows:

\[
RMSE = \sqrt{ \frac{1}{P \cdot N} \sum_{k=1}^{P} \left( I_{cal}^{k}(V_{exp}, x) - I_{exp}^{k} \right)^2 },
\]
where \( PN \) denotes the number of measured data points, and \( I_{\exp}^k \) and \( V_{\exp}^k \) stand for the observed current and voltage. In addition, the PV determination characteristic problem—which has to do with discovering a solution in the solution space that lessens the objective function—is revealed by the form of \( x \).

3. MRIME Algorithm for PV Parameter Estimation

The RIME algorithm draws inspiration from natural processes, specifically the growth of soft and hard rime particles, to design its optimization strategy. The positions of rime agents, or particles, represent the solution vectors in the search space. It mimics the associated environmental conditions in two phases: the Soft-Rime Search (SRS) and Hard-Rime Puncture (HRP) [29]. It requires several key steps to perform optimization, as follows.

3.1. Rime Initialization Phase

The population is initialized with \( Nm \) rime agents, each represented as a rime particle with \( D \) dimensions. A random search is employed in the initialization process to determine the positions of rime agents in the search space.

Consequently, the population of rime agents, denoted as \( R_{\text{POP}} \), is succinctly expressed using the positions of individual rime particles, represented by \( R_{m_{i,j}} \) in Equation (10).

\[
R_{\text{POP}} = \left[ R_{m_{i,j}} \right]_{Nm \times D} = \\
\begin{bmatrix}
R_{m_{1,j}} & R_{m_{2,j}} & \ldots & R_{m_{i,j}} & \ldots & R_{m_{D,j}} \\
R_{m_{1,1}} & R_{m_{2,1}} & \ldots & R_{m_{i,1}} & \ldots & R_{m_{D,1}} \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
R_{m_{1,D}} & R_{m_{2,D}} & \ldots & R_{m_{i,D}} & \ldots & R_{m_{D,D}} 
\end{bmatrix}, \quad (10)
\]

where \( R_{\text{POP}} \) is the population matrix, which consists of the vectors of the rime agents \( (Nm \times 1) \), and each rime agent vector consists of several design parameters \( (1 \times D) \).

These positions are subject to limits, with upper \( (Up) \) and lower \( (Lo) \) boundaries defining the permissible range for each dimension. Adopting a conventional approach observed in many population-based algorithms, the rime population undergoes initialization through a random search process during the initial phase. The resulting expression for the position \( R_{m_{i,j}} \) during this initialization is detailed below.

\[
R_{m_{i,j}} = Lo_j + rd_j \cdot Up_j - Lo_j, \quad i = 1: Nm, j = 1: D, \quad (11)
\]

where \( rd_j \) is a randomly selected number inside the range \([0, 1]\).

3.2. SRS Phase

The algorithm simulates the freezing of rime particles on the surface of an object, mimicking the soft-rime growth process. Rime agents move in the search space with the influence of wind force and their own randomness, ensuring broad coverage in the early iterations. The position update of rime agents is determined using a formula that includes the best rime agent’s position, environmental factors, and randomness, as follows:

\[
R_{m_{i,j}}^* = R_{\text{best,}j} + rd_2 \cdot \beta \cdot \cos(\theta) \cdot AD \cdot Up_j - Lo_j + Lo_j, \quad \text{if } rd_2 < E, \quad (12)
\]

where the degree of adhesion (“AD”) characterizes the proximity between the best rime agent and a randomly chosen rime agent, with “AD” constrained within the range \([0, 1]\). The modified position of the rime agent \( i \) in the dimension \( j \) at the iteration after the SRS phase, denoted by \( R_{m_{i,j}}^* \), is determined based on the position of the best rime agent in the population \( (R_{\text{best,}j}) \). The directional control is governed by the interplay of “\( rd_2 \)” and
“cos(θ),” where “rdv” is a random number in the range [-1, 1]. Also, “rdw” is a random number in the range [0, 1], while θ is defined in Equation (13).

\[
\theta = \left( \frac{It}{It_{\text{max}}} \right) \left( \frac{\pi}{10} \right),
\]

(13)

In this context, the symbol “It” denotes the iteration count index, while “It_{max}” represents the total number of iterations.

The environmental factor, represented by “β,” models external conditions and ensures the convergence of the rime population, as specified in Equation (14).

\[
\beta = 1 - \frac{1}{\omega} \left\{ \text{round} \left( \frac{\omega \cdot It}{It_{\text{max}}} \right) \right\},
\]

(14)

The function “round” is employed to round numerical values, and the parameter “ω” is introduced to regulate the segmentation of the step function, with a default value of 5 as per [29].

Additionally, the variable “rdv” is a random number within [0, 1], and “E” signifies the attachment coefficient, influencing the coalescence probability of the rime agent. The attachment coefficient gradually increases throughout the search process, as follows:

\[
E = \left( \frac{It}{It_{\text{max}}} \right)^{1/2},
\]

(15)

3.3. HRP Phase

In strong wind conditions, the algorithm emulates the simpler and more regular growth of hard-rime particles. The HRP mechanism facilitates information exchange between agents to improve convergence and escape local optima, as follows:

\[
Rm_{\text{new}}_{ij} = \begin{cases} 
Rm_{\text{best}}_{ij} & rd_4 < \text{Fit}^*(Rm_i) \quad ; \quad i = 1 : Nm, \ j = 1 : D, \\
Rm^*_{ij} & \text{Else}
\end{cases},
\]

(16)

where \(Rm_{\text{new}}_{ij}\) indicates the newly created position of the rime agent \(i\) in the dimension \(j\), while “rdv” is a random number within [0, 1]. As shown, the positions of rime agents are updated based on the fitness values and normalized fitness values (\(\text{Fit}(Rm)\)), promoting crossover between agents, where

\[
\text{Fit}^*(Rm_i) = \frac{\text{Fit}(Rm_i)}{\sqrt{\sum_{j=1}^{Nm} (\text{Fit}(Rm_j))^2}},
\]

(17)

where \(\text{Fit}(Rm)\) is the value of the fitness function regarding the current position of the rime agent \(i\).

3.4. Proposed PDLO Incorporation

In this paper, the PDLO is incorporated to enhance the searching capabilities and diversity of the RIME algorithm. The PDLO is commonly used in differential evolution (DE) algorithms for optimization [44]. This operator enhances population diversity by merging information from two randomly chosen individuals to update the current rime particle’s position. PDLO, an extension of DE, adapts the mutation strategy to amplify exploration and exploitation within the search space. The mutation formula in PDLO incorporates a polynomial function, injecting non-linear characteristics into the mutation operation. To execute the integrated PDLO, two random integers (index1 and index2) are
drawn from the population. Subsequently, the newly derived position of rime agent $i$ can be formulated as follows:

$$R_{m_{\text{new}_i}} = R_{m_i} + \varphi \cdot (R_{m_{\text{index1}}_i} - R_{m_{\text{index2}}_i}), \quad i = 1: Nm,$$

where $\varphi$ is a generated random number between 0 and 1. Thus, the update involves the weighted sum of the difference between two randomly selected elements ($R_{m_{\text{index1}}_i}$ and $R_{m_{\text{index2}}_i}$), while the weight $\varphi$ controls the contribution of this difference to the update.

3.5. Positive Greedy Selection (PGS) Phase

After generating the new positions of the rime particles by the HRP-SRS phases (Equations (12) and (16)) or the PDLO (Equation (18)), the PGS mechanism is employed to compare fitness values before and after the update. If the updated fitness value is better, the suboptimal solution is replaced with the optimal one, enhancing the global solution quality. This mechanism actively replaces agents during updates, to ensure a more optimal population evolution.

3.6. Iterative Process

Figure 3a,b displays the main steps of the standard RIME against the proposed MRIME optimizer, where the entire process is iteratively performed until a predefined number of iterations ($I_{\text{Max}}$) is reached. At each iteration, the proposed MRIME updates the positions of rime agents utilizing the SRS and the HRP phases or the PDLO mechanism, evaluates fitness values, and performs PGS. In the proposed MRIME algorithm with PDLO, the inclusion of a polynomial function enables fine-tuned control over the impact of each mutation vector component, contributing flexibility to the exploration process. The introduction of randomness through permutation and the variables adds effectiveness to the exploration of the search space. The optimal rime agent in the swarm, determined by the best fitness value, is output as the solution to the optimization problem.
(a) The standard RIME optimizer.
Figure 3. Main steps of the standard RIME and the proposed MRIME optimizers.

4. Simulation Results

In this section, the proposed MRIME algorithm, along with the conventional RIME algorithm, is expanded to estimate PV parameters for two distinct commercial systems—R.T.C. France and STM6-40/36. The R.T.C. France cell is a commercially available silicon cell operating at 1000 W/m² sun irradiance and a temperature of 33 degrees Celsius. The second module, STM6-40/36, consists of 36 monocrystalline cells linked in series, each with dimensions of 38 mm × 128 mm, operating at 51 °C and an irradiation of 1000 W/m² [45].

For both PV systems, two cases are explored, involving different equivalent circuits: ONE-DM (Case 1) and TWO-DM (Case 2). In both algorithms, a population of one hundred rime particles is considered, with a maximum limit of one thousand iterations. Additionally, each technique undergoes twenty different running times for comprehensive analysis.

4.1. First Test Investigation: R.T.C. France Cell

4.1.1. Case 1: ONE-DM

In the current case, the ONE-DM characteristics of the R.T.C. France cell are extracted using the suggested MRIME and the RIME. Table 1 lists the five unknown ONE-DM parameters for which the experiment’s best outcomes were obtained for every approach. The
results show that the suggested MRIME outperforms the RIME and comparator approaches in terms of competitiveness. This means that the regular RIME obtained an RMSE of $9.9755 \times 10^{-4}$, whereas the MRIME obtained the best RMSE value of $9.8602 \times 10^{-4}$. Additionally, the PV-derived electrical parameters utilizing the reported optimization approaches are displayed in the table; these include the Classified perturbation mutation PSO (CPMPSO) [46], HEAP Optimizer [47], multi-verse optimizer (MVO) [48], Lightning Attachment Procedure Optimization (LAPO) [49], particle swarm optimization (PSO) [50], Enhanced MPA (EMPA) [47], neighborhood scheme-based Laplacian MBA (NLBMA) [51], a performance-guided JAYA (PGJAYA) [52], Forensic-Based Investigation Optimizer (FBI) [53], Barnacles Mating Optimizer (BMA) [54], Enriched Harris Hawks optimization (EHHO) [10], Jellyfish Search (JFS) Optimizer [47], Ant Lion Optimizer (ALO) [55], Growth optimizer GO [38], flexible PSO (FPSO) [3], Hybrid Firefly and Pattern Search (HFAPS) [56], Equilibrium Optimizer (EO) [47], hybrid PSO-GWO algorithm (PSOGWO) [57], and Marine Predator Algorithm (MPA) [47]. Moreover, the table specifies the assessed parameters of (MRIME and RIME), which are $(57.37254497 \Omega$ and $53.71865291 \Omega$), $(0.760557 \text{A}$ and $0.760776 \text{A})$, $(1.485377$ and $1.481184)$, $(0.036257632 \Omega$ and $0.036377096 \Omega)$, and $(3.3686 \times 10^{-1} \mu \text{A}$ and $3.2301 \times 10^{-1} \mu \text{A}$) for the shunt resistance, photo-current, ideality factor for d1, series resistance, and saturation current for d1, respectively. Additionally, electrical variables acquired using various inspirational optimizers are expressed in this table.

Table 1. Extracted PV cell parameters based on MRIME versus RIME and other reported methods applied for the ONE-DM of the R.T.C. France cell.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$L_h$ (A)</th>
<th>$L_d$ ($\mu$A)</th>
<th>$n$</th>
<th>$R_{sh}$ ($\Omega$)</th>
<th>$R_s$ ($\Omega$)</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRIME</td>
<td>0.760557</td>
<td>3.36869 $\times 10^{-1}$</td>
<td>1.485377</td>
<td>57.37254497</td>
<td>0.036257632</td>
<td>9.8602 $\times 10^{-4}$</td>
</tr>
<tr>
<td>RIME</td>
<td>0.760776</td>
<td>3.23021 $\times 10^{-1}$</td>
<td>1.481184</td>
<td>53.71865291</td>
<td>0.036377096</td>
<td>9.9755 $\times 10^{-4}$</td>
</tr>
<tr>
<td>MPA[47]</td>
<td>8.184927</td>
<td>7.94459 $\times 10^{-2}$</td>
<td>1.285180059</td>
<td>92.14823504</td>
<td>0.004537611</td>
<td>1.487 $\times 10^{-2}$</td>
</tr>
<tr>
<td>FBS[53]</td>
<td>8.217030039</td>
<td>2.72156 $\times 10^{-2}$</td>
<td>1.215208065</td>
<td>6.2358999986</td>
<td>0.004814219</td>
<td>9.88 $\times 10^{-4}$</td>
</tr>
<tr>
<td>JFS[47]</td>
<td>8.193182</td>
<td>4.72 $\times 10^{-2}$</td>
<td>1.250052</td>
<td>14.97462</td>
<td>0.004679</td>
<td>9.477 $\times 10^{-3}$</td>
</tr>
<tr>
<td>PGJAYA[52]</td>
<td>8.2167</td>
<td>0.002284</td>
<td>58.1472</td>
<td>773.8117</td>
<td>0.3435</td>
<td>1.5455 $\times 10^{-4}$</td>
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<tr>
<td>EO[47]</td>
<td>8.209153</td>
<td>2.85 $\times 10^{-2}$</td>
<td>1.218068</td>
<td>7.714703</td>
<td>0.004815</td>
<td>2.888 $\times 10^{-3}$</td>
</tr>
<tr>
<td>CPMPSO[46]</td>
<td>8.21689146</td>
<td>0.00224195</td>
<td>1.07641028</td>
<td>763.535149</td>
<td>0.34381405</td>
<td>1.53903 $\times 10^{-3}$</td>
</tr>
<tr>
<td>FPSO[3]</td>
<td>8.2186</td>
<td>0.001436</td>
<td>56.9854</td>
<td>130.2813</td>
<td>0.2409</td>
<td>2.8214 $\times 10^{-3}$</td>
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<tr>
<td>GO[38]</td>
<td>8.192967</td>
<td>4.31808 $\times 10^{-3}$</td>
<td>1.244346</td>
<td>15.103921</td>
<td>0.004710</td>
<td>8.51347 $\times 10^{-3}$</td>
</tr>
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<td>HFAPS[56]</td>
<td>8.1992</td>
<td>0.154161</td>
<td>74.5795</td>
<td>1448.2590</td>
<td>0.2396</td>
<td>4.9863 $\times 10^{-2}$</td>
</tr>
<tr>
<td>EHO[10]</td>
<td>8.2224</td>
<td>0.000001</td>
<td>80.6915</td>
<td>1806.0252</td>
<td>0.1835</td>
<td>5.9507 $\times 10^{-2}$</td>
</tr>
<tr>
<td>PSO[50]</td>
<td>8.2027</td>
<td>2.8852</td>
<td>1.6052</td>
<td>33.8855</td>
<td>0.0019</td>
<td>1.0195 $\times 10^{-1}$</td>
</tr>
<tr>
<td>PSOGWO[57]</td>
<td>8.2132</td>
<td>9.6768</td>
<td>1.7463</td>
<td>38.8968</td>
<td>0.0011</td>
<td>1.2700 $\times 10^{-1}$</td>
</tr>
<tr>
<td>MVO[48]</td>
<td>8.2527</td>
<td>0.063908</td>
<td>69.2388</td>
<td>134.4813</td>
<td>0.1341</td>
<td>8.3800 $\times 10^{-2}$</td>
</tr>
<tr>
<td>BMA[54]</td>
<td>8.1950</td>
<td>3.1015</td>
<td>1.6130</td>
<td>100.0000</td>
<td>0.0019</td>
<td>1.0244 $\times 10^{-1}$</td>
</tr>
<tr>
<td>LAPO[49]</td>
<td>8.2155</td>
<td>8.1491</td>
<td>1.7258</td>
<td>5.0000</td>
<td>0.001</td>
<td>1.3813 $\times 10^{-1}$</td>
</tr>
<tr>
<td>EMPA[47]</td>
<td>8.21195</td>
<td>3.59 $\times 10^{-2}$</td>
<td>1.232551</td>
<td>7.560713</td>
<td>0.004742</td>
<td>3.847 $\times 10^{-3}$</td>
</tr>
<tr>
<td>NLBMA[51]</td>
<td>8.1467</td>
<td>0.0022</td>
<td>1.0839</td>
<td>5.0000</td>
<td>0.0045</td>
<td>3.3610 $\times 10^{-2}$</td>
</tr>
<tr>
<td>HEAP[47]</td>
<td>8.200974</td>
<td>4.49 $\times 10^{-2}$</td>
<td>1.246924</td>
<td>11.87468</td>
<td>0.004696</td>
<td>7.425 $\times 10^{-3}$</td>
</tr>
</tbody>
</table>

The corresponding convergence lines can be seen in Figure 4. The MRIME converged extremely quickly in the first 60 iterations, as depicted in this figure, demonstrating the MRIME’s excellent convergence capacity. Additionally, Figure 5 shows the twenty obtained RMSE objectives for Case 1’s RIME and MRIME. This figure illustrates that the RMSE of RIME is between $[9.9755 \times 10^{-4}$ and $2.5096 \times 10^{-4}$], but the RMSE of MRIME is between $[9.8602 \times 10^{-4}$ and $1.0035 \times 10^{-4}$]. It can be established from the figure that the enhancements of the MRIME approach are 30.878%, 1.156%, 46.525%, and 99.634%, respectively.
respectively, when compared to the mean, best, worst, and standard deviation of the outcomes of the RIME techniques. These results corroborate the superiority of the developed MRIME for the ONE-DM of the R.T.C. France cell. Consequently, the suggested MRIME yielded the highest value, indicating that MRIME outperforms RIME in terms of stability, accuracy, and efficacy when determining ONE-DM parameters through comparison. It is reliable that the MRIME identified the validity with the ONE-DM.

Figure 4. Convergence lines of RIME and MRIME for the ONE-DM of the R.T.C. France cell.

For the ONE-DM, the simulated and measured I-V and P-V characteristics are shown in Figure 6a,b. It can be proven that the data created by the MRIME technique are almost the same as the data obtained through experimentation, indicating that the MRIME technique proved effective in obtaining the power and current with diverse voltage levels. As illustrated in Figure 7a,b, the absolute errors between the simulated and measured currents are between $2.85343 \times 10^{-9}$ and $6.24849 \times 10^{-6}$, whereas the absolute error between the simulated and measured powers is between $1.95909 \times 10^{-6}$ and $1.4581 \times 10^{-3}$.
4.1.2. Case 2: TWO-DM

In the current case, the TWO-DM characteristics of the R.T.C. France cell are extracted using the suggested MRIME and the RIME. Table 2 lists the seven unknown TWO-DM parameters for which the experiment’s best outcomes were obtained for every approach. The results show that the suggested MRIME outperforms the RIME and comparator approaches in terms of competitiveness. This means that the regular RIME obtained an RMSE of \(9.9382 \times 10^{-4}\), whereas the MRIME obtained the best RMSE value of \(9.8251 \times 10^{-4}\). Moreover, the table specifies the assessed parameters of (MRIME and RIME), which are \(55.64800559\ \Omega\) and \(53.58354831\ \Omega\), \(0.760780758\ \text{A}\) and \(0.760864277\ \text{A}\), \(1.999974446\) and \(1.827202939\), \(1.482783518\) and \(1.448694376\), \(0.036767981\ \Omega\) and \(0.036173672\ \Omega\), \(8.0438 \times 10^{-7}\ \text{A}\) and \(4.3113 \times 10^{-8}\ \text{A}\), and \(2.19744 \times 10^{-7}\ \text{A}\) and \(3.25421 \times 10^{-7}\ \text{A}\) for the shunt resistance, photo-current, ideality factor for d1, ideality factor for d2, series resistance, saturation current for d1, and saturation current for d2, respectively.

Figure 6. (a) I-V and (b) P-V characteristics of the proposed MRIME for the ONE-DM of the R.T.C. France cell.

Figure 7. The absolute errors between the simulated and measured currents and powers concerning the MRIME for the ONE-DM of the R.T.C. France cell.
Table 2. Electrical parameters of the proposed MRIME and the standard RIME for the TWO-DM of the R.T.C. France cell.

<table>
<thead>
<tr>
<th>Applied Algorithm</th>
<th>RIME</th>
<th>MRIME</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{Ph}$ (A)</td>
<td>0.760684277</td>
<td>0.760780758</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>0.036173672</td>
<td>0.036767981</td>
</tr>
<tr>
<td>$R_{Sh}$ (Ω)</td>
<td>53.58354831</td>
<td>55.64800559</td>
</tr>
<tr>
<td>$I_{S1}$ (A)</td>
<td>$4.3113 \times 10^{-8}$</td>
<td>$8.0438 \times 10^{-7}$</td>
</tr>
<tr>
<td>$\eta_1$</td>
<td>1.827202939</td>
<td>1.999974446</td>
</tr>
<tr>
<td>$I_{S2}$ (A)</td>
<td>$3.25421 \times 10^{-7}$</td>
<td>$2.19744 \times 10^{-7}$</td>
</tr>
<tr>
<td>$\eta_2$</td>
<td>1.482783518</td>
<td>1.448694376</td>
</tr>
<tr>
<td>RMSE</td>
<td>$9.9382 \times 10^{-4}$</td>
<td>$9.8251 \times 10^{-4}$</td>
</tr>
</tbody>
</table>

Table 3 presents a comparison between the proposed MRIME technique and various optimization tools for the TWO-DM system that have been documented in literature, such as the flower pollination algorithm [58], teaching–learning–based ABC [59], TLBO [60], ABC [61], Cat Swarm Algorithm (CSA) [62], SCA [12], and generalized oppositional TLBO [4]. It is demonstrated that the proposed MRIME technique outperforms other approaches in obtaining the lower RMSE.

Table 3. Comparative assessment between the proposed MRIME technique and various optimization tools for the TWO-DM of the R.T.C. France cell.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRIME</td>
<td>$9.8251 \times 10^{-4}$</td>
</tr>
<tr>
<td>RIME</td>
<td>$9.9382 \times 10^{-4}$</td>
</tr>
<tr>
<td>ABC [61]</td>
<td>$1.28482 \times 10^{-3}$</td>
</tr>
<tr>
<td>Teaching–learning–based ABC [59]</td>
<td>$1.50482 \times 10^{-3}$</td>
</tr>
<tr>
<td>Generalized oppositional TLBO [4]</td>
<td>$4.43212 \times 10^{-3}$</td>
</tr>
<tr>
<td>TLBO [60]</td>
<td>$1.52057 \times 10^{-3}$</td>
</tr>
<tr>
<td>CSA [62]</td>
<td>$1.22 \times 10^{-3}$</td>
</tr>
<tr>
<td>SCA [12]</td>
<td>$9.86863 \times 10^{-4}$</td>
</tr>
<tr>
<td>Flower pollination algorithm [58]</td>
<td>$1.934336 \times 10^{-3}$</td>
</tr>
</tbody>
</table>

The corresponding convergence lines can be seen in Figure 8. The MRIME converged extremely quickly in the first 50 iterations, as depicted in this figure, demonstrating the MRIME’s excellent convergence capacity. Additionally, Figure 9 shows the thirty obtained RMSE objectives for Case 1’s RIME and MRIME. This figure illustrates that the RMSE of RIME is between [9.9382 × 10^-4 and 3.1870 × 10^-3], but the RMSE of MRIME is between [9.8251 × 10^-4 and 1.0135 × 10^-3]. It can be established from the figure that the enhancements of the MRIME approach are 45.3824%, 1.1379%, 68.1989%, and 99.0358%, respectively, when compared to the mean, best, worst, and standard deviation of the outcomes of the RIME techniques. These results corroborate the superiority of the developed MRIME for the TWO-DM of the R.T.C. France cell. Consequently, the suggested MRIME yielded the highest value, indicating that MRIME outperforms RIME in terms of stability, accuracy, and efficacy when determining TWO-DM parameters through comparison. It is reliable that the MRIME identified the validity with the TWO-DM.
For the TWO-DM, the simulated and measured I-V and P-V characteristics are shown in Figure 10a,b. It can be proven that the data created by the MRIME technique are almost the same as the data obtained through experimentation, indicating that the MRIME technique proved effective in obtaining the power and current with diverse voltage levels. As seen from Figure 10a,b, the absolute errors between the simulated and measured currents are between $2.34255 \times 10^{-9}$ and $6.33737 \times 10^{-6}$, whereas the absolute errors between the
simulated and measured powers are between $1.93966 \times 10^{-6}$ and $1.4684 \times 10^{-3}$. In Figures 6 and 10, negative values of voltage, current, and power indicate specific conditions of reverse bias situations. Therefore, based on the experimental study provided by [63], the polarity of the voltage applied to the module is opposite to its normal operating polarity.

4.2. Simulation Results for STM6_40/36 PV Module

4.2.1. Case 1: ONE-DM

In the current case, the ONE-DM characteristics of the STM6_40/36 PV module are extracted using the suggested MRIME and the RIME. Table 4 lists the five unknown ONE-DM parameters for which the experiment’s best outcomes were obtained for every approach. The results show that the suggested MRIME outperforms the RIME and comparator approaches in terms of competitiveness. This means that the regular RIME obtained an RMSE of $2.1693 \times 10^{-3}$, whereas the MRIME obtained the best RMSE value of $1.7690 \times 10^{-3}$. Additionally, the PV-derived electrical parameters utilizing the reported optimization approaches are displayed in the table, such as Enhanced MPA (EMPA) [47], Simulated Annealing (SA) [64], equilibrium optimizer (EO) [47], improved shuffled complex evolution (ISCE) [65], gorilla troops optimization (GTO) [47], hybridizing cuckoo search/biogeography-based optimization (BHCS) [63], Marine Predator Algorithm (MPA) [47], Jellyfish Search (JFS) [47], three-point based approach (TPBA) [66], heap-based algorithm (HBA) [47], forensic-based investigation (FBI) [53], and improved cuckoo search (ImCSA) algorithm [67]. Moreover, the table specifies the assessed parameters of (MRIME and RIME), which are $(17.86858 \, \Omega \text{ and } 16.80129 \, \Omega)$, $(1.663482 \, A \text{ and } 1.663482 \, A)$, $(1.537805 \text{ and } 1.5074212)$, $(0.003772 \, \Omega \text{ and } 0.004785 \, \Omega)$, and $(2.04 \, \mu A \text{ and } 1.55 \, \mu A)$ for the shunt resistance, photo-current, ideality factor for d1, series resistance, and saturation current for d1, respectively. Additionally, electrical variables acquired using various inspirational optimizers are expressed in this table. The corresponding convergence lines can be seen in Figure 11. The MRIME converged extremely quickly in the first 60 iterations, as depicted in this figure, demonstrating the MRIME’s excellent convergence capacity. Additionally, Figure 12 shows the thirty obtained RMSE objectives for Case 1’s RIME and MRIME. This figure illustrates that the RMSE of RIME is between $[2.1693 \times 10^{-3} \text{ and } 3.0364 \times 10^{-3}]$, but the RMSE of MRIME is between $[1.7690 \times 10^{-3} \text{ and } 2.2155 \times 10^{-3}]$. It can be established from the figure that the enhancements of the MRIME approach are $85.3678\%$, $18.4506\%$, $92.7036\%$, and $98.9158\%$, respectively, when compared to the mean, best, worst, and standard deviation of the outcomes of the RIME techniques. These results corroborate the superiority of the developed MRIME for the ONE-DM of the STM6_40/36 PV module.
Consequently, the suggested MRIME yielded the highest value, indicating that MRIME outperforms RIME in terms of stability, accuracy, and efficacy when determining ONE-DM parameters through comparison. It is reliable that the MRIME identified the validity with the ONE-DM of the STM6_40/36 PV module.

Table 4. Electrical parameters accomplished by the proposed MRIME and the standard RIME for the ONE-DM of STM6_40/36.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$I_{ph}$ (A)</th>
<th>$I_{s1}$ (µA)</th>
<th>$R_s$ (Ω)</th>
<th>$R_{sh}$ (Ω)</th>
<th>$\eta_1$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRIME</td>
<td>1.663482</td>
<td>2.04</td>
<td>0.004772</td>
<td>16.80129</td>
<td>1.537805</td>
<td>1.7690 x 10^{-3}</td>
</tr>
<tr>
<td>RIME</td>
<td>1.663482</td>
<td>1.55</td>
<td>0.00427</td>
<td>15.9283</td>
<td>1.5203</td>
<td>1.73 x 10^{-3}</td>
</tr>
<tr>
<td>BHCS [63]</td>
<td>1.6639</td>
<td>1.74</td>
<td>0.004025</td>
<td>16.24408</td>
<td>1.52314</td>
<td>1.73 x 10^{-3}</td>
</tr>
<tr>
<td>MPA [47]</td>
<td>1.65702</td>
<td>2.46</td>
<td>0.003831</td>
<td>31.50673</td>
<td>1.55904</td>
<td>3.496 x 10^{-3}</td>
</tr>
<tr>
<td>EO [47]</td>
<td>1.663629</td>
<td>1.78</td>
<td>0.004025</td>
<td>16.24408</td>
<td>1.52314</td>
<td>1.73 x 10^{-3}</td>
</tr>
<tr>
<td>JFS [47]</td>
<td>1.662589</td>
<td>1.84</td>
<td>0.004105</td>
<td>16.96607</td>
<td>1.52679</td>
<td>1.807 x 10^{-3}</td>
</tr>
<tr>
<td>SA [64]</td>
<td>1.6609</td>
<td>5.90</td>
<td>0.004999</td>
<td>26.7742</td>
<td>1.66602</td>
<td>3.399 x 10^{-3}</td>
</tr>
<tr>
<td>EMPA [47]</td>
<td>1.663418</td>
<td>2.03</td>
<td>0.003788</td>
<td>16.878</td>
<td>1.53713</td>
<td>1.769 x 10^{-3}</td>
</tr>
<tr>
<td>ImCSA [67]</td>
<td>1.663971</td>
<td>2</td>
<td>0.002914</td>
<td>15.84051</td>
<td>1.5335</td>
<td>1.794 x 10^{-3}</td>
</tr>
<tr>
<td>ISCE [65]</td>
<td>1.6639078</td>
<td>1.74</td>
<td>0.004274</td>
<td>15.9283</td>
<td>1.5203</td>
<td>1.73 x 10^{-3}</td>
</tr>
<tr>
<td>HBA [47]</td>
<td>1.661527</td>
<td>5.51</td>
<td>0.000001</td>
<td>23.6426</td>
<td>1.65869</td>
<td>3.33 x 10^{-3}</td>
</tr>
<tr>
<td>GTO [47]</td>
<td>1.663905</td>
<td>1.74</td>
<td>0.004274</td>
<td>15.92829</td>
<td>1.52030</td>
<td>1.73 x 10^{-3}</td>
</tr>
<tr>
<td>FBI [53]</td>
<td>1.66391</td>
<td>1.74</td>
<td>0.004281</td>
<td>15.91743</td>
<td>1.52007</td>
<td>1.73 x 10^{-3}</td>
</tr>
<tr>
<td>TPBA [66]</td>
<td>1.6632</td>
<td>2.77</td>
<td>0.004186</td>
<td>16.7328</td>
<td>1.5656</td>
<td>1.774 x 10^{-3}</td>
</tr>
</tbody>
</table>

Figure 11. Convergence lines of RIME and MRIME for the ONE-DM of the STM6_40/36 PV module.
For the ONE-DM, the simulated and measured I-V and P-V characteristics are shown in Figure 13(a,b). It can be proven that the data created by the MRIME technique are almost the same as the data obtained through experimentation, indicating that the MRIME technique proved effective in obtaining the power and current with diverse voltage levels. As illustrated in Figure 13, the absolute errors between the simulated and measured currents are between $3.58408 \times 10^{-9}$ and $3.4662 \times 10^{-5}$, whereas the absolute errors between the simulated and measured powers are between 0 and $8.7605 \times 10^{-2}$.

4.2.2. Case 2: TWO-DM of STM6_40/36 PV Module

In the current case, the characteristics of the STM6-40/36 PV module are extracted using the suggested MRIME and the RIME. Table 5 lists the seven unknown TWO-DM parameters for which the experiment’s best outcomes were obtained for every approach. The results show that the suggested MRIME outperforms the RIME and comparator approaches in terms of competitiveness. This means that the regular RIME obtained an RMSE of $1.9468 \times 10^{-3}$, whereas the MRIME obtained the best RMSE value of $1.6988 \times 10^{-3}$. Additionally, the PV-derived electrical parameters utilizing the reported optimization approaches are displayed in the table, such as the ensemble particle swarm optimizer (EPSO).
[68], improved Rao-based chaotic optimization (LCROA) [69], bat algorithm (BA) [21], directional bat algorithm (DBA) [70], novel bat algorithm (NBA) [70], and fractional chaotic-ensemble particle swarm optimizer (FC-EPSO) algorithm [71]. Moreover, the table specifies the assessed parameters of (MRIME and RIME), which are (17.04779 Ω and 14.54013 Ω), (1.66375 A and 1.666086 A), (1.876731 and 2), (1.361409 and 1.363856), (0.005601 Ω and 0.006291 Ω), (6.007 μA and 7.509 μA), and (2.61 × 10⁻¹ μA and 3.01 × 10⁻¹ μA) for the shunt resistance, photo-current, ideality factor for d1, ideality factor for d2, series resistance, saturation current for d1, and saturation current for d2, respectively. Additionally, electrical variables acquired using various inspirational optimizers are expressed in this table.

Table 5. Electrical parameters accomplished by the proposed MRIME and the standard RIME for the TWO-DM of STM6_40/36.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>( I_{ph} ) (A)</th>
<th>( I_{S1} ) (μA)</th>
<th>( I_{S2} ) (μA)</th>
<th>( R_s ) (Ω)</th>
<th>( R_{sh} ) (Ω)</th>
<th>( \eta_1 )</th>
<th>( \eta_2 )</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRIME</td>
<td>1.66375</td>
<td>6.007</td>
<td>2.61 × 10⁻¹</td>
<td>0.005601</td>
<td>17.04779</td>
<td>1.876731</td>
<td>1.361409</td>
<td>1.6988 × 10⁻³</td>
</tr>
<tr>
<td>RIME</td>
<td>1.666086</td>
<td>7.509</td>
<td>3.01 × 10⁻¹</td>
<td>0.006291</td>
<td>14.54013</td>
<td>2</td>
<td>1.363856</td>
<td>1.9468 × 10⁻³</td>
</tr>
<tr>
<td>BA [70]</td>
<td>1.637941</td>
<td>1.59</td>
<td>3.94 × 10⁻⁵</td>
<td>0.003887</td>
<td>24.6958</td>
<td>1.504536</td>
<td>1.4783</td>
<td>2.194577 × 10⁻²</td>
</tr>
<tr>
<td>EPSO [68]</td>
<td>1.6648</td>
<td>16.70</td>
<td>6.21 × 10⁻⁶</td>
<td>0.5000</td>
<td>16.858</td>
<td>1.16649</td>
<td>1.87067</td>
<td>1.8307 × 10⁻³</td>
</tr>
<tr>
<td>HPO</td>
<td>1.663702</td>
<td>4.06</td>
<td>5.57 × 10⁻¹⁰</td>
<td>0.008726</td>
<td>17.82614</td>
<td>1.688851</td>
<td>1</td>
<td>1.696271 × 10⁻³</td>
</tr>
<tr>
<td>LCROA [69]</td>
<td>1.6637</td>
<td>72.2</td>
<td>3.28 × 10⁻⁶</td>
<td>0.16717</td>
<td>16.7419</td>
<td>1.5739</td>
<td>2.000</td>
<td>1.712 × 10⁻³</td>
</tr>
<tr>
<td>NBA [70]</td>
<td>1.662865</td>
<td>6.60</td>
<td>1.61 × 10⁻⁶</td>
<td>0.004653</td>
<td>16.694049</td>
<td>1.678806</td>
<td>1.511867</td>
<td>1.82684 × 10⁻³</td>
</tr>
<tr>
<td>FC-EPSO [71]</td>
<td>1.6634</td>
<td>1.85</td>
<td>9.72 × 10⁻⁵</td>
<td>0.01101</td>
<td>16.5914</td>
<td>1.5818</td>
<td>1.5445</td>
<td>1.772 × 10⁻³</td>
</tr>
<tr>
<td>DBA [70]</td>
<td>1.663860</td>
<td>1.80</td>
<td>3.66 × 10⁻⁵</td>
<td>0.004167</td>
<td>16.066503</td>
<td>1.524098</td>
<td>1.43939</td>
<td>1.731960 × 10⁻³</td>
</tr>
</tbody>
</table>

The corresponding convergence lines can be seen in Figure 14. The MRIME converged extremely quickly in the first 45 iterations, as depicted in this figure, demonstrating the MRIME’s excellent convergence capacity. Additionally, Figure 15 shows the thirty obtained RMSE objectives for Case 2’s RIME and MRIME. This figure illustrates that the RMSE of RIME is between [1.9468 × 10⁻³ and 8.1478 × 10⁻¹], but the RMSE of MRIME is between [1.6988 × 10⁻³ and 2.7435 × 10⁻⁴]. It can be established from the figure that the enhancements of the MRIME approach are 50.4215%, 12.7368%, 66.3287%, 76.9046%, and 99.634%, respectively, when compared to the mean, best, worst, and standard deviation of the outcomes of the RIME techniques. These results corroborate the superiority of the developed MRIME for the TWO-DM of the STM6_40/36 PV module. Consequently, the suggested MRIME yielded the highest value, indicating that MRIME outperforms RIME in terms of stability, accuracy, and efficacy when determining TWO-DM parameters through comparison. It is reliable that the MRIME identified the validity with the TWO-DM of the STM6_40/36 PV module.
Additionally, Table 6 presents the statistical analysis and the percentage of improvement of the statistical analysis comparing the efficacy of the proposed MRIME approach to that of the standard RIME, EPSO [68], BA [70], FC-EPSO [71], LCROA [69], DBA [70], and NBA [70]. The results demonstrate that the suggested HPO approach outperforms reported optimizers in terms of overall capability. The minimum, standard deviation (SD), maximum, and mean of the RMSE are successfully attained by the suggested HPO technique, with $1.6988 \times 10^{-3}$, $2.0308 \times 10^{-3}$, $2.7435 \times 10^{-3}$, and $2.6355 \times 10^{-4}$, respectively.
Table 6. Statistical analysis of MRIME versus other techniques for the TWO-DM of the STM6-40/36 PV module.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Min.</th>
<th>Mean</th>
<th>Max.</th>
<th>SD</th>
<th>Improvement %</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRIME</td>
<td>1.6988 × 10⁻³</td>
<td>2.0308 × 10⁻³</td>
<td>2.7435 × 10⁻³</td>
<td>2.6355 × 10⁻⁴</td>
<td></td>
</tr>
<tr>
<td>RIME</td>
<td>1.9468 × 10⁻³</td>
<td>4.0962 × 10⁻³</td>
<td>50.4215%</td>
<td>66.3287%</td>
<td>1.1411 × 10⁻³</td>
</tr>
<tr>
<td>BA [70]</td>
<td>2.1946 × 10⁻²</td>
<td>92.2591%</td>
<td>1.092023%</td>
<td>1.01448059%</td>
<td>2.407 × 10⁻²</td>
</tr>
<tr>
<td>DBA [70]</td>
<td>1.7319 × 10⁻³</td>
<td>1.9095%</td>
<td>0.004934%</td>
<td>0.00372976%</td>
<td>2.893 × 10⁻³</td>
</tr>
<tr>
<td>NBA [70]</td>
<td>1.8268 × 10⁻³</td>
<td>7.0052%</td>
<td>0.007598%</td>
<td>63.8922%</td>
<td>1.430 × 10⁻³</td>
</tr>
<tr>
<td>LCROA [69]</td>
<td>1.712 × 10⁻³</td>
<td>0.7694%</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>FC-EPSO [71]</td>
<td>1.772 × 10⁻³</td>
<td>4.1293%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>EPSO [68]</td>
<td>1.8307 × 10⁻³</td>
<td>7.2033%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

For the TWO-DM, the simulated and measured I-V and P-V characteristics at the 20 experimental voltage points are shown in Figure 16a,b. It can be proven that the data created by the MRIME technique are almost the same as the data obtained through experimentation, indicating that the MRIME technique proved effective in obtaining the power and current with diverse voltage levels. As illustrated in Table 7 and Figure 17a,b, the absolute errors between the simulated and measured currents are between 5.09971 × 10⁻⁶ and 2.5773 × 10⁻⁵, whereas the absolute errors between the simulated and measured powers are between 0 and 7.5541 × 10⁻².

![Figure 16](image-url)  
(a)  
(b)  
Figure 16. (a) I-V and (b) P-V characteristics of the proposed MRIME for the TWO-DM of the STM6-40/36 PV module.

Table 7. Simulated and experimental currents and powers and the absolute errors established by the proposed MRIME technique for the TWO-DM of the STM6-40/36 PV module.

<table>
<thead>
<tr>
<th>Point</th>
<th>Vexp</th>
<th>Iexp</th>
<th>Isim</th>
<th>Pexp</th>
<th>Psim</th>
<th>Absolut IAE</th>
<th>Absolut PAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>1.663</td>
<td>1.665365</td>
<td>0</td>
<td>0</td>
<td>5.59422 × 10⁻⁶</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0.118</td>
<td>1.663</td>
<td>1.665139</td>
<td>0.196234</td>
<td>0.196486</td>
<td>4.57617 × 10⁻⁶</td>
<td>0.000252425</td>
</tr>
<tr>
<td>3</td>
<td>2.237</td>
<td>1.661</td>
<td>1.661072</td>
<td>3.715657</td>
<td>3.715819</td>
<td>5.2353 × 10⁻⁷</td>
<td>0.000161859</td>
</tr>
<tr>
<td>4</td>
<td>5.434</td>
<td>1.653</td>
<td>1.654842</td>
<td>8.982402</td>
<td>8.992412</td>
<td>3.39332 × 10⁻⁷</td>
<td>0.010009956</td>
</tr>
<tr>
<td>5</td>
<td>7.26</td>
<td>1.65</td>
<td>1.651098</td>
<td>11.979</td>
<td>11.98697</td>
<td>1.20484 × 10⁻⁷</td>
<td>0.007968949</td>
</tr>
<tr>
<td>6</td>
<td>9.68</td>
<td>1.645</td>
<td>1.645317</td>
<td>15.9236</td>
<td>15.92667</td>
<td>1.0071 × 10⁻⁷</td>
<td>0.003071927</td>
</tr>
<tr>
<td>7</td>
<td>11.59</td>
<td>1.64</td>
<td>1.63852</td>
<td>19.0076</td>
<td>18.99044</td>
<td>2.19143 × 10⁻⁷</td>
<td>0.017157251</td>
</tr>
<tr>
<td>8</td>
<td>12.6</td>
<td>1.636</td>
<td>1.632709</td>
<td>20.6136</td>
<td>20.57213</td>
<td>1.08307 × 10⁻⁶</td>
<td>0.041466645</td>
</tr>
<tr>
<td>9</td>
<td>13.37</td>
<td>1.629</td>
<td>1.626133</td>
<td>21.77973</td>
<td>21.7414</td>
<td>8.2178 × 10⁻⁶</td>
<td>0.038327374</td>
</tr>
<tr>
<td>10</td>
<td>14.09</td>
<td>1.619</td>
<td>1.617132</td>
<td>22.81711</td>
<td>22.78539</td>
<td>3.489 × 10⁻⁶</td>
<td>0.026318517</td>
</tr>
<tr>
<td>11</td>
<td>14.88</td>
<td>1.597</td>
<td>1.602077</td>
<td>23.76336</td>
<td>23.8389</td>
<td>2.57728 × 10⁻⁵</td>
<td>0.075541147</td>
</tr>
</tbody>
</table>
Figure 17. (a,b) The absolute errors between the simulated and measured currents and powers concerning the MRIME for the ONE-DM of the STM6-40/36 PV module.

5. Conclusions

This study introduces the Modified RIME (MRIME) algorithm, an advanced optimization method that integrates the Polynomial Differential Learning Operator (PDLO) with the conventional RIME algorithm. Unlike traditional RIME methods, MRIME incorporates non-linear elements through PDLO, enhancing its adaptability, convergence rate, and overall search capability. Notably, MRIME addresses both the one-diode model (ONE-DM) and TWO-DM, encompassing various equivalent circuit configurations essential for accurately characterizing photovoltaic (PV) modules. Through comprehensive simulations and comparisons with contemporary methods and standard RIME, the MRIME approach demonstrated significant improvements, underscoring its novelty and efficacy in enhancing PV parameter estimation. The enhanced MRIME algorithm was successfully implemented on two commercial PV systems, and both PV models’ benefits and robustness were shown to be significantly greater than those of conventional RIME algorithms and prior results. A robust correlation between simulated and real data was found during the MRIME efficacy tests on the PV ONE-DM and TWO-DM, demonstrating the algorithm’s performance and dependability. Hence, the MRIME technique is a promising development in PV parameter identification optimization methods.
As future studies, the proposed MRIME algorithm could include sensitivity analysis to certain parameters, computational complexity, or constraints in handling specific types of data or scenarios. Also, the research area could be extended to involve exploring alternative optimization techniques, integrating additional data sources or features, or investigating novel approaches to parameter estimation in photovoltaic systems. Moreover, potential real-world applications and implications of the improved MRIME algorithm could be explored.

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**References**


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