InGaN/GaN tandem solar cell parameter estimation: a comparative study

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Abstract: In this paper, two hybrid estimation approaches, hybrid genetic algorithm (TR-GA) and hybrid particle swarm optimization (TR-PSO), are used to estimate single-diode model InGaN/GaN solar cell parameters from J–V experimental data under AM0 illumination. These parameters are photocurrent density (\(J_{ph}\)), reverse saturation current density (\(J_s\)), ideality factor (\(A\)), series resistance (\(R_s\)), and shunt resistance (\(R_{sh}\)). The trust region (TR) method used in both approaches provides the initial conditions and helps to avoid the problem of premature convergence (due to local minimum). Simulation results based on the minimization of the mean square error between experimental and theoretical J–V characteristics show that both applied methods have a similar degree of efficiency in terms of precision, whereas the TR-PSO method is more efficient in terms of convergence speed. The effect of different extracted parameters on the characteristics J–V and P–V is evaluated in a simulation study of an identified model.

Key words: Photovoltaic cells, parameter extraction, single-diode solar cell model, genetic algorithms, trust region, particle swarm optimization

1. Introduction

Photovoltaic energy systems have a huge potential and constitute a high interest in both the scientific and industrial communities. This interest is due to the increasing demand for energy in most industrial sectors and to environmental constraints [1]. Improving solar cell conversion efficiency has become an urgent issue of research, mainly due to the diverse applications of photovoltaic energy in terrestrial and space domains. This task has spurred a great effort in the improvement of existing semiconductor materials as well as in the development of new ones.

The early p–n junctions in crystalline silicon-based (c-Si) solar cells had a 15%–20% conversion efficiency and were followed by thin-film solar cells with a typical efficiency factor ranging from 10% to 15%. Solar cells of a more recent generation such as III–V compound multijunction (MJ) (tandem) rely on organic materials [2].

The III–V nitride semiconductors (InN, GaN, AIN) and their alloys have received much interest in the last two decades, due to their exceptional physical properties, such as their adjustable band gap which can cover all the solar spectrum [3, 4]. Indium gallium nitride (InGaN) layers were developed next and rapidly exploited in electronics and optoelectronics devices such as diodes and sensors as well as solar cells [5, 6]. The heterostructure InGaN/GaN photovoltaic cell can achieve energy conversion efficiency of over 50% [7].

Solar cell behavior can be best described by current density–voltage (J–V) and power density–voltage (P–V) characteristics, which are generally affected by various electrical parameters \((J_{ph}, J_s, R_s, R_{sh}, A)\).
Identification and extraction of these parameters is a necessary and crucial step in apprehending the physical mechanisms involved within the solar cell, not only to simulate its behavior, but also to increase its efficiency.

Many methods of optimization have been used for parameter estimation of solar cells, including conventional methods such as the Newton–Raphson method \[8\] and the Lambert function-based method \[9\], but these methods are strongly dependent on the initial guess and highly prone to being trapped into a local minimum \[10\].

Evolutionary computation techniques have been widely used in nonlinear, multimodal, and multivariable optimization problems \[11\], and their prowess has prompted their use in solar photovoltaic cell parameter extraction, such as particle swarm optimization (PSO) \[12\], genetic algorithm (GA) \[13\], artificial bee swarm optimization (ABSO) \[14\], harmony search (HS) \[15\], simulated annealing (SA) \[16\], pattern search (PS) \[17\], cuckoo search (CS) \[18\], differential evolution (DE) \[19\]. Most of these potent optimization algorithms depend strongly on the selection of the initials conditions and can fall into local optima thus may fail to converge \[20\].

Circumventing these drawbacks, solutions involving combining swarm-based algorithms with a local search model method were proposed, such as the hybrid semianalytical and modified Hooke–Jeeves method (SA-MHJ) \[21\], hybrid approach based on genetic algorithm and the Nelder–Mead simplex search method (GA-NM) \[22\], and hybrid Nelder–Mead simplex search method and modified particle swarm optimization technique (NM-MPSO) \[23\].

In this paper, the focus will be on the use of two hybrid approaches based on the TR-GA and TR-PSO methods in estimating five solar cell electrical parameters ($J_{ph}$, $J_s$, $R_s$, $R_{sh}$, $A$) in order to enable adequate simulation of the behavior of an InGaN/GaN single-diode photovoltaic cell.

2. Photovoltaic cell modeling and problem formulation

2.1. InGaN/GaN solar cell modeling

The InGaN/GaN solar cell structure is shown in Figure 1 \[3\]. It contains three regions, a P region of GaN doped with Mg, a GaN layer representing the Si-doped N region, and an intrinsic region held in sandwich between the two layers, basically containing a thin InGaN layer, which constitute the tandem solar cell deposited on a sapphire substrate.

$J$–$V$ characteristics of the single-diode model shown in Figure 2 are given by Eq. (1) \[24\]:

$$J = J_{ph} - J_s \times \left\{ \exp\left[\frac{q \times (V + R_s \times J)}{(A \times k \times T)}\right] - 1 \right\} - \frac{V + R_s \times J}{R_{sh}},$$

where $J$ is the solar cell current density, $J_{ph}$ is the photocurrent density, $J_s$ is the reverse saturation current density, $q$ is the electron charge ($1.6 \times 10^{-19}$ C), $k$ is the Boltzmann constant ($1.38658 \times 10^{-23}$ J/K); $T$ is the operating temperature (298 K), $A$ is the ideality factor of the junction, $R_s$ is the series resistance, and $R_{sh}$ is the shunt resistance.

2.2. Parameter estimation problem

The problem of estimating solar cell parameters can be viewed as an optimization issue involving minimizing the mean square error (MSE) between calculated and actual currents. It is the goal of this paper to estimate the set of parameters making the MSE value minimal. MSE is thus used as the objective function and is given
in [25]:

\[ X = \sum_{i=1}^{M} [J_{i}^{exp} - J(V_{i}^{exp}, \theta)], \]

where \( \theta = (J_{ph}, J_{s}, R_{s}, R_{sh}, A) \), \( J_{i}^{exp} \) is the experimental current density corresponding to the experimental voltage \( V_{i}^{exp} \), and \( M \) is the number of experimental data. Hybrid estimating methods used will be developed in the ensuing sections.

### 3. Description of the TR-GA and TR-PSO hybrid methods

#### 3.1. Justification for the use of an initializing method (TR) for the Ga and PSO

Difficult optimization challenges have been addressed successfully using heuristic algorithms such as PSO and GAs. The latter has been used in solar cell parameter identification with mitigated results for its elevated percentage of parameter estimation errors [26, 27]. PSO-inherent parameters such as particle number and prerogative may lead to early convergence, i.e. local optimum [27, 28]. An adequate starting point may counterbalance this shortcoming and can lead to sound and meaningful results which may speed up convergence. TR is the technique that can adequately address this issue, and it will be used for both estimated techniques used.
3.1.1. Description of trust region method

TR, among optimization tools, is a significant means in achieving an elevated convergence rate. Even on large current variation, TR has proven to be highly effective in parameter extraction from experimental data [29].

The goal of the TR method is to minimize the system of equations $f_i(x) = 0$ in order to determine the values of $x_i$ corresponding to a set of parameters $(J_{ph}, J_s, J_{sh}, A)$ which suit the problem.

The first iteration of the method is made so that $f_i = x_0 = f_0$, where $x_0$ is the initial value of $x$ and $f_0$ is the initial value of $f$.

Thus, for iteration $k$, the subproblem indicated in Eq. (3) must be solved [29].

$$\min_{p \in \mathbb{R}^n} m_k(p) = f_k + g_k^T p + \frac{1}{2} p^T B_k p, \quad \text{for } \|p\| \leq \Delta_k,$$

where $f_k = f(x_k)$ is the function value at point $x_k$, $g_k = \nabla f(x_k)$ is the gradient of $f(x_k)$, $B_k = \nabla^2 f(x_k)$ is the Hessian matrix of $f(x_k)$, and $\Delta_k$ is the trust region radius.

3.2. Description of the hybrid trust region with genetic algorithm (TR-GA) method

The main objective of the genetic algorithm is to find the estimated values of parameters $(J_{ph}, J_s, R_s, R_{sh}, A)$ that minimize the MSE. The structure of the TR-GA is illustrated by a flowchart given in Figure 3.

![Figure 3. Flowchart illustrating the TR-GA method.](image-url)
3.2.1. Initial population

The initial population represents the starting values of parameters randomly selected from the appropriate search ranges that were determined by trust region (TR) algorithm.

The TR algorithm provided in MATLAB is applied using the curve fitting tool [30], in which the fitting model approaching Eq. (1) is simplified into following formula:

\[ J = J_{ph} - J_s \times \left[ \exp \left( \frac{38.90672}{A} \times V \right) - 1 \right] - J_{sh}, \]  

(4)

where:

- The number 38.90672 represents the value of \( q \div (k \times T) \).
- Considering \( R_s \approx 0 \) and \( R_{sh} \gg V + (R_s \times J) \) makes \( J_{sh} \) near constant [31].
- \( V + (R_s \times J) \) is approximated by \( V \) [32].

By using the values of \((J_{ph}, J_s, J_{sh}, A)\) obtained from the TR algorithm, it is possible to deduce approximately the search ranges that must be used by GA and PSO algorithms to correctly estimate the parameter values. The genetic algorithm GA relies on the following operators: selection, crossover, and mutation.

3.2.2. Selection

At this first step, selection of the individuals (corresponding to a set of solar cell parameter values) of a population that survived and can reproduce is performed. This selection means giving the individuals that have the smallest value of the objective function a higher probability to reproduce one or several descendants in the next generation and to contribute to the evolution of the solution [33, 34].

3.2.3. Crossover

Crossover is an operator that ensures the mixing and recombination of the parental genes to form descendants with new potentials. It corresponds to an exchange of genetic materials between two parents (individuals) chosen randomly from the parents selected previously to form two new chromosomes (or children) [33, 34].

3.2.4. Mutation

Mutation is a process of swapping a random bit in a chromosome [33, 34]. To improve the quality of the population, in this step, a very low probability is chosen.

3.3. Description of the hybrid trust region with particle swarm optimization algorithm (TR-PSO) method

In order to ensure the quality of the results, the TR-PSO method was tested and applied to optimize different parameters of the model. This method is based on the estimation of values of \((J_{ph}, J_s, R_s, R_{sh}, A)\) that lower the objective function value. The search ranges for these parameters are determined in the same way as in the previous method (TR-GA). This optimization method, as described in the flowchart depicted in Figure 4, is based on the collaboration of particles, where each particle has a potential to be a solution in the search space. A swarm of particles flies over the search space searching for the global optimum. A particle i (a potential solution, corresponding to a set of solar cell parameter values) of the swarm is modeled by its position vector...
\[ x_i = (x_{i1}; x_{i2}; \ldots; x_{in}) \] which is defined by Eq. (5) and its velocity vector \( v_i = (v_{i1}; v_{i2}; \ldots; v_{in}) \) represented by Eq. (6). This particle keeps the best position denoted \( p_i = (p_{i1}; p_{i2}; \ldots; p_{in}) \) in memory. The best position reached by all particles of the swarm are rated \( p_g = (p_{g1}; p_{g2}; \ldots; p_{gn}) \) \(^{[35, 36]} \). The global optimum is then decided from this new group of positions depending on the one giving the lowest objective function value.

\[ x_i(t + 1) = x_i(t) + v_i(t + 1), \quad (5) \]

\[ v_{ij} = v_{ij}(t) + c_1 r_1 (p_{ij} - x_{ij}(t)) + c_2 r_2 (p_{gj}(t) - x_{ij}(t)), \quad (6) \]

where \( c_1 \) and \( c_2 \) are constants, called acceleration coefficients, and \( r_1 \) and \( r_2 \) are two random numbers taken from \([0, 1]^{[35, 36]} \).

4. Results and discussion

In order to validate the simulation results obtained using optimization methods described above, a comparison with experimental J–V characteristics of an InGaN/GaN solar cell under concentrated AM0 of illumination was realized \(^{[3]} \).

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**Figure 4.** Flowchart illustrating the TR-PSO method.
Figure 5 and Table 1 show the J–V characteristics of the experimental result compared to the proposed TR algorithm and the extracted parameters for Eq. (4) using the same algorithm, respectively.

Tables 2 and 3 summarize the tuning parameters of GA and PSO algorithms.

**Table 1.** The search ranges and values of parameters extracted by TR method.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Search ranges</th>
<th>TR algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J_{ph}$ ($A/cm^2$)</td>
<td>[-∞, +∞]</td>
<td>0.009</td>
</tr>
<tr>
<td>$J_s$ ($A/cm^2$)</td>
<td>[-∞, +∞]</td>
<td>$9.698 \times 10^{-13}$</td>
</tr>
<tr>
<td>$J_{sh}$ ($A/cm^2$)</td>
<td>[0, 0.01]</td>
<td>0.005</td>
</tr>
<tr>
<td>$A$</td>
<td>[1, 4]</td>
<td>3.287</td>
</tr>
<tr>
<td>RMSE</td>
<td></td>
<td>$2.3991 \times 10^{-4}$</td>
</tr>
</tbody>
</table>

**Table 2.** GA constants.

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>20</td>
</tr>
<tr>
<td>Number of variables</td>
<td>5</td>
</tr>
<tr>
<td>Crossover probability</td>
<td>0.5</td>
</tr>
<tr>
<td>Mutation probability</td>
<td>0.01</td>
</tr>
<tr>
<td>Fitness limit</td>
<td>$10^{-8}$</td>
</tr>
</tbody>
</table>

**Table 3.** PSO Constants.

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>20</td>
</tr>
<tr>
<td>Number of variables</td>
<td>5</td>
</tr>
<tr>
<td>Personal acceleration coefficient (C1)</td>
<td>1.49</td>
</tr>
<tr>
<td>Social acceleration coefficient (C2)</td>
<td>1.49</td>
</tr>
<tr>
<td>Fitness limit</td>
<td>$10^{-8}$</td>
</tr>
</tbody>
</table>

The search ranges and the best values of parameters estimated by TR-GA and TR-PSO methods are tabulated in Table 4.

**Table 4.** The search ranges and values of parameters extracted by GA and PSO methods.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Search ranges</th>
<th>GA</th>
<th>PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>$J_{ph}$ ($A/cm^2$)</td>
<td>[0.001, 0.1]</td>
<td>0.0044</td>
<td>0.0043</td>
</tr>
<tr>
<td>$J_s$ ($A/cm^2$)</td>
<td>[$10^{-13}$, $10^{-12}$]</td>
<td>$9.30 \times 10^{-13}$</td>
<td>$9.84 \times 10^{-13}$</td>
</tr>
<tr>
<td>$R_{sh}$ (Ω)</td>
<td>[1 K, 10 K]</td>
<td>3029.27</td>
<td>4140.455</td>
</tr>
<tr>
<td>$R_s$ (Ω)</td>
<td>[0.01, 100]</td>
<td>2.59</td>
<td>0.50</td>
</tr>
<tr>
<td>A</td>
<td>[3.28, 3.29]</td>
<td>3.2820</td>
<td>3.2835</td>
</tr>
</tbody>
</table>
Figures 6 and 7 clearly indicate that the estimated data obtained using TR-GA and TR-PSO methods are in close agreement with the experimentally measured data.

It is obvious from Figure 8 that TR-GA and TR-PSO methods achieved significantly low values of MSE, $8.50 \times 10^{-9}$ and $5.98 \times 10^{-9}$ respectively, but the TR-PSO method is more efficient in terms of convergence speed; the TR-GA method reaching a value of $8.50 \times 10^{-9}$ after 105 iterations, whereas the TR-PSO method reaches almost the same value $5.98 \times 10^{-9}$ after 1 iteration.

In Figures 9–18, the effect of different parameters extracted by TR-PSO on the electrical behavior of the InGaN/GaN solar cell is shown.

From Figures 9 and 10, it is easy to observe that the value of the short-circuit current density ($J_{sc}$) and maximum power point (MPP) are directly proportional to photocurrent density ($J_{ph}$), whereas the open circuit voltage ($V_{oc}$) decreases slightly.

Figures 11 and 12 indicate that the reverse saturation current density has inverse relationship with the open circuit voltage ($V_{oc}$), and the lower the value of saturation current is the better the maximum power output is.

From Figures 13 and 14, it can be seen that the open circuit voltage decreases when the ideality factor decreases; therefore, the power density decreases.
Figures 15 and 16 show that the slope of the curve decreases in the area where the cell operates as a constant voltage generator with increasing series resistance; therefore, the maximum power density decreases.

Figures 17 and 18 show that the slope of the curve increases in the area where the cell operates as a current source with increasing shunt resistor, and so does the maximum power density.

Figure 9. J–V cell characteristics for different values of $J_{ph}$.

Figure 10. P–V cell characteristics for different values of $J_{ph}$.

Figure 11. J–V cell characteristics for different values of $J_s$.

Figure 12. P–V cell characteristics for different values of $J_s$.

Figure 13. J–V cell characteristics for different values of ideality factor $A$.

Figure 14. P–V cell characteristics for different values of ideality factor $A$. 
5. Conclusion

This paper presents two methods to determine the electrical parameters of a single-diode solar cell model from the experimental J–V characteristics of an InGaN/GaN photovoltaic cell under AM0 of illumination. The extraction of these parameters is formulated as a nonconvex optimization problem. The resolution of this fundamental optimization problem relies on the value of the mean square error which is the fitting difference between the mathematical and experimental models. The simulation results show that both techniques (TR-PSO and TR-GA) are very promising in determining electrical parameters in the term of precision, but the TR-PSO approach is more efficient in solving the optimization problem in terms of convergence speed.

References


