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Impact of Optimization Algorithm Choice on Nonlinear Global Model for Photovoltaic Energy Generation Forecasting

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ABSTRACT The article explores the relevance of choosing the optimization algorithm to obtain accurate parameter estimates in photovoltaic (PV) systems, with the aim of improving the energy efficiency of solar energy. Advances in photovoltaic module analysis models have resulted in the development of global non-linear models (GNLM), which offer a more accurate representation of the I-V characteristics under various environmental conditions. Metaheuristic algorithms have stood out for their ability to handle the complexity of these nonlinear models. Therefore, the careful choice of the optimization algorithm is fundamental to guarantee consistent and reliable results in the estimation of the model parameters, contributing to maximizing energy efficiency. The study seeks to investigate whether different optimization tools can improve the accuracy and efficiency of parameter estimation, resulting in improved modeling and performance prediction of PV systems in different conditions.

KEYWORDS Energy Production, GNLM, NMAEP, Optimization Algorithms, Photovoltaic.

I. INTRODUCTION

The use of solar energy is undergoing remarkable global growth, driven by a significant reduction in the costs of solar technology [1]. This increase is a result of the introduction of highly efficient and affordable photovoltaic modules into markets, stimulated by international government incentives and intense competition among solar panel manufacturers [2]. Within this scenario, it becomes clear that the pursuit of optimizing the utilization of solar energy drives technological innovation, resulting in a continuous improvement in the energy efficiency of PV modules and the consequent reduction of costs associated with this technology.

The purpose of mathematical models for photovoltaic modules has been to seek a better understanding of their operation [3]. However, this requires a deep understanding of the underlying physical processes and key factors influencing the performance of PV cells [4]. Such models perform various functions across a wide range of areas related to PV systems, from planning and simulation to control and performance evaluation, as well as in site identification and correct sizing. Therefore, it is important to have an accurate and reliable model capable of handling a variety of operational conditions [5].

The classical models used in the performance analysis of PV modules include the Single Diode Model (SDM), Double Diode Model (DDM), and Triple Diode Model (TDM) [6]. Among these models, the SDM, as depicted in Fig. 1, stands out as the most widespread in the literature due to its simplicity [7]. Classical models are effective in parameter extraction under standard test conditions (STC); however, their limitation in handling the variability of characteristic curves in the face of factors such as temperature (T) and irradiance (G) has led to the development of global nonlinear models (GNLM) [7]. This new approach, while generally maintaining the structure of conventional electrical circuits, introduces new parameters or electrical sub-parameters related to T and G, which are expressed through nonlinear equations. This adaptation enables a more precise and comprehensive representation of the behavior of PV modules under a variety of environmental conditions [3], [8]–[15].

The accurate estimation of unknown parameters is one of the important steps in modeling PV modules [16]. From a modeling perspective, there is an unmet expectation due to the lack of data provided by manufacturers, especially regarding the resistors of the module's equivalent circuit, which imposes considerable challenges on this task [17]. In this sense, a variety of methodologies are used to solve nonlinear transcendental equations, which can be classified into three main categories: analytical techniques, deterministic structures and meta-heuristic structures [4]. Analytical techniques are recognized for their simplicity of implementation, but often compromise the effectiveness of the model due to

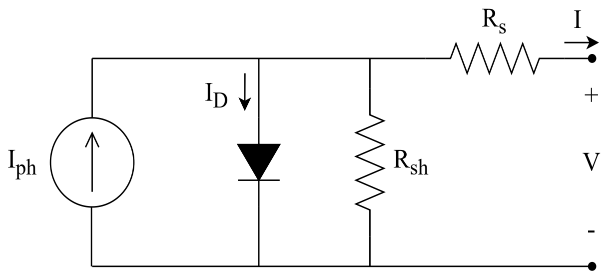

FIGURE 1. Electrical Circuit of the SDM.

the need for assumptions and the relevance of arbitrarily designated points. For example, deterministic algorithms such as Newton-Raphson and Lambert's W-functions are based on gradient methods, which makes them susceptible to inappropriate initial values and prone to getting stuck in local optima [4].

Thus, metaheuristic algorithms are regarded as a superior solution for overcoming the limitations of deterministic and analytical approaches [2]. Through the formulation of an objective function and careful selection of optimization algorithms, these methods allow for accurate estimation of module parameters, even in the face of the inherent complexity of variable environmental conditions. Some examples of metaheuristic algorithms used to solve optimization problems are swarm-based, such as Bacteria Foraging Optimization (BFO) [18], Dandelion Optimizer (DO) [19], nature-inspired, such as Artificial Rabbits Optimization (ARO) [20], African Vultures Optimization Algorithm (AVOA) [21], Chimp Optimization Algorithm (ChOA) [22], Dingo Optimization Algorithm (DOA) [23], Dung beetle optimizer (DBO) [24], Flying Foxes Optimization (FFO) [25], Tuna Swarm Optimization (TSO) [26], Zebra Optimization Algorithm (ZOA) [27]; physics and chemistry-based, such as Transient Search Algorithm (TSA) [28]; population-based, such as Chaos Game Optimization (CGO) [29].

In [2], the authors present an application of CGO to estimate the parameters of the TDM photovoltaic model. The results obtained were compared with six other optimization algorithms, demonstrating that CGO outperformed in terms of error value obtained and regarding the number of iterations until convergence. In another study conducted by [30], GPCSO is introduced with the aim of extracting parameters from mathematical models of photovoltaic (PV) cells and modules quickly and accurately. This work includes comparisons with various analytical, numerical, and hybrid methods documented in the literature. The results reveal a higher complexity in extracting PV parameters for the double diode model, however, this model proves to be more accurate at low irradiation levels than the single diode model. Based on a wide range of comparisons, the authors conclude that the proposed method efficiently and accurately determines the parameters of the mathematical model that characterize PV cells and modules. The study presented in [31] addresses the extraction of PV module parameters using FFO, which is compared to other well-known metaheuristic optimizers. The results indicate that, despite requiring more computational time compared to others, FFO's ability to optimize multiple parameters simultaneously results in a more efficient optimization process. Hence, the literature demonstrates a growing importance in the accuracy of optimization algorithms, also taking into account the number of iterations and the speed at which these algorithms perform. Consequently, the choice of the most appropriate algorithm for a given task is of paramount importance, as optimization algorithms exhibit significant variations in various aspects, such as their ability to handle different types of problems, computational efficiency, robustness against various forms of input data, ease of implementation, and ability to deal with specific constraints. While some algorithms are specifically developed to solve particular problems, others have a broader approach and can be applied to a variety of situations [32].

Therefore, the fundamental purpose of this article is to extend the evaluation of the effectiveness of optimization algorithms conducted in [33] in the context of the parameter estimation process of the GNLM proposed by [3]. However, to maximize the utility of this model and obtain optimized results of its parameters, it is necessary to explore the effectiveness of various optimization tools available. Therefore, the article focuses on a new comparative evaluation of 12 optimization techniques: ARO, AVOA, BFO, CGO, ChOA, DBO, DO, DOA, FFO, TSA, TSO, ZOA, compared to the other algorithms tested in [33]. This analysis aims to determine which of these optimizers exhibit superior performance alongside the GNLM in the task of predicting the energy generated throughout a day.

The article is structured as follows: Section II provides a detailed description of the GNLM used in this study. Section III explores the methodology employed used in this study. The results are presented in Section IV. Finally, Section V highlights the main conclusions of this work.

II. GLOBAL NON-LINEAR MODELS

Currently, there is a series of works in the literature that seek to generalize the PV module model [3], [9], [12], [13], [34], [35], adapting its parameters for any G and T condition. These models, known as GNLMs, have driven a new research area due to their ability to adjust the parameters of the SDM based on transposition equations derived from the physical behavior of the PV module or mathematical adjustments. It is noted that the proposed GNLMs have more parameters or sub-parameters compared to classical models (SDM, DDM, and TDM). Despite the greater complexity associated with GNLMs, they have been shown to accurately determine the behavior of the PV module under various environmental conditions. Additionally, an additional advantage is the ability to perform the parameter estimation process only once, using a set of training curves that represent different environmental conditions.

Among these models, the GNLM proposed by [3] stands out by proposing a model based on one of the classic models, the SDM. Although the adjustments made by this model do not apply to all SDM parameters, the transposition equations consider that the parameters G and T have several sub-parameters, resulting in an increase in the total number of parameters. Within this expanded set, four are related to series resistance, three to parallel resistance, and one to ideality factor. Additionally, the other two parameters that characterize the behavior of the PV module (I_{sc} and V_{oc}) are predefined through explicit equations dependent on the remaining eight parameters. In this way, the complete model encompasses ten parameters, forming the set $\Gamma = (R_{s,ref1}$, $R_{s,ref2}$, k_{Rs}, γ_{Rs}, $R_{sh,ref}$, k_{Rsh}, γ_{Rsh}, n_{ref}, I_{ph}, and $I_{sat})$.

As mentioned earlier, the GNLM proposed by [3] is based on the SDM. Therefore, by using the equivalent electrical circuit of the PV module model, as shown in Fig. 1, it is possible to obtain the relationship between the current and voltage of the PV module, which can be expressed as follows:

$$I = I_{ph} - I_{sat}\left[e^{\left(\frac{V+IR_s}{nV_t}\right)} - 1\right] - \frac{V+IR_s}{R_{sh}}, \quad (1)$$

where I_{ph} is the photogenerated current, R_s is the series resistance, R_{sh} is the shunt resistance, and I_D, which represents the current flowing through the diode, is defined by:

$$I_D = I_{sat}[e^{\left(\frac{V+IR_s}{V_t}\right)} - 1], \quad (2)$$

where V_t, can be written as follows:

$$V_t = \frac{N_s KT}{q}, \quad (3)$$

where N_s is the number of cells in series, K is the Boltzmann constant $(1.38 \cdot 10^{-23} J/K)$, q is the electron charge $(1.602 \cdot 10^{-19} C)$, and T is the cell temperature in Kelvin.

This model consists of two distinct phases: the first one is dedicated to determining the reference parameters, while the second one focuses on the training process. It's worth noting that [3] opted for the Pattern Search (PS) optimization algorithm to conduct this process.

A. Determination of reference parameters

For the first stage of the model, aimed at determining the reference parameters, basic constants such as the Boltzmann constant (k) and the elementary charge of the electron (q) are defined, followed by constructive constants of the photovoltaic modules, the number of PV cells in series in the module construction (N_s), as well as a reference I-V curve provided. Through the reference curve that can be under any conditions of G and T, the quantities G_{ref}, T_{ref}, $I_{mp,ref}$, $V_{mp,ref}$, $I_{sc,ref}$, and $V_{oc,ref}$ are assigned. Then, based on the quantities obtained from the reference curve, the values of maximum series resistance ($R_{s,max}$) and minimum parallel resistance ($R_{sh,min}$) are calculated as follows:

$$R_{s,max} = \frac{V_{oc} - V_{mp}}{I_{mp}}, \quad (4)$$

where V_{oc} and V_{mp} represent the open-circuit voltage and the maximum power voltage, respectively, while I_{mp} is the maximum power current for the I-V curve analyzed in the reference stage.

$$R_{sh,min} = \frac{V_{mp}}{I_{sc} - I_{mp}}, \quad (5)$$

where I_{sc} is the short-circuit current for the I-V curve analyzed in the reference stage.

Thus, in order to constrain the optimization algorithm search within a zone where the parameters still have physical meaning according to the module's characteristics. Finally, using the previously calculated values as limits, the optimization algorithm is used to estimate the remaining parameters of interest for the first stage: $R_{s,ref}$, $R_{sh,ref}$, n_{ref}, $I_{sc,ref}$, and $V_{oc,ref}$ [3].

B. Training process

In the second stage, a set of six I-V curves, known as training curves, is defined with different values of irradiance and temperature, this choice was made based on the work [36], which showed that a larger number of curves does not bring sufficient gains relative to the computational cost. After this definition, the same optimization algorithm used in the first stage is applied. The measured values of V_{oc} and I_{sc} from the training curves are compared with the estimated values obtained by:

$$I_{sc} = [I_{sc,ref} + \alpha_{I_{sc}}(T - T_{ref})]\left(\frac{G}{G_{ref}}\right), \quad (6)$$

where $\alpha_{I_{sc}}$ is the short-circuit current thermal coefficient.

$$V_{oc} = V_{oc,ref} + \beta_T(T - T_{ref}) + \beta_G V_t ln\left(\frac{G}{G_{ref}}\right), \quad (7)$$

where β_T is the open-circuit voltage thermal coefficient and β_G is the open-circuit voltage irradiance coefficient.

Thus, the optimization algorithm seeks a value that results in the smallest sum of errors between the experimental curves and the estimated curves. To achieve this, an adjustment of the thermal and irradiance coefficients values, $\alpha_{I_{sc}}$, β_T, and β_G, is performed using new coefficients that better fit the curves used in the training stage. This process minimizes the absolute error between the estimated and measured characteristics of the N training curves, according to the equations:

For $\alpha_{I_{sc}}$:

$$\sum_{n=1}^{N_c} error_{I_{sc}} = \sum_{n=1}^{N_c} |I_{sc,est} - I_{sc,med}|, \quad (8)$$

for β_T and β_G:

$$\sum_{n=1}^{N_c} error_{V_{oc}} = \sum_{n=1}^{N_c} |V_{oc,est} - V_{oc,ref}|, \quad (9)$$

where N_c represents the number of curves evaluated during training, the subscript "est" denotes the estimated value, and "ref" indicates the reference value.

Subsequently, another optimization process is initiated aiming to find the coefficients responsible for modeling R_s and R_{sh}. However, the objective function of this optimization problem is expressed as an error function. In this process, the Mean Absolute Error in Power (MAEP) is applied as the stopping criterion, as most applications using an electrical model of a diode aim for an accurate estimate of the power generated by the PV module. The MAEP is defined as follows:

$$MAEP = \frac{\sum_{j=1}^{N_{points}} |P_{j,med} - P_{j,est}|}{N_{points}}, \quad (10)$$

where P_{med} is the measured power of the curves provided by the National Renewable Energy Laboratory (NREL) experimental test, and P_{est} is the power estimated by the model, while N_{points} is the number of points present on the measured P-V curve.

The equation that describe R_s as a function of G and T are:

$$R_{sh} = R_{sh,ref}[1 + \kappa_{Rsh}(T - T_{ref})] \left(\frac{G}{G_{ref}}\right)^{\gamma R_{sh}}, \quad (11)$$

where, $R_{sh,ref}$ represents the portion of R_{sh} for the reference condition, k_{Rsh} is the coefficient of variation of R_s with temperature and γ_{Rsh} is the coefficient of variation of R_s with irradiance, where $\gamma_{Rsh} \leq 0$.

The equation that describe R_{sh} as a function of G and T are:

$$R_s = R_{s,ref2}[1 + \kappa_{Rs}(T - T_{ref})] + R_{s,ref1} \left(\frac{G}{G_{ref}}\right)^{\gamma Rs}, \quad (12)$$

where, $R_{s,ref1}$ and $R_{s,ref2}$ represent plots of $R_{s,ref}$ in relation to the variation of irradiance and temperature, respectively:

$$R_{s,ref} = R_{s,ref1} + R_{s,ref2}, \quad (13)$$

γ_{Rs}, k_{Rs} are the coefficients of variation of R_s with irradiance and temperature, in that order, where $\gamma_{Rs} \leq 0$.

In the model proposed by [3], it is assumed that the ideality factor remains constant under different environmental conditions. Therefore, the value obtained during the first stage will be used in all other environmental conditions to which the module is subjected, i.e.:

$$n = n_{ref}. \quad (14)$$

Thus, the complete model encompasses eight parameters ($R_{s,ref1}$, $R_{s,ref2}$, k_{Rs}, γ_{Rs}, $R_{sh,ref}$, k_{Rsh}, γ_{Rsh}, and n_{ref}) that are estimated. The two remaining parameters of the SDM are calculated explicitly based on the other parameters, with their equations represented as follows:

$$I_{ph} = I_{sc}\left(1 + \frac{R_s}{R_{sh}}\right), \quad (15)$$

$$I_{sat} = \frac{I_g - \frac{V_{oc}}{R_{sh}}}{e^{\frac{V_{oc}}{V_t}-1}}. \quad (16)$$

Finally, Fig. 2 illustrates the graphical representation of the steps to perform the Silva model.

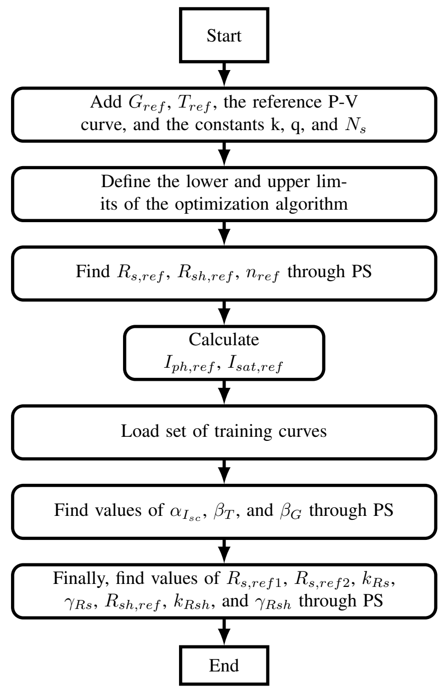

FIGURE 2. Flowchart of the Silva model through PS.

III. METHODOLOGY

In order to ensure uniformity in the comparison of optimization algorithms, it is necessary to maintain the procedures established previously, as detailed in [33]. Modeling PV modules often involves optimization challenges, where model parameters are adjusted to minimize discrepancies between theoretical and experimental curves, performed under different environmental conditions [13]. Therefore, the importance of selecting a robust optimization algorithm capable of generating consistent and reliable results is emphasized, especially when optimizing parameters to maximize model efficiency. Thus, it is fundamental to establish quantitative indicators that allow the comparison of optimization algorithm performance and, among the analyzed algorithms, identify a potential optimizer capable of solving nonlinear problems with high efficiency.

A. Simulation Conditions

In this article, experimentally obtained I-V curves were adopted, which are publicly available at the NREL [37]. This database is widely recognized and used in research related to modeling and parameter extraction due to its transparency and impartiality, as seen in [3], [8]–[14].

Similar to [33], the same reference and training curves were chosen for three distinct technologies: monocrystalline silicon (xSi), located in Golden, Colorado, USA, polycrystalline silicon (mSi), located in Cocoa, Florida, USA, and cadmium telluride (CdTe), also located in Cocoa, Florida, USA, as presented in Table 1. The curves highlighted in bold in the table correspond to those used in the reference phase.

TABLE 1. Curves selected for reference stage and model training

mSi460A8		xSi11246		CdTe75368	
$G(W/m^2)$	$T(°C)$	$G(W/m^2)$	$T(°C)$	$G(W/m^2)$	$T(°C)$
1270	36	1122	58	1310	42
1001	60	964	57	1106	40
828	35	**754**	**51**	**951**	**47**
687	**37**	595	46	715	44
491	33	392	43	565	33
277	29	283	42	356	36

The top three optimization algorithms undergo a validation phase, where they will be evaluated under two main conditions:

- Profile of a sunny day, Fig. 3 and 4;
- Profile of a cloudy day, Fig. 5 and 6.

B. Evaluation criteria

In [32], the three main criteria that can be used for the evaluation and comparison of optimization algorithms are presented:

- **Efficiency:** This criterion is directly related to the amount of computational resources required to achieve a solution. Essentially, efficient algorithms are those that operate more quickly. Efficiency is generally assessed considering two main aspects: the number of evaluations and the execution time. A lower number of evaluations and shorter execution time indicate higher efficiency of the algorithm.
- **Reliability:** This criterion concerns the consistency of the algorithm in solving different optimization problems. The success rate is the most common parameter used to assess reliability, measuring how many problems are successfully solved within a predefined tolerance. Additionally, the average of the objective function values and constraint violations are also considered to measure the reliability of the algorithm.
- **Quality of Algorithmic Output:** This criterion is important for evaluating the ability of an optimization algorithm to produce high-quality solutions for different types of problems. Generally, there are two main criteria employed to assess this quality: known solution and

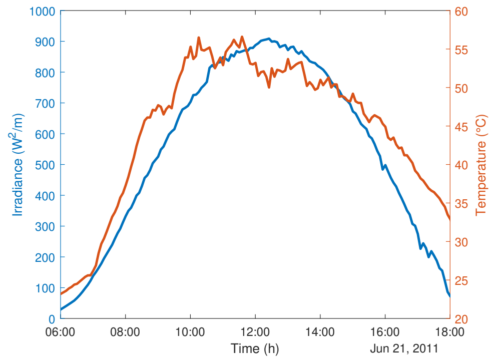

FIGURE 3. Variations in irradiance and temperature on a sunny day (mSi and CdTe).

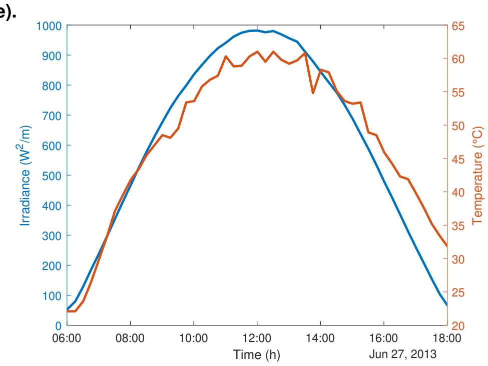

FIGURE 4. Variations in irradiance and temperature on a sunny day (xSi).

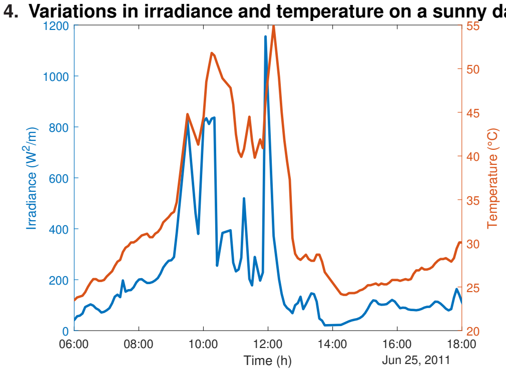

FIGURE 5. Variations in irradiance and temperature on a cloudy day (mSi and CdTe)

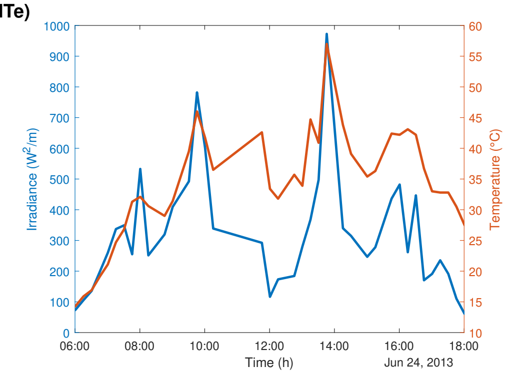

FIGURE 6. Variations in irradiance and temperature on a cloudy day (xSi).

unknown solution. The former refers to the quality of the solution produced by the algorithm compared to the already known solution to the problem, while the latter addresses the quality of the solution generated when the expected solution for a problem is unknown.

As highlighted in [33], this work chose to select two fundamental metrics to evaluate the comparisons made: the average value of the objective function and the quality of the solution produced by the algorithm. This choice is supported by the nature of the GNLM modeling process, which is run only once, allowing the parameters to be extrapolated to other environmental conditions. In other words, for this type of problem, the optimization algorithm must seek maximum accuracy in the model under analysis.

Therefore, for the metric of the average of the objective function values, the Normalized Mean Absolute Error in Power (NMAEP) was chosen as the figure of merit, as normalizing the power errors for various environmental conditions transforms the error into a comparable representation across different power levels:

$$NMAEP = \frac{MAEP}{P_{mp}} \cdot 100\%. \tag{17}$$

For the metric of solution quality, the decision was made to evaluate the performance of the three optimization algorithms that demonstrated the highest effectiveness during the training stage. This validation process selected the sets of environmental conditions from Fig. 3-6.

Overall, other important aspects were considered in the optimization algorithms, as described in the Table 2.

TABLE 2. Properties applied to all optimization algorithms.

Properties	Values
Maximum number of iterations	10,000
Function value termination tolerance	2.22×10^{-16}
Max stall iteration	500

IV. RESULTS

In [33], several optimization algorithms were analyzed, including the Artificial Bee Colony (ABC) [38], Artificial Ecosystem-based Optimization (AEO) [39], Adaptive Wind Driven Optimization (AWDO) [40], Drone Squadron Optimization (DSO) [16], Guaranteed Convergence Particle Swarm Optimization (GCPSO) [41], Grey Wolf Optimizer (GWO) [42], Pattern Search (PS) [43], Particle Swarm Optimization (PSO) [41], Wind Driven Optimization (WDO) [44], Whale Optimization Algorithm (WOA) [45]. This study extends this evaluation to include twelve new algorithms (ARO, AVOA, BFO, CGO, ChOA, DBO, DO, DOA, FFO, TSA, TSO, ZOA), totaling 22 optimization algorithms analyzed. Most algorithms used in this work are available on the MathWorks forum. However, GPCSO was built as mentioned by [30], and the PSO and PS algorithms are native to MATLAB itself. Thus, the study aims to identify the best optimization algorithms to predict the energy generation of PV modules of three different technologies using the GNLM proposed by [3].

In the first stage of the evaluation, an analysis of the average performance of the generated models was performed using training curves. In summary, the goal was to determine which model achieved the lowest local minimum among all considered algorithms. During this evaluation process, the average NMAEP value obtained by the optimization algorithms was examined in 10 distinct repetitions for each of the studied technologies. The use of these multiple repetitions is to mitigate any potential biases introduced by the inherent randomness of most optimization techniques. Therefore, conducting 10 repetitions contributed to ensuring a more accurate and unbiased evaluation of the performance of the evaluated algorithms.

In this context, Table 3 provides a detailed analysis of the average NMAEP for each optimization algorithm when applied to the model, focusing on the training curves of xSi, mSi, and CdTe modules, respectively. In each of these technologies, Table 3 highlights the three best average values obtained in green and the three worst in red for each of the technologies. Then, the average performance of each of the results is summed, and from the lowest value, a ranking is made in ascending order. Additionally, a column has been introduced to denote the algorithm speed applied to the model as follows: completion within less than 15 minutes categorized as “high”; between 15 and 30 minutes labeled as “medium”; and exceeding 30 minutes classified as “low”. Moreover, it’s pertinent to mention that the computer utilized for this task is equipped with 16 GB of RAM and has a 7th generation Intel Core i7 7500U processor. By adopting as a selection criterion the top three optimization algorithms according to the overall ranking, it emerges that the FFO, ARO, and GCPSO techniques stand out as the most effective in this initial evaluation phase. Thus, it is also analyzed that algorithms such as ABC, ChOA and WDO did not show satisfactory performance in most of the evaluated technologies, standing out negatively and reaching the last positions in the overall ranking compared to the other analyzed optimization methods.

In the second phase of this study, a performance evaluation of the FFO, ARO, and GCPSO optimizers was conducted under the climatic conditions illustrated in Fig. 3 - 6, and for each of the technologies the worst optimization algorithm was also used for comparison purposes. This stage aims to assess the ability of GNLM, in conjunction with the top-performing optimization algorithms, to accurately estimate the power output closest to the reference power. The module temperature and irradiance conditions on the evaluated day serve as inputs to the model generating the complete I-V curve of the module under those conditions. However, only the maximum power point will be evaluated to verify the efficiency of GNLM in predicting generation output. It is

TABLE 3. Average NMAEP by optimization algorithm and Performance Ranking of optimization algorithms for each PV module technology applied in Silva's model.

OPTIMIZATION	ALGORITHM SPEED	xSi	mSi	CdTe	SUM OF AVERAGES	RANKING
FFO	MEDIUM	**0.42196**	**0.35600**	**0.36951**	1.14747	1
ARO	HIGH	0.42197	**0.35598**	0.36995	1.14789	2
GCPSO	MEDIUM	**0.42197**	0.36163	**0.36518**	1.14877	3
DSO	LOW	0.42205	0.35672	0.37012	1.14889	4
BFO	LOW	**0.42197**	0.35975	0.36995	1.15166	5
TSA	LOW	0.42287	0.35837	0.37163	1.15288	6
DO	LOW	0.42695	0.35685	0.36972	1.15353	7
PSO	HIGH	0.45777	0.36351	0.36994	1.19123	8
AVOA	HIGH	0.44653	0.36559	0.39733	1.20944	9
DBO	MEDIUM	0.43017	0.35766	0.42416	1.21198	10
CGO	LOW	0.42470	0.36540	0.42416	1.21426	11
WOA	LOW	0.45607	0.36667	0.42187	1.24460	12
PS	HIGH	0.52450	**0.35438**	**0.36876**	1.24764	13
GWO	MEDIUM	0.43124	0.36416	0.46027	1.25567	14
TSO	HIGH	0.44234	0.36070	0.52853	1.33157	15
AEO	MEDIUM	0.49571	0.41702	0.74713	1.65986	16
ZOA	MEDIUM	0.49294	0.61577	0.55388	1.66259	17
DOA	HIGH	0.53147	0.42506	1.08991	2.04645	18
AWDO	HIGH	0.59242	**2.04191**	0.59123	3.22556	19
WDO	LOW	**1.37024**	0.42327	**1.51014**	3.30365	20
CHOA	HIGH	**1.18928**	**1.08943**	**1.14430**	3.42301	21
ABC	LOW	**1.37437**	**0.71578**	**1.53231**	3.62247	22

important to note that the reference data used during this stage are publicly provided by NREL.

As mentioned in Section III, each evaluated technology will be subjected to an irradiance profile both on sunny and cloudy days, being evaluated to demonstrate the accuracy of the best optimization algorithms obtained in the first phase. Initially, the results will be analyzed to determine the difference between the reference power and the power estimated by the selected optimization algorithms. Through this point-to-point power difference, it is possible to determine the energy error throughout the day, as well as calculate the Integral Absolute Error (IAE).

In Fig. 7-9, the results obtained for the three technologies are presented, using the GNLM together with the best optimization algorithms and the worst optimization algorithm for each of the technologies, evaluated in a sunny profile. When analyzing these figures, it is observed that the maximum power errors are around 3W, especially at the beginning and end of the day, periods of low irradiance, in which the model exhibits behavior above the expected. It is important to note that, as the model proposed by [3] is based on SDM, it is natural for the model to present slightly higher errors under low irradiance conditions.Furthermore, regarding the optimization algorithms used and the applied metrics, it is noted that ARO and GCPSO demonstrate quite similar behaviors, while FFO presents a slight discrepancy compared to the others. In sunny profiles, for xSi and mSi technologies, GCPSO and ARO demonstrate superior performance. However, for CdTE technology, it is noted that FFO exhibits a slightly more pronounced difference, making it more suitable for this specific application.

In Fig. 10-12, the results obtained for the three technologies are presented, using the GNLM together with the best algorithms and the worst optimization algorithm for each technology, evaluated in a cloudy profile. As in sunny days, the results reveal that the power errors and IAE obtained, when compared to the best result among the best optimization algorithms, are around 1%. When comparing the best result with the worst optimization algorithm, in the worst scenario this percentage difference extrapolates to about 48.83%. Additionally, it is observed that, similar to the sunny profile, ARO and GCPSO demonstrate quite similar behaviors, while the FFO shows a slight discrepancy compared to the others. However, it is worth noting that,

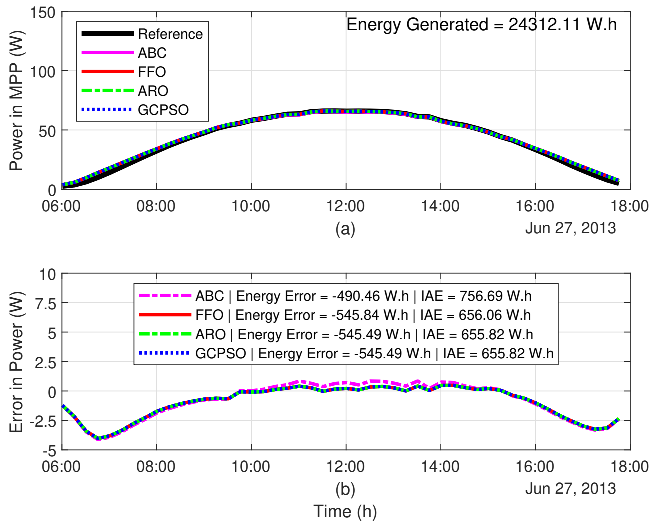

FIGURE 7. The estimated power compared to the reference power on a sunny day for the xSi PV module.

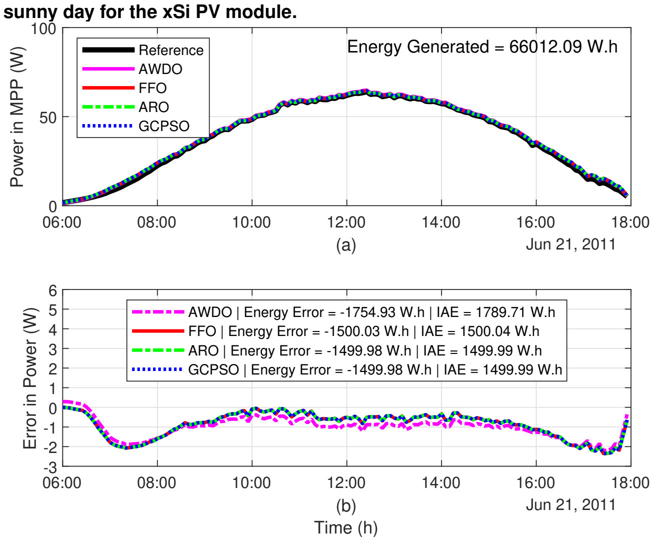

FIGURE 8. The estimated power compared to the reference power on a sunny day for the mSi PV module.

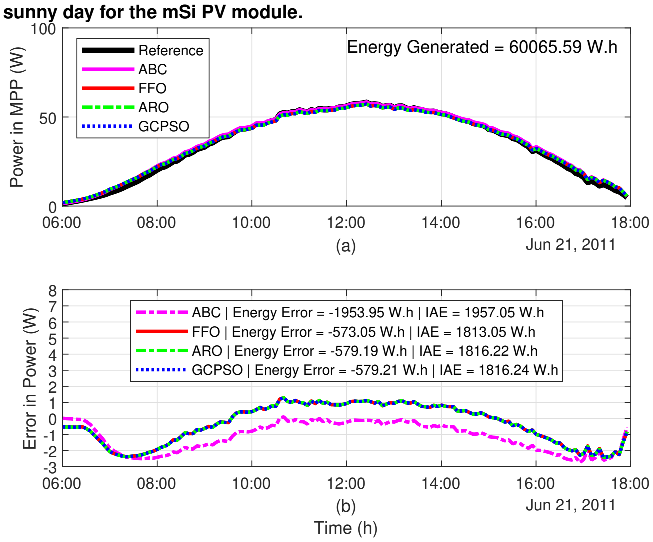

FIGURE 9. The estimated power compared to the reference power on a sunny day for the CdTe PV module.

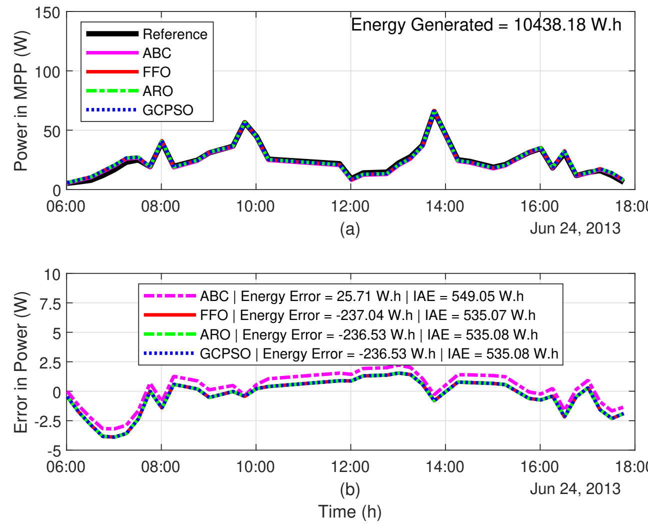

FIGURE 10. The estimated power compared to the reference power on a cloudy day for the xSi PV module.

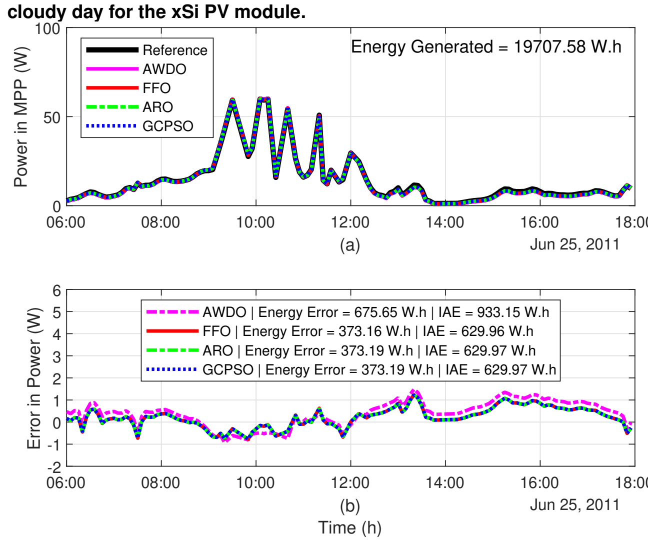

FIGURE 11. The estimated power compared to the reference power on a cloudy day for the mSi PV module.

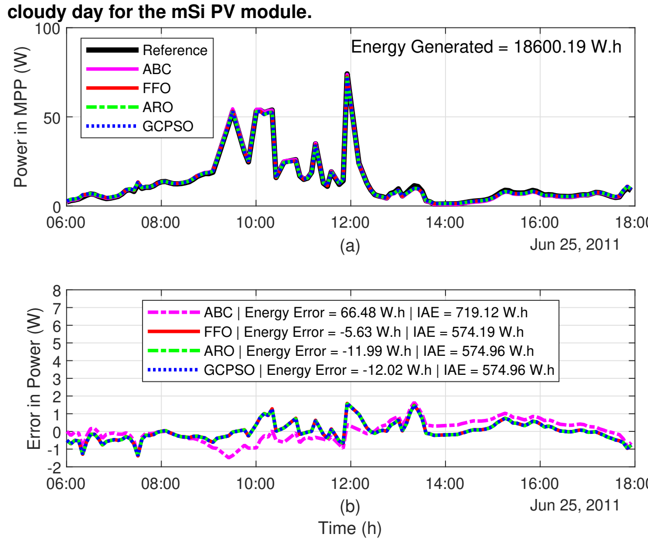

FIGURE 12. The estimated power compared to the reference power on a cloudy day for the CdTe PV module.

in this condition evaluated for all technologies, the FFO exhibits a slightly more pronounced difference, indicating that the algorithm can achieve superior performance compared to the other evaluated algorithms. Another point of this analysis is that the direct comparison of IAE values showed that, both in the sunny and cloudy situations, the best optimization algorithms perform better than the worst algorithm established in the previous stage.

V. CONCLUSION

In summary, after a detailed analysis of the model proposed by [3], the present study extended the analysis of various optimization algorithms applied to the first GNLM focusing on predicting the energy generation of PV modules of three different technologies. Initially, 22 algorithms were evaluated, and the results indicated that FFO, ARO, and GCPSO stood out as the most effective, while others such as AEO, ABC, and ChOA showed unsatisfactory performance. In a second phase, the FFO, ARO, and GCPSO optimizers were subjected to varying environmental conditions, demonstrating that while ARO and GCPSO exhibited similar behaviors, FFO showed a slight advantage under certain conditions, especially in CdTe technology. The results also revealed that the errors associated with the use of the best optimizers were similar compared to the energy generated throughout the day, both in sunny and cloudy conditions. Thus, this study provides significant insights into the effectiveness of optimization algorithms in predicting PV energy generation, contributing to the identification of opportunities for applying more advanced methods capable of enhancing the optimization process of the GNLM developed by [3]. Additionally, such findings may suggest promising candidates for optimizing future GNLM developed by other researchers.

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AUTHOR'S CONTRIBUTIONS

CAVALCANTE JUNIOR, V.M.: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Software, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing. **FERNANDES, T.A.:** Data Curation, Methodology, Validation. **FREITAS, R.A:** Data Curation, Investigation, Methodology, Software, Visualization, **AMÂNCIO, N.A.M.A.S.:** Data Curation, Methodology, Validation. **BRADASCHIA, F.:** Formal Analysis, Funding Acquisition, Project Administration, Resources, Supervision, Writing – Review & Editing. **CAVALCANTI, M.C.:** Project Administration, Resources, Supervision, Writing – Review & Editing.

PLAGIARISM POLICY

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