International Journal of Intelligent Communication and Computer Science
Vol. 3, No. 1, 2025, Pages 16-30.

Solar PV Model Parameter Estimation via Improved Artificial Hummingbird Optimization

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Research Paper

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Received: 2 Jan. 2025, Revised: 11Apr. 2025 Accepted: 15 Apr. 2025

Abstract:

For effective simulation, design, and control of PV systems, solar photovoltaic (PV) models must have accurate parameter estimation. However, the nonlinear and multi-modal nature of the PV model equations makes this a challenging optimization task. In this study, an Improved Artificial Hummingbird Optimization (IAHO) algorithm is proposed to improve the performance of parameter estimation for solar PV models. The improvement incorporates adaptive control strategies and enhanced exploration mechanisms to prevent premature convergence and ensure a better balance between exploration and exploitation. The performance of the proposed IAHO is validated on standard single-diode and double-diode PV models using manufacturer-provided data. Comparative results against other well-known optimization techniques demonstrate that IAHO achieves superior estimation accuracy, faster convergence, and better stability across multiple runs. The proposed method is quite useful tool for PV model calibration in renewable energy applications.

Keywords: Solar PV, Parameter Estimation, Artificial Hummingbird Algorithm, Metaheuristic Optimization

1. Introduction

Significant progress has been made in renewable energy technology, particularly in solar photovoltaic (PV) systems, as the need of renewable energy is increasing day by day. The need for more sustainable energy alternatives, coupled with growing environmental concerns, has led to a greater emphasis on solar energy. This energy has proved to be one of the most useful renewable energies worldwide [1]. Due to this reason, research efforts have shifted towards improving the performance of PV systems. Achieving these goals requires a deep understanding of how PV systems behave under different conditions and the development of methods to optimize their performance in real-world applications.
A fundamental component of this effort is the development of accurate mathematical models that can represent the electrical behaviour of PV cells and modules under diverse operating conditions. These models are critical for simulating the performance of solar panels across different climates, time of day, and seasonal variations, and for facilitating the design of efficient PV systems. Accurate PV models allow for better predictions of energy output, system optimization, and fault detection, all of which are essential for maximizing the economic and environmental benefits of solar energy [2].

Frequently used PV models are the single-diode model (SDM) [3] and the double-diode model (DDM) [4]. Both models aim to simulate the current-voltage (I-V) characteristics of solar panels, which are crucial for understanding how the solar panel performs under different conditions of light intensity and temperature. The SDM is simpler and uses a single diode to represent the photovoltaic cell's behaviour, while the DDM extends this approach by introducing an additional diode to capture more complex behaviours, particularly under high-intensity light or extreme temperature conditions. These models are governed by several key parameters that include photocurrent, diode ideality factor, series resistance, shunt resistance, and reverse saturation current. Each of these parameters plays a vital role in determining the accuracy of the model and must be estimated as precisely as possible for realistic simulations.

However, the process of estimating these parameters is inherently challenging due to the nonlinear and transcendental nature of the equations governing the PV models. Nonlinearities arise because the relationship between voltage, current, and power in a solar cell is governed by exponential and logarithmic functions, which are difficult to solve analytically. Furthermore, the transcendental equations often do not have closed-form solutions and must be approached through numerical methods. Consequently, the estimation of these parameters becomes a complex optimization issue, where the primary purpose is to reduce the error between the model's predicted output and actual measured data, a task complicated by the high sensitivity of the parameters and the nonlinear nature of the underlying equations.

Traditional parameter extraction techniques, such as curve fitting and analytical methods, have been used extensively for this purpose. However, these methods suffer from several significant limitations. For example, curve fitting techniques can be highly sensitive to the initial guesses of parameters, leading to issues with local minima—situations where the optimization process converges to a solution that is not the global best. Additionally, these methods struggle to perform well when the input data is noisy or incomplete, which is often the case in real-world applications. Analytical methods, on the other hand, rely on simplifying assumptions that may not always hold true in practice, further limiting their accuracy and applicability.

To overcome these limitations, metaheuristic optimization algorithms are emerged as an alternative for parameter estimation. These algorithms are capable of navigating complex, multimodal search spaces without requiring gradient information, making them well-suited to handle the nonlinearities and complexities of PV parameter estimation. Unlike traditional methods, metaheuristics do not rely on explicit mathematical models of the system but instead use adaptive search strategies to explore the solution space. As a result, they are less prone to getting stuck in local minima and can provide robust solutions even under noisy or incomplete data conditions.

Several metaheuristic optimization algorithms have been successfully applied to PV parameter estimation, with notable examples including Particle Swarm Optimization (PSO) [5], Genetic Algorithms (GA) [6], and Artificial Bee Colony (ABC) [7]. PSO, for instance, mimics the social behaviour of birds flocking together to find an optimal solution, while GA takes inspiration from the process of natural selection and evolution. Similarly, ABC is inspired by the foraging behaviour of bees, and it uses a population-based approach to search for the optimal solution. Each of these algorithms has shown varying degrees of success in precisely calculating the parameters of both SDM and DDM models, with some demonstrating greater robustness and efficiency under certain conditions.

Despite the progress made with metaheuristic algorithms, challenges remain on the basis of computational cost, convergence speed, and the handling of large-scale systems. Nonetheless, ongoing advancements in optimization techniques continue to push the boundaries of PV system performance modelling, offering promising directions for future research and application.

Among the newer nature-inspired algorithms, the Artificial Hummingbird Optimization (AHO) [8] algorithm has shown promise due to its flexible foraging behaviour, directional flight patterns, and ability to switch between local and global search modes. Inspired by the intelligent food-searching strategies of real hummingbirds, AHO offers a novel balance between exploration and exploitation, which is particularly beneficial for solving nonlinear optimization problems.

However, like many metaheuristics, the original AHO may still face challenges such as premature convergence, imbalanced search capabilities, and sensitivity to control parameters. To address these limitations, this paper proposes an IAHO algorithm, which incorporates several enhancements aimed at boosting convergence speed, avoiding local optima, and improving robustness. The improvements include adaptive flight strategy control, diversity preservation techniques, and refined fitness-based learning mechanisms.

In this research article, the proposed IAHO algorithm is applied to estimate the unknown parameters of solar PV models and evaluate its performance. The outputs are validated using real-world PV module data provided by manufacturers, and the performance of IAHO is compared with other established optimization algorithms. The findings demonstrate that the proposed method offers significant improvements in parameter estimation, making it a valuable tool for PV system modelling, simulation, and control in renewable energy applications.

1.1 Motivation

The rapid growth of solar photovoltaic (PV) technology has made it an essential contributor to global renewable energy production. To ensure efficient energy conversion and reliable performance prediction, accurate modelling of PV systems is crucial. However, the performance of PV cells and modules is inherently nonlinear and influenced by various internal and external factors, such as temperature, irradiance, and material properties. Accurately estimating the model parameters (e.g., photocurrent, diode saturation current, ideality factor, series and shunt resistances) is fundamental for the development of reliable PV models.

Traditional analytical methods often struggle with the highly nonlinear and multimodal nature of the PV parameter estimation problem, leading to suboptimal results or convergence to local minima. To overcome these limitations, metaheuristic optimization techniques have gained popularity due to their flexibility and robustness. Among them, the Artificial Hummingbird Optimization (AHO) algorithm has shown promise; however, like many algorithms, it may face certain problems like premature convergence or slow convergence speed.

To deal with such problems, an IAHO algorithm is proposed, incorporating adaptive mechanisms and enhanced search strategies to improve convergence performance and estimation accuracy. This research aims to leverage IAHO for precise PV model parameter estimation, thereby improving simulation fidelity and enabling more effective PV system design, monitoring, and control.

1.2 Objectives

The main objectives of this work are:

1. Developing an improved version of the AHO algorithm
2. To apply the IAHO algorithm for estimating the parameters of single-diode PV models by minimizing the error between the estimated and measured characteristics.
3. To validate the effectiveness of IAHO through comparison with actual experimental data and demonstrate its superiority over conventional methods and standard AHO.
4. Evaluating the performance of IAHO across different iteration levels, highlighting its scalability and robustness under varying computational constraints.

1.3 Organization of the Paper

In section 2, we have review of the related literature. Section 3 introduces the proposed methodology based on the IAHO algorithm. Section 4 presents the simulation results and performance analysis. The last section, Section 5 concludes the paper with key outcomes and outlines potential directions for future research.

2. Literature Survey

In recent years, numerous techniques have been proposed for accurate parameter estimation of solar photovoltaic (PV) models, with a strong focus on improving precision, computational efficiency, and convergence stability.

Rajasekar et al. (2013) [9] introduced the Bacterial Foraging Algorithm (BFA) for PV parameter estimation. This nature-inspired algorithm mimics the foraging behaviour of bacteria and was effectively applied to extract key parameters such as photocurrent, diode saturation current, and resistances. The method proved to be robust in handling the non-linearity of the PV model and yielded accurate estimations.

Jordehi et al. (2016) [10] provided a comprehensive review of PV parameter estimation techniques, categorizing them into analytical, numerical, and metaheuristic approaches. The study emphasized the increasing popularity of bio-inspired algorithms due to their flexibility and ability to avoid local minima. The review also identified challenges such as computation time and parameter sensitivity that remain unsolved in many existing methods.

El-Sayed et al. (2016) [11] proposed a novel parameter estimation technique and presented its performance at the IEEE Photovoltaic Specialists Conference. Their approach focused on improving the accuracy of the extracted parameters and was validated through both simulation and experimental analysis, showing enhanced performance over traditional techniques.

Jadli et al. (2017) [12] developed a novel technique for making calculation of parameter of PV models that simplified the extraction process while maintaining a high degree of accuracy. This method was successfully tested on various PV modules and proved effective for real-time applications.

Kang et al. (2018) [13] proposed an upgraded format of the Cuckoo Search Algorithm (CSA) for estimating PV model parameters. Their enhancements addressed convergence speed and accuracy issues, and experimental results demonstrated the method's superiority over traditional CSA and other metaheuristic algorithms.

Chen et al. (2018) [14] introduced a hybrid algorithm combining Teaching–Learning-Based Optimization (TLBO) and ABC for PV parameter estimation. The hybrid strategy leveraged both exploration and exploitation abilities, resulting in improved convergence and accuracy compared to standalone optimization techniques.

Jordehi et al. (2018) [15] further proposed the Enhanced Leader Particle Swarm Optimization (ELPSO), which modified the standard PSO by improving the leader selection mechanism. This improved the overall convergence behaviour and accuracy in extracting PV model parameters.

Venkateswari et al. (2021) [16] conducted a detailed review of parameter estimation methods used in solar PV systems. They highlighted the transition from traditional mathematical modelling to intelligent optimization techniques. Their study stressed the importance of hybrid and adaptive strategies for improving model accuracy.

Table 1: Summary of Literature on PV Parameter Estimation Techniques

Author(s)	Method / Algorithm	Key Contribution
Rajasekar et al. [9]	BFA	Nature-inspired method for PV parameter extraction
Jordehi et al. [10]	Literature Review	Classification of analytical, numerical, and metaheuristic methods
El-Sayed et al. [11]	Novel Estimation Technique	Presented at IEEE PVSC with simulation & experimental validation
Jadli et al. [12]	Simplified Extraction Method	Accurate and efficient for real-time applications
Kang et al. [13]	CSA	Enhanced convergence and accuracy
Chen et al. [14]	TLBO + ABC	Combined exploration and exploitation
Jordehi et al. [15]	ELPSO	Modified PSO with improved leader selection
Venkateswari et al. [16]	Review Study	Shift from traditional to intelligent optimization
Ayyarao et al. [17]	War Strategy-Inspired Algorithm	Novel bio-inspired method based on tactical decisions
Haddad et al. [18]	AHA	Used real-time environmental data in optimization
El-Sehiemy et al. [19]	AHO	Benchmarked against other metaheuristics
Ayyarao et al. [20]	AHO with Multi-objective Functions	Comparative study on fitness functions

Ayyarao et al. (2022) [17] presented a unique algorithm inspired by war strategies, offering a new perspective in PV parameter estimation. Their algorithm simulated tactical decisions and demonstrated a strong ability to find global optima, outperforming several existing algorithms.

Haddad et al. (2022) [18] explored the Artificial Hummingbird Algorithm (AHA) under realistic outdoor conditions for solar module parameter estimation. Their work stands out for using real-time irradiance and temperature values, integrating the hummingbird's foraging strategy into optimization. The study validated AHA's ability to accurately predict PV behaviour in variable environmental conditions, demonstrating better performance than conventional methods.

El-Sehiemy et al. (2023) [19] applied the Artificial Hummingbird Optimizer (AHO) for electrical parameter extraction in PV modules. The optimizer was benchmarked against multiple metaheuristic algorithms and showed faster convergence and higher accuracy. The study highlighted the effectiveness of AHO in handling nonlinear PV characteristics and emphasized its potential for real-world deployment.

Ayyarao et al. (2024) [20] advanced their previous work by applying the Artificial Hummingbird Optimization (AHO) using multiple objective functions for solar PV parameter estimation. Their comparative study on different fitness functions revealed that objective function selection significantly impacts the algorithm's accuracy and convergence behaviour. This paper not only validates AHO's adaptability but also opens doors for customized optimization strategies based on application-specific goals.

3. Proposed Method

Photovoltaic (PV) cell modelling is very important in designing, simulation, and optimization of solar energy systems. Among the various mathematical models developed, the Single Diode Model (SDM) is widely accepted because of the balance between accuracy and simplicity. The SDM is primarily used to replicate the non-linear electrical behaviour of PV cells and modules under various environmental conditions.

3.1 Equivalent Circuit Description

The single diode model is based on the electrical equivalent circuit of a solar cell, which comprises a current source (I_{ph}) in parallel with a diode, a shunt resistance (R_{sh}), and a series resistance (R_s) in series with the entire network.

The photocurrent source (I_{ph}) represents the current generated due to the absorption of photons. The diode models the behaviour of the p–n junction. The series resistance (R_S) accounts for internal resistive losses due to connections and material properties. The shunt resistance (R_{sh}) models leakage currents due to non-ideal insulation or impurities in the PV cell.

This model is effective in simulating the I–V and P–V characteristics of a solar cell and is thus extensively used in performance analysis and maximum power point tracking (MPPT) techniques.

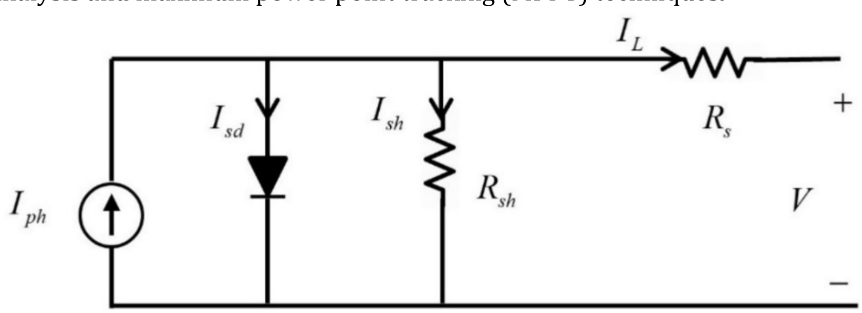

Figure 1: Equivalent circuit representing single diode model

The current continuity equation can be written as

$$I_L = I_{ph} - I_d - I_{sh} \tag{1}$$

where,

$$I_d = I_{sd}\left(e^{\frac{q\{V_L + I_L R_S\}}{nkT}} - 1\right) \text{ and } I_{sh} = \frac{V_L + I_L R_S}{R_{sh}} \tag{2}$$

Plugging equation 2 in equation 1 we get

$$I_L = I_{ph} - I_{sd}\left(e^{\frac{q\{V_L + I_L R_S\}}{nkT}} - 1\right) - \frac{V_L + I_L R_S}{R_{sh}} \tag{3}$$

The objective function can be written as

$$F_{obj} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N}[I_{L.mes} - I_{L.calc}]^2\right)} \tag{4}$$

3.2 Artificial Hummingbird Algorithm (AHA)

The AHA optimization method mimics their natural ability to locate, evaluate, and remember food sources, effectively balancing the exploration and exploitation phases—two critical components of optimization algorithms.
Similar to other metaheuristic techniques, AHA operates by structuring the search process into exploration, where the algorithm seeks new potential solutions, and exploitation, where it refines existing solutions to achieve better outcomes. The framework of AHA consists of three core components:

1. **Food Sources** – These represent the potential solutions to the optimization problem. Each food source is evaluated based on specific attributes such as nectar content, quality, replenishment rate, and time since its last visitation.
2. **Hummingbirds** – These agents explore and assess different food sources, dynamically updating their knowledge about the environment. They remember the locations of previously visited food sources and share information with others, facilitating collective intelligence.
3. **Visit Table** – This table keeps track of how frequently each food source is visited. It is continuously updated during each iteration of the algorithm, ensuring an adaptive and efficient search process.

The optimization process in AHA is guided by three primary foraging strategies that govern the movement and decision-making of hummingbirds:

- **Directed Foraging** – Hummingbirds selectively visit high-quality food sources, optimizing their search for the best solutions.
- **Territorial Foraging** – They defend and revisit specific food sources within their territory, refining local solutions.
- **Migratory Foraging** – When local resources become scarce, hummingbirds relocate to new regions, facilitating broader exploration of the solution space.

The flow chart in Figure 2, outlines the key steps and logical flow of the IAHO algorithm, beginning with the initialization of the population and algorithm parameters. The process continues with fitness evaluation and the application of foraging behaviours inspired by hummingbird flight strategies, such as axial, diagonal, and omnidirectional movements. Adaptive mechanisms are integrated to enhance convergence speed and avoid local optima. The global best solution is updated iteratively based on the foraging performance of the agents. The population is kept evolving by the algorithm until a termination criterion—like a maximum number of iterations or a suitable fitness level—is satisfied. The optimal or nearly optimal solution that the swarm discovered is the end result.

3.2.1 Initialization

A hummingbird population is dispersed at random among the available food sources in the manner described [18]. The algorithm's initialization phase is this distribution process, in which each hummingbird is given a position that represents a possible solution to the optimization problem.

$$x_i = LU + rand(0,1) \times \left(UP - LU\right) \qquad i = 1,\ldots n \tag{5}$$

Where LU and UP represent the lower and upper bounds of the search space, respectively, each food source position corresponds to a candidate solution for the optimization problem at hand. The position of each food source is initialized using a random vector whose elements are uniformly distributed in the range [0,1], ensuring diversity in the initial population.
The initialization of the visit table of food sources is as follows.:

$$VT_{i,j} = \begin{cases} 0 & if\ i \neq j \\ null & i = j \end{cases} \qquad i = 1,\ldots\ldots n; \quad j = 1,\ldots,n \tag{6}$$

As for the visit table, a value of null defines that a hummingbird is currently feeding at a specific food source. When a hummingbird has just visited a food source, the table is updated to reflect that event. For a given iteration, the visit table entry shows that the corresponding hummingbird has interacted with the food source during the current iteration.

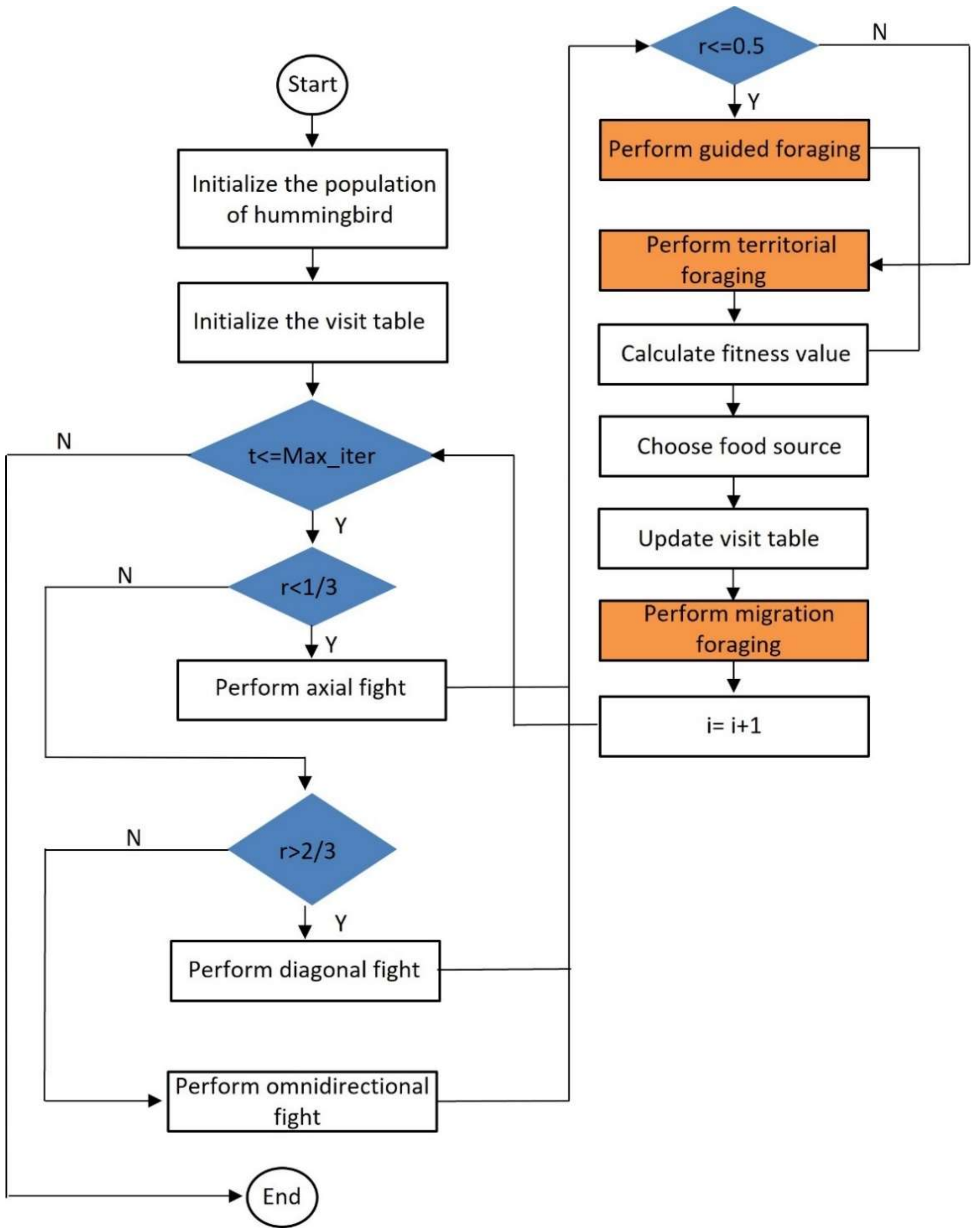

Figure 2: Flow chart for IAHO algorithm

3.2.2. Guided foraging

In the guided foraging phase, each hummingbird navigates toward the food source with the highest nectar concentration based on available knowledge. The movement behaviour during this phase can be categorized into three distinct flight types:

Axial Flight
This type of flight involves movement along one of the coordinate axes. It enables the hummingbird to explore the search space in a controlled, dimension-wise manner.

$$AF^{(i)} = \begin{cases} 1 & if \quad i = randi([1,s]) \\ 0 & otherwise \end{cases} \qquad i = 1,......s; \tag{7}$$

Diagonal Flight
Diagonal flight involves movement along a combination of coordinate directions, allowing the hummingbird to travel in a straight line through a multi-dimensional space, covering multiple dimensions simultaneously.

$$AF^{(i)} = \begin{cases} 1 & if\ i = P(j),\ j \in [1,k],\ P = randperm(k),\ k \in \left[2, \left[r_1 * (s-2)\right] + 1\right] \\ 0 & else \end{cases} \qquad i = 1,.....d \tag{8}$$

Omnidirectional Flight
In omnidirectional flight, the hummingbird can move in any direction, providing the most flexible and exploratory movement pattern among the three types. The below given is the definition of omnidirectional flight:

$$AF^{(i)} = 1 \qquad i = 1,....,s \tag{9}$$

where r_1 is a random number (0, 1) and $randperm(k)$ creates a number permutation from 1 to k and $randi[1,s]$ is a random number between 1 and s. The mathematical formula for simulating directed foraging behaviour with an appropriate food source is provided below:

$$x_i^{'}(t+1) = x_i(t) + \phi_1.\left[x_g(t) - x_i(t)\right] \tag{10}$$

Where, $x_i(t)$ is the current position of the i^{th} hummingbird at time *t*, $x_g(t)$ is the position of the guiding (or target) food source with a higher nectar concentration, ϕ_1 is a guided factor sampled from a standard normal distribution (mean = 0, standard deviation = 1).
The hummingbird's newly calculated position is next assessed by figuring out the nectar replenishment rate, which, in the context of the optimization issue, corresponds to the objective function value. In comparison to the hummingbird's present food source, this assessment aids in determining the candidate's quality or fitness. The new site offers a better solution to the issue if the candidate food source's nectar replenishment rate is discovered to be higher than the present source's. Consequently, the hummingbird moves to the more promising food source and forsakes its existing one, increasing the algorithm's overall convergence behaviour. The latest position update for the food source can be mathematically described as follows:

$$x_i(t+1) = \begin{cases} x_i(t) & f(x_i(t)) \le f(x_i^{'}(t+1)) \\ x_i^{'}(t+1) & f(x_i(t)) > f(x_i^{'}(t+1)) \end{cases} \tag{11}$$

3.2.3 Territorial foraging

Within its own territory, a hummingbird can effortlessly move to a nearby location in search of food. This movement represents a localized exploration process, allowing the hummingbird to discover new food sources in its immediate surroundings. Often, such exploration may lead to the discovery of a food source that offers a higher nectar replenishment rate than its current location, encouraging the hummingbird to update its position.

$$x_i^{'}(t+1) = x_i(t) + \phi_2.\left[x_i(t)\right] \tag{12}$$

ϕ_2 is a guided factor sampled from a standard normal distribution (mean = 0, standard deviation = 1).

This behaviour forms the basis of the local foraging strategy, where the hummingbird focuses its search within a confined region. The strategy models the natural foraging tendencies of real hummingbirds, who often revisit and explore areas within their established territory in search of improved nectar yields.

3.2.4. Migration foraging

The migration of a hummingbird from a food source with the lowest nectar replenishment rate to a newly generated, randomly placed food source can be described in the following way:

$$x_{wor}(t+1) = Lb + r \cdot (Ub - Lb) \tag{13}$$

In this context, the variable representing the food source with the lowest nectar replenishment rate refers to the least productive or most depleted location among the available food sources in the hummingbird's environment. Over time, this source becomes less attractive due to its inability to regenerate nectar efficiently, prompting the need for migration.

To simulate realistic foraging behaviour, a hummingbird is assumed to use a combination of directed and territorial foraging strategies. In each iteration, it visits food sources sequentially, following a visit table that maintains the current foraging pattern. This sequence is only maintained if no replacements or migrations are triggered across all food sources.

4. Simulation and Results

The single-diode model is widely used to represent the electrical behaviour of a photovoltaic (PV) cell, as it closely aligns with empirical measurements obtained under various operating conditions. This model captures the non-linear characteristics of a real PV cell and is defined by five key parameters that need to be identified for accurate modelling and simulation. The objective in this context is to estimate the following five unknown parameters:

These parameters play a crucial role in determining the I–V (current–voltage) characteristics of the PV cell. Since they cannot be directly measured, they must be extracted through optimization techniques that minimize the difference between the modelled and experimentally observed performance of the PV cell.

To ensure realistic parameter estimation and avoid divergence during optimization, appropriate lower and upper bounds are set for each parameter. These bounds help define the search space for the optimization algorithm. The specific values of the lower and upper bounds for each of the five parameters are provided in Table 2.

Table 2: List and bounds of parameters

Parameter	LB	UB
$I_{ph}(A)$	1	0
$I_{sd}(\mu A)$	1	0
$R_{sh}(\Omega)$	100	0
$R_s(\Omega)$	0.5	0
η	2	1

The Figure 3, illustrates the convergence behaviour of the Improved Artificial Hummingbird Optimization (IAHO) algorithm over successive iterations. As the algorithm progresses, the best score typically improves (decreases for minimization problems), indicating that the algorithm is effectively exploring the search space and refining candidate solutions. The curve demonstrates the algorithm's ability to converge toward an optimal or near-optimal solution, with a sharp improvement in the early stages followed by gradual stabilization as it approaches convergence. This plot serves as a performance indicator for both convergence speed and solution quality.

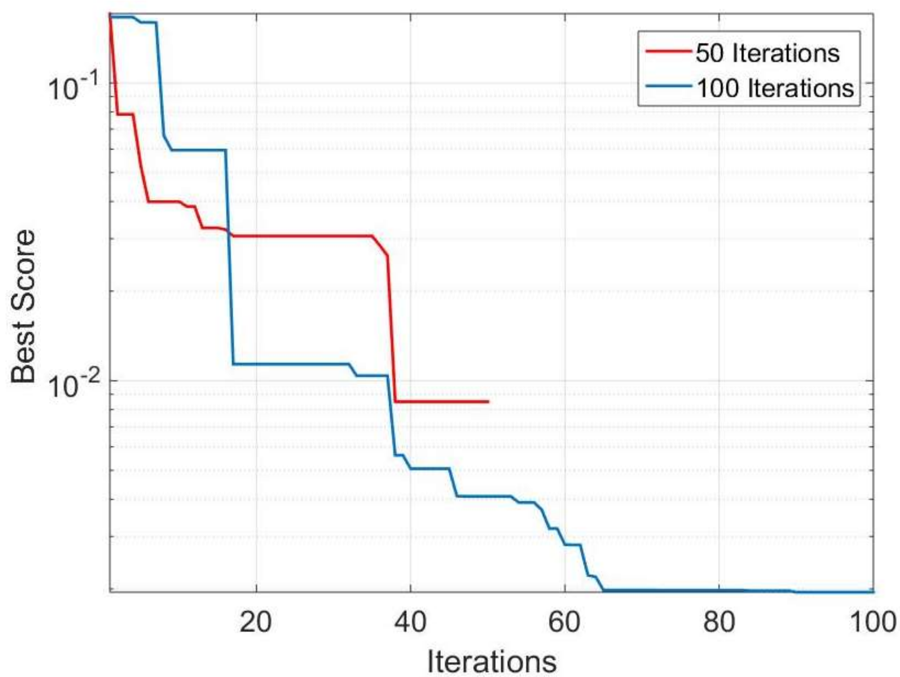

Figure 3: Best Score vs. Iterations for IAHO algorithm

In this figure, results are plotted for two different iteration counts: 50 and 100. The comparison shows that with 50 iterations, the algorithm achieves a reasonable approximation of the optimal solution, but with 100 iterations, the convergence is more refined and stable, leading to a more accurate and lower objective function value. This demonstrates the algorithm's scalability and improved precision with increased computational effort.

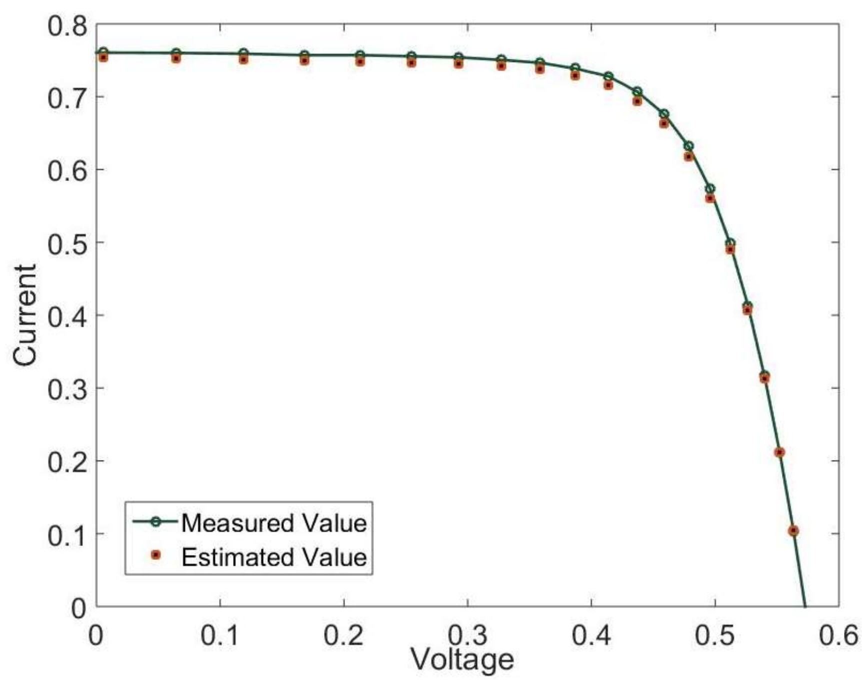

Figure 4: V vs I curve for measured and estimated values (50 Iterations)

The Figure 4,5 presents the voltage-current (V-I) curve comparing the estimated data obtained through the Improved Artificial Hummingbird Optimization (IAHO) algorithm with actual measured experimental data. The measured curve represents the real-world performance of the photovoltaic (PV) cell under specific operating conditions, while the estimated curve is derived by applying the IAHO algorithm to identify the optimal parameters of the PV model (such as photocurrent, diode saturation current, series and shunt resistances, and diode ideality factor).

In Figure 4, the voltage and current measurements obtained from the system are illustrated by a solid green curve, while the corresponding estimated values—derived using the proposed estimation algorithm—are depicted as red circular markers. A close examination of the figure reveals that the estimated values align closely with the measured data across the entire range. Although there are minor deviations between the two sets of values, these differences are minimal and fall within an acceptable margin of error, thereby validating the accuracy and reliability of the estimation technique at this stage.

The data presented in Figure 4 is the result of running the estimation algorithm for 50 iterations. At this point, the model has had sufficient time to learn and adjust its internal parameters based on the measured input data. The near-overlap of the red circles and the green curve shows that the estimator is effectively capturing the underlying dynamics of the system.

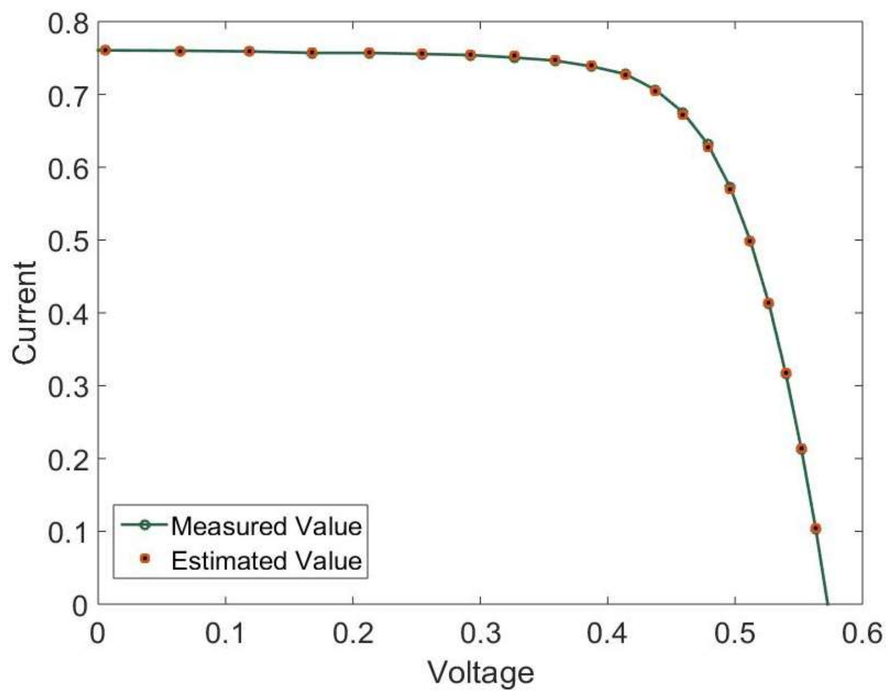

Figure 5: V vs I curve for measured and estimated values (100 Iterations)

Figure 5 presents a similar comparison after 100 iterations. With additional iterations, the estimation becomes even more refined. The red markers in Figure 5 exhibit an even closer match to the measured green curve, with a noticeable reduction in estimation error. This improvement highlights the effectiveness of the iterative process in enhancing the estimation accuracy over time.

The progressive enhancement from 50 to 100 iterations demonstrates the robustness of the proposed estimation method and its ability to converge towards the actual system behaviour with continued processing. These results confirm that the algorithm not only performs well in initial iterations but also improves significantly as it continues to learn from the data.

At 50 iterations, the estimated values closely followed the measured voltage and current waveforms, with only slight deviations visible in certain regions. The average estimation error for the V-I curve at this stage was calculated to be approximately 0.0085. This indicates a reasonably good level of accuracy even in the early stages of iteration.

As the number of iterations increased to 100, the estimator showed significant improvement in accuracy. The estimated values almost completely overlapped with the measured data, and the average estimation error in the V-I curve reduced to 0.0019. This substantial reduction in error demonstrates the convergence behaviour of the algorithm and its ability to learn the underlying system characteristics more effectively over time.

The close alignment between the two curves demonstrates the accuracy and robustness of the IAHO in modelling the nonlinear behaviour of PV cells. The minimal deviation across the entire voltage range indicates that IAHO effectively captures the key characteristics of the cell, making it a reliable tool for parameter extraction and system simulation. This validation also confirms the algorithm's potential for real-time PV performance analysis and optimization tasks.

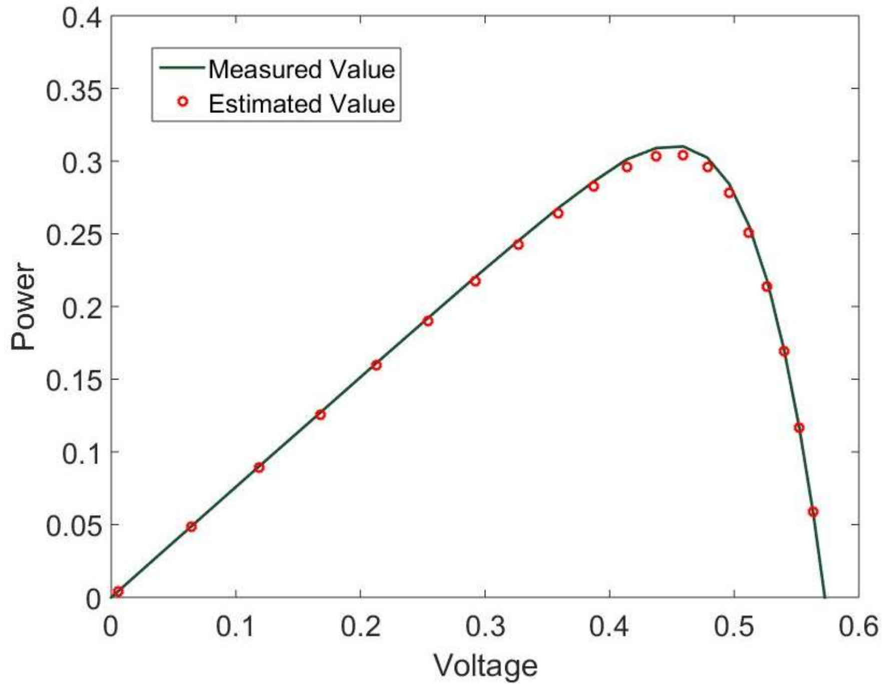

Figure 6: P vs V curve for measured and estimated values (50 Iterations)

In Figure 6, the relationship between power (P) and voltage (V) is depicted for both measured and estimated values after 50 iterations of the estimation algorithm. The measured P-V curve is shown as a solid green line, while the estimated values are represented by red circular markers. As observed, the estimated data closely follows the trend of the measured curve, indicating a strong agreement between the two. Although there are slight deviations at certain voltage levels, these differences are minimal and do not significantly impact the overall accuracy of the estimation. This result demonstrates the estimator's capability to capture the nonlinear characteristics of the power-voltage relationship, even in the earlier stages of convergence.

Figure 7 illustrates the same P-V relationship, but after 100 iterations. In this case, the estimated values (again shown as red circles) align even more closely with the measured green curve, suggesting an improvement in estimation accuracy due to the increased number of iterations. The slight discrepancies observed in Figure 6 are further reduced in Figure 7, confirming that the estimation algorithm benefits from additional iterations and gradually refines its output to better match the true system behaviour.

Together, Figures 6 and 7 highlight the convergence properties of the estimation method. The enhanced alignment between measured and estimated P-V values with increasing iterations validates the robustness and reliability of the algorithm in modelling the power-voltage characteristics of the system.

The Figures, illustrate the P-V curve of the PV cell, which shows how the output power varies with respect to the terminal voltage under given environmental conditions (e.g., irradiance and temperature). The curve is generated using the parameters estimated by the Improved Artificial Hummingbird Optimization (IAHO) algorithm and reflects the nonlinear behavior of PV systems. Initially, as the voltage increases from zero, the output power also increases, reaching a peak known as the Maximum Power Point (MPP). Beyond this point, further increases in voltage result in a rapid drop in power output due to the reduction in current. Identifying the MPP is crucial for optimizing energy harvesting, as it represents the operating condition at which the PV system delivers its maximum possible power. The smooth and accurate shape of the curve confirms that the IAHO algorithm is quite useful in accurately estimating model parameters that reflect real PV behaviour. This curve is also instrumental for developing and testing MPPT algorithms in practical PV systems.

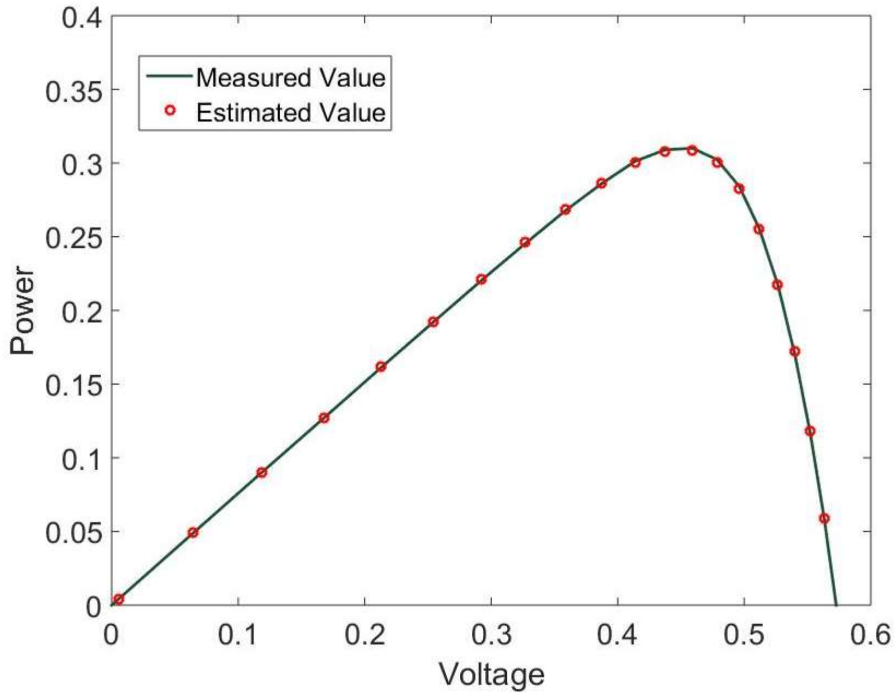

Figure 7: P vs V curve for measured and estimated values (100 Iterations)

5. Conclusion

In this work, a robust estimation algorithm was proposed to accurately predict key electrical parameters—voltage, current, and power—within a dynamic system. The method is based on iterative refinement, allowing it to progressively improve estimation accuracy with each iteration. By utilizing measured data and comparing it against estimated outputs, the algorithm effectively captures the underlying behaviour of the system.
In this work, a robust estimation algorithm was proposed for accurately predicting voltage, current, and power in a dynamic electrical system. The method employs an iterative approach, refining its predictions over time based on measured data. This enables the estimator to closely track the system's behaviour and adapt to its nonlinear characteristics.
The performance of the given technique was evaluated through a series of simulations, with results analysed after 50 and 100 iterations. At both stages, comparisons between measured and estimated values of voltage, current, and power showed strong alignment. The estimator demonstrated high accuracy even in earlier iterations, with minor deviations that decreased significantly as the iteration count increased. This improvement confirms the convergence behaviour of the algorithm and highlights its effectiveness in capturing system dynamics.
These findings validate the proposed approach as a reliable and practical tool for parameter estimation in electrical systems. Its ability to deliver accurate results with minimal error supports its potential use in real-time system monitoring, predictive control, and fault detection applications.

Looking ahead, future work may focus on extending the method to more complex and nonlinear systems, incorporating adaptive learning mechanisms, or validating its performance under diverse operating conditions to further assess its scalability and robustness in real-world implementations.

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