

Research Article

Parameter estimation of the STM6-40/36 photovoltaic module using hybrid atom search particle swarm optimization

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ABSTRACT

Background: One of the most promising solutions suggested to meet the growing global demand for renewable energy is the efficient utilization of photovoltaic (PV) systems. Metaheuristic algorithms are frequently chosen over other approaches in the literature for parameter assessment of PV cells and modules due to their reliability and speed.

Methods: For parameter determination of the STM6-40/36 PV module, this study proposes the h-ASPSO algorithm, a hybrid of particle swarm optimization (PSO) and atom search optimization (ASO) methods.

Results: After several rounds of optimization using h-ASPSO, the root mean square error (RMSE) for the objective function was found to be 0.0017298. The strength and promise of h-ASPSO in identifying unknown PV model parameters are validated by the excellent agreement between the predicted and observed current and power measurements. Additionally, five metaheuristic algorithms from the literature were compared to h-ASPSO's statistical performance, confirming the superiority of the proposed method.

Conclusion and Implications: The research highlights h-ASPSO's potential as a reliable optimization tool, contributing to the advancement of renewable energy technologies and their integration into the energy landscape.

Introduction

In recent years, there has been a significant increase in the use of solar energy worldwide through photovoltaic (PV) and thermal systems, with the aim of promoting a cleaner environment, reducing the consumption of fossil fuels and mitigating climate change. However, PV systems often encounter failures due to adverse harsh environmental conditions and aging, resulting in reduced solar energy use efficiency and serious safety hazards. To improve the efficiency of PV systems, it is crucial to evaluate the real-time performance of PV arrays using precise modeling techniques based on measured current-voltage (I-V) curve data. Various models such as single-diode, double-diode, triple-diode and PV module models have been successfully used to replicate PV system behavior. The accuracy of these models largely depends on the precision of their parameters. Although manufacturers may provide model parameters periodically, these parameters may fluctuate over time due to wear and failure. Surmounting this challenge requires defining model parameters based on experimental current-voltage characteristic curves. For this purpose, researchers have developed a number of parameter identification techniques, including analytical methods, numerical methods, and metaheuristic algorithms (1).

Analytical methods provide simple and fast solutions. However, accuracy in determining photovoltaic cell parameters may decrease due to native approximations. The nonlinear properties of photovoltaic cell models contribute to the reduction of the accuracy of analytical methods and lead to model degradation, especially in the face of significant changes in the external environment. Numerical methods such as Lambert W functions and Newton-Raphson iterations usually start by choosing a random initial value and then monitor its convergence. The accuracy of the solution decreases not only with the choice of initial values but also with the increase in the number of defined parameters. Furthermore, these methods are affected by the scale of the optimization problem, causing calculation times to extend. Unlike numerical methods, the choice of initial values for meta-heuristic algorithms, also known as global optimization techniques, generally has minimal impact on the solution results. The main reason for this

is that metaheuristics have both local and global search capabilities, eliminating the need for gradient information from objective functions. As a result, they can overcome local optima efficiently compared to numerical methods. As a result, they are known to be simple, accurate, fast and extremely robust. These remarkable features have garnered much attention and have been used effectively in optimizing problems in various domains (2).

To date, the parameter extraction challenge of PV models has been addressed by numerous metaheuristic algorithms, such as bald eagle search (BES) (3) and elite learning adaptive differential evolution (ELADE) (4), genetic algorithm based on non-uniform mutation (GAMNU) (5), weighted mean of vectors (INFO) (6), improved cuckoo search optimization (ICSO) (7), enhanced teaching-learning-based optimization (ETLBO) (8), improved reptile search algorithm (RSALF) (9), Runge-Kutta optimizer (RUN) (10), hybrid gazelle-Nelder-Mead (GOANM) (11), adaptive sine-cosine particle swarm optimization (ASCA-PSO) (12) and enhanced prairie dog optimizer (En-PDO) (13). Compared to analytical and numerical methods, the metaheuristic algorithms given in these studies have demonstrated the ability to yield satisfactory results for estimating PV model parameters. However, these algorithms have their disadvantages such as premature convergence, being trapped in local minima, and sensitivity to parameter changes.

In 2019, Zhao et al. announced atom search optimization (ASO), inspired by fundamental molecular dynamics (14). ASO has significant disadvantages despite its numerous benefits. These include limited exploitation capabilities, the possibility of getting trapped in local optima, and an inadequate balance between exploration and exploitation (15–20). Integrating ASO with other optimizers is a highly successful approach to enhance its capabilities for both exploration and exploitation, hence improving its overall effectiveness. In order to optimize both exploration and exploitation, Barshandeh and Haghza-deh (21) employed a hybrid approach that combines the tree-seed algorithm with Levy flight. In order to enhance the exploration process, Abd Elaziz et al. (22) employed the sine-cosine algorithm as a local search operator.

Jadhav and Joshi (23) incorporated sunflower optimization to improve the search efficiency, whereas Eker et al. (15) introduced simulated annealing to strengthen the local search capabilities.

It should be noted that the combination of two algorithms might lead to increased computational costs, particularly when addressing intricate engineering problems in spaces with many dimensions (24). Academic literature indicates that improved versions of ASO have shown the potential to develop algorithms that are more efficient (17). However, achieving a balance between the actions of investigating and exploiting remains a challenging endeavor. Therefore, it is imperative to cultivate a skillful equilibrium strategy to optimize difficulties (25). To achieve this objective, a crucial field of study involves amalgamating the most effective components of several algorithms into a unified entity, while incorporating mechanisms that can adapt to maintain a harmonious equilibrium between exploration and exploitation. The concept serves as the fundamental basis of our investigation. This study has developed a novel hybrid approach that integrates the advantages of ASO with particle swarm optimization, in accordance with the underlying logic. Particle swarm optimization demonstrates fast convergence, although it is susceptible to premature convergence on local optima while solving optimization problems (26). Particle swarm optimization often improves the efficiency of other algorithms due to its simple structure, easy implementation, and benefits (20).

The objective of the hybrid atom search particle swarm optimization technique (h-ASPSO) is to optimize the balance between the exploration and exploitation stages, resulting in improved search efficiency (20). To accomplish this, we combine the global search capability of ASO with the social reasoning capacity of particle swarm optimization. In this paper, the h-ASPSO algorithm is proposed in the estimation of STM6-40/36 photovoltaic module parameters.

The primary contributions of our study include the integration of the global search capability of ASO with the social thinking ability of particle swarm optimization, resulting in enhanced search efficiency. The proposed algorithm has been shown to effectively improve the parameter extraction of STM6-40/36 PV module for the first time in the literature. Our study includes comparisons with several recent approaches in the literature, including BES (3), improved JAYA (IJAYA) (3), memetic adaptive differential evolution (MADE) (3), teaching-learning-based optimization (TLBO) (3), and enhanced gradient-based optimizer (EGBO) (3). Simulation results confirm the statistical success, reliability, and accuracy of the h-ASPSO algorithm.

Methods

Overview of PSO

PSO, inspired by the social behavior of bird flocks, is one of the evolutionary methods proposed by Kennedy and Eberhart (27). PSO employs a swarm of particles traversing the search space to find the best solution, during which they all examine the best particle encountered on their path. In short, particles consider both the best solution found so far and their own best solutions. Eqs. (1) and (2) constitute the mathematical model of the PSO algorithm. Upon examining these equations, it can be observed that each particle (solution) in PSO considers its current position, current velocity, distances to P_{best} , and G_{best} (best solution so far) in order to update its position.

$$V_i(iter+1) = \omega \times V_i(iter) + c_1 \times rand \times (P_{best,i} - X_i(iter)) + c_2 \times rand \times (G_{best} - X_i(iter)) \quad (1)$$

$$X_i(iter+1) = X_i(iter) + V_i(iter+1) \quad (2)$$

Where, ω represents the inertia weight function, c_1 and c_2 are acceleration factors, $V_i(iter)$ and $X_i(iter)$ denote the velocity and position of particle i at iteration $iter$, respectively, and $rand$ is a random number between 0 and 1.

The right-hand side of Equation (1) consists of three parts. The first part ($\omega \times V_i(iter)$) provides exploration capability to the PSO algorithm, the second part ($c_1 \times rand \times (P_{best,i} - X_i(iter))$) represents the personal thinking of particles (solutions), and the last part ($c_2 \times rand \times (G_{best} - X_i(iter))$) represents the collaboration among particles. The PSO algorithm begins by randomly placing particles (solutions) in the problem space. In each iteration, the velocities and positions of particles are computed using Eqs. (1) and (2). The process of updating particle positions is terminated once the desired maximum iteration count is reached.

Overview of ASO

Atom search optimization (ASO), a recent physics-based global optimization method, was proposed by Zhao et al., inspired by molecular dynamics (15). Matter in nature is composed of constantly moving atoms, and atomic motion adheres to the principles of classical mechanics. The relationship between atoms in a system arises from Newton's second law, which considers the interaction force (F_i) acting on a specific atom i and the constraint (G_i). The motion equation of atoms is given in Eq. (3) (14).

$$F_i + G_i = m_i \times a_i \quad (3)$$

where a_i and m_i indicate the acceleration and mass of atom i , respectively. The interaction force ($F'_{ij}(iter)$) between atoms i and j can be expressed in dimension d and iteration $iter$ using the following equation (14).

$$F'_{ij}(iter) = -\eta(iter) \times [2(h_{ij}(iter))^{13} - (h_{ij}(iter))^7] \quad (4)$$

In here, $\eta(iter)$ denotes the depth function used to adjust repulsion or attraction regions, and it can be defined as (14)

$$\eta(iter) = \alpha \times \left[1 - \frac{(iter-1)}{iter_{max}} \right]^3 \times e^{-20 \times iter/iter_{max}} \quad (5)$$

where $iter_{max}$ is the total number of iterations and α is the depth weight. h_{ij} in Eq. (4) is defined with the following form (14)

$$h_{ij}(iter) = \begin{cases} h_{min} & \text{for } h_{ij} < h_{min} \\ \frac{r_{ij}(iter)}{\sigma(iter)} & \text{for } h_{min} \leq h_{ij} \leq h_{max} \\ h_{max} & \text{for } h_{max} < h_{ij} \end{cases} \quad (6)$$

Here, $h_{min} = g(t) + 1.1$ and $h_{max} = 1.24$ represent the lower and upper bounds of h respectively, while $\sigma(iter)$ denotes the length scale. The drift factor g enables the algorithm's transition from exploration to exploitation, and it is given in Eq. (7).

$$g(iter) = 0.1 \times \sin\left(\frac{\pi \times iter}{2 \times iter_{max}}\right) \quad (7)$$

The total force acting on atom i in the d th dimension can be expressed as follows, where $rand$ represents a random number generated between 0 and 1 (14).

$$F_i^d(iter) = \sum_{j \in K_{best}} rand_j \times F_{ij}^d(iter) \quad (8)$$

The constraint force can be written as $G_i^d(iter) = \lambda(iter) \times [x_{best}^d(iter) - x_i^d(iter)]$ where $x_{best}^d(iter)$ is the best atom position at the iteration $iter$. $\lambda(iter)$ is Lagrangian multiplier, and its definition is given in Eq. (9) (14)

$$\lambda(iter) = \beta \times e^{-20 \times iter/iter_{max}} \quad (9)$$

Where β represents the multiplier weight. The acceleration of the i th atom at iteration $iter$ is expressed as follows, where the mass of the i th atom at iteration $iter$ is denoted by $m_i(iter)$ (14).

$$a_i^d(iter) = \frac{F_i^d(iter) + G_i^d(iter)}{m_i^d(iter)} \quad (10)$$

The mass of the i th atom can be computed as follows (14).

$$M_i(iter) = e^{\frac{Fit_{best}(iter) - Fit_i(iter)}{Fit_{worst}(iter) - Fit_{best}(iter)}} \quad (11)$$

$$m_i(iter) = \frac{M_i(iter)}{\sum_{j=1}^N M_j(iter)} \quad (12)$$

Here, $Fit_{best}(iter)$ and $Fit_{worst}(iter)$ represent the minimum and maximum fitness values of i th atom in iteration, $iter$ respectively, and $Fit_i(iter)$ represents the fitness function value. To enhance exploration ability, it is essential to interact with neighboring atoms possessing higher fitness values. To streamline the ASO algorithm, the position and velocity of i th atom at iteration ($iter + 1$) can be expressed as follows (14).

$$V_i(iter + 1) = rand \times V_i(iter) + a_i(iter) \quad (13)$$

$$X_i(iter + 1) = X_i(iter) + V_i(iter + 1) \quad (14)$$

The ASO algorithm is characterized by two fundamental control parameters (α and β), which are assigned values of 50 and 0.2, respectively.

2.3. Working mechanism of h-ASPSO algorithm

It is possible to combine two algorithms by integrating the beneficial characteristics of metaheuristic optimization techniques, and there are numerous instances of this approach documented in the literature (15–20). In (20), a low-level co-evolutionary diverse hybrid method is proposed to collect PSO and ASO. The concept underlying the hybrid h-ASPSO is to merge the exploration ability of ASO with the social cognitive ability (g_{best}) in PSO. In this case, the following two equations are used to change the velocity and position (20).

$$V_i(iter + 1) = \omega \times V_i(iter) + c_1 \times rand \times a_i(iter) + c_2 \times rand \times (g_{best} - X_i(iter)) \quad (15)$$

$$X_i(iter + 1) = X_i(iter) + V_i(iter + 1) \quad (16)$$

The weight function ω in Eq. (15) decreases linearly based on the number of iterations and is represented as follows.

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times iter \quad (17)$$

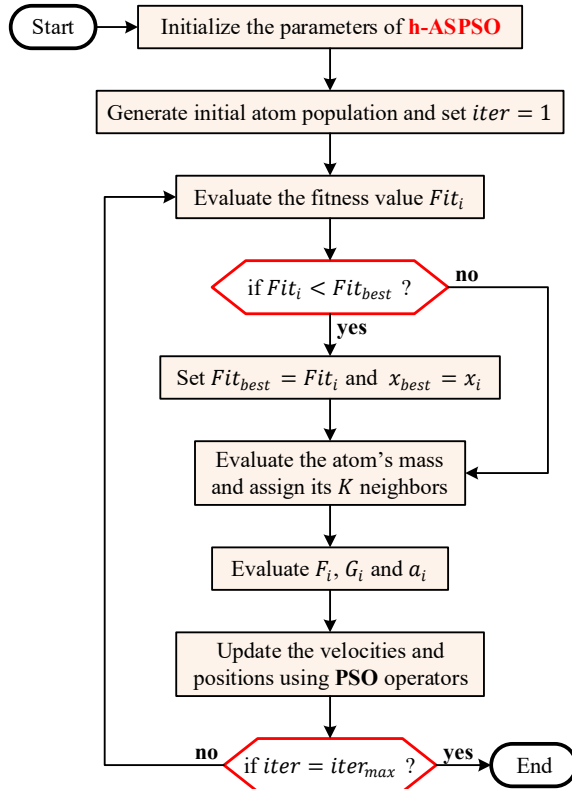


Figure 1. Flowchart of h-ASPSO

In this study, the parameters ω_{max} , ω_{min} , c_1 , and c_2 were configured as 0.9, 0.4, 0.5, and 1.5, respectively. The flowchart of the h-ASPSO algorithm is depicted in detail in Figure 1, and this fusion algorithm will be introduced for the first time in the parameter estimation of the solar PV model in this work.

Photovoltaic model and problem formulation

The PV module model is shown in Figure 2, and it consists of PV cells;

$N_s \times N_p$ where N_s and N_p represent the number of series and parallel diodes, respectively.

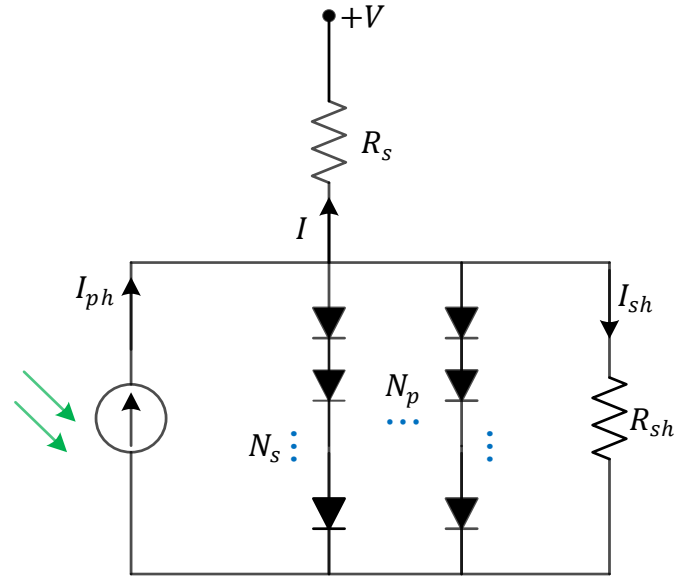


Figure 2. Equivalent mathematical model of a PV model

The output current is given in Equation (18) (4).

$$I = I_{ph} N_p - I_{sd} N_p \left[e^{\frac{q(V + IR_s)}{nkT}} - 1 \right] - \frac{VN_p}{R_{sh}} + IR_s \quad (18)$$

Here, I represents the cell output current, I_{ph} denotes the current generated by the PV cell, I_{sd} stands for the saturation current, q denotes the elementary charge ($1.60217646 \times 10^{-19}$ C), V is the output voltage, R_s represents the series resistance, n is the diode ideality factor, k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), T signifies the cell temperature in Kelvin, and R_{sh} is the shunt resistance (28). It is necessary to determine five unknown parameters (I_{ph} , I_{sd} , R_s , R_{sh} and n) in the PV module model.

To solve the parameter determination problem of the PV module using h-ASPSO, it is essential to define and optimize an objective function. This article aims to minimize the error between the measured and predicted current data. The root means square error (RMSE) provided in Equation (19) is employed as the objective function where N stands for the total number of the data.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (I_{measured} - I_{estimated})^2} \quad (19)$$

Results

In the h-ASPSO algorithm, a population size of 40 and a maximum number of iterations of 500 were performed 30 times for the extraction of the photovoltaic module parameters. The limits of the parameters in the STM6-40/36 module, the optimum values estimated with h-ASPSO and the values of the statistical criteria for the RMSE objective function are given in Table 1. The relatively low standard deviation of the RMSE (1.7454×10^{-3}) is due to the fact that the h-ASPSO algorithm finds similar values in each run, and the algorithm's statistical stability is strong.

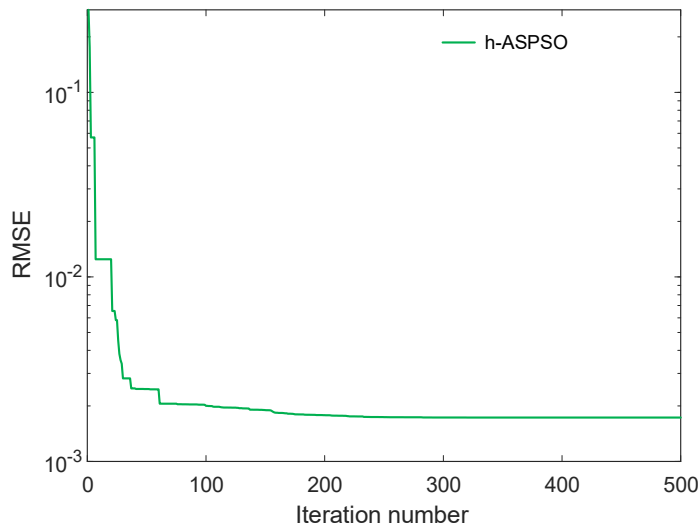
The convergence curve by the number of iterations of the RMSE minimized by h-ASPSO is shown in Figure 3. As shown in the figure, the h-ASPSO algorithm reached the global RMSE (0.001729813709941) before reaching the 300th iteration. The current-voltage and power-voltage curves of the model with the parameter h-ASPSO are shown in Figure 4 and Figure 5 respectively. The STM6-40/36 PV module at 51 °C ($N_s = 36$ ve $N_p = 1$) has a total of 20 current-voltage data.

Table 1. Parameter range of STM6-40/36 and estimated parameters by h-ASPSO

Parameter	Limits	Estimated by h-ASPSO
(A) I_{ph}	[0, 2]	1.663904777397630
(μ A) I_{sd}	[0, 50]	1.738656866112831
(Ω) R_s	[0, 0.36]	0.004273771343857
(Ω) R_{sh}	[0, 1000]	15.92829400757943
n	[1, 60]	1.520302919687353
RMSE	Minimum	0.001729813709941
	Maximum	0.001729813709941
	Mean	0.001729813709941
	Standard deviation	1.745419584478499 $\times 10^{-18}$

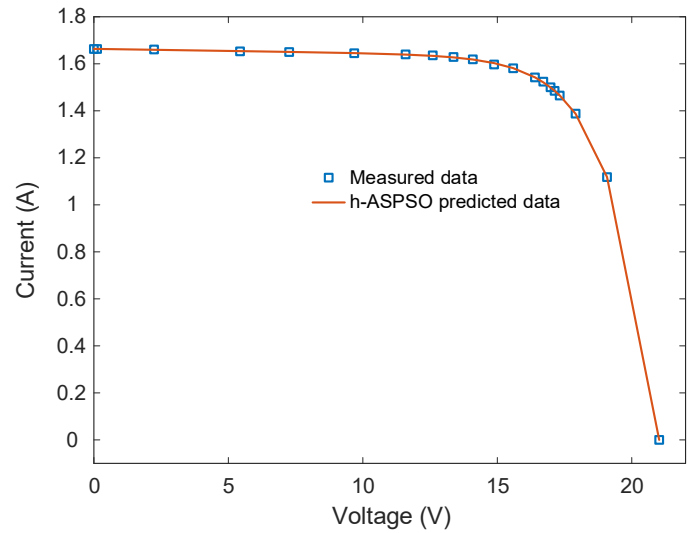
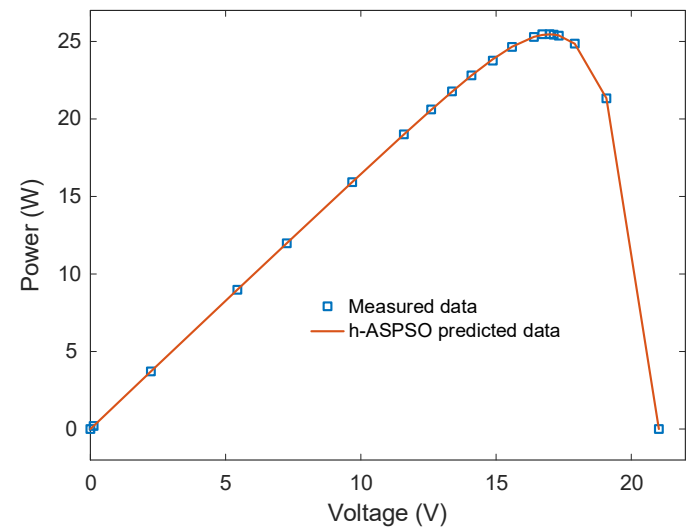
The current and power data measured in Figure 4 and Figure 5 are very compatible with the current and the power data estimated with h-ASPSO. These results confirm that the h-ASPSO has precisely and accurately adjusted the parameters.

To test the performance of h-ASPSO, comparisons were made with the results in the literature such as BES (3), IJAYA (3), MADE (3), TLBO (3) and EGBO (3) algorithms. Table 2 shows the optimum values of the parameters I_{ph} , I_{sd} , R_s , R_{sh} and n using different algorithms and the corresponding best RMSE values. Table 3 shows the minimum, maximum, mean and standard deviation values of RMSE for the STM6-40/36 module. Although the minimum RMSE (0.0017298) values were obtained with h-ASPSO, BES, MADE and EGBO, the lowest standard deviation (1.7454 $\times 10^{-18}$) was found with only h-ASPSO. As a result, the performance of h-ASPSO in accurate and accurate determination of the parameters of the photovoltaic module is superior to that of other algorithms.

**Figure 3.** Convergence curve of RMSE for STM6-40/36 module

Discussion

The accurate extraction of parameters for PV modules is fundamental to optimizing their performance, especially in the context of increasing global reliance on solar energy. The introduction highlights the challenges faced by PV systems, including environmental stressors and the degradation of model parameters over time, emphasizing the need for precise parameter estimation techniques. While analytical and numerical methods have traditionally been employed, their limitations in handling nonlinear properties and computational complexity have led researchers to explore metaheuristic algorithms for parameter extraction. Metaheuristic algorithms offer distinct advantages over traditional methods, with their ability to efficiently explore solution spaces and overcome local optima. However, existing algorithms have exhibited shortcomings such as premature convergence and sensitivity to parameter changes.

**Figure 4.** I-V characteristic curve of STM6-40/36 module**Figure 5.** P-V characteristic curve of STM6-40/36 module**Table 2.** Comparison of STM6-40/36 module parameters and RMSE

Algorithm	(A) I_{ph}	(μ A) I_{sd}	(Ω) R_s	(Ω) R_{sh}	n	RMSE
h-ASPSO (novel approach)	1.6639	1.7387	0.0043	15.9283	1.5203	0.0017298
BES	1.6639	1.7387	0.0043	15.9283	1.5203	0.0017298
IJAYA	1.6637	1.8353	0.0040	15.9449	1.5263	0.0017548
MADE	1.6639	1.1387	0.0043	15.9283	1.5203	0.0017298
TLBO	1.6638	1.7307	0.0043	15.9955	1.5198	0.0017305
EGBO	1.6639	1.7300	0.0043	15.9283	1.5203	0.0017298

Table 3. RMSE statistical metric values of various methods in the STM6-40/36 module

Algorithm	Minimum	Maximum	Mean	Standard deviation
h-ASPSO	0.0017298	0.0017298	0.0017298	1.7454 $\times 10^{-18}$
BES	0.0017298	0.0017298	0.0017298	5.6525 $\times 10^{-18}$
IJAYA	0.0017548	0.0025223	0.0019305	0.000191
MADE	0.0017298	0.0017298	0.0017298	8.49 $\times 10^{-18}$
TLBO	0.0017305	0.0205930	0.0043487	0.00345
EGBO	0.0017298	0.0017298	0.0017298	8.22 $\times 10^{-18}$

This sets the stage for the introduction of the h-ASPSO algorithm, which combines the strengths of ASO and PSO to achieve a balance between exploration and exploitation.

The results presented in the results section underscore the effectiveness of the h-ASPSO algorithm in accurately estimating parameters for the STM6-40/36 PV module. Specifically, the algorithm demonstrates robustness and stability, as evidenced by consistently low RMSE values across multiple runs. The convergence curve further illustrates the algorithm's efficiency in reaching the global

minimum swiftly, within a relatively small number of iterations.

Moreover, the comparison with existing algorithms highlights the superior performance of h-ASPSO in terms of both RMSE values and standard deviation. While other algorithms also yield low RMSE values, the h-ASPSO algorithm stands out for its consistency and reliability, as indicated by the lowest standard deviation. This emphasizes the algorithm's potential as a promising technique for accurate parameter extraction in PV systems.

The successful application of h-ASPSO in this study not only addresses the specific challenge of parameter extraction for the STM6-40/36 PV module but also underscores its broader applicability in optimizing PV systems. By providing a robust and effective solution, the h-ASPSO algorithm contributes to the advancement of solar energy technologies and facilitates the transition to a cleaner and more sustainable energy future.

Future research could explore the applicability of the h-ASPSO algorithm to different types of PV modules and investigate enhancements to further improve its performance and efficiency. Additionally, the development of hybrid approaches, integrating the strengths of multiple algorithms, could lead to even more powerful optimization techniques for addressing the evolving challenges in the field of solar energy technology. In conclusion, the h-ASPSO algorithm represents a significant advancement in parameter extraction for PV systems, with far-reaching implications for the optimization and advancement of solar energy technologies.

Conclusion

The goal of this research is to use the cutting-edge h-ASPSO method to precisely estimate the parameters in the STM6-40/36 PV module. Using h-ASPSO, we reduced the RMSE objective function and used the results from numerous runs to evaluate the algorithm's statistical performance. The extremely low standard deviation and the difference between the highest and lowest values of the RMSE objective function demonstrated that the h-ASPSO algorithm possesses a stable structure. In addition, the h-ASPSO's alignment with the measured I-V and P-V characteristic curves, as well as its good convergence profile, have been verified. Using RMSE values as a statistical indicator, we compared the BES, IJAYA, MADE, TLBO, and EGBO algorithms found in the literature. An RMSE standard deviation value of 1.7454×10^{-18} has been determined by the h-ASPSO to be the best and most accurate. Subsequent studies could evaluate the suitability of the h-ASPSO algorithm for other PV module types and explore potential upgrades to optimize its performance and efficiency. In addition, the advancement of hybrid methodologies, which combine the advantages of several algorithms, has the potential to enhance optimization procedures for tackling the changing obstacles in the domain of solar energy technology. To summarize, the h-ASPSO technique is a notable improvement in parameter extraction for PV systems, which has wide-ranging implications for optimizing and advancing solar energy technology.

Authors contribution

All authors contribute equally.

Declaration of Competing Interests

The authors have no conflict of interest with anybody anywhere.

Data availability

All data are presented within the manuscript.

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