Estimation for Model Parameters and Maximum Power Points of Photovoltaic Modules Using Stochastic Fractal Search Algorithms

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ABSTRACT The performance of a photovoltaic (PV) power generation system could be improved through the optimal control and operation of a PV module which is one of the fundamental components of this system. Thus, an appropriate PV module model along with precise knowledge of its parameters is necessary. This paper proposes a novel technique to estimate the source current, the saturation current of diodes, the shunt resistance, the series resistance, the ideality coefficient of diodes and the maximum power points (MPPs) of PV modules at the same time. This estimation problem can be described by the minimization of the root mean squared error (RMSE) of the powers obtained from the PV module through estimation and experiment. The improved stochastic fractal search (ISFS) algorithm is proposed to solve this minimization with two modifications. The first replaces the logarithmic function with the exponential function in the standard deviation of the diffusion technique to improve the exploration ability efficiently in the search space. The second utilizes the sine map instead of the uniform distribution in both the diffusion and update techniques for improving the performance of the ISFS algorithm. Numerical results demonstrate the remarkable ability of the ISFS algorithm in obtaining both the model parameters and MPPs of the PV module with high accuracy. The comparison shows that the ISFS algorithm outperforms other meta-heuristic algorithms such as a stochastic fractal search (SFS) algorithm, a particle swarm optimization (PSO) algorithm, and an improved particle swarm optimization (IPSO) algorithm in the proposed parameter estimation application.

INDEX TERMS Estimation, maximum power point, meta-heuristic algorithms, model parameter, photovoltaic modules.

I. INTRODUCTION Solar energy, in general, and PV power systems, in particular, have become very popular for providing electrical energy for industrial production and domestic life. This is due to its numerous advantages such as infinite supply, simple extraction, quick installation, fewer emissions, less noise pollution, etc. [1]. The PV power systems have remarkably contributed to the power source structure of a power system and possess abundant potential. Problems related to how to exploit and operate efficiently the PV power system have been raised recently. The PV power system consists of PV modules which are interconnections of PV cells. Currently, a PV cell is popularly described by a single-diode model [2], [3]. This simple model shows an effective description of the PV cell. In some other applications, the PV cell needs to be modelled in more detail than the single-diode model, the PV cell is then described by a double-diode model [4]. As the detail of the PV cell is required to be increased in some situations, the PV cell is represented by a triple-diode model [5]. The utilization of the PV cell model should be analyzed and selected reasonably for each specific application to achieve the best descriptive effect. The specific application dictates which model is used. Amongst the above descriptions of the...
PV cell, the triple-diode model is the most complex model and the single-diode model is the simplest one. The single-diode model achieves the lowest computational complexity as well as the best trade-off between simplicity and precision. Thus, the single-diode model is chosen for the research described in this paper.

Table 1 show the definitions of the abbreviations utilized in this paper.

### Table 1. Abbreviation.

| Abbreviation | Definition |
|--------------|------------|
| PV           | Photovoltaic |
| MPP          | Maximum power point |
| RMSE         | Root mean squared error |
| SFS          | Stochastic fractal search |
| ISFS         | Improved stochastic fractal search |
| PSO          | Particle swarm optimization |
| IPSO         | Improved particle swarm optimization |
| GA           | Genetic algorithm |
| ABC          | Artificial bee colony |
| COA          | Coyote optimization algorithm |
| FPA          | Flower pollination algorithm |
| PSA          | Projectile search algorithm |
| TGOA         | Tree growth-based optimization algorithm |
| SOA          | School-based optimization algorithm |
| GWO          | Grey wolf optimization |
| SAIW         | Simulated-annealing inertia weight |
| PO           | Perturbation and observation |
| Inc          | Incremental conductance |
| STC          | Standard testing condition |
| NOC          | Normal operating condition |
| PID          | Proportional-integral-derivative |
| PI           | Proportional-integral |
| FL           | Fuzzy logic |
| ANN          | Artificial neural network |

Additionally, Table 2 shows symbols which are utilized for mathematical descriptions of the estimation problem of model parameters and MPPs of PV modules.

Previous research works have shown that the electrical energy generated from the PV modules is significantly dependent on the operational conditions of the irradiance and the temperature [1]. Therefore, when these conditions are changed, the output power of the PV modules changes as well. This means that an appropriate control strategy should be proposed to ensure the adaptive and optimal operation of the PV modules. This is mainly modelled by the mathematical description of the PV module with elements of the current source, diodes, shunt resistance and series resistance of the PV cells. Then, the source current of the PV cell, saturation current and ideality coefficient of the diode and the shunt resistance and series resistance of the PV cell should be determined and updated during the operational process in the adaptive and optimal control problem of the PV module. However, manufacturers of the PV module only provide basic parameters such as voltage, $U_{MPP}$, current, $I_{MPP}$, and power, $P_{MPP}$, at an MPP; open-circuit voltage, $U_{oc}$; and short-circuit current, $I_{sc}$, in the STC with the irradiance, $G_{STC} = 1000$ (W/m²), and the temperature, $T_{STC} = 298.15$ (°K). This shows that the available specification of the PV modules in the datasheet of the manufacturer cannot fulfil the requirements of the adaptive and optimal control problem of the PV module.
In addition, all parameters of the PV module always change under various operation conditions that are far from the STC. Therefore, it is important to obtain as complete a set of parameters of the PV module as possible for controlling adaptively and optimally the PV power system.

Recently, analytical techniques, numerical techniques, and meta-heuristic algorithm-based techniques have been introduced to achieve the model parameters of the PV module.

The analytical techniques are based on the relationship of the model parameters of the PV module between the STC and the various operating conditions as well as the data given by the manufacturers and experiments. It is realized that the algebraic equations of the PV module descriptions are non-linear expressions which must be simplified through an explicit model representation with first- and second-order approximation models [6], or Nyquist and Bode plots [7]. The above assumptions have reduced the accuracy of the estimated parameters. This parameter estimation problem is then solved by a truncated Taylor series-based solving technique [6], or Lambert function [8] showing the complexity of the analytical technique. Furthermore, initial estimations are also necessary in some cases [9]. If the initializations are not appropriate, this will affect the final convergence values of the parameter estimation problem and the error percentage of estimation will be significant.

Numerical techniques are presented to overcome several disadvantages of the analytical techniques. These include Newton-Raphson techniques [10], [11] and Levenberg-Marquardt techniques [12]. The disadvantages of the Newton-Raphson technique are the required computational burden, dependence on reasonably accurate initialization of estimated parameters, and poor convergence ability. The disadvantage of the Levenberg-Marquardt technique is the significant computational time since a Jacobian matrix is required as part of the parameter estimation procedure.

Recently, meta-heuristic algorithms have been applied to the parameter estimation of the PV module due to their reliability and efficiency. The meta-heuristic algorithms include GA, PSO, ABC, FPA, PSA, TGOA, and SOA. The above algorithm-based estimation results show several disadvantages summarized in Table 3.

The above analyses show that the meta-heuristic algorithms have overcome many disadvantages of the previous parameter estimation techniques including the analytical and numerical techniques. However, these meta-heuristic algorithm-based techniques still have disadvantages such as being highly dependent on initializations, requiring many controlling parameters, and needing a large number of convergence iterations.

This paper proposes an ISFS algorithm-based parameter estimation technique for a PV module. The SFS algorithm is inspired by the random fractal growth phenomenon [21]. The SFS algorithm has fewer controlling parameters than other meta-heuristic algorithms [22], [23], [24]. In addition, the SFS algorithm has a high ability to achieve global optimal solutions with an acceptable number of iterations [21].

| Algorithm               | Disadvantage                                                                 | Reference |
|-------------------------|------------------------------------------------------------------------------|-----------|
| ABC algorithm           | The exploitation ability is poor.                                             | [2]       |
| PSO-ABC algorithm       | There are many tuning parameters.                                             | [4]       |
| COA                     | The procedure of producing new solution generations is complicated.          | [5]       |
| FPA                     | The algorithm performance mainly depends on a probability factor.             | [11]      |
| Binary-coded GA         | • Solution of estimated parameters is affected by the restriction of string lengths; | [13]      |
| Real-coded GA           | • There are many tuning parameters.                                           | [14]      |
| PSO algorithm           | • The estimation procedure requires a longer estimation time;                | [15]      |
| SIAW-PSO algorithm      | • There are many tuning parameters.                                           | [16]      |
| Damping bound-handling approach-based PSO algorithm | There are many tuning parameters.                                             | [17]      |
| PSA                     | TGOA                                                                          | [18]      |
| SOA                     |                                                                              | [19]      |

These are the reasons why the SFS algorithm is popularly applied for solving various optimization problems.

Table 4 shows the wide applicability of the SFS algorithm in many various fields. The SFS algorithm-based achievements confirm the effectiveness and superiority of the SFS algorithm with its ability to maintain the balance between exploration and exploitation as well as the ease of being used in optimization applications with fewer tuning parameters. This means that the SFS algorithm is an appropriate choice to apply to the parameter estimation problem of the PV module. This is a novel proposal which has not been mentioned in...
The ISFS algorithm is a variant of the SFS algorithm modifying the standard deviation of the diffusion technique and the uniform distribution of both the diffusion and updating techniques to improve the SFS algorithm performance. The ISFS algorithm is applied to estimate the model parameters of the PV module consisting of the source current of the PV module, $I_{ph}$; the saturation current, $I_0$ and ideality coefficient, $a$ of the diode in the model of the PV module; and the shunt resistance, $R_s$, and series resistance, $R_s$, of the PV module, which are unavailable in the datasheet of the manufacturers.

Additionally, the MPP of a PV module on the voltage-current ($U-I$) and voltage-power ($U-P$) characteristics should also be determined and updated to ensure that the PV module is always operated adaptively and optimally under various operational conditions. There are currently many techniques applied to determine MPPs of the PV modules such as PO algorithms [34], [35] and InC algorithms [36], [37]. Several previous studies show that the PO algorithm exhibits disadvantages such as oscillations around the MPP in steady-state conditions, deviations from the MPP in quickly changing conditions of the irradiance and temperature and requirements of an appropriate perturbation step size [38]. Similarly, the InC algorithm also has drawbacks such as slow convergence abilities with small perturbation step sizes, oscillations around the MPP in steady-state conditions with large perturbation step sizes and divergence of the operating point from the MPP [39]. To overcome the disadvantages of the PO algorithm, a step of determining the short-circuit current of the PV module is added during the search process of the MPP to ensure that there is no deviation from the MPP under quick variations of atmospheric conditions [34]. Additionally, the fixed perturbation step size is replaced by a variable one depending on power changes to ensure that the modified PO algorithm identifies the most accurate MPP during the search process [35]. Furthermore, the PO algorithm is also modified with the two-step-based technique. The first step is large for fast convergence to MPP as the power difference is large and the second step is small for eliminating oscillations around the MPP. The obtained results show that the modified PO algorithm is better than the traditional PO algorithm in the convergence performance as well as the accuracy of the achieved MPP of the PV module [40]. Additionally, the disadvantages of the InC algorithm are also overcome by combining the InC algorithm with the GWO algorithm-based PID controller to minimize steady-state oscillations at the MPP. The obtained results show the effectiveness of the improved InC algorithm with a reduction of steady-state oscillations around the MPP as well as better tracking performance of the MPP of the PV module [37]. In addition, the fixed step size in the InC algorithm is also improved by an adaptive step size with variations. This is based on how far away the current operating point is from a new MPP. The achievements of the modified InC algorithm show a feasible solution to improve the ability to determine MPPs with high accuracy and fast computational time [41]. It is realized that the above-presented improvements have not yet overcome all the disadvantages of the PO and InC algorithms. Each solution has been individual because the total solution can lead to complexity for the MPP tracking of the PV module. Another approach recommended for this problem is based on techniques such as the FL-based technique [42] and the ANN-based technique [43]. The FL-based technique is developed to identify the MPP of the PV module. This technique is based on FL rules which are set for each membership function. The results from using the FL-based technique are better than those obtained by the PO algorithm with the oscillations around the MPP in steady-state conditions being reduced [42]. By using the ANN-based technique, the voltage at the MPP is identified with the training data of the irradiance and temperature. The results of tracking MPPs of the PV module by using the ANN-based technique show superior tracking ability and speed compared to other techniques such as the PO algorithm-based technique and the InC algorithm-based technique. However, the ANN-based technique also has the disadvantage of requirements relating to training data and time. This affects the performance of the MPP tracking of the PV module [43]. Similarly, the above techniques of using ANN and FL still have disadvantages. Recently, the PSO algorithm-based technique was employed to identify MPPs of the PV module [44], [45]. The objective functions are formulated by the extracted power of the PV module. The PSO algorithm is applied to maximize the obtained power of the PV module under various atmospheric conditions. Importantly, this algorithm is also developed for the MPP tracking problem under partial shading conditions [46], [47]. However, the above analyses have shown the disadvantages of the PSO algorithm compared with the SFS and ISFS algorithms. Therefore, the ISFS algorithm is proposed to estimate the MPPs of the PV module under various irradiances and temperatures in this paper. The estimation of both the model parameters and MPPs of the PV module is novelly proposed in this paper which is necessary for improving the optimal exploitation efficiency of PV power systems. This combined estimation has been less mentioned in previous studies due to limitations of the analytical, numerical and meta-heuristic algorithm-based techniques [1], [2], [4] [25], [31]. Most of the previous studies have independently performed the estimation of the model parameters [2], [4] and MPPs [1], [25], [34] of the PV module. This inhibits the update of variations including the model parameters and MPPs of the PV module as synchronously and quickly as possible and certainly affects the results of the optimal and adaptive operation of the PV power system. The estimation results of the model parameters and MPPs of the PV modules using the ISFS algorithm are compared with the PSO, IPSO, and SFS algorithms to confirm the effectiveness of the proposal. The PSO algorithm is one of the popular meta-heuristic algorithms and is often selected to solve optimization problems because of its simplicity and ease of implementation. Comparisons in previous studies showed that the PSO algorithm is better than other meta-heuristic algorithms such as ABCs, FPAs, GAs, PSAs,
TGOAs, and SOAs in parameter estimation applications but there has not been yet any comparison between the PSO algorithm and the SFS algorithm, especially in the parameter estimation application of the PV module. Additionally, the objective of this paper is to solve the problem of estimating both model parameters and MPPs of the PV module simultaneously. Previous studies showed the disadvantages of using analytical techniques in the model parameter estimation application of the PV module. Moreover, it is very difficult to identify MPPs of the PV module by using analytical techniques. Most approaches for determining MPPs of the PV module have focused on PO and InC algorithms so far. The PO and InC algorithms are widely applied to identify MPPs of the PV module. However, it seems that these algorithms cannot be applied to estimate the model parameters of the PV module. The above analyses show that a proposal for the estimation of both the model parameters and MPPs of the PV module is presented in Section III. The experimental results achieved are presented in Section IV. Finally, the effectiveness of the proposed novel approach is highlighted in Section V.

II. MODELING OF A PV MODULE

A PV module is typically made up of interconnected PV cells. There are three popular models to describe a PV cell including the single-, double-, and triple-diode models. Amongst the models, the single-diode model achieves the lowest computational complexity as well as the best trade-off between simplicity and precision. Thus, the single-diode model is chosen to describe the PV cell in this paper. The description of the PV cell is shown in Fig. 1 [3].

Then, the mathematical model of the PV cell is given by:

\[
I_{ph} = I_{ph} - I_D - \frac{U_{ph}^{SD}}{R_{sh}^{SD}}
\]

\[
I_D = I_0 \exp \left( \frac{q}{aSD} \frac{U_{SD}^{SD}}{kT} \right) - 1
\]

\[
U_{SD} = U_{c}^{SD} + R_s^{SD} I_{c}^{SD}
\]

As a result, the load current of the PV cell is as follows:

\[
I_{c}^{SD} = I_{ph}^{SD} - I_{D}^{SD} \left[ \exp \left( \frac{q}{aSD} \frac{U_{SD}^{SD}}{kT} \right) - 1 \right]
\]

\[
- \frac{U_{SD}^{SD} + R_s^{SD} I_{c}^{SD}}{R_{sh}^{SD}}
\]

From the alignment of the PV cell, the PV module is described in Fig. 2 [48].

The load current of the PV module is given by:

\[
I = N_p a I_{ph} - N_p a I_0 \left[ \exp \left( \frac{q}{a_k T} \frac{U}{N_{se}} + \frac{R_s I}{N_{pa}} \right) - 1 \right]
\]

\[
- \frac{N_p a U}{N_{se} R_{sh}} + \frac{R_s I}{R_{sh}}
\]

Then, the power of the PV module is as follows:

\[
P = \frac{N_p a R_s I_{ph} U}{(R_{sh} - R_s)}
\]

\[
- \frac{N_p a R_s I_0 U}{(R_{sh} - R_s)} \left[ \exp \left( \frac{q}{a_k T} \frac{U}{N_{se}} + \frac{R_s I}{N_{pa}} \right) - 1 \right]
\]

\[
- \frac{N_p a U^2}{N_{se} (R_{sh} - R_s)}
\]

\[
P = f \left( I_{ph}, I_0, R_s, R_{sh}, a \right)
\]
III. ESTIMATION FOR MODEL PARAMETERS AND MPPs

A. ESTIMATION FOR MODEL PARAMETERS AND MPPs

It is realized that there are five model parameters, \( I_{ph}, I_0, R_s, R_{sh}, \) \( a \) in (8) which need to be estimated from the model of the PV module. In addition, the MPPs also need to be identified, especially for the application of MPP tracking. The MPP, \( P_{MPP}(U_{MPP}, I_{MPP}) \) is unique in the \( U-I \) and \( U-P \) characteristics, Fig. 3.

![MPP description](image)

**FIGURE 3.** MPP description.

Therefore, the estimation problem is described by the minimization of the RMSE of the powers of the PV module between the estimation and experiment. Then, the model parameters, \( I_{ph}, I_0, R_s, R_{sh}, a \) and MPP, \( P_{MPP}(U_{MPP}, I_{MPP}) \) are estimated through the following RMSE minimization of the powers of the PV module.

In this paper, the RMSE of the powers of the PV module is the objective function given by:

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_i^{\text{est}} - P_i^{\text{exp}})^2}
\]

The constraints of this parameter estimation problem are as follows:

\[
I_{ph}^{\text{min}} < I_{ph} < I_{ph}^{\text{max}}
\]

\[
R_s^{\text{min}} < R_s < R_s^{\text{max}}
\]

\[
R_{sh}^{\text{min}} < R_{sh} < R_{sh}^{\text{max}}
\]

\[
a^{\text{min}} < a < a^{\text{max}}
\]

\[
U_{MPP}^{\text{min}} < U_{MPP} < U_{MPP}^{\text{max}}
\]

\[
i_{MPP}^{\text{min}} < I_{MPP} < i_{MPP}^{\text{max}}
\]

The SFS and ISFS algorithms are proposed to estimate the model parameters, \( I_{ph}, I_0, R_s, R_{sh}, a \), and MPP, \( P_{MPP}(U_{MPP}, I_{MPP}) \) of the PV module respectively and are presented in more detail in the next sections.

B. ESTIMATION FOR MODEL PARAMETERS AND MPPs BY USING A SFS ALGORITHM

The SFS algorithm is based on the random fractal growth phenomenon in nature including the diffusion and update techniques in searching for solutions [21]. Each optimal position discovered by the SFS algorithm is an estimation result.

The Gaussian walk is utilized throughout the diffusion technique to produce points with a preset maximum diffusion number, \( n_{md} \), encircling each particle for diffusing around its position and performing the exploitation.

The Gaussian walk is explained in detail below.

\[
GW = G(p_i, \delta) = r \times (p_{best} - p_i)
\]

The Gaussian function is described as follows:

\[
G(p_i, \delta) = \frac{1}{\delta \sqrt{2\pi}} e^{-\frac{(p_{i} - p_{best})^2}{2\delta^2}}
\]

The standard deviation is given by:

\[
\delta = \left| \frac{\log(n_G)}{n_G} \times (p_{best} - p_i) \right|
\]

The position of each particle is updated in line with the positions of other particles throughout the updating technique. The exploration is then implemented by each particle using two statistical techniques.

\[
I_{ph}(G, T) = \left( \frac{G}{G_{STC}} \right) I_{ph}(T)
\]

\[
I_{ph}(T) = I_0(T) \exp \left[ \frac{V_{oc,STC} + \mu U_{oc}(T - T_{STC})}{a N_{se} U_1(T)} \right] + \left( V_{oc,STC} + \mu U_{sc}(T - T_{STC}) \right) R_{sh} \]

\[
I_0(G, T) = \left[ 1 + \frac{R_s}{R_{sh}} \left( I_{sc,STC} + \mu U_{sc}(T - T_{STC}) \right) \right] \frac{(U_{oc,STC} + \mu U_{oc}(T - T_{STC}) + a N_{se} U_1 \ln(G))}{R_{sh}} \left( \exp \left[ \frac{(U_{oc,STC} + \mu U_{oc}(T - T_{STC}) + a N_{se} U_1 \ln(G))}{a N_{se} U_1} \right] - \exp \left( \frac{(I_{sc,STC} + \mu I_{sc}(T - T_{STC}) + a N_{se} U_1 \ln(G))}{a N_{se} U_1} \right) \right) \right] \]

\[
R_{sh}(G) = \left( \frac{G_{STC}}{G} \right) R_{sh,STC}
\]

\[
R_s(G, T) = \frac{T}{T_{STC}} \left( 1 - \eta \ln \left( \frac{G}{G_{STC}} \right) \right) R_s,STC
\]
The first statistical technique is described by:

\[ p'_i (j) = \begin{cases} 
    p_{r1} (j) - r \times [p_{r2} (j) - p_i (j)] & \text{if } \gamma_i < r \\
    p_i (j) & \text{otherwise}
\end{cases} \quad (25) \]

\[ \gamma_i = 1 - \frac{\text{rank} (p_i)}{n_s} \quad (26) \]

The second statistical technique is described by:

\[ p'_i (j) = \begin{cases} 
    p_i (j) - r \times [p'_{r1} (j) - p_{\text{best}} (j)] & \text{if } r < 0.5 \\
    p_i (j) + r \times [p'_{r1} (j) - p'_{r2} (j)] & \text{otherwise}
\end{cases} \quad (27) \]

It is realized that the SFS algorithm performance can be improved through the initialization of the solutions, the creation of a new solution and the update of the solution. This results in the reduction of the computational time and increased accuracy of the estimation of the model parameters, \( l_{\text{ph}}, I_0, R_s, R_{sh}, a, \) and MPP, \( P_{\text{MPP}}(U_{\text{MPP}}, I_{\text{MPP}}) \) of the PV module. This paper proposes an improved SFS algorithm with mentioned modifications. The detail of the ISFS algorithm is presented in the next section.

C. ESTIMATION FOR MODEL PARAMETERS AND MPPs BY USING A ISFS ALGORITHM

As mentioned, the ISFS algorithm modifies the procedures of the initialization of the solutions, the creation of a new solution, and the update of the solution in the SFS algorithm.

It is realized that the essential execution of the meta-heuristic algorithms, in general, and the SFS, in particular, is more typically the randomization of each particle using a uniform distribution as well as dealing with challenges of non-linear and multi-modal complicated objective functions. Chaotic maps are then recommended to utilize as an alternative to a random uniform distribution \([50], [51], [52]\). Amongst the chaotic maps, a sine map is one of the simplest and most easily applied chaotic maps chosen to improve the performance of the SFS algorithm in this paper \([53], [54]\). The random uniform distribution is represented by the sine map in the initialization of the solutions. This creates a diverse initial solution space that contributes to improving the exploitation ability of the algorithm.

The sine map is shown as follows:

\[ z_{i+1} = \sin (\pi z_i) \quad (28) \]

Additionally, previous studies have shown that the exploration and exploitation ability of the meta-heuristic algorithms are extremely important \([50], [51], [52]\). This certainly applies to the SFS algorithm as well. Therefore, in the creation of a new solution for the ISFS algorithm, the standard deviation in the diffusion technique is computed via the exponential function instead of the logarithmic function for enhancing the exploration ability of the algorithm \([55]\). This modification allows limiting the number of Gaussian jumps as the number of iterations increments. Then, the exploration performance of the ISFS algorithm is improved in the search space.

The standard deviation is re-written as:

\[ \delta = \left\lfloor \exp \left( -n_G \right) \times (p_{\text{best}} - p_i) \right\rfloor \quad (29) \]

Moreover, the Gaussian walk is also modified with the sine map and re-described for improving the quality of the solutions as follows:

\[ GW = G (p_i, \delta) + z \times (p_{\text{best}} - p_i) \quad (30) \]

Simultaneously, the first and second updating techniques are respectively modified with the sine map as follows:

\[ p'_i (j) = \begin{cases} 
    p_{r1} (j) - z \times [p_{r2} (j) - p_i (j)] & \text{if } \gamma_i < z \\
    p_i (j) & \text{otherwise}
\end{cases} \quad (31) \]

\[ p'_i (j) = \begin{cases} 
    p_i (j) - z \times [p'_{r1} (j) - p_{\text{best}} (j)] & \text{if } z < 0.5 \\
    p_i (j) + z \times [p'_{r1} (j) - p'_{r2} (j)] & \text{otherwise}
\end{cases} \quad (32) \]

The ISFS algorithm-based estimation results are compared with the SFS estimation results. This comparison validates the effectiveness of the proposed ISFS algorithm in the estimation application of the model parameters, \( l_{\text{ph}}, I_0, R_s, R_{sh}, a, \) and MPP, \( P_{\text{MPP}}(U_{\text{MPP}}, I_{\text{MPP}}) \) of the PV module. In addition, the ISFS algorithm-based estimation results are compared with the estimation results achieved by the PSO and IPSO algorithms to re-confirm the effectiveness and superiority of the ISFS algorithm in the estimation application of the model parameters, \( l_{\text{ph}}, I_0, R_s, R_{sh}, a, \) and MPP, \( P_{\text{MPP}}(U_{\text{MPP}}, I_{\text{MPP}}) \) of the PV module for adaptive and optimal control problems.

In this SFS and ISFS algorithm-based parameter estimation application of the PV module, each position of the particle is described by an estimation vector, \( p \), as follows:

\[ p = [l_{\text{ph}}, I_0, R_s, R_{sh}, a, U_{\text{MPP}}, I_{\text{MPP}}] \quad (33) \]

There are seven parameters of the PV module that require to be estimated in this paper. These are the basic and necessary parameters required in the control and operation problems of the PV module.

Fig. 4 is the flowchart of the SFS algorithms. In this flowchart, the SFS algorithm is shown with function blocks with solid and black lines on the left-hand side whereas the ISFS algorithm is shown with dashed and blue lines on the right-hand side. In the ISFS algorithm, the solution initialization, the procedure of creating a new solution, and the procedure of updating the solution are modified to improve the performance of the SFS algorithm. The solution initialization of the ISFS algorithm is modified and based on the sine map which creates variety in the search space of the solutions. This improves the exploitation ability of the ISFS algorithm. Moreover, the procedures of creating a new solution and updating the solution are also based on the sine map which enhances the exploration ability of the ISFS algorithm. Thus, the algorithm performance of the ISFS algorithm is improved in terms of the convergence value and speed. This results in the improvement of the estimation results of the model parameters and MPPs of the PV module.
D. Parameter Tuning of Meta-Heuristic Algorithms

The SFS, ISFS, PSO and IPSO algorithms are the meta-heuristic algorithms proposed to be used for the parameter estimation application of the PV module in this paper. In the meta-heuristic algorithm-based applications, the selection of optimal parameters of the meta-heuristic algorithms is a great challenge affecting the quality of achieved optimal solutions [56]. There are two kinds of parameter settings of the meta-heuristic algorithms including parameter tuning, known as off-line tuning; and parameter control, known as on-line tuning [57]. In this paper, parameter tuning is described and applied to determine optimal parameters of the SFS, ISFS, PSO, and IPSO algorithms because of the appropriateness and requirement of the parameter estimation application of the PV module. The parameter tuning allows identifying the optimal parameters of the SFS, ISFS, PSO and IPSO algorithms before the given algorithms are applied to estimate the parameters of the PV module. The values of algorithm parameters are fixed in the initialization and do not vary during the operation.

It is realized that the problem of determining the optimal tuning parameters of the SFS, ISFS, PSO and IPSO algorithms can be formulated as optimization problems. All these algorithms are optimization algorithms. Therefore, the optimization of the meta-heuristic parameters is called meta-optimization. Additionally, this paper proposes to solve the meta-optimization by applying meta-heuristic algorithms. Then, it is called the meta-meta-heuristic approach consisting of the meta-level and the base level [58], [59].

A meta-heuristic solves the meta-optimization based on populations of solutions at the meta-level. A solution is a set of the parameters of the meta-heuristic. The values of the swarm size, maximum iteration and maximum diffusion are optimized in the SFS and ISFS algorithms whereas the values of the swarm size, maximum iteration, individual cognition coefficient, social learning coefficient and inertia weight are optimized in the PSO and IPSO algorithms.

Each solution of the meta-level corresponds to an independent meta-heuristic at the base level working on populations of solutions of the original optimization problem in general and the parameter estimation problem of the PV module in particular.

IV. Experimental Results

The commercial multi-crystal PV module, Kyocera KC200GT-215, is used to conduct the experiments in the estimation problem of the model parameters and MPPs. Table 5 is the parameters in the datasheet of the commercial multi-crystal PV module, Kyocera KC200GT-215, which cannot fully satisfy the parameter requirements in the control and operation issues of the PV module. In addition, the values of the parameters in the datasheet are obtained in the STC with the irradiance, $G_{STC} = 1000$ (W/m²), and temperature, $T_{STC} = 298.15$ (°K). When the irradiance, $G$, 

![FIGURE 4. Flowchart of SFS algorithms.](image-url)
and temperature, \( T \), are changed and are different from the irradiance, \( G_{STC} \), and temperature, \( T_{STC} \), in the STC, the parameters in the datasheet will change accordingly. This re-confirms that the estimation of the model parameters and MPPs of the PV module is necessary to satisfy the requirements of obtaining additional parameters which are unavailable in the datasheet of the manufacturers as well as to update the variations of the model parameters and MPPs during the control and operation process of the PV module. The sample number of the power of the PV module, Kyocera KC200GT-215, \( N \), is 34.

**TABLE 5. Parameters in the datasheet of the commercial multi-crystal PV module, Kyocera KC200GT-215.**

| Parameter                        | Value  |
|----------------------------------|--------|
| Power at the MPP, \( P_{MPP}(W) \) | 200    |
| Voltage at the MPP, \( V_{MPP}(V) \) | 26.3   |
| Current at the MPP, \( I_{MPP}(A) \) | 7.61   |
| Open-circuit voltage, \( V_{oc}(V) \) | 32.9   |
| Short-circuit current, \( I_{sc}(A) \) | 8.21   |
| Temperature coefficient of \( I_{oc}, \mu_{oc}(A/C) \) | \(-1.23 \times 10^1\) |
| Temperature coefficient of \( V_{oc}, \mu_{oc}(A/C) \) | \(3.18 \times 10^1\) |
| Number of PV cells in series, \( N_{ser} \) | 54     |
| Number of PV cells in parallel, \( N_{par} \) | 1      |

**TABLE 6. Parameters of the SFS and ISFS algorithms.**

| Parameter and procedure | Value |
|-------------------------|-------|
| Swarm size, \( n_s \)   | SFS   | ISFS   |
| Maximum iteration, \( \text{Iter}_{max} \) | 1000 | 1000 |
| Maximum diffusion, \( n_{md} \) | 1 | 1 |
| Procedure of initializing solutions | Random distribution | Sine map by using (29) |
| Procedure of creating a new solution | Gaussian walk by using (22) | Sine map-based Gaussian walk by using (30) |
| Procedure of updating the solution | Update by using (25) and (27) | Sine map-based update by using (31) and (32) |

**TABLE 7. Parameters of The PSO and IPSO Algorithms.**

| Parameter                        | Value |
|----------------------------------|-------|
| Swarm size, \( n_s \)            | PSO   | IPSO   |
| Maximum iteration, \( \text{Iter}_{max} \) | 1000 | 1000 |
| Individual cognition coefficient, \( c_1 \) | 2 | 2 |
| Social learning coefficient, \( c_2 \) | 2 | 2 |
| Inertia weight, \( w \)           | 0.6   | Sine map |

Tables 6-7 show the parameters of the SFS, ISFS, PSO and IPSO algorithms. Table 6 are the parameters of the SFS and ISFS algorithms where the swarm size, \( n_s \), is 50; the maximum iteration number, \( \text{Iter}_{max} \), is 1000; the maximum diffusion number, \( n_{md} \), is 1. These parameters are achieved by using the meta-meta-heuristic approach.

Furthermore, Table 6 also shows the difference between the SFS and ISFS algorithms in the solution initialization, the procedure of creating a new solution and the procedure of updating the solution. These chaotic map-based modifications are to create variety in the search space of the solutions for enhancing the exploitation and exploration abilities of the ISFS algorithm through the procedures of creating a new solution and updating the solution. These are expected to improve the ISFS algorithm performance through convergence value and speed. The sine map is the chaotic map chosen and is applied in the procedures for initializing solutions, creating a new solution and updating the solution in the ISFS algorithm.

To compare and validate the effectiveness of the proposal using the ISFS algorithm-based estimation application, the PSO and IPSO algorithms are introduced and applied to estimate the model parameters and MPPs of the PV module [60]. The comparisons between the ISFS, SFS, PSO and IPSO are implemented with the same condition of the swarm size, \( n_s \), and the maximum iteration number, \( \text{Iter}_{max} \). Similarly, by using the meta-meta-heuristic, the parameters of the PSO and IPSO algorithms are shown in Table 7, where the swarm size, \( n_s \), is 50; the maximum iteration number, \( \text{Iter}_{max} \), is 1000; the individual cognition and social learning coefficients, \( c_1 \) and \( c_2 \), are both 2 respectively; the inertia weights, \( w \), are 0.6 and the sine map in the PSO and IPSO algorithms respectively. These parameters are achieved by using the meta-meta-heuristic approach. The difference between the PSO and IPSO algorithms is in the inertia weight [61], [62]. The chaotic inertia weight creates the best balance between local and global search processes. This improves the convergence performance of the PSO algorithm.

**TABLE 8. Estimation space of the model parameters and MPPs of the PV module.**

| Parameter                        | Limit |
|----------------------------------|-------|
| Source current of the PV module, \( I_{s}(A) \) | Min: 0 Max: 10 |
| Saturation current of diodes of the PV module, \( I_{sd}(mA) \) | Min: 0 Max: 1 |
| Series resistance of the PV module, \( R_s(\Omega) \) | Min: 0 Max: 2 |
| Shunt resistance of the PV module, \( R_{sh}(\Omega) \) | Min: 0 Max: 10000 |
| Ideality coefficient of diodes of the PV module, \( a \) | Min: 1 Max: 2 |
| Voltage of the PV module at the MPP, \( U_{MPP}(V) \) | Min: 0 Max: 50 |
| Current of the PV module at the MPP, \( I_{MPP}(A) \) | Min: 0 Max: 10 |

Table 8 is the estimation space of the model parameters, \( I_{ph}, I_0, R_s, R_{sh}, a, \) and MPP, \( P_{MPP}(U_{MPP}, I_{MPP}) \), of the PV module showing the minimum and maximum limitations of each estimated parameter.

**TABLE 9. Scenario of various irradiance and temperature conditions.**

| Scenario | Irradiance, \( G(W/m^2) \) | Temperature, \( T(\degree K) \) |
|----------|----------------------------|-------------------------------|
| 1        | 1000                       | 298.15                        |
| 2        | 800                        | 298.15                        |
| 3        | 600                        | 298.15                        |
| 4        | 400                        | 298.15                        |
| 5        | 200                        | 298.15                        |
| 6        | 1000                       | 323.15                        |
| 7        | 1000                       | 348.15                        |
Table 9 shows the scenarios of various irradiance and temperature conditions with $G = 200-1000$ (W/m²) and $T = 298.15-348.15$ (°K).

Table 10 is the estimation results of the model parameters and MPPs of the PV module by using the PSO, IPSO, SFS, and ISFS algorithms with $G = 200-1000$ (W/m²) and $T = 298.15-348.15$ (°K).

Figs. 5-6 show the $U-I$ and $U-P$ characteristics of the PV module obtained by the experiment and ISFS algorithm-based estimation with $G = 1000$ (W/m²) and $T = 298.15$ (°K). These characteristics confirm the estimation accuracy of the model parameters, $I_{ph} = 8.2010$ (A), $I_0 = 0.1781$ ($\mu$A), $R_s = 0.2201$ ($\Omega$), $R_{sh} = 951.9300$ ($\Omega$), $a = 1.3340$; and the MPP, $U_{MPP} = 27.0460$ (V), $I_{MPP} = 7.5699$ (A), $P_{MPP} = 204.7355$ (W) of the PV module when using the ISFS algorithm.

In another scenario with $G = 800$ (W/m²) and $T = 298.15$ (°K), Table 9, the $U-I$ and $U-P$ characteristics of the PV module obtained by the experiment and ISFS algorithm-based estimation are shown in Figs. 7-8. These characteristics confirm the estimation accuracy of the model parameters, $I_{ph} = 6.5680$ (A), $I_0 = 0.1388$ ($\mu$A), $R_s = 0.2688$ ($\Omega$), $R_{sh} = 1169.5500$ ($\Omega$), $a = 1.3170$; and the MPP, $U_{MPP} = 26.0292$ (V), $I_{MPP} = 6.2176$ (A), $P_{MPP} = 161.8392$ (W) of the PV module when using the ISFS algorithm.
If scenario 2 is compared with scenario 1, then it is realized that \( G = 1000-800 \) (W/m\(^2\)) is decreased and \( T = 298.15 \) (\(^{0}\)K) is constant. This leads to the model parameters, \( I_{ph} \), \( I_{0} \), and \( a \) decreasing and the other model parameters, \( R_{sh} \) and \( R_{s} \), increasing with the power at the MPP, \( P_{MPP} \), being reduced.

In scenario 3, the \( U-I \) and \( U-P \) characteristics of the PV module obtained experimentally are compared to the ISFS algorithm-based estimation shown in Figs. 9-10. These characteristics show that the ISFS algorithm-based estimation results of the model parameters, \( I_{ph} = 4.9390 \) (A), \( I_{0} = 0.1035 \) (\( \mu \)A), \( R_{s} = 0.3478 \) (\( \Omega \)), \( R_{sh} = 1545.8700 \) (\( \Omega \)), \( a = 1.3080 \); and the MPP, \( U_{MPP} = 25.0227 \) (V), \( I_{MPP} = 4.1730 \) (A), \( P_{MPP} = 118.3574 \) (W) of the PV module are accurate.

Scenario 3 is compared with scenarios 1 and 2. The comparison shows that \( G = 1000-600 \) (W/m\(^2\)) is decreased and \( T = 298.15 \) (\(^{0}\)K) is constant, the model parameters, \( I_{ph} \), \( I_{0} \), and \( a \) decrease and the other model parameters, \( R_{sh} \) and \( R_{s} \), increase with the power at the MPP, \( P_{MPP} \), being reduced.

The \( U-I \) and \( U-P \) characteristics for scenario 4, Figs. 11-12, validate the accuracy of the ISFS algorithm-based estimation results of the model parameters, \( I_{ph} = 3.2850 \) (A), \( I_{0} = 0.0692 \) (\( \mu \)A), \( R_{s} = 0.5179 \) (\( \Omega \)), \( R_{sh} = 2273.5800 \) (\( \Omega \)), \( a = 1.2770 \); and the MPP, \( U_{MPP} = 23.9991 \) (V), \( I_{MPP} = 3.1422 \) (A), \( P_{MPP} = 75.4100 \) (W). Scenario 4 is next compared with scenarios 1-3. The comparison shows that \( G = 1000-400 \) (W/m\(^2\)) is decreased and \( T = 298.15 \) (\(^{0}\)K) is constant. The model parameters, \( I_{ph} \), \( I_{0} \), and \( a \) decrease, the other model parameters, \( R_{sh} \) and \( R_{s} \), increase with the power at the MPP, \( P_{MPP} \), being reduced.

Similarly, the accuracy of the ISFS algorithm-based estimation results of the model parameters, \( I_{ph} = 1.5920 \) (A), \( I_{0} = 0.0352 \) (\( \mu \)A), \( R_{s} = 1.0014 \) (\( \Omega \)), \( R_{sh} = 4389.3600 \) (\( \Omega \)), \( a = 1.2390 \); and the MPP, \( U_{MPP} = 22.8106 \) (V), \( I_{MPP} = 1.5568 \) (A), \( P_{MPP} = 35.5115 \) (W) of the PV module is also confirmed in the conditions of scenario 4 through
the $U-I$ and $U-P$ characteristics Figs. 13-14. Scenario 5 is compared with scenarios 1-4. The comparison shows that $G = 1000-200$ (W/m$^2$) is decreased and $T = 298.15$ (°K) is constant. The model parameters, $I_{ph}$, $I_0$, and $a$ then decrease, the other model parameters, $R_{sh}$ and $R_s$, increase with the power at the MPP, $P_{MPP}$, being reduced.

When temperature, $T$, is constant, $T = 298.15$ (°K), and the irradiance, $G$, is decreased, $G = 1000-200$ (W/m$^2$); the model parameters, $I_{ph}$, $I_0$, and $a$ decreased, whereas the other model parameters, $R_{sh}$ and $R_s$, increased as shown in Table 10. This shows that the irradiance, $G$, and the temperature, $T$, have affected the model parameters, $I_{ph}$, $I_0$, $a$, $R_{sh}$, and $R_s$, in the model of the PV module.

Similarly, the MPPs have been influenced by the irradiance, $G$, and the temperature, $T$, as well. Then, the MPP moves in the direction that the power at the MPP, $P_{MPP}$, is reduced as in Table 10.

More specifically, Fig. 15 shows the MPPs, MPP$_1$-MPP$_5$, of the PV module which are estimated by the ISFS algorithm.
where \( MPP_1, P_{MPP1} = 204.7355 \) (W) at \( G = 1000 \) (W/m\(^2\)) and \( T = 298.15 \) (°K); \( MPP_2, P_{MPP2} = 161.8392 \) (W) at \( G = 800 \) (W/m\(^2\)) and \( T = 298.15 \) (°K); \( MPP_3, P_{MPP3} = 118.3574 \) (W) at \( G = 600 \) (W/m\(^2\)) and \( T = 298.15 \) (°K); \( MPP_4, P_{MPP4} = 75.4100 \) (W) at \( G = 400 \) (W/m\(^2\)) and \( T = 298.15 \) (°K); and \( MPP_5, P_{MPP5} = 35.5115 \) (W) at \( G = 200 \) (W/m\(^2\)) and \( T = 298.15 \) (°K).

\( G = 1000 \) (W/m\(^2\)) is constant and \( T = 298.15-323.15 \) (°K) is increased. The model parameters, \( I_{ph}, I_0 \) and \( a \), increase as well as the other model parameters, \( R_{sh} \) and \( R_s \), and the power at the MPP, \( P_{MPP} \), is reduced.

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**FIGURE 16.** \( U-I \) characteristics of the PV module obtained by experiment and ISFS algorithm-based estimation with \( G = 1000 \) (W/m\(^2\)) and \( T = 323.15 \) (°K).

**FIGURE 17.** \( U-P \) characteristics of the PV module obtained by experiment and ISFS algorithm-based estimation with \( G = 1000 \) (W/m\(^2\)) and \( T = 323.15 \) (°K).

It is assumed that \( G = 1000 \) (W/m\(^2\)) and \( T = 323.15 \) (°K) in scenario 6, the \( U-I \) and \( U-P \) characteristics of the PV module obtained by experiment and ISFS algorithm-based estimation are shown in Figs. 16-17. These characteristics confirm the estimation accuracy of the model parameters, \( I_{ph} = 8.2880 \) (A), \( I_0 = 0.2058 \) (µA), \( R_s = 0.3077 \) (Ω), \( R_{sh} = 952.1200 \) (Ω), \( a = 1.3648 \); and the MPP, \( U_{MPP} = 24.0400 \) (V), \( I_{MPP} = 7.4969 \) (A), \( P_{MPP} = 180.2255 \) (W) of the PV module by using the ISFS algorithm.

Scenario 6 of \( G = 1000 \) (W/m\(^2\)) and \( T = 323.15 \) (°K) is compared with scenario 1. The comparison shows that

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**FIGURE 18.** \( U-I \) characteristics of the PV module obtained by experiment and ISFS algorithm-based estimation with \( G = 1000 \) (W/m\(^2\)) and \( T = 348.15 \) (°K).

**FIGURE 19.** \( U-P \) characteristics of the PV module obtained by experiment and ISFS algorithm-based estimation with \( G = 1000 \) (W/m\(^2\)) and \( T = 348.15 \) (°K).

For scenario 7, the \( U-I \) and \( U-P \) characteristics of the PV module obtained by experiment and ISFS algorithm-based estimation are shown in Figs. 18-19. These characteristics validate the estimation accuracy of the model parameters, \( I_{ph} = 8.3770 \) (A), \( I_0 = 0.2176 \) (µA), \( R_s = 0.4308 \) (Ω), \( R_{sh} = 953.7500 \) (Ω), \( a = 1.3921 \); and the MPP, \( U_{MPP} = 20.9641 \) (V), \( I_{MPP} = 7.3199 \) (A), \( P_{MPP} = 153.4551 \) (W) of the PV module by using the ISFS algorithm.

Scenario 7 is then compared with scenarios 1 and 6. This comparison is where \( G = 1000 \) (W/m\(^2\)) is constant and \( T = 298.15-348.15 \) (°K) is increased. The model parameters, \( I_{ph}, I_0, \) and \( a \), and the other model parameters, \( R_{sh} \) and \( R_s \), increase, and the power at the MPP, \( P_{MPP} \), is reduced.
The above analyses show when the irradiance, $G = 1000$ (W/m$^2$), is constant and the temperature, $T = 298.15-348.15$ (°K), is increased, the model parameters, $I_{ph}$, $I_0$, and $a$, and the other model parameters, $R_{sh}$ and $R_s$, also increase as shown in Table 10. Then, the MPP is moved in the direction that the power at the MPP, $P_{MPP}$, is reduced as shown in Table 10.

More specifically, Fig. 20 shows the MPPs, MPP$_6$-MPP$_8$, of the PV module which are estimated by the ISFS algorithm where the MPP$_6$, $P_{MPP6} = 204.7355$ (W) at $G = 1000$ (W/m$^2$) and $T = 298.15$ (°K); MPP$_7$, $P_{MPP7}$ = 180.2255 (W) at $G = 1000$ (W/m$^2$) and $T = 323.15$ (°K); and MPP$_8$, $P_{MPP8}$ = 153.4551 (W) at $G = 1000$ (W/m$^2$) and $T = 348.15$ (°K). From Figs. 15 and 20, it is realized that the power of the PV module at the MPP is decreased when the irradiance, $G$, is decreased and the temperature, $T$, is constant. This is the same when the irradiance, $G$, is constant and the temperature, $T$, is increased. Table 11 shows the effect of the irradiance, $G$, and the temperature, $T$, on the power, $P_{MPP}$, achieved at the MPP of the PV module.

When the irradiance, $G$, is constant, the power, $P_{MPP}$, at the MPP is inversely proportional to the temperature, $T$ (cases 1-2); and when the temperature, $T$, is constant, the power, $P_{MPP}$, at the MPP is directly proportional to the irradiance, $G$ (cases 3 and 5). When both the irradiance, $G$, and the temperature, $T$, are decreased, the power, $P_{MPP}$, at the MPP is decreased (case 4); and when both the irradiance, $G$, and the temperature, $T$, are increased, the power, $P_{MPP}$, at the MPP increases (case 6). This observation is very useful for predicting the achieved power at the MPP, $P_{MPP}$, under various atmospheric conditions.

The estimation precision of the model parameters and MPPs of the PV module are also shown specifically through powers obtained experimentally and the PSO, IPSO, SFS and ISFS algorithm-based estimations of the PV module with $G = 1000$ (W/m$^2$) and $T = 298.15$ (°K) in Tables 12-13. Table 12 contains the powers obtained by the experiments and the PSO, IPSO, SFS and ISFS algorithm-based estimations of the PV module with $G = 1000$ (W/m$^2$) and $T = 298.15$ (°K). From these achieved powers, a comparison is performed between the powers obtained experimentally and the PSO, IPSO, SFS and ISFS algorithm-based estimations of the PV module with $G = 1000$ (W/m$^2$) and $T = 298.15$ (°K). It is observed that the characteristic of the ISFS algorithm-based estimated power nearly matches the characteristic of the experimental power in Fig. 21. The characteristics of the SFS and IPSO algorithms-based estimated powers have almost the same differences compared with the characteristic
TABLE 13. Error percentages of the obtained powers between experiment and the PSO, IPSO, SFS, and ISFS algorithm-based estimations of the PV module with $G=1000$ (W/m$^2$) and $T=298.15$ (°K).

| Data | Error percentage of estimated power (%) |
|------|----------------------------------------|
|      | PSO | IPSO | SFS | ISFS |
| 1    | 11.24 | 6.65 | 5.42 | 0.025 |
| 2    | 10.36 | 6.27 | 5.99 | 0.038 |
| 3    | 10.30 | 6.16 | 5.97 | 0.047 |
| 4    | 11.23 | 6.96 | 5.48 | 0.045 |
| 5    | 11.04 | 6.10 | 5.50 | 0.048 |
| 6    | 10.89 | 6.34 | 5.46 | 0.037 |
| 7    | 10.15 | 6.76 | 5.49 | 0.018 |
| 8    | 11.92 | 6.41 | 5.55 | 0.012 |
| 9    | 11.15 | 6.66 | 5.53 | 0.016 |
| 10   | 10.04 | 6.72 | 5.43 | 0.035 |
| 11   | 10.99 | 6.61 | 5.40 | 0.037 |
| 12   | 10.67 | 6.02 | 5.51 | 0.027 |
| 13   | 11.51 | 6.70 | 5.46 | 0.011 |
| 14   | 11.58 | 6.22 | 5.50 | 0.034 |
| 15   | 11.33 | 6.21 | 5.48 | 0.022 |
| 16   | 10.92 | 6.64 | 5.47 | 0.041 |
| 17   | 11.26 | 6.20 | 5.43 | 0.034 |
| 18   | 10.74 | 6.58 | 5.49 | 0.027 |
| 19   | 10.53 | 6.15 | 5.63 | 0.031 |
| 20   | 11.24 | 6.31 | 5.39 | 0.027 |
| 21   | 10.79 | 6.83 | 5.52 | 0.016 |
| 22   | 10.90 | 6.55 | 5.48 | 0.030 |
| 23   | 10.22 | 6.95 | 5.51 | 0.033 |
| 24   | 11.31 | 6.51 | 5.49 | 0.045 |
| 25   | 10.37 | 6.80 | 5.54 | 0.046 |
| 26   | 10.85 | 6.72 | 5.50 | 0.041 |
| 27   | 11.62 | 6.94 | 5.54 | 0.029 |
| 28   | 11.25 | 6.17 | 5.51 | 0.018 |
| 29   | 10.82 | 7.04 | 5.47 | 0.041 |
| 30   | 10.32 | 6.90 | 5.86 | 0.039 |
| 31   | 11.69 | 6.16 | 5.92 | 0.020 |
| 32   | 11.41 | 6.42 | 5.42 | 0.026 |
| 33   | 11.56 | 5.99 | 5.38 | 0.028 |
| 34   | 11.10 | 6.71 | 5.43 | 0.018 |

FIGURE 21. Powers obtained by experiment and PSO, IPSO, SFS, and ISFS algorithm-based estimations of the PV module with $G=1000$ (W/m$^2$) and $T=298.15$ (°K).

Figs. 22-23 are the error percentages of the obtained powers of the PV module with $G=1000$ (W/m$^2$) and $T=298.15$ (°K) between the experiment and the PSO, IPSO, SFS and ISFS algorithm-based estimations of data from 1 to 17 and from 18 to 34 respectively. It is realized that the error percentages of the obtained powers of the PV module with $G=1000$ (W/m$^2$) and $T=298.15$ (°K) between the experiment and the ISFS algorithm-based estimation have the smallest error percentages when compared with the error percentages of the SFS, IPSO and PSO algorithm-based estimations whereas the PSO algorithm-based results have the largest error percentages. For more detail, Table 13 shows that the error percentages of the obtained powers are always less than 0.048% with the ISFS algorithm whereas the errors are always greater than 5.38%, 5.99%, and 10.04% with the SFS, IPSO and PSO algorithms respectively. This comparison further confirms the accuracy of the ISFS algorithm-estimated parameters, as well as the significant improvement of the ISFS algorithm-based estimation results compared to the PSO, IPSO and SFS algorithm-based estimation results.
This shows the effectiveness of improvements in the proposed procedures of initializing solutions, creating a new solution and updating the solution based on chaotic maps.

**TABLE 14.** Convergence of The PSO, IPSO, SFS, and ISFS algorithms in the estimation application of the model parameters and MPP with $G = 1000$ (W/m$^2$) and $T = 298.15$ ($^o$K).

| Algorithm | Convergence value | Convergence iteration number |
|-----------|------------------|----------------------------|
| PSO       | 0.0088           | 538                        |
| IPSO      | 0.0036           | 426                        |
| SFS       | 0.0021           | 404                        |
| ISFS      | 0.000062         | 216                        |

Table 14 shows the convergence value and iteration number of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP with the scenario of $G = 1000$ (W/m$^2$) and $T = 298.15$ ($^o$K). In this scenario, the convergence value and iteration number are significantly improved when utilizing the ISFS algorithm in the estimation application. The convergence value of the ISFS algorithm, 0.000062, is better than the convergence values, 0.0021, 0.0036, and 0.0088, of the SFS, IPSO and PSO algorithms respectively. Additionally, the convergence iteration number of the ISFS algorithm, 216, is also better than the convergence iteration numbers, 404, 426 and 538, of the SFS, IPSO and PSO algorithms respectively.

**Fig. 24.** Convergence characteristics of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP with $G = 1000$ (W/m$^2$) and $T = 298.15$ ($^o$K).

In the scenario with $G = 800$ (W/m$^2$) and $T = 298.15$ ($^o$K), Table 15 shows the convergence value and iteration number of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP. The convergence value of the ISFS algorithm is 0.000058 compared with the convergence values, 0.0026, 0.0032, and 0.0092 of the SFS, IPSO and PSO algorithms respectively. Furthermore, the convergence iteration number of the ISFS algorithm is 207 compared with the convergence iteration numbers, 415, 421 and 529 of the SFS, IPSO and PSO algorithms respectively. The comparisons show that the convergence of the ISFS algorithm is significantly improved in the estimation application of the model parameters and MPP with $G = 800$ (W/m$^2$) and $T = 298.15$ ($^o$K) because of the improved procedures of initializing solutions, creating a new solution, and updating the solution. The solution initialization of the ISFS algorithm is better than that of the SFS, IPSO and PSO algorithms through the sine map, Fig. 25. This is one of the advantages of the ISFS algorithm which is that the convergence iteration number is always less than that of the SFS, IPSO and PSO algorithms.

**TABLE 15.** Convergence of The PSO, IPSO, SFS, and ISFS algorithms in the estimation application of the model parameters and MPP with $G = 800$ (W/m$^2$) and $T = 298.15$ ($^o$K).

| Algorithm | Convergence value | Convergence iteration number |
|-----------|------------------|----------------------------|
| PSO       | 0.0092           | 529                        |
| IPSO      | 0.0032           | 421                        |
| SFS       | 0.0026           | 415                        |
| ISFS      | 0.000058         | 207                        |

**Fig. 25.** Convergence characteristics of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP with $G = 800$ (W/m$^2$) and $T = 298.15$ ($^o$K).

Fig. 24 shows that the solution initialization of the ISFS algorithm is better than that of the SFS, IPSO and PSO algorithms. This confirms the effectiveness of the proposal in the sine map-based initialization procedure of solutions. The improvements are also shown in the procedures of creating a new solution and updating the solution to retain the balance between the exploration and exploitation of globally optimal solutions.

Similarly, when $G = 600$ (W/m$^2$) and $T = 298.15$ ($^o$K), the convergence characteristics of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP are shown in Fig. 26. This shows that
TABLE 16. Convergence of The PSO, IPSO, SFS, and ISFS algorithms in the estimation application of the model parameters and MPP with $G = 600$ (W/m$^2$) and $T = 298.15$ ($^\circ$K).

| Algorithm | Convergence value | Convergence iteration number |
|-----------|------------------|----------------------------|
| PSO       | 0.0090           | 534                        |
| IPSO      | 0.0034           | 425                        |
| SFS       | 0.0025           | 410                        |
| ISFS      | 0.000060         | 212                        |

The convergence characteristic of the ISFS algorithm is better than that of the SFS, IPSO and PSO algorithms, especially in the solution initialization. Table 16 shows the convergence value and iteration number of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP with $G = 600$ (W/m$^2$) and $T = 298.15$ ($^\circ$K). The convergence value of the ISFS algorithm, 0.000060, is better than the convergence values, 0.0025, 0.0034 and 0.0090 of the SFS, IPSO and PSO algorithms respectively. The convergence iteration number of the ISFS algorithm, 212, is better than the convergence iteration numbers, 410, 425 and 534 of the SFS, IPSO and PSO algorithms respectively. Both the convergence value and iteration number of the ISFS algorithm are better than those of the SFS, IPSO and PSO algorithms.

This is similar to the convergence characteristics for the scenarios of $G = 400$ (W/m$^2$) and $T = 298.15$ ($^\circ$K), Fig. 27, and $G = 200$ (W/m$^2$) and $T = 298.15$ ($^\circ$K), Fig. 28. The above scenarios assumed that $G$ is decreased and $T$ is constant. The convergence characteristics of the ISFS algorithm with the sine map-based solution initialization are also better than the convergence characteristics of the SFS, IPSO and PSO algorithms. This shows that the performance of the ISFS algorithm is not dependent on the conditions of $G$ and $T$. It is always better than the performance of the SFS, IPSO and PSO algorithms.

Table 17 shows the convergence value and iteration number of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP with $G = 400$ (W/m$^2$) and $T = 298.15$ ($^\circ$K).
0.0089, of the SFS, IPSO and PSO algorithms respectively. The convergence iteration number of the ISFS algorithm, 214, is better than the convergence iteration numbers, 407, 429 and 537, of the SFS, IPSO, and PSO algorithms respectively.

TABLE 18. Convergence of The PSO, IPSO, SFS, and ISFS algorithms in the estimation application of the model parameters and MPP with. \( G = 200 \text{ (W/m}^2\text{)} \) and \( T = 298.15 \text{ (°K)} \).

| Algorithm | Convergence value | Convergence iteration number |
|-----------|-------------------|-----------------------------|
| PSO       | 0.0091            | 537                         |
| IPSO      | 0.0037            | 429                         |
| SFS       | 0.0022            | 413                         |
| ISFS      | 0.000073          | 221                         |

Moreover, Table 18 shows the convergence value and iteration number of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP with \( G = 200 \text{ (W/m}^2\text{)} \) and \( T = 298.15 \text{ (°K)} \). As with the scenarios of \( G = 400 \text{ (W/m}^2\text{)}, 600 \text{ (W/m}^2\text{)}, 800 \text{ (W/m}^2\text{)} \) and \( 1000 \text{ (W/m}^2\text{)} \), the convergence value of the ISFS algorithm, 0.000073, is better than the convergence values, 0.0022, 0.0037 and 0.0091, of the SFS, IPSO and PSO algorithms respectively. In addition, the convergence iteration number of the ISFS algorithm, 221, is better than the convergence iteration numbers, 413, 429 and 537, of the SFS, IPSO and PSO algorithms respectively.

In another scenario, the irradiance, \( G \), is assumed to increase to 1000 (W/m\(^2\)) which is compared with the previous scenarios of 800 (W/m\(^2\)), 600 (W/m\(^2\)), 400 (W/m\(^2\)) and 200 (W/m\(^2\)), as well as the temperature, \( T \), is assumed to increase to 323.15 (°K) compared with the previous scenario of 298.15 (°K).

TABLE 19. Convergence of The PSO, IPSO, SFS, and ISFS algorithms in the estimation application of the model parameters and MPP with. \( G = 1000 \text{ (W/m}^2\text{)} \) and \( T = 323.15 \text{ (°K)} \).

| Algorithm | Convergence value | Convergence iteration number |
|-----------|-------------------|-----------------------------|
| PSO       | 0.0087            | 546                         |
| IPSO      | 0.0028            | 431                         |
| SFS       | 0.0019            | 423                         |
| ISFS      | 0.000055          | 219                         |

Table 19 shows the convergence value and iteration number of the PSO, IPSO, SFS and ISFS algorithms in the estimation application of the model parameters and MPP with \( G = 1000 \text{ (W/m}^2\text{)} \) and \( T = 323.15 \text{ (°K)} \). The convergence value of the ISFS algorithm, 0.000055 is better than the convergence values, 0.0019, 0.0028 and 0.0087, of the SFS, IPSO and PSO algorithms respectively. Additionally, the convergence iteration number of the ISFS algorithm, 219, is better than the convergence iteration numbers, 423, 431 and 546, of the SFS, IPSO and PSO algorithms respectively. This is also shown through the convergence characteristics of the ISFS, SFS, IPSO and PSO algorithms, Fig. 29. It is realized that the effectiveness of the improved procedures of initializing solutions, creating a new solution and updating the solution is re-confirmed, especially the procedure of sine map-based solution initialization.

An additional scenario is presented to validate the proposal where the irradiance, \( G \), is assumed to increase to 1000 (W/m\(^2\)) compared with the previous scenarios of 800 (W/m\(^2\)), 600 (W/m\(^2\)), 400 (W/m\(^2\)) and 200 (W/m\(^2\)), and the temperature, \( T \), is assumed to increase to 348.15 (°K) compared with the previous scenarios of 323.15 (°K) and 298.15 (°K).

TABLE 20. Convergence of The PSO, IPSO, SFS and ISFS Algorithms in the estimation application of the model parameters and MPP with \( G = 1000 \text{ (W/m}^2\text{)} \) and \( T = 348.15 \text{ (°K)} \).

| Algorithm | Convergence value | Convergence iteration number |
|-----------|-------------------|-----------------------------|
| PSO       | 0.0096            | 521                         |
| IPSO      | 0.0043            | 418                         |
| SFS       | 0.0038            | 397                         |
| ISFS      | 0.000076          | 206                         |
The error percentages of the ISFS algorithm-based power estimations are significantly less compared to the ones obtained from the SFS, IPSO and PSO algorithms.

In addition, the estimation results of the model parameters and the MPP of the PV module are also confirmed through the performance of the ISFS, SFS, IPSO and PSO algorithms. The performance of the ISFS algorithm is always better than that of the SFS, IPSO and PSO algorithms in the estimation of the model parameters and the MPP of the PV module in terms of the convergence value and iteration number.

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