Enhanced social network search algorithm with powerful exploitation strategy for PV parameters estimation

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Abstract
In this paper, an enhanced social network search algorithm (ESNSA) has been proposed to model the solar photovoltaic (PV) modules accurately and efficiently. The proposed algorithm is introduced to minimize the least root-mean-square error (RMSE) between the calculated and experimental data for the single, double, and triple diode models of Kyocera KC200GT, STM6(40/36), and Photowatt-PWP201 modules. The original SNSA was inspired by users on social networks and their many moods, including imitation, conversation, disputation, and innovation mood. Two strategies are presented for the ESNSA. The first strategy is the powerful exploitation strategy (PES), which is intended to increase the SNSA’s performance by boosting searching around the best view of all users. The second strategy is to suggest an adaptable parameter to aid in the exploitation of iterations in the end. Diverse comparisons and statistical analyses for validation purposes are carried out for mono-crystalline STM6(40/36), multicrystalline KC200GT, and polycrystalline photowatt-PWP201 modules. The comparative studies and statistical measures show the consistency and accurateness of the proposed ESNSA. As a numerical application, for the mono-crystalline STM6(40/36) PV module, the proposed ESNSA achieves the least RMSE of 1.751631E−3, 1.769953E−3, and 1.696504E−3, respectively for the three models. Also, it shows high robustness compared to the original SNSA as it acquires the least standard errors for the three models of 2.56E−18, 1.76E−6, and 1.24E−5, respectively. Moreover, the proposed ESNSA provides a higher convergence speed where it is approximately reached to the least RMSE in less than 60%, 50%, and 60% of the iterations for the three models, respectively. Nevertheless, the proposed ESNSA provides better performance than miscellaneous published approaches in minimizing the RMSE, with high robust indices.

KEYWORDS
powerful exploitation strategy, PV parameters estimation, social network search algorithm, triple diode modeling
1 | INTRODUCTION

Nowadays, fossil fuels are considered the primary source of electricity production. However, the depletion of these resources, their environmental pollution, and increased electrical energy demand create a necessity for increasing the use of renewable energy besides the nonrenewable resources. These renewable energy resources reduce CO2 emission related to electricity generation and consequently they are environmentally friendly and do not cause pollution. This requires attention to renewable energy resources such as solar, wind, and geothermal energy to make the future sources. These new energy sources are environmentally friendly, nonpolluting, and cost-effective, with great reliability. As a result, these energy sources have been hybridized and optimally constructed to meet the desired load using HOMER software. Photovoltaic (PV) is one of the solar green energies that can produce electricity from sunlight via different types of solar cells. In comparison to wind energy, there has been a significant expansion in solar PV capacity, due to its simplicity, throughout the world. It is noteworthy that approximately 80% of global PV systems have been installed in the previous 5 years, with PV capacity already reaching 500 GW and predicted to approach 1 TW by 2022, with a yearly growth rate of 25%-30%.

It is required to develop accurate modeling of PVs to be used in diverse applications. The overall performance of the PV system relies on its unidentified parameters, and it plays a pivotal role in the simulation, control, and optimization of PV power generation cases. Lots of models using the equivalent circuit method have been developed by scientists, in the last two decades, to attain PV systems’ characteristics in diverse conditions and emulate PV systems. These models are single diode (SDM), double diodes (DDM), and three diode (TDM) models. Because of the nonlinearity and intermittence of the meteorological data, the cell parameters can change with the external environment which makes the PV cell parameters’ extraction as a significant challenge. Accordingly, it is essential to develop a feasible and efficient technique to extract the parameters of the PV systems from the current-voltage measurement data.

To estimate the parameters of solar PV models, two types of techniques have been utilized which are analytical techniques and numerical techniques. In the analytical methods, the information manifested in the manufacturers’ data-sheet is essentially used to models $I-V$ characteristics such as short circuit current, open-circuit voltage, maximum power voltage, and maximum power current. Although the analytical methods are easy to implement, their accuracy depends significantly on the readings of designated variables, and if the values are incorrect, a result with large inaccuracy will appear in certain circumstances.

The researchers have proposed numerical methods to address the demerits of the analytical techniques. They take into consideration all measured $I-V$ points which raise confidence level. Two categories of numerical methods have been illustrated: deterministic and meta-heuristic. The deterministic techniques include the Newton–Raphson approach, Lambert W-functions, and the iterative curve fitting. Many model constraints, such as convexity and differentiability, must be met by these techniques. However, because of their sensitivity to beginning settings, they may become trapped in the local optimum solution. The second category is meta-heuristic algorithms which have been extensively applied in the last decade for PV parameter estimation. Most of the meta-heuristic algorithms are probabilistic and population-based optimizers that are commonly inspired by nature. The meta-heuristic algorithms have lots of merits such as they do not require continuity, convexity, or differentiability of objective functions. Myriads of meta-heuristic algorithms have been successfully implemented for the PV models’ parameter extraction involving simulated annealing (SA), three point-based approaches (TPBA), hybridized cuckoo search/biogeography-based-optimizer (BHCS), improved teaching-learning-based optimizers (ITLBO), improved CS algorithm (ImCSA), improved shuffled complex evolution (ISCE), logistic chaotic Rao optimization algorithm (LCROA), enhanced leader particle swarm optimization (EPSO), fractional chaotic ensemble PSO (FC-EPPO) algorithm, bat algorithm (BA), novel BA (NBA), and directional BA (DBA), artificial electric field algorithm (AEFA), grey wolf optimization (GWO), Rao algorithm (RAO), PSO, supply demand optimization, slime mold algorithm (SMA), lightning attachment procedure optimizer (LAPO), hybridized firefly with pattern search techniques (HFAPS), forensic-based investigations (FBI) algorithm, and artificial ecosystem-based optimizer (AEO).

Additional improvements have been proposed to the meta-heuristics by emerging two or more optimizers that can enhance the performance of the individual algorithm, and consequently enhance the effectiveness and attractiveness when applying to complex optimization problems. In Chen and Yu, a CSA has been merged with biogeography-based optimization and applied on the SDM and DDM. Additionally, an improved whale optimization algorithm (WOA) with a balance between local exploitation and global exploration has been employed on both SDM and DDM. To precisely describe the $I-V$ and $P-V$ curves, a custom neural network, in
Sabry et al. was used to investigate the performance of a PV module under certain weather circumstances. However, to suit the PV module data in this study, numerous common mathematical model formulations, including Gaussian, exponential, and polynomial models, should be used first. In Chen et al., a maximum power tracking controlling scheme of PV module has been presented where the Lévy flight tactic was integrated with quantum PSO to change the particles mutation equation and boost their diversity in the population.

In Chen et al., the opposition-based learning scheme and the Nelder-mead simplex concept have been combined with sine cosine algorithm and applied on SDM and DDM. Furthermore, multiple learning backtracking search (MLBS) algorithms, improved shuffled complex evolution algorithm (ISCE) and TLBO-artificial bee colony, were employed to estimate the parameters of SDM and DDM via diverse experimental data sets. In Rizk-Allah Rizk and El-Fergany, searching-based learning strategies and hill-climbing strategies have been added to heap-based optimizer and employed on TDM. An improved opposition-based WOA has been presented to extract the parameters of SDM, DDM, and TDM. However, after semilarge iterations' number, it approximately reached stability. Therefore, most of these algorithms need a large number of iterations to converge since they depend on numerous control parameters.

From the previous literature, it is obvious that several approaches have been used to estimate the characteristics of the PV module reliably and precisely; nevertheless, additional research into the reliability and accuracy of these techniques is still needed. In addition, the accurate modeling of PV modules using the triple diode model is required to be enhanced. Consequently, an enhanced social network search algorithm (ESNSA) is proposed in this study for estimating these electrical parameters considering the single, double, and triple diode models. The original SNSA is motivated by users on social networking in various moods such as conversation, imitation, innovation, and disputation that used to share the new views of users about a new event. In this paper, SNSA’s performance is enhanced via two modifications. First, a powerful exploitation strategy (PES) is designed to boost the search around the best view of all users. Second, since the support of exploitation is required at the late stage of iterations, an adaptive parameter is designed for this process. As this parameter increases, more support to the exploitative characteristic increases via the presented powerful exploitation strategy. The original SNSA and the proposed ESNSA are established in Section 3, while Section 4 characterizes the discussion and simulation results for three modules. Lastly, Section 5 provides a conclusion remark for this study.

2 PROBLEM FORMULATION

For decades, the most widespread representation of solar cells is the Shockley-diode-based equivalent circuits. In industrial applications, the nonlinear I–V characteristics of PV systems are illustrated when using SDM, DDM, and TDM. The properties of each model are manifested in the next section. The output current (I), in these models, is assessed from the module output voltage (V) at a certain temperature and irradiation where the whole I–V characteristic curve is attained.

2.1 SDM

The SDM is extensively utilized to represent the features of solar cells. In the equivalent circuit of SDM, the PV cell is represented as the current source and put in parallel with a single diode. The losses are characterized by two lumped resistors: series resistance ($R_s$) and shunt resistance ($R_{sh}$). In accordance with the Shockley diode equation, the output current (I) can be denoted as follows,
where \( \eta_1 \) and \( I_{S1} \) define the ideality factor and the reverse saturation current of the diode, respectively, while \( I \) and \( I_{ph} \) express the output current and photocurrent of the cell, respectively. Moreover, \( V \) and \( V_{th} \) characterize the terminal voltage and the thermal voltage of the PV cell, whilst \( R_S \) and \( R_{sh} \) manifest the series resistance and the shunt resistance, respectively. The thermal voltage \( (V_{th}) \) can be assessed as follows:

\[
V_{th} = \frac{K_BT}{q},
\]

where \( K_B \) designates the Boltzmann’s constant; the symbols \( (T) \) and \( (q) \) depict, respectively the absolute temperature and the electron’s charge. In this model, there are five unidentified parameters \( (I_{ph}, I_{S1}, \eta_1, R_p, \) and \( R_S) \). These five parameters are required to be projected using the PV cell’s \( I-V \) data.

### 2.2 DDM

This model can be represented by two parallel diodes, photo-current source, and series and shunt resistances. The \( I-V \) relationship can be manifested according to Shockley diode equations for the two diodes, and the output current is denoted as:

\[
I = I_{ph} - \frac{V + IR_S}{R_{sh}} - I_{S1}\left[\exp\left(\frac{V + IR_S}{\eta_1 V_{th}}\right) - 1\right] - I_{S2}\left[\exp\left(\frac{V + IR_S}{\eta_2 V_{th}}\right) - 1\right],
\]

where \( \eta_2 \) and \( I_{S2} \) define the ideality factor and the reverse saturation current of the second diode, respectively. Thus, there are seven unidentified parameters \( (I_{ph}, I_{S1}, I_{S2}, \eta_1, \eta_2, R_p, \) and \( R_S) \), which are required to be projected using the PV cell’s \( I-V \) data.

### 2.3 TDM

This model can be represented by three parallel diodes, photo-current source, and series and shunt resistances as displayed in Figure 1. The \( I-V \) relationship of this model can be manifested according to Shockley diode equations for the three diodes and the output current is denoted as follows:

\[
I = I_{ph} - \frac{V + IR_S}{R_{sh}} - I_{S1}\left[\exp\left(\frac{V + IR_S}{\eta_1 V_{th}}\right) - 1\right] - I_{S2}\left[\exp\left(\frac{V + IR_S}{\eta_2 V_{th}}\right) - 1\right] - I_{S3}\left[\exp\left(\frac{V + IR_S}{\eta_3 V_{th}}\right) - 1\right],
\]

where \( \eta_3 \) and \( I_{S3} \) defines the ideality factor and the reverse saturation current of the third diode, respectively. There are nine parameters \( (I_{ph}, I_{S1}, I_{S2}, I_{S3}, R_S, R_{sh}, \eta_1, \eta_2, \) and \( \eta_3) \), in the TDM, which require to be projected using the PV cell’s \( I-V \) data.

### 2.4 Objective function formulation

The difference between \( I-V \) curves can be developed by the RMSE and formulated as illustrated as follows:

\[
\text{RMSE} = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \left[ I_{exp}^j - I_{cal}^j(V_{exp}, X) \right]^2},
\]

where \( I_{exp}^j \) and \( V_{exp} \) characterize, respectively the values of current and voltage related to the \( j \)th experimental reading, while \( M \) defines the data readings’ number. Also, \( X \) designates the optimization problem’s decision parameters. Accordingly, the expression \( (I_{cal}^j(V_{exp}, X)) \) denotes the calculated current output.

### 3 ENHANCED SOCIAL NETWORK SEARCH ALGORITHM

#### 3.1 Original SNSA

The SNSA is inspired by users in social networks, where they attempt to be popular via several moods of imitation, conversation, disputation, and innovation. These moods are mechanisms used to share the new views of users about a new event. Mathematical modeling and explanation of such moods are illustrated as follows.
3.1.1 I Imitation mood

In this mood, if there is a new event with an interesting idea, the users can mimic the famous persons who express their opinions by striving to post a topic. This mood is mathematically formulated in Equation (6):

\[
X_{i,\text{new}} = X_j + \text{rand}(-1, 1) \times R,
\]

\[
R = \text{rand}(0, 1) \times r,
\]

\[
r = X_i - X_j,
\]

where \(X_i\) and \(X_j\) refer, respectively, to the current \(i\)th view of the user and a randomly selected view of the user, where \(i \neq j\). \(\text{rand}(-1, 1)\) and \(\text{rand}(0, 1)\) are, respectively, random vectors inside the ranges \([-1, 1]\) and \([0, 1]\). Moreover, \((R)\) represents the shock radius that establishes imitation space, and \((r)\) reveals the popular radius of user \(j\).

3.1.2 Conversation mood

In this mood, users can increase the information about an event by gaining knowledge from each other and exploring thoughts about the event through other views, then they can develop a new sight of the event. This mood can be mathematically formulated as follows:

\[
X_{i,\text{new}} = X_k + R,
\]

\[
R = \text{rand}(0, 1) \times D,
\]

\[
D = \text{sign}(f_i - f_j) \times (X_i - X_j),
\]

where \(X_i\) and \(X_j\) are two random selected views of users. \(D\) depicts the disparity in user views, whereas \(X_k\) indicates the current vector of view of the \(i\)th user, where \(i, j,\) and \(k\) are not equal. Furthermore, the expression \((\text{sign}(f_i - f_j))\) provides the sign function of the difference between \(f_i\) and \(f_j\) that depicts the movement direction of \(X_k\). It is worth noting that the user’s perspective on the event shifts as a result of talks with the \(j\)th user.

3.1.3 Disputation mood

In this mood, the users can describe their beliefs through comments or forming groups sections and defend themselves about it; however, they can be affected by other commenters or participants of a virtual community formed to debate a certain point of view. The new affected view is formulated as follows:

\[
X_{i,\text{new}} = X_i + \text{rand}(0, 1) \times (M_x - (\text{AF} \times X_i)),
\]

\[
M_x = \frac{\sum_{m=1}^{N} X_m}{N},
\]

\[
\text{AF} = 1 + \text{round}(-\text{rand}(0, 1)),
\]

where \(M_x\) is the average of the opinions of members in the commentators, and \(\text{AF}\) is the admitting effect that demonstrates the statement from users on the viewpoint in talks and is expressed as an integers value of 1 or 2. The symbol (round) adjusts the real input to the nearest integer value, while \((N)\) specifies population numbers.

3.1.4 Innovation mood

In this mood, the individuals share their personal beliefs and experiences about a specific event in creative and innovative ways. Therefore, a novel idea is produced, and the new affected view can be formulated as follows:

\[
X_{i,\text{new}} = tX_j^d + (1 - t) \times n_j^d,
\]

\[
n_j^d = \text{LB}^d + \text{rand}(0, 1) \times (\text{UB}^d - \text{LB}^d),
\]

\[
t = \text{rand}(0, 1),
\]

where \(d\) indicates the \(d\)th variable; \(\text{UB}^d\) and \(\text{LB}^d\) represent the upper and lower boundaries for each dimension \(d\); \(n_j^d\) is a new created view for each dimension \(d\); \(X^d_j\) refers to the \(j\)th view for each dimension \(d\) by another user where \(i \neq j\). \(X_{i,\text{new}}\) comprises an interchange between a pre-existing idea \((n_j^d)\) and the newer thinking \((n_j^d)\).

Accordingly, a modification inside one dimension \((X_{i,\text{new}}^d)\) generates a generalized shift in the fundamental notion that may be seen as a new point of view to be conveyed. Therefore, this process is mathematically formulated as:

\[
X_i = \begin{bmatrix} x_{i,1}^1 \ x_{i,2}^2 \ ... \ x_{i,d}^d \end{bmatrix},
\]

\[
X_{i,\text{new}} = \begin{bmatrix} x_{i,1}^1 \ x_{i,2}^2 \ ... \ x_{i,d}^d \ x_{i,d,\text{new}} \ ... \ x_{i,D}^D \end{bmatrix},
\]

where \(X_i\) and \(X_{i,\text{new}}\) are the old and new view of user \(i\); \(x_{i,d}^d\) and \(x_{i,d,\text{new}}^d\) are the old and new \(d\)th variable in the interval \([1, D]\) of user \(i\) while \(D\) manifests the problem variables’ number.

As depicted in Equation (10), \(x_{i,d,\text{new}}^d\) represents a modification within one dimension \((d)\) and substituted with the existing dimension \(x_{i,d}^d\). Thus, a new perspective on the event is developed in line with the \(d\)th viewpoint.
3.1.5 | Network rules

A set of rules are defined by each social network and these rules are considered by the users in sharing their viewpoints. Limitation of the users’ views is developed according to:

\[ X_{i,\text{new}} = \min(X_{i,\text{new}}, UB^d) \text{ and } X_{i,\text{new}} = \max(X_{i,\text{new}}, LB^d), \quad d = 1, 2, ..., D, \quad i = 1, 2, ..., N. \] (11)

3.1.6 | Replacement strategy

The mechanism of the SNSA is developed with diverse moods, whereas the opinion of each user will be changed, and new view are used depending on its worth. To illustrate, if the new thought is better than the existing thought, it will be accepted. Hence, the value of a new idea can be evaluated via its obtained objective function of \( X_{\text{new}} \) that can be mathematically computed and contrasted to the exiting one (\( X_i \)) as follows:

\[ X_i = \begin{cases} X_i, & f(X_{i,\text{new}}) > f(X_i), \\ X_{i,\text{new}}, & f(X_{i,\text{new}}) < f(X_i), \end{cases} \] (12)

To implement the algorithm, the number of users \( N \), the number of iterations \( \text{MaxIter} \), and limits of the variables have to be exhibited, whereas the initial view for the users is established via Equation (13):

\[ X_i = LB + \text{rand}(0, 1) \times (UB - LB), \] (13)

where \( X_i \) is the basic view vector for the user \( i \), and UB and LB constitute the upper and lower boundaries, accordingly. The key stages of the standard SNSA are shown in Figure 2.

3.2 | ESNSA with powerful exploitation strategy

In this section, an ESNSA with a PES is proposed to enhance the performance of the SNSA.

SNSA’s performance is enhanced via two modifications. First, a PES is designed to boost the search around the best view of all users. Thus, the updating mechanism of the standard SNSA is modified, and the views of some users will be updated as follows:

\[ X_{i,\text{new}}^d = X_{\text{best}}^d + t \times r, \]
\[ r = X_i - X_j, \]
\[ t = \text{rand}(0, 1), \] (14)

where \( X_{\text{best}} \) is the best view over all users in each iteration that achieves the minimum fitness value.

Second, since the support of exploitation is required at the late stage of iterations, an adaptive parameter \( (\alpha) \) is designed via Equation (15):

\[ \alpha = \frac{t}{2 \times T_{\text{max}}}. \] (15)

From this formula, the parameter \( (\alpha) \) is increased linearly with the increase of iterations until it is reached to 0.5 at the maximum number of iterations. As this parameter increases, more support to the exploitative characteristic increases via the presented PES. Figure 3 describes the main steps of the proposed ESNSA. Also, a pseudo-code is added in the appendix in the manuscript illustrating the code steps in detail. As shown, the steps of ESNSA application for optimal PV parameters estimation can be summarized as follows:

Step 1: Load the experimental data of the studied PV module or cell.
Step 2: Defining the population number, the iterations maximum number, and the limits of the control variables.
Step 3: Level 1 (Initialization): Randomly initiate the individual of each view of the user, which represents the control variables. These variables are the unidentified parameters of the PV module or cell which are different based on the PV model. For the SDM, five unidentified parameters are handled \( (I_{ph}, I_{S1}, \eta_1, R_P, \text{and } R_S) \). For the DDM, seven unidentified parameters are handled \( (I_{ph}, I_{S1}, I_{S2}, \eta_1, \eta_2, R_P, \text{and } R_S) \). For the TDM, nine unidentified parameters are handled \( (I_{ph}, I_{S1}, I_{S2}, I_{S3}, R_S, R_{sh}, \eta_1, \eta_2, \text{and } \eta_3) \).
Step 4: The fitness function of the overall RMSE is evaluated using Equation (5).
Step 5: Level 2 (increasing popularity): Update the individuals via one of the four moods.
Step 6: Check for the violated variables to set to the nearest bound using Equation (11).
Step 7: Check the new view by the network rules using Equation (12).
Step 8: Evaluate the fitness function of the overall RMSE is evaluated using Equation (5).
Step 9: Level 3 (termination criteria): Repeat Steps 5–8 until reaching the maximum iteration numbers.
As demonstrated, the suggested PES of Equation (14) is not triggered until over half of the iterations have been completed. This status preserves the ESN- SA’s strong diversification capacity in identifying new potential sectors. Furthermore, the suggested PES is merged in an increasing probability since the parameter ($\alpha$) is increased linearly as the number of iterations increases. As a result, the more iterations there are, the more the search is focused on the region surrounding the greatest view of the users. This stage promotes exploitation while also allowing for diversity in the discovery of new viable locations. Based on this mechanism, considerable assistance is suggested to the standard SNSA to improve the searching ability around the best perspective of the users, with the objective of improving its global search capabilities and avoiding being caught in a local optimum.
In this section, the proposed ESNSA and the original SNSA are used for STM6(40/36), KC200GT, and Photowatt-PWP201 to derive the electrical parameters of the three models. Two PV modules are considered, which are monocrystalline STM6(40/36) with 36 cells and multicrystalline KC200GT with 54 cells with temperatures of 51 and 25°C, accordingly, have irradiation of 1000 W/m². Polycrystalline Photowatt-PWP201 is the
third module, which has 36 cells in series at irradiation of 1000 W/m² and temperature of 45°C. For these three modules, the upper (UB) and lower (LB) limits of the PV parameters are illustrated in Table 1.

### 4.1 STM6(40/36) PV module

For this PV module, the proposed ESNSA and the original SNSA are applied 30 times considering the SDM, DDM, and TDM. Table 2 lists their obtained definitive five, seven, and nine SDM, DDM, and TDM parameters recovered by the proposed ESNSA and the original SNSA, respectively. Also, this table illustrates the minimum value of RMSE related to the parameters of each model. The optimal adaption value for the SDM is 1.751631E−3 for the original SNSA approach and 1.729814E−3 for the suggested ESNSA technique, as shown in Table 2. Also, the best adaption values for the DDM derived by the original SNSA and the suggested ESNSA approaches are 1.769953E−3 and 1.696504E−3, respectively. Furthermore, the best adaption values for the TDM derived by the original SNSA and the suggested ESNSA approaches are 2.30797E−3 and 1.702455E−3, respectively. Therefore, the proposed ESNSA provides better performance in minimizing the RMSE for three models compared to the SNSA.

For a detailed statistical comparison between the proposed ESNSA and the original SNSA, Table 3 shows the five metrics (best, average, worst, standard deviation, and standard error). As shown, the proposed ESNSA has better stability and search accuracy than the original SNSA since:

1. The proposed ESNSA acquires the least average RMSE of 1.729814E−3, 1.719878E−3, and 1.73768E−3, respectively for the SDM, DDM, and TDM while the original SNSA obtains average RMSE of 1.896078E−3, 2.235356E−3, and 2.829747E−3, respectively.
2. Also, the proposed ESNSA acquires the least worst RMSE of 2.052124E−3, 1.729814E−3, and 1.729814E−3 for the SDM, DDM, and TDM, respectively.
3. Moreover, the proposed ESNSA acquires lower standard deviations and errors than the original SNSA. The standard errors of SDM, DDM, and TDM for the original SNSA and the proposed ESNSA, as shown in this table, are (1.66E−5, 2.56E−18), (5.35E−5, 1.76E−6), and (6.08E−5, 1.24E−5), respectively.

On the SDM, DDM, and TDM, 30 runs for both the original SNSA and the proposed ESNSA have been developed, as shown in Figure 4. For the three models described,
the results of the 30 runs reveal that the suggested ESNSA is more resilient than the original SNSA. It shows the high robustness of the proposed ESNSA compared to the original SNSA for the three mentioned models.

Furthermore, a comparative assessment has been developed in Table 4 between the proposed ESNSA, the original SNSA, and other recently reported techniques which are SA, TPBA, BHCS, ITLBO, ImCSA, and ISCE, LCROA, EPSO, FC-EPSO algorithms, hybrid successive discretization algorithm (HSDA), BA, NBA, DBA, and SNSA provides higher minimum RMSE with 1.7120E−3, 1.8307E−3, 1.7720E−3, 2.1946E−2, 1.8268E−3, 1.7320E−3, and 1.7700E−3, respectively.

For the TDM, the proposed ESNSA provides the minimum, mean, and maximum RMSE of 1.7025E−3, 1.7377E−3, and 2.0521E−3, respectively. On the other side, the AEFA obtains a closer value of minimum RMSE of 1.7203E−3 but the related mean and maximum were not recorded while the SNSA provides the minimum, mean, and maximum RMSE of 2.30797E−3, 2.829747E−3, and 3.346434E−3, respectively.

Moreover, the convergence characteristics shown in Figures 5–7 illustrate that the proposed ESNSA expresses a strong performance compared to the original SNSA for the three models. As shown, the speed of convergence of the proposed ESNSA is very high compared to the original SNSA where the proposed ESNSA has approximately reached the least fitness in less than 60%, 50%, and 60% of the iterations for the SDM, DDM, and TDM, respectively. On the other side, the original SNSA is still improving the fitness value even with 100% of the iterations.

| TABLE 3 | Statistical indices of SNSA and proposed ESNSA for STM6(40/36) PV module |
|---|---|
| **RMSE** | **SDM** | **Proposed ESNSA** | **DDM** | **Proposed ESNSA** | **TDM** | **Proposed ESNSA** |
| **Best** | 1.751631E−3 | 1.729814E−3 | 1.769953E−3 | 1.729814E−3 | 2.30797E−3 | 1.702455E−3 |
| **Average** | 1.896078E−3 | 1.729814E−3 | 2.235356E−3 | 1.719878E−3 | 2.829747E−3 | 1.73768E−3 |
| **Worst** | 2.15061E−3 | 1.729814E−3 | 3.201008E−3 | 1.729814E−3 | 3.346434E−3 | 2.052124E−3 |
| **Standard deviation** | 9.07835E−05 | 1.40165E−17 | 2.92781E−4 | 9.65719E−06 | 3.33071E−4 | 6.80342E−05 |
| **Standard error** | 1.66E−5 | 2.56E−18 | 5.35E−5 | 1.76E−6 | 6.08E−5 | 1.24E−5 |

Abbreviations: DDM, double diode model; SNSA, social network search algorithm; RMSE, root mean square error; SDM, single diode model; TDM, three diode model.
Furthermore, Figure 8 maps the estimated data and the measured data for the powers and the currents at each point of the TDM of this module which characterize the closeness between the estimated data and the measured data when estimating the data with the proposed ESNSA.

### 4.2  |  **KC200GT PV module**

The definite five, seven, and nine parameters of SDM, DDM, and TDM, respectively, extracted by the proposed ESNSA and the original SNSA are characterized in Table 4.
Table 5. As shown in Table 5, the original SNSA and the proposed ESNSA techniques assess the optimal adaptation value of $8.803511 \times 10^{-3}$ and $6.36658 \times 10^{-4}$, respectively, for the SDM. Additionally, the optimal adaptation value obtained by the original SNSA and the proposed ESNSA for the DDM and TDM are $(8.5517 \times 10^{-3}, 3.62795 \times 10^{-4})$ and $(1.0290206 \times 10^{-2}, 3.60584 \times 10^{-4})$, respectively. This table illustrates the minimum value of RMSE related to the parameters of each model. The statistical analysis of the five metrics (best, average, worst, standard deviation, and standard error) shown in Table 6 illustrates that the proposed ESNSA manifests good stability and high search accuracy than the original SNSA. As shown, the standard deviations of SDM, DDM, and TDM for the original SNSA and the proposed ESNSA are $(1.4612 \times 10^{-3}, 1.2818 \times 10^{-4})$, $(2.4465 \times 10^{-3}, 6.0120 \times 10^{-4})$, $(6.9886 \times 10^{-3}, 3.60584 \times 10^{-4})$, respectively. Thirty runs have been developed for both the original SNSA and the proposed ESNSA on the SDM, DDM, and TDM as depicted in Figure 9. The results of the 30 runs show the robustness of the proposed ESNSA compared to the original SNSA for the three mentioned models. Furthermore, a comparative assessment has been developed in Table 7 between the proposed ESNSA, the original SNSA, and other recently reported techniques which are CPMPSO,54 PSO,9 LAPO,28 PSOGWO,55 BMA,56 NLBMA,57 PGJAYA,58 FPSO,59 HFAPS,29 FBI,30 EHHO,60 MVO,61 and HSDA53 for the three models. The results show that the proposed ESNSA manifests the minimum RMSE values for the three models compared to the original SNSA and other techniques. Moreover, the convergence characteristics shown in Figure 10 illustrate that the proposed ESNSA expresses a strong

**Table 5** Extracted parameters SNSA and proposed ESNSA for KC200GT PV module

|        | SDM   | DDM   | TDM   |
|--------|-------|-------|-------|
|        | SNSA  | Proposed ESNSA | SNSA  | Proposed ESNSA | SNSA  | Proposed ESNSA |
| $I_{ph}$ | 8.196552 | 8.216767 | 8.203365 | 8.216108 | 8.196578 | 8.216264 |
| $R_s$  | 0.004666 | 0.004826 | 0.004645 | 0.004881 | 0.004616 | 0.004858 |
| $R_{sh}$ | 13.71273 | 6.280163 | 11.17001 | 6.495963 | 13.55363 | 6.428224 |
| $I_{s1}$ | 4.98E−08 | 2.62E−08 | 5.57E−08 | 3.01E−10 | 3.57E−08 | 4E−09 |
| $\eta_1$ | 1.253654 | 1.212905 | 1.953981 | 1.044226 | 1.614634 | 1.138231 |
| $I_{s2}$ | - | - | 5.15E−08 | 4.35E−08 | 5.25E−08 | 4.82E−09 |
| $\eta_2$ | - | - | 1.25601 | 1.266049 | 1.258124 | 1.903027 |
| $I_{s3}$ | - | - | - | - | 1.13E−08 | 4.14E−08 |
| $\eta_3$ | - | - | - | - | 1.592395 | 1.296186 |
| RMSE   | 8.803511E−3 | 6.36658E−4 | 8.5517E−3 | 3.62795E−4 | 1.0290206E−2 | 3.60584E−4 |

Abbreviations: DDM, double diode model; ESNSA, enhanced social network search algorithm; RMSE, root mean square error; SDM, single diode model; SNSA, social network search algorithm; TDM, three diode model.
performance compared to the original SNSA for the three models. Furthermore, Figure 11 maps the estimated data and the measured data for the powers and the currents at each point of the TDM of this module which characterizes the closeness between the estimated data and the measured data when estimating the data with the proposed ESNSA.

### 4.3 PHOTO WATT-PWP201 PV module

The definite five, seven, and nine parameters of SDM, DDM, and TDM, respectively, extracted by the proposed ESNSA and the original SNSA are characterized in Table 8. As shown in Table 8, the original SNSA and the proposed ESNSA techniques assess the optimal adaptation value of 2.4347E−03 and 2.4251E−03, respectively, for the SDM. Additionally, the optimal adaptation value obtained by the original SNSA and the proposed ESNSA techniques for the DDM and TDM are (2.4410E−03, 2.4251E−03) and (2.5091E−03, 2.4251E−03), respectively. This table illustrates the minimum value of RMSE related to the parameters of each model. The statistical analysis of the five metrics (best, average, worst, standard deviation, and standard error) shown in Table 9 illustrate that the proposed ESNSA manifests good stability and high search accuracy than the original SNSA. As shown, the standard deviations of SDM, DDM, and TDM for the original SNSA and the proposed ESNSA are (2.6000E−05, 3.4700E−17), (1.5100E−04, 5.7600E−08), (1.2999E−04, 1.4600E−05), respectively. Thirty runs have been developed for both the original SNSA and the proposed ESNSA on the SDM, DDM, and TDM as depicted in Figure 12. The results of the thirty runs show the robustness of the proposed ESNSA compared to the original SNSA for the three mentioned models. Furthermore, a comparative assessment has been developed in Table 10 between the proposed ESNSA, the original SNSA, and other recently reported techniques which are SMA, RAO optimizer, PSO, BHCS, ImCSA, ISCE, HFAPS, and SA, LAPO, FBI, HSDA. BHCS, SSA, RCGA, CSA, PSO, sunflower optimization, Gray Wolf-Cuckoo Search (GW-CS), AEO for the three models. The results show that the proposed ESNSA manifests the minimum RMSE values for the three models compared to the original SNSA and other

### Table 6 Statistical indices of SNSA and proposed ESNSA for KC200GT PV module

| RMSE      | SDM     | DDM     | TDM     |
|-----------|---------|---------|---------|
|           | SNSA    | Proposed ESNSA | SNSA    | Proposed ESNSA | SNSA    | Proposed ESNSA |
| Best      | 8.8035E−03 | 6.3666E−04 | 8.5517E−03 | 3.6280E−04 | 1.0290E−02 | 3.6058E−04 |
| Average   | 1.2558E−02 | 7.0231E−04 | 1.5129E−02 | 1.0209E−03 | 1.9645E−02 | 1.6195E−03 |
| Worst     | 1.4790E−02 | 1.1674E−03 | 2.1884E−02 | 2.6403E−03 | 3.7637E−02 | 5.5302E−03 |
| Standard deviation | 1.4612E−03 | 1.2818E−04 | 2.4465E−03 | 6.0120E−04 | 6.9886E−03 | 1.3846E−03 |
| Standard error | 2.6678E−04 | 2.3402E−05 | 4.4667E−04 | 1.0976E−04 | 1.2759E−03 | 2.5278E−04 |

Abbreviations: DDM, double diode model; ESNSA, enhanced social network search algorithm; RMSE, root mean square error; SDM, single diode model; SNSA, social network search algorithm; TDM, three diode model.

![Figure 9](image-url)  
RMSE of SNSA and proposed ESNSA for KC200GT PV module. DDM, double diode model; ESNS, enhanced social network search; SDM, single diode model; SNS, social network search; TDM, three diode model
techniques. Moreover, the convergence characteristics shown in Figure 13 illustrate that the proposed ESNSA expresses a strong performance compared to the original SNSA for the three models. Furthermore, Figure 14 maps the estimated data and the measured data for the powers and the currents at each point of the TDM of this module which characterizes the closeness between the estimated data and the measured data when estimating the data with the proposed ESNSA.

### 5 Conclusion

In this article, an ESNSA has been proposed and effectively applied for extracting the parameters of solar PV modules. In ESNSA, the powerful exploitation strategy and an adaptive parameter have been emerged to the original SNSA to boost the searching around the best view of all users and support the exploitation at the late stage of iterations. The proposed ESNSA is compared with the original SNSA in detail on three PV modules to further validate performance. The statistical data about fitness value and efficacy gained by the proposed ESNSA are recorded and compared with the original SNSA and other recent and reported techniques. The comparison reveals that the proposed ESNSA is better than the original SNSA and other recent and reported techniques, with greater robustness, and accuracy efficacy for the mono-crystalline STM6(40/36), multicrystalline KC200GT, and polycrystalline Photowatt-PWP201 PV modules.

- For the STM6(40/36) PV module, for the three models, the suggested ESNSA obtains the lowest RMSE of 1.751631E−3, 1.769953E−3, and 1.696504E−3, respectively. It also has a higher level of robustness than the original SNSA, since it obtains the lowest standard errors for the three models of 2.56E−18, 1.76E−6, and 1.24E−5, respectively. Furthermore, the suggested ESNSA enables faster convergence, with the least RMSE being obtained in fewer than 60%, 50%, and 60% of iterations for the three models, respectively.
- For the KC200GT PV module, for the three models, the suggested ESNSA obtains the lowest RMSE of

| Optimizer | Min (RMSE) | Mean (RMSE) | Max (RMSE) |
|-----------|------------|-------------|------------|
| SDM       |            |             |            |
| CPMPSO    | 1.53903E−03| –           | –          |
| LAPO      | 1.3813E−01 | 2.2513E−01  | 3.7493E−01 |
| PSO       | 1.0195E−01 | 3.4467E−01  | 5.3291E−01 |
| BMA       | 1.0244E−01 | 1.2442E−01  | 1.4986E−01 |
| PSOGWO    | 1.2700E−01 | 3.5490E−01  | 7.6074E−01 |
| NLBMA     | 3.3610E−02 | 3.3610E−02  | 3.3610E−02 |
| PGJAYA    | 1.5455E−04 | –           | –          |
| FPSO      | 2.8214E−02 | –           | –          |
| HFAPS     | 4.9863E−02 | –           | –          |
| EHHO      | 5.9507E−02 | –           | –          |
| MVO       | 8.3800E−02 | –           | –          |
| HSDA      | 1.84393E−02| –           | –          |
| FBI       | 7.3400E−04 | –           | –          |
| SNSA      | 8.8035E−03 | 1.2558E−02  | 1.4790E−02 |
| Proposed ESNSA | 6.3666E−04 | 7.0231E−04  | 1.1674E−03 |

| Optimizer | Min (RMSE) | Mean (RMSE) | Max (RMSE) |
|-----------|------------|-------------|------------|
| DDM       |            |             |            |
| PSO       | 1.2970E−01 | 4.5668E−01  | 7.9194E−01 |
| LAPO      | 1.1696E−01 | 1.2798E−01  | 1.3230E−01 |
| PSOGWO    | 1.2178E−01 | 1.3013E−01  | 1.3540E−01 |
| BMA       | 1.2492E−01 | 2.1858E−01  | 3.0902E−01 |
| NLBMA     | 3.3043E−02 | 3.3043E−02  | 3.3043E−02 |
| HSDA      | 1.19036E−02| –           | –          |
| FBI       | 9.6200E−04 | –           | –          |
| SNSA      | 8.5517E−03 | 1.5129E−02  | 2.1884E−02 |
| Proposed ESNSA | 3.6280E−04 | 1.0209E−03  | 2.6403E−03 |

| Optimizer | Min (RMSE) | Mean (RMSE) | Max (RMSE) |
|-----------|------------|-------------|------------|
| TDM       |            |             |            |
| FBI       | 7.2100E−04 | –           | –          |
| SNSA      | 1.0290E−02 | 1.9645E−02  | 3.7637E−02 |
| Proposed ESNSA | 3.6058E−04 | 1.6195E−03  | 5.3502E−03 |

| Figure 10 | Convergence curves of SNSA and proposed ESNSA for KC200GT PV module. DDM, double diode model; ESNSA, enhanced social network search algorithm; SDM, single diode model; SNSA, social network search algorithm; TDM, three diode model
Figure 11  Simulated and experimental I–V and P–V curves of KC200GT module with three diode model, (A) I–V and (B) P–V curve

Table 8  Extracted parameters SNSA and proposed ESNSA for PWP201 PV Module

|        | SDM          | DDM          | TDM          |
|--------|--------------|--------------|--------------|
|        | SNSA         | Proposed ESNSA | SNSA         | Proposed ESNSA | SNSA         | Proposed ESNSA |
| $I_{ph}$ | 1.030710754  | 1.030514299  | 1.030296825  | 1.030514298    | 1.028649538  | 1.030514299    |
| $R_{S}$ | 0.03331481   | 0.033368639  | 0.033180743  | 0.033368639    | 0.03278908   | 0.033368639    |
| $R_{sh}$ | 27.49853442 | 27.27728509  | 29.05162489  | 27.27728685    | 36.44786551  | 27.27728224    |
| $I_{s1}$ | 3.57606E−06  | 3.48226E−06  | 3.48226E−08  | 3.48226E−08    | 0             | 2.67356E−14    |
| $\eta_{1}$ | 1.354045499 | 1.351189858  | 1.35118986   | 1.35118986     | 1.339973597  | 1.351079183    |
| $I_{s2}$ | -            | -            | 3.59767E−06  | 3.90203E−16    | 3.90264E−06  | 3.48226E−06    |
| $\eta_{2}$ | -            | -            | 1.356158468  | 1.353571822    | 1.36722247   | 1.351189856    |
| $I_{s3}$ | -            | -            | -            | -              | 3.69878E−07  | 5.75273E−21    |
| $\eta_{3}$ | -            | -            | -            | -              | 1.482825328  | 1.99698943     |
| RMSE   | 2.4347E−3    | 2.4251E−3    | 2.4410E−3    | 2.4251E−3      | 2.5091E−3    | 2.4251E−3      |

Abbreviations: DDM, double diode model; ESNSA, enhanced social network search algorithm; RMSE, root mean square error; SDM, single diode model; SNSA, social network search algorithm; TDM, three diode model.

Table 9  Statistical indices of SNSA and proposed ESNSA for PWP201 PV module

|        | SDM         | DDM          | TDM          |
|--------|-------------|--------------|--------------|
|        | SNSA        | Proposed ESNSA | SNSA        | Proposed ESNSA | SNSA        | Proposed ESNSA |
| RMSE   | 2.4347E−03  | 2.4251E−03    | 2.4410E−03   | 2.4251E−03     | 2.5091E−03  | 2.4251E−03     |
|        | 2.4680E−03  | 2.4250E−03    | 2.6020E−03   | 2.4250E−03     | 3.1910E−03  | 2.4290E−03     |
|        | 2.5470E−03  | 2.4250E−03    | 3.1800E−03   | 2.4250E−03     | 5.5110E−03  | 2.5030E−03     |
|        | 2.6000E−05  | 3.4700E−17    | 1.5100E−04   | 5.7600E−08     | 7.1200E−04  | 1.4600E−05     |
|        | 4.7469E−6   | 6.3353E−18    | 2.7569E−05   | 1.0516E−8      | 1.2999E−04  | 2.6656E−6      |

Abbreviations: DDM, double diode model; ESNSA, enhanced social network search algorithm; RMSE, root mean square error; SDM, single diode model; SNSA, social network search algorithm; TDM, three diode model.
**TABLE 10** Comparative assessment of SNSA and proposed ESNSA for PWP201 module

| Optimizer | Min (RMSE) | Mean (RMSE) | Max (RMSE) |
|-----------|------------|-------------|------------|
| SDM       |            |             |            |
| RAO²⁵     | 2.8220E−03 | 3.2960E−03  | 4.2554E−01 |
| PSO⁹      | 2.4390E−03 | 2.3666E−02  | 9.7700E−02 |
| SMA²⁷     | 2.8110E−03 | 3.3530E−03  | 1.0799E−02 |
| HFAPS²⁹   | 2.4251E−03 | -           | -          |
| ISCE¹⁹    | 2.4251E−03 | 2.4251E−03  | 2.4251E−03 |
| ImCSA¹⁸   | 2.4250E−03 | 2.4251E−03  | 2.4251E−03 |
| SA¹⁴      | 2.6170E−03 | -           | -          |
| HSDA³³    | 2.4251E−03 | -           | -          |
| FBI³⁰     | 2.425E−03  | 2.426E−03   | 2.435E−03  |
| SNSA       | 2.4347E−03 | 2.4680E−03  | 2.5470E−03 |
| Proposed ESNSA | 2.4251E−03 | 2.4250E−03  | 2.4250E−03 |
| DDM       |            |             |            |
| PSO⁹      | 3.3925E−03 | -           | -          |
| LAPO²⁸    | 3.2734E−02 | 4.3132E−02  | 5.7507E−02 |
| FBI³⁰     | 2.4250E−03 | 2.4310E−03  | 2.4430E−03 |
| HSDA³³    | 2.587754E−03 | -         | -          |
| SNSA       | 2.4410E−03 | 2.6020E−03  | 3.1800E−03 |
| Proposed ESNSA | 2.4251E−03 | 2.4250E−03  | 2.4250E−03 |
| TDM       |            |             |            |
| RCGA      | 1.5300E−02 | -           | -          |
| CSA       | 3.2000E−03 | -           | -          |
| SSA       | 1.3500E−02 | -           | -          |
| BHCS      | 3.6790E−03 | -           | -          |

**TABLE 10** (Continued)

| Optimizer | Min (RMSE) | Mean (RMSE) | Max (RMSE) |
|-----------|------------|-------------|------------|
| PSO       | 2.7000E−03 | -           | -          |
| SFO       | 8.2500E−02 | -           | -          |
| GW-CS     | 3.7000E−03 | -           | -          |
| AEO¹¹     | 2.4800E−03 | -           | -          |
| FBI³⁰     | 2.426E−03  | 2.437E−03   | 2.46E−03   |
| SNSA       | 2.5091E−03 | 3.1910E−03  | 5.5110E−03 |
| Proposed ESNSA | 2.4251E−03 | 2.4290E−03  | 2.5030E−03 |

**FIGURE 12** RMSE of SNSA and proposed ESNSA for PWP201 PV module

**FIGURE 13** Convergence curves of ESNSA versus SNSA for PWP201 module. DDM, double diode model; ESNS, enhanced social network search; SDM, single diode model; SNS, social network search; TDM, three diode model

(Continues)
6.36658E−4, 3.62795E−4, and 3.60584E−4, respectively. It also has a higher level of robustness than the original SNSA, since it obtains the lowest standard deviations for the three models of 1.2818E−04, 6.0120E−04, and 3.60584E−4, respectively.

• For the PWP201 PV module, for the three models, the suggested ESNSA obtains the lowest RMSE of 2.4251E−03, respectively. It also has a higher level of robustness than the original SNSA, since it obtains the lowest standard deviations for the three models of 3.4700E−17, 5.7600E−08, and 1.4600E−05, respectively. On the other hand, the standard deviations of SDM, DDM, and TDM for the original SNSA are 2.6000E−05, 1.5100E−04, 1.2999E−04, respectively.

Nevertheless, the proposed ESNSA provides better performance than miscellaneous published approaches in minimizing the RMSE, with high robust indices.

ACKNOWLEDGMENT

This study was supported by Taif University Researchers Supporting Project number (TURSP-2020/86), Taif University, Taif, Saudi Arabia.

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How to cite this article: Shaheen AM, Elsayed AM, Ginidi AR, El-Sehiemy RA, Elattar E. Enhanced social network search algorithm with powerful exploitation strategy for PV parameters estimation. *Energy Sci Eng*. 2022;10:1398-1417. doi:10.1002/es3.1109
APPENDIX
Table A1 shows the pseudo-code of the proposed ESNSA and its steps in detail.

| TABLE A1 | Pseudo-code of the proposed ESNSA |
|-----------|-----------------------------------|

**Algorithm 1 ESNSA**

| Input: Population size ($N$), maximum number of iterations (MaxIter), lower bounds (LB) and upper bounds (UB) |
|---------------------------------------------------------------|
| Output: Optimal fitness value (minimum RMSE) |
| 1: procedure ESNSA |
| 2: Set $I_t = 0$ |
| 3: Initialize the view of users ($X_i$), $X_i = LB + \text{rand} \times (UB - LB)$ |
| 4: Evaluate the fitness function of each user $i$ as ($f(X_i)$) |
| 5: Extract ($X_{best}$) with the minimum fitness |
| 6: while ($I_t < \text{MaxIter}$) do |
| 7: for $i = 1$ to $N$ do/* Looping for update each view of user */ |
| 8: Randomly generate Mood as an integer value from range $1-4$ |
| 9: If Mood = 1, Apply the imitation model to generate ($X_{i,new}$), $j = \text{rand}(N-1); j \neq i; R = \text{rand}(1,D) \times \text{rr}; X_{i,new} = X_j + (1-2*\text{rand}(1,D)) \times R$; |
| 10: Elseif Mood = 2, Apply the conversation model to generate ($X_{i,new}$), $k = \text{rand}(N-1); k \neq i; j = \text{rand}(N-1); j \neq i; \text{rr} = \text{sign}(f(i) - f(j)) \times (X_j - X_i); X_{i,new} = X_k + \text{rand}(1,D) \times \text{rr}$; |
| 11: Elseif Mood = 3, Apply the disputation model to generate ($X_{i,new}$), $M_x = \text{mean}(X_i); AF = 1 + \text{round}($rand$); X_{i,new} = X_i + \text{rand}(1,D) \times (M_x - (AF \times X_i))$; |
| 12: Else, Apply the innovation model to generate ($X_{i,new}$), $M_x = \text{mean}(X_i); j = \text{rand}(N-1); j \neq i; t = \text{rand}; n_{new} = LB + \text{rand} \times (UB - LB); X_{i,new} = t \times X_j + (1-t) \times n_{new}$; |
| 13: End if |
| 14: Evaluate the adaptive parameter ($\alpha$), $\alpha = I_t/(2 \times \text{MaxIter})$ |
| 15: If ($I_t > \text{MaxIter}/2$), then |
| 16: If ($\text{rand} \leq \alpha$), then |
| 17: Apply the PES to generate ($X_{i,new}$), $j = \text{rand}(N-1); j \neq i; \text{rr} = X_j - X_i; t = \text{rand}; X_{i,new} = X_{best} + t \times \text{rr}$; |
| 18: End if |
| 19: End if |
| 20: Control the new view by the network rules, $X_{i,new} = \min(X_{i,new}, \text{UB}); X_{i,new} = \max(X_{i,new}, \text{LB})$; |
| 21: Evaluate the fitness function of each new user ($f(X_{i,new})$) |
| 22: If ($f(X_{i,new}) < f(X_i)$), then |
| 23: Apply the replacement strategy, $X_i = X_{i,new}$ |
| 24: If ($f(X_{i,new}) < f(X_{best})$), then |
| 25: Update $X_{\text{best}}, X_{\text{best}} = X_{i,new}$ |
| 26: End if |
| 27: End if |
| 28: End for |
| 29: End while |
| 30: return $\text{Best}/*$ Return the best fitness value */ |
| 31: End procedure |