Available online at www.sciencedirect.com
ScienceDirect
Energy Reports 9 (2023) 174–185
www.elsevier.com/locate/egyr

2022 9th International Conference on Power and Energy Systems Engineering (CPESE 2022), Doshisha University, Kyoto, Japan, 9–11 September 2022

Parameter extraction for photovoltaic models with tree seed algorithm

Ayşe Beşkirli[a,b,*], İdiris Dağ[a]

[a] Department of Computer Engineering, Eskişehir Osmangazi University, 26480, Eskişehir, Türkiye
[b] Department of Computer Engineering, Karamanoğlu Mehmetbey University, 70200, Karaman, Türkiye

Received 15 October 2022; accepted 22 October 2022
Available online 8 November 2022

Abstract

Evaluation, simulation and optimization of PV systems is very important for fast and accurate parameter extraction based on current–voltage and power–voltage characteristic curves of photovoltaic models. Therefore, researchers used many metaheuristic algorithms to estimate the parameters of various PV modules. In this study, tree seed algorithm (TSA) was used for parameter estimation of the STM6-40/36 PV module. In the basic TSA, there are two different resolution mechanisms for balancing both local and global search technique. For this reason, basic TSA was preferred for parameter extraction of the PV module. The parameter results obtained by TSA were compared with those found by some other algorithms in the literature. According to the comparison result, the lowest root mean square error (RMSE) was obtained with the TSA algorithm. When the convergence graphs are examined, it is seen that TSA converges faster than other algorithms. When the box plots are analyzed, the results obtained by TSA have fewer outliers than the results of other algorithms, showing that TSA has a stable structure. In addition, a ranking graph was drawn according to the results obtained by all algorithms at each run time, and it was seen that TSA had the lowest RMSE value at all run times. Thus, it is concluded that TSA is a very competitive method for the PV module problem.

Peer-review under responsibility of the scientific committee of the 9th International Conference on Power and Energy Systems Engineering, CPESE, 2022.

Keywords: Photovoltaic models; PV module model; Parameter extraction; I–V and P–V characteristic; Tree seed algorithm

1. Introduction

As a result of, the growing population and developing industry, the demand of countries for energy is increasing day by day [1]. In addition to these, many alternative renewable energy sources such as solar, wind, geothermal and hydroelectricity are attracting great attention in order to combat increasing environmental problems such as the reduction of fossil fuels and the deterioration of ecological balance [2,3]. Among these sources, the fact that solar energy is sustainable and abundant is accepted as one of the promising renewable energy sources in order to meet the increasing energy demand and to ensure that environmental problems reach a minimum level [4]. Converting

* Corresponding author at: Department of Computer Engineering, Eskişehir Osmangazi University, 26480, Eskişehir, Türkiye.
E-mail addresses: aysebes@kmu.edu.tr (A. Beşkirli), idag@ogu.edu.tr (İ. Dağ).

https://doi.org/10.1016/j.egyr.2022.10.386

Peer-review under responsibility of the scientific committee of the 9th International Conference on Power and Energy Systems Engineering, CPESE, 2022.

the energy from the sun to electrical energy with photovoltaic (PV) models is one of the most popular methods used recently [3,5]. For this reason, it is very important to simulate the real behavior of the PV model and to estimate the parameters correctly for the optimization of the parameters of the solar panel based on the measured current–voltage (I–V) data [1,6]. For various models such as single diode, double diode, triple diode, PV modules are commonly used to represent the connection between current–voltage and power–voltage [7]. The functionality and performance of the models whose parameters are predicted are known to represent the real behavior of solar panels. For this reason, it is very important to use an effective method for accurate parameter estimation which provides maximum energy efficiency from PV models.

Recently, researchers have proposed many meta-heuristic algorithms to improve the performance of PV models in the literature [8–14]. As we search the literature, the estimation of the parameters of the STM6-40/36 PV module model with the tree seed algorithm (TSA) has not been studied before. Some application scenarios of TSA are as follows: Çınar et al. redesigned TSA by using swap, shift, and symmetry transformation operators to solve the traveling salesman problem with TSA and named the proposed algorithm as DTSA. The experimental results obtained were compared with well-known meta-heuristic algorithms such as ACO, GA, SA, STA, ABC and some variants of these algorithms. As a result of the analysis, it was said that the proposed DTSA is a qualified and competitive solver for the traveling salesman problem [15]. Jiang et al. proposed a new method by combining an adaptive seed production mechanism with a linearly varying regulation mechanism for TSA to achieve optimal solution of complex problems more effectively. The suggested method is named as STSA. STSA has been tested with 24 different test functions and also PVD and T/CSD problems have been solved. According to the experimental results, it has been found that the recommended STSA has been significantly improved for the solution of optimization problems [16]. Çınar trained TSA with FF MLP ANN and used 18 different data sets (4-bit Encoder Decoder, Iris, XOR13, Banknote, XOR6, 3-bit Parity, XOR9, Sinus, Sigmoid, Breast Cancer, Balloon, Diabetic, Heart, Twonorm, Spambase, Ringnorm, 3-bit XOR and Cosine) in the experiments. Experimental results were compared with ABC, ACO, ES, PSO, GA, PBIL, BBO and GWO algorithms. It was deduced from results of analysis that TSA was the best in 18 problems for the average classification rates [17]. Güngör et al. developed TSA for benchmark and CEC2015 problems. The developed method was compared with the results of some meta-heuristic algorithms such as DE, PRSA, GA, PSO, and ABC. Experimental analysis results show that the developed method is better than the basic method in terms of solution quality, robustness and convergence properties [18]. Köse suggested TSA based PID control method for optimal control of AVR in his study. To show the performance of TSA, it was compared with ABC, IKA, BBO, LUS, DEA, PSO and PSA algorithms in the literature. The comparison result showed that TSA had a better performance [19]. Jiang et al. have integrated two features from the sine–cosine algorithm into the algorithm to improve the discovery capability of TSA. The proposed new algorithm is named as TSASC. For the purpose of test the performance of the proposed algorithm, 30 different comparison functions and various engineering problems were used to solve them. According to the results of the analysis, it has been said that the proposed TSASC algorithm is quite effective for solving the engineering problem [20]. Beşkirli, proposed a new hybrid method for increasing the solution quality in continuous optimization problems of TSA. The proposed new method is named HTSA. The proposed algorithm has been tested on comparison functions and also compared with algorithms such as HS, ABC, PSO. Seeing that HTSA has given very promising results [21]. TSrA and TSrAeig modified by Bujok as an alternative to the TSA are observed to provide more promising results [22]. Literature to extract parameters for the STM6-40/36 PV module. In this paper, the tree seed algorithm is constructed for the STM6-40/36 PV module parameter estimation.

The results obtained were compared with the results of GOA (grasshopper optimization algorithm) [23], ASO (atom search optimization) [24], GSA (gravitational search algorithm) [25], AOA (arithmetic optimization algorithm) [26], CSS (charged system search) [27] algorithms and HS (harmony search algorithm) [28] in the literature.

The study's remaining portions are arranged as follows: The TSA is introduced in the following section. The STM6-40/36 PV module is introduced in Section 3, and the problem formulations are provided. Experimental results and comparisons with those of other methods are provided in Section 4. The conclusion and recommendations for further research are provided in the Section 5.

2. Tree seed algorithm

In nature, trees are dispersed to the soil surface through their seeds. These seeds grow over time to form new trees. Connection between trees and seeds are inspired to be developed the TSA as a new algorithm in 2015 [29].

Thus, the position of trees–seeds corresponds to probable optimum solutions of the problems. These solutions are used to obtain the fitness value of the optimization problems. In the algorithm, the new seed location production process is controlled by the ST (Search Tendency) parameter. ST parameter takes a value in the range of [0,1]. A high value for the ST parameter provides a strong local search and fast convergence, while a low value for the ST parameter causes a strong global search while converging slowly. In fact, TSA's exploration and exploitation capability is controlled by the ST parameter [30]. The seed will be produced from the tree positions and with Eq. (1), the best positions of the tree population are calculate and Eq. (2) is used to update the seed size [31].

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times \left(B_j - T_{r,j}\right) \tag{1}$$

$$S_{i,j} = T_{i,j} + \alpha_{i,j} \times (T_{i,j} - T_{r,j}) \tag{2}$$

Where, α is the randomly generated scaling factor in the range of $[-1, 1]$. i and r represent different indices. B_j represents the best tree position obtained, $T_{r,j}$ represents the randomly selected tree position, $S_{i,j}$ represents the jth dimension of the ith seed produced from ith tree. In TSA, more than one seed is produced for each tree. This number of seeds is determined by a random number between 10% and 25% of the population size [32]. Initial tree positions in TSA are determined using Eq. (3) [33].

$$T_{i,j} = L_{j,min} + r_{i,j}\left(H_{j,max} - L_{j,min}\right) \tag{3}$$

Where, $L_{j,\min}$ represents the lower limit of the search space, while $H_{j,\max}$ represents the upper limit of the search space. $r_{i,j}$ is a random value generated for each dimension and position in the range [0,1].

3. Photovoltaic module model for STM6-40/36

PV module consists of a combination of cells connected in series or parallel. The STM6-40/36 PV module model examined in this study consists of 36 serial cells [34]. Thus, the model was designed according to 36 serial cells. The data of the PV module were obtained from the related study [35]. The objective function of the STM6-40/36 PV module model is given in Eq. (4).

$$I_L = I_{ph}N_P - I_{sd}N_P\left[exp\left(\frac{q\left(V_L + I_L\frac{N_S}{N_P}R_S\right)}{N_S nkT}\right) - 1\right] - \frac{V_L + I_L\frac{N_S}{N_P}R_S}{\frac{N_S}{N_P}R_{sh}} \tag{4}$$

In Eq. (4), the parameters to be extracted for the STM6-40/36 are I_{ph}, I_{sd}, R_s, R_{sh} and n [36]. These parameters are located in each cell in the PV module and represent the photo generated current, reverse saturation current, series resistance, shunt resistance and diode ideal factor, respectively. I_L in this formula represents the output current and V_L represents the voltage of the PV. The parameter values of the STM6-40/36 PV module are given in Table 1 [3].

Table 1. Parameter values.

Parameters	PV module model (STM6-40/36)	
	Lower limit	Upper limit
I_{ph} (A)	0	2
I_{sd} (A)	0	50×10^{-6}
R_S (Ω)	0	0.36
R_{sh} (Ω)	0	1000
n	1	60

The root mean square error (RMSE) used to measure the total error between the measured and simulated current is given in Eq. (5).

$$\mathrm{RMSE}(x) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f_k\left(V_L, I_L, x\right)^2} \tag{5}$$

Where, N represents the number of measured current–voltage data, while x indicates that the solution vector consists of unknown parameters. The smaller the RMSE value, the better the results of the simulation model will be [37].

4. Experimental results

I–V and P–V characteristics were investigated by obtaining the values of I_{ph}, I_{sd}, R_s, R_{sh} and n parameters in 30 000, 60 000 and 90 000 MaxFEs by obtaining I–V data of STM6-40/36 PV module at 1000 W/m^2 light intensity and 51 °C. Obtained results are presented in tables and graphs.

In Table 2, parameter values of TSA algorithm and GOA, AOA, ASO, HS, GSA and CSS algorithms are given as a result of 30 000 MaxFEs. It has been seen that the smallest RMSE value obtained according to these parameter values belongs to the TSA algorithm. Thus, the fact that the TSA algorithm has the least RMSE value has shown that it is more successful than other algorithms.

Table 2. PV module model results.

	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	n	RMSE
TSA	1.660188326	3.08E−06	0.002883775	24.597646179	1.585750565	**2.655050E−03**
GOA	1.857026110	1.24E−02	0.000000000	6.4394634870	4.602326724	1.985234E−01
AOA	1.770421213	9.20E−09	0.001723604	1000.0000000	1.078359260	2.162097E−01
ASO	1.535686642	1.00E−03	0.007120160	288.55814266	3.932144780	3.198393E−01
HS	1.670449148	2.39E−05	0.000000000	1000.0000000	1.877103859	1.987254E−02
GSA	1.653132374	7.44E−06	0.000000032	449.13413523	1.697917617	5.264253E−03
CSS	1.743647302	8.73E−04	0.000049888	910.24957671	2.803054202	1.012207E−01

The convergence graphs of the TSA algorithm and the GOA, AOA, ASO, HS, GSA and CSS algorithms are given in Fig. 1, and it is seen that the fastest convergence process is performed with the TSA algorithm. The algorithms that converge closest to the TSA algorithm are GSA, HS, CSS, GOA, AOA and ASO algorithms, respectively. When the box plots given in Fig. 2 are examined, it is seen that the TSA algorithm achieves a more stable result than other algorithms.

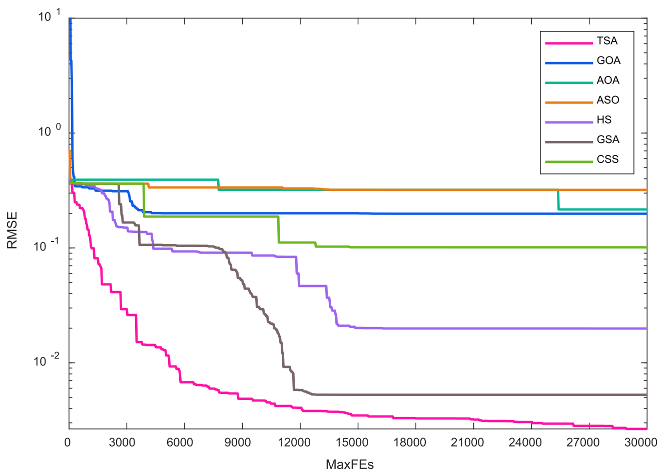

Fig. 1. Convergence graph of algorithms.

The ranking processes of the algorithms according to the RMSE values obtained after 30 run times are given in Fig. 3. When the figure was analyzed, it was seen that the TSA algorithm had the lowest RMSE value in all run times. The best RMSE value after TSA was obtained with the HS algorithm. The fact that TSA achieved the best value at all run times shows the stability of the algorithm.

Fig. 4 shows the I–V and P–V characteristics of the best model estimated by TSA. When the characteristic features are examined, it is clearly seen that the results of standard data and simulation data are in harmony with each other.

Table 3 displays the parameter values of the TSA algorithm as well as the GOA, AOA, ASO, HS, GSA, and CSS algorithms as a result of 60 000 MaxFEs. The TSA method has been shown to have the least RMSE value

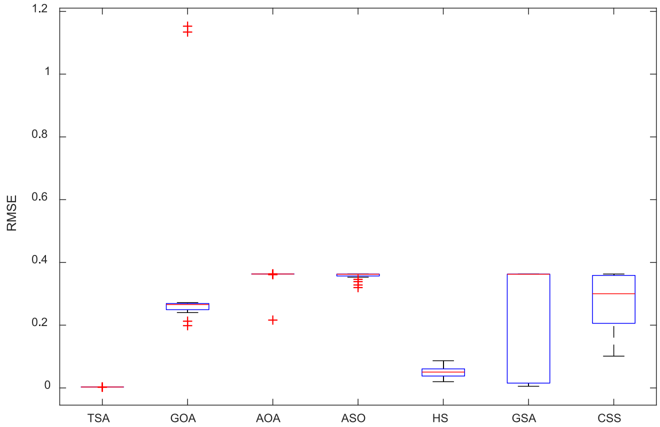

Fig. 2. Box plot of algorithms.

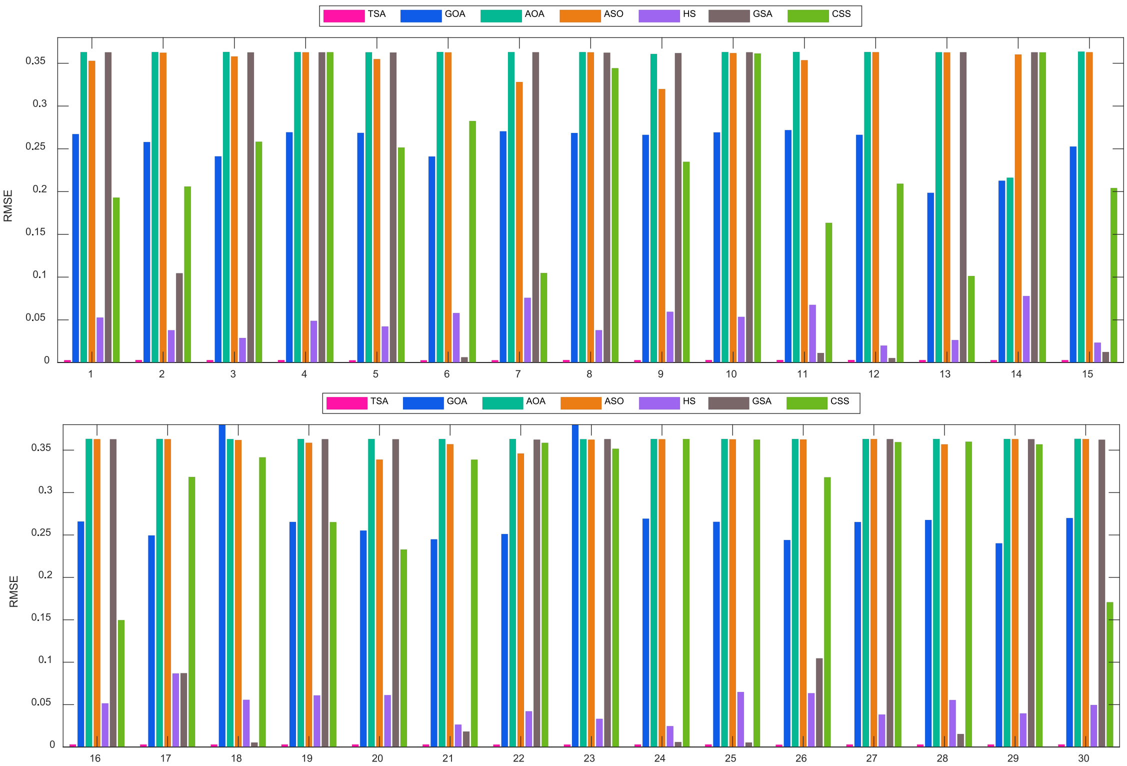

Fig. 3. Ranking of RMSE values.

based on these parameter settings. As a result, the TSA algorithm is more successful than other algorithms since it has the lowest RMSE value.

Fig. 5 depicts the convergence graphs of the TSA algorithm and the GOA, AOA, ASO, HS, GSA, and CSS algorithms, demonstrating that the TSA method performs the quickest convergence process. GSA, HS, CSS, GOA, ASO, and AOA algorithms are the ones that converge closest to the TSA algorithm. Examining the box plots in Fig. 6, it is clear that the TSA method generates a more stable outcome than other techniques.

Fig. 7 depicts the algorithm ranking processes based on the RMSE values acquired after 30 run times. When the data was examined, it was discovered that the TSA method had the lowest RMSE value across all run times.

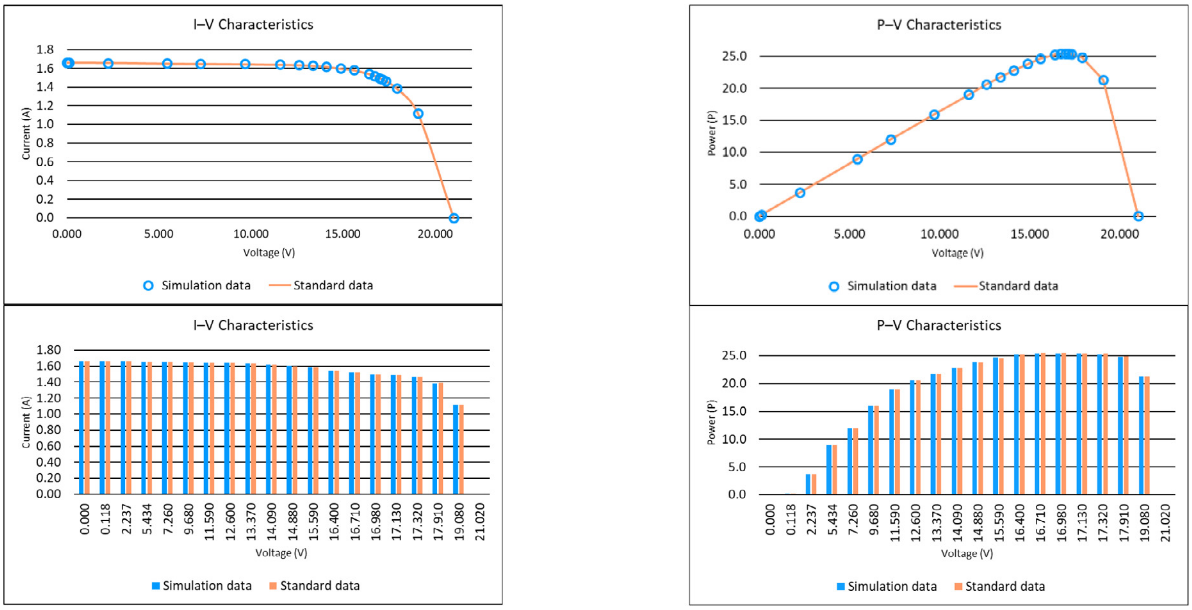

Fig. 4. I–V and P–V characteristics.

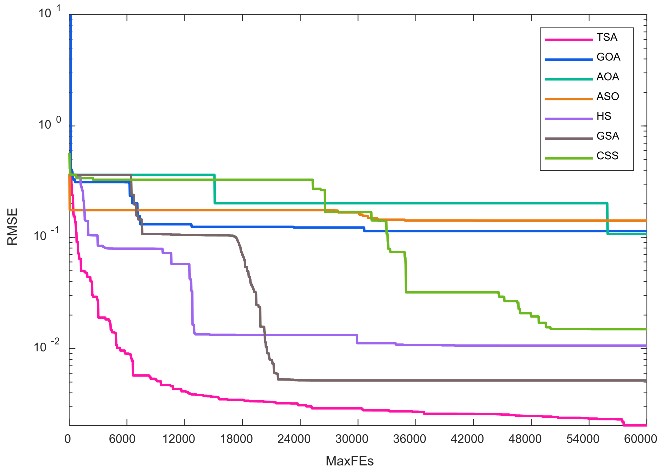

Fig. 5. Convergence graph of algorithms.

Table 3. PV module model results.

	I_{ph} (A)	I_{sd} (μA)	R_s(Ω)	R_{sh} (Ω)	n	RMSE
TSA	1.661341742	2.31E−06	0.003441203	19.50840800	1.552106412	**2.040362E−03**
GOA	1.787889883	6.30E−04	0.000000000	5.010040863	2.709393581	1.135736E−01
AOA	1.690023860	1.78E−05	0.000207961	1000.000000	1.788468992	1.071619E−01
ASO	1.701946943	1.00E−03	0.000171697	764.7237432	2.977171082	1.413311E−01
HS	1.661214334	1.34E−05	0.000000000	1000.000000	1.783442167	1.063400E−02
GSA	1.653397308	7.37E−06	0.000000009	286.7866457	1.696694498	5.166639E−03
CSS	1.669395664	1.44E−05	0.000878521	322.0171504	1.794080021	1.493225E−02

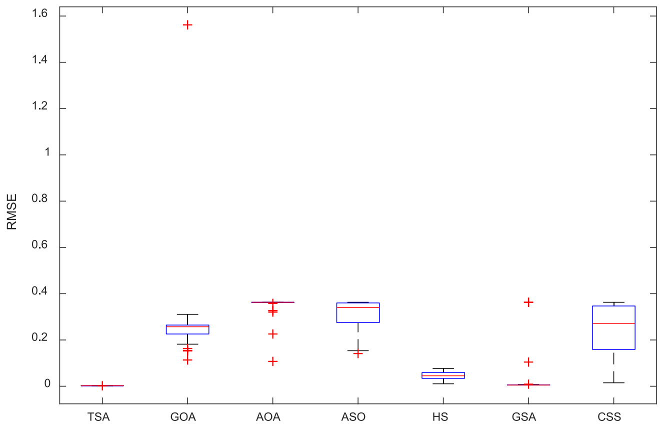

Fig. 6. Box plot of algorithms.

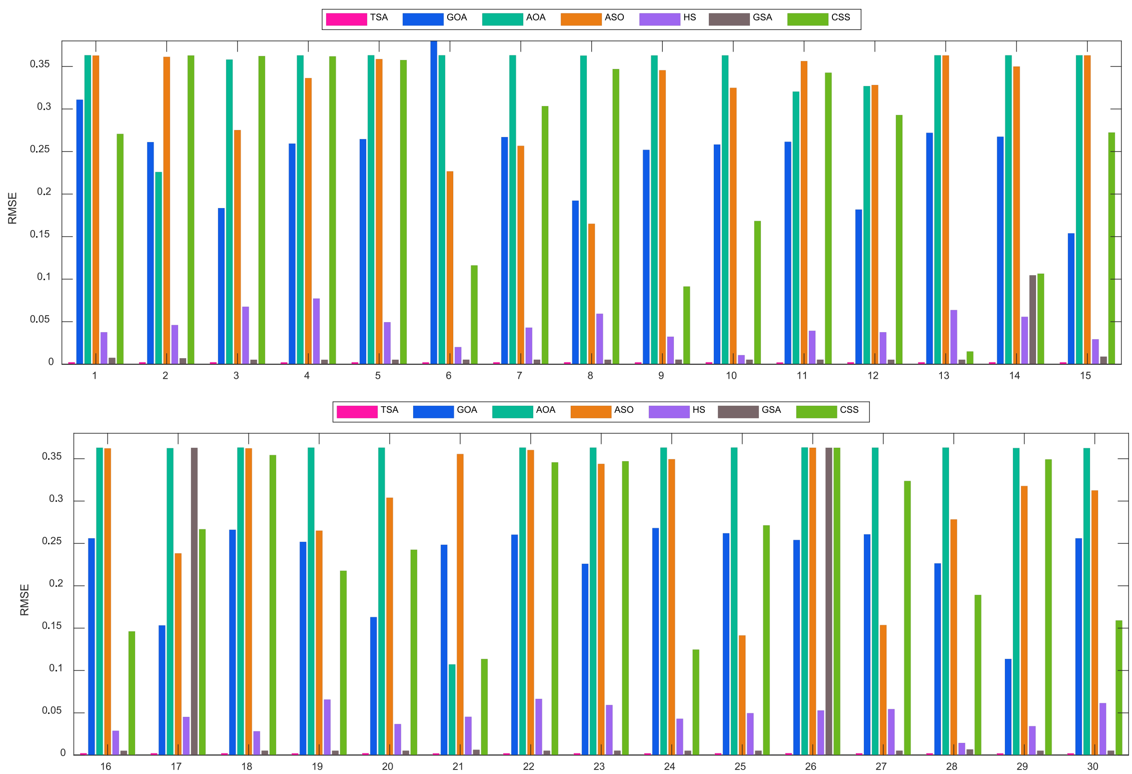

Fig. 7. Ranking of RMSE values.

The GSA method produced the best RMSE result after TSA. The fact that TSA produced the best result at all run times demonstrates the algorithm's stability.

Fig. 8 depicts the $I-V$ and $P-V$ features of the best TSA-estimated model. When the typical characteristics are analyzed, it is evident that the findings of the standard data and the simulation data agree.

Table 4 lists the parameter values for the TSA algorithm as well as the GOA, AOA, ASO, HS, GSA, and CSS algorithms as a result of 90 000 MaxFEs. It has been observed that the TSA method has the least RMSE value computed based on these parameter settings. Because the TSA method has the lowest RMSE value of all the algorithms, this proves that it is more effective than the others.

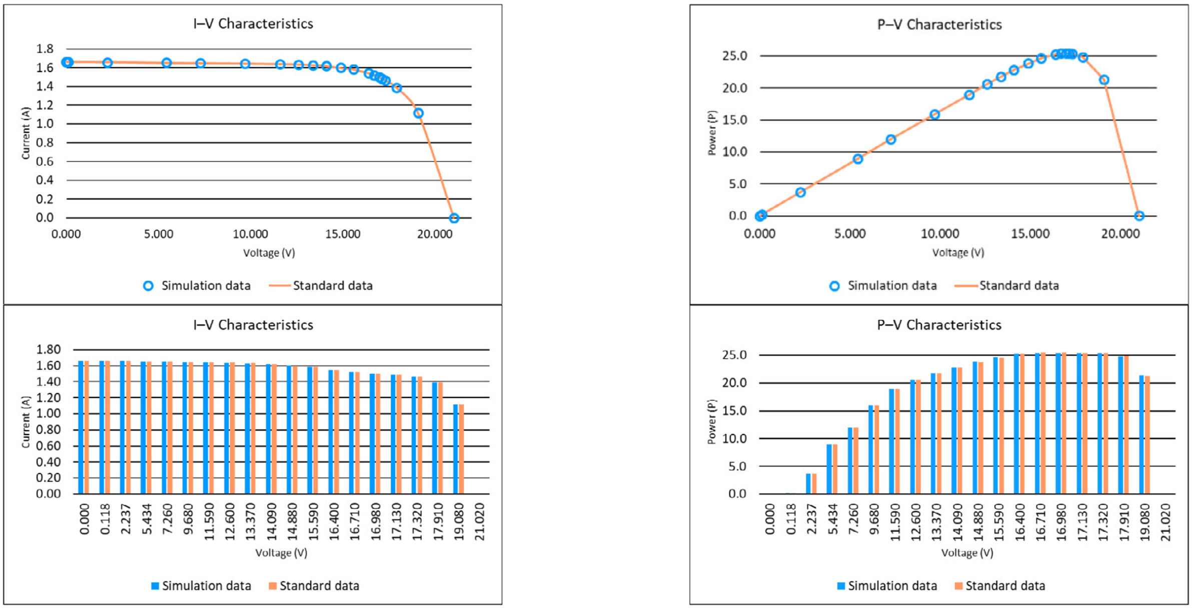

Fig. 8. I–V and P–V characteristics.

Table 4. PV module model results.

	I_{ph} (A)	I_{sd} (µA)	R_s (Ω)	R_{sh} (Ω)	n	RMSE
TSA	1.662647184	2.31E−06	0.003371139	18.05161553	1.552386191	**1.876204E−03**
GOA	1.759226045	3.32E−04	0.000000000	7.115942521	2.486890433	9.056183E−02
AOA	1.652296572	1.30E−05	0.000000000	1000.000000	1.790203859	2.712704E−02
ASO	1.743055044	6.93E−04	0.000000000	439.2431023	2.716415766	9.468269E−02
HS	1.657104236	1.01E−05	0.000000000	1000.000000	1.741687871	7.103148E−03
GSA	1.653140647	7.37E−06	0.000000000	346.3442650	1.696631603	5.213914E−03
CSS	1.656812275	2.46E−05	0.001298023	650.0742946	1.886175415	2.957386E−02

The convergence graphs of the TSA algorithm and the GOA, AOA, ASO, HS, GSA and CSS algorithms are given in Fig. 9, and it is seen that the fastest convergence process is performed with the TSA algorithm. The algorithms that converge closest to the TSA algorithm are GSA, HS, AOA, CSS, GOA and ASO algorithms, respectively. When the box plots given in Fig. 10 are examined, it is seen that the TSA algorithm achieves a more stable result than other algorithms.

Fig. 11 displays the algorithms' ranking procedures based on the RMSE values attained after 30 runtimes. The TSA algorithm had the lowest RMSE value among all run times when the figure was assessed. After TSA, the GSA algorithm produced the best RMSE value. The stability of the algorithm is demonstrated by the fact that TSA consistently achieved the best value.

The I–V and P–V properties of the top model as determined by TSA are shown in Fig. 12. Examining the distinguishing characteristics reveals that the findings of the simulated data and the standard data are in harmony with each other.

5. Conclusion

In this study, TSA algorithm is used for parameter extraction of STM6-40/36 PV modules, which is one of the real-world engineering problems. The I–V and P–V characteristic analyzes at 30 000, 60 000 and 90 000 MaxFEs were performed through graphical solutions. When these graphs were analyzed, it was seen that the TSA algorithm is superior to other algorithms. At the same time, convergence and box graphs of the algorithms are depicted to show efficiency of the TSA algorithm on determining the optimized parameters of the PV module. When the convergence

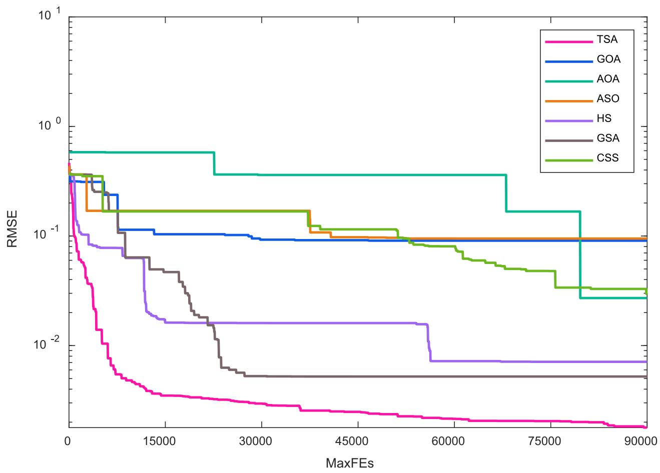

Fig. 9. Convergence graph of algorithms.

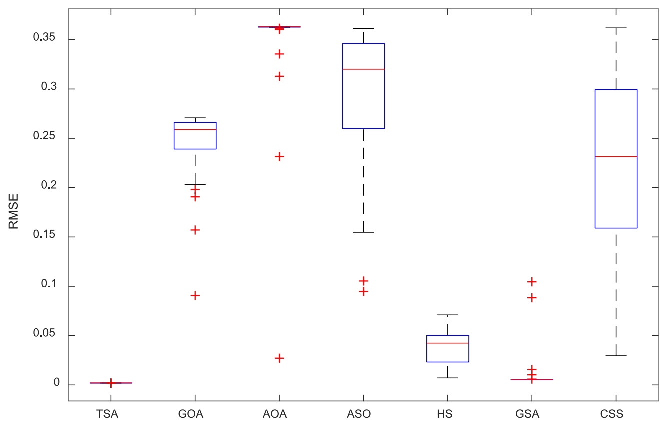

Fig. 10. Box plot of algorithms.

graphs are examined, TSA showed a fast convergence compared to other algorithms and obtained the optimum RMSE result. When box plots of results are examined, the robustness of TSA compared to other algorithms can be observed. All algorithms were run for 30 run time according to MaxFEs stopping criterion and the RMSE results obtained were presented as a ranking graph. Thus, it was seen that TSA obtained a lower RMSE value than other algorithms for each of the 30 000, 60 000 and 90 000 MaxFEs values. The experimental results indicate that TSA algorithm is more successful than the other algorithms. As a future studies on photovoltaic models, the improved TSA will be applied to estimate parameters of the objective function of the STM6-40/36 PV module.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

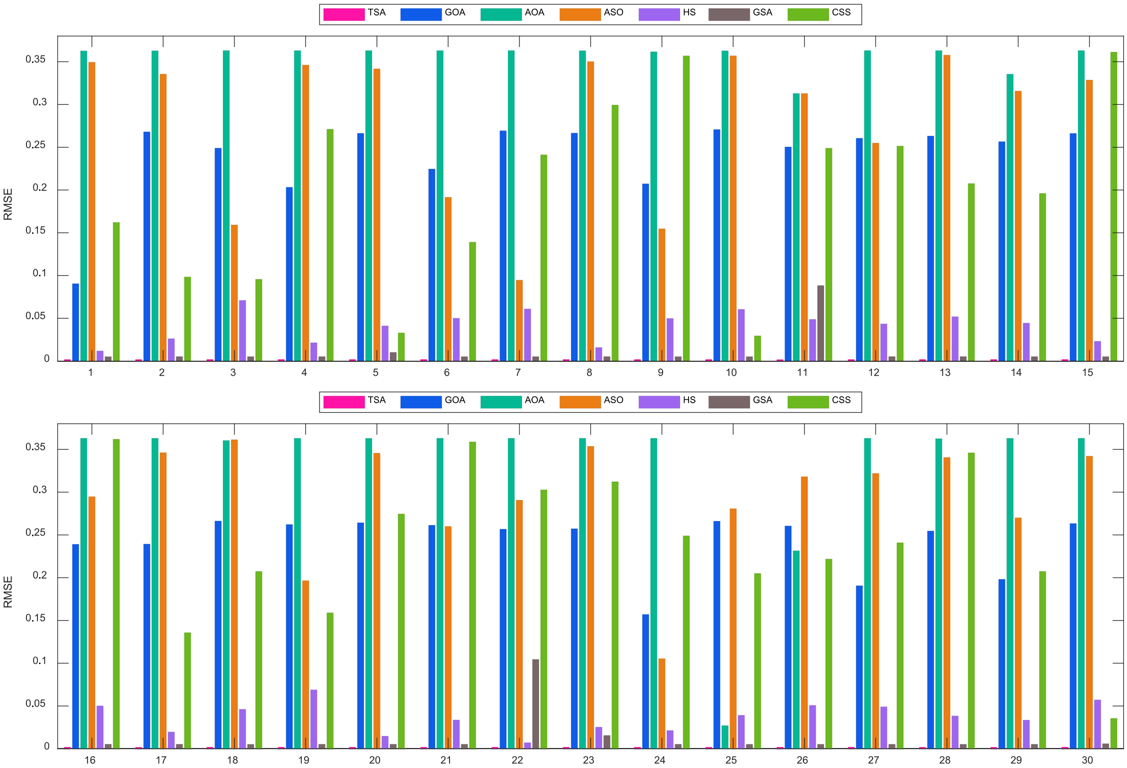

Fig. 11. Ranking of RMSE values.

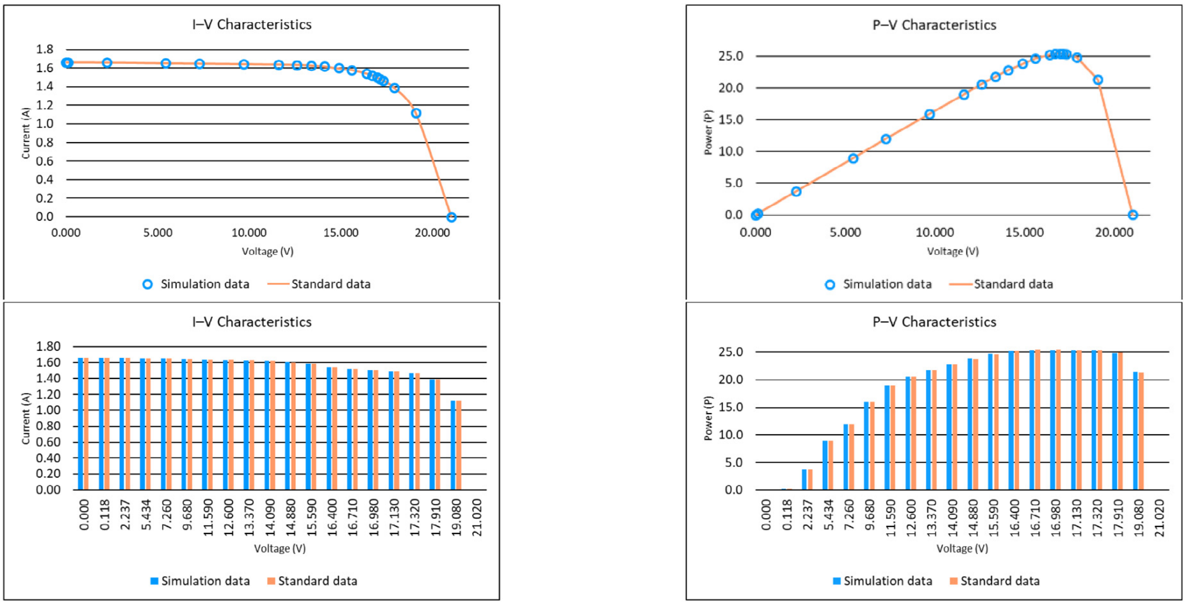

Fig. 12. $I-V$ and $P-V$ characteristics.

References

[1] Long W, Cai S, Jiao J, Xu M, Wu T. A new hybrid algorithm based on grey wolf optimizer and cuckoo search for parameter extraction of solar photovoltaic models. Energy Convers Manage 2020;203:112243.
[2] Aslan M, Gunduz M, Kiran MS. A jaya-based approach to wind turbine placement problem. Energy Sources A: Recovery Util Environ Effects 2020;1–20.
[3] Abdel-Basset M, El-Shahat D, Sallam KM, Munasinghe K. Parameter extraction of photovoltaic models using a memory-based improved gorilla troops optimizer. Energy Convers Manage 2022;252:115134.
[4] Farah A, Belazi A, Benabdallah F, Almalaq A, Chtourou M, Abido MA. Parameter extraction of photovoltaic models using a comprehensive learning Rao-1 algorithm. Energy Convers Manage 2022;252:115057.
[5] Li S, Gu Q, Gong W, Ning B. An enhanced adaptive differential evolution algorithm for parameter extraction of photovoltaic models. Energy Convers Manage 2020;205:112443.
[6] Tefek MF. Artificial bee colony algorithm based on a new local search approach for parameter estimation of photovoltaic systems. J Comput Electron 2021;20(6):2530–62.
[7] Xiong G, Zhang J, Shi D, He Y. Parameter extraction of solar photovoltaic models using an improved whale optimization algorithm. Energy Convers Manage 2018;174:388–405.
[8] Kharchouf Y, Herbazi R, Chahboun A. Parameter's extraction of solar photovoltaic models using an improved differential evolution algorithm. Energy Convers Manage 2022;251:114972.
[9] AbdElminaam DS, Houssein EH, Said M, Oliva D, Nabil A. An efficient heap-based optimizer for parameters identification of modified photovoltaic models. Ain Shams Eng J 2022;13(5):101728.
[10] Yu Y, Wang K, Zhang T, Wang Y, Peng C, Gao S. A population diversity-controlled differential evolution for parameter estimation of solar photovoltaic models. Sustain Energy Technol Assess 2022;51:101938.
[11] Wang J, Yang B, Li D, Zeng C, Chen Y, Guo Z, et al. Photovoltaic cell parameter estimation based on improved equilibrium optimizer algorithm. Energy Convers Manage 2021;236:114051.
[12] Premkumar M, Jangir P, Sowmya R, Elavarasan RM, Kumar BS. Enhanced chaotic JAYA algorithm for parameter estimation of photovoltaic cell/modules. ISA Trans 2021;116:139–66.
[13] Liu Y, Heidari AA, Ye X, Liang G, Chen H, He C. Boosting slime mould algorithm for parameter identification of photovoltaic models. Energy 2021;234:121164.
[14] Xu S, Qiu H. A modified stochastic fractal search algorithm for parameter estimation of solar cells and PV modules. Energy Rep 2022;8:1853–66.
[15] Cinar AC, Korkmaz S, Kiran MS. A discrete tree-seed algorithm for solving symmetric traveling salesman problem. Eng Sci Technol Int J 2020;23(4):879–90.
[16] Jiang J, Xu M, Meng X, Li K. STSA: A sine tree-seed algorithm for complex continuous optimization problems. Physica A 2020;537:122802.
[17] Cinar AC. Training feed-forward multi-layer perceptron artificial neural networks with a tree-seed algorithm. Arab J Sci Eng 2020;45(12):10915–38.
[18] Gungor I, Emiroglu BG, Cinar AC, Kiran MS. Integration search strategies in tree seed algorithm for high dimensional function optimization. Int J Mach Learn Cybern 2020;11(2):249–67.
[19] Köse E. Optimal control of AVR system with tree seed algorithm-based PID controller. IEEE Access 2020;8:89457–67.
[20] Jiang J, Han R, Meng X, Li K. TSASC: tree–seed algorithm with sine–cosine enhancement for continuous optimization problems. Soft Comput 2020;24(24):18627–46.
[21] Beşkirli M. Performance analysis of tree seed algorithm for small dimension optimization functions. Adv Electr Comput Eng 2020;20(2):65–72.
[22] Bujok P. Enhanced tree-seed algorithm solving real-world problems. In: Conference enhanced tree-seed algorithm solving real-world problems. p. 12–6.
[23] Saremi S, Mirjalili S, Lewis A. Grasshopper optimisation algorithm: Theory and application. Adv Eng Softw 2017;105:30–47.
[24] Zhao W, Wang L, Zhang Z. Atom search optimization and its application to solve a hydrogeologic parameter estimation problem. Knowl-Based Syst 2019;163:283–304.
[25] Rashedi E, Nezamabadi-pour H, Saryazdi S. GSA: A gravitational search algorithm. Inform Sci 2009;179(13):2232–48.
[26] Abualigah L, Diabat A, Mirjalili S, Elaziz M Abd, Gandomi AH. The arithmetic optimization algorithm. Comput Methods Appl Mech Engrg 2021;376:113609.
[27] Kaveh A, Talatahari S. A novel heuristic optimization method: charged system search. Acta Mech 2010;213(3):267–89.
[28] Woo G Zong, Hoon K Joong, Loganathan GV. A new heuristic optimization algorithm: Harmony search. Simulation 2001;76(2):60–8.
[29] Kiran MS. TSA: Tree-seed algorithm for continuous optimization. Expert Syst Appl 2015;42(19):6686–98.
[30] Kiran MS, Hakli H. A tree–seed algorithm based on intelligent search mechanisms for continuous optimization. Appl Soft Comput 2021;98:106938.
[31] Aslan M, Beskirli M, Kodaz H, Kiran MS. An improved tree seed algorithm for optimization problems. Int J Mach Learn Comput 2018;8(1):20–5.
[32] El-Fergany AA, Hasanien HM. Tree-seed algorithm for solving optimal power flow problem in large-scale power systems incorporating validations and comparisons. Appl Soft Comput 2018;64:307–16.
[33] Beşkirli M. Solving continuous optimization problems using the tree seed algorithm developed with the roulette wheel strategy. Expert Syst Appl 2021;170:114579.

[34] Gao X, Cui Y, Hu J, Xu G, Wang Z, Qu J, et al. Parameter extraction of solar cell models using improved shuffled complex evolution algorithm. Energy Convers Manage 2018;157:460–79.
[35] Li S, Gong W, Yan X, Hu C, Bai D, Wang L. Parameter estimation of photovoltaic models with memetic adaptive differential evolution. Sol Energy 2019;190:465–74.
[36] Yu S, Heidari AA, Liang G, Chen C, Chen H, Shao Q. Solar photovoltaic model parameter estimation based on orthogonally-adapted gradient-based optimization. Optik 2022;252:168513.
[37] Song S, Wang P, Heidari AA, Zhao X, Chen H. Adaptive Harris hawks optimization with persistent trigonometric differences for photovoltaic model parameter extraction. Eng Appl Artif Intell 2022;109:104608.