Journal of Computer Science
https://dergipark.org.tr/en/pub/bbd
Anatolian Science

ISSN,e-ISSN: 2548-1304
Volume:IDAP-2023, pp:172-179, 2023
https://doi.org/10.53070/bbd.1346267
Research Paper

Improved Reptile Search Algorithm for Optimal Design of Solar Photovoltaic Module

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Received:Aug.19,2023 Accepted:Aug.22,2023 Published:Oct.18,2023

Abstract—This study focuses on the vital role of parameter extraction in optimizing and evaluating solar photovoltaic (PV) systems, as it directly influences their efficiency in converting solar energy to electricity. Researchers have extensively explored the application of various metaheuristic algorithms to accurately estimate solar PV parameters due to their crucial significance, leading to an extensive body of literature on the subject. However, the search for a robust and user-friendly optimizer with high convergence ability remains a challenging task that demands further research. To address this challenge, the study conducts a comprehensive comparative analysis of the RSALF optimizer, an innovative metaheuristic algorithm combining the reptile search algorithm (RSA) with Lévy flight (LF), for parameter extraction of PV model parameters using the Photowatt-PWP201 PV module as a case study. The experimental results demonstrate the RSALF optimizer's remarkable accuracy in parameter estimation, consistently yielding lower root mean square error values and closely aligning with experimental data. Moreover, comparative analysis with other recent optimization approaches highlights the RSALF optimizer's superiority, making it a promising tool for advancing the optimization of PV models and facilitating more efficient and sustainable solar energy utilization.

Keywords: *Reptile search algorithm, Lévy flight concept, parameter identification, photovoltaic model*.

1. Introduction

Parameter extraction plays a pivotal role in the optimization, simulation, and evaluation of solar photovoltaic (PV) systems, as it directly impacts the efficiency of converting solar energy into electricity (Ekinci et al., 2023). Given its crucial importance, researchers have devoted substantial efforts to exploring the application of various metaheuristic algorithms for accurately estimating solar PV parameters, as evidenced by a plethora of existing literature on the subject (Izci, Ekinci, Dal, et al., 2022; B. Xu et al., 2022; S. Xu & Qiu, 2022). However, identifying a robust and user-friendly optimizer that possesses high convergence ability remains a challenging task, demanding extensive research.

In light of the above, the need for optimization algorithms with enhanced capability becomes apparent, as they hold the potential to further improve the performance of solar PV systems through effective parameter extraction. The primary objective of this study is to tackle this challenge by conducting a comprehensive comparative analysis of the reptile search algorithm, RSA (Abualigah et al., 2021), in combination with Lévy flight, LF (X.-S. Yang & Deb, 2013), termed as the RSALF optimizer (Ekinci & Izci, 2023), for parameter extraction of PV model parameters in the context of the Photowatt-PWP201 PV module. This novel metaheuristic algorithm promises to provide a valuable contribution to the field.

In order to evaluate the efficacy of the proposed RSALF optimizer, we present experimental results obtained through its application to the determination of optimal solar PV model parameters. The selected case study involves the Photowatt-PWP201 PV module, which serves as a representative scenario for evaluating the performance of the RSALF optimizer with respect to existing other methods. Through various analyses, we interpret the results and draw meaningful conclusions regarding the effectiveness of the proposed approach in optimizing PV models.

The experimental results of the PV module optimization utilizing the RSALF optimizer demonstrate remarkable accuracy in parameter estimation. Specifically, the RSALF optimizer consistently yields lower root mean square error (RMSE) values, signifying its superior performance in accurately estimating the I-V and P-V characteristics of the PV module. Moreover, the close agreement between the experimental and estimated values further highlights the accurate modeling capabilities of the RSALF optimizer.

To strengthen the claim of the RSALF optimizer's superiority, we perform a comparative analysis with several other recent optimization approaches, including the generalized oppositional teaching learning based optimization (Chen et al., 2016), multiple learning backtracking search algorithm (Yu et al., 2018), improved jaya algorithm (Yu et al., 2017), cuckoo search algorithm (X. S. Yang & Deb, 2009), particle swarm optimization (Kennedy & Eberhart, 1995) and random reselection particle swarm optimization (Fan et al., 2022). The results of the comparison showcase the RSALF optimizer's dominance, as it consistently achieves the lowest RMSE value among all the considered methods. Thus, not only does it exhibit accurate parameter estimation but also outperforms well-established approaches, establishing its prowess in optimizing PV models.

In summary, the experimental findings consistently demonstrate that the RSALF optimizer surpasses other optimization approaches in terms of accurate parameter estimation, low RMSE values, and alignment with experimental data. These results underscore the significant contribution and effectiveness of the RSALF optimizer in the domain of PV model optimization. As a promising and advanced metaheuristic algorithm, RSALF holds great potential for advancing the field of solar PV system optimization and parameter extraction, paving the way for more efficient and sustainable solar energy utilization.

2. RSA with LF

The original form of RSA has been reported by Abualigah et al., in 2021 (Abualigah et al., 2021) and its power has been demonstrated for different applications (Almotairi & Abualigah, 2022; Can et al., 2023; Emam et al., 2023; Izci, Ekinci, Budak, et al., 2022; Izci & Ekinci, 2023). An improved version of this algorithm named RSA with LF, RSALF, has been reported by Ekinci & Izci in 2023 (Ekinci & Izci, 2023). The RSALF optimizer makes use of the potential of the LF to improve the capacity of RSA. Random motion in a region of interest can be performed via LF (X.-S. Yang & Deb, 2013). This feature makes the LF a good candidate for global search capacity of metaheuristic algorithms (Ekinci et al., 2022; Izci et al., 2023). Fig. 1 illustrates the two dimensional LF for 100 steps.

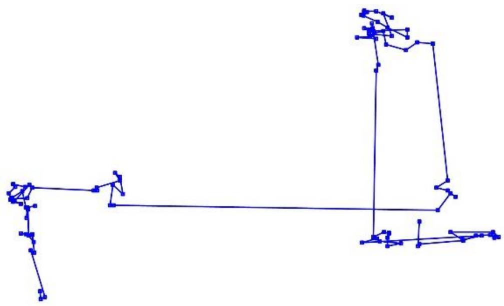

Fig. 1. Illustration of two-dimensional LF in 100 steps

The LF concept can be explained as $L(s) \sim |s|^{-1-\beta}$ where β is the index within $(0, 2]$ (Izci, Ekinci, Eker, et al., 2022). The following definition can be used to mathematically represent the LF distribution (Izci, 2021) where s stands for the step length and μ denotes the transmission parameter and γ is a control parameter that arranges the scale of the distribution.

$$L(s, \gamma, \mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} e^{\left(-\frac{\gamma}{2(s-\mu)}\right)} \left(\frac{1}{(s-\mu)^{3/2}}\right); \ 0 < \mu < s < \infty \\ 0; \ s \leq 0 \end{cases} \tag{1}$$

In terms of Fourier transform, the LF distribution is defined as $F(k) = e^{(-\alpha|k|^{\beta})}$ where α is a scaling parameter and β is the distribution index within $(0, 2]$. The step length is described as follows where u and v have the Gaussian distribution.

$$s = \left(\frac{u}{|v|^{(1/\beta)}}\right) \tag{2}$$

In here, u and v can be obtained as $u \sim N(0, {\sigma_u}^2), v \sim N(0, {\sigma_v}^2)$ where σ_u and σ_v are the standard deviations and $\sigma_v = 1$ whereas σ_u is calculated as follows.

$$\sigma_u = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{(\beta-1)/2}}\right)^{1/\beta} \tag{3}$$

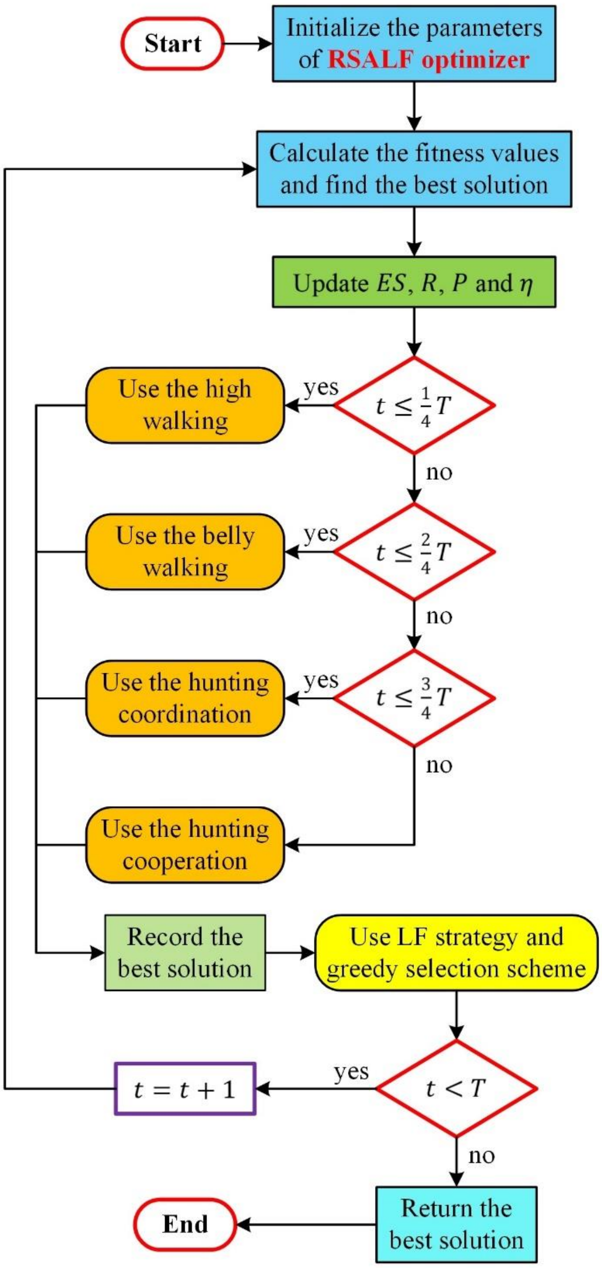

Fig. 2. Flowchart for RSALF optimizer

The employment of the LF within the RSALF optimizer makes sure the population diversity. To better explain the structure of the RSALF optimizer, it can be described as follows. The LF operates after each iteration using the following expression in order to update search agents.

$$x_i^{LF} = x_i + (2 \cdot rand - 1) \cdot Levy(\beta) \cdot (x_{best} - x_i) \tag{4}$$

In here, the solution generated by LF is shown by x_i^{LF} and the current solution is represented by x_i whereas x_{best} is the best solution obtained so far and $rand$ is a random number within $[0, 1]$. The RSALF optimizer also employs a greedy selection scheme (Ekinci & Izci, 2023) meaning better new solutions are improved further for the next iterations while worse ones are eliminated with the following definition in every iteration:

$$x_i(t+1) = \begin{cases} x_i^{LF}, fitness(x_i^{LF}) \leq fitness(x_i) \\ x_i, fitness(x_i^{LF}) > fitness(x_i) \end{cases} \tag{5}$$

where the i^{th} search agent in the next iteration is denoted by $x_i(t+1)$. The x_i (current solution) is replaced by x_i^{LF} (the one LF obtains) for cases where the former one has an equal or lower fitness value. Otherwise, the x_i is kept which allows avoiding solutions with poor quality. Another advantage of the RSALF optimizer is to allow the solutions moving across flat fitness landscapes (Ekinci & Izci, 2023). The optimization process of the RSALF optimizer ends with the satisfaction of the termination condition ($t = T$). RSALF optimizer's detailed flowchart is provided in Fig. 2.

3. Photovoltaic module model and objective function

The photovoltaic (PV) module model captures the relationship between the incident solar irradiance, temperature, and the electrical characteristics of the module. The related model is typically based on the equivalent circuit model, which represents the PV module as an electrical circuit with various components. The main components of the equivalent circuit model include a current source, a diode, a series resistance, and a shunt resistance. The model assumes that the PV module can be represented as a single diode connected in parallel with a current source. Fig. 3 represents the equivalent circuit of a PV module where N_p and N_s are denoting the number of cells in parallel and series respectively.

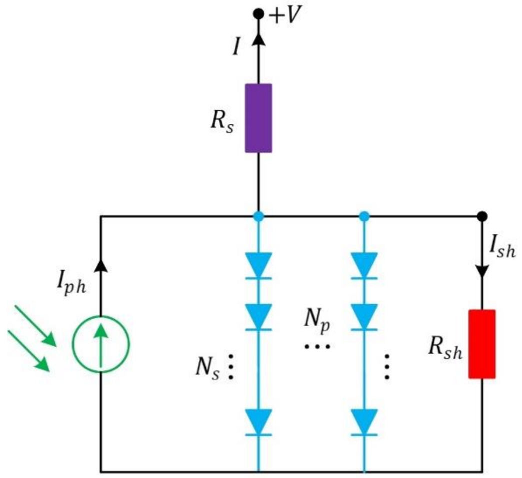

Fig. 3. Equivalent circuit of PV model

Since the solar cells are connected in series largely, the N_p value equals to 1. Therefore, the mathematical model of a PV module can be represented as follows where I is the output current of the PV cell, V is the voltage across the PV cell terminals, I_{ph} is the photocurrent generated by the cell under illumination, I_{sd} is the diode saturation current, R_s and R_{sh} are the series resistance and the shunt resistance of the cell, respectively, n is the diode ideality factor, V_t is the thermal voltage, approximately equal to kT/q, where k is Boltzmann's constant, T is the temperature in Kelvin, and q is the elementary charge.

$$I = I_{ph} - I_{sd}[e^{\frac{(V+IR_sN_S)}{(nN_SV_t)}} - 1] - \frac{(V+IR_sN_s)}{R_{sh}N_s} \tag{6}$$

4. Results and analysis

For this study, the Photowatt-PWP 201 data set is adopted which consists of 25 pairs of current voltage values measured at a temperature of $45°C$ and an irradiance of $1000\ W/m^2$ for 36 photovoltaic panels made of polycrystalline silicon cells connected in series. For the fair comparison purpose, the total iteration is set to $T = 1000$ and the population size $N = 50$ while all the algorithms are run for 30 individual times. Table 1 displays the optimized parameters of the PV module parameters obtained using RSALF optimizer along with upper and lower bounds. The results indicate the achievement of a high accuracy in parameter estimation suggesting the RSALF optimizer's effecacy in fine-tuning the parameters of the PV module.

Table 1. Lower, upper boundaries and estimated parameters of PV module

Parameter	Lower bound	Upper bound	Optimized by RSALF
I_{ph} (A)	0	2	1.03051429930735
I_{sd} (μA)	0	50	3.48226278470423
R_s (Ω)	0	2	1.20127101314577
R_{sh} (Ω)	0	2000	981.982212446243
n	1	50	48.6428347213304

Fig. 4 presents the absolute current error with respect to voltage measurement. Furthermore, Fig. 5 and Fig. 6 illustrate the I-V and P-V curve characteristics, respectively, of the PV module optimized using the RSALF optimizer. The figures demonstrate that the optimized model accurately captures the behavior of the PV module, as the curves closely match the experimental data.

Table 2 compares the estimated parameters and RMSE values for the PV module obtained using RSALF optimizer with other more recent optimization approaches, including multiple learning backtracking search algorithm (MLBSA) (Yu et al., 2018), generalized oppositional teaching learning based optimization (GOTLBO) (Chen et al., 2016), improved jaya algorithm (IJAYA) (Yu et al., 2017), cuckoo search algorithm (CS) (X. S. Yang & Deb, 2009), particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) and random reselection particle swarm optimization (Fan et al., 2022). Furthermore, Table 3 presents the statistical results comparatively. The results highlight the RSALF optimizer's superior performance, as it achieves the lowest RMSE value among all the compared methods. This emphasizes the significance of the RSALF optimizer in accurately modeling the behavior of the Photowatt-PWP 201 PV module.

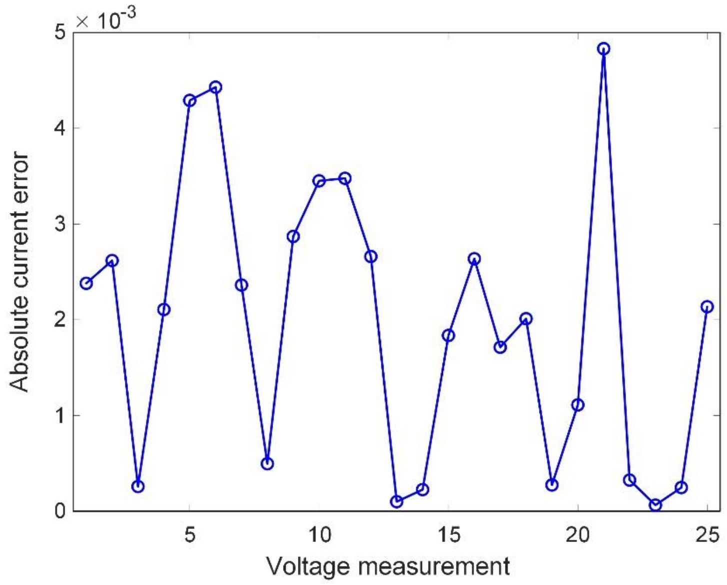

Fig. 4. Absolute current error with respect to voltage measurements

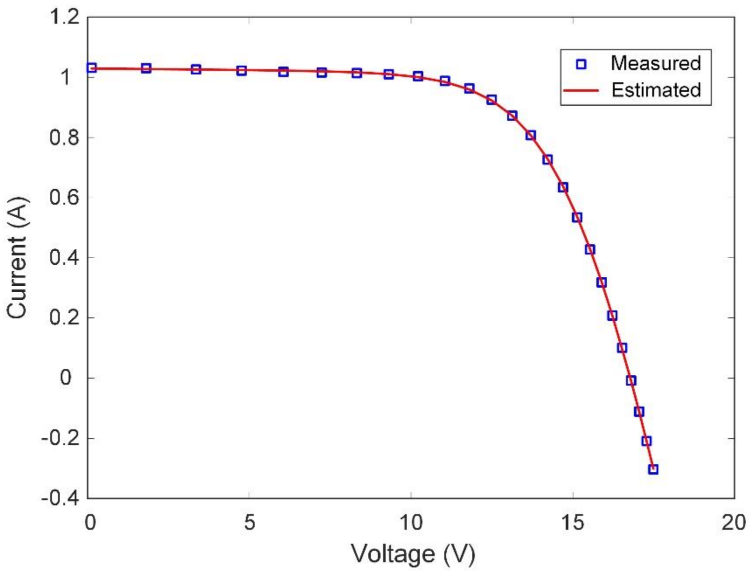

Fig. 5. PV module I-V curve characteristics

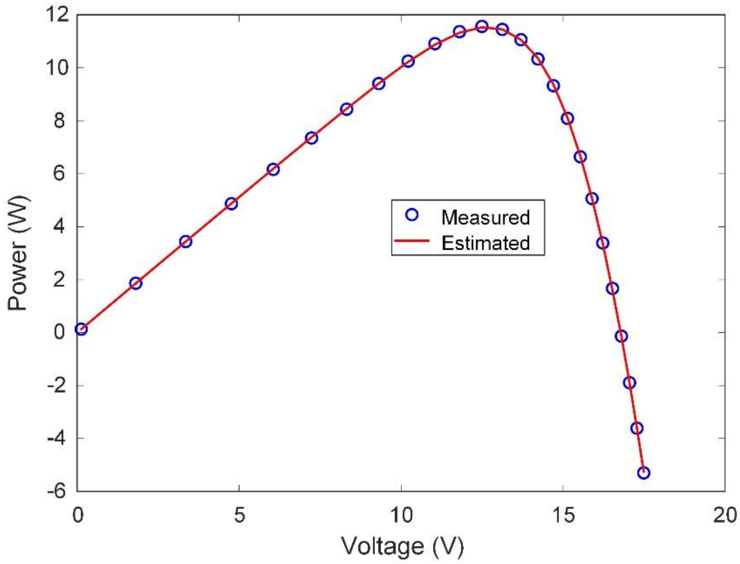

Fig. 6. PV module P-V curve characteristics

Table 2. The determined parameters and RMSE values for PV module model

Algorithm	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	n	RMSE
RSALF (proposed)	1.0305	3.4823	1.2013	981.98	48.643	**2.4251E−03**
MLBSA (Yu et al., 2018)	1.0305	3.4823	1.2013	981.98	48.643	**2.4251E−03**
GOTLBO (Chen et al., 2016)	1.0305	3.4441	1.2025	980.05	48.600	2.4255E−03
IJAYA (Yu et al., 2017)	1.0307	3.5367	1.1996	977.04	48.703	2.4268E−03
CS (X. S. Yang & Deb, 2009)	1.0294	3.7326	1.1959	1148.6	48.908	2.4450E−03
PSO (Kennedy & Eberhart, 1995)	1.0303	3.6399	1.1967	1032.2	48.813	2.4282E−03
PSOCS (Fan et al., 2022)	1.0305	3.4823	1.2013	981.98	48.643	**2.4251E−03**

Table 3. The statistical indicator data of RMSE of different algorithms for PV module model

Algorithm	RMSE			
	Minimum	Maximum	Mean	Standard deviation
RSALF (proposed)	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	**2.6992E−17**
MLBSA (Yu et al., 2018)	**2.4251E−03**	3.6478E−03	2.4709E−03	2.2259E−04
GOTLBO (Chen et al., 2016)	2.4255E−03	2.7525E−03	2.4877E−03	7.4249E−05
IJAYA (Yu et al., 2017)	2.4268E−03	6.4710E−03	2.6365E−03	7.4574E−04
CS (X. S. Yang & Deb, 2009)	2.4450E−03	2.6473E−03	2.5152E−03	5.0324E−05
PSO (Kennedy & Eberhart, 1995)	2.4282E−03	3.1526E−01	1.3531E−01	1.4463E−01
PSOCS (Fan et al., 2022)	**2.4251E−03**	2.4282E−03	2.4252E−03	5.9113E−07

5. Conclusion

Efficiently converting solar energy into electricity relies heavily on optimizing solar PV systems, with parameter extraction playing a vital role in this optimization process. In pursuit of improved PV system performance, researchers have extensively explored various metaheuristic algorithms to estimate solar cell parameters accurately, showcasing promising results under different conditions. Nonetheless, despite the existing research, the quest for optimization algorithms with high convergence ability persists, aiming to further enhance solar PV systems through precise parameter extraction. This study addresses this challenge by introducing and evaluating the RSALF optimizer, which combines the effectiveness of the RSA with the additional global search capability of LF, resulting in enhanced performance. The proposed RSALF optimizer is specifically applied to parameter extraction in the Photowatt-PWP201 solar PV module. The experimental results demonstrate the exceptional accuracy of the RSALF optimizer in parameter estimation, consistently surpassing other competitive approaches. The RSALF optimizer yields results that closely align with experimental data, closely matching the I-V and P-V curve characteristics of the optimized models. In-depth comparative analysis with other recent optimization approaches reaffirms the RSALF optimizer's superiority, as it achieves the lowest RMSE values among all considered methods. The RSALF optimizer proves to be a promising solution for optimizing PV models and facilitating more efficient solar energy utilization.

References

Abualigah, L., Elaziz, M. A., Sumari, P., Geem, Z. W., & Gandomi, A. H. (2021). Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer. *Expert Systems with Applications*, 116158. https://doi.org/10.1016/j.eswa.2021.116158

Almotairi, K. H., & Abualigah, L. (2022). Improved reptile search algorithm with novel mean transition mechanism for constrained industrial engineering problems. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-022-07369-0

Can, Ö., Andiç, C., Ekinci, S., & Izci, D. (2023). Enhancing transient response performance of automatic voltage regulator system by using a novel control design strategy. *Electrical Engineering*, *105*(4), 1993–2005. https://doi.org/10.1007/s00202-023-01777-8

Chen, X., Yu, K., Du, W., Zhao, W., & Liu, G. (2016). Parameters identification of solar cell models using generalized oppositional teaching learning based optimization. *Energy*, *99*, 170–180. https://doi.org/10.1016/j.energy.2016.01.052

Ekinci, S., & Izci, D. (2023). Enhanced reptile search algorithm with Lévy flight for vehicle cruise control system design. *Evolutionary Intelligence*, *16*(4), 1339–1351. https://doi.org/10.1007/s12065-022-00745-8

Ekinci, S., Izci, D., Abu Zitar, R., Alsoud, A. R., & Abualigah, L. (2022). Development of Lévy flight-based reptile search algorithm with local search ability for power systems engineering design problems. *Neural Computing and Applications*, *34*(22), 20263–20283. https://doi.org/10.1007/s00521-022-07575-w

Ekinci, S., Izci, D., Eker, E., Abualigah, L., Thanh, C.-L., & Khatir, S. (2023). Hunger games pattern search with elite opposite-based solution for solving complex engineering design problems. *Evolving Systems*. https://doi.org/10.1007/s12530-023-09526-9

Emam, M. M., Houssein, E. H., & Ghoniem, R. M. (2023). A modified reptile search algorithm for global optimization and image segmentation: Case study brain MRI images. *Computers in Biology and Medicine*, *152*, 106404. https://doi.org/10.1016/j.compbiomed.2022.106404

Fan, Y., Wang, P., Heidari, A. A., Chen, H., HamzaTurabieh, & Mafarja, M. (2022). Random reselection particle swarm optimization for optimal design of solar photovoltaic modules. *Energy*, *239*, 121865. https://doi.org/10.1016/j.energy.2021.121865

Izci, D. (2021). Design and application of an optimally tuned PID controller for DC motor speed regulation via a novel hybrid Lévy flight distribution and Nelder–Mead algorithm. *Transactions of the Institute of Measurement and Control*, *43*(14), 3195–3211. https://doi.org/10.1177/01423312211019633

Izci, D., & Ekinci, S. (2023). The promise of metaheuristic algorithms for efficient operation of a highly complex power system. In S. Mirjalili & A. Gandomi (Eds.), *Comprehensive Metaheuristics* (1st ed., pp. 325–346). Elsevier. https://doi.org/10.1016/B978-0-323-91781-0.00017-X

Izci, D., Ekinci, S., Budak, C., & Gider, V. (2022). PID Controller Design for DFIG-based Wind Turbine via Reptile Search Algorithm. *2022 Global Energy Conference (GEC)*, 154–158. https://doi.org/10.1109/GEC55014.2022.9986617

Izci, D., Ekinci, S., Dal, S., & Sezgin, N. (2022). Parameter Estimation of Solar Cells via Weighted Mean of Vectors Algorithm. *2022 Global Energy Conference (GEC)*, 312–316. https://doi.org/10.1109/GEC55014.2022.9986943

Izci, D., Ekinci, S., Eker, E., & Demirören, A. (2022). Multi-strategy modified INFO algorithm: Performance analysis and application to functional electrical stimulation system. *Journal of Computational Science*, *64*, 101836. https://doi.org/10.1016/j.jocs.2022.101836

Izci, D., Ekinci, S., Mirjalili, S., & Abualigah, L. (2023). An intelligent tuning scheme with a master/slave approach for efficient control of the automatic voltage regulator. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-023-08740-5

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *Proceedings of ICNN'95-International Conference on Neural Networks*, *4*, 1942–1948.

Xu, B., Heidari, A. A., Zhang, S., Chen, H., & Shao, Q. (2022). Extremal Nelder–Mead colony predation algorithm for parameter estimation of solar photovoltaic models. *Energy Science & Engineering*, *10*(10), 4176–4219. https://doi.org/10.1002/ese3.1273

Xu, S., & Qiu, H. (2022). A modified stochastic fractal search algorithm for parameter estimation of solar cells and PV modules. *Energy Reports*, *8*, 1853–1866. https://doi.org/10.1016/j.egyr.2022.01.008

Yang, X.-S., & Deb, S. (2013). Multiobjective cuckoo search for design optimization. *Computers & Operations Research*, *40*(6), 1616–1624. https://doi.org/10.1016/j.cor.2011.09.026

Yang, X. S., & Deb, S. (2009). Cuckoo search via Lévy flights. *2009 World Congress on Nature and Biologically Inspired Computing, NABIC 2009 - Proceedings*, 210–214. https://doi.org/10.1109/NABIC.2009.5393690

Yu, K., Liang, J. J., Qu, B. Y., Chen, X., & Wang, H. (2017). Parameters identification of photovoltaic models using an improved JAYA optimization algorithm. *Energy Conversion and Management*, *150*, 742–753. https://doi.org/10.1016/j.enconman.2017.08.063

Yu, K., Liang, J. J., Qu, B. Y., Cheng, Z., & Wang, H. (2018). Multiple learning backtracking search algorithm for estimating parameters of photovoltaic models. *Applied Energy*, *226*, 408–422. https://doi.org/10.1016/j.apenergy.2018.06.010