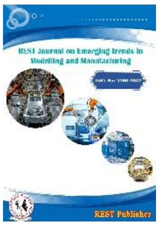
DOI: http://doi.org/10.46632/jemm/9/1/7

**REST Journal on Emerging trends in Modelling and Manufacturing**
**Vol: 9(1), March 2023**
**REST Publisher; ISSN: 2455-4537**
**Website: http://restpublisher.com/journals/jemm/**



# Renewable Energy Systems Design with Soft Computing and Evolutionary Algorithms

***S. Sumathi, M. Malukannan, S. Gobinath, J. Prabhakaran, A. Anitha**
*Mahendra Engineering College, Namakkal, Tamil Nadu, India.*
*Corresponding author Email: sumathis@mahendra.info

**Abstract:** *Renewable energy systems play a vital role in addressing global energy demands and reducing environmental impacts through the use of sustainable resources like solar and wind. However, their efficiency and reliability are often challenged by the variability and uncertainty of these resources, leading to difficulties in system optimization and decision-making. This research addresses these limitations by employing fuzzy logic to manage uncertainties and evolutionary algorithms to optimize system configurations and performance. Fuzzy logic provides a robust framework for handling imprecise data, enabling adaptive decision-making, while evolutionary algorithms efficiently explore design spaces to identify optimal solutions. The proposed methodology is validated through case studies involving solar and hybrid energy systems, showcasing significant improvements in energy efficiency, reliability, and cost-effectiveness. This work offers a scalable and systematic approach to overcoming the challenges in renewable energy system design, contributing to the development of sustainable and resilient energy solutions.*

**Keywords:** *Renewable energy, Fuzzy logic, Particle swam optimization, Photovoltaic.*

## 1. Introduction

The modern world has seen a rapid increase in energy consumption due to modernisation and population growth. Over the past few decades, a variety of unconventional energy sources have been developed to provide energy concurrently with conventional sources of energy in order to fulfil the growing demand for energy and effectively utilise these resources [1]. Due to its incredibly long lifespan, low maintenance needs, absence of toxic waste, and availability, solar energy is more feasible of the most popular alternatives to conventional energy, including wind, sun, geothermal, tidal, and biogas. Maximum power extraction, as it relates to solar Photo Voltaic (PV) systems, is the process of obtaining the most electrical power possible from the solar panels under specific circumstances. However, a number of variables, such as the temperature, shade, sunlight intensity, and the system performance, affect how much power solar PV panels can produce at any particular time. It is important to use a suitable technique to track Maximum Power Point (MPP) production as solar energy production fluctuates with irradiance variations. Due to fluctuating irradiance, power extraction from solar photovoltaics (PV) varies continually during the day from morning to evening, making it imperative to maximise power extraction. The idea of maximal extraction of power from solar PV is presented in order to satisfy the rapidly growing load need. Solar PV systems are usually designed and managed to maximise power extraction. This includes maximising battery storage, minimising shade, employing high-efficiency components, optimising panel tilt and orientation, and performing routine maintenance [2]. Over the last ten years, solar power generation has grown rapidly [3,4]. One benefit of solar power generation is that it is ecologically benign, noiseless, and requires less maintenance. Enhancing photovoltaic (PV) efficiency is a primary research objective that contributes to the cost competitiveness of PV technology in comparison to traditional energy sources [5,6]. Due to its nonlinear current-voltage (I-V) properties, which produce a distinct MPP on the power-voltage (P-V) curve, photovoltaics presents a significant task. Power converters and Maximum Power Point Tracking (MPPT) are required to guarantee the best possible use of solar energy sources and increase efficiency. Extracting the most power possible under various temperature and radiation circumstances is the aim of MPPT. Fractional open-circuit voltage and short-circuit current, incremental conductance, perturb and observe (P&O) are some of the MPPT algorithms that have been researched. To build the MPPT, the solar panel design was linearised into a circuit that was similar to Thevenin [7]. Solar photovoltaics is the most popular and remarkable type of renewable energy generating. One renewable energy source that can minimise carbon emissions, lower power costs, and help create a more reliable and eco-friendlier source of energy is solar photovoltaic systems. From modest residential installations to massive industrial or utility-scale networks, solar photovoltaic systems come in a wide range of sizes and capacities. However, the PV array's nonlinear output-voltage features make it challenging to operate at maximum power or achieve peak output at all times. On the power-voltage function, the maximum power can be delivered by a single pair of power-voltage points. Due to the continuous nature of PV generation, the power-voltage feature varies with changes in the surrounding environment each short while. With the decline of traditional energy sources and their negative impacts on the environment, the role of alternative sources of energy in producing energy has taken precedence in the modern world. Compared to other energy sources, solar-based energy generation has become increasingly popular due to its affordability, environmental friendliness, and quick price reduction. Making the most of power extraction is essential to a solar PV system's ability to produce the most electricity, which increases its economic and ecological viability. In addition to decreasing dependency on fossil fuels for energy generation, it enables utilities, organisations, and households to maximise their solar resources [8]. PVs are essential to the global shift to renewable energy because they provide a sustainable and clean substitute for traditional power generation techniques. However, environmental factors affect their performance, thus efficient methods to optimise energy output are required. This requirement is met by MPPT approaches, which maximise electricity generation by optimising PV system operating conditions. An MPPT based on fuzzy adaptive PSO is discussed in this paper. In order to increase the MPPT controller's performance and discover an optimal global strategy for both PSC and uniform irridiation, the research is motivated by the goal of combining the benefits of fuzzy control with PSO while maintaining the simple form of PSO. Fuzzy logic-based controllers have been used for a variety of engineering challenges, especially those with nonlinear dynamics. Fuzzy controller design relies on plant expertise rather than an exact mathematical framework. To increase the rate of convergence, the fuzzy controller constantly changes the PSO variable. According to simulation results, the controller can monitor the global MPP under both uniform irridiation and PSC, which has various local MPP. Compared to the settling time using a standard PSO controller, the suggested controller settles data 14% better with PSC in general and thirty percent quicker with consistent irradiation.

## 2. Literature Review

Barzola-Monteses et al., have stated that the management of energy supply and demand presents a number of difficulties for less developed or emerging nations. The disparity between the supply and demand for energy significantly affects a nation's ability to prosper economically. For policymakers to promptly recognise the abrupt shift in the need for electricity under specific circumstances, energy output prediction is essential. Temperature, reservoir volume, river flow, and energy cost are some of the variables that affect how effective hydropower facilities are. It is challenging to forecast and control a plant's operating output due to these considerations. Consequently, capacity scheduling and energy system management depend on precise and dependable energy production estimates [9]. Luck et al., have improved the flexibility for combined design and management utilising Soft Actor-Critic (SAC) with the presence of difficult optimisation challenges. The method improves on this strategy by fusing model-based optimisation with policy variables. It was used in systems that included batteries and photovoltaic (PV) panels, but its limits came from its on-policy nature and limited time horizons [10]. Chen and Jackson et al., have concentrated on explicitly learning system factors, presuming that the dynamics of the system are parameterised. However, these methods are limited when simulating complex energy systems where design choices are directly tied to specified costs or benefits [11, 12]. Wu et al., have used principal component analysis and an ensemble smoother employing multiple data integration to reverse the tracer dataset in order to predict the spatial distributions of perforations in the fragmented system. The tracer analysis is used in conjunction with an Ensemble Kalman Filter-based integration of data technique to forecast the EGS's long-term function. Markov Chain Monte Carlo sequence was used to correct fracture system realisations and stress-based tomography was used to characterise the fracture network [13]. Zhou et al., have suggested a deep neural network-accelerated inversion technique to determine the 2D fracture field's fractal dimension and fracture density. In order to determine changeable fracture positions and layouts [14]. Ringel et al., have presented a 3D fracture network stochastic characterisation using Markov Chain Monte Carlo. Designing and optimising geothermal development to maximise heat recovery is based on these more trustworthy geological models [15]. Wang et al., have presented a developmental sampling aided optimisation technique that used a local surrogate to speed up search and a global RBF model to select the best offspring [16]. Wei et al., have used a gradient boosting classifier as a surrogate model to identify suitable subjects for real-world value assessment [17]. Liu et al., have created a surrogate-aided multi-population particle swarm optimiser that employs resemblance dispersion clustering to build multiple subswarms and direct the exploration of each subswarm while adding a diversity maintenance strategy. The majority of the techniques discussed above exhibit good performance on optimisation issues with smaller dimensions [18].

# 3. Research Methodology

The first step in the study process is to identify and analyse the difficulties in optimising renewable energy systems, with a particular emphasis on the unpredictability and variable of energy sources such as wind and solar. Fuzzy logic is used to handle imprecise input and enable adaptive decision-making in unpredictable situations in order to overcome these difficulties. This enhances the ability to handle varying energy sources by enabling more precise system modelling. The design space is then explored using evolutionary algorithms, like differential evolution or genetic codes, which optimise system configurations for improved performance. The method is then validated using solar energy systems, where the performance of the optimised systems is compared to conventional models. To make sure it can be used with different renewable energy setups, the approach is further validated for scalability. This strategy eventually seeks to improve renewable energy systems' affordability, dependability, and energy efficiency in order to support adaptable and sustainable energy solutions.

## Conventional Particle Swarm Optimization (PSO)

Conventional Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm inspired by the collective movement of birds or fish in search of food. Each candidate solution, known as a particle, moves through the search space by adjusting its position based on both its own experience and that of the entire swarm. The algorithm maintains a fixed set of parameters, including acceleration coefficients and inertia weight, without employing adaptive mechanisms or hybrid modifications.

In a D-dimensional search space, a swarm of N-particles is initialized with random positions and velocities. Each particle has a personal best position $P_i$ representing the best solution it has found, and the swarm maintains a global best position g, which is the best solution found by any particle. The movement of a particle is governed by an iterative process where its velocity and position are updated according to predefined equations.

The velocity update equation incorporates three components: the influence of the previous velocity, the attraction towards the personal best position, and the attraction towards the global best position. Mathematically, the velocity update for particle *i* in dimension *j* at iteration *t*+1 is expressed in equation (1):

$$v_{i,j}^{t+1} = w \,.\, v_{i,j}^{t} + c_1 r_1 \left(p_{i,j} - x_{i,j}^{t}\right) + c_2 r_2 \left(g_j - x_{i,j}^{t}\right) \tag{1}$$

where www is the inertia weight that balances exploration and exploitation, $c_1$ and $c_2$ are acceleration coefficients that control the influence of the personal and global best positions, respectively, and $r_1$ and $r_2$ are random values uniformly distributed in the range [0,1], introducing stochastic behavior to the algorithm.

Once the velocity is updated, the new position of the particle is computed in equation (2):

$$x_{i,j}^{t+1} = x_{i,j}^{t} + v_{i,j}^{t+1} \tag{2}$$

To ensure stability in the search process, the velocity is often constrained within a predefined range, typically represented in equation (3):

$$v_{i,j}^{t+1} = \min\left(\max\left(v_{i,j}^{t+1}, -v_{max}\right), v_{max}\right) \tag{3}$$

where $v_{max}$ is the maximum velocity allowed. This prevents particles from making excessively large jumps, which could hinder convergence.

The algorithm iterates through velocity and position updates until a stopping criterion is met, which may be a maximum number of iterations, an acceptable error threshold, or negligible improvement in the global best solution. Conventional PSO, while effective for many optimization problems, relies on fixed parameter settings, making it susceptible to premature convergence or stagnation in complex search landscapes. Nonetheless, its simplicity and efficiency make it widely used in various applications, including renewable energy optimization and engineering design. Figure 1 shows the flow diagram of conventional PSO.

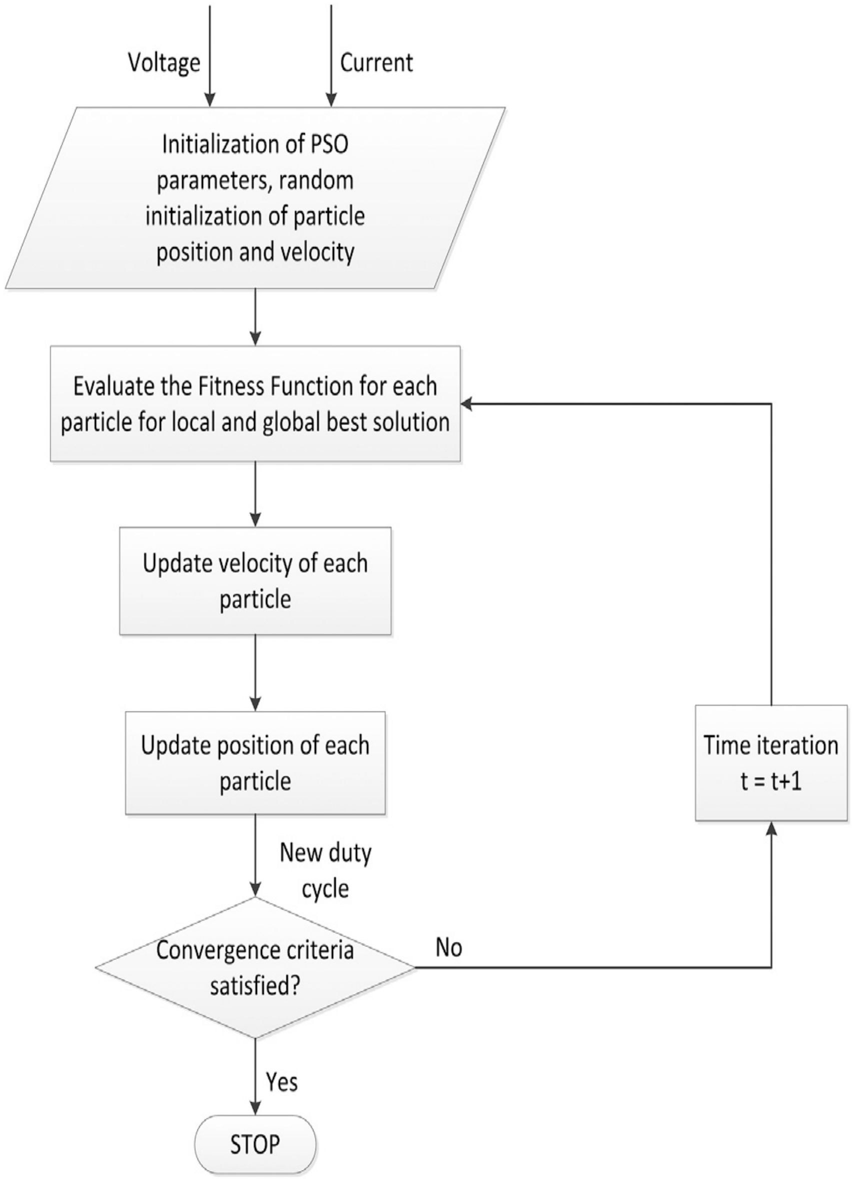


**Figure 1.** Flow diagram of conventional PSO

### Fuzzy Adaptive Particle Swarm Optimization (FAPSO) Definition

FAPSO is an enhanced version of PSO that integrates fuzzy logic to dynamically adjust control parameters such as inertia weight and acceleration coefficients. The primary goal is to improve convergence speed, exploration-exploitation balance, and robustness in solving complex optimization problems. In standard PSO, particles update their positions and velocities using fixed or linearly varying parameters. However, FAPSO employs a Fuzzy Inference System (FIS) to adaptively adjust these parameters based on swarm behavior, leading to better adaptability to dynamic search spaces.

The standard PSO algorithm updates the velocity and position of each particle in a search space as followed in equation (4) & (5):

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \quad (4)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (5)$$

where:

- $v_i^t$ is the velocity of particle *i* at iteration *t*.

- $x_i^t$ is the position of particle *i*.
- $pbest_i$ is the personal best position of particle *i*..
- $gbest$ is the global best position.
- $r_1$,$r_2$ ~ $U$ (0,1) are random numbers.
- $c_1$ , $c_2$ are acceleration coefficients.
- ω is the inertia weight.

In FAPSO, fuzzy logic is applied to dynamically adjust ω, $c_1$ and $c_2$ based on the swarm's behavior. A Fuzzy Inference System (FIS) uses input variables such as swarm diversity (*D*) and Convergence Rate (*CR*) to determine optimal values for ω.

**Fuzzy Adaptation of Inertia Weight**

The inertia weight ω affects the convergence speed and stability of the algorithm. A fuzzy rule base adjusts ω as:

$$\omega = \text{FIS}\,(D, CR) \tag{6}$$

where:

- Swarm Diversity (*D*) is defined as:

$$D = \frac{1}{N}\sum_{i=1}^{N} \| x_i - gbest \| \tag{7}$$

It measures how spread out the particles are.

- Convergence Rate (*CR*) is computed as:

$$CR = \frac{|f(gbest^{(t)}) - f(gbest^{(t-1)})|}{f(gbest^{(t-1)})} \tag{8}$$

It quantifies the improvement in the global best solution.

Using a fuzzy rule-based system, ω is adjusted dynamically:

- If *D* is high and *CR* is low, then increase ω to enhance exploration.
- If *D* is low and *CR* is high, then decrease ω to promote exploitation.

The fuzzy sets for *D* and *CR* are defined using linguistic variables such as {Low, Medium, High}, and an inference engine determines the new ω using membership functions.

**Adaptive Acceleration Coefficients**

Similarly, $c_1$ (cognitive component) and $c_2$ (social component) are adjusted:

$$c_1 = c_1, min + \frac{(c_1, \max - c_1, min)}{1 + e^{-k(D - D_m)}} \tag{9}$$

$$c_2 = c_2, max + \frac{(c_2, \max - c_2, min)}{1 + e^{-k(D - D_m)}} \tag{10}$$

where $D_m$ is a threshold diversity level and *k* is a scaling factor.

By integrating fuzzy logic with PSO, FAPSO achieves improved adaptability, making it suitable for complex renewable energy system optimization, where parameter settings significantly impact convergence speed and solution quality. Figure 2 displays the block diagram of fuzzy controller and figure 3 illustrates the flowchart of the proposed fuzzy adaptive PSO controller.

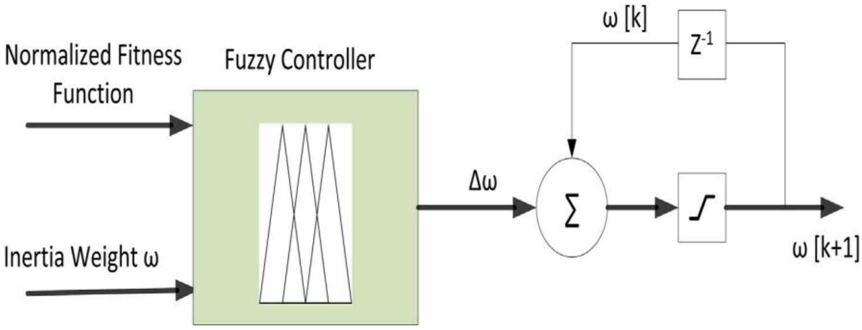


**Figure 2.** Block diagram of fuzzy controller

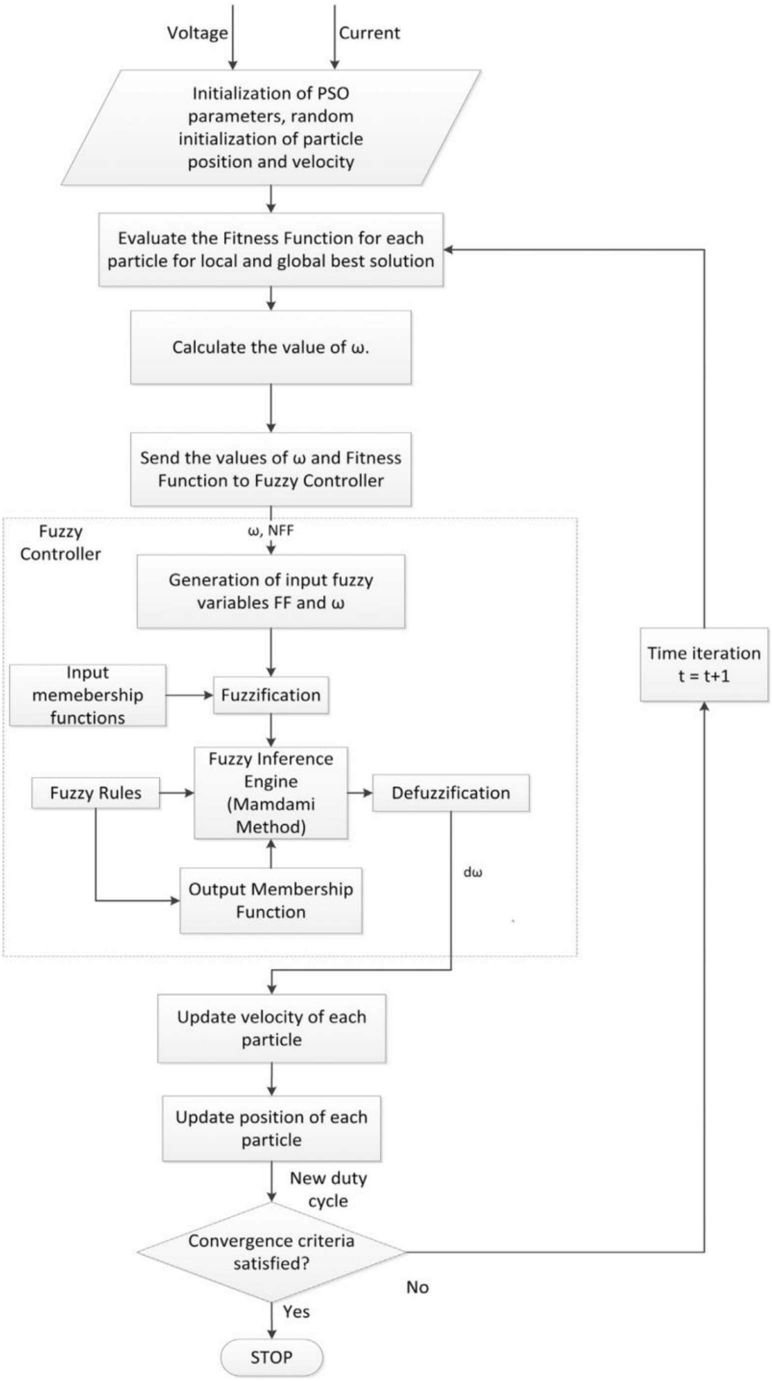


**Figure 3.** Flowchart of the proposed fuzzy adaptive PSO controller

## 4. Result and Discussion

**Table 1.** Theoretical Comparison with Standard PSO

| Criterion | Standard PSO | FAPSO |
|---|---|---|
| Convergence Speed | Moderate | Faster due to dynamic adaption |
| Solution Quality | Good | Better, due to enhanced search mechanism |
| Computational Cost | Lower | Slightly higher, but more efficient |
| Premature Convergence | High | Lower due to adaptive inertia weight |
| Robustness | Moderate | Higher, as FAPSO adapts to different problem landscape |

The table 1 shows the Theoretical Comparison with Standard PSO. When compared to traditional PSO, the use of FAPSO in the design of renewable energy systems shows enhanced convergence speed, solution quality, and robustness. FAPSO successfully strikes a balance between exploration and exploitation by dynamically modifying the acceleration coefficients and inertia weight using fuzzy logic, hence minimising premature convergence. According to theoretical research, FAPSO produces high-performance and cost-effective solutions by achieving faster optimisation in issues like energy dispatch and photovoltaic-storage system sizing. It has less computing overhead than conventional PSO while yet being more flexible with regard to nonlinear constraints. Furthermore, by optimising system components according to variations in demand, FAPSO improves reliability in hybrid renewable energy designs. Overall efficiency is increased through the effective handling of multi-objective scenarios made possible by the dynamic tweaking of search parameters. FAPSO is more robust and scalable in the face of variable energy supply situations than static parameter-based methods. Even in situations that change quickly, stable solutions are guaranteed by the adaptive process. FAPSO is a promising method for optimising renewable energy systems, especially PV applications, because of these benefits. However, because fuzzy logic computations are involved, the method's computational cost is still somewhat higher. To improve performance while preserving computing economy, more hybridisation approaches could be used into future research.

## 5. Conclusion

The design of renewable energy systems is improved by FAPSO, which uses fuzzy logic to dynamically modify search parameters, increasing convergence speed and solution quality. Its adaptive method guarantees effective optimisation of energy dispatch models, hybrid configurations, and photovoltaic-storage systems. FAPSO is more robust and scalable when dealing with nonlinear constraints than normal PSO. The technique is appropriate for intelligent energy management since it minimises premature convergence while preserving computational viability. The performance benefits of fuzzy inference exceed the computational cost increase. The flexibility of FAPSO guarantees steady solutions in a range of operating circumstances, improving the use of renewable energy. Hybrid metaheuristics may be investigated in future studies for more efficiency gains. Its application in actual energy optimisation problems would be strengthened by empirical validations.

## References

1. A. Gaga, F. Errahimi, N. Es-Sbai (2020), Design and Implementation of MPPT Solar System Based on the Enhanced P&O Algorithm Using Labview, International Renewable and Sustainable Energy Conference (IRSEC), 203–208.
2. P.K. Pathak, A.K. Yadav, P.A. Alvi (2022), Reduced oscillations based perturb and observe solar maximum power point tracking scheme to enhance efficacy and speed of a photovoltaic system, J. Eng. Res. 11 (2B), 112–125.
3. Guozden, T., Carbajal, J. P., Bianchi, E., and Solarte, A. (2020), Optimized Balance between Electricity Load and Wind-Solar Energy Production. Front. Energ. Res. 8, 16. doi:10.3389/fenrg.2020.00016
4. Sohani, A., Hoseinzadeh, S., Samiezadeh, S., and Verhaert, I. (2021), Machine Learning Prediction Approach for Dynamic Performance Modeling of an Enhanced Solar Still Desalination System. J. Therm. Anal. Calorim. doi:10.1007/s10973-021-10744-z
5. Alizadeh, H., Alhuyi Nazari, M., Ghasempour, R., Shafii, M. B., and Akbarzadeh, A. (2020), Numerical Analysis of Photovoltaic Solar Panel Cooling by a Flat Plate Closed-Loop Pulsating Heat Pipe. Solar Energy 206, 455–463. doi:10.1016/j.solener.2020.05.058

6. Maleki, A., Haghighi, A., El Haj Assad, M., Mahariq, I., and Alhuyi Nazari, M. (2020), A Review on the Approaches Employed for Cooling PV Cells. Solar Energy 209, 170–185. doi:10.1016/j.solener.2020.08.083
7. Nguyen, B. N., Nguyen, V. T., Duong, M. Q., Le, K. H., Nguyen, H. H., and Doan, A. T. (2020), Propose a MPPT Algorithm Based on Thevenin Equivalent Circuit for Improving Photovoltaic System Operation. Frontier Energ. Res. 8. doi:10.3389/fenrg.2020.00014
8. P.K. Pathak, S. Padmanaban, A.K. Yadav, P.A. Alvi, B. Khan (2022), Modified incremental conductance MPPT algorithm for SPV-based grid-tied and stand-alone systems, IET Generation, Transmission & Distribution 16 (4), 776–791.
9. Barzola-Monteses J, Gomez-Romero J, Espinoza-Andaluz M, Fajardo W (2022), Hydropower production prediction using artificial neural networks: an Ecuadorian application case. Neural Comput Appl 34(16), 13253–13266.
10. Luck, K. S., Amor, H. B., and Calandra, R. (2020), Data-efficient Co-Adaptation of Morphology and Behaviour with Deep Reinforcement Learning. In Proceedings of the Conference on Robot Learning, pp. 854–869. PMLR, May 2020. URL https://proceedings.mlr.press/v100/luck20a.html. ISSN: 2640-3498.
11. Chen, T., He, Z., and Ciocarlie, M. (2020), Hardware as Policy: Mechanical and Computational Co-Optimization using Deep Reinforcement Learning, November 2020. URL http://arxiv.org/abs/2008.04460.
12. Jackson, L., Walters, C., Eckersley, S., Senior, P., and Hadfield, S. (2021), Orchid: Optimisation of robotic control and hardware in design using reinforcement learning. In 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 4911–4917. doi:10.1109/IROS51168.2021.9635865.
13. Wu H, Fu P, Hawkins AJ, Tang H, Morris JP (2021), Predicting thermal performance of an enhanced geothermal system from tracer tests in a data assimilation framework. Water Resources Research. 57:e2021WR030987.
14. Zhou Z, Roubinet D, Tartakovsky DM (2021), Thermal experiments for fractured rock characterization: theoretical analysis and inverse modeling. Water Resources Research. 57:e2021WR030608.
15. Ringel LM, Jalali M, Bayer P (2021), Stochastic Inversion of Three-Dimensional Discrete Fracture Network Structure With Hydraulic Tomography. Water Resources Research. 57:e2021WR030401.
16. Wang X, Wang GG, Song B, Wang P, Wang Y (2019), A novel evolutionary sampling assisted optimization method for high-dimensional expensive problems. IEEE Transactions on Evolutionary Computation. 23, 815-27.
17. Wei F-F, Chen W-N, Yang Q, Deng J, Luo X-N, Jin H, et al. (2020), A classifier-assisted level-based learning swarm optimizer for expensive optimization. IEEE Transactions on Evolutionary Computation. 25, 219-33.
18. Liu Y, Liu J, Jin Y (2021), Surrogate-assisted multipopulation particle swarm optimizer for high-dimensional expensive optimization. IEEE Transactions on Systems, Man, and Cybernetics: Systems.