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Original Article

A Novel Modified PSO Algorithm to Optimise the PV Output Power of Grid-Connected PV System

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Abstract *- In this paper, a modified Particle Swarm Optimisation (PSO) algorithm for optimisation has been presented. The modified PSO algorithm can optimise nonlinear and multivariate problems that require minimal parameterisation but usually lead to efficient, reasonable solutions. The results show that the promising search capability of the optimisation algorithm is useful. It provides better outcomes for various test functions. The obtained result has been compared with the Camel algorithm. Due to many advantages, the particle swarm optimisation algorithm is the most effective and best for MPP tracking in a PV array's partial shading conditions (PSC). Even though overall PSO in partial shading conditions (PSC) ensures global MPP, it has some drawbacks, including local maximum capture because of random population initialisation, longer tracking times, more extensive search areas, output power fluctuations, and longer stabilisation. A novel modified PSO-based MPPT mechanism to extract global maximum power (GMP) from photovoltaic systems. The newly developed PSO algorithm has been compared with the existing MPPT method. In the second part of the article, a novel modified PSO algorithm is implemented on a PV hybrid system connected with a grid, and performance has been checked with different loads. Simulation of different parts of the PV system is developed with the help of MATLAB/ Simulink. The DC/AC and bi-directional DC/DC converters that serve as the foundation of the proposed hybrid network's power management are used in the proposed control. MATLAB/Simulink is used to show how well the suggested control works.*

Keywords *- Multidimensional test function, Novel modified PSO algorithm, Parameter setting optimisation algorithm, Camel algorithm, MPPT, PV system.*

1. Introduction

Optimisation problems are common in many real-world applications, such as finance, economics, transportation, medicine, and engineering. Experts in these fields routinely use optimisation techniques to find the best options and trade-offs that maximise the trades of the best choices. Alternatively, maximise profits, sales, efficiency, and more while minimising costs, risks, and losses [1-3]. The basic idea behind a novel modified PSO algorithm for optimisation is to create an algorithm that moves around the surrounding space of the fitness function or test function and looks for the best position [4, 5]. The algorithm demonstrates that a novel modified PSO algorithm can have better results faster and cheaper than the camel algorithm [6-8]. The algorithm has not used the gradient of the problem being optimised; also algorithm does not require the problem to be differentiable [9-12].

The algorithm's objective is to minimise the given two variables' test function. Test functions are two variables differentiable function test function could be a non-differentiable function defined by weights of neural networks [13, 14]. The concepts behind the optimisation process are. A single particle (which can be viewed as a potential problem solver) can determine "how good" the current position is [15, 16].

We benefit not only from the knowledge gained while exploring the problem space but also from the knowledge gained and shared by other particles [17]. The probability factor of the velocity of each particle causes the particle to move through an unknown region of the problem space. This property, combined with an excellent initial swarm distribution, allows extensive problem space exploration, significantly increasing the probability of finding optimal solutions efficiently [18].

Multimodal dimensional test functions are interesting not only because of the challenges of avoiding local optima or finding multiple global optima simultaneously but also because some real-world problems exhibit such capabilities[19-21].

2. Literature Review

G. C. Kryonidis [22] In this paper, software tools perform the simulation of an electrical network under a stability state. Its high capability is strong integration even for varied generations, showing its ability to contribute and replicate network extensions quickly and authentically. The present simulations are a combination of MATLAB and Open DSS. It is concluded that the technique is initiated for solving the unbalancing in power flow, whereas the previous techniques are implemented for the droop control of DG units. In this simulation, it is proved that it is straightforward and valuable for low-voltage network extension. The simulation proves that this software tool is useful for simple and extended LV network by showing the effectiveness of the suggested tool and that implementation is easy and user-friendly compared to the other traditional software products based on the time domain.

Rajiv K. Varma et al. [23] In this paper, it is proved that the secondary drawback of solar power generation is that it generates the harmonic in the grid's power when it is synchronised with the grid. So, filters and FACTS devices are needed to minimise the harmonic contents in the grid's power by using higher-level inverters. Reactive VAR reimbursement is needed for FACTS devices to be utilised at the side of the load to boost the quality of power. The main lead of solar energy is that this is environmentally friendly, low cost and feasible compared to conventional power generation.

Rajiv K. Varma et al. [24] Normally, loads are inductive or capacitive, which is why the load can let go or absorb reactive VAR other than this, SP is connected to the grid with an inverter (power electronics device), which announces a large amount of reactive VAR.

Bhukya M. N. et al. [25] In this paper, a new topology of PV inverter for PV generation is proposed. This topology consists of a novel MPPT technique for partial shading recognition using ANN, dc-dc single I/P and multiple O/P converters and ordinary multilevel inverters with minimum switches.

The suggested topology has proved to harvest the maximum solar radiant power in any climatic situation. This paper proposes a novel PV inverter topology for solar power generation. The voltage obtained from PV generation is catered for SIMO converter, and the voltage obtained from PV generating is segregated into four individual voltages having numerable magnitudes.

It is clear from the obtained experimental results that the suggested novel topology is suitable for shaping the voltage and current as sinusoidal having 31 levels and catering the advantage to maintain the power factor as unity.

It is authentic to mention that in any weather conditions, the PV assemblage topology extracts maximum power to cater for the low cost.

D.V. Bozalakov et. al [26-28]. In this paper, a few classical control are used through which the voltage level has been controlled with the help of active and reactive powers and a modified control is scrutinised.

The altered damping control techniques are used at a regional control algorithm to maintain the unbalanced voltage on inverter terminals.

Rajiv K. Varma et al. [29, 30] and Ali M. Eltamaly et al. In this paper, the authors proposed that with the high penetration in every network, the active power of distributed generation should always be more than the total load demand of every network. MLDG systems have various advantages simultaneously with new challenges like, voltage and balancing, power quality issues, frequency issues, VR and compensation of reactive VAR.

3. Materials and Methods

The multidimensional test function describes how well the positions of ith particles in multidimensional space are relative to the desired target, and we model the problem as a simple optimisation in d dimensions, where d dimensions are optimised [31].

The position of the multidimensional algorithm is the velocity of the particle to be manipulated, which are the d component, so the position of the ith particle maybe is xi(xi,0,..., xi,d), and the velocity vi (vi,0,

The Novel modified pso position of ith particle is updated with equations (1) and (2).

$$V_{t+1}=\omega_t\, V_t + c_1\, r_1\, (\mathrm{g} - x_t) - c_2\, r_2\, (\mathrm{P} - x_t) \quad (1)$$

$$x_{t+1}= x_t + V_{t+1} \quad (2)$$

Where, x_t and V_t are the current positions and current velocity of the ith particle, whereas P is the best to position fitness value, g is the position that obtains its best fitness value by an entire swarm, c_1, c_2 are learning constant whereas r_1, r_2 are the random number in the range of [0,1] and ω_t the damping parameter regulates the transition between the exploration and exploitation phases in the presented algorithm [32, 33].

3.1. Sphere Function

The Spherical test function can describe in equation (3) and presented in figure-1.

$$f(x) = \sum_{i=1}^{n} x_i^2 \quad (3)$$

Here n is the dimension the evaluation is done in the range of 5≤ x_i ≥5. Spherical functions are known to have a global minimum for x = (0, 0...0). Figure 1 shows a two-dimensional spherical function [25].

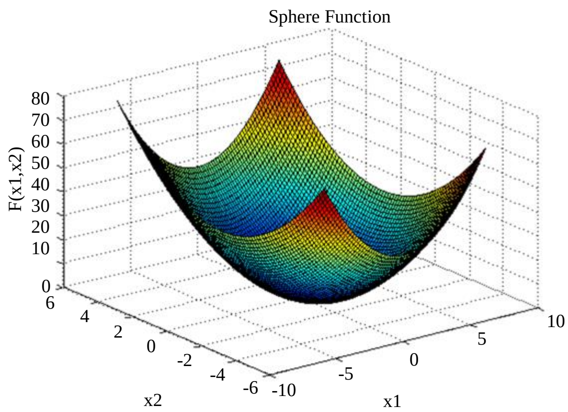

Fig. 1 Two-dimension sphere function

3.2. Exponential Function

The exponential test function can be described as (equation (4)):

$$f(x) = -e^{-0.5\sum_{i=1}^{n} x_i^2} \quad (4)$$

Here, n is the dimension the evaluation is done in the range of -5 ≤ x_i ≥5. Figure 2 shows a two-dimensional exponential function at different ranges[26, 27].

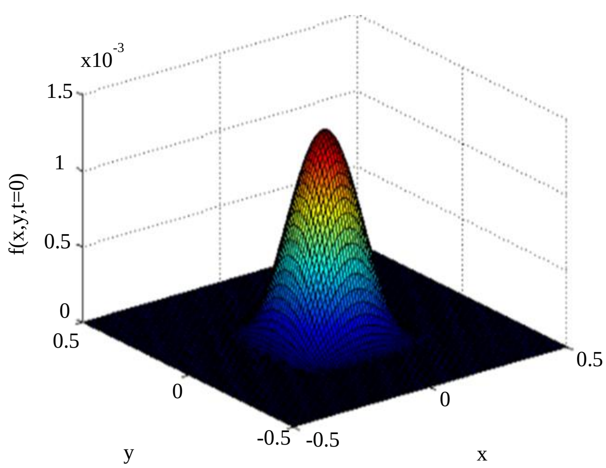

Fig. 2 Two-dimension exponential function

3.3. Ackley Function

The Ackley test function can be described as (equation (5)):

$$f(x) = -20e^{-0.2\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right)} - e^{-0.2\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n} cos2\pi x_i}\right)} + e^1 + 20 \quad (5)$$

Here n (1,2,3…) is the dimension the evaluation is done in the range of -32 ≤ x_i ≥32. Figure 3 shows a two-imensional Ackley function at different ranges[34, 35]. The global minima of Ackley function is – 0.34 at x=(0,0,0..0).

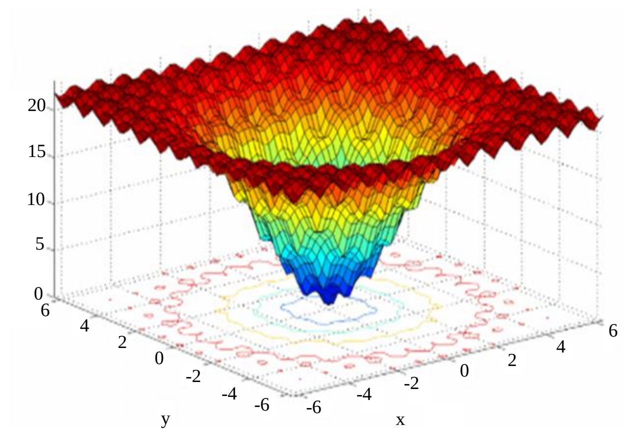

Fig. 3 Two-dimension ackley test function

3.4. Rastrigin Function

The Rastrigin function has some local minima. Although highly multimodal, the positions of the minima are regularly spaced. Here n (1,2,3…) is the dimension of the evaluation is done in the range of -5 ≤ x_i ≥5 [36]. Figure 4 shows a two-dimensional Rastrigin function at different ranges. The global minima of the Rastrigin test function is – 0.2F42 at x=(0,0,0..0). Rastrigin test function is a highly multimodal function. The Rastrigin function can write as (equation(6)):

$$f(x) = \sum_{i=1}^{n}(x_i^2 - \cos(2\pi x_i) + 10n) \quad (6)$$

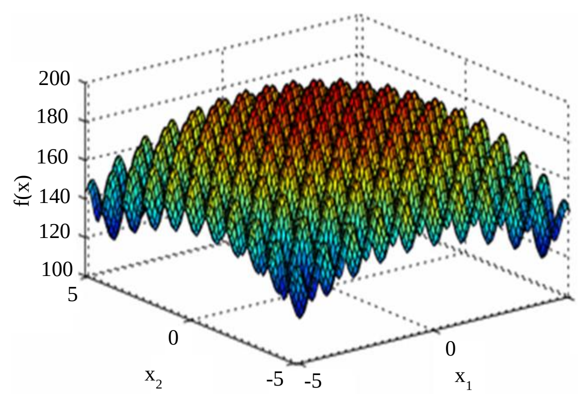

Fig. 4 Tow dimension rastrigin function

3.5. Griewank Function

The Griewank function (Figure-5)[1] is often used to test convergence optimisation algorithms [31]. With the increase in the dimensionality of the function, the number of minima increases exponentially. The griewank test is defined in the equation-(7).

$$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 + \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \quad (7)$$

Table 1. Compression of camel algorithm to novel modified PSO algorithm for optimisation

Test function	Result obtained by novel modified PSO algorithm for optimisation (Iteration 100)	Result obtained by the camel algorithm
Sphere function	-3.9309*10^{-11}	0
Exponential function	-1.3665*10^{-13}	0
Ackley function	-0.34	0
Rastrigin function	– 0.242	0
Griewank function	0.0085278	0
Schwefel function	0	0

Table 2. PSO parameters

PSO Parameters	Magnitudes
Swarm coefficient C_1	2.5
Swarm coefficient C_2	2.5
Min weighting coefficient Wmin	0.6
Max weighting coefficient Wmax	0.9
Iteration k	100
Swarm size n	20
Lower limit of variables Δd(k)min	[-0.2, -0.22]
Upper limit of variables Δd(k)max	[0.2, 0.22]

The global minima of the function is -0.008527 in the range of [-100,100]i, where i is the test function [37]. The Gleewank function is a classic multimodal benchmark function consisting of a quadratic convex function and an oscillatory non-convex function.

The relative importance of the two main parts of Griewank varies by dimension[38, 39]. Unlike most test functions, optimising the Griewank function produces strange behaviour. The Griewank function is initially more challenging and becomes easier to optimise as the dimension increases[40].

3.6. Schwefel Function

The Schwefel test function shown in Figure -6 is a complex problem with many local optimisation points. The number of dimensions (two-dimension schwefel) may be selected to a favoured number [41, 42]. Schwefel function given as (equation (8)):

$$f(x) = 418.9829n - \sum_{i=1}^{n} x_i \tag{8}$$

Where, n is the dimension (n=1, 2, 3….), the evaluation is usually done in the range -500 ≤ xi ≤ 500. The Schwefel function has a global minimum fmin = 0 at x = (420.9687). The two-dimensional function of Schwefel is shown in Figure 6 [43-45]. A flowchart of a novel modified PSO algorithm has been shown in Figure -7. The optimum value of two-dimensional test functions obtained from the Camel algorithm has been compared with the novel modified PSO algorithm (shown in Table -1).

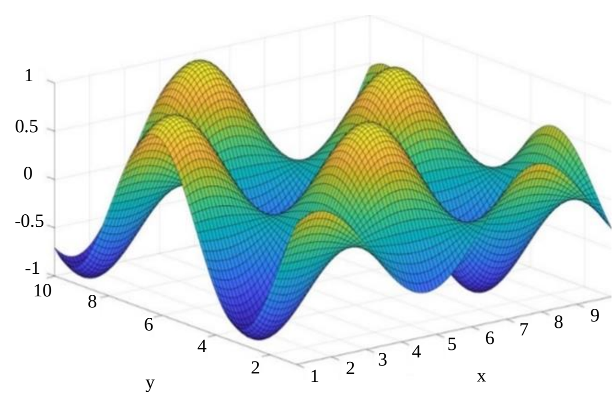

Fig. 5 Two-dimension griewank function

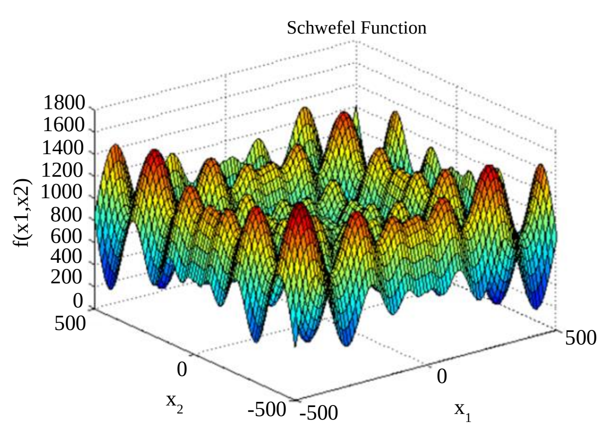

Fig. 6 Two-dimension schwefel function

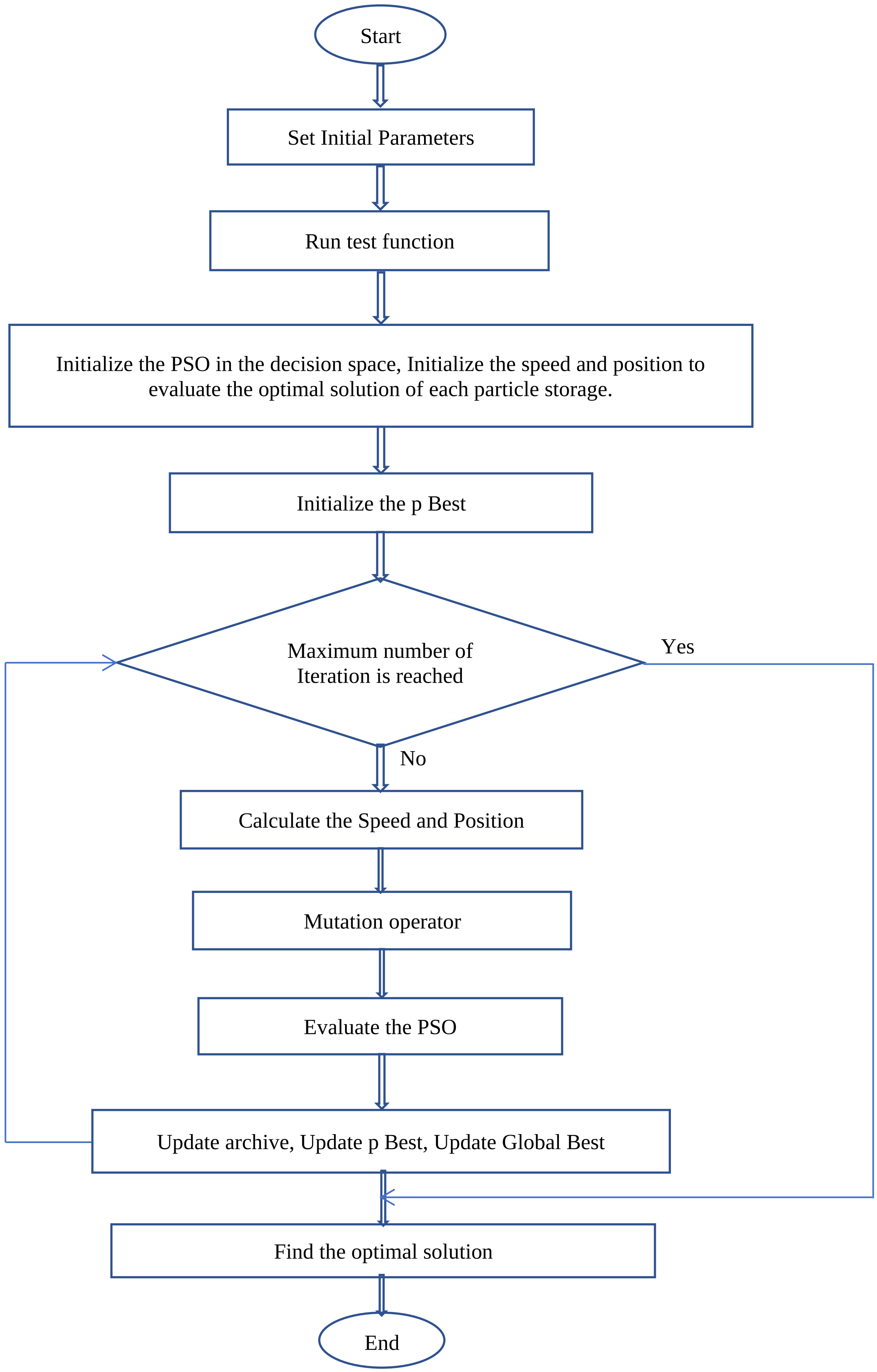

Fig. 7 Flowchart of novel modified PSO algorithm

Table 3. Tracked output under various Irradiation

Irradiation (W/m^2)	Tracked output with P& O algorithm (W)	Tracked output with novel modified PSO algorithm (W)
200	21.2	24.1
400	51.5	55.8
600	103.3	96.2
800	121.6	122.92
1000	145.7	149.43

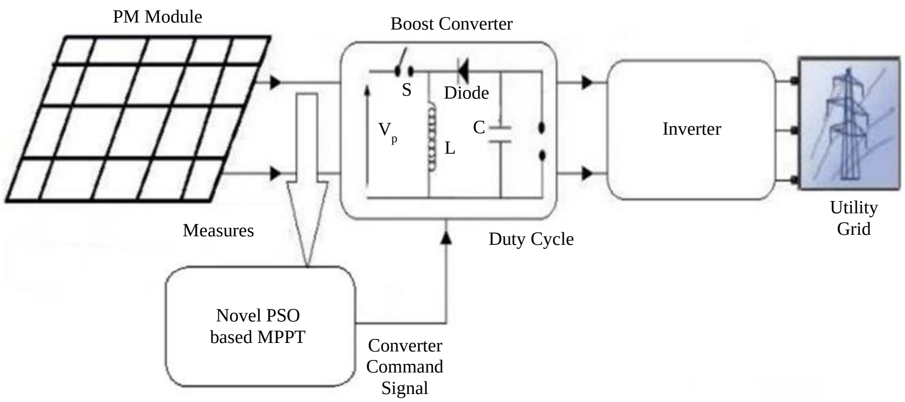

Fig. 8 Proposed design (a) Grid-connected solar PV with novel PSO-based MPPT [38,39,40]

3.7. Modeling of PV Array

The PSO algorithm is a development of a computational process based on the behaviour of birds in nature (swarm behaviour). It is used in almost all areas of optimisation and computational intelligence. The algorithm guides search optimisation through cooperation and competition between the objects that make up the intelligent swarm. Equation (9) governs the next position and velocity of the particle.

$$\begin{cases} x_i^{(k+1)} = x_i^k + v_i^{(k+1)} \\ v_i^{(k+1)} = w(k).v_i^{(k)} + c_1.r.(x_{pbesti}^k - x_i^{(k)}) + c_2.r.(x_{pbesti}^k - x_i^{(k)}) \\ w(k) = w_{max} - \left(\frac{w_{max}-w_{min}}{k_{max}}\right).k \\ F(k) = \sum_{i=1}^{N} |e(i)| \end{cases} \quad (9)$$

K = 1, 2, 3, …..n
x_i^k= ith particle position
v_i^k= ith particle velocity
P_{best}= Best position
k = number of iteration
G_{best}= Best position reached by the particle of the swarm
r = Random generated number from -1 to 1
$F(k)$= Fitness function

Figure 8 (a) shows how the model is schematically arranged. MATLAB Simulink has been used to create a simulated model of the actual process that agrees with the physical model to increase productivity. The P&O approach is used in the first step to look for the first local maximum swiftly. In every control cycle, a small amount (Vc) of the operating voltage is altered to check if the algorithm is moving up or down the P-V curve (shown in Figure-8(b)).

The PSO is turned on in the second step to look for the GMP. The converged value from the first stage, Vconv, serves as the beginning condition for the first particle. Table -2 represents the PSO parameters in the proposed algorithm that highly influence the performance of our design.

PV array tracked output power with various Irradiations is presented in table-3.In PSO, a set of randomly generated solutions (initial population) spans the design space, and the population is spread over reasonable solutions through several iterations (strokes) based on the amount of design information absorbed and shared by all members.

4. Results And Discussion

The global minima (Logarithmic Convergence) for two-dimensional test functions have been represented in Figure-9-13. The optimum value of two-dimensional test functions obtained from the Camel algorithm has been compared with the novel modified PSO algorithm.

Figure-9 represents the Global minima for the Share test function. Global minima for the Exponential test function have been represented in Figure- 10 whereas Fig-11, Figure-12, and Figure-13 show the Global minima for the Ackley test function, Global minima for the Rastrigin test function, and Global minima for the Griewank test function respectively.

Figure 14 and 15 shows the PV characteristics and VI characteristics of the PV panel, respectively, at 35˚C and 25W/m^2. The analysis was carried out to check the power converter's operation and the proposed system's operation, that is, the control pulse converter (as shown in Figure 16), which controls the output voltage of the step-up converter. Grid frequency is an important parameter to check the feasibility of a robust power system. For a robust power system, frequency should be constant in magnitude with variation in load. In our prosed MATLAB design, Grid frequency is constant (equal to 50 Hz) at steady state, and it varies between 50 Hz to 51 Hz at low load (steady state) shown in Figure - 17. PV current, PV power, and PV voltage are shown in Figure 18. solar array performance parameters (a) PV Current, (b) Power, and (c) PV voltage with PSO and MPPT (P&O).

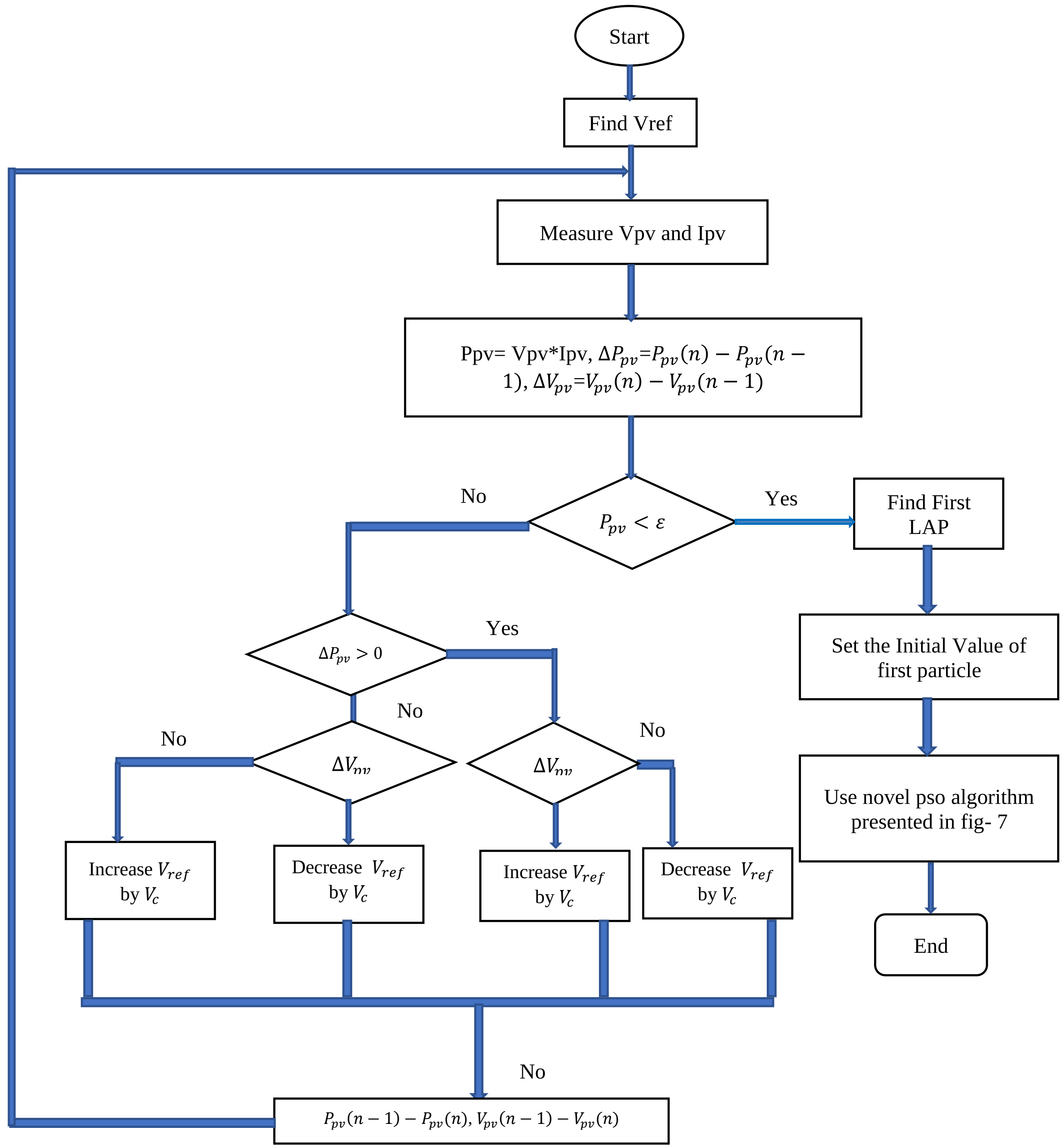

Fig. 8 Proposed design (b) Flow chart of PSO-based MPPT

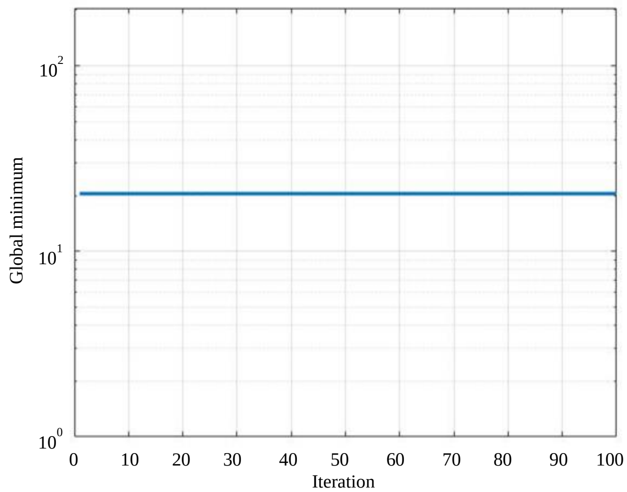

Fig. 9 Global minima for Share test function

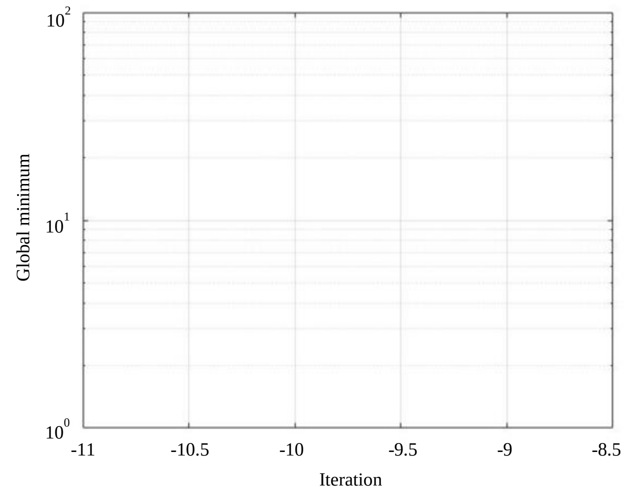

Fig. 12 Global minima for rastrigin test function

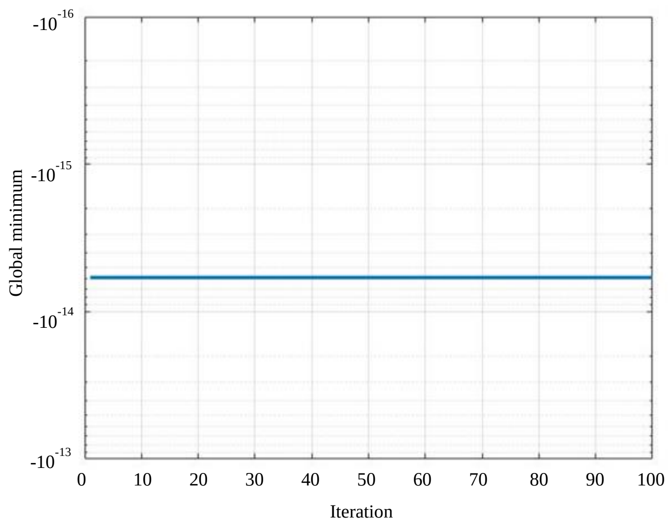

Fig. 10 Global minima for exponential test function

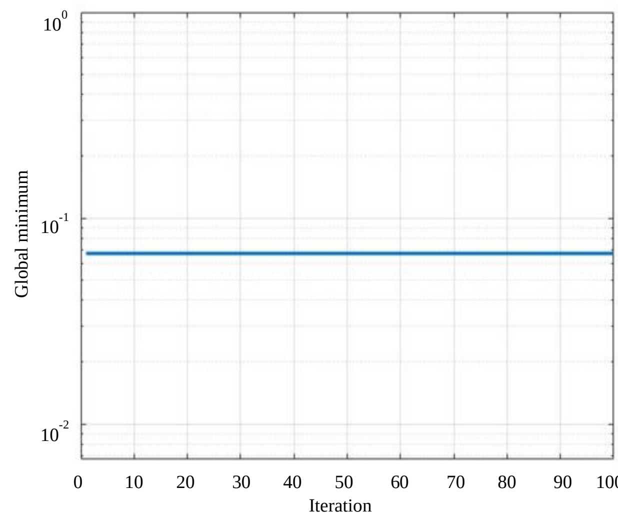

Fig. 13 Global minima for griewank test function

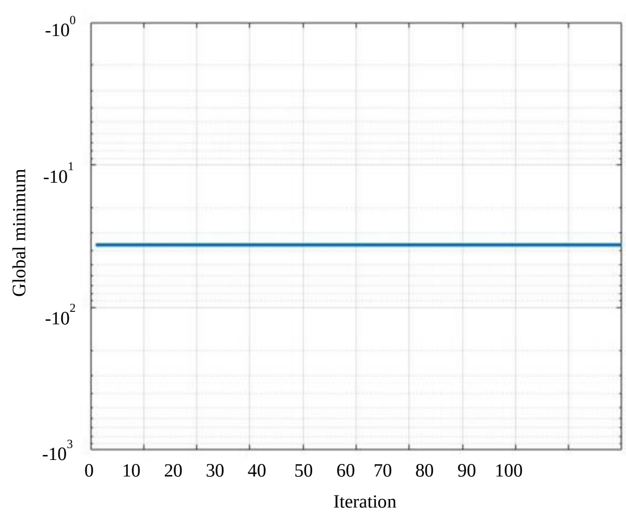

Fig. 11 Global minima for ackley test function

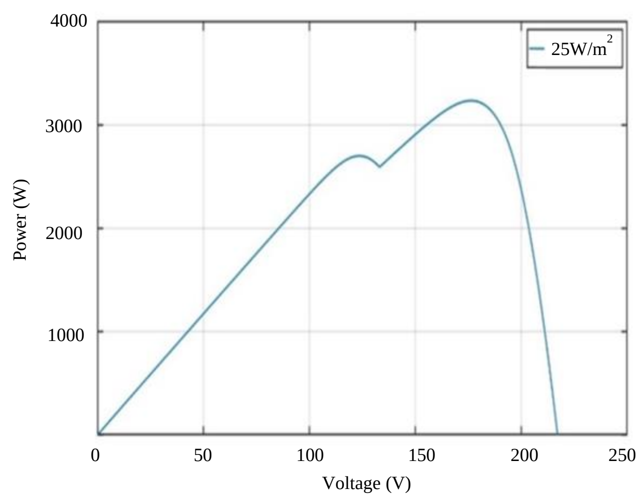

Fig. 14 PV curve with PSO and MPPT (P&O)

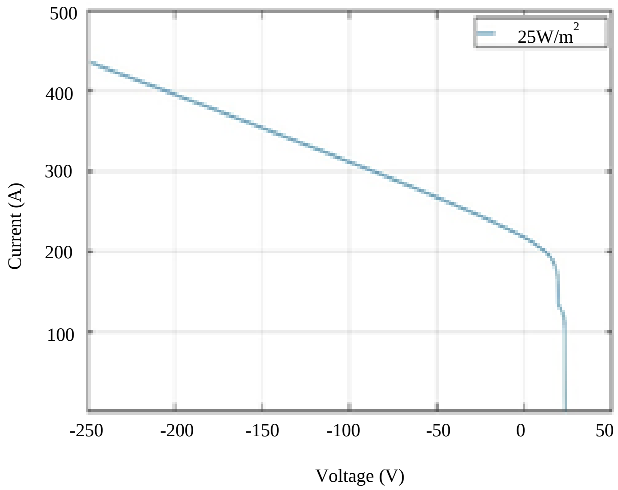

Fig. 15 VI curve with PSO and MPPT (P&O)

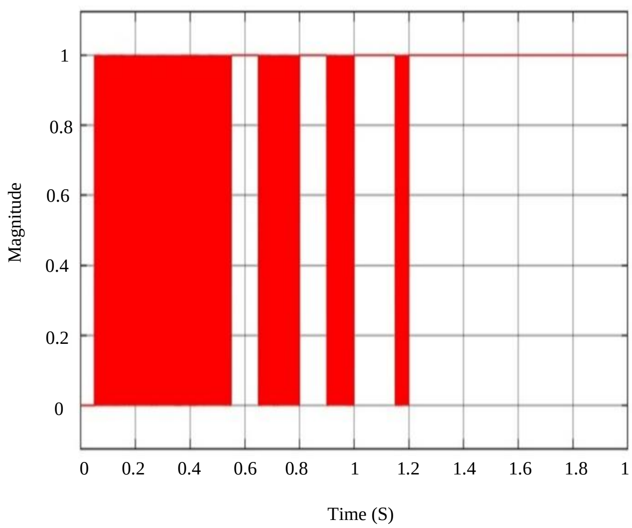

Fig. 16 Duty cycle with PSO and MPPT (P&O)

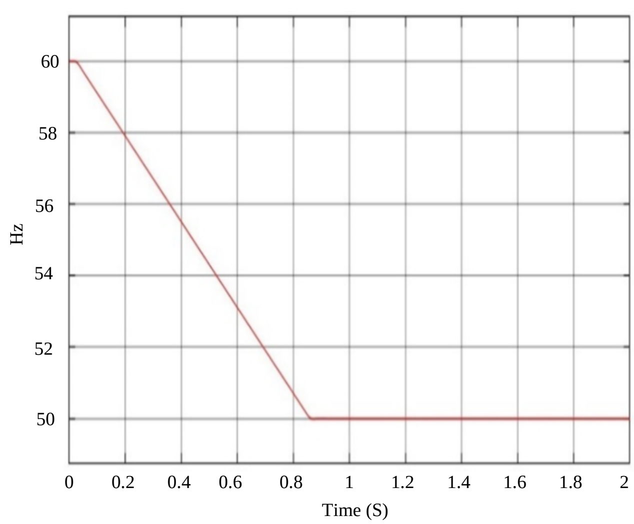

Fig. 17 Grid frequency with PSO and MPPT (P&O)

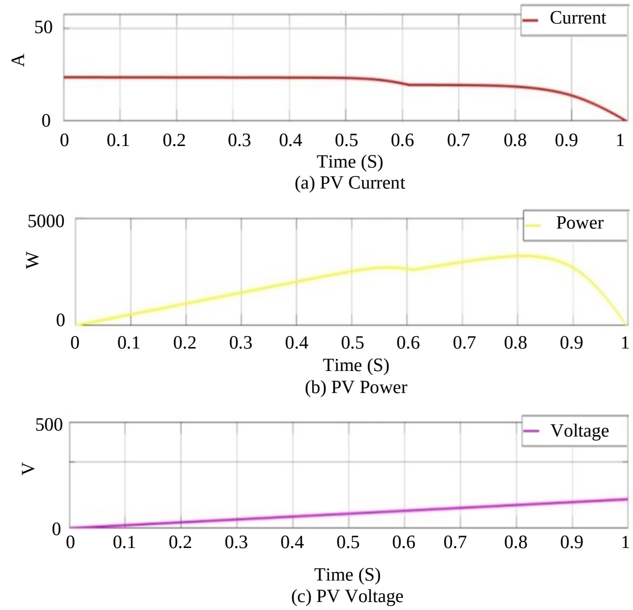

Fig. 18 Solar array performance parameter (a) PV Current (b) PV Power (c) PV voltage with PSO and MPPT (P&O)

5. Conclusion

The algorithm's simple structure and efficient search capabilities allow it to process multivariate test functions efficiently and find optimal solutions even in the most challenging cases. The results show that the newly modified PSO algorithm can achieve excellent results in the early stages of the search process for most test functions and that the algorithm can be used in real-time applications to solve time-critical optimisation problems.

Our work's new and modified PSO algorithm has been widely used in various benchmark problems and domains due to its features and superior performance compared to PSO and Camel algorithms Shows. This algorithm can further improve performance and convergence speed. While tracking MPP, traditional MPPT techniques such as perturbed and observed, incremental conductance, and hill-climbing frequently fail; thus, they are tracked in place of MPP.

To track the global MPP MPPT (i.e. P & O) in this case, a newly modified PSO algorithm-based MPPT is applied. Because of this, it is straightforward and provides more accurate MPP when compared to others for various partial shading conditions (PSCs), which are observed through simulation (MATLAB Simulink), both steady state and dynamic and which perform better when compared to the Camel approach.

Acknowledgments

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