

A REFINED PSO BASED APPROACH TO MPPT FOR STAND ALONE PV SYSTEM

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Received: July 11, 2024; Revised: September 14, 2024; Accepted: February 28, 2025

Abstract

This paper presents a control method that plays an important role in ensuring that power output aligns with maximum capacity. Many tracking algorithms are required for this application. Incremental conductance is used often, particularly with more difficult calculations. This paper introduces a new improved particle swarm optimisation (IPSO-based) MPPT technique for photovoltaic systems. This original approach, which used a stepwise approach to assign values to the weighting factors and cognitive and social parameters, has been modified. The MPPT control scheme proposed intends to fix the IPSO-based MPPT algorithm's inherent flaw, as well as bring about a reduction in the variances. It's capable of finding and identifying the maximum power point under nonuniform insolation. The Photovoltaic Systematic Process is simulated using the Simulink programme along with various control schemes. After this simulation, the results are compared to the conventional incremental conductance technique. To test the validity of previously studied methods, the previous research is used. The resulting MPPT maximisation is extraordinary when insolation and temperature change has affected a portrait. This is proof that using the intended method results in the best possible outcome.

Keywords: Efficiency; GBest; MPPT; PSO; PV Panel

Introduction

There has been a surge in the use of renewable energy sources due to the depletion of traditional energy sources. The photovoltaic (PV) system's rapid development in the last decade is present throughout renewable resources. The transfiguration competency is limited due to the use of nonlinear voltage/current features of PV modules. In order to attain superlative PV energy generation under global power point tracking, maximum power point tracking (MPPT) algorithms are absolutely necessary (Ahmed and Salam, 2015).

Many MPPT control strategies have been found in the literary works in the category of management. Among the numerous MPPT techniques described in literature, one of the most commonly-used MPPT techniques is (Mamarelis *et al.*, 2014) the perturb and observe (P&O). It is widely installed in commercial PV inverter using low cost microprocessors. Despite the simplicity and reliability of the algorithm, it inherently has two main drawbacks. First, when the tracking reaches the vicinity of the MPP, the operating point is forced

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DOI: <https://doi.org/10.55766/sujst5755>

Suranaree J. Sci. Technol. 32(2):010358(1-10)

to go back and forth around MPP, resulting in unending oscillation in the output power. This divergence also results in energy loss (Priyadarshi *et al.*, 2020; Xu *et al.*, 2020; Pattanayak *et al.*, 2023). This paper presents an improved particle swarm optimisation (IPSO) MPPT method in order to track the global maximum power under uniform irradiance and partial shading conditions. To increase the tracking speed, initial particles are placed so that they are near the UIC duty cycle or at various peaks within the PSC distribution (Panda *et al.*, 2020b). The definitions of abbreviations used throughout the article are listed in Table 1.

Table 1. Definitions of abbreviations used throughout the article

PV	Photovoltaic
MPPT	Maximum power point tracking
P&O	Perturb and observe
IPSO	Improved particle swarm optimisation
UIC	Uniform irradiance condition
PSC	Partially shaded condition
QPSO	Quantum particle swarm optimisation
AF	acceleration factor

Proposed Particle Swarm Optimisation Algorithm

The Improved Particle Swarm Optimization (IPSO)-based MPPT algorithm is a progressive technique used to improve the energy accumulation process in Solar PV system. It enhances the standard PSO to more effectively track the Maximum Power Point (MPP) of photovoltaic (PV) systems. IPSO adjusts key parameters, such as inertia weight and acceleration coefficients, dynamically to improve convergence speed and avoid local optima. In IPSO, particles represent potential solutions (duty cycles for the PV system), each with a position (solution) and velocity (rate of change). The particles update their positions based on their personal best position and the global best found by the swarm. The algorithm uses an adaptive inertia weight, starting high to encourage exploration and decreasing as it converges to refine the solution. The acceleration coefficients, influencing personal and global bests, are also adjusted to balance between global search and local refinement. The velocity update equation integrates these adaptive parameters to prevent excessive oscillations around the MPP. Boundary conditions ensure the particles remain within the feasible range of duty cycles, improving stability. This algorithm efficiently tracks the MPP by converging quickly and accurately under varying environmental conditions. As a result, IPSO-based MPPT offers

faster, more reliable power optimization for PV systems compared to traditional methods.

Gaussian and Cauchy probability transports to achieve haphazardly refreshing PSO conditions. This paper focuses on PSO strategic dissemination, using Gaussian and Cauchy probability. This new technique makes use of Gauss' probability and/or is located somewhere between the age [0,1] Cauchy's probability. The normal distribution is a familia (family) of continuous probability distributions (Gd). Two parameters allow you to customise the location and the number of members in each family. Thus, it is the Gaussian distribution's theorem of local to central limits that is important. To quickly find local estimates, the regular Gaussian distribution does not have a mean or variance. This was created using the distribution Cauchy with the distribution Cd. Between [0,1] on the random Gaussian distribution and Gd, the social share is 0. The random number between 0 and 1 was used in the cognitive interval [0,1] region.

The updated speed equation is calculated by:

$$V_i^{K+1} = K \cdot (W \cdot V_i^k + C_1 G_d() (Pbest_i^k - X_i^k) + C_2 C_d() (Gbest^k - X_i^k)) \quad (1)$$

$$K = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|} \quad (2)$$

where: $\varphi = C_1 + C_2, \varphi > 4$,
 V_i represents the velocity of particle i ,
 X_i represents the position of particle i ,
 W is the inertia weight,
 C_1, C_2 are the learning factors,
 $Pbest$ is the personal best position,
 $Gbest$ is the global best position

Regulation of system convergence can be done by the system itself. Receipt of shrinkage factor analysis (CFA) must be greater than 4.0 in order to prevent certificate expiration. The multi-like slow erreaction reduction, however, has been reduced thanks to the increased K factor. Constant multipliers K should be set to 0,729 for C_1 and C_2 in general usage.

- Group Size-Group size is a good way to bootstrap particles: it determines the number of particles in the group and also their classification into large particle classes. The greater part of each iteration overlay may be searched with a swarm. However, if you increase the number of particles, the unpredictability of a machine focus is heightened, and the task becomes an exercise in sporadic parallel analysis (Panda *et al.*,

2020a). Finding the best possible solution requires less surface area on which to formulate inquiries. The cross-approval strategy is a good choice for using the heuristics in the manufacturing process, as opposed to carrying out each calculation separately (Mirhassani *et al.*, 2014).

- Number of iterations- If you're trying to find a successful solution, the problem is related to the number of iterations to that solution. The number of iterations may be excessive, resulting in unnecessary additional computational complexity (as long as the number of iterations is the only stop condition) (Raj *et al.*, 2016). It may finish too soon.
- Coefficient of acceleration- The random effects on overall particle velocity of the cognitive and social components are evaluated using C_1 , C_2 , R_1 , and R_2 (Rabah *et al.*, 2023). If $C_1 = C_2 = 0$, the particle speed will stay constant and maintain its current flight until it hits the search limits (assuming no inertia). For all particles to be separate escalators, it must be true that C_1 is greater than zero and C_2 is zero. The particle performs a local search. Also, if $C_2 > 0$ and $C_1 = 0$, the whole group is attracted to a single point (Avila and Pozo, 2017; Dileep and Singh, 2017). When the values of C_1 and C_2 are equal, then the y-value of the parts will attract.
- There could be a divergence in actions or a break in cycles if C_1 and C_2 are used. Speed, C_2 , in the direction of the global particle and C_1 , in the direction of the individual particles, can be clearly seen when using equation in the PSO algorithm; each particle constantly checks the corners of its problem space to see if they have moved out of the best (fitness) solution in the space so far. To preserve your health, you should call it the strongest particle of life.
- The global PSO monitoring version's best iteration is the latest and greatest value of any particle. The speed and optimum location of each particle (acceleration) adjustment is always maintained throughout a PSO phase. To obtain the C_1 and C_2 acceleration constants, a random acceleration term is utilized, which pulls each particle to the best and the best location (Mammeri *et al.*, 2023). This value gives a quick and easy solution for most problems around the world for the best outcome. It has no effect on the rate of convergence whether or not the value of a

share goes up. In the local small districts, the minimum is not reached, but with bigger national districts, convergence happens more quickly, which is preferable for the larger districts (Bachikh *et al.*, 2023; Priyadarshi *et al.*, 2023).

The qubit concept and rotating doors use advances in demographics to increase the number of people with unique characteristics (Brahmi *et al.*, 2023a). Therefore, it can be avoided by using adaptive likelihood and chaotic sequence mutations when an adaptive likelihood or chaotic sequence mutation is placed in the best location. Quantum and angle are similar to particular condition and do not rely on PSO position and particle velocity, which is mostly complete. In other words, Quantum particle swarm optimisation (QPSO) has superior searchabilities, as a result of which it has great search capabilities. With a tubing, two quantum states can be preserved at the same time.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (3)$$

$$|\alpha|^2 + |\beta|^2 = 1 \quad (4)$$

$$|\psi\rangle = \sin \theta |0\rangle + \cos \theta |1\rangle \quad (5)$$

The position of particles in QPSO can be described as:

$$x_{id} = p_{id} \pm \frac{L}{2} \ln\left(\frac{1}{u}\right) \quad (6)$$

Where in Quantum-inspired Particle Swarm Optimization (QPSO) unique parameters, the following equation can be used to calculate acceleration factors.

$$\alpha = (1 - 0.5) \cdot \frac{t_{max} - t}{t_{max}} + 0.5 \quad (7)$$

And the local attractor p can be expressed as:

$$p = \varphi \cdot pbest + (1 - \varphi) \cdot gbest \quad (8)$$

The fan enclosure is evenly distributed [0,1]." The flowchart of the QPSO figure 1 is in place. Until algorithm parameters are set, calculation and a very sharp focus are put in place (e.g. population calculation and particle). Furthermore, well-being of the particles and the particles themselves are valued and reported as $pbest$ and $gbest$ (Li *et al.*, 2019; Abdelkader *et al.*, 2023; Brahmi *et al.*, 2023b). The QPSO algorithm equation is then used to refresh the particles. The algorithm carries out the algorithm, finishing when it comes to the end, and

provides the maximum value, such as in the case of the stop criterion. In the second step, the algorithm begins again.

The targeted feature F varies due to various environmental conditions. Whenever the following criterion is satisfied, the agent must be started again to ensure the new MPP is applied. Simulation and modeling has been done in MATLAB/Simulink. The load resistance, as well as the DC/DC boost converter, is implemented via PSO MPPT control on a PI controller, alongside a 2 PV array.

To ensure that the PV panel delivers maximum power and optimal voltage, the actual output voltage of the PV panel is compared to the optimum voltage of the VPPT-based PSO (Parandhman and Karthikeyan, 2022; Sahu and Das, 2022; Indumathi and Sivalingam, 2024). This algorithm, which was used to monitor MPPT where the P-V characteristic shows multiple local MPPs, is now in use with PV devices. Sustaining maximum power and locating the voltage or current at which the solar array produces the maximum output power are important considerations when monitoring and maintaining an MPPT solar array. While optimizing, the solution vector of module voltages (V_1, V_2 , etc.) should be tested (Sangwongwanich *et al.*, 2017; Pradhan *et al.*, 2020; Panda and Patnaik, 2022). If D is the number of modules, then that vector will be tested. Previously, the non-linear optimization problem could only be stated:

$$X = (V_1, V_2, V_3 \dots V_D); F(X) = \text{Array power PPV} \quad (9)$$

$F(X)$ is a function that transforms the input vector X to the photovoltaic array power PPV. V_{PV} is restricted to $(0.05 V_{OC} < V_1 < 0.85 V_{OC})$.

$$\frac{|P(s_{i+1}) - P(s_i)|}{P(s_i)} > \Delta P \quad (10)$$

This condition ensures that the relative change in power between two successive states, S_i and S_{i+1} exceeds a predefined threshold ΔP . The flow chart of the proposed PSO algorithm is shown in Figure 1.

Simulation Models and Results

The PSO-based MPPT algorithm is used to optimize the duty cycle of the DC-DC converter to ensure that the PV panel operates at the MPP. The algorithm works by representing the duty cycle of the converter as a particle in the PSO algorithm. A swarm of particles (duty cycles) is generated, each representing a potential solution to the optimization problem (achieving the maximum output power). The particles' positions (duty cycle values) and velocities are updated iteratively based on the personal best position (maximum power found by a particle) and the global best (maximum power found by the entire swarm). By dynamically adjusting the duty cycle, the PSO algorithm ensures that the system continuously operates at the optimal point, even when irradiance or temperature changes. In this section, the results of research and at the same time the comprehensive discussion are given. Results are presented in figures, graphs and tables for better understanding.

The PV modules are made up of 18 cells, and two of them have been divided into four separate groups. A diode bypass connects every community. The three classes are all lit (one kW per square metre), while only a small portion of one of the classes is lit by 0.5 kW per square metre of solar irradiation. In the PV array, solar insolation, temperature, and voltage are all included. PV voltage, which is also known as PV voltage, boosts the converter by acting as a controlled voltage source. A MOSFET switch, a 120 mH-inductive, a 750- μ F condenser, and an R-load power of 250 megawatts make up the DC/DC Boost converter. In order to minimise PV voltage fluctuations, a 15 μ F input filter is connected to the PV array. To control the transition, the 20KHz PWM technique is used. The MPPT block receives the PV current and voltage as inputs. The PV voltage of the series. Where V_{OC} is each module's open circuit capacity,

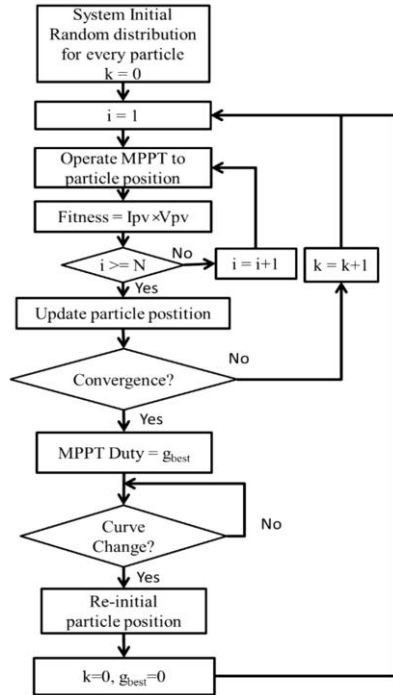


Figure 1. Flow chart for proposed PSO

$i=1, 2, 3 \dots D$. The PSO code was written in MATLAB, PSO programme parameters are shown in Table 2. Figure 2 shows the irradiation and maximum power tracked plot in relation to simulation time.

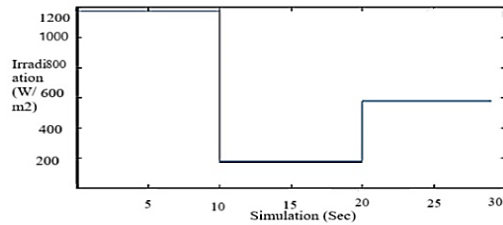


Figure 2. Plot of Variable Irradiation With respect to time & Plot of Maximum Power Tracked by the Proposed System Under Given Conditions

Table 2. Parameters used in PSO algorithm

Parameters	Value
No. of particles (N)	10
No. of dimensions (D)	1 or 2
Maximum velocity(V_{max})	2.70 V
No. of iterations ($Iter_{max}$)	80
ΔP	0.15
C_1	1.6
C_2	1.2
W_{max}	0.9
W_{min}	0.4
r_1, r_2	$0 < r_1, r_2 < 1$

Particle Swarm Optimization is used to design and optimise power point monitoring systems that monitor power in variable radiation scenarios. Signal generation varies weather irradiation data in the system, while the energy optimization and monitoring of algorithms use improved particle swarm optimization. Figure 3 represents variation of duty cycle of PV system with respect to time. The PSO-based MPPT algorithm is used to optimize the duty cycle of the DC-DC converter to ensure that the PV panel operates at the MPP. The algorithm works by representing the duty cycle of the converter as a particle in the PSO algorithm.

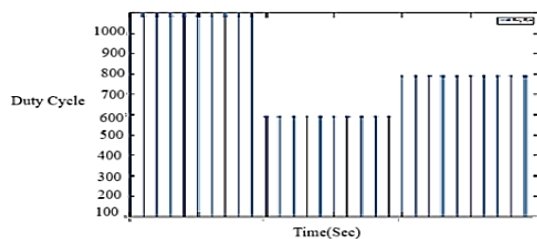


Figure 3. Variation of Duty Cycle with Respect to Proposed Working Condition

It is possible to quickly monitor the amount of energy a particle swarm optimization (PSO) optimises by using parameters imported from PSO. To ensure that the device is optimally controlled under given irradiance and temperature conditions, the optimization of the particle swarm is intended. Figure 4 illustrates comparative assessment of maximum power tracked by the proposed system under given condition.

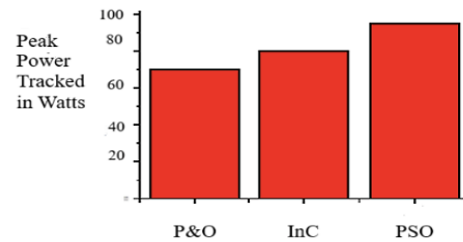


Figure 4. Comparative Assessment of Maximum Power Tracked by the Proposed System Under Given Conditions

The result is listed in Table 3, which clearly demonstrates that PSO achieved the highest peak power, followed by InC and then P&O.

For fixed irradiation, the value of C_1 , C_2 in this model will be validated; for variable irradiation, the value of C_1 , C_2 will be varied.

Table 3. Comparative assessment of MPPT methods

Method	Peak Power Tracked
P & O	70 Watts
INC	80 Watts
PSO	95 Watts

Case-1: Varying C_1 and C_2 at Fixed Irradiation

The Table 4 shows the data sheet of the PV Panel used for simulation.

Table 4. PV Panel Data sheet

Parameters	value
Power At Max. Power Point (P_{mpp})	180 W
Open Circuit Voltage (V_{oc})	43.64 V
Short Circuit Current (I_{sc})	5.45 A
Voltage At Max. Power Point (V_{mp})	36.36 V
Current At Max. Power Point (I_{mp})	4.95 A
Duty Cycle at Max. Power Point (D_{mpp})	0.88

The following tables represent a comparison of convergence times for various values of acceleration factors i.e C_1 and C_2 by specifying iterations at fixed irradiation.

Case-2: Varying C_1 and C_2 at Variable Irradiation

Table 5 shows the values of all parameters used for the analysis. When performing a simulation, both the primary parameters, such as acceleration factor and radiation dosage, are varied. In this experiment, the acceleration factor (AF) value is increased from 0.4 to 2.0 while irradiation is variable is shown in Table 4. Additionally, outputs are studied. When C_1 and C_2 are fixed at 0.4 shown in Table 6, the convergence time taken to get converged at maximum power of 85W is 3.02s (Aamri and Benchagra, 2018).

Table 5. Parameters with values applied

Parameters	value
L	12.8mH
Ci	5 μ F
Co	140 μ F
Ro	200 Ω
Fs	20*10 ³ Hz
Perturbation Time	0.1s

Table 6. Values of C_1 & C_2 with simulation result

Parameters	Result
C_1	0.4
C_2	0.4
Pmax	85W
Convergence Time	3.02s

Figure 5 shows the resulted PV curve showing maximum power of 85W. After oscillating for 3.02 seconds the maximum power point is tracked to be at 85W. The below figure indicated MPP has been attained at 63V.

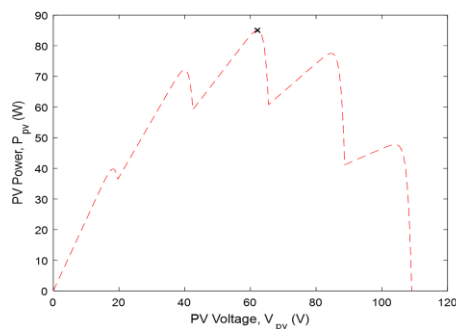


Figure 5. Resulted PV Curve for C_1 & C_2 of 0.4

PV panel voltage, current, power and duty cycle are shown in Figure 6. All parameters, including panel voltage, current, output power, and duty cycle, reached a steady state after oscillating for 3.02 seconds. The convergence results for different values of C_1 and C_2 is listed in Table 7.

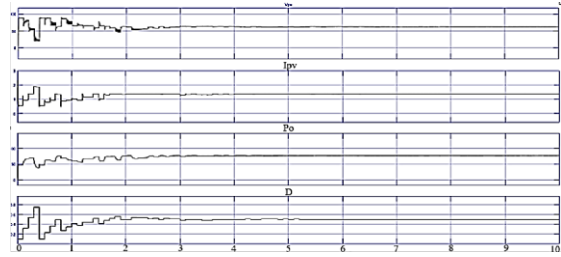


Figure 6. PV panel voltage, current, power and duty cycle

Table 7. Convergence results for various values of C_1 and C_2

Simulation No.	Parameter	Value	Result
1.	C_1	0.2	Particles converges (within 2% of P_{mpp}) after 43 rd Iteration.
	C_2	0.2	
	W	0.1	
	R	0.4	
2.	C_1	0.2	Failed to converge even after 50 iterations (Pmax reached = 91W)
	C_2	0.2	
	W	0.1	
	R	0.4	
3.	C_1	0.5	Failed to converge even after 50 iterations (Pmax reached = 139.6W, Velocity is very small).
	C_2	0.5	
	W	0.5	
	R	0.5	
4.	C_1	0.5	Failed to converge even after 50 iterations (Same result as last Simulation).
	C_2	0.5	
	W	0.5	
	R	5	
5.	C_1	0.5	Particles got MPP in 11 iterations but keep oscillating around MPP with big variations.
	C_2	0.5	
	W	0.9	
	R	5	
6.	C_1	0.5	MPP in 8 iterations. Failed to converge but oscillations are not large (about 10% of P_{mpp}). May be useful with shifting MPP).
	C_2	0.5	
	W	0.9	
	R	1	
7.	C_1	0.5	Converge in 10 iterations. Remain at MPP for next iterations (static).
	C_2	0.5	
	W	0.5	
	R	1	

- a) If C_1 and C_2 are set at 0.5, the convergence time required to achieve a maximum power of 85W is 4.3 seconds depicted in Table 8.

Table 8. Values of C_1 & C_2 with simulation result

Parameters	Result
C_1	0.5
C_2	0.5
Pmax	85W
Convergence Time	4.3s

PV panel voltage, current, power and duty cycle are shown in Figure 8. All the values such as panel voltage, current, output power and duty cycle are attained steady state after oscillating for 4.3 seconds.

In Figure 7, the red dashed line shows the power output over iterations, illustrating how the PSO algorithm searched for the maximum power output.

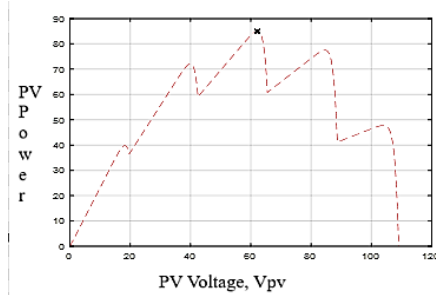


Figure 7. PV Curve for C_1 and C_2 value of 0.5

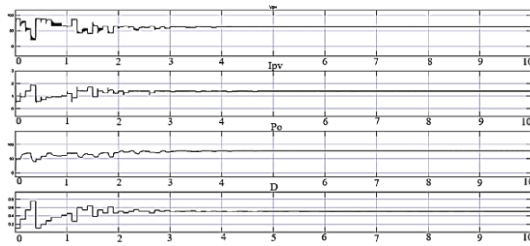


Figure 8. PV panel voltage, current, power and duty cycle at $C_1=C_2=0.5$

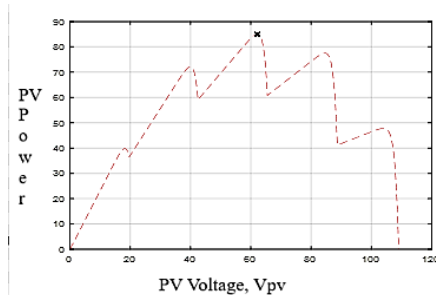


Figure 9. PV Curve for C_1 and C_2 value of 0.6

- b) When C_1 and C_2 are fixed at 0.6, the convergence time taken to get converged at maximum power of 85W is 4.8s shown in Table 9.

Table 9. Values of C_1 and C_2 with simulation result

Parameters	Result
C_1	0.6
C_2	0.6
Pmax	85W
Convergence Time	4.8s

Figure 9 illustrates the PV curve resulting in maximum power of 85 W. The maximum power point is found to be 85W after the machine has

oscillated for 4.8 seconds (Panda *et al.*, 2022; Khan *et al.*, 2018).

Figure 7 shows the resulted PV curve showing maximum power of 85W. After oscillating for 4.3seconds the maximum power point is tracked to be at 85W. The below figure indicated MPP has been attained at 64V.

According to the figure, MPP has been achieved at 63V. PV panel voltage, current, power and duty cycle are shown in Figure 10 for C_1 and C_2 value of 0.6. All the values such as panel voltage, current, output power and duty cycle are attained steady state after oscillating for 4.8seconds.

In Figure 8 the initial fluctuations in all plots are due to the transient response of the system as it adjusts to reach the steady state. The stabilization in all parameters (V_{pv} , I_{pv} , P_o and D) demonstrates that the system successfully achieves equilibrium, possibly at the maximum power point. The duty cycle (D) directly impacts the PV voltage and current, as it controls the converter to maximize output power (P_o).

Figure 10 initially, all parameters display variations, presumably attributable to the system's transient response and maximum power point tracking (MPPT). With time, they stabilise, signifying that the system attains steady-state operation. The photovoltaic voltage and current vary as the duty cycle is optimised for maximum power output. The output power indicates the system is attaining a consistent maximum. The duty cycle regulates the converter's function, guaranteeing effective power extraction from the photovoltaic system.

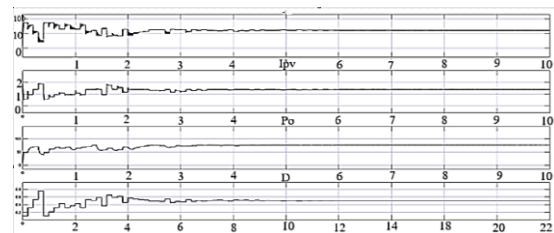


Figure 10. PV panel voltage, current, power and duty cycle at $C_1=C_2=0.6$

- c) When C_1 and C_2 are fixed at 1, the convergence time taken to get converged at maximum power of 85W is 6.3s.

Figure 11 shows the resulted PV curve showing a maximum power of 85W. After oscillating for 6.3 seconds, the maximum power point is tracked to be at 85W. The below figure indicated MPP has been attained at 63V. PV panel voltage, current, power, and duty cycle are shown in Figure 12 at $C_1=C_2=1.0$. All the values such as panel

voltage, current, output power, and duty cycle are attained in steady state after oscillating for 6.3 seconds. Table 10 shows the simulation result with C_1 and C_2 at 1.0.

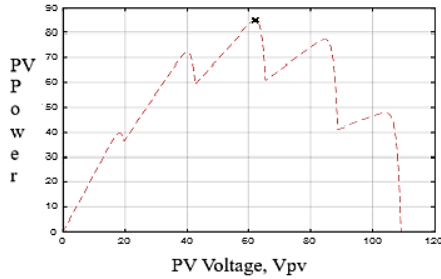


Figure 11. PV Curve for C_1 and C_2 value of 1.0

Table 10. Values of C_1 and C_2 with simulation result

Parameters	Result
C_1	1.0
C_2	1.0
Pmax	85W
Convergence Time	6.3s

In Figure 12, I_{pv} exhibits initial oscillations that stabilise over time, signifying a transitory reaction prior to reaching equilibrium. Likewise, P_o exhibits variations, ultimately stabilising, indicating the optimisation of power distribution. The duty cycle (D) indicates system control modifications, achieving stability following early disturbances. The charts probably illustrate the performance of a power electronic converter or photovoltaic system in dynamic conditions, demonstrating its stability and adaptability over time.

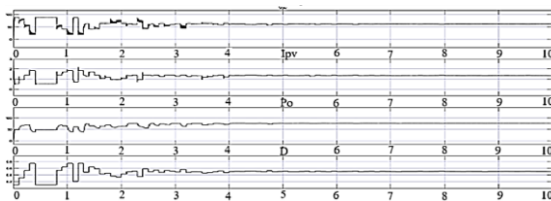


Figure 12. PV panel voltage, current, power, and duty cycle at $C_1=C_2=1.0$

- d) When C_1 and C_2 are fixed at 2.0, the system does not converge to the maximum power point.

Figure 13 shows the resulted PV curve showing a maximum power of 50W, which is not the maximum power as clearly seen in the figure. After oscillating for 10 seconds, the maximum power point is tracked to be at 50W. Table 11 shows the simulation result with C_1 and C_2 at 2.0.

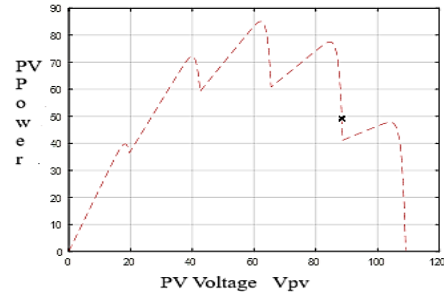


Figure 13. PV Curve for C_1 and C_2 value of 2.0

Table 11. Values of C_1 and C_2 with simulation result

Parameters	Result
C_1	2.0
C_2	2.0
Pmax	49W
Convergence Time	Not converged to maximum power

PV panel voltage, current, power and duty cycle are shown in Figure 14. All the values such as panel voltage, current, output power and duty cycle are attained in steady state after oscillating for 10 seconds.

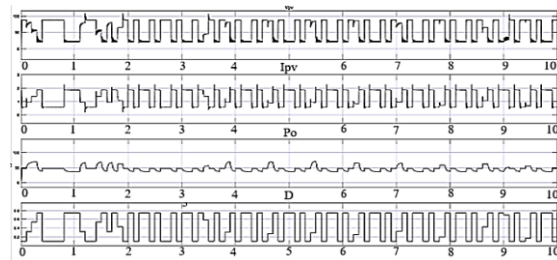


Figure 14. PV panel voltage, current, power and duty cycle at $C_1=C_2=2.0$

The simulation data presented in the table below are the results of varying C_1 and C_2 as PV curve and curves for PV Panel voltage, current, power, and duty cycle. This graph demonstrates that when the acceleration factor increases past 0.4, convergence time, so does the value. It means the maximum power will take longer to track. Table 12 shows simulation result with different values of C_1 and C_2 .

Table 12. Values of C_1 and C_2 with simulation result

C_1	C_2	Convergence time(sec)
0.4	0.4	3.02
0.5	0.5	4.3
0.6	0.6	4.8
1.0	1.0	6.3
2.0	2.0	Not converged to maximum power

Conclusion

Simulated results show that acceleration factor has no effect on maximum power tracking. When using the PV curve, the maximum power reached for each case was apparent. The other graph illustrates how different PV panel voltages, currents, power outputs, and duty cycles vary as acceleration factor changes. Clearly, when the acceleration factor increases from 0.4 to 2.0, tracking speed takes longer to converge. In order to avoid oscillation and obtain maximum tracking efficiency, the best value for acceleration factor is found to be between 0.4 and 0.6. By developing more effective power converters with soft computing MPPT controller systems, researchers are striving to increase the operational efficiency of solar photovoltaic systems. Setting an intelligent maximum power monitoring system as the foundation for an effective charger controller. For photovoltaic storage purposes, connect the charge controller to the battery. Connect the inverter system to the high performance application.

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