
OPTIMIZING MAXIMUM POWER POINT TRACKING ON PHOTOVOLTAIC ARRAYS USING ANT COLONY OPTIMIZATION AND PARTICLE SWARM OPTIMIZATION ALGORITHMS

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Submitted : 23 November 2021; Revision : 14 January 2022; Accepted : 2 March 2022

ABSTRACT

Solar power plants, in general, cannot produce maximum power by themselves; the characteristics of the PV voltage generally follow the battery voltage or the load that is connected directly to the PV. The intensity of light received by the PV modules does not all get uniform irradiation, so the power produced is not optimal and causes multi-peak. A Maximum Power Point Tracking (MPPT) system is needed to optimize power from PV. However, the often used methods are still trapped in local peaks and long convergence times. In this study, we compare the performance of each algorithm to find the maximum power point (MPP) and tracking time using two methods, namely Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). This study uses 6 selected cases that can occur in 6 solar panel modules arranged in series. Characteristic curves in 6 cases were generated using MATLAB SIMULINK for tracking to find the maximum power point using the ACO and PSO algorithms. The ACO has an efficiency of 99.4910% and tracking failure 7 times in 6 cases in 10 trials of each case, while the PSO algorithm has an efficiency of 99.1043% and tracking failure seven times in 6 cases in 10 trials each case. The efficiency comparison of the ACO algorithm is 0.39% better than the PSO algorithm, while the PSO method is faster in tracking.

Keywords Ant Colony Optimization; Particle Swarm Optimization; Maximum Power Point Tracking; Convergent Time.

Paper type Research paper

INTRODUCTION

In general, PV cannot produce optimally because the PV voltage will usually follow the battery's voltage connected to the PV. Maximum Power Point Tracking (MPPT) technology can help control the PV module to work at the maximum power point or Maximum Power Point (MPP) to produce optimal PV power. For PV to produce a higher maximum current and voltage, it is necessary to use several PV modules connected in series or parallel to get a higher current and voltage. The modules connected in parallel or series are called PV arrays. Suppose shadows of trees partially cover the PV array modules, clouds, buildings and so on. In that case, not all of the modules get the same irradiation, where each PV module has different or unbalanced results, so the total output power of the PV array is very high decrease. In addition, the hot-spot effect caused by partial shading tends to damage the PV cells and affect the safety of the PV system [1]. Therefore, more comprehensive tracking is needed when experiencing partial shadows. Conventional methods widely used for MPPT include Perturb and Observe (P&O), fractional open-circuit voltage, and incremental conductance. This conventional method has a slow response and is unsatisfactory in solving the problem of rapid environmental change and overcoming the non-linearity of PV. The rapid change in irradiation due to weather factors, the P&O method failed to track MPP [2].

The latest research related to the manufacture of the MPPT algorithm in Partial Shading conditions is using Artificial Intelligence (AI) based control methods such as Artificial Neural Network [3] *Adaptive-Neuro-Fuzzy Inference System* [4] and Fuzzy Logic Control [5]. However, the very large data is needed for fuzzification process in fuzzy logic control will burden the computational process. Likewise, the large amount of data makes the training process slow with the neural network method.

Several researchers then proposed several methods to improve the quality of MPPT tracking, such as extremum-seeking control, ripple correlation control, etc. These methods can accurately track MPPs and improve dynamic and steady-state tracking performance. However, these methods cannot overcome the output curve with multi-peak caused by partial shadow conditions in the PV array [6]. Therefore, it is very important to develop an algorithm that accurately tracks the global MPP on a complex and non-linear output curve.

The MPPT problem under partial shadow becomes an optimization problem. The metaheuristic algorithm can obtain global peaks using a randomization number to avoid local peaks. Metaheuristic algorithms imitate animal behavior intending to find optimization of a function. Popular metaheuristic algorithms include Genetic Algorithm (GA), Harmony Search (HS), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO) [7].

This study will compare efficiency and tracking time of each Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) algorithms in MPPT under partial shadow. According to Purnomo [8], Ant Colony Optimization (ACO) is a metaheuristic optimization algorithm. This algorithm was inspired in finding the path from the colony to the food. So, this algorithm solves a computational problem that can be solved through the shortest and fastest path. Particle Swarm Optimization (PSO) is a metaheuristic algorithm that researchers widely use because it is simple, flexible, and easy to implement. Animals, namely birds, inspire this algorithm.

METHOD

The output of PV voltage and current has non-linear characteristics, as the irradiation and temperature change, causing the peak point of the maximum PV power to vary. PV cannot work automatically to find its maximum power point so it needs control to find its maximum power point. So the role of MPPT is needed to track the maximum power point of the PV.

Data retrieval

This study uses 6 PV modules installed in series, the purpose of installing PV modules in series is to get a graph with 6 varying peaks. This PV module is modeled using Matlab Simulink software and simulated by changing the solar irradiation in each PV module to get a PV graph of current and voltage and the location of different maximum power points. The PV module used in PV array modeling with SIMULINK is the SunPower SPR-X20-250-BLK module. The specifications for the SunPower SPR-X20-250-BLK module at STC, namely the light intensity of 1000 W/m² and the module temperature of 25°C, are shown in Table 1.

TABLE I. PV MODULE SPECIFICATIONS.

Rated maximum power (P_{mp})	249,952 W
Voltage at Pmax (V_{mp})	42,8 V
Current at Pmax (I_{mp})	5,84 A
Open-circuit voltage (V_{oc})	50,93 V
Short-circuit current (I_{sc})	6,2 A

The purpose of this MPPT is to obtain V_{ref} , which will be compared with V from the PV array so that an error is obtained, which is the input of the PI controller. This PI controller will later adjust the duty cycle of the Boost Converter to control the PV array output voltage.

MPPT simulation using ACO and PSO algorithms

The ACO algorithm is modeled like the behavior of foraging ants. The concept of the ACO algorithm is based on communication between ants. When ants search for food, these ants leave footprints (pheromones), these footprints will be information for other ants to reach the food source. The closer the distance between the food, the less evaporation will occur, increasing the amount of pheromones. The more pheromones, the ants will follow the footprints [9]. The MPPT control flowchart using the ACO algorithm is shown in Figure 1.

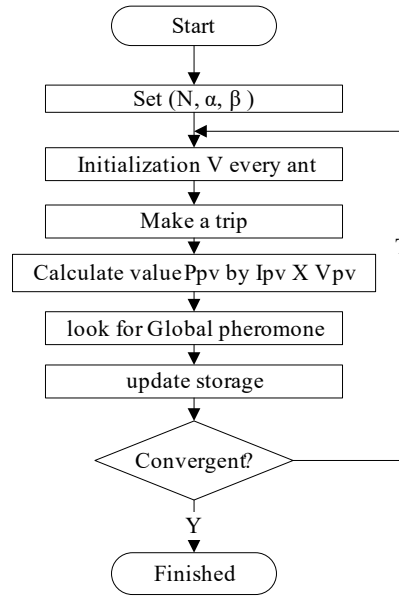


Figure 1. MPPT Flowchart with ACO

TABLE II. ACO PARAMETER SETTING.

Parameter	Value
number of ants (k)	5
Pheromone (τ)	1
Evaporasi (ρ)	0.5
Pheromone effect (α)	1
Pheromone effect (β)	2
Tolerance ($\epsilon 1$)	1

The steps for the PSO calculation process are as follows.

1. The initialization of the parameter value of the algorithm of the number of ants (N), the effect of the magnitude of the pheromone value (α, β).
2. Calculate the distance between D_i each V_i with the chosen solution ($i = 1 \dots m$) and the best solution V_{best} in storage.

$$D_i = |V_i - V_{best}| \quad (1)$$

3. Place ants randomly at each point.
4. Arrangement of the route of the visit of each ant that has been distributed to each point.
5. Calculation of the route length of each ant between points for the next cycle.
6. Empty the tabu list, and repeat from step 3 if needed, the tabu list needs to be emptied to be filled again with a new order in the next cycle, if the maximum number of cycles has not yet converged.

Probability to visit [8].

$$P_{ij} = \frac{\tau_{ij}^\alpha \times \eta_{ij}^\beta}{\sum \tau_{ij}^\alpha \times \eta_{ij}^\beta} \quad (2)$$

The PSO algorithm modeled the behavior of a flock of birds in foraging. The population in the PSO is called the swarm and the individual is called the particle. Each particle moves at a speed adapted from the search area and stores it as the best position ever reached. PSO is based on the social behavior of flocks of birds. Social behavior consists of individual actions and influences from other individuals in a group [11]. The MPPT control flowchart using the PSO algorithm is shown in Figure 2.

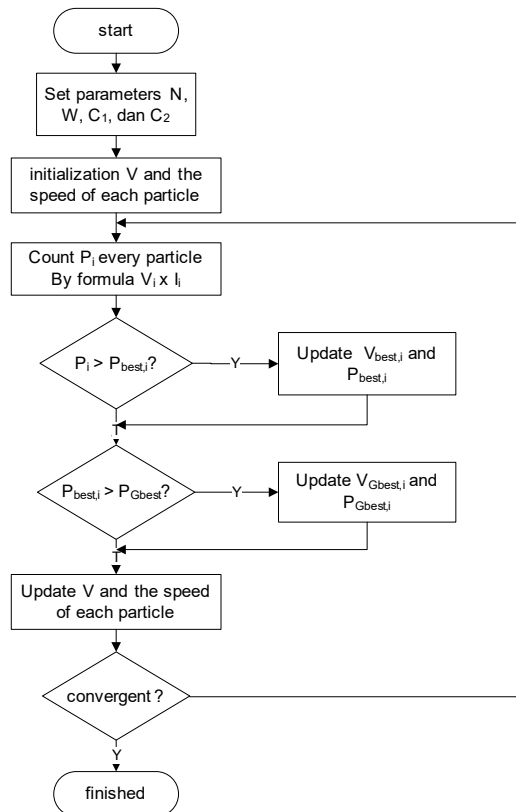


Fig. 2. MPPT flowchart with PSO

TABLE III. PSO PARAMETER SETTING

Parameter	Value
Number of particles (k)	5
Inertial weight (w)	0.4
Cognition-only learning factor (C ₁)	2.1
Social-only learning factor (C ₂)	2.1
Tolerance (ε ₁)	1

The steps for the PSO calculation process are as follows.

- Step 1 : Determine the number of particles (*O*), inertial weight (*W*), and learning factor (*C*₁, *C*₂).
- Step 2 : Initialize the position and velocity for each particle randomly.
- Step 3 : Substitute the initial position into the objective function to evaluate the fitness value for each particle.
- Step 4 : Compare the fitness value with the individual best position memory (*P*_{best}) on each particle to get a better position and update the best.
- Step 5 : Compare the best fitness value and the best fitness swarm value. If the best fitness value is higher than the fitness best, update best.
- Step 6 : Use Equation (3) to update the particle's velocity and Equation (4) to update the particle's position.
- Step 7 : Repeat steps 4 through 6 until the global optimal location is reached.

The velocity of the particle is updated by Eq [12].

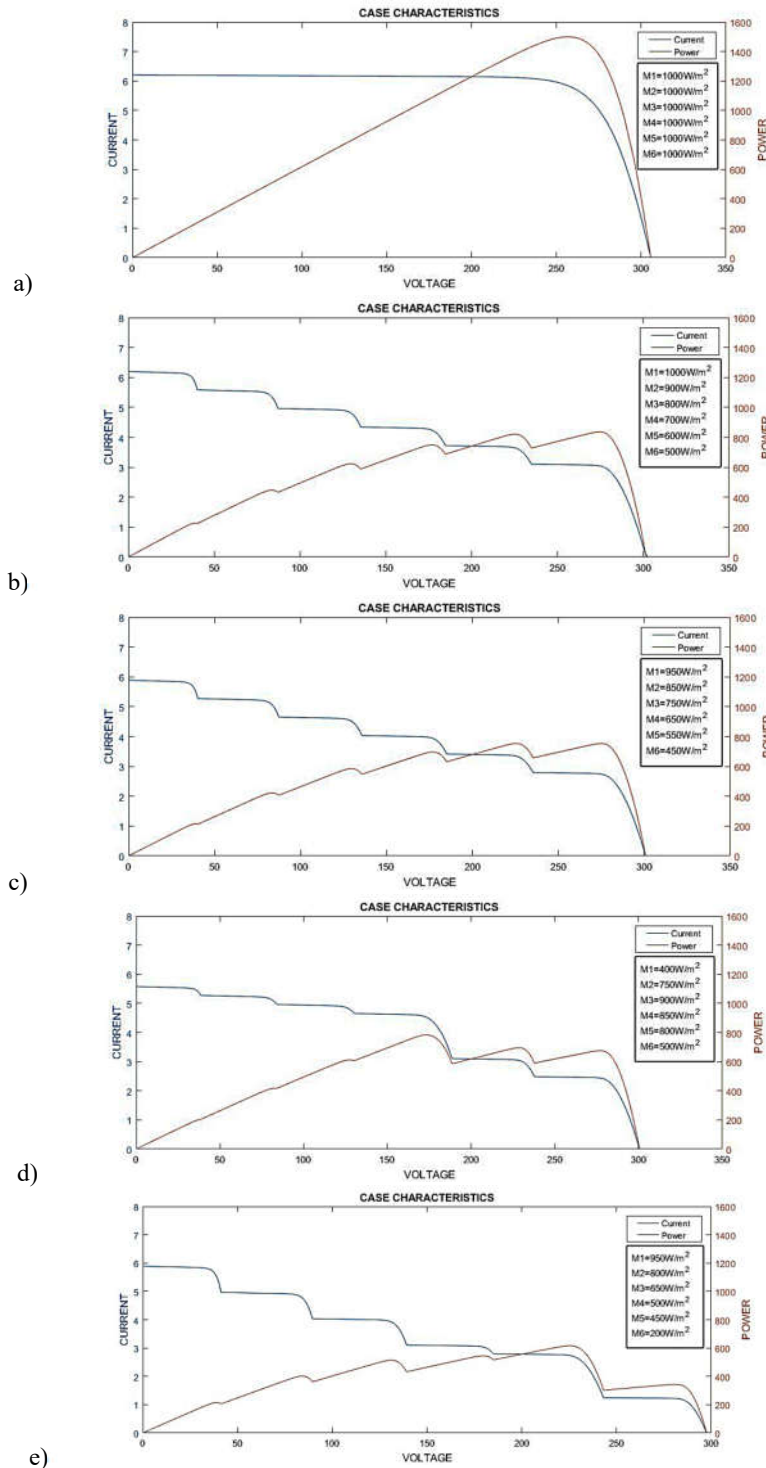
$$V_i^{j+1} = W \times V_i^j + C_1 \times rand1(\cdot) \times (P_{best,i} - P_i^j) + C_2 \times rand2(\cdot) \times (G_{best} - P_i^j) \quad (3)$$

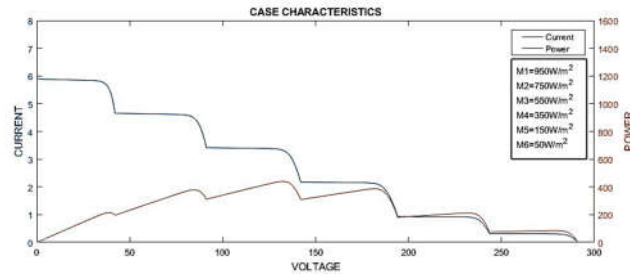
the position of the particle is updated by Equation

$$P_i^{j+1} = V_i^{j+1} + P_i^j \quad (4)$$

DISCUSSION

The ACO and PSO algorithms were tested in tracking MPP using 6 PV modules by varying solar irradiation in Matlab Simulink Software. This study, there are 6 test scenarios to determine tracking efficiency and the length of time tracking in the global MPP search. The resulting characteristics of the 6 cases are shown in the figure below.





f)

Figure 3. Characteristics I-V and P-V (a) case 1 (b) case 2 (c) case 3 (d) case 4 (e) case 5 and (f) case 6.

MPP tracker of 6 curves generated from various shadow patterns. The ACO and PSO Algorithms track each curve for 10 trials each by taking data on the Ppv, Vref, number of iterations, tracking time, and program execution time for each tracking, then calculating the efficiency of tracking and taking the average, best value, and worst of all. Vref is a reference voltage sent by MPPT to the comparator so that the PV array works at that voltage point. Ppv is the power generated by the PV array when the voltage is following Vref. The number of iterations and the tracking time indicate the number of times the program iterated and the program time to reach a convergent state. Execution time is the program execution time using MATLAB software. The algorithm's efficiency is the comparison between the tracked power and the actual MPP, while the PV efficiency is the ratio between the PV power generated and the maximum power that PV can produce when fully illuminated.

TABLE IV. ACO TRACKING RESULTS TO FIND MPP IN CASE 1.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	1499,6364	257,2156	9	0,538	99,9946	99,9946
2	1499,6688	257,0316	7	0,411	99,9967	99,9967
3	1499,4549	256,3183	9	0,535	99,9825	99,9825
4	1499,6641	257,015	8	0,476	99,9964	99,9964
5	1498,7027	254,7623	8	0,479	99,9323	99,9323
6	1499,6236	256,8747	9	0,539	99,9937	99,9937
7	1499,3767	256,0743	9	0,539	99,9772	99,9772
8	1499,4902	256,4313	8	0,479	99,9848	99,9848
9	1499,6919	257,1401	9	0,539	99,9983	99,9983
10	1499,6688	257,0316	7	0,419	99,9967	99,9967
Average	1499,4978	256,5894	8	0,495	99,9853	99,9853
Best	1499,6919	257,1401	9	0,539	99,9983	99,9983
Worst	1498,7027	254,7623	8	0,479	99,9323	99,9323

From Table 4, it can be concluded that the results of ACO tracking to find MPP in the first case are excellent. From 10 attempts, ACO managed to track MPP in the first case without any failure in tracking it. So the chance of success of the ACO algorithm in tracking the first case MPP is 99%. The ACO's best tracking results to find MPP in the first case.

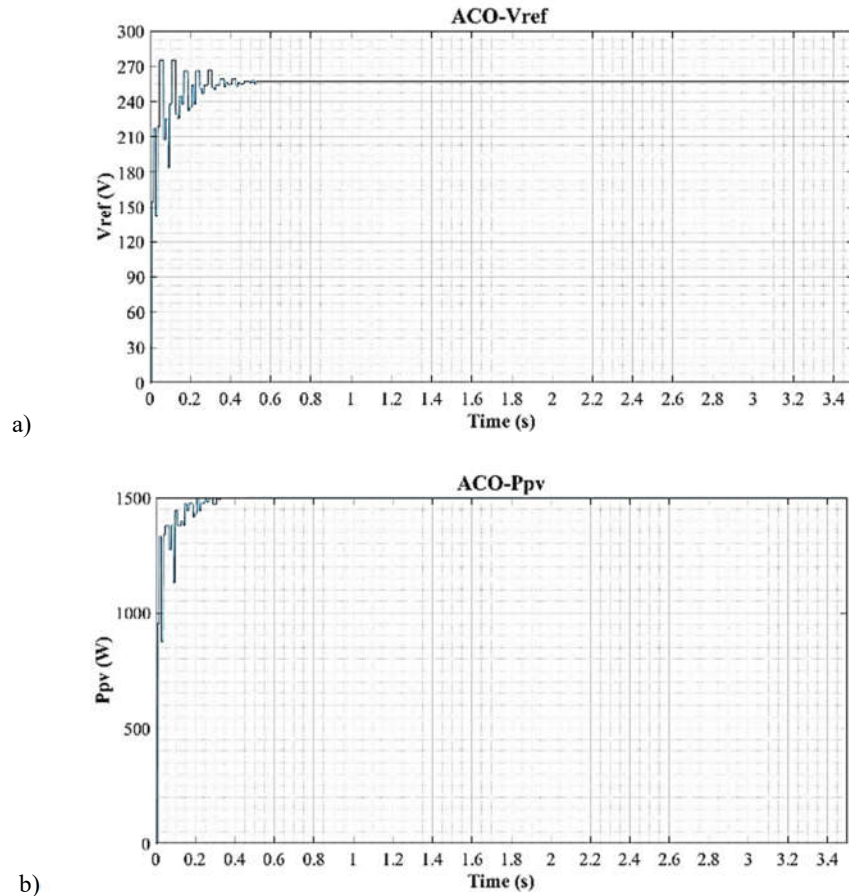


Figure 4. (a) change in Vref (b) change in Ppv in the best tracking of the first case ACO algorithm.

In Figure 4 it can be seen that the best efficiency is at a voltage of 257 V with a power of 1499.6919W and an algorithm efficiency of 99.9983%. The number of iterations for tracking with the best efficiency is 9 iterations with a tracking time of 0.539 seconds.

TABLE V. ACO TRACKING RESULTS TO FIND MPP IN CASE 2.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	836,3826	274,094	22	1,319	99,9984	55,7693
2	836,1941	273,835	19	1,139	99,9759	55,7567
3	836,3548	274,055	28	1,679	99,9951	55,7674
4	836,3548	274,055	28	1,679	99,9951	55,7674
5	836,2783	273,950	67	4,019	99,9859	55,7623
6	836,3905	274,314	10	0,599	99,9993	55,7698
7	836,3874	274,100	42	2,519	99,9990	55,7696
8	835,9143	273,453	12	0,719	99,9424	55,7380
9	836,3826	274,094	22	1,319	99,9984	55,7693
10	836,3954	274,123	49	2,939	99,9999	55,7701
Average	836,3034	274,007	29	1,793	99,9889	55,7640
Best	836,3954	274,123	49	2,939	99,9999	55,7702
Worst	835,9143	273,453	12	0,719	99,9425	55,7381

From 5 it can be concluded that the results of ACO tracking to find MPP in the second case are very good. Out of 10 attempts, ACO managed to track MPP in the second case without any failure in tracking it. So the chance of success of the ACO algorithm in tracking MPP in the second case is 99%.

TABLE VI. ACO TRACKING RESULTS TO FIND MPP IN CASE 3.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	784,1572	173,0022	21	1,259	99,9925	52,2869
2	784,2052	173,2264	19	1,139	99,9986	52,2901
3	784,2108	173,2881	12	0,719	99,9993	52,2905
4	695,3778	228,6084	41	2,459	88,6717	46,3672
5	784,2023	173,2023	15	0,899	99,9982	52,2899
6	784,211	173,2541	12	0,719	99,9993	52,2905
7	784,2134	173,266	25	1,499	99,9996	52,2907
8	695,375	228,6124	39	2,339	88,6713	46,3670
9	784,2052	173,2988	25	1,499	99,9986	52,2901
10	784,1874	173,1417	12	0,719	99,9963	52,2889
Average	766,4345	-	22	1,325	97,7325	51,1052
Best	784,2134	173,266	25	1,499	99,9996	52,2907
Worst	695,375	228,6124	39	2,339	88,6713	46,3670

From table 6, it can be concluded that the results of ACO tracking to find MPP in the third case. From 10 attempts, the ACO algorithm, 8 times succeeded in tracking MPP and 2 times failed to track it. So the chance of success of the ACO algorithm in tracking MPP in the third case is 80%. The ACO algorithm failed to track MPP 2 times because it was stuck at the 5th local peak with a voltage of 228. Where in this third case there are 6 peaks, from the characteristic curve in the 3rd case, the global peak is at the 4th peak and the others are local peaks.

TABLE VII. ACO TRACKING RESULTS TO FIND MPP IN CASE 4.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	753,8942	225,6806	69	4,139	99,9985	50,2690
2	696,9241	176,9121	33	1,979	92,4419	46,4703
3	753,9032	225,6505	43	2,579	99,9997	50,2696
4	753,8281	225,371	14	0,839	99,9898	50,2646
5	753,9047	225,6446	13	0,779	99,9999	50,2697
6	753,8529	225,4586	18	1,079	99,9930	50,2663
7	753,9004	225,656	79	4,739	99,9993	50,2694
8	753,8934	225,604	21	1,259	99,9984	50,2690
9	753,892	225,6871	18	1,029	99,9982	50,2689
10	753,8092	225,3045	11	0,659	99,9872	50,2634
Average	748,1802	-	31	1,908	99,2406	49,8880
Best	753,9047	225,6446	13	0,779	99,9999	50,2697
Worst	696,9241	176,9121	33	1,979	92,4419	46,4703

From table 7 it can be concluded that the results of ACO tracking to find MPP in case four. From 10 attempts, the ACO algorithm, 9 times succeeded in tracking MPP and 1 time failed to track it. So the chance of success of the ACO algorithm in tracking MPP in the fourth case is 90%. The ACO algorithm failed to track MPP once because it was stuck at the 4th local peak with a voltage of 176V. Where in this fourth case there are 6 peaks, from the characteristic curve in the 4th case, the global peak is at the 5th peak and the others are local peaks.

TABLE VIII. ACO TRACKING RESULTS TO FIND MPP IN CASE 5.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	616,5503	225,3001	12	0,719	99,9996	41,1110
2	616,5525	225,247	21	1,259	99,9999	41,1112
3	616,5464	225,3828	15	0,899	99,9989	41,1108
4	616,5526	225,2507	18	1,079	99,9999	41,1112
5	616,5518	225,2683	26	1,559	99,9998	41,1111
6	616,5521	225,2418	60	3,599	99,9999	41,1112
7	616,5483	225,3428	15	0,899	99,9993	41,1109

8	616,5435	225,158	13	0,779	99,9985	41,1106
9	616,5488	225,3318	47	2,819	99,9993	41,1109
10	616,5519	225,2388	20	1,199	99,9998	41,1111
Average	616,5498	-	24	1,481	99,9995	41,1110
Best	616,5526	225,2507	18	1,079	99,9999	41,1112
Worst	616,5435	225,158	13	0,779	99,9985	41,1106

From table 8, it can be concluded that the results of ACO tracking to find MPP in the fifth case are very good. From 10 attempts, ACO managed to track MPP in the fifth case without any failure in tracking it. So the chance of success of the ACO algorithm in tracking MPP in the fifth case is 99%.

TABLE IX. ACO TRACKING RESULTS TO FIND MPP IN CASE 6.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	439,5947	132,3447	36	2,159	99,9999	29,3118
2	439,5947	132,3298	58	3,479	99,9999	29,3118
3	439,5947	132,3251	37	2,219	99,9999	29,3118
4	439,5947	132,3121	46	2,759	99,9999	29,3118
5	439,5947	132,3921	25	1,499	99,9999	29,3118
6	439,5785	132,1573	11	0,659	99,9963	29,3107
7	439,5947	132,2917	22	1,319	99,9999	29,3118
8	439,5947	132,3165	44	2,639	99,9999	29,3118
9	439,5948	132,3387	76	4,559	99,9999	29,3118
10	439,5947	132,3902	18	1,079	99,9999	29,3118
Average	439,5930	-	37	2,237	99,9995	29,3117
Best	439,5948	132,3387	76	4,559	99,9999	29,3118
Worst	439,5785	132,1573	11	0,659	99,9963	29,3107

From table 9, it can be concluded that the results of the ACO tracking to find MPP in the sixth case are very good. From 10 attempts, ACO managed to track MPP in the sixth case without any failure in tracking it. So the chance of success of the ACO algorithm in tracking MPP in the sixth case is 99%.

TABLE X. PSO TRACKING RESULTS TO FIND MPP IN CASE 1.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	1499,6801	257,071	11	0,659	99,9975	99,9975
2	1499,6915	257,112	14	0,839	99,9982	99,9982
3	1499,6811	257,155	12	0,719	99,9975	99,9975
4	1499,6964	257,129	15	0,899	99,9986	99,9986
5	1499,6103	256,829	10	0,599	99,9928	99,9928
6	1499,6872	257,097	12	0,719	99,9979	99,9979
7	1499,6945	257,123	13	0,779	99,9984	99,9984
8	1499,6090	256,825	11	0,659	99,9927	99,9927
9	1499,6953	257,135	14	0,839	99,9985	99,9985
10	1499,6549	256,983	7	0,419	99,9958	99,9958
Average	1499,6700	-	12	0,713	99,9968	99,9968
Best	1499,6964	257,129	12	0,899	99,9986	99,9986
Worst	1499,6090	256,825	11	0,659	99,9927	99,9927

From table 10, it can be concluded that the results of the PSO tracking to find MPP in the first case obtained good results. From 10 attempts, PSO succeeded in tracking MPP in the first case, there were no failures in tracking it, so the probability of success of the PSO algorithm in tracking MPP in the first case is 99%. PSO's best tracking results to look for MPP in the first case.

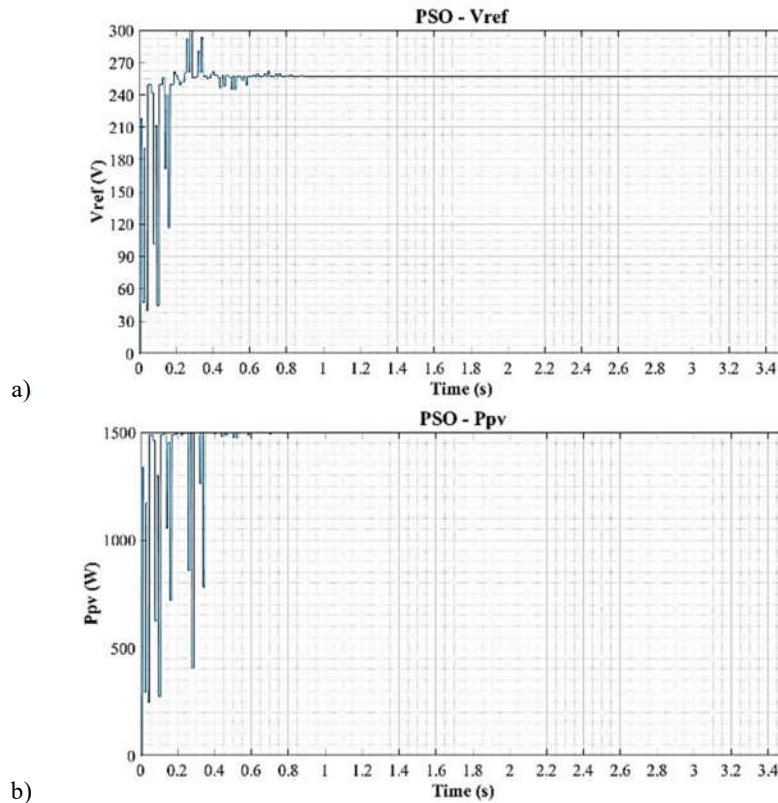


Fig. 5 (a) change in Vref (b) change in Ppv in the best tracking of the first case PSO algorithm.

Figure 5 shows that the tracking with the best efficiency is at a voltage of 257 V with a power of 1499.6964 W and an algorithm efficiency of 99.9986%. The number of iterations for tracking with the best efficiency is 12 iterations with a tracking time of 0.899 seconds.

TABLE XI. PSO TRACKING RESULTS TO FIND MPP IN CASE 2.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	836,3909	274,2996	11	0,659	99,9994	55,7698
2	821,4761	225,4092	16	0,959	98,2162	54,7753
3	836,3921	274,2581	11	0,719	99,9995	55,7699
4	836,3951	274,1403	12	0,719	99,9999	55,7701
5	836,3941	274,1779	13	0,779	99,9998	55,7700
6	836,3909	274,3012	14	0,839	99,9994	55,7698
7	821,4737	225,4177	11	0,659	98,2159	54,7752
8	836,3951	274,1403	12	0,719	99,9999	55,7701
9	836,3954	274,1207	15	0,899	99,9999	55,7701
10	821,4737	225,4177	11	0,659	98,2159	54,7752
Average	831,9177	259,5683	12	0,761	99,4646	55,4716
Best	836,3954	274,1207	15	0,899	99,9999	55,7701
Worst	821,4737	225,4177	11	0,659	98,2159	54,7752

From table 11, it can be concluded that the results of the PSO tracking to find MPP in the second case obtained good results. From 10 attempts, PSO succeeded in tracking MPP in the second case, succeeded 7 times and failed 3 times in tracking it, so that the probability of success of the PSO algorithm in tracking MPP in the second case is 70%. The PSO algorithm failed to track MPP 3 times because it was stuck at the 5th local peak in experiments 2,7 and 10 with a voltage of 225V. Where in this second case there are 6 peaks, from the characteristic curve in the 2nd case, the global peak is at the 6th peak and the others are local peaks.

TABLE XII. PSO TRACKING RESULTS TO FIND MPP IN CASE 3.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	784,2039	173,2202	12	0,719	99,9985	52,2901
2	784,2051	173,299	12	0,719	99,9986	52,2902
3	784,1883	173,1459	11	0,659	99,9965	52,2891
4	784,208	173,2395	13	0,779	99,999	52,2904
5	784,2089	173,2916	13	0,779	99,9991	52,2904
6	784,2145	173,2709	10	0,599	99,9998	52,2908
7	784,2061	173,2307	10	0,779	99,9987	52,2902
8	784,2134	173,2656	13	0,779	99,9997	52,2907
9	695,3571	228,5417	11	0,659	88,6691	46,3659
10	784,2081	173,2401	10	0,599	99,999	52,2904
Average	775,3213	-	11	0,707	98,8658	51,6978
Best	784,2145	173,2709	10	0,599	99,9998	52,2908
Worst	695,3571	228,5417	11	0,659	88,6691	46,3659

From table 12, it can be concluded that the results of the PSO tracking to find MPP in the third case obtained good results. From 10 attempts, PSO succeeded in tracking MPP in the third case, succeeded 9 times and failed 1 time in tracking it, so that the probability of success of the PSO algorithm in tracking MPP in the third case is 90%. The PSO algorithm failed to track MPP once because it was stuck at the 5th local peak with a voltage of 228. Where in this third case there are 6 peaks, from the characteristic curve in the 3rd case, the global peak is at the 4th peak and the others are local peaks.

TABLE XIII. PSO TRACKING RESULTS TO FIND IN CASE 4.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	753,8856	225,5757	14	0,839	99,9974	50,2685
2	753,8971	225,6713	11	0,659	99,999	50,2693
3	753,8673	225,7484	11	0,659	99,995	50,2673
4	753,9028	225,592	9	0,539	99,9997	50,2696
5	753,8964	225,6146	12	0,719	99,9989	50,2692
6	753,8964	225,6146	13	0,779	99,9989	50,2692
7	696,9245	176,9162	13	0,779	92,442	46,4704
8	753,9038	225,649	13	0,779	99,9998	50,2697
9	753,9763	225,5422	12	0,719	99,999	50,2745
10	695,6341	250	5	0,299	92,2708	46,3843
Average	742,3784	-	11	0,677	99,9999	49,5012
Best	753,9763	225,5422	12	0,719	99,9999	50,2745
Worst	695,6341	250	5	0,299	92,2708	46,3843

From table 13, it can be concluded that the results of the PSO tracking to find MPP in the fourth case obtained good results. From 10 attempts, PSO managed to track MPP in the fourth case, succeeded 9 times and failed 1 time in tracking it, so that the probability of the PSO algorithm being successful in tracking MPP in the fourth case is 90%. The PSO algorithm failed to track MPP 2 times because it was stuck at the 4th local peak in experiment 7 with a voltage of 176V and the 10th experiment stuck at the 6th local peak with a voltage of 250V. Where in this second case there are 6 peaks, from the characteristic curve in the 4th case, the global peak is at the 5th peak and the others are local peaks.

TABLE XIV. PSO TRACKING RESULTS TO FIND MPP IN CASE 5.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	616,5113	225,5519	12	0,719	99,9933	41,1085
2	545,1524	179,6603	11	0,659	88,4194	36,3503
3	616,5522	225,2429	13	0,779	99,9999	41,1112
4	545,1389	179,6273	14	0,839	88,4173	36,3494
5	616,5509	225,2262	13	0,779	99,9997	41,1111
6	616,5525	225,2513	11	0,659	99,9999	41,1112
7	616,552	225,2407	14	0,839	99,9999	41,1112
8	545,1288	178,6025	11	0,659	88,4156	36,3488
9	545,1389	179,6273	14	0,837	88,4173	36,3494

10	616,5133	225,5466	11	0,659	99,9936	41,1086
Average	595,1204	-	12	0,743	95,3655	39,2059
Best	616,5525	225,2513	11	0,659	99,9999	41,1112
Worst	545,1288	178,6025	11	0,659	88,4156	36,3488

From table 14, it can be concluded that the results of the PSO tracking to find MPP in the fifth case obtained poor results. From 10 attempts, PSO succeeded in tracking MPP in the fifth case, succeeded 7 times and failed 4 times in tracking it, so that the probability of the PSO algorithm being successful in tracking MPP in the fifth case is 60%. The PSO algorithm failed to track MPP 4 times because it was stuck at the 4th local peak with a voltage of 179V. Where in this fifth case there are 6 peaks, from the characteristic curve in the 5th case, the global peak is at the 5th peak and the others are local peaks.

TABLE XV. PSO TRACKING RESULTS TO FIND MPP IN CASE 6.

Test	Ppv (W)	Vref (V)	Iteration	Convergent time (s)	Algorithm Efficiency (%)	PV.Efficiency (%)
1	439,5917	132,455	12	0,719	99,9994	29,3116
2	439,5947	132,383	11	0,659	99,9999	29,3118
3	439,5947	132,379	13	0,779	99,9999	29,3118
4	439,5947	132,333	12	0,719	99,9999	29,3118
5	378,8598	84,7934	20	1,299	86,1839	25,2621
6	439,5946	132,314	11	0,659	99,9999	29,3118
7	378,8598	84,7934	25	1,499	86,1839	25,2621
8	439,5947	132,362	11	0,659	99,9999	29,3118
9	439,5928	132,449	11	0,659	99,9996	29,3117
10	439,5947	132,359	12	0,719	99,9999	29,3118
Average	433,5207	-	13	0,809	97,2366	28,9068
Best	439,5947	132,383	11	0,659	99,9999	29,3118
Worst	378,8598	84,7934	25	1,499	86,1839	25,2621

From table 15, it can be concluded that the results of the PSO tracking to find MPP in the sixth case obtained good results. From 10 attempts, PSO succeeded in tracking MPP in the sixth case, succeeded 9 times and failed 2 times in tracking it, so that the probability of the PSO algorithm being successful in tracking MPP in the sixth case is 80%. The PSO algorithm failed to track MPP 2 times because it was stuck at the 2nd local peak with a voltage of 84V. Where in the sixth case there are 6 peaks, from the characteristic curve in the 6th case the global peak is at the 3rd peak and the others are local peaks.

TABLE XVI. PERCENTAGE OF THE ALGORITHM'S AVERAGE EFFICIENCY ADVANTAGE

Scenario	Tracking Time(s)		Percentage of Excellence
	ACO	PSO	ACO
Case 1	99,9853	99,9968	-0,01
Case 2	99,9889	99,4646	0,52
Case 3	97,7325	98,8658	-1,13
Case 4	99,2406	99,9999	-0,76
Case 5	99,9995	97,6809	2,32
Case 6	99,9995	98,6182	1,38
Average Percentage			0,39

From the 6 case scenarios, the efficiency of the ACO algorithm is 0.39% superior to the PSO algorithm. The PSO algorithm has a worse average efficiency because it is often trapped in the local maximum. The ACO algorithm is more suitable for tracking many peaks because getting caught in local maximums is not easy. The number of coefficients that control the tracking causes the ACO algorithm to be 0.78 s slower in tracking time compared to the PSO algorithm.

TABLE XVII. PERTAGE OF LEAD TIME TRACKING

Scenario	Tracking Time(s)		Percentage of Excellence	
	ACO	PSO	ACO-PSO	PSO-ACO
Case 1	0,495	0,713	0,22	-0,22
Case 2	1,793	0,749	-1,04	1,04
Case 3	1,325	0,707	-0,62	0,62
Case 4	1,908	0,677	-1,23	1,23
Case 5	1,481	0,743	-0,74	0,74
Case 6	2,237	0,809	-1,43	1,43

Average Percentage

-0,81

0,81

CONCLUSION

Based on the study results, the average efficiency of the ACO algorithm was 99.4910% in 6 cases and 10 trials in each case. Tracking time is 0.81 s slower than PSO. The average efficiency of the PSO algorithm was 99.1043% in 6 cases and 10 trials in each case. Tracking time is 0.81 s faster than ACO. It can be concluded that the ACO algorithm has an overall average efficiency that is 0.39% superior to PSO, but has a tracking time of 0.81 s longer than the PSO algorithm.

REFERENCES

- [1] H. Li, D. Yang, W. Su, J. Lu, and X. Yu. "An Overall Distribution Particle Swarm Optimization MPPT Algorithm for Photovoltaic System under Partial Shading". IEEE. Trans. on Indus. Electr., pp. 1-11, April 2019, doi: 10.1109/TIE.2018.2829668.
- [2] D. Haji, and N. Genc, "Fuzzy and P&O Based MPPT Controllers under Different Conditions". IEEE, ICRERA, Paris, Prancis, pp. 649-655, October 2018. doi: 10.1109/ICRERA.2018.8566943.
- [3] R. Divyasharon, N. R. Banu, and D. Devaraj, "Artificial Neural Network based MPPT with CUK Converter Topology for PV Systems Under Varying Climatic Conditions". IEEE, INCOS, Tamilnadu, India, April 2019, doi: 10.1109/INCOS45849.2019.8951321.
- [4] K. Amara, A. Fekik, D. Hocine, M. L. Hamida, E. Bourenana, T. Bakir, and A. Malik. "Improved Performance of a PV Solar Panel With Adaptive Neuro Fuzzy Infernce System ANFIS Based MPPT". IEEE, ICRERA, Paris, France, pp. 1098-1101, Oct. 2018, doi: 10.1109/ICRERA.2018.8566818.
- [5] J. I. Corcau, and L. Dinca, "Modeling and Analisis of a Fuzzy Type MPPT Algorithm". IEEE, EDPE, The High Tratas, Slovakia, pp. 230-234, Oct. 2019, doi: 10.1109/EDPE.2019.8883925.
- [6] C. M. Mendonca, and D. H. Thomas, "Particle Swarm Optimization of the GMPPT of Photovoltaic Energy Generation under Different Partial Shadding Conditions". IEEE, ISGT, Gramado, Brazil, Sept. 2019, doi: 10.1109/ISGT-LA.2019.8895283.
- [7] H. D. Purnomo. Cara Mudah Belajar Metode Optimasi Metaheuristik Menggunakan Matlab. Yogyakarta: GAVA MEDIA, 2014.
- [8] Yang, X. S. Nature-Inspired Metaheuristic Alghorithms Second Edition. United Kingdom: Luniver Press, 2010.
- [9] R. W. Dewantoro, P. Sihombing, and Sutarman, "The Combination of Ant Colony Optimization (ACO) and Tabu Search (TS) Algorithm to Solve the Traveling Salesman Problem (TSP)". IEEE, ELTICOM, Medan, Indonesia, sept. 2019, doi: 10.1109/ELTICOM47379.2019.8943832.
- [10] D.P. Hindriyanto. Belajar metode Optimasi Metaheuristik Menggunakan Matlab. Yogyakarta: Gava Media, 2014.
- [11] I. Dubey, and M. Gupta "Uniform Mutation and SPV rule Based Optimized PSO Algorithm for TSP Problem".IEEE, ICECS, Coimbatore, India, pp. 168-172, Oct. 2017, doi: 10.1109/ECS.2017.8067862.
- [12] Suyanto. Swarm Intelligenca Komputasi Modern untuk Optimasi. Bandung: Informatika, 2017.