

Comparative analysis of evolutionary-based maximum power point tracking for partial shaded photovoltaic

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ABSTRACT

The characteristics of the photovoltaic module are affected by the level of solar irradiation and the ambient temperature. These characteristics are depicted in a V-P curve. In the V-P curve, a line is drawn that shows the response of changes in output power to the level of solar irradiation and the response to changes in voltage to ambient temperature. Under partial shading conditions, photovoltaic (PV) modules experience non-uniform irradiation. This causes the V-P curve to have more than one maximum power point (MPP). The MPP with the highest value is called the global MPP, while the other MPP is the local MPP. The conventional MPP tracking technique cannot overcome this partial shading condition because it will be trapped in the local MPP. This article discusses the MPP tracking technique using an evolutionary algorithm (EA). The EAs analyzed in this article are genetic algorithm (GA), firefly algorithm (FA), and fruit fly optimization (FFO). The performance of MPP tracking is shown by comparing the value of the output power, accuracy, time, and tracking effectiveness. The performance analysis for the partial shading case was carried out on various populations and generations.

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1. INTRODUCTION

In a solar power generation system, there is a solar charge controller (SCC) device. This device is used to optimize the power harvest of photovoltaic (PV) modules. In another sense, it is increasing the efficiency and performance of the solar power generation unit. In modern solar power systems, generally, the SCC device is already a set with the inverter. A set of these devices is usually used for stand-alone or grid-tied systems. The advanced SCC device has a feature to optimize electric power harvest, namely the maximum power point tracking (MPPT) technique. This MPPT feature is used to track the maximum power point (MPP), where at this point, the maximum power harvesting process occurs [1]–[3]. The MPP point can be reached if the system operating voltage is set to the MPP voltage [4], [5].

Many studies have been carried out to apply this MPPT technique, both with conventional methods and with advanced algorithms. Lagdani *et al.* [6] compared the performance between three conventional algorithms, namely incremental conduction, perturb and observe, also fuzzy logic. Tracking carried out specifically for partial shading cases requires more advanced methods or algorithms. For the algorithm, Zouga *et al.* [7] has designed a particle swarm optimization (PSO) implementation for grid-tied solar PV

systems. Genetic algorithm (GA) was applied to the MPPT technique designed by Ibrahim *et al.* [8]. The comprehensive study conducted by Zafar *et al.* [9] comparing the performance of several evolutionary algorithms (EA) such as PSO, cuckoo search (CS), grasshopper optimization (GHO), and gray wolf optimization (GWO) for partial shading conditions. Other studies, such as the implementation of the MPPT technique using the shuffled frog by Mohammadinodoushan *et al.* [10] and inspired by the squirrel search by Fares *et al.* [11]. And Mao *et al.* [12] have also conducted a study of classification and summarization of the MPPT technique using conventional and intelligent techniques likewise, what has been done by Ahmad *et al.* [13].

This article discusses the performance analysis of several EA implemented in the MPPT technique under partial shading conditions. The algorithms compared are GA, firefly algorithm (FA), and fruit fly optimization (FFO). Performance analysis is carried out in a model of an electric power generation system on a PV module. The PV module is modeled with partial shading conditions with three variations of irradiation. The PV module modeling is done using Simulink, while the evolutionary algorithms (EAs) implementation modeling is done using the MATLAB program. Tracking performance analysis is done by comparing several algorithm parameters. The tracking technique test was carried out in the same environment with variations in the number of generations. In this article, the algorithm parameters analyzed are; output power, accuracy, tracking time, and effectiveness.

2. METHOD

The research method proposed in this article is modeling the characteristics of solar panels undergoing partial shading and implementing an EA in the MPPT technique. This research model is a solar panel with 6 solar cells in series and 3 in parallel. The implementation of the EA on the MPPT technique is to compare GA, FA, and FFO. The three EAs were tested with variations in the number of individuals and the number of generations. In addition, it was also tested with three kinds of sunlight insolation conditions, namely uniform, half partially shaded, and one-third partially shaded. Variations in the number of individuals tested were 20, 40, 60, and 80. At the same time, the variations in the number of generations were 20, 40, 60, 80, and 100. This was done to optimize the number of main parameters in each implementation of the MPPT technique. The specific parameters for each EAs are described in each algorithm approach in the following subsection.

2.1. Partial shading PV model

Partial shading is a condition that is often experienced by solar panel arrays, especially those installed in locations with many objects in the vicinity. The location can be on the roof of a building or in an open field. Partial shading is a condition where the solar panel gets non-uniform radiation on all its PV cells [14], [15]. There are parts of PV cells that get perfect irradiation, and there are parts of PV cells that get imperfect irradiation [16]. This will cause a voltage difference between the perfectly irradiated PV cells and those that are not. Striking voltage differences will reduce the efficiency of harvesting power from solar panels [17], [18].

Figure 1(a) shows the modeling of the PV module system that has partial shading. Partial conditions are described in 3 different irradiations: perfect, medium perfect, and half perfect. The physical condition of the partially shaded PV module, in reality, is also shown in Figure 1(b).

The model system described as an array of PV modules. The model formula for PV array is implemented inside the PV array box. Inside the box, array of several solar cell connected in 8 series and 3 parallel. Besides, each solar cell has the characteristic that formulated the output of its current. The current depends on the change of irradiation level and surface temperature. This formula is described in the next sub section. Then, the output of the PV array measured in value of its voltage and current. The power is calculated by multiplying the current and voltage. So, we have the dataset of PV current (I_{ps}), voltage (V_{ps}), and power (P_{ps}). The dataset will create I-V curve and P-V curve. Then, the dataset of this PV model system will be sent to the algorithm program EAs to do the MPP tracking simulation.

2.2. Problem formulation

The modeled solar panel module showed in Figure 2 consists of several PV cell connections and the observations of these characteristics are represented in the (1)-(5).

$$I = I_{pv} - I_o \left[\exp \left(\frac{V+I.R_s}{a.V_T} \right) - 1 \right] - \frac{V+I.R_s}{R_p} \quad (1)$$

a is the ideal diode constant, V_T is the thermal junction voltage, with V_i is found by (2).

$$V_T = \frac{N_s \cdot k \cdot T}{q} \tag{2}$$

N_s is the number of PV cells connected in series, k is the Boltzmann constant (J/K), T is the ambient temperature (F), and q is the electron charge (C).

$$I_{pv} = \frac{G}{G_n} [I_{pvn} + K_t(T - T_n)] \tag{3}$$

G is the degree of solar irradiation W/m^2 , K_t is the current/temperature coefficient (A/K).

$$I_0 = I_{0n} \left(\frac{T}{T_n}\right)^3 \exp\left[\frac{q \cdot E_g}{a \cdot k} \left(\frac{1}{T_n} - \frac{1}{T}\right)\right] \tag{4}$$

E_g is the energy gap constant,

$$I_{0n} = \frac{I_{scn}}{\exp\left(\frac{V_{ocn}}{a \cdot V_T n}\right) - 1} \tag{5}$$

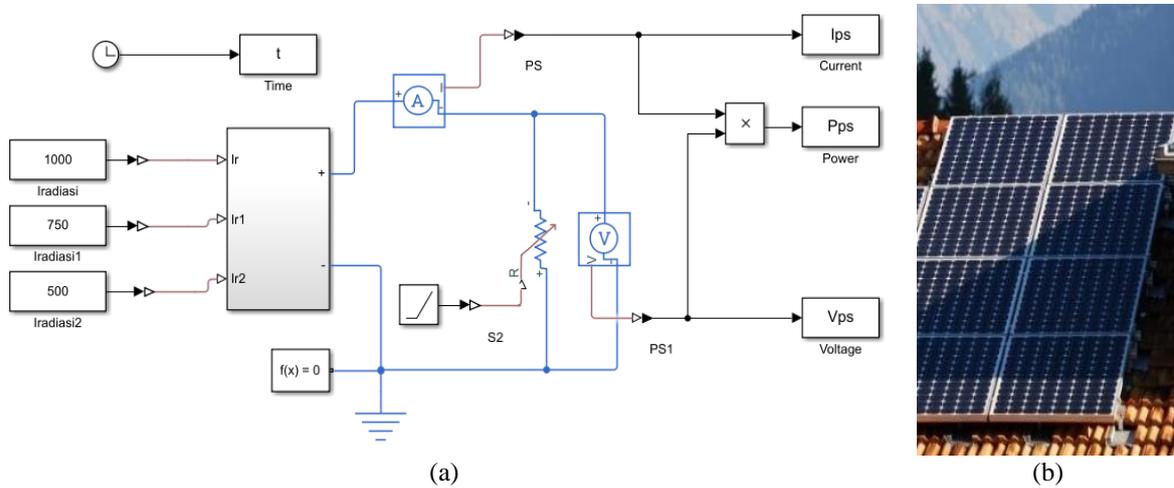


Figure 1. Modelling media for simulating MPPT (a) model of partially shaded PV module in simulink and (b) partially shaded PV in reality

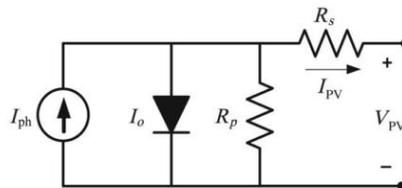


Figure 2. The series of the solar panel model

2.3. EAs used for MPPT modelling

Figures 3(a)-3(c) showed the workflow of three EAs used in this research. The EAs were tested in the original concept without any modification or hybridization of the algorithm. All the EAs were also tested in 10 iterations and make the number of generations as termination criteria. The EAs workflow always started with parameter initialization that contains some number of variable sets as algorithm’s constant. The general variables are like the number of individuals and the number of generations. All of special variables for each EA described in the sub section. After that is the evaluation for any solution for each EA calculated by the same fitness function as the PV formula described before. Then the searching process of each EA that described in more detailed in the next sub section. After the final searching process, the iteration will be

repeated until termination criteria are met. The algorithm is ended when termination criteria are met, the algorithm will determine the best-valued individual and make it the solution for problem optimization.

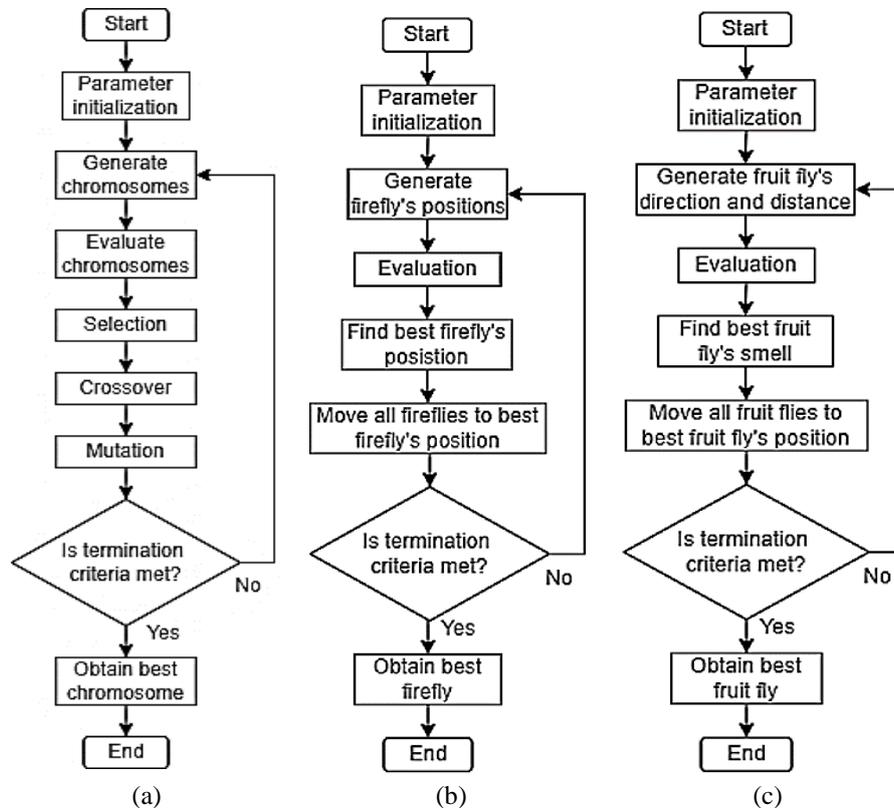


Figure 3. Workflow of EAs used in research, (a) genetic algorithm, (b) fire fly algorithm, and (c) fruit fly algorithm

2.3.1. Genetic algorithm

GA is a search or tracking technique inspired by natural processes. The idea is to imitate the concepts of reproduction and natural selection in calculating for finding a solution to a problem. This technique was first discovered by John Holland in 1960 [19]–[22]. The search process imitates the natural selection process which maintains only individuals with high fitness values to survive. The search begins with the generation of a random number of individuals called chromosomes. This chromosome is a representation of the solution to the problem, where the fitness value will be checked. The selected chromosomes will be reproduced through crosses. This process is similar to the mating process of individuals in the evolutionary process, which requires a pair of parents to give birth to a new individual. This chromosome will then mutate. The combination of new and old individuals will create a new population for the next generation. That serial process will continue until a number of generations is reached. The optimization solution will be found in the chromosome which has the highest fitness value in the last generation. There are several advantages of GA compared to other algorithms: i) GA only performs a few mathematical calculations related to the problem to be solved, ii) GA has natural operators which make the algorithm effectively run for global searches, and iii) GA has the flexibility to be hybridized with other methods.

2.3.2. Fire fly algorithm

The FA is included in the swarm artificial intelligence method. It was used by Yusran *et al.* [23] AI to investigate the load ability of an integrated distributed generation. The firefly attractiveness is controlled by its light intensity (I), related as a fitness function of the objective function [24]–[27]. The first stage of this FA algorithm is population generation, just like most other EAs. The population is generated with a predetermined number of individuals and a randomly determined individual position. Then calculate the light intensity for each individual with the (6):

$$I(r) = \frac{I_s}{r^2} \quad (6)$$

where $I(r)$ is the light intensity of each fire fly at r as distance and I_s is intensity of the source. At any distances with steady light absorption, the $I(r)$ changes according to the r distance by (7):

$$I(r) = I_o e^{-\gamma r^2} \quad (7)$$

where I_o is light intensity of initial condition, γ is the coefficient of light absorption, r is the distance between fireflies. The attractiveness of each firefly is matched to the light intensity that is seen by another firefly around it; the different of attractiveness of β can be specified for the distance r by (8).

$$\beta = \beta_o e^{-\gamma r^2} \quad (8)$$

If there are two fireflies, that are i and j , then the range r can be obtained to the point at x_i and x_j so that it can be calculated by (9).

$$r = \|x_i - x_j\| = \sqrt{(x_i - x_j)^2} \quad (9)$$

The movement of fireflies which is influenced by the level of firefly attractive is expressed in (10):

$$x_{new} = x_{old} + \beta e^{-\gamma r^2} (x_i - x_j) + \alpha (Rand - 0.5) \quad (10)$$

where x_{old} is the old position, while x_2 and x_1 is the position of the nearest fireflies. The second term of (10) is related to the movement of fireflies, while the third term is random parameter as valued by α . Rand is a random number generated from Gaussian distribution or uniform distribution ranged from 0 to 1. The best fireflies are obtained on the last generation based on their brightness they have. In the next stage, the fitness of fireflies is updated by light intensity value of each firefly.

2.3.3. Fruit fly algorithm

FFO is one of the optimizations search approach that is inspired by the behavior of fruit fly. This algorithm is introduced by Pan in 2011 [28]. In terms of smell and vision ability, fruit flies are superior compared to other species. Fruit fly moves into the food affected to the smell. Furthermore, they could also reach their food by using their vision ability [29].

FFO have two important steps namely smell phase and vision phase. In the smell phase, the fruit flies move into the food by using their smelling ability. After their position is near the food, the vision phase is carried out [30]. This second step is used to identify their nearest food. The FFO steps described [31];

- Generate population,
- Initialize population's position,
- Update position of each fruit fly, with described equations

$$X_i = X_{axes} + randomValue \quad (11)$$

$$Y_i = Y_{axes} + randomValue \quad (12)$$

- Calculate distance of each fruit fly to initial position, by (13).

$$Dist_i = \sqrt{x_i^2 + y_i^2} \quad (13)$$

- Calculate smell concentration, by (14).

$$Smell_i = 1/Dist_i \quad (14)$$

- Detect the best fruit fly which has highest smell concentrate,
- Finally save the smell concentrate value and its position,
- The fruit flies will repeat this process until they find their food [32]–[35].

3. IMPLEMENTATION

Figure 4(a) shows the difference in the performance of a PV module modeled under uniform insolation and partially shaded insolation conditions. The graph is a P-V curve that represents the characteristics of the PV module in response to sunlight. Where the response depends on the intensity of sunlight and ambient temperature, the example in Figure 4(a), the PV module, when subjected to uniform insolation, can generate electric power of 463.6 W, while subjected to partial shading, it comes to only 241.9 W. This shows a reduction in power harvest of 52%. In the partial shading graph, there are 3 power peaks, 2 points are local peaks, 1 highest point is global peak. Such is the effect of partial shading experienced by an array or a PV module in a PV system. Figure 4(b) shows the shape of the P-V curve and the position of the MPP depend on the intensity of sunlight and ambient temperature. The higher the sun's intensity, the higher the short-circuit current and power-the higher the ambient temperature, the lower the voltage.

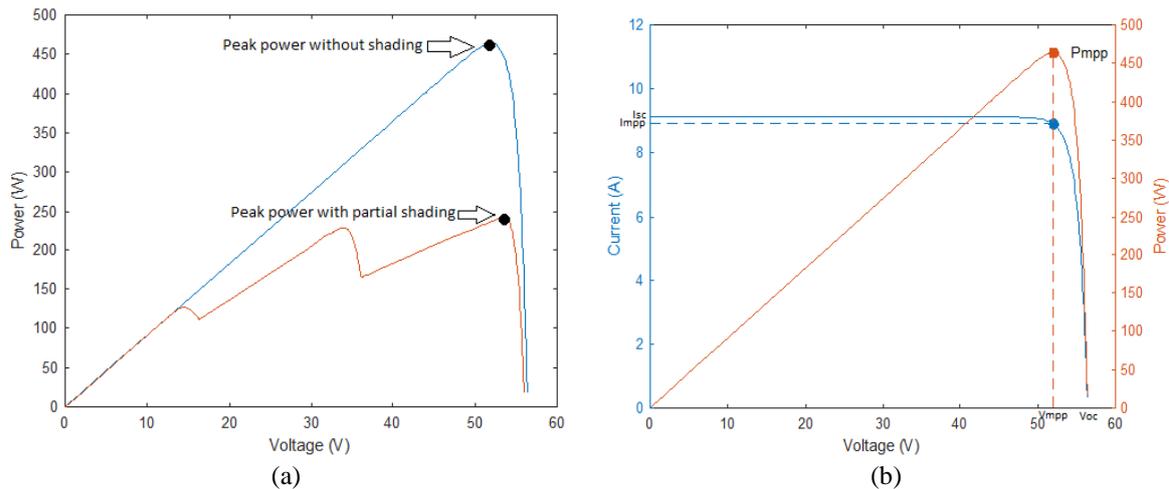


Figure 4. Simulation result for PV characteristic modelling (a) P-V curve of a PV module in uniform insolation versus partially shaded insolation and (b) I-V and P-V characteristic

3.1. MPPT in partial shading model

The MPP is where this point has the maximum power harvest that can be produced by a PV module or PV module array. There is a voltage where if the PV module is operated at that voltage, the system will operate at maximum power harvest conditions. This voltage is called V_{mpp} . Metaheuristic-based search algorithms such as the EA can deal with partial shading conditions. Algorithms like this will be able to track global peak points (global MPP) accurately. In this study, the EAs tested were GA, FA, and FFO.

A simple algorithm such as perturb and observe (P&O) applied to the MPPT technique that applies to uniform insolation conditions will have efficient and accurate MPP tracking. However, if applied to partial shading conditions, this will no longer apply. That is because the simple algorithm will be stuck at a local peak point, where this point is not the actual MPP but local MPP.

3.2. MPPT-GA approach

The MPPT technique with a GA approach is simulated with MATLAB. The algorithm parameters are the number of genes of 8, the probability of mutation of 0.1, and the probability of crossing over 0.6. The representation of the individual is the number of problem-solving. In this study, the solution to the problem is the voltage values (V_{pv}) at the x coordinate. In contrast, the representation of fitness is the quality of completion. What is meant by quality of completion is the solar panel output power (P_{pv}). The steps for tracking MPP with the GA approach are:

- Generation of individual chromosomes: this generation process adjusts the parameter values for the number of individuals and the number of genes that have been set. The number of individuals affects the number of solutions in the search process. At the same time, the number of genes affects the resolution of the search. The higher the value of the number of individuals and the number of genes, the more accurate the search process. As a trade-off, the search process takes longer. Each individual is raised with the value of the genes that make up the binary code. Coding: chromosome coding is done by the binary code method as a representation of real numbers. The coding uses (15).

$$x = x_{min} + (x_{max} - x_{min}) \frac{\sum_{i=1}^n b_i \cdot 2^{n-i}}{2^n - 1} \quad (15)$$

x_{min} is the lower bound actual decimal number of V_{pv} , x_{max} is the upper limit real decimal number of V_{pv} . The binary code for the number of gene-bits representing the chromosome converted into a real decimal number with a range of 0 to 2 to the power of the number of genes. The range of this representation value is compared with the range of V_{pv} values so that the target voltage value is obtained for each represented chromosome.

- Evaluation: after that, an evaluation process is carried out to determine the fitness value of each chromosome. The V_{pv} value is entered into (16).

$$I = I_{pv} - I_o \left[\exp\left(\frac{V+I.R_s}{a.V_T}\right) - 1 \right] - \frac{V+I.R_s}{R_p} \quad (16)$$

Thus, the current value (I) is obtained. Then the value of I is multiplied by V_{pv} , so that the power value (P_{pv}) is obtained. Then, this P_{pv} value is considered as a representation of fitness or fitness for each chromosome. The higher the P-value, the chromosome has greater the chance of surviving in the population.

- Selection: after evaluation, the chromosomes are selected using the rank selection method. This method sorts the position of chromosomes in the population-based on their fitness value. Sorting is done by placing the chromosomes that have a higher fitness value to a higher position. After sequencing, the chromosomes that are ranked in the lowest half of the number of individuals are destroyed. Therefore, only half of the number of chromosomes remains in the population.
- Crossover: chromosomes that survive the selection operation will be operated in crossover operation which is done by n-point method. This selection process produces two child chromosomes from each pair of parental chromosomes. Parental chromosomes here are represented by chromosomes representing the results of the selection operation. In this method, all representational chromosomes will be crossed. The number of exchanged or crossed genes depends on the probability of crosses that have been initialized previously. The greater the probability value, the more genes are crossed.
- Mutation: all chromosomes operated mutation using a binary code method. The selection of mutation points is made randomly. The genes that occupy the position of the mutation points are changed in value. If previously 1 becomes 0, and vice versa.
- Next-generation loop: these mutated chromosomes are then stored in an array. This array is then used as a symbolic chromosome value. Because this mutation operator is the last operation in each regeneration process, the chromosome representation of the result of this mutation operation is preserved for the following generation process.

3.3. MPPT-FA approach

The MPPT technique approach using the FA is carried out with the parameters α 0.5, β 0.5, and γ 0.01. In this MPPT-FA approach, the search solution value or voltage (V_{pv}) is represented by the individual coordinate positions of the firefly. In comparison, the fitness value or output power (P_{pv}) is represented by the level of illumination of the firefly. The MPPT approach steps with FA are:

- Population position initialization: All individuals generated in a population are located at one search point. It is from this point that the search begins. The initial positioning of this population was randomized.
- Initialization of positions: After that, all individuals are deployed in different positions. Each of these individuals has 2 parameters whose values are different from those of others: illumination and movement. Light intensity which represents P_{pv} power can be calculated by the (17).

$$light\ intensity = \frac{1}{I \times V_{pv}} \quad (17)$$

I is the PV module current and V_{pv} is PV module voltage.

- Calculate distance: This stage is to determine the distance of each individual with other individuals. This affects the resolution of the MPP voltage point search (V_{mpp}).
- Calculate attractiveness: This stage is to define the attractiveness between one individual and another individual.
- Calculate movement: This stage is to determine the movement aspect of the firefly. Firefly will choose the movement that has the smallest value and the highest level of light intensity as per (10).

- Evaluation: after the movement calculation of the fireflies on the V_{pv} axis, then an evaluation is carried out for each firefly. The firefly position point with the highest fitness value or P_{pv} is used to search for the firefly population in the next generation.

3.4. MPPT-FFO approach

The MPPT technique approach using fruit fly optimization has an x-coordinate range of 20 parameters and a y-coordinate range of 30. The MPP tracking stages are:

- Generation of group positions: these positions are generated at the x and y coordinates. The number of individuals raised follows the value of the last number of individuals.
- Individual distribution: each move spread along the x and y axes. In this study, the individual movement represents the voltage point V_{pv} .
- Calculate distance: at this stage, the distance of each individual is calculated from the starting point of the group.
- Calculate smell: this stage is an evaluation stage for each individual, where the smell value for each individual represents the fitness value, namely P_{pv} . Individuals who have the highest smell value are considered the most superior individuals. The fitness value is obtained by entering the search solution into (14) and multiplying it by V_{pv} to produce P_{pv} output power.
- Furthermore, the individual who has the highest fitness or smell value will be used as a point of generation for the fruit fly group population in the next generation. The best individual in each generation will be stored in the array. All individuals are then evaluated at the end of the algorithm to get the best individual from all generations. The individual representing the V_{mpp} is considered as the optimum search solution.

4. RESULTS AND DISCUSSION

This section shows the simulation results of the MPPT model run with GA, FA, and FFO. The performance compared for the three algorithms implemented in the MPPT technique to overcome partial shading is the value of output power, accuracy, time, and tracking effectiveness. Tests were carried out on the ratio and level of solar irradiation and the number of individuals and generations variations.

4.1. MPPT at various insolation

This test was carried out for three variations of partial shading. The three variations simulate the PV module at the same input of sunlight intensity, which is 1000 W/m². The number of individuals parameter is 16, and the number of generations is 20.

Figure 5 shows 3 conditions of shading. Figure 5(a) is uniform shading, it can be seen that conventional tracking algorithms such as P&O only excel when the PV module is subjected to uniform irradiation conditions. Meanwhile, in Figure 5(b) that has half under partial shading irradiation conditions, P&O is trapped at the local MPP point. Same thing happened in Figure 5(c) that has one third partial shaded condition. On the other hand, EAs can perform MPPT under both uniform and partial shading conditions. MPPT carried out by EAs can reach global MPP.

In Figure 6, it is also seen that in 3 conditions of shading or insolation, In Figure 6(a), the MPPT-FFO approach suffers defeat compared to other algorithms, including P&O. The MPPT-FFO tracking accuracy failed to reach around 100% due to the lack of this algorithm in optima search on 2-dimensional variables. Figures 6(b) and 6(c) shows that the EAs succeed to track the MPP in their highest accuracy.

Table 1 shows that there are striking performance characteristics of each algorithm used, including P&O and EAs. Under partial shading conditions, P&O produces P_{mpp} and accuracy is much lower than EAs (GA, FA, and FFO) because they are trapped in local MPP. However, P&O indeed has a much faster tracking time than EAs. Judging from the comparison between EAs, almost all EAs approaches have P_{mpp} and high accuracy. This means that EAs are reliable for MPPT under all irradiation conditions. However, there is a striking tracking time between EAs. Where GA is always longer, followed by FA, then FFO. This is due to the complexity of the parameters and stages of the tracking program for each EAs. Where indeed, FFO has the most straightforward optima search path.

4.1. MPPT at various parameter

In this test, the parameters that become influential factors are the number of individuals and generations. This test is only performed on EAs, namely GA, FA, and FFO. In this test, one parameter considered is tracking accuracy and generation attainment. Other parameters such as time are not taken into account because if the number of individuals and the number of generations is increased, the tracking time will be longer.

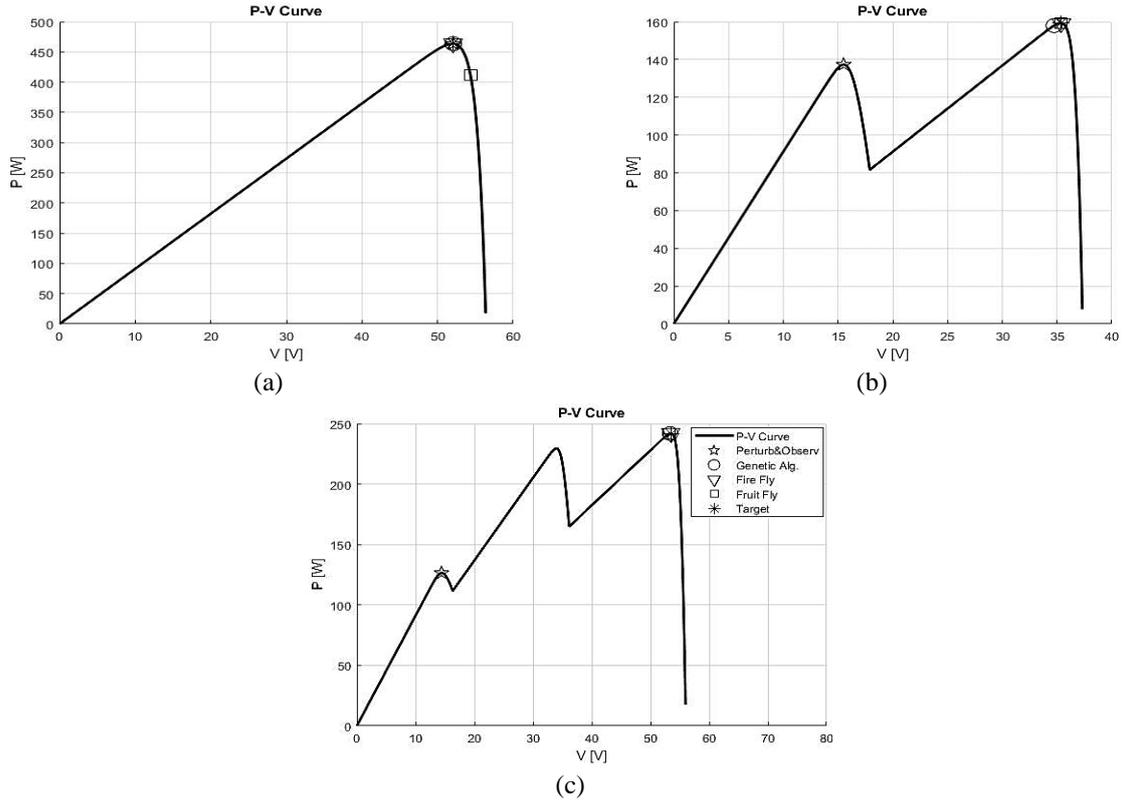


Figure 5. P-V curve of MPPT simulated to P&O, GA, FA, and FFO (a) under uniform insolation, (b) under half partially shaded insolation, and (c) under one third partially shaded insolation

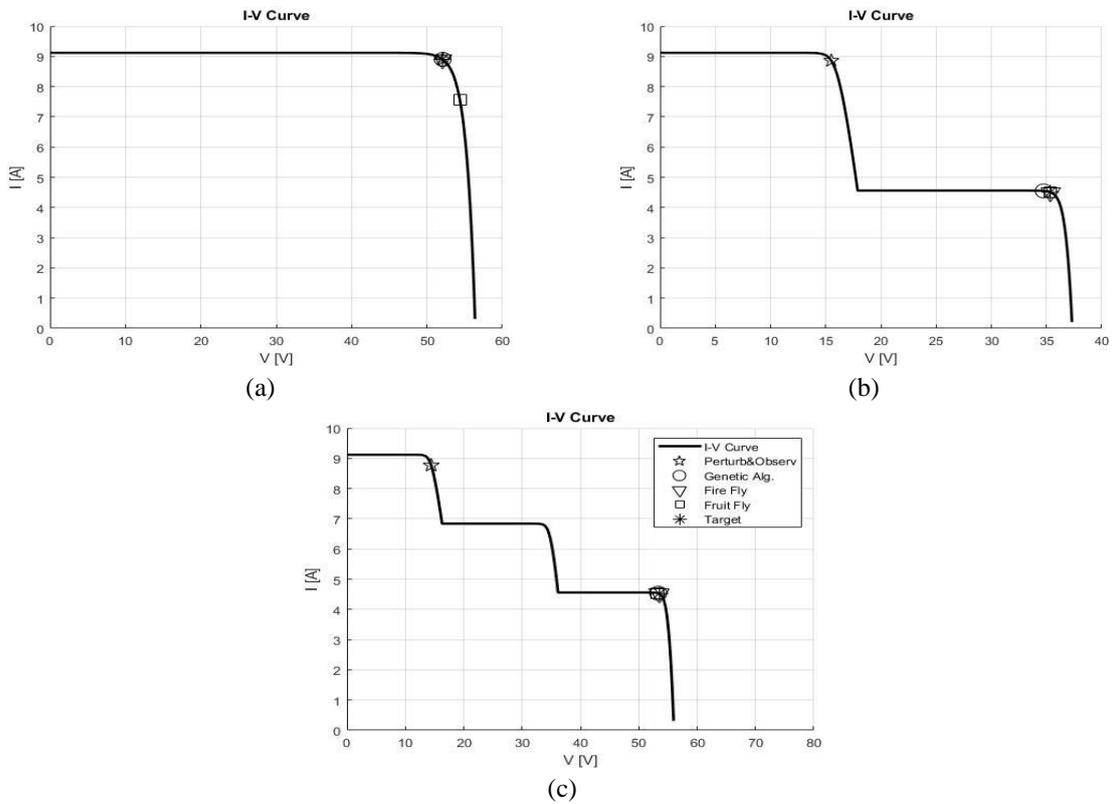


Figure 6. I-V curve of MPPT simulated to P&O, GA, FA, and FFO (a) under uniform insolation, (b) under half partially shaded insolation, and (c) under one third partially shaded insolation

Table 1. The performance of P&O and EAs at MPPT

Approach algorithm	Uniform insolation			Half partially shaded			One third partially shaded		
	P_{mpp} (W)	Acc. (%)	Time (s)	P_{mpp} (W)	Acc. (%)	Time (s)	P_{mpp} (W)	Acc. (%)	Time (s)
P&O	463	100	0.0007254	137	43.8	0.0007267	126	27	0.0007067
GA	463	100	0.12809	157	98.2	0.12247	241	99.8	0.11991
FA	463	100	0.00863	159	100	0.01007	241	100	0.0086268
FFO	411	95.6	0.00614	159	100	0.00849	241	99.5	0.0057307

The test results using MATLAB and Simulink shown in Tables 2 and 3 found that the number of individuals did not significantly affect the accuracy. At the same time, the number of generations correlated with accuracy on FA and FFO. Of the three EAs, FA has the highest correlation to the variation in the number of generations. The number of individuals and the number of generations did not significantly affect the accuracy of GA.

Table 2. The MPPT accuracy in % of EAs at various number of individuals

Approach algorithm	Number of individuals				Correlation (%)
	20	40	20	40	
GA	99.65	99.80	99.87	99.28	51.01
FA	98.58	98.58	98.58	98.58	79.00
FFO	98.44	98.38	98.58	98.58	79.12

Table 3. The MPPT accuracy in % of EAs at various number of generations

Approach algorithm	Number of individuals					Correlation (%)
	20	40	20	40	100	
GA	99.93	99.43	100.00	100	98.99	46.16
FA	100.00	99.60	98.90	98.00	96.40	96.90
FFO	99.80	99.60	98.90	97.90	96.28	95.66

4.2. EAs MPPT convergence

Figure 7 showed that the FA has fastest convergence result among the others. The test results that FA reaches 10 generations in average to make it convergence to find the optima (P_{mpp}). Besides, GA reaches 23 generation in average, and FFO reaches 36 generations in average to find the optima.

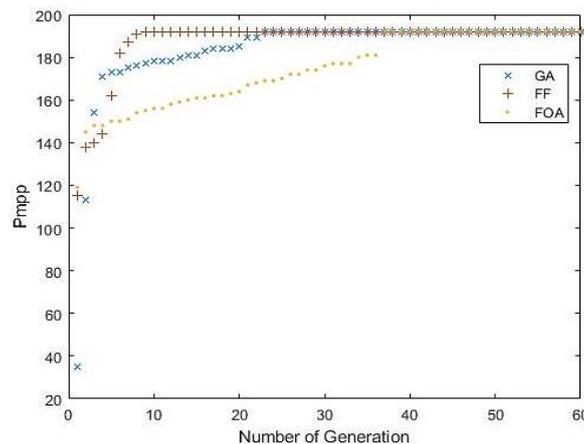


Figure 7. The convergence graph of EAs

5. CONCLUSION

The EA-based algorithm applied to the MPPT technique can overcome partial shading conditions with an accuracy rate above 95%. With a metaheuristic-based search model, EAs can search for global optima points instead of local optima. These global optima point is the P_{mpp} output power generated at V_{mpp} . The MPPT technique approach with EAs was also tested with the number of individuals and the number of

generations varying. This determines the correlation or influence of these parameters on the optimal point tracking performance MPP. From these tests, it can be concluded that the performance of GA is not affected by the number of individuals and the number of generations, unlike the case with FA and FFO. The correlation between the number of generations operated on the performance of FA and FFO is very high, which is more than 95%. The more generations, the less effective the FA and FFO operations on the MPPT technique. The optimal number of generations is 20. The same thing is added with the tracking time, which will exactly be longer. From the convergence test, FA has the best result in speed of convergence instead of GA and FFO. It only needs about 10 generations to reach convergence in MPP tracking.

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