Investigating The Effect of Various Converters & Implementation of Golden Eagle Optimization in Determining MPP in Solar Cells

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DECLARATION OF CANDIDATES

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for award of any degree or diploma.

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List of Acronyms

MPPT	Maximum Power Point Tracking
MPP	Maximum Power Point
GEO	Golden Eagle Optimization
PSO	Particle Swarm Optimization
CS	Cuckoo Search
GA	Genetic Algorithm
FFA	Fire Fly Algorithm
AC	Ant Colony
P&O	Perturb & observe
IC	Incremental Conductance
PV	Photovoltaic
LM	Local Maxima
GM	Global Maxima
PSC	Partial Shading Condition
RMS	Root Mean Square
GHG	Green House Gas
MSW	Municipal Solid Waste
HHO	Harris Hawks Optimization
PSS	Power System Stabilizer
SCV	Special Collecting Vehicles
GAMS	General Algebraic Modeling System
ANNs	Artificial Neural Network System
VWS	Voltage Window Search
SSJ	Search Skip Judge
DE	Differential Evolution
FPA	Flower Pollinating Algorithm
SSA	Slap Swarm Algorithm
GWO	Gray Wolf Optimization
DCB	Duty Cycle Boundary
GMPPT	Global Maximum Power Point Tracking

Acknowledgements

We would like to start off in the name of Allah, for the divine favor he bestowed upon us allowed us to see through the murky mist of the world and follow the luminous trail he intended for us.

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Abstract

Solar panels are frequently subjected to varying degrees of irradiance which causes the panels to work at a lower efficiency than normal. Maximum power point tracking (MPPT) attempts to maximize the power produced by the solar panels. Recent methods have used intelligent optimization algorithms in MPPT to reduce the tracking time to as low as possible. The Golden Eagle Optimization (GEO) algorithm is a recent algorithm inspired by the prey selection and hunting criteria of Golden Eagles which has shown promising results in other benchmark tests. The purpose of this thesis is to investigate the viability of GEO as a possible algorithm for use in MPPT along with finding the effect of different converters on the MPPT circuit.

The GEO algorithm was tested by constructing a MATLAB Simulink model of a typical solar panel circuit and simulating the circuit under different irradiances. The converter used in the circuit was varied between Buck, Boost & Buck-Boost for every test case. In order to test the viability and performance of the GEO algorithm, two other well-known algorithms that are used in MPPT were also simulated in the constructed circuit using the same test cases that were used for GEO. The results obtained for all three algorithms were compared in terms of settling time, convergence time, and maximum obtained power. The outputs of the algorithms were also compared in terms of converters and it was found that the boost converter provided the most desirable output. The comparisons also show that even though GEO tends to oscillate at the beginning of the search procedure, it outperforms the other two algorithms in terms of converging time and settling time in almost all of the test cases.

Keywords: MPPT, Settling time, Convergence time, Global maxima, Converters, Buck, Boost, Buck-boost, Partial shading.

Chapter 1

Introduction

The world has an ever-increasing demand of energy although the major energy sources used today are not inexhaustible rather the deposit of these energy sources are diminishing at very fast pace. Other than the fact that we are running out of energy sources it is also necessary to look at the impact of the use of these energy sources on the environment since in recent years the effect of climate change has become more apparent through the consecutive disasters that have been taking place all around the globe.

The current demand for an alternative energy source has two basic requirements one of which is that the source is able to satisfied that energy requirement off the world both in present and in the future. Another requirement is that the energy sources need to be environment friendly as in the current condition of the environment cannot be ignored. The requirements mentioned above are made by some of the renewable energy sources that are currently being used in a small scale to meet the energy demand. One such energy source is the solar energy which is the major kind of renewable energy used today since it is available to a certain degree throughout the world and it can be harvested easily compared to wind and hydroelectric energy. Although significant advancement has been made in solar energy harvesting it is not enough to replace the current energy sources such as coal and natural gases due to low efficiency in energy conversion from solar energy to electrical energy.

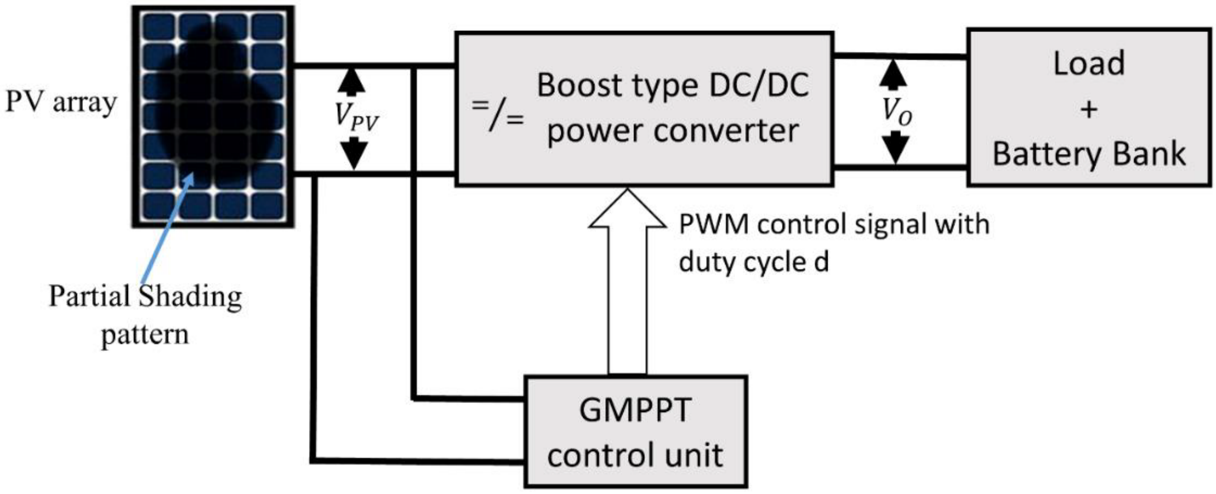


Figure 1.1 : Maximum power point tracking (MPPT) control for a photovoltaic (PV) system.

There are multiple factors that contribute to the inefficiency of the solar energy harvesting process and one of them is solar radiation is constantly changing throughout the day and at different time of the day light comes from different directions so there is a possibility that the solar panels may face partial shading conditions which significantly reduces the efficiency of the solar panels which is already low.

There are mainly two ways to get around this problem one of them is mechanical tracking and the other one is maximum PowerPoint tracking. Mechanical tracking requires moving parts which are more prone to failure has high initial cost and require frequent maintenance on the other hand maximum PowerPoint tracking or MPPT is and inverter-based electronics architecture that controls the PV module in such a way second it can extract maximum power under different shading condition.

Although maximum PowerPoint tracking has being around for a long time throughout the years it has seen some people changes pressure significantly proved its performance in terms of maximum Power point tracking time and also the highest power obtained for a certain irradiance. There are multiple techniques used to obtain MPPT initially simple techniques such as Perturb and observe, constant current and voltage technique and hill climb method they used but more recent MPPG techniques use algorithms such as particle swarm optimization and cuckoo search algorithm. The problem with initial techniques where that they got easily trapped in local Optima introducing machines. Later on, these early methods were modified to increase efficiency such as modified E and who did nick that improved the convergence problem at rapidly changing weather but couldn’t increase the efficiency. The block diagram of MPPT control for a PV system is shown in **Figure 1.1**.

Algorithms used to improve MPPT increased the efficiency of the solar panels while presenting different tradeoffs and it is advantageous such as high initial fluctuation or longer convergence time. The target is to minimize a tradeoff and find a balanced way to reach the maximum Power Point, the main advantage is that there are new algorithms being created every now and then so they can be tested for better performance compared to other algorithms.

Above it is seen that efforts are being made to further improve the efficiency of solar panels by employing different algorithms and techniques for MPPT as an improvement over the existing ones. Even if the efficiency remains constant, it did draw bags such as steady state errors and rapid response can also be improved by new algorithms increase the stability and reliability of solar energy so that it can one day replace conventional energy sources such as coal and natural gas.

1.1 Operation of Solar Cell

In **Figure 1.2** a single diode model of PV array is shown[1]. The model incorporates the resistances added by parallel and series connections. With an antiparallel diode, a single PV cell may operate as a DC source. The output current (I) is proportional to the irradiance intensity (G). The model takes into account the impacts of irradiance and temperature[2]. The red line shows the ideal PV cell where the total current $I = I_{pv} - I_o$. The current produce by the light is I_{pv} and the current passes through the diode is I_o which is given in equation (1).

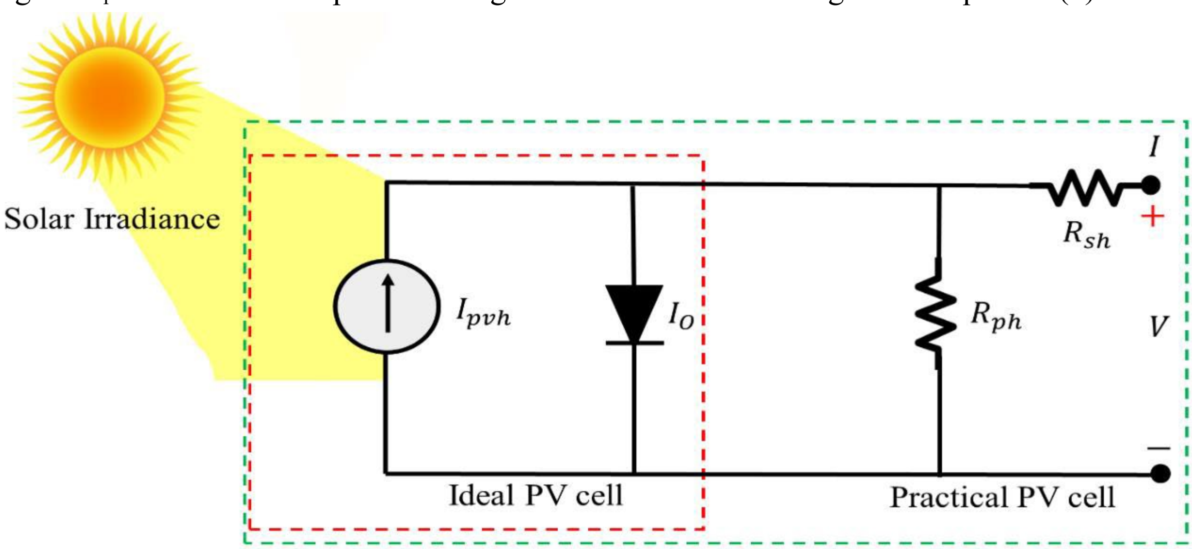


Figure 1.2 : PV cell with a single diode model.

$$I = I = I_{Pv} - I_0 \left[\exp\left(\frac{v}{\alpha v_T} \right) - 1 \right] \tag{1}$$

$$I = I_{Pv} - I_0 \left[\exp\left(\frac{v + IR_{sh}}{\alpha v_T} \right) - 1 \right] - \left(\frac{v + IR_{sh}}{R_{ph}} \right) \tag{2}$$

$$v_T = \frac{N_s KT}{q} \tag{3}$$

$$I = I_{pv} N_p - N_p I_0 \left[\exp\left(\frac{v + IR_{\mathrm{sh}\,eq}}{N_s \alpha v_T} \right) - 1 \right] - \left(\frac{v + IR_{\mathrm{sh}\,eq}}{R_{pheq}} \right) \tag{4}$$

R_{sh} and R_{ph} are the intrinsic resistance connected to this practical model and it advance the circuit which is found by the equation (2). The number of series cells are connected is N_s and parallel connected cells are N_p found in equation (3)and(4).

1.2 Partial Shading and Bypass Diode

PV arrays works more efficiently when there is uniform irradiance. In uniform irradiance the power of PV array is maximum in series connection. But the irradiance in not uniformly distributed in the PV cells. That's why the power decreases by the reduction of current[3]. In **Figure 1.3** a PV array is connected with the bypass diode for the mismatch of the irradiance[4].

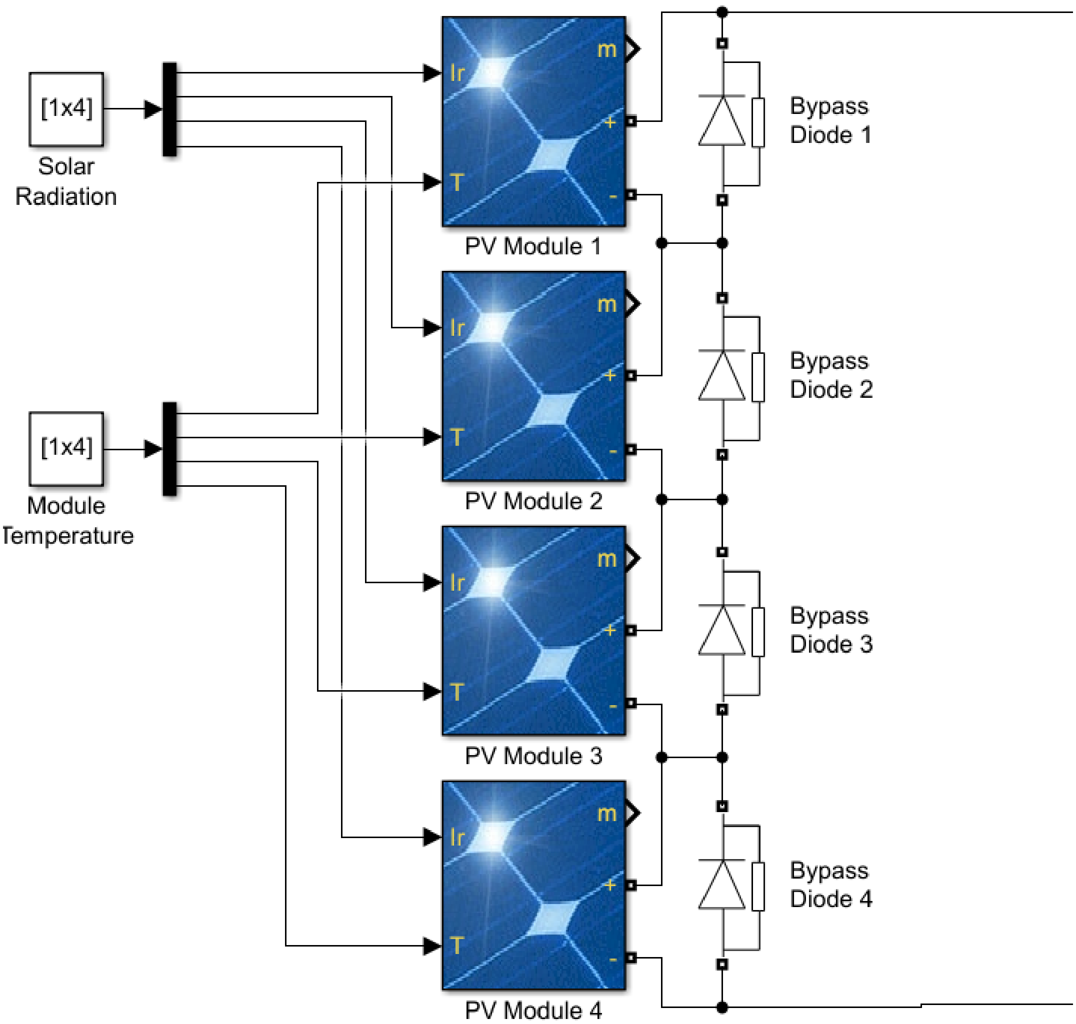


Figure 1.3 : PV array with bypass diode in series connection

When the irradiance is uniform them there is only one maximum point in P-V characteristics curve. In case of non-uniform or PSC there are multiple peaks found in P-V curve[5]. These peaks are called Local Maxima (LM) & Global Maxima (GM) are shown in **Figure 1.4** [6]. To find the Global maxima MPPT is used. The name of the PV module is Tata Power Solar System TP250MBZ. In Table 1.1 the specification of the PV module has shown.

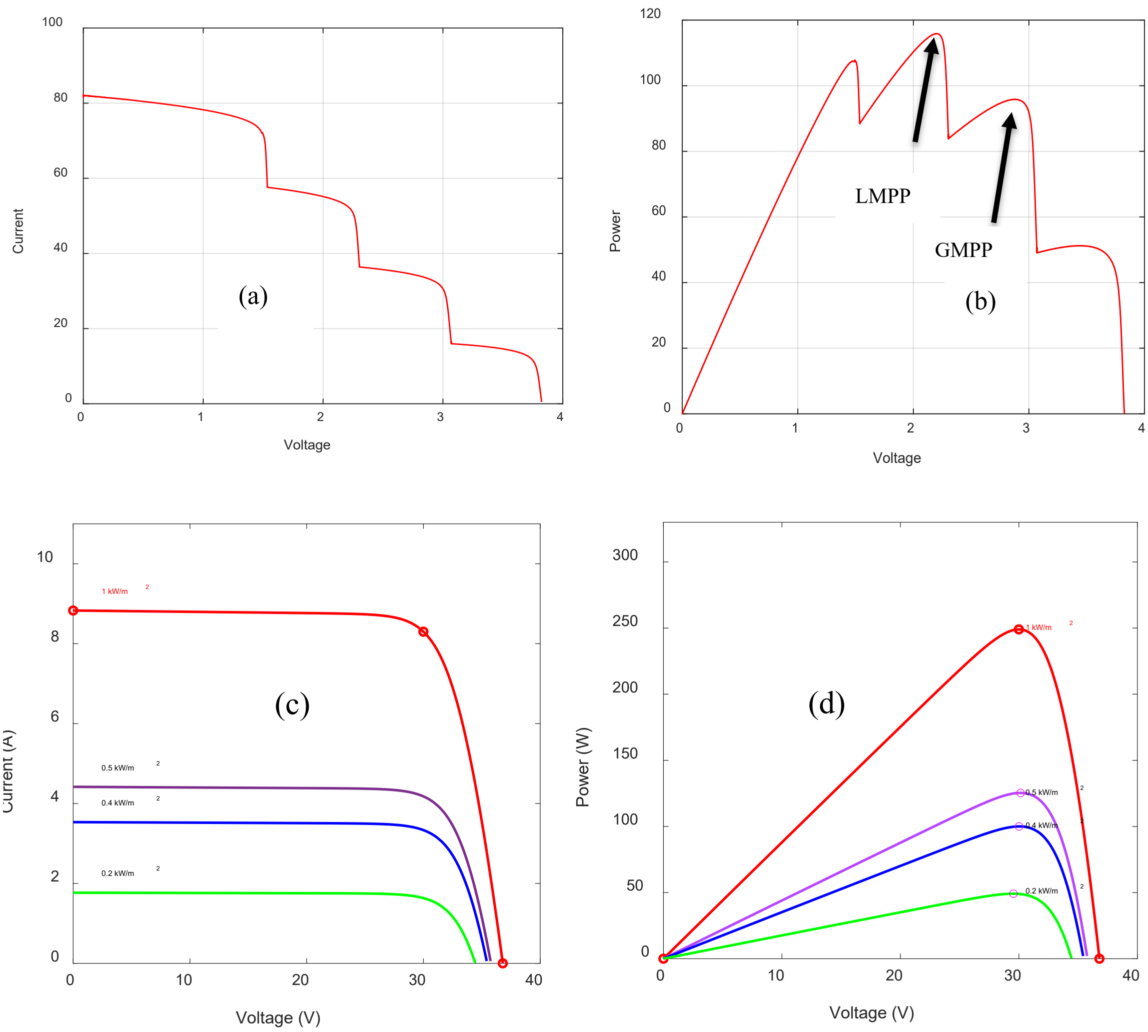


Figure 1.4 : Characteristics curve of PV array under PSC (a) & (b) and Uniform condition (c) & (d)

Table 1.1 Characteristics of Tata Power Solar System TP250MBZ PV array

Parameters	TP250MBZ
Maximum Power (W)	249 W
Open circuit voltage Voc (V)	36.8 V
Voltage at maximum power point Vmp (V)	30 V
Temperature coefficient of Voc (%/deg.C)	-0.33
Cells per module (Ncell)	60
Short-circuit current Isc (A)	8.83 A
Current at maximum power point Imp (A)	8.3 A
Temperature coefficient of Isc (%/deg.C)	0.063805

1.3 Background and Motivation

Maximum Power Point (MPP) is a technique of determining the maximum power point. It is usually used in the photovoltaic system for determining the maximum power of PV array. There are two ways of determing the MPP. By using the conventional method and the other one is the soft computing method. Conventional method includes Pertub & Observe (P&O) , Incremental Conductance (IC) , Fractional Open Circuit Voltage and Fixed Voltage method. But these tradiomal methods have some drawbacks like high oscillation and slow initial response. That's why an intelligent optimization technique is needed to use the determine the MPP. The optimization technique also performs better in Partial Shading Condition (PSC). There are many optimization technique used for determining MPP. Such as PSO, CA, AC, FFA, GA, etc. But these algorithms have slow initial response or it got trap in the local optima without reaching the global optima. The Golden Eagle Optimization is a natured inspired algorithm which has shown fast convergence in all the benchmark tests[7]. The motivations behind the work :

- For MPPT determination there are two principle criteria: Convergence time & stabilizing time.
- Algorithms also need to effectively find the global optima in all partial shading conditions.
- Most algorithms used for MPPT now are either slower than the desired speed or sometimes tend to get trapped in the local optima.
- The success GEO has shown in the benchmark tests makes it a promising algorithm to outperform the current algorithms in use in MPPT.

1.4 Objectives

- Simulating MPPT control of PV arrays using Particle Swarm Optimization (PSO), Cuckoo Search Algorithm (CSA) & GEO and comparing their convergence time, stabilizing time, and efficiency across different irradiances.

- Simulating MPPT control of PV arrays by using buck, boost & buck-boost converters using the above-mentioned algorithms and comparing the outputs.

Chapter 2

Literature Review

There are mainly two types of approaches for optimization which is under soft computing. Such as Deterministic and Meta heuristic approaches. In real world problem soft computing has been used to solve the problems. Optimal PV model parameter estimate, experimental data is used to validate, is a recent use of these techniques[8]. An optimizer which is based on population-based eagle strategy gradient with chaotic (ESCGBO) is used to estimate the static and dynamic parameter of PV. When it came to discovering the single diode and double diode which has 5-parameter and 7-parameter static PV models, the ESCGBO outperformed the other meta-heuristic strategies. Several runs (30) were executed to assess performance through numerical analysis, and the accuracy is determined by root mean square (rms) error to compare across various algorithms[9]. For efficient municipal solid waste (MSW) management, a fuzzy optimization technique is used.

2.1 Optimizations

The goal of the optimization was to maximize the amount of waste moved from dump sites while lowering greenhouse gas (GHG) emissions and transportation expenses. There are some decision variables which included the amount of waste moved from each station, the truck trips numbers, the amount of revenue made on a certain day, and so on[10]. The Harris Hawks Optimization (HHO) is used for determining the optimal size of PV. The goal was to reduce power losses caused by network and also improvement of the voltage profile. The many choice variables, such as voltage, solar plant active and reactive power, and phase angle at different buses, were all constrained in some way. The HHO outperformed the other algorithms, resulting in a 64.42% reduction in power loss for the bus systems[11]. The optimal tuning of power system stabilizers (PSS) which determine the factors for damping out minimum oscillation with low frequency. It is connected in interconnected power systems with multi machines running with various operation conditions. The Fire Fly Algorithm (FFA) was pitted against the Particle swarm optimization (PSO) and the genetic algorithm (GA). The PSS lead-lag structure's stabilizer returns and multiple constants were the decision variables to be improved. The optimal PSS parameters were determined using an e objective function based on eigen values. By raising the damping ratio, the intention was to diminish low-frequency oscillations. FFA outperformed the other algorithms in terms of transient response, convergence speed, and computational cost, improving network system dynamic stability[12]. Four alternative multi-objective meta-heuristic strategies are utilized to maximize two objectives of a blood supply chain network. The social benefit is maximized while expenditures and pollutants are kept to a minimum. Blood was collected from a blood transfusion center and transported to a blood breakdown facility using special collecting vehicles (SCV). The objective was to determine the best SCV routes with the lowest transportation costs, the lowest carbon emissions, and the most blood collected that could be utilized. Because the quantity of blood sub-products and the volume of blood at transfusion sites were both unknown, a normal distribution was used. According to the conclusions of the article, increasing the number of SCVs or their carrying capacity will increase route distance, pollution emissions, and prices, resulting in a greater societal effect. As a result, it was necessary to make a trade-off decision[13]. At various phases of the supply chain, the number of optimized objectives are two: overall cost reduction and job employment maximization. Controlling the returning waste product has an influence on the environment as well. The model took into account the ideal number and location of facilities, the quantity of avocados to be delivered from each center, the ideal number of jobs to be filled, and the amount of product to be kept to fulfill demand. The impact of purchasing costs, increasing a facility's capacity, and changing demand were all subjected to a sensitivity analysis. The study concluded that increasing product demand resulted in a significant rise in job possibilities[14].

2.2 MPPT

PS can occur when solar PV modules are coupled in series. In the case of PSC, it is observed that the module that has a lower irradiance incident on it, uses up power generated in the other modules [15]. In **Figure 1.4** the I-V and P-V curves vary for a typical solar cell for varying degrees of irradiance. Different methods have been used so far in order to minimize tracking time and maximize global power in MPPT. Control parameters that are used in MPPT include the direct control method, where the duty cycle is controlled by the code, and the indirect control method, where other variables like voltage are controlled by the code[16]. In PSC, where the solar panel fails to reach the global maxima, a version of PSO was tried to be implemented to solve the issue [17]. Hybrid systems combining solar PV, wind, and fuel cells were implemented using MPPT. These hybrid systems tend to use a unified algorithm to trace the maximum power of several energy sources simultaneously and thus don't require expensive equipment [17]. In cases like these, MPP can be found using Artificial Neural Network (ANN)[18]. Studies have compared the performance of PSO, ACO, ANNs, and Fuzzy logic along with other intelligent algorithms in improving MPPT in solar panels [19]. Older technologies like P&O were enhanced and tested for use in MPPT [20]. Many of the recent intelligent algorithms use MPPT control by the direct method where the duty cycle acts as the control factor [21]. The advantages and disadvantages of using the direct or indirect control approach are evaluated using MPPT control methods. From the comparison between the direct and indirect methods, it was observed that the indirect method suffered from high steady-state oscillations and was very slow to react to fast changes in irradiance. Furthermore, the indirect technique requires a voltage controller, which means more components are required in the circuit [22]. The outputs obtained from different soft computing methods, traditional methods, and intelligent optimization were compared. The factors that were compared for the different methods included transient efficiency along with convergence and settling times. According to the study, skipping algorithms such as the voltage window search (VWS) and search skip judge (SSJ) have a worldwide power convergence rate of 100 percent. Soft computing approaches like the Flower pollination algorithm (FPA), achieved GMPP convergence of 50%, which was unexpected, however, it was noted that optimizer parameter adjustment is crucial for GMPPT success. PSO-SSJ and some of the other hybrid approaches had a GMPPT convergence rate of 93 percent [16]. FPA was employed for GMPPT and it was compared to other algorithms like PSO and differential evolution (DE). After comparison, FPA was found to be better statistically

[23]. In the case of different PSC, the PSO is changed to monitor the GMPP. One of the major problems was to restart the entire algorithm to relocate the global maxima whenever the irradiance changed [24]. To monitor the GMPP under static and dynamic PSC, a hybrid slap swarm algorithm (SSA) with grey wolf optimizer (GWO) is adopted. PSO and P&O were used to compare the approach. After the comparison, it was seen that the hybrid method fared better in terms of convergence speed and tracking time. It is noteworthy that when a ten-cell setup of a solar panel was used and tested with P&O, it was seen that the method skipped a peak that was not mentioned in the paper anywhere [25]. On comparing the immune firefly algorithm to the normal firefly method for MPPT, it was observed that the former was faster in tracking the GMPPT than the latter [26]. Another interesting approach was taken by the SSA where it was successful in achieving a better result by limiting the search space of plausible solutions. Another approach where peak skipping was observed was HC[27].

2.3 Converters

The sunlight irradiance is considered as a dc source. To find the maximum power point dc-dc converter is used in mppt technique. There is many well-known dc-dc converter. Among them Buck, Boost, Buck-Boost are commonly used for mppt. Buck converter is a step-down dc-dc converter. An inductor or a capacitor is used in buck converter for step down the voltage. The duty cycle of buck converter can be determined by equation (5).

$$D = \frac{V_o}{V_{in}} \tag{5}$$

Boost converter is a dc-dc step up converter. It is used to increase the voltage of the circuit keeping the power same. Boost converter is most popular in mppt. Using a diode and a transistor the voltage can be increased in boost converter. The voltage is increased by increasing the duty cycle of the converter. The duty cycle can be determined by equation (6).

$$D = 1 - \frac{V_{in}}{V_o} \tag{6}$$

Buck-Boost is a dc-dc converter. It is used for step up or step down the voltage of a circuit. It is a combination of buck and boost converter. Buck boost converter is used for determining the mppt. If the duty cycle is less than 0.5 then it works as a buck converter. But if the duty cycle is greater than 0.5 then it works as a boost converter. The duty cycle of a buck boost converter can be determined by equation (7).

$$D = \frac{V_o}{V_o + V_{in}} \tag{7}$$

Chapter 3

Methodology

In order to make the results comparable to other algorithms MATLAB was chosen to simulate the MPPT algorithm. Simulation is also a significant methodological way of designing new prototypes and verifying their performance. The simulation required designing of a circuit which is connected to a PV array and combining the code for the algorithm with this setup in order to obtain maximum PowerPoint for any given irradiance.

3.1 GEO Algorithm

The main objective of this paper is to evaluate the performance of golden eagle optimization MPPT control that was done using the general outline of the algorithm in order to implement it in the MPPT system. GEO is a nature inspired metaheuristic algorithm based on the hunting behavior of Golden Eagles which can be used to solve global optimization problems. The algorithm is designed based on the intelligence of Golden Eagles turning speed at different phases are there hunting which takes place in a circular path .[28]During the initial stages of the hunt the golden eagle tends to search the area for better prey which is called cruise propensity and as the search progresses Golden Eagles tends to fixate on the best prey location which is called attack propensity finally attacking the best prey. In general terms the best prey is the global Optima.

The flow chart in **Figure 3.1** is used to understand how the algorithm reaches to the solution of a certain problem. The golden eagle optimization algorithm has two main parameters which are varied throughout the simulation to reach the solution and those are the attack propensity and the cruise propensity. During the initial stages of the search the attack propensity is low and the cruise propensity is high as the search progresses the true value of cruise propensity decreases and develop attack propensity increases. Another feature of the algorithm which was not present in the original algorithm is the ability to replace the worst prey location with the best relocation randomly after the algorithm is half way through its search.

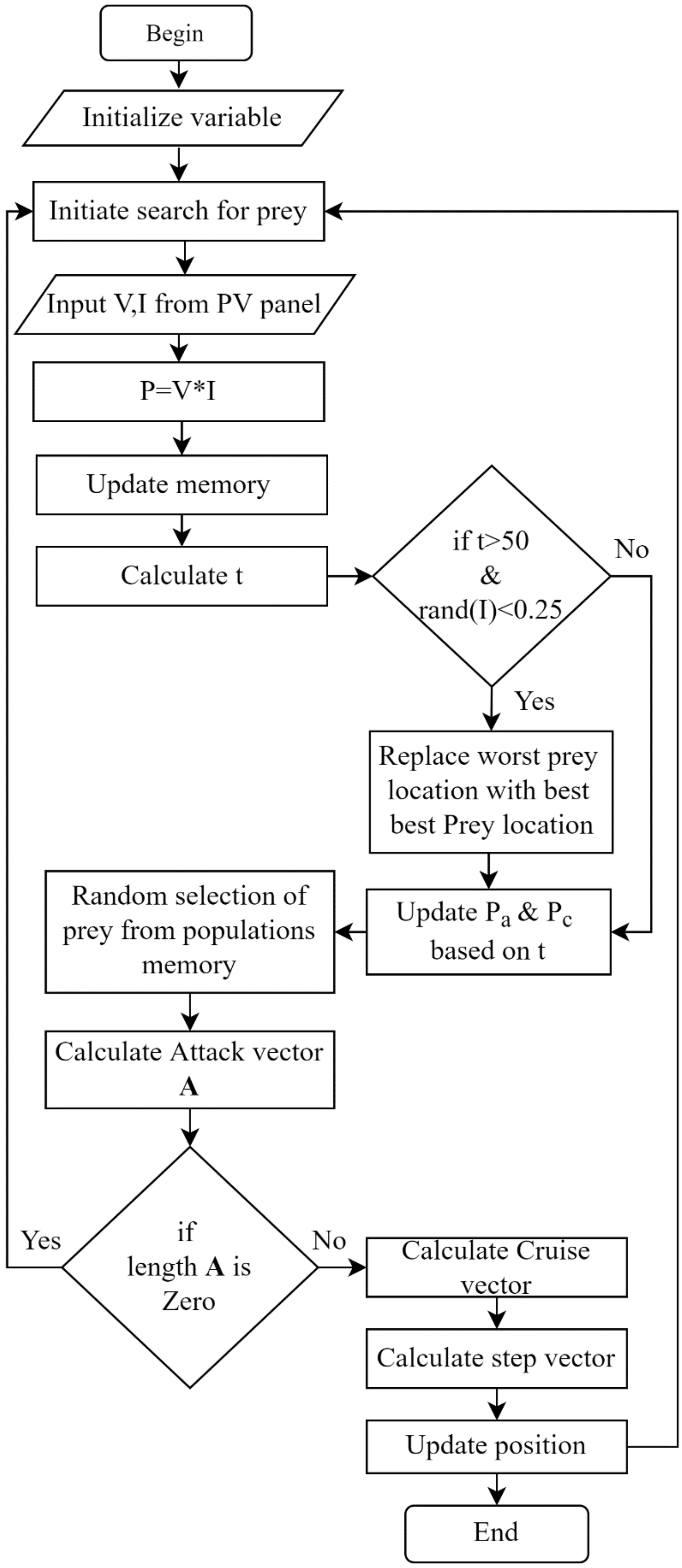


Figure 3.1 : Flowchart outlining the steps used by GEO to reach MPP [7]

At the beginning of the hunt which is when the search starts the attack propensity has a low value whereas the cruise propensity has a high value which means that the Eagles are looking for better prey. As the search progresses the attack propensity value increases and cruise propensity value decrease as shown in **Figure 3.2**. The above-mentioned behavior of the golden eagle is mathematically modeled for implementation in the simulation. In each iteration the Eagles are randomly assigned a prey location from the flock memory after that and the attack and cruise propensity are calculated for that iteration. During the search each eagle is designated only one prey which can also be called one to one mapping.

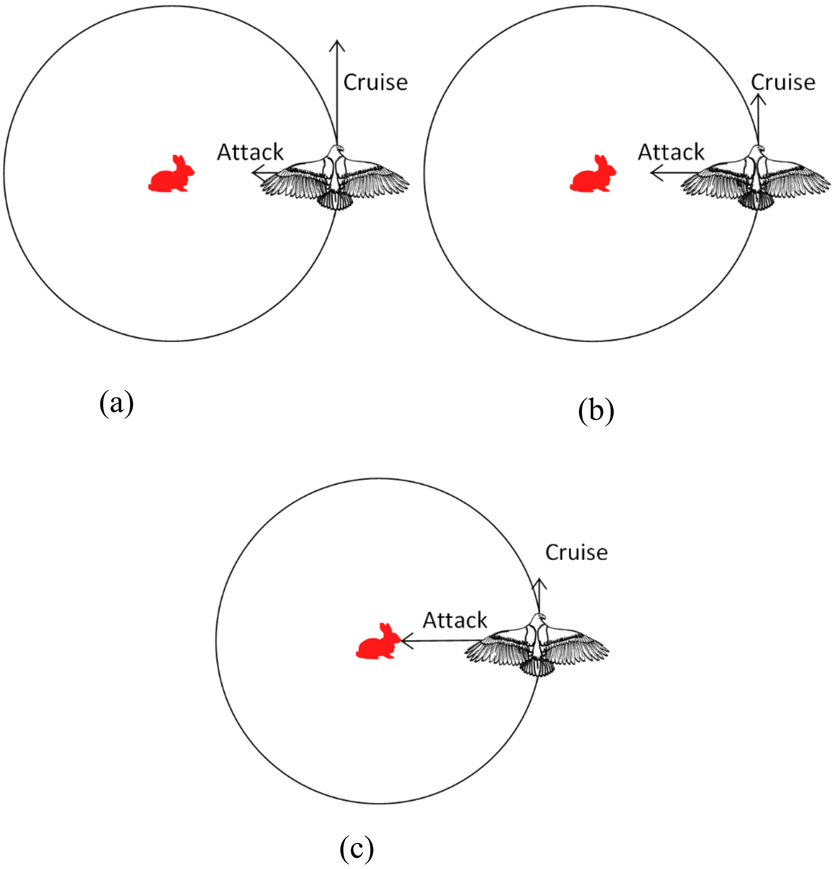


Figure 3.2 : Attack and Cruise propensity at the (a)beginning (b)middle (c)end of the search

The attack vector is calculated using (8).

$$\overrightarrow{A_i} = \overrightarrow{X_f^*} - \overrightarrow{X_i} \qquad (8)$$

where $A_i = [a_{1,} a_2, \dots, a_3]$ is the attack vector, $X_i = [x_1, x_2, \dots, x_n]$ is the decision/design variables vector, f and i are eagles and $X_f^* = [x_1^*, x_2^*, \dots, x_n^*]$ is the location of the selected prey. Cruise vector, c_k, is calculated using (9), (10), (11).

$$h_1 x_1 + h_2 x_2 + \dots + h_n x_n = d \Rightarrow \sum_{j=1}^{n} h_j x_j = d \tag{9}$$

$$\sum_{j=1}^{n} a_j x_j = \sum_{j=1}^{n} a_j{}^t x_j{}^* \tag{10}$$

$$c_k = \frac{d - \sum j, j \neq k a_j}{a_k} \tag{11}$$

where $H = [h_1, h_2, \dots, h_n]$ is the normal vector. In destination point C, $c_{k,}$ is the k-th element, a_j is the j-th attack vector element, d is the right-hand side of (9) and k is the index of the fixed variable. The eagles moves to search in new unvisited areas due to change in cruise vector which can be defined as exploration phase of the algorithm. The displacement of Golden eagle is determined by both the attack and the cruise vector. Equation (12) represents the Step vector of eagle i.

$$\triangle x_i = \vec{r_1} p_a \frac{\vec{A_i}}{\|\vec{A_i}\|} + \vec{r_2} p_c \frac{\vec{C_i}}{\|\vec{C_i}\|} \tag{12}$$

$$\|\vec{A_i}\| = \sqrt{\sum_{j=1}^{n} a_j^2}, \|\vec{C_i}\| = \sqrt{\sum_{j=1}^{n} c_j^2} \tag{13}$$

where P_a is the attack coefficient and P_c is the cruise coefficient calculated using equations (16) and (17). $\vec{r_1}$ and $\vec{r_2}$ are random vectors where the elements range between [0,1] while $\|Ai\|$ and $\|Ci\|$ are the Euclidean norm of the attack and cruise vectors shown in (13). Equation (14) is used to calculate the new search location that corresponds to the updated duty cycle from the previous duty cycle

$$x_{new} = x_{old} + \triangle x_i^a \tag{14}$$

Controlling factor t is calculated using (15):

$$t = (\frac{y}{z})*100 \qquad (15)$$

where z is the best target in the flock memory and y is the worst flock memory target. As the difference between the worst and the best prey decreases, the value P_a increases whereas P_c decreases.

$$p_a = p_a^0 + \frac{t}{T}\left|p_a^T - p_a^0\right| \qquad (16)$$

$$p_c = p_c^0 - \frac{t}{T}\left|p_c^T - p_c^0\right| \qquad (17)$$

where T=100, P_a^T and P_c^T are final cruise and attack propensity values while P_a^0 and P_c^0 are initial final cruise and attack propensity values. Now, the final part of the algorithm is to replace the worst solutions. When controlling factor t exceeds 50, there is 25% chance that the eagle with the worst prey location in its memory will be brought closer to the best prey location in the flock memory. This allows the eagles to focus search in areas with better prey which speeds up the convergence to the best prey location.

3.2 MATLAB

MATLAB provides Multiple features one of which is an easily programmable environment in order to simulate different conditions for MPPT systems. In order to simulate the system Simulink was used for a multi domain simulation and a model-based design. The system level design simulation and automatic code generation combined with the continuous test and verification of the embedded systems gives a basic estimate of the performance of an MPPT algorithm[29].

3.3 Irradiation Case Selection

Four cases of irradiant shown in **Table 3.1** were selected in order to test the performance of GEO algorithm among which one was uniformly radiance case where all the PV modules received the same light intensity and the other three where partial shading conditions where is the PV modules received different levels of irradiance. The value for all four cases were taken from different papers in order to be able to compare the results of GEO algorithm with other algorithms used for MPPT.

Table 3.1 Irradiance values for each case

Test number	Irradiance in PV modules(W/m^2)			
	Module1	*Module2*	*Module3*	*Module4*
Case1	1000	1000	1000	1000
Case2	1000	500	400	200
Case3	1000	950	170	250
Case4	800	550	320	150

3.4 Simulation Setup Design

3.4.1 PV Module Simulation

For the PV module the single diode model of solar cells where used which are available by default in the simulator. The PV module available in Simulink can be configured according to different models available in the software database. After selecting a model 4 identical PV modules were connected in series to form a PV array, This PV array are implemented as masked subnets in Simulink. There were two parameters that could be varied in this PV aerial which are temperature and irradiance. Since the objective of this paper is to verify their efficiency of GEO and different lighting conditions so the temperature of the PV array was kept constant for all the simulations.

3.4.2 Implementation of GEO Algorithm

Simulink function block in **Error! Reference source not found.** was used for the implementation of GEO algorithm since this function block allows user to define functions which is needed for the simulation and this code is executed while the simulation is running. The input for this function block is the voltage and current output from the PV array and the output of this block is duty cycle calculated using the GEO algorithm.

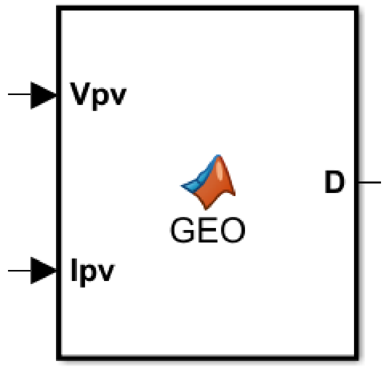
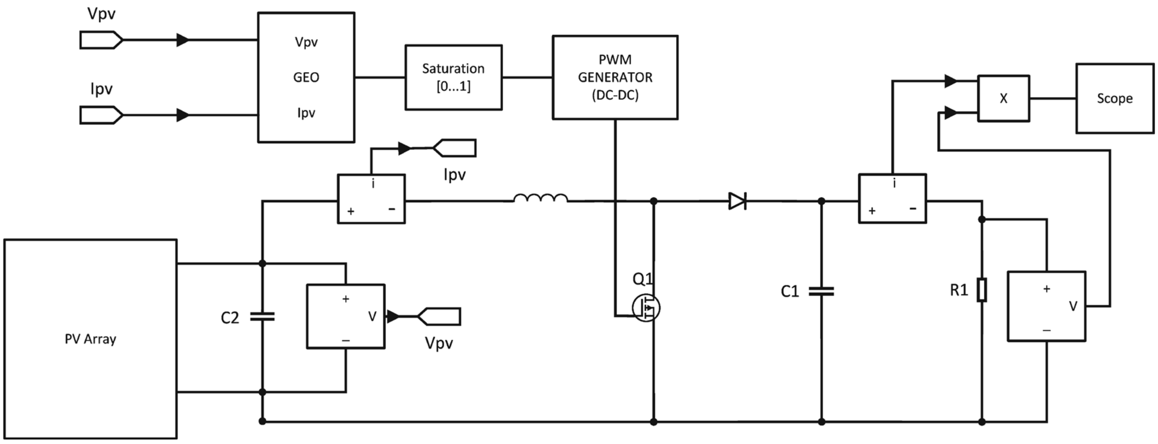


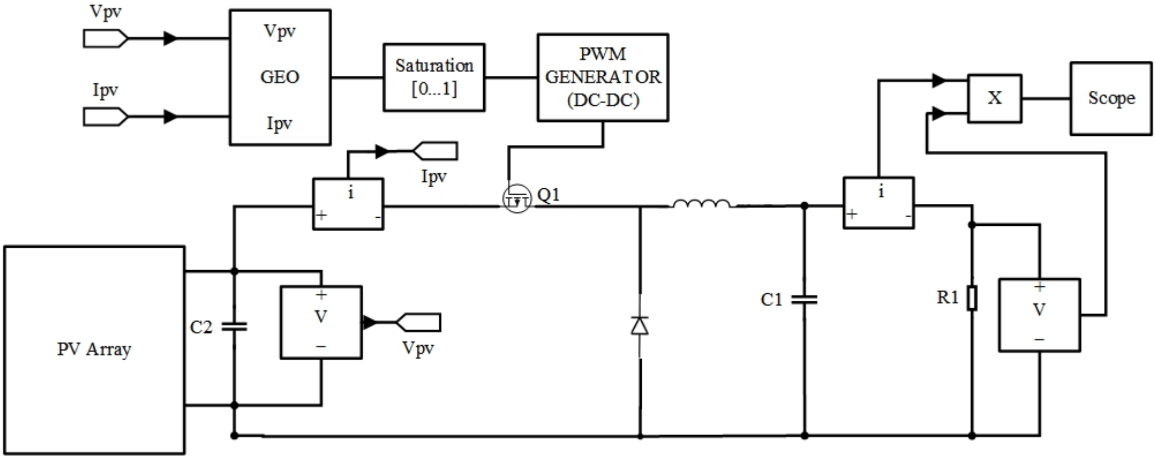
Figure 3.3 : Simulink function block for GEO MPPT code

3.4.3 Converter Circuit Design

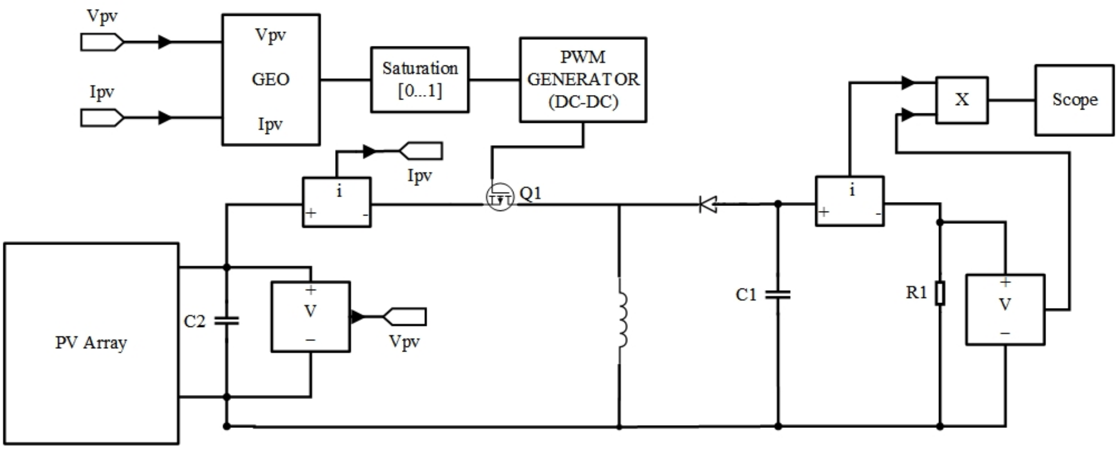
In this paper three types of converters were used to evaluate the performance of GEO and they are boost converter, buck converted and buck-boost converter shown in Figure 3.4. While designing the converter circuits the value of the capacitors, resistors and inductors were found through trial and error as the voltage input of the converter circuit changes from time to time so it is not possible to calculate an exact value for the converter circuits using conventional formulas. After GEO algorithm has been implemented using all three circuits for comparison particle swarm optimization algorithm and Cuckoo search algorithm which are two of the most commonly used algorithms for MPPT are implemented in the same circuits and simulations are run for the same four cases of irradiance used for GEO while keeping other conditions constant.



(a)



(b)



(c)

Figure 3.4: Block diagram of (a) Boost (b) Buck (c) Buck-Boost converter

3.5 PSO Algorithm

Particle Swarm optimization is nature inspired metaheuristic algorithm which uses a model based on the movement of particles where the movement of particles is guided by their own best-known position into search space also including the entire swarms best known position. This search for a better location by the swam of particles is mathematically modeled to form the particle swarm optimization algorithm.[30] In the algorithm each member of the population is called a particle and whole group of particles is called a swarm where each particle represents an individual solution there are two conditions that particles in PSO replicate which are each succeeding solution is influenced by the optimal solution previously found by the particle itself along with the best solution found within the whole swarm shown in Figure 3.5 . As the search progresses eventually all the particles converge to the same solution which in in general terms of algorithms is called the global Optima. Particle swarm optimization is among the very first algorithms used for MPPT and it is also among the most popular algorithm till now so it can be used as a reference point for comparison of the performance of the GEO algorithm.

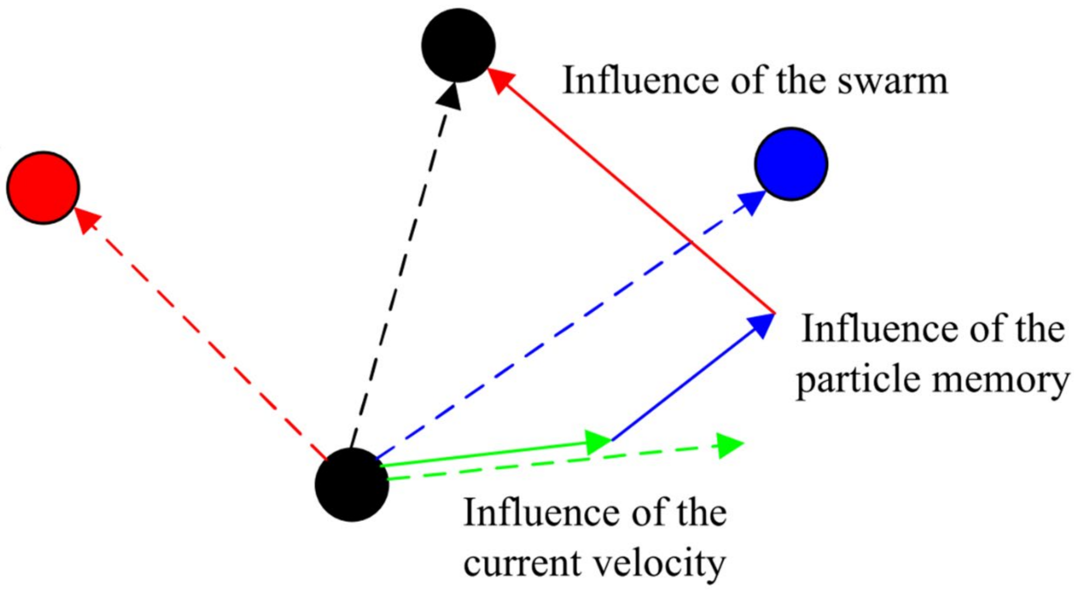


Figure 3.5 : Working principle of PSO

3.6 Cuckoo Search Algorithm

Cuckoo search algorithm is also a metaheuristic optimization algorithm which is used to solve optimization problems and it is based on the breeding and egg laying habits of the bird. Birds lay their own eggs in the nest of other birds and those eggs grow and become mature if the host bird is unable to identify and remove them from its nest. The Cuckoo birds immigrate in search of a better place to lay their eggs hoping to eventually reaching the best place for laying their eggs which in terms of the algorithm is the global Optima. An important feature of the Cuckoo search algorithm is the levy flight mechanism it is responsible for the fast convergence of this algorithm. During a levy flight depart takes random walk in which the step length is calculated based on the heavy tailed probability distribution where the distance from the starting point tends to a stable distribution after a large number of steps. Another part of the Cuckoo search algorithm is immigration of Cuckoo where it sets out to search for better habitat where the host birds' eggs have more similarities to the cuckoo's own eggs so that there is less chance of the host bird detecting the Cuckoo's eggs. Cuckoo formed groups in different areas and the best nest location is set as the goal point for all the other Cuckoo to immigrate to that area.[31] This algorithm has been selected for comparison with GEO due to its fast convergence time and high efficiency.

Chapter 4

Results & Analysis

This section demonstrates the results obtained by the simulation of the three algorithms. The results were evaluated by observing and analyzing the voltage-time, current-time, and power-time graphs. All the algorithms were allowed to run for 1 second in every simulation case and the external temperature experienced by the solar cells in every case was taken as 25 °C. The performance of the three algorithms was judged by using three different converters. The three converters used were boost converter, buck converter, and buck-boost converter. From the obtained results it can be concluded that GEO gives consistent convergence and convergence time under all scenarios, without getting trapped in the local optima.

Initially, the performance of particle swarm optimization (PSO), cuckoo search algorithm (CS), and golden eagle optimization (GEO) are compared using a boost converter across all the test cases mentioned in the previous section. Next, the converter was changed to a buck converter, and the same simulation procedures were repeated. Finally, the simulations of the three algorithms were run by using a buck-boost converter. The following sections contain a more detailed comparison and depiction of the obtained waveforms.

4.1 Simulation Results Using Buck Converter

The values of irradiances used to test the algorithms were chosen in such a manner that they reflect the irradiances solar panels experience in real life. For the circuit with a boost converter, case II seemed to be the most testing condition for all three algorithms. In case II, both CS and GEO had their slowest convergence and settling times, and PSO took substantially longer than 1s to stabilize. It can be seen that the values obtained for maximum power, convergence time, and settling time are similar when comparing the findings obtained to other literature [32]. For PSO & CS, settling times are 0.3452 & 0.3192 seconds with their maximum powers being 998.7 W & 991.7 W. As mentioned earlier, these values resemble the findings from other literature. The differences found in some of the cases were due to the usage of different numbers or models of PV modules. In the following sections the voltage, current, and power variation graphs of individual cases are shown and explained in greater detail.

Case I:

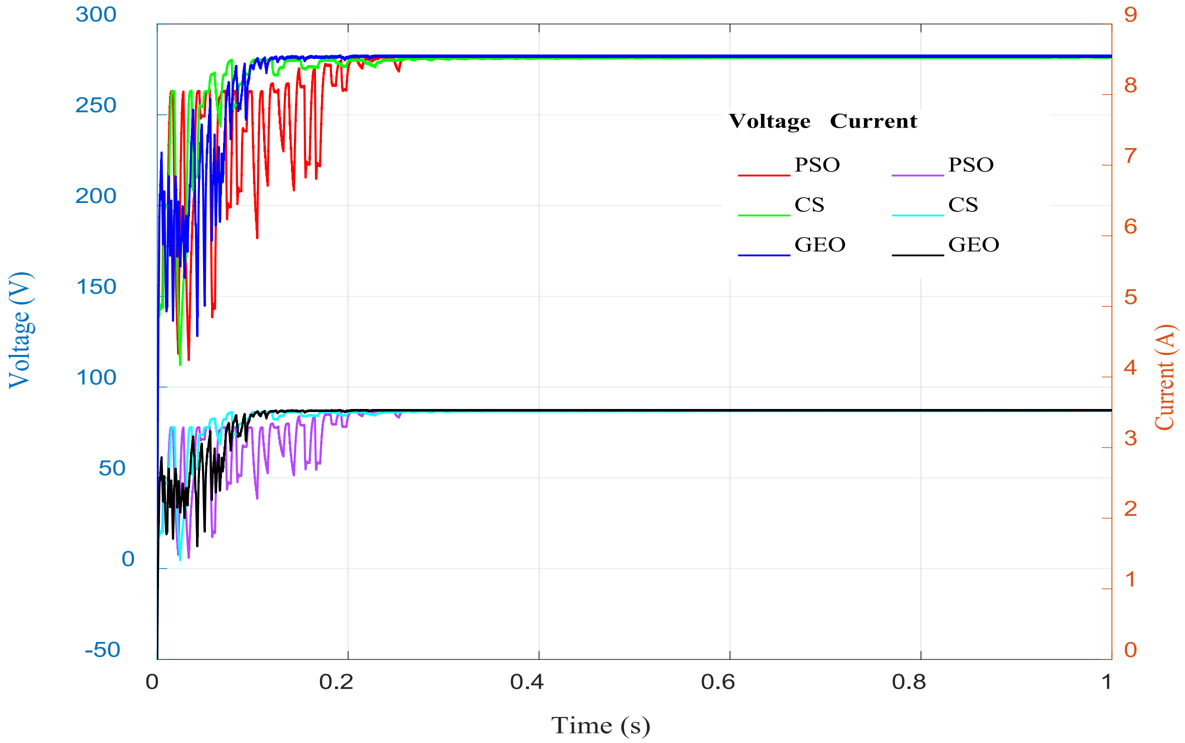


Figure 4.1: Case I output voltage & current of Boost converter in PV array.

Case I was the uniform irradiance case and all three algorithms produced satisfactory results. The efficiencies obtained by PSO, CSA & GEO were 99.9%, 99.3%, and 99.9% as observed in table 1. In **Figure 4.1**, the output voltage and current for all three algorithms can be observed. The peak voltage found was 282.7 V and the current peaked at 3.534 A. There were high oscillations present in both the voltage and current waveforms in the initial stages as is expected from the algorithms since the initial stage is the exploration stage. However, it can be observed that GEO converges to the maximum point fastest in the case of voltage and lags only slightly behind CSA in terms of current. But PSO is very slow in terms of convergence in both the cases of voltage and current. For case, I, the global maxima for power found was at 999.2 W. GEO got the closest to finding the global maxima and settled at 998.6 W with PSO reaching a similar maximum power. However, CSA fell behind with a maximum power of 991.9 W. From Figure 4.2 it can be seen that for overall output power, GEO was the fastest in both convergence time and settling time with values of 0.1831s and 0.2292s. The convergence and settling time values for PSO and CSA were 0.3361 & 0.3452 and 0.2698 & 0.3192. Despite oscillations being present at the beginning of all three cases, CSA had oscillations for the least amount of time and PSO had significant oscillations well after the power had settled for the other two algorithms.

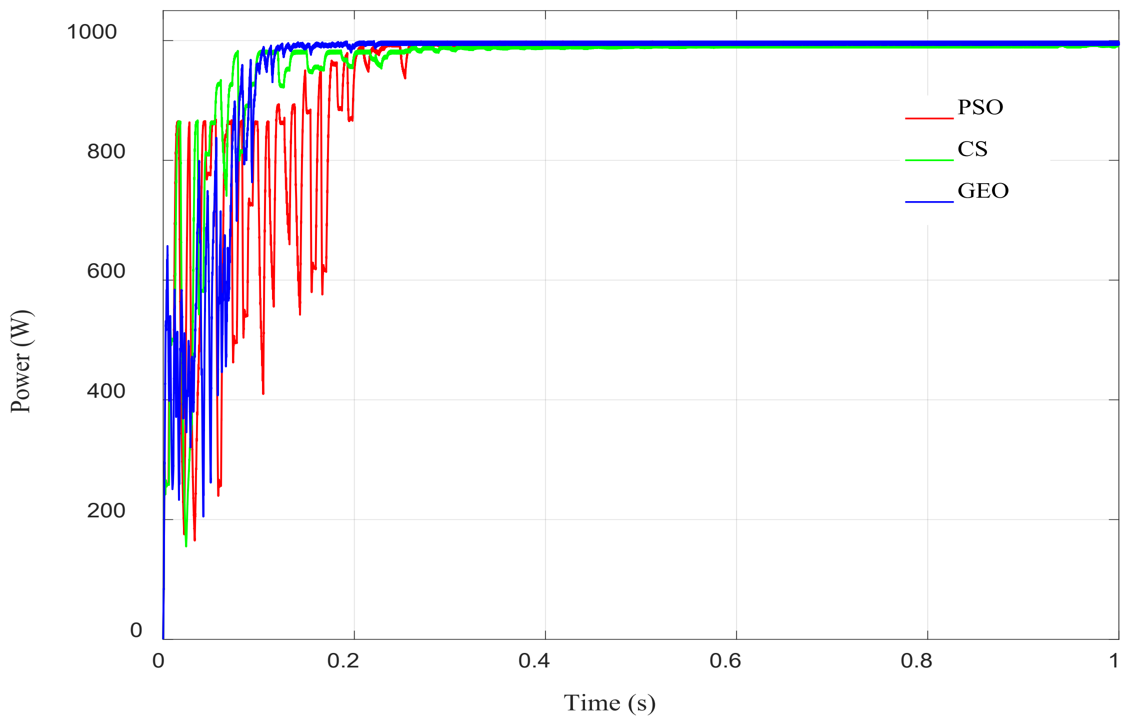


Figure 4.2 : Case I MPP convergence of three different algorithms of boost converter.

Case II:

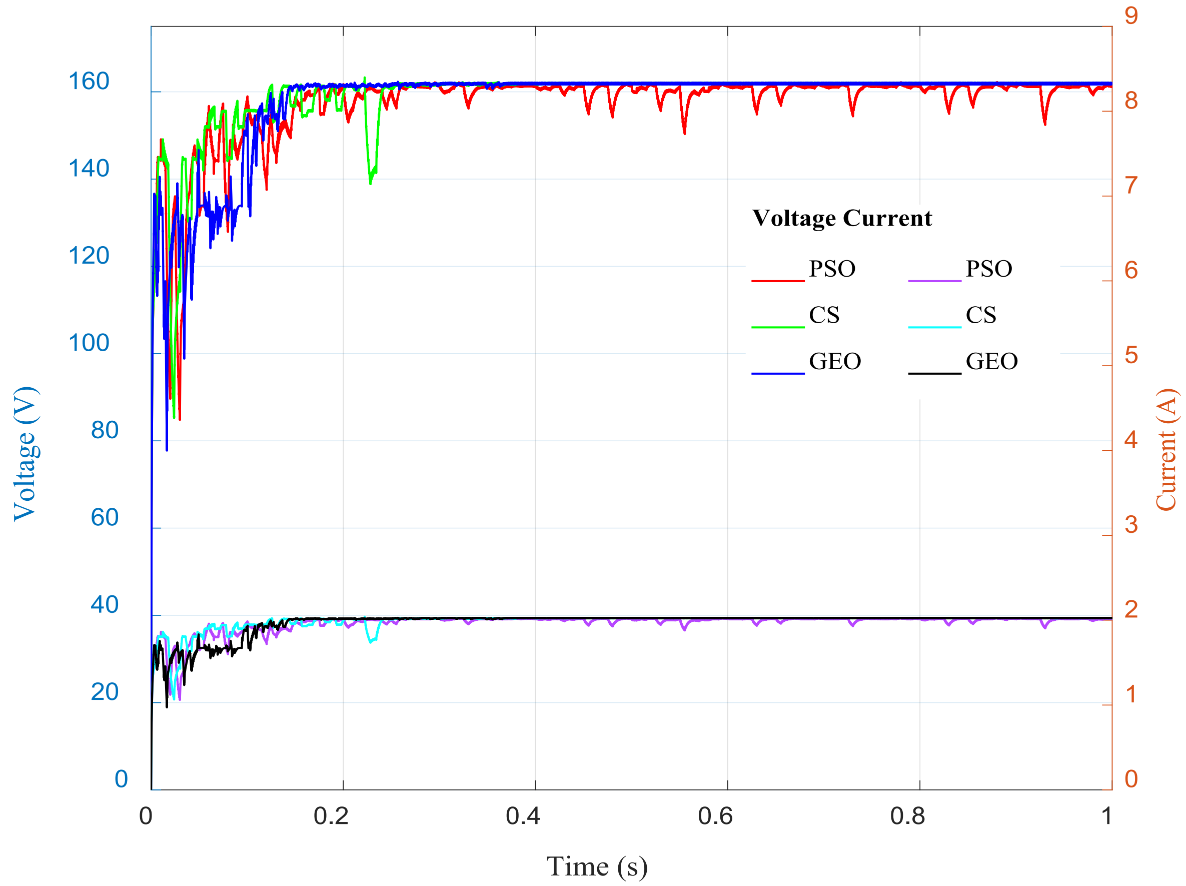


Figure 4.3: Case II output voltage & current of Boost converter in PV array.

All the algorithms managed to successfully reach the MPP in this case as well. However, this proved to be the most challenging case in terms of oscillations and the time required to reach MPP. From Table 4.1 it can be seen that there are significant differences in the convergence times observed for the three algorithms. The voltage and current graphs in

Figure **4.3** follow the same trend as observed in the first case. However, in this case, large oscillations in voltage and small oscillations in current were observed for PSO up to 1s. GEO also demonstrated slight oscillations in voltage in this case. The peak voltage and current were found as 162.2 V and 2.029 A. In case II the maximum power was found to be 329.1 W. On comparing the three algorithms in Figure 4.4, it can be seen that GEO gives 328.3 W, PSO & CSA both achieve 329.1 W. However, the fact that PSO achieves the maximum power is undermined by the fact that its power had not settled even into 1 second. In this case, as well CS showed a lower amount of oscillations compared to the other two algorithms in the power waveforms. Another significant thing to note is that all of the algorithms performed their worst in terms of convergence and settling time in case II. Despite the oscillation factor, GEO had the fastest settling time of 0.2962 s and CS had a settling time of 0.3843 s.

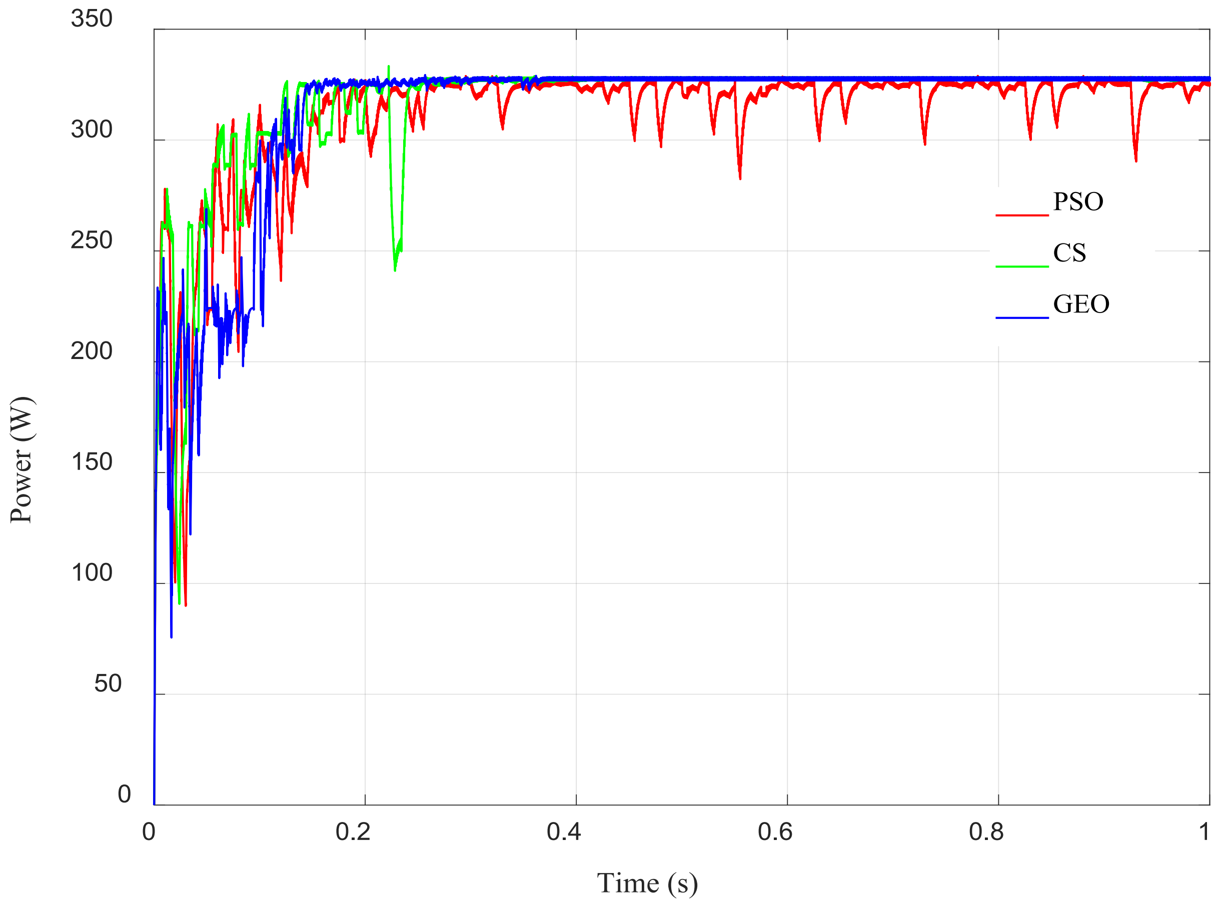


Figure 4.4: Case II MPP convergence of three different algorithms of boost converter.

Case III:

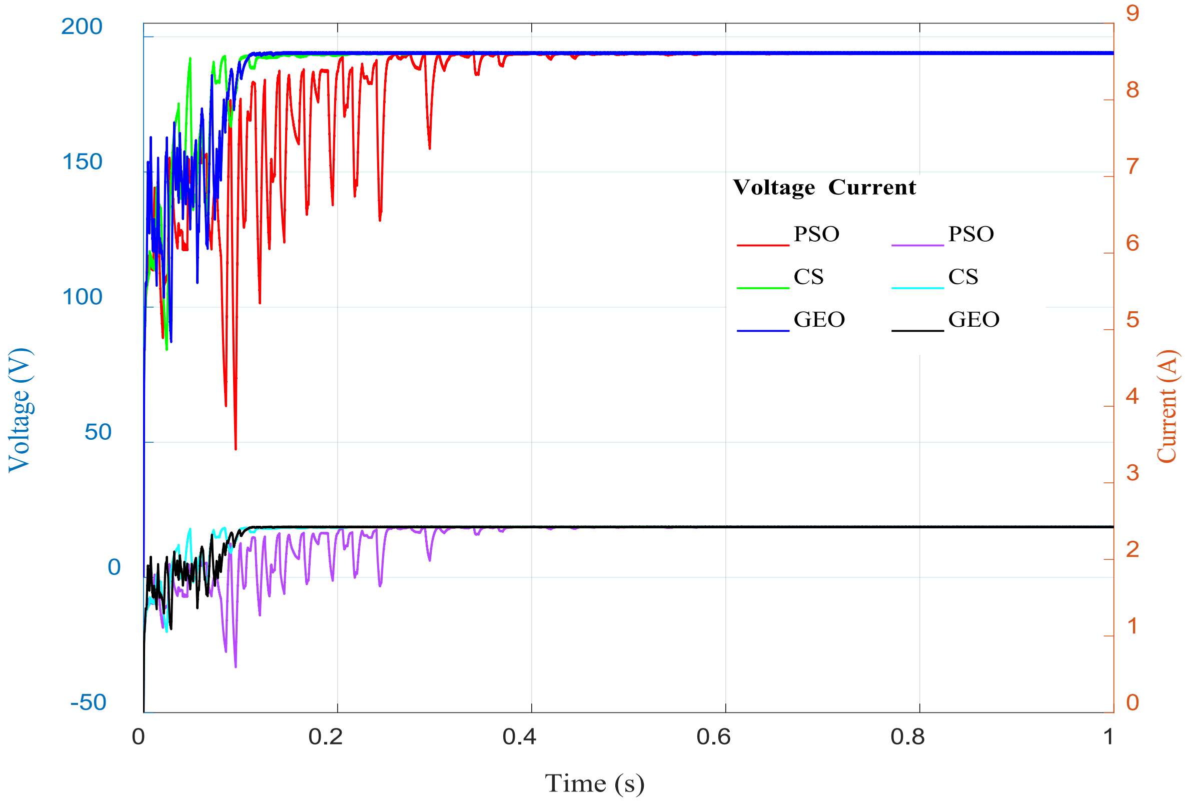


Figure 4.5: Case III output voltage & current of Boost converter in PV array.

From Figure 4.5 it can be seen that in this case the peak voltage and currents were 194.6 V and 2.432 A. PSO again depicted the longest and highest oscillations. The observed efficiencies for the algorithms are 99.9%, 99.9%, and 99.8% for PSO, CSA, and GEO respectively. From Table 4.1 it is observed that the stable power outputs were 472 W, 472W, and 471.5 W for the algorithms, showing that all of them succeeded in not getting trapped in one of the local optima. The distinction between the algorithms was therefore done via observing the convergence and settling times from Figure 4.6. From Table 4.1 it can also be observed that PSO was the slowest to converge at 0.2602 seconds and the slowest to stabilize at 0.5741 seconds. For GEO and CS, the stabilizing and settling times were 0.1140s & 0.1288s and 0.1143 & 0.2164. PSO also shows drops in power right up to the point where it stabilizes. GEO shows no such power drops and is the fastest in terms of converging and settling.

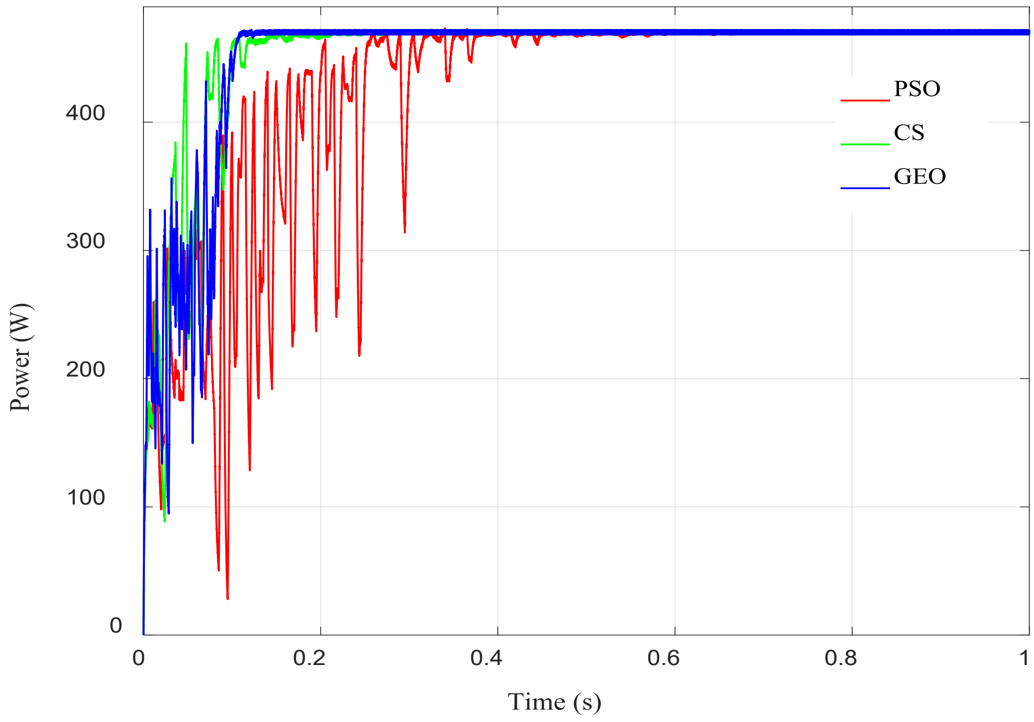


Figure 4.6: Case III MPP convergence of three different algorithms of boost converter.

Case IV:

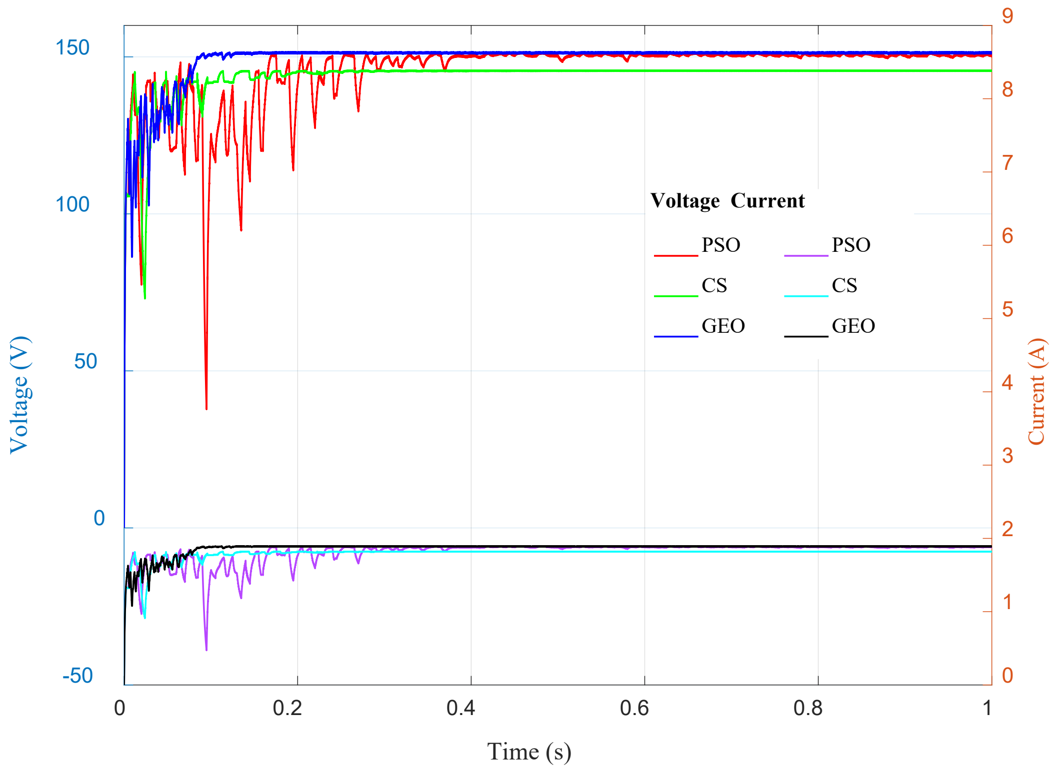


Figure 4.7: Case IV output voltage & current of Boost converter in PV array.

In this case, the peak voltage and current were found to be 151.5 V and 1.894 A as can be observed in Figure 4.7. Again, the same trends were observed in terms of voltage and current in the graph. There were high oscillations at the beginning and PSO exhibited the highest oscillations. However, one exception in case IV from the other cases was the fact, that although GEO and PSO were able to reach the maximum power, CS got trapped in the local optima. It is observed that the efficiencies of GEO, PSO, and CS are 99.9%, 99.7%, and 92.3% respectively. From Figure 4.8 it is seen that the maximum power obtained by GEO was 286.9 W and the maximum power obtained by CS was 265.1 W. The converging and settling times of the algorithms were: 0.2559 s & 0.6953 s for PSO, 0.1440s & 0.3077 s for CS and 0.1126 & 0.1710 for GEO. Therefore, not only did GEO find the maximum available power but also was the fastest to do so.

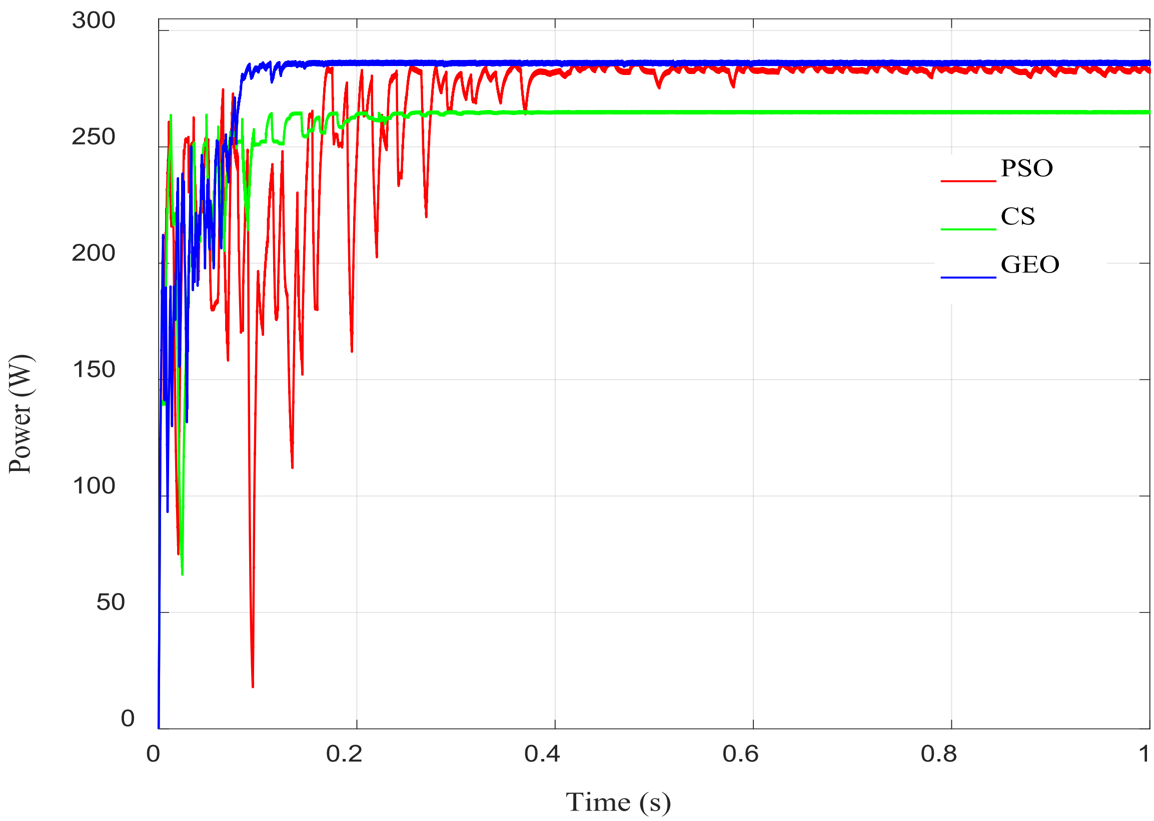


Figure 4.8: Case IV MPP convergence of three different algorithms of boost converter.

Table 4.1 RESULT COMPARISON OF GEO, PSO & CS FOR BOOST CONVERTER.

	Algorithm	Case No	Converging time (s)	Settling Time GMMP (s)	Max Power (W)	Power at GM (W)	Efficiency (%)
BOOST	PSO	Case 1	0.2698	0.3192	998.7	999.2	99.9
		Case 2	0.3203	>1	328.9	329.1	99.9
		Case 3	0.2602	0.5741	472.0	472.3	99.9
		Case 4	0.2553	0.6953	286.2	287.2	99.7
	CS	Case 1	0.3361	0.3452	991.9	999.2	99.3
		Case 2	0.2223	0.3843	328.3	329.1	99.8
		Case 3	0.1143	0.2164	472.0	472.3	99.9
		Case 4	0.1440	0.3077	265.1	287.2	92.3
	GEO	Case 1	0.1831	0.2292	998.6	999.2	99.9
		Case 2	0.2655	0.2962	328.3	329.1	99.8
		Case 3	0.1140	0.1288	471.5	472.3	99.8
		Case 4	0.1126	0.1710	286.9	287.2	99.9

4.2 Simulation Results Using Buck Converter

This section depicts the simulation results obtained by using a buck converter instead of a boost converter. All parameters except for the converter were kept the same. The simulation circuit with the buck converter was tested using the same four test conditions mentioned above. The results obtained were:

Case I:

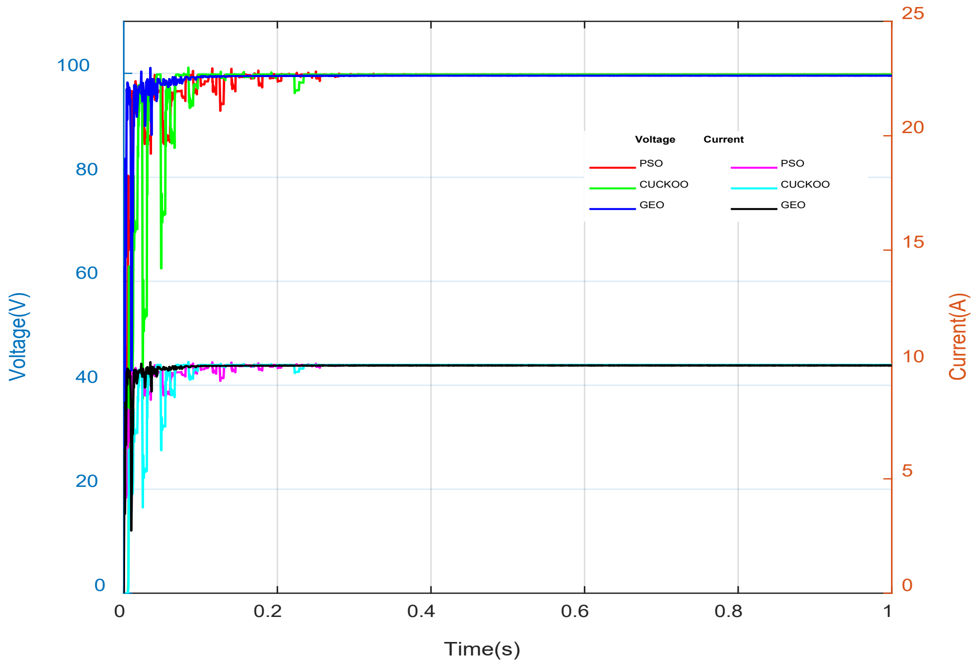


Figure 4.9: Case I output voltage & current of Buck converter in PV array.

The same trend is observed in Figure 4.9 for voltage and current that we observe in case I of boost converter. There are high initial oscillations in voltage for all three algorithms. The voltage peaks at 102.3 V and the current peaks at 44.7 A. All three algorithms eventually stabilize in terms of voltage and current but GEO stabilizes much earlier than the other two algorithms. In Figure 4.10 it can be observed that all three algorithms were very close to reaching the global maxima of power which was 995 W. The efficiencies obtained by PSO, CSA, and GEO were 99.5%, 99.6%, and 99.1% respectively. Even though GEO had slightly lower efficiency than the other two algorithms in this case, in terms of settling time and convergence time, GEO outperformed the other two algorithms significantly as can be seen from Table 4.2. In terms of oscillation, the general trends observed in the case of the boost converters were repeated in the case of the buck converter as well. All three algorithms had high initial oscillations, with PSO having oscillations for the longest amount of time. But it is important to note that CS had longer oscillations with a buck converter compared to boost converter.

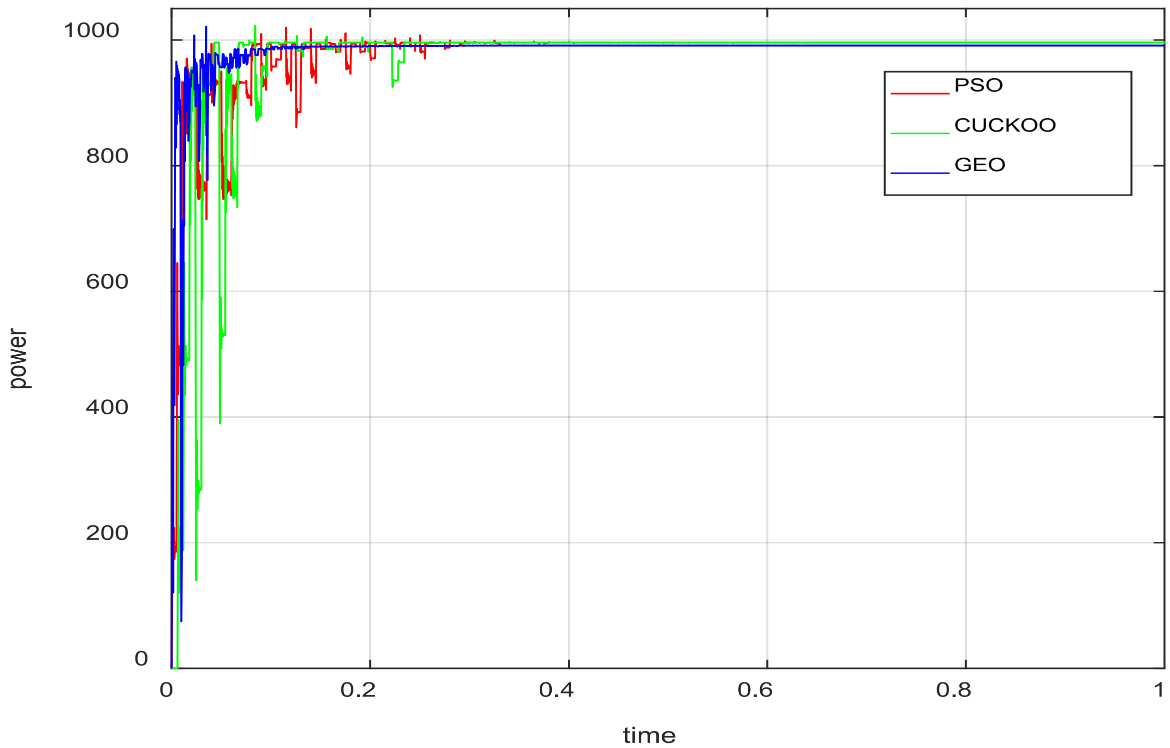


Figure 4.10: Case I MPP convergence of three different algorithms of buck converter.

Case II:

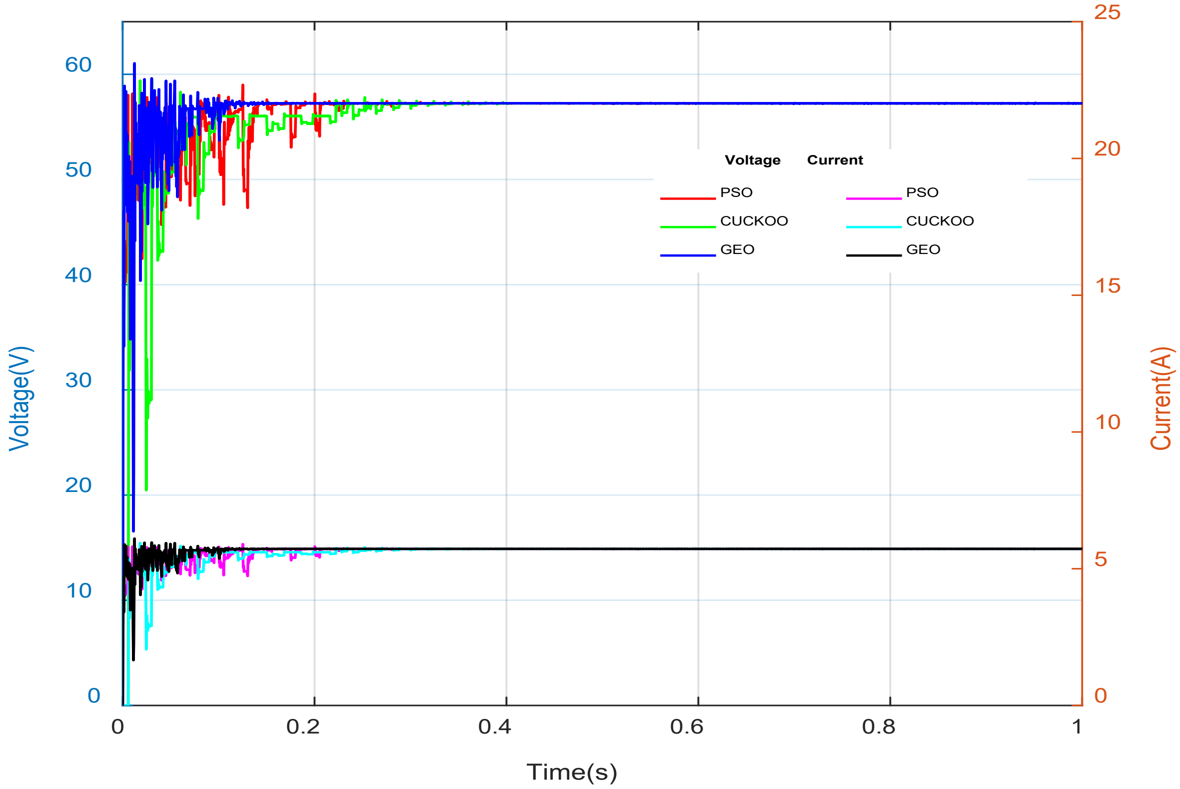


Figure 4.11: Case II output voltage & current of Buck converter in PV array.

In case II the results obtained for all the algorithms with a buck converter were better than the results obtained in the case of a boost converter. From Figure 4.11 it can be observed that the peak voltage and currents were obtained by all three algorithms. Furthermore, the oscillations subsided fairly quickly in all three cases. In the case of voltage, CS had the most erratic oscillations while in the case of current it was PSO that oscillated for the longest amount of time. From Figure 4.12 it is observed that CS took the longest time to settle into a stable power. The convergence speed of the three algorithms was 0.2234 s for PSO, 0.2376 s for CS, and 0.1342 s for GEO. Table 4.2 also shows that the trend in the settling time is the same as that of convergence time with GEO being the first to stabilize. Unlike case II of the boost converter circuit, PSO had no problem settling down within the 1 s of the simulation.

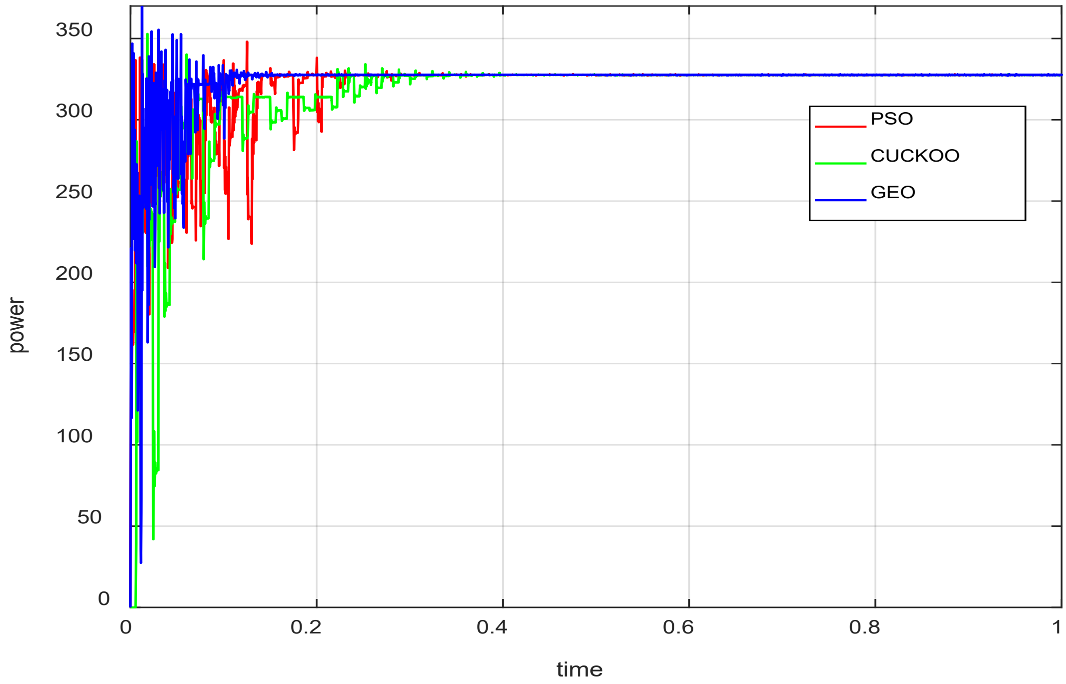


Figure 4.12: Case II MPP convergence of three different algorithms of buck converter.

Case III:

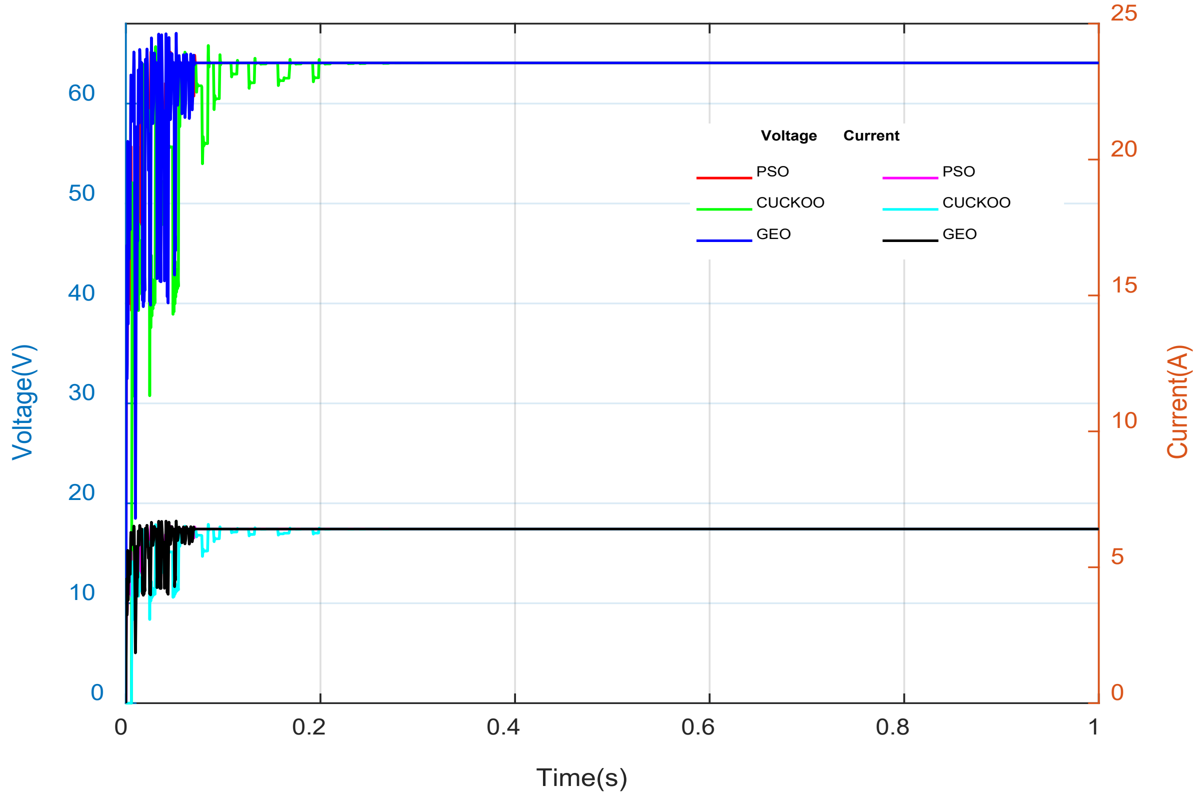


Figure 4.13: Case III output voltage & current of Buck converter in PV array.

For case III, again, the general trends were the same as that in the case of the boost converter circuit. From Figure 4.13 it can be observed that GEO and PSO follow almost the same trajectory in determining the maximum voltage and maximum power. CS was the slowest in stabilizing in terms of both voltage and power. From Figure 4.14 & Table 4.2 it is observed that the waveform for power follows the same trend as the waveform for voltage and current. All three algorithms have high initial oscillation, but GEO and PSO settle to the maximum power much quicker than CS. The efficiencies obtained by the algorithms are the same for all three algorithms: 86.9% for all three algorithms. The overall energy harvested was lower in case III compared to the boost converter circuit for all three algorithms. The settling times achieved by PSO, CS, & GEO are 0.0768 s, 0.2176 s, and 0.0923 s respectively.

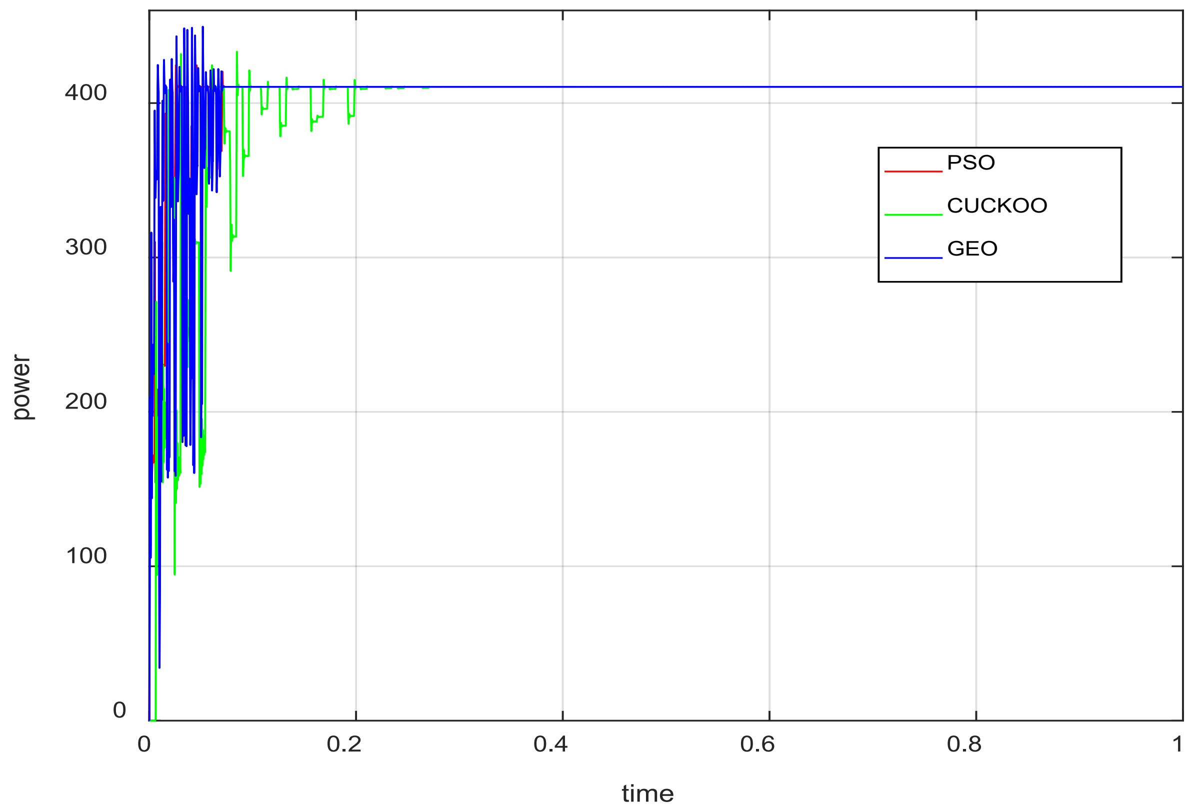


Figure 4.14: Case III MPP convergence of three different algorithms of buck converter.

Case IV:

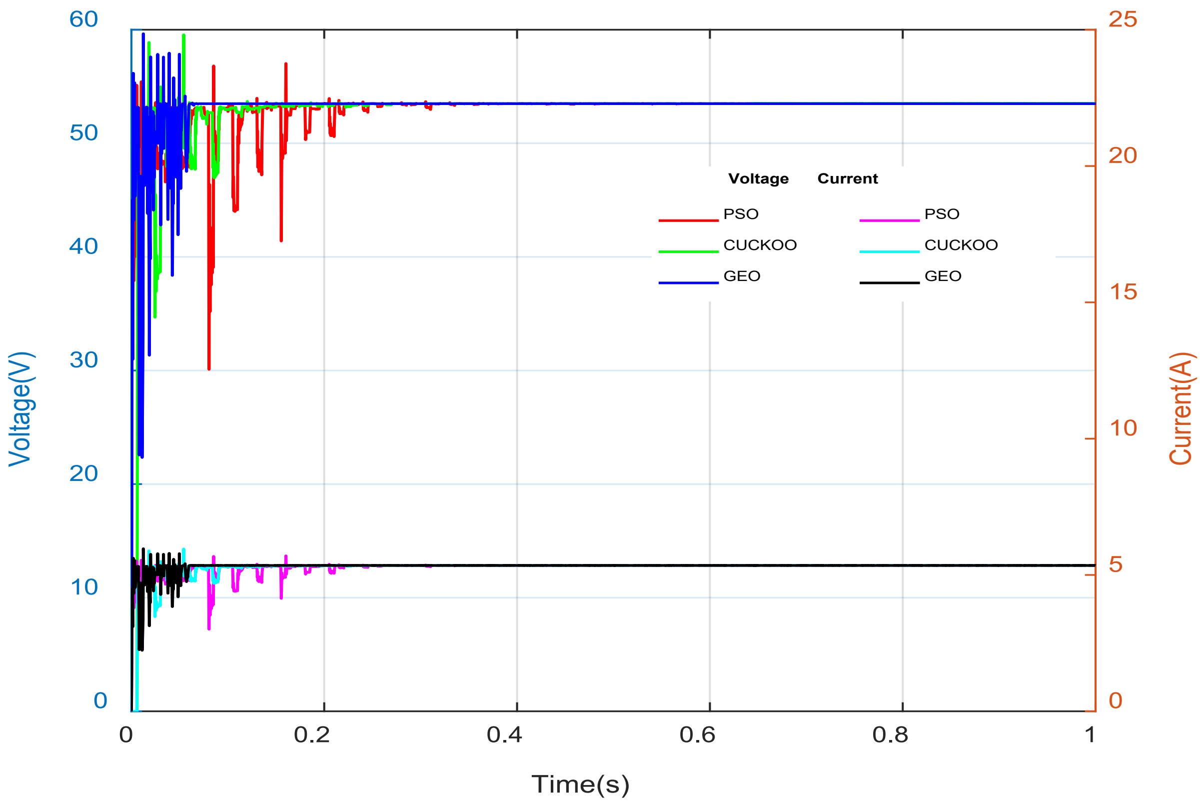


Figure 4.15: Case IV output voltage & current of Buck converter in PV array.

CS performed better in case IV with a buck converter compared to a boost converter. shows that all three algorithms neared peak voltage and current, with GEO being the fastest to stabilize in both voltage and current. However, PSO had high oscillations in both voltage and current and took the longest to stabilize. In case IV of the boost converter, CS had gotten trapped in the local optima resulting in lower efficiency. But from Table 4.2 it can be observed that the efficiencies of case IV for PSO and CS is 99.6%. GEO takes the lead with an efficiency of 99.7%. From Figure 4.16 it can also be observed that GEO was the fastest to converge and settle in terms of power along with having the highest efficiency. In case IV, significant oscillations are seen in the power waveform for all three algorithms.

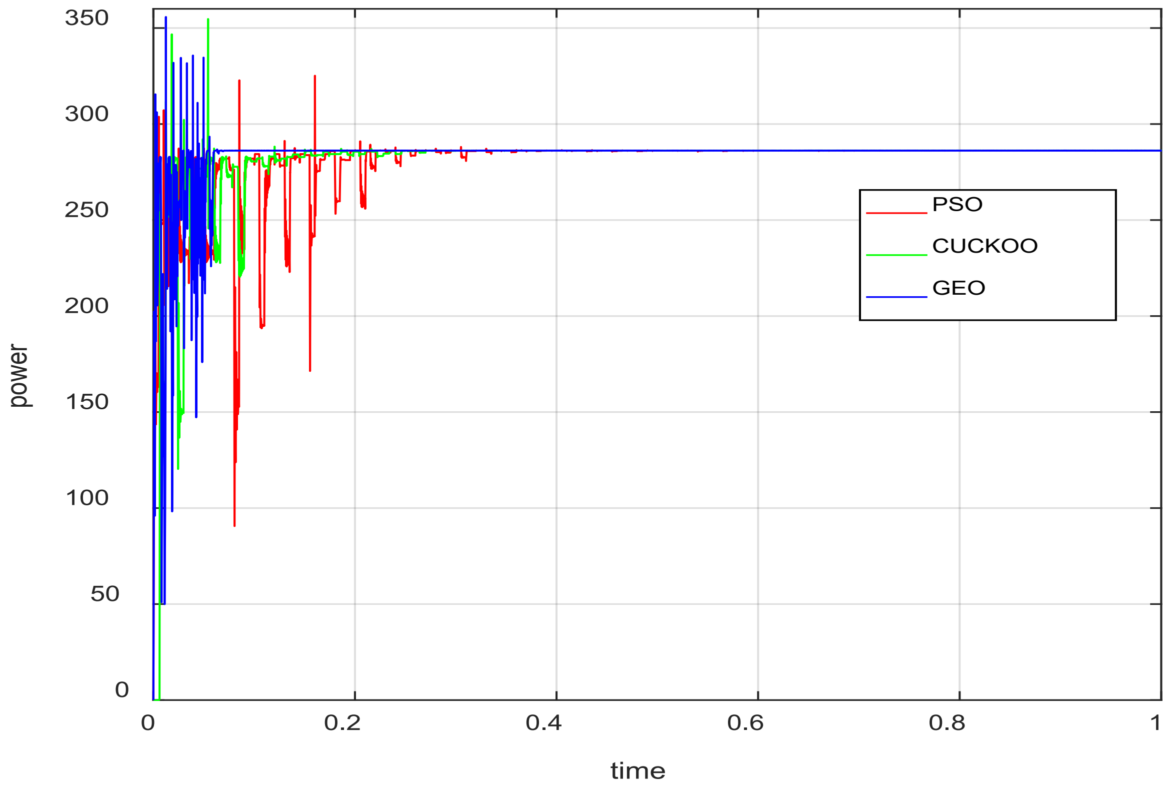


Figure 4.16: Case IV MPP convergence of three different algorithms of buck converter.

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Table 4.2 RESULT COMPARISON OF GEO, PSO & CS FOR BUCK CONVERTER.

	Algorithm	**Case no**	**Converging time (s)**	**Settling time GMPP (s)**	**Max power (W)**	**Power at GM (W)**	**Efficiency (%)**
BUCK	PSO	Case 1	0.1947	0.2804	995.0	999.2	99.5
		Case 2	0.2234	0.2789	328.3	330.1	99.4
		Case 3	0.0685	0.0768	410.5	472.3	86.9
		Case 4	0.1809	0.2829	286.2	287.2	99.6
	CS	Case 1	0.1205	0.2365	995.0	999.2	99.6
		Case 2	0.2376	0.3443	328.2	330.1	99.4
		Case 3	0.1148	0.2176	410.7	472.3	86.9
		Case 4	0.2156	0.2439	286.0	287.2	99.6
	GEO	Case 1	0.1067	0.1789	991.0	999.2	99.1
		Case 2	0.1342	0.1739	328.9	330.1	99.6
		Case 3	0.0823	0.0923	410.5	472.3	86.9
		Case 4	0.9801	0.9810	286.2	287.2	99.7

4.3 Simulation Results Using Buck-Boost Converter

This section depicts the simulation results obtained by using a buck-boost converter instead of a boost converter. All parameters except for the converter were kept the same. The simulation circuit with the buck converter was tested using the same four test conditions mentioned above. The results obtained were:

Case I:

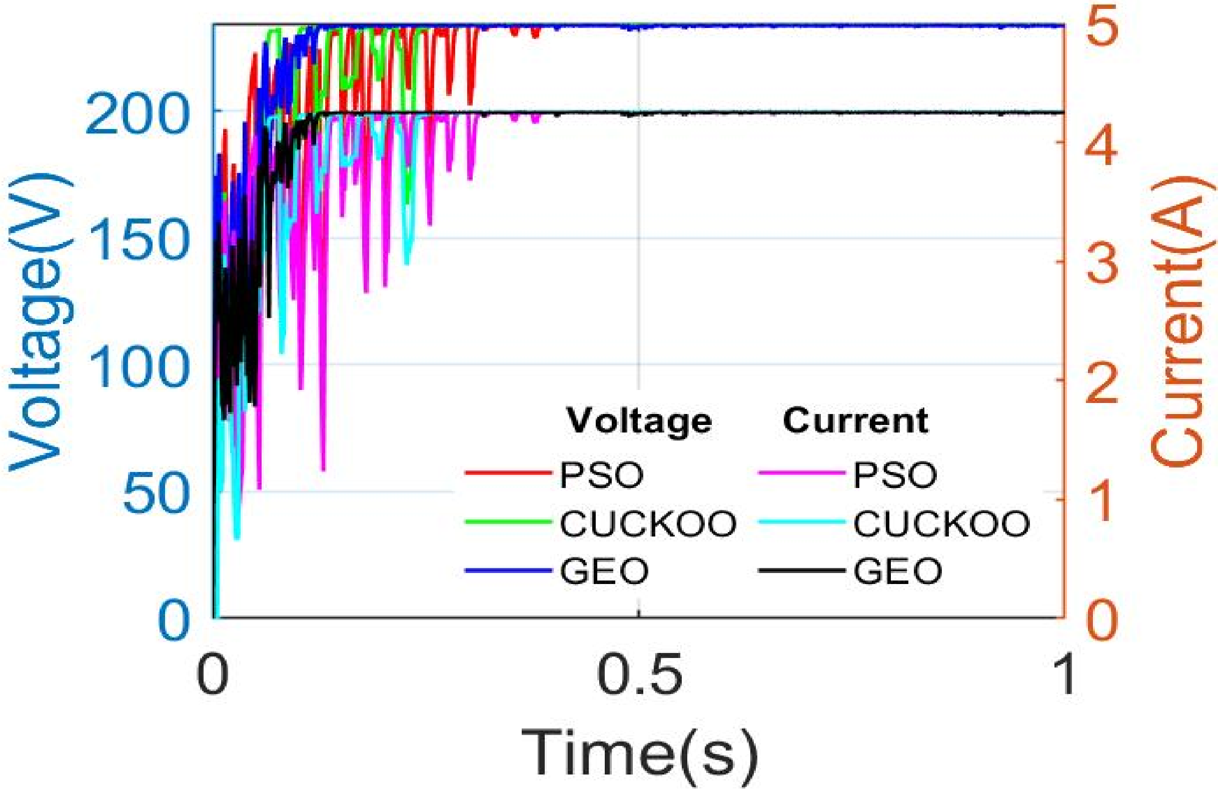

Figure 4.17: Case I output voltage & current of buck-boost converter in PV array.

In the simulations with a buck-boost converter, the amount of oscillations is the highest. It can be seen in Figure 4.17 & Figure 4.18 that the waveforms for all three algorithms had minor oscillations well after reaching the stabilizing voltage, power, and current. The efficiencies of PSO, CS, and GEO are 99.9%, 99.8%, and 99.7% respectively for case I. Furthermore, the converging time and settling time are worse for all three algorithms compared to those found in the cases of buck and boost converters. GEO stabilizes at 0.1892 s, PSO stabilizes at 0.3729 s, and CS stabilizes at 0.2754 s.

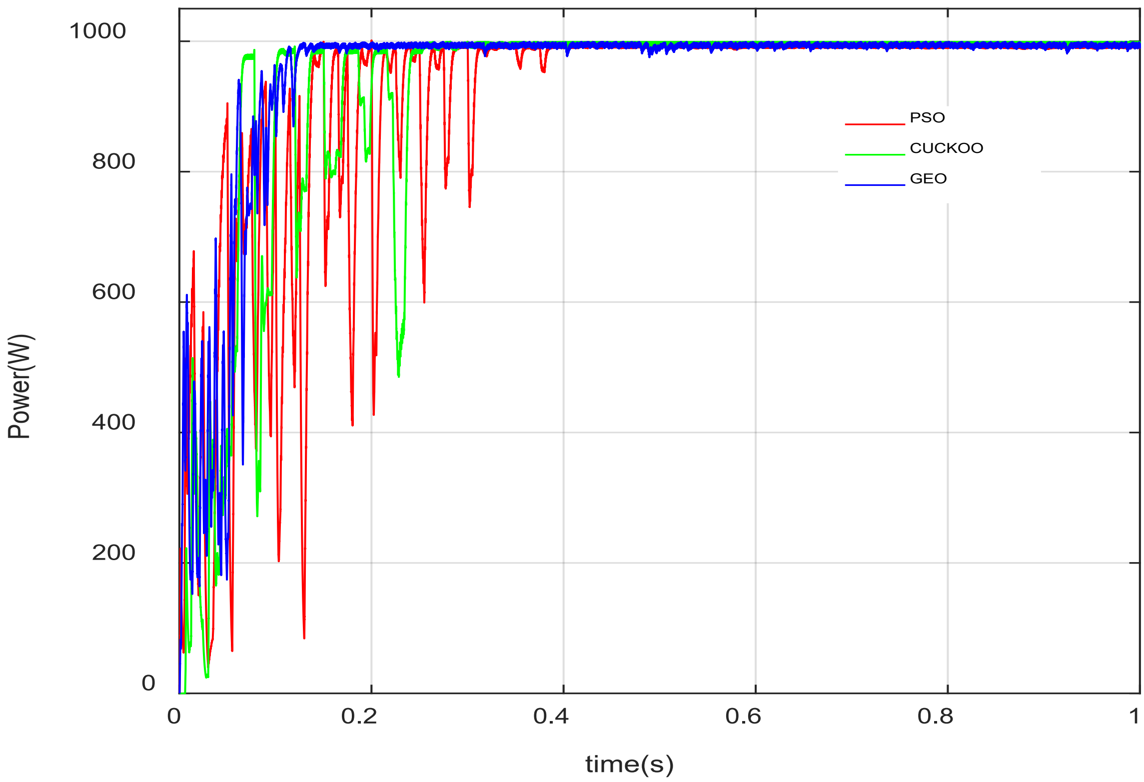

Figure 4.18: Case I MPP convergence of three different algorithms of buck-boost converter.

Case II:

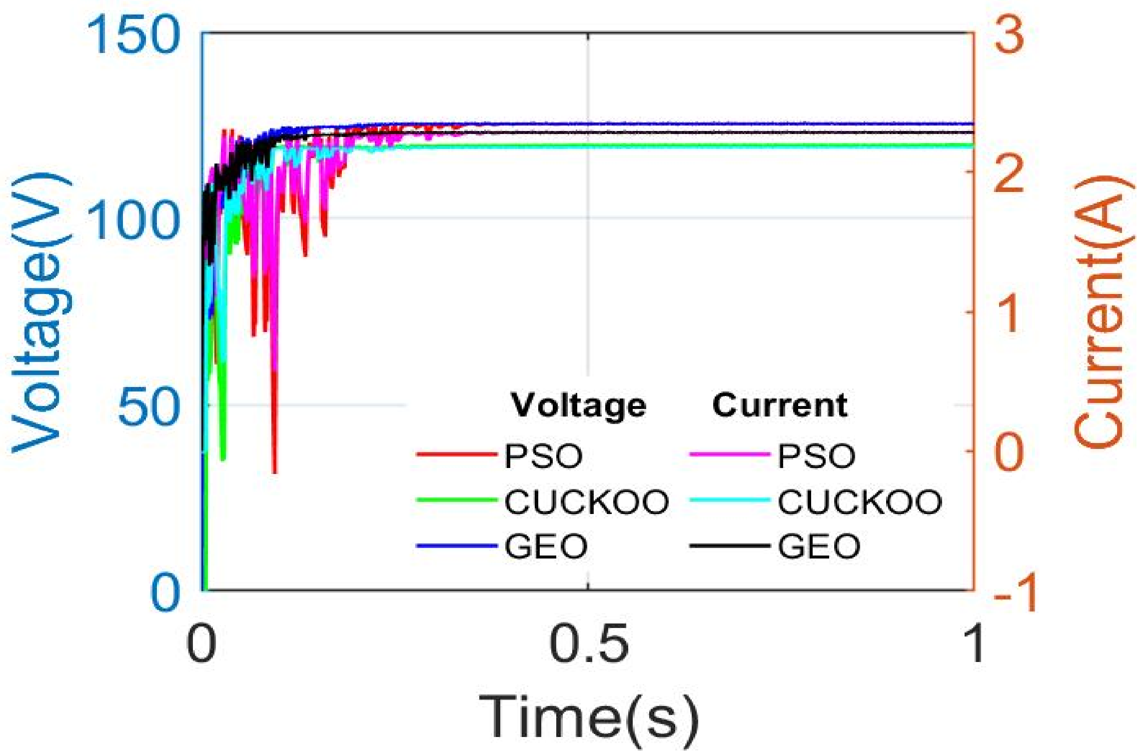

Figure 4.19: Case II output voltage & current of buck-boost converter in PV array.

The same trend is observed in case II as was observed in case I. Figure 4.19 shows that there were discrepancies between the peak voltages and currents found by the different algorithms. GEO performed the worst in case II of the buck-boost converter. Figure 4.20 shows that GEO had not stabilized well into 1 s of the simulation and was showing small oscillations throughout. Even though all three algorithms had efficiencies of over 99%, their performance in terms of oscillation and stabilization was not satisfactory. Along with containing high initial oscillations, they also contained minor oscillations throughout. The settling times of PSO and CS were 0.3002 s and 0.3353 s.

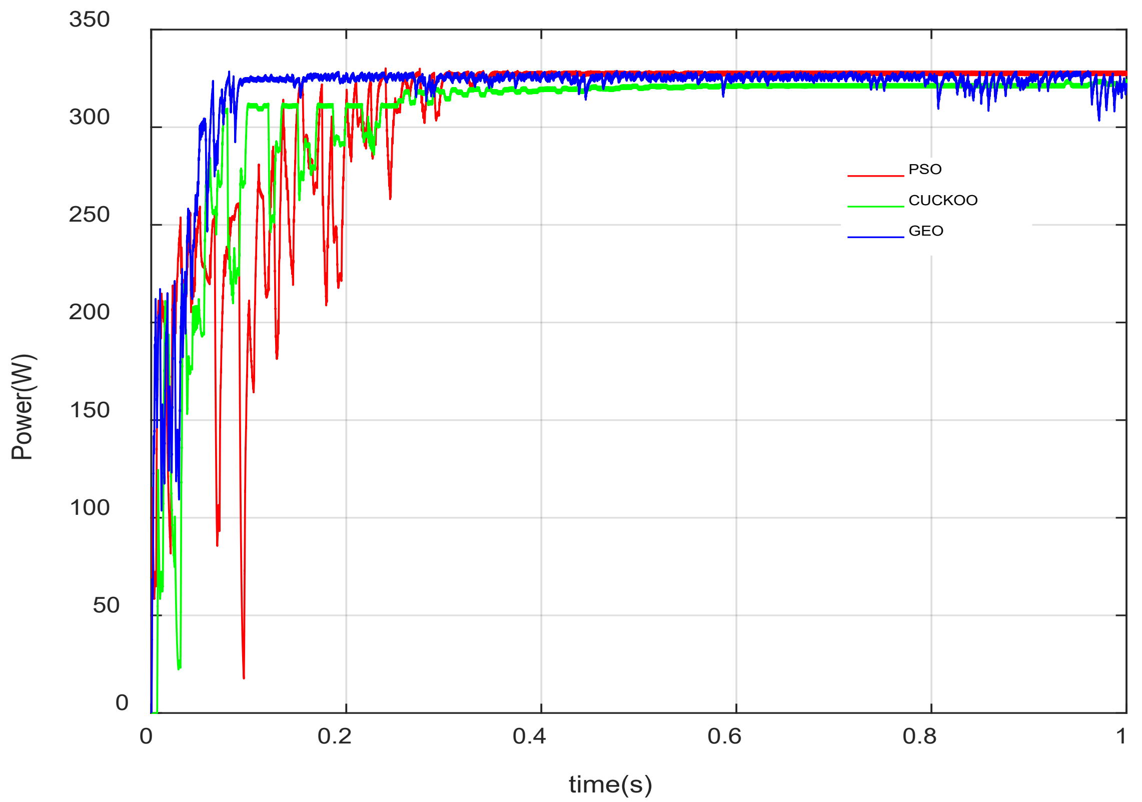

Figure 4.20: Case II MPP convergence of three different algorithms of buck-boost converter.

Case III:

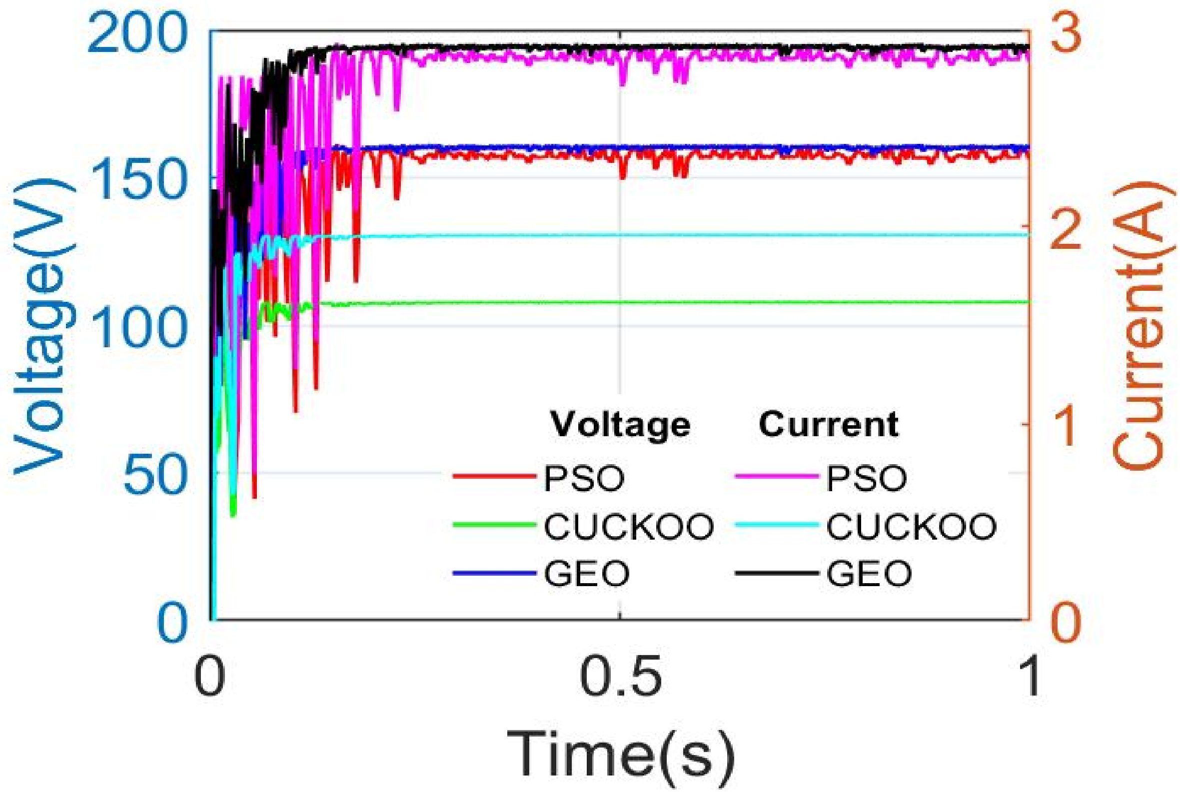

Figure 4.21: Case III output voltage & current of buck-boost converter in PV array.

In case III, CS performed the worst. It got trapped in the local optima again and had a very low efficiency of 47.1 % as seen from **Table 4.3**. However, even though CS couldn't reach the global optima, it had a relatively fast convergence time and settling time of 0.1243 s and 0.1624 s. GEO was the only algorithm that showed good efficiency and relatively fast settling time. PSO got very close to the global maxima but, failed to settle down even into 1 s. From Figure 4.21 it is apparent that CS failed to reach the peak voltage and current. Figure 4.22 shows that even though GEO managed to settle down in terms of power, there were still minor oscillations present.

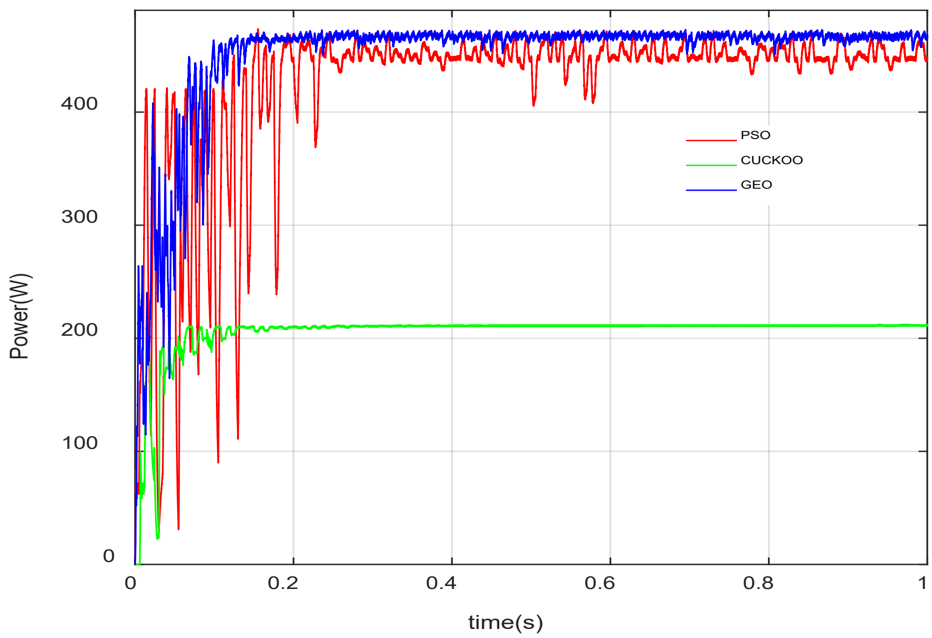

Figure 4.22: Case III MPP convergence of three different algorithms of buck-boost converter.

Case IV:

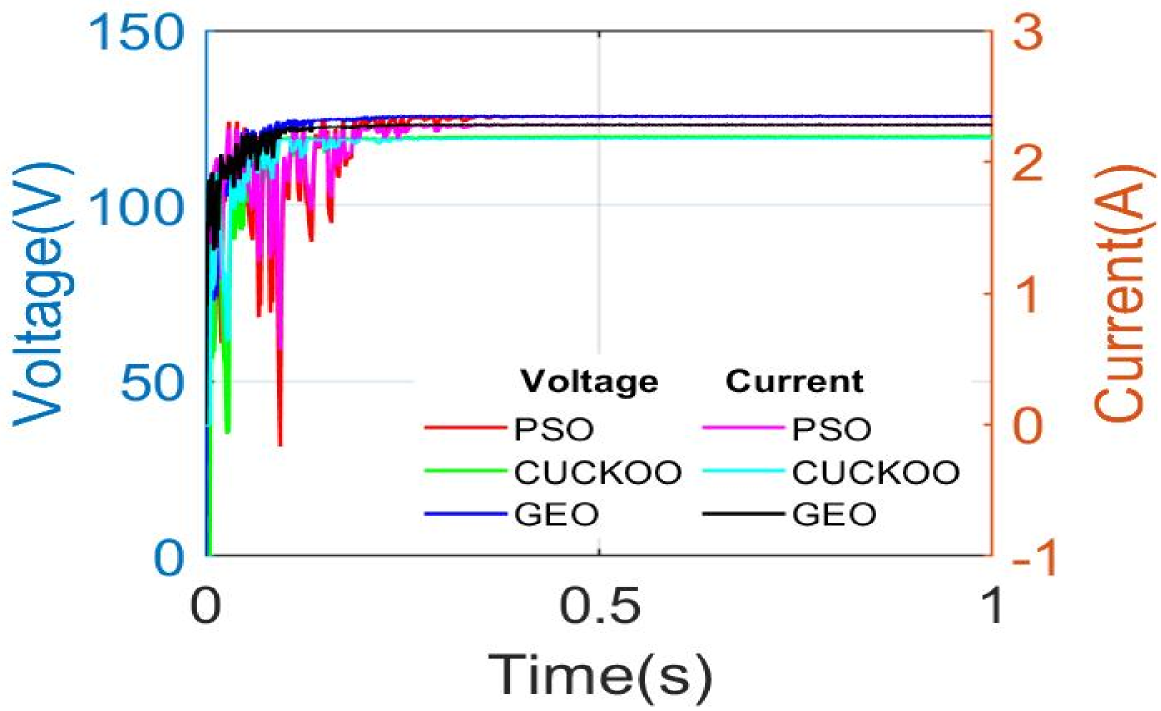

Figure 4.23: Case IV output voltage & current of buck-boost converter in PV array.

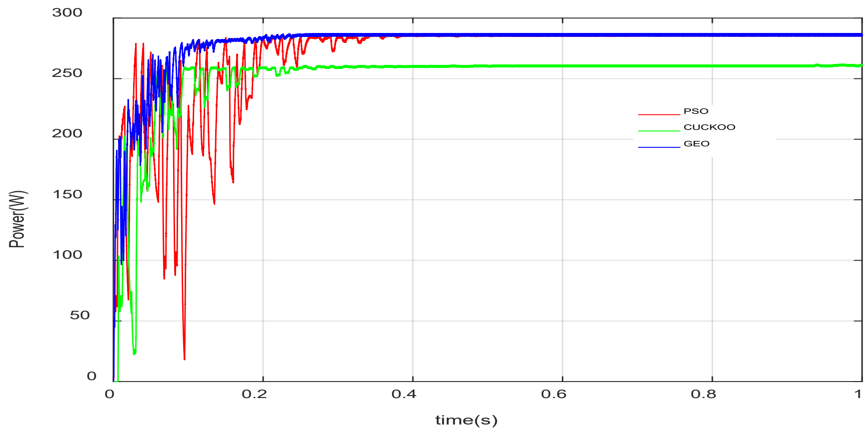

Figure 4.24: Case IV MPP convergence of three different algorithms of buck-boost converter.

Finally, in case IV of the simulation with buck-boost converter, further discrepancies in the results are observed. The efficiencies obtained by the three algorithms are 97.6% for PSO, 98.5% for GEO, and CS again gets trapped in the local optima with an efficiency of 88.8%. From Figure 4.23 and Figure 4.24 it can be seen that the stabilizing voltage, current, and power are lower for CS. However, from Table III, it can be seen that CS has the fastest settling time in case IV with a magnitude of 0.2457 s. GEO lags slightly behind CS with a settling time of 0.2610 s and PSO has the worst settling time in case IV of 0.2783 s. Just like the other three cases with a buck-boost converter, case IV also contained significant oscillations throughout the oscillation even after settling power was reached.

Table 4.3: RESULT COMPARISON OF GEO, PSO & CS FOR BUCK-BOOST CONVERTER.

	Algorithm	**Case no**	**Converging time (s)**	**Settling time GMPP (s)**	**Max power (W)**	**Power at GM (W)**	**Efficiency (%)**
Buck-Boost	PSO	Case 1	0.3189	0.3729	995.7	999.2	99.6
		Case 2	0.2903	0.3002	328.9	329.1	99.9
		Case 3	0.1902	>1	454.0	472.3	96.1
		Case 4	0.2783	0.3353	281.2	287.2	97.9
	CS	Case 1	0.2616	0.2754	997.9	999.2	99.8
		Case 2	0.2835	0.3353	320.3	329.1	97.3
		Case 3	0.1243	0.1624	222.3	472.3	47.1
		Case 4	0.1145	0.2457	255.1	287.2	88.8
	GEO	Case 1	0.1534	0.1892	996.6	999.2	99.7
		Case 2	0.1255	>1	327.3	329.1	99.4
		Case 3	0.1448	0.1758	468.5	472.3	99.2
		Case 4	0.2528	0.2610	282.9	287.2	98.5

4.4 Analysis

On comparing the results obtained from the three algorithms, it is apparent that GEO outperformed PSO & CS. Even though there were cases where PSO or CS either stabilized faster or exhibited greater efficiency, they failed to maintain their superiority throughout most of the cases. GEO proved to be the most consistent algorithm in terms of convergence and efficiency in uniform and partial shading conditions.

All three algorithms seemed to perform the best when a boost converter was used to regulate the circuit. Buck-boost produced the worst results among the three converters tested. All of the three algorithms behaved unpredictably with the use of a buck-boost converter. Furthermore, very high oscillations were observed in all of the cases for all the algorithms. However, the observed oscillations might be due to lack of tuning of the circuit as the power seems to stabilize in most of the cases and only minor oscillations were observed near the end of the simulation.

In some of the cases the convergence times were faster with a buck converter than a boost converter but only slightly. Anomalous spikes of power were observed in the case of buck converter which were not present while using a boost converter. Furthermore, CS had a very high tendency of getting trapped in the local optima when buck or buck-boost converters were used. CS was the only algorithm that got trapped in local optima in different cases for all three converters. GEO on the other-hand showed no tendency to get trapped in the local optima for any of the cases with any of the converters. In the few cases where GEO didn’t lead in terms of convergence time and settling time, the winning algorithm only took the edge slightly. Apart from case II in section 4.3, GEO always managed to achieve an efficiency of above 90% and the failure of GEO in this case could be attributed to the buck-boost circuit not being tuned to its proper limit.

Chapter 5

Conclusion

The objective of this thesis was to test the viability of GEO as a probable algorithm for use in MPPT along with determining the effect that different converters have on the algorithms used. From the obtained simulation results it can be concluded that GEO promises to improve on the current MPPT algorithms in use today. GEO was the most stable algorithm out of the three that were tested. It outperformed the other two algorithms in terms of convergence speed and reliability in reaching the global maxima of power. It also exhibited minimal tendency to get trapped in the local optima. GEO, just like CS and PSO, performed the best when a boost converter was used in the circuit. Even though there were a few cases where buck converter produced faster convergence times, it was usually accompanied by a tendency to have high oscillations. The results obtained from using the buck-boost converter hint that it might be necessary to tune the circuit further and thus leaves scope for future work. Nevertheless, with the results obtained from this study, it can be expected that boost converters give a more stable output for MPPT. Furthermore, GEO's stable performance in partial shading conditions and in uniform irradiance make it a very interesting prospect for the future. In spite of GEO managing to have faster convergence and settling times than the other two algorithms, its large starting oscillations with all of the converters is something that can be worked on to make the algorithm more efficient for MPPT and make solar power more viable in daily life applications like solar-powered rickshaws.

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