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MPPT BASED ON MODIFIED FIREFLY ALGORITHM

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ABSTRACT

The global demand for electrical energy is constantly increasing while the production of fossil fuel based energy is declining and therefore the obvious choice of clean energy source which is abundant and could provide security for the future development is sun's energy. This paper summarizes the modeling of PV module and PV characteristics under shaded conditions. The power voltage characteristic of photovoltaic array is non-linear and it exhibits multiple peaks including many local peaks and one global peak under non-uniform irradiances. In order to track the global peak, MPPT is the important component of PV systems. Though many review papers discussed the conventional techniques such as P&O, incremental conductance, ripple correlation control and only very few attempts have been made with intelligence MPPT techniques. This paper also discusses the various algorithms based on Fuzzy Logic, Artificial Neural Network, Ant Colony Optimization, Genetic Algorithm and Particle Swarm Optimization applied to maximum power point tracking in photovoltaic systems under changing irradiance conditions. This paper is intended to introduce a conceptual MPPT technique based on Firefly Algorithm (FA). The proposed approach employs FFA algorithm to find the maximum (or) minimum peak from the obtained multi-peaks using MATLAB.

Index Terms— *MPPT, FFA, fireflies , light intensity , local peak , global peak , Distance , lbest , gbest.*

I. INTRODUCTION

Solar photovoltaic (PV) energy investment is rapidly increasing worldwide due to its long term economic prospects and more crucially, concerns over the environment. In addition to the PV panels, The solar PV system also consists of few power electronic converters which is used to connects its output to the grid. The power electronics converters normally used are, (a) the DC-DC converter to boost the PV output DC, and the (b)DC-AC inverter for AC conversion. Generally, the Maximum Power Point Tracking (MPPT) algorithm is incorporated with the DC-DC converter to raise the level of the solar PV array output voltage, and to achieve the maximum energy extraction. Also, The photovoltaic (PV) cell directly converts solar energy into electricity. A unique point on the I-V or P-V curve of a PV cell, called the Maximum Power Point, the PV system is active with the maximum efficiency and produces the maximum output power. Hence, it is essential to include a MPPT module in the PV system so that the PV arrays are able to deliver the maximum available power.

II. OBJECTIVE OF THIS PAPER

This method proposed an improved maximum power point tracking (MPPT) method for the photovoltaic (PV) system using a Firefly Algorithm (FFA). Additional feature of this method is reduction of the steady state oscillation once the maximum power point is located. The proposed method has the ability to track maximum power point for the extreme environmental condition such as fluctuation of insolation and partial shading condition. Algorithm is simple and can be computed very rapidly; thus its implementation using a low cost microcontroller is possible. To evaluate this proposed, PSIM simulation carried out.

III. MAXIMUM POWER POINT TRACKING (MPPT)

Due to high initial cost of PV power generation systems and its low energy conversion efficiency, a PV system is generally operated to extract maximum power from the PV source. In order to optimize the utilization of PV systems, maximum power-point tracking (MPPT) is generally employed, which requires power electronic interfaces such as dc–dc converter and/or inverter. The objective of MPPT is to extract maximum power generated by the PV systems under varying condition of temperature and solar insolation. A major challenge in PV systems is to tackle its nonlinear current–voltage ($I-V$) characteristics, leading to a unique maximum power point (MPP) on its power–voltage ($P-V$) characteristic curve. The process of MPPT is complicated by the fact that the $P-V$ curves vary largely with solar insolation and temperature.

Generally, the PV panels are connected in series and parallel so as to meet the load power demand. When climatic conditions vary, the MPP of the PV system also changes its position and several methods have been presented for tracking the MPP. These methods include perturb and observe (P&O), incremental conductance , short circuit current, open circuit voltage, load current/load voltage maximization technique, fuzzy control, neural network- based schemes , etc. A detailed comparison of various methods for tracking MPP in PV systems is extensively discussed in. The tracking methods discussed in these papers are effective and time tested under uniform solar insolation, where there is only one MPP in the $P-V$ curve of the PV system for a given temperature and insolation. In large PV systems, partially shaded condition (PSC) occurs wherein PV modules receive different solar insolation due to shadow of building, moving clouds, and other neighbouring objects.

The output power of the PV array decreases largely due to PSC and the quantum of power lost depend on system configuration, shading pattern and the bypass diodes incorporated in the PV modules. The effect of PSC on PV system has been investigated in several publications. The immediate effect of PSC is that the resulting PV characteristic curve becomes complex with multiple peaks. Conventional methods of tracking MPP are based on “hill climbing” technique and these methods are not effective in reaching the global optima, when the PV system under PSC exhibits multiple peaks; rather most of the conventional methods may converge to local MPP leading to power loss.

Extracting maximum power from partially shaded PV arrays can be categorized into four groups. In the first group, modified MPP techniques which are capable of converging to global maximum power point (GMPP) are employed and the second category utilizes different array reconfigurations. The third group describes different PV system architectures and the fourth category involves different converter topologies such as multilevel inverters. Though not highlighted, a closer examination of the work in. clearly indicates that the last three categories are costlier, require more components, and involve complex control and higher switching loss in comparison with modified MPPT techniques that fall under first category. In general, modified MPP algorithms always guarantee convergence to GMPP, system independence, and higher tracking efficiency.

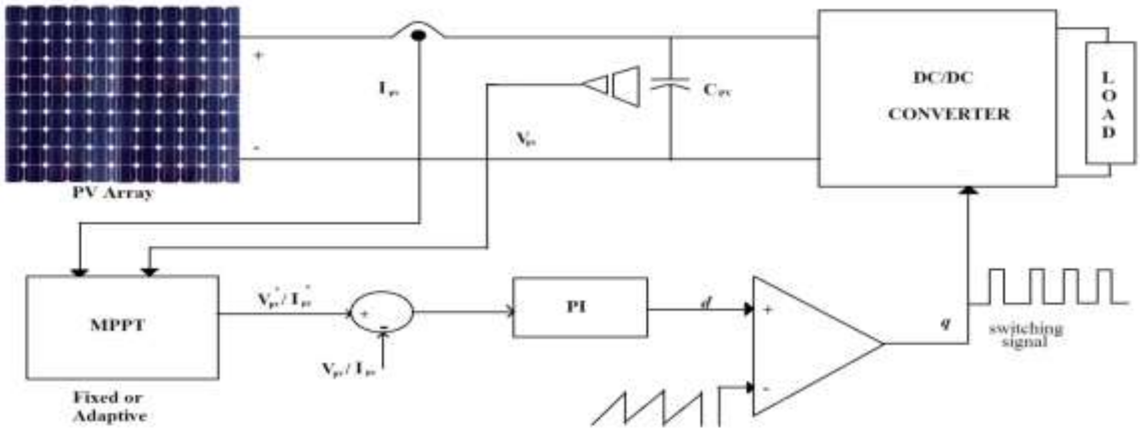

Fig.1. A Typical Voltage or Current based MPPT system

IV. INTRODUCTION OF FA AND ITS APPLICATION TO GMPP TRACKING

The FA is a population-based optimization and is introduced by Yang. This optimization algorithm is inspired by the movement of lightning bugs-commonly known as fireflies. The flashing light of fireflies is an amazing sight in the summer sky in the tropical and temperate regions. Two fundamental functions of such flashes are to attract mating partners and to attract potential prey. In addition, flashing may also serve as a protective warning mechanism. The rhythmic flash, the rate of flashing and the amount of time form part of the signal system that brings both sexes together. For simplicity in describing Firefly Algorithm, the following three assumptions are made:

1) All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;

2) The attractiveness between two fireflies is proportional to relative brightness and the less brighter one will move toward the more brighter one. If there is no brighter one in a firefly colony, each one will move randomly

3) The brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function. Let i and j be two fireflies positioned at Xi and Xj, respectively. Let the distance between these two fireflies is denoted as rij. In a single dimensional space, we can write

$$r_{ij} = |x_i - x_j| \qquad \text{------ (1)}$$

The degree of attractiveness, β is a function of distance between two fireflies and is given by

$$\beta(r) = \beta_0 e^{-\gamma^2}\ ,\ n \geq 1 \qquad \text{-------- (2)}$$

In the aforementioned equation, γ, which controls the decrease of light intensity, is termed as absorption coefficient and is between 0 and 10 and n = 2. The symbol $\beta 0$ is initial attractiveness and is chosen as 1, such that the brightest firefly strongly determines the position of other fireflies in its neighbourhood.
Assuming that the brightness of firefly i is less than that of j, the new position of firefly i is given by the following equation:

$$x_i^{t+1} = x_i^{t} + \beta_0 e^{-\gamma r^2}{}_{ij}\left(x^t{}_j - x^t{}_i\right) + \alpha_1(\text{rand} - 0.5) \text{--- (3)}$$

Here, random movement factor α is constant throughout the program and falls in the range [0, 1] and rand is a random number uniformly distributed between 0 and 1 for each movement of firefly. A large amount of α makes the movement to explore the solution through the distant search space and the smaller α tends to facilitate local search.

VI. FFA ALGORITHM:

1. Begin:
2. Initialize the algorithm parameters:
3. MaxGen: maximal number of generations
4. γ: the light absorption coefficient
5. r: the specific distance from the light source
6. d: the domain space
7. Define objective function of f(x), where x=(x1,........,xd)
8. Generate an initial population of the fireflies or xi(i=1,2 ,..., n)
9. Determine light intensity of Ii at xi via f(xi)
10. While (t < MaxGen)
11. For i = 1 to n (all n fireflies);
12. For j=1 to n (n fireflies)
13. If (Ij> Ii),
14. move firefly i towards j by
15. end if
16. Attractiveness varies with the distance r via Exp [-γr2];
17. Evaluate new solutions and update light intensity;
18. End for j;
19. End for i;
20. Rank the fireflies and find the current best;
21. End while;
22. Post process results and visualization;
23. End procedure

VII. FIREFLY TOPOLOGIES

Two general classifications of neighbourhoods are being discussed in Firefly topologies

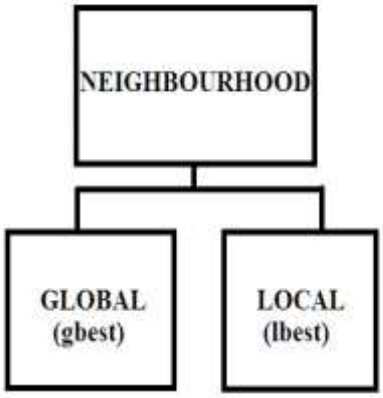

Fig.2. Classification of neighbourhoods in Firefly

VIII. Topology.

The hierarchy shown in figure 4 shows the general classification of neighbourhoods under swarm topologies.

The comparisons between these topologies are discussed as follows:

1. *Global best(gbest)* is of the form of fully connected network.

2. *Local best(lbest)* can be examined according to the topologies structure.

The following figures clearly shows the difference between the *global best* and the *local best.*

Also second difference is that,

1. *Gbest* converges fast but may be trapped in a local optima.
2. *Lbest* is slower in convergence but has more chance to find the optimal solution.

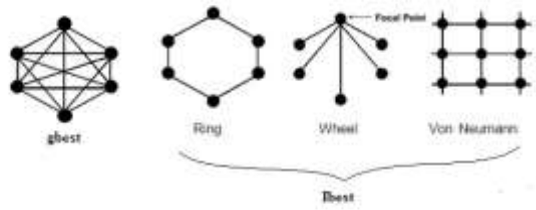

Fig.3. Comparison of Global and local best.

IX. APPLICATION OF FA TOWARD MPPT

The block diagram of the FA-based MPPT scheme is given in Fig 1. Here, the PV array is interfaced to the load through the boost converter. For a population of fireflies, i.e., duty ratios, the digital controller measures *Vpv* and *Ipv* and computes the output power. The steps of FA algorithm toward MPPT are described below:

STEP 1: Parameter Setting: Fix the constants of the FA, namely, βo, γ, n,α, population size *N*, and the termination criterion. In this algorithm, the position of the firefly is taken as a duty cycle *d* of the dc–dc converter. The brightness of each firefly is taken as generated power *Ppv* of the PV system, corresponding to the position of this firefly.

STEP 2: *Initialization Of Fireflies*: In this step, the fireflies are positioned in the allowable solution space between *d*min to *d*max where *d*min and *d*max represent the minimum and maximum values of the duty ratio of the dc–dc converter. In this paper, *d*min is taken as 2% and *d*max is set at 98%. Thus, position of each firefly represents the duty ratio of the dc–dc converter. It may be noted that increased number of fireflies results in higher computing time while, a lesser number of fireflies will result in a local maximum. Hence, in this paper, the number of fireflies is chosen as 6.

STEP 3: *Brightness Evaluation:* In this step, the dc–dc converter is operated corresponding to the position of each firefly (i.e., duty ratio) sequentially. For each duty ratio, the corresponding PV output power, *Ppv* is taken as the brightness or light intensity of the respective firefly. This step is repeated for position of all fireflies in the population.

STEP 4: *Update The Position Of Fireflies:* The firefly with maximum brightness remains in its position and the remaining fireflies update their position.

STEP 5: Terminate the program if the termination criterion is reached; else go to step 3. The optimization algorithm is terminated once the displacement of all fireflies in consecutive steps reaches a set minimum value. Once the program is terminated, the dc–dc converter operates at the optimum duty cycle corresponding to GMPP.

STEP 6: Reinitiate the FA if the solar insolation changes, which is detected by the digital controller by sensing the change in the power output.

X. SIMULATION RESULTS

The feasibility of the proposed MPPT based on Particle Swarm Optimization was verified in MATLAB using Simulink with the help of S-function (a commercially available software package dedicated for power electronic converter simulations) and proposed algorithm was simulated based on the following specifications:

Table.1. Parameters Of Boost Converter

Switching Frequency, f_s	**50KHz**
Capacitor, C	**470µH**
Inductor, L	**1.812mH**
Internal resistance of Inductor, r_L	**0.394Ω**

XI. SIMULATED CIRCUIT

The Fig.4 shows the proposed simulation circuit for MPPT based on FFA Algorithm. Here the value for output voltage, output current and output power are displayed simultaneously as shown in the Fig.4. Also sub-function blocks for MPPT Controller and Cuk Converter are shown in the Fig.5 and Fig.6 respectively.

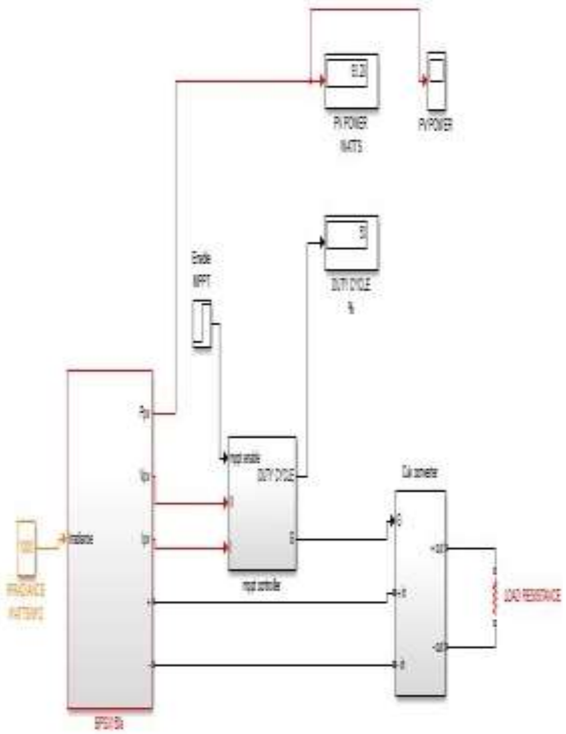

Fig.4. Main Simulation of proposed converter.

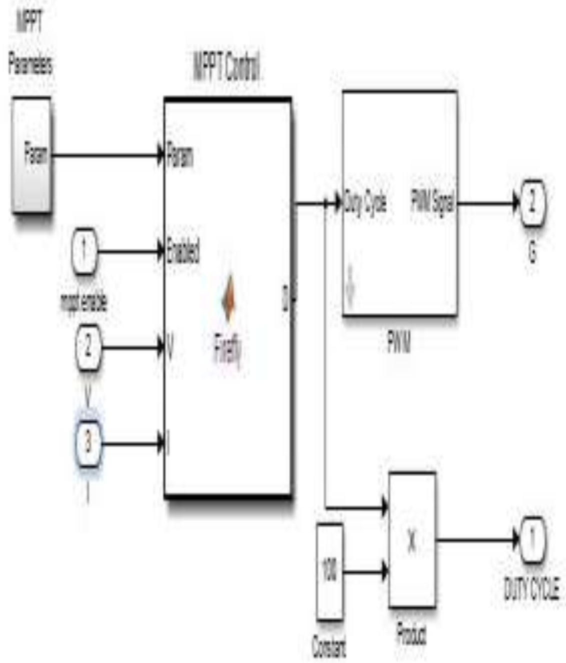

Fig.5. Sub-Function Simulation block for MPPT Controller.

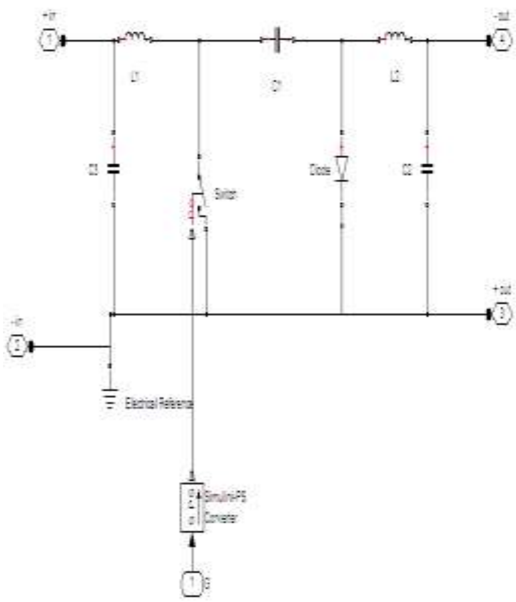

Fig.6. Sub-Function Simulation Circuit For Cuk Converter.

XII. SIMULATION RESULTS

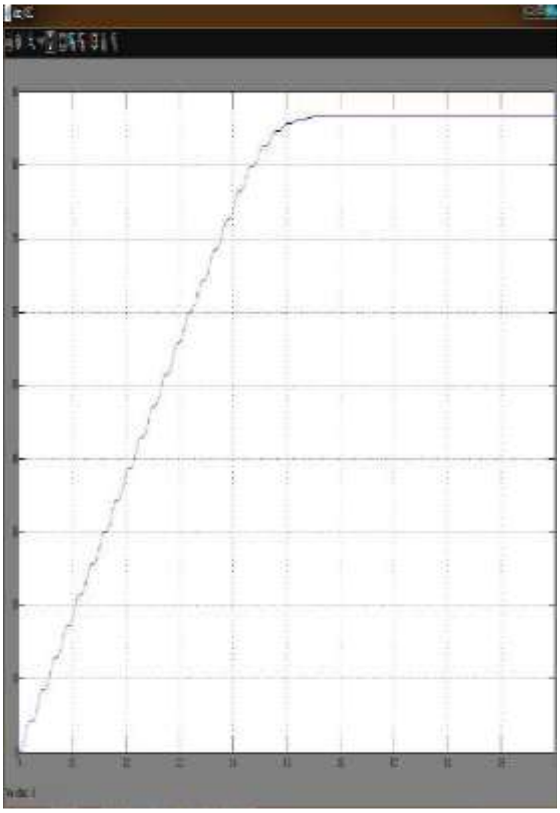

Fig.7. Simulated Waveform for Output Power

The performance is better in terms of both rise to the voltage and the voltage magnitude. While we achieve a voltage magnitude of 32 V in modified FF algorithm, only 24 V is obtained using the P&O approach for all other initial conditions remaining same.

XIII. CONCLUSION AND FUTURE SCOPE

The intensive and massive use of energy from the solar cell is essential for providing solutions to environmental problems. Implementing the MPPT algorithm through digital controllers is easier if it is possible to minimize error functions. The differences between the various MPPT techniques are very slight and they can be evaluated according to the situation. For a particular application, selecting a particular MPPT is a tough task and this paper will be a good reference for the researchers who work with MPPT.

This section is to discuss on the possibility of future extension for this title of research. The future improvement should be concentrated more on the limitations and weaknesses of this project.

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