

# Optimized MPPT for Grid tied Transformer Less PV System: A Comparative Analysis

Janardhan Gurram<sup>1\*</sup>, N.N.V Surendra Babu<sup>2</sup> & G.N.Srinivas<sup>3</sup>

<sup>1</sup>Senior Assistant Professor, EEE Dept., CVR College of Engineering, Hyderabad, Telangana, India

<sup>2</sup>Associate Professor, EEE Dept., ANURG University, Hyderabad, Telangana, India.

<sup>3</sup>Professor, EEE Dept., JNTU Hyderabad, Telangana, India

**Abstract:** For grid-tied photovoltaic (PV) systems, Maximum Power Point Tracking (MPPT) algorithms based on artificial neural networks (ANNs) are prone to initialization issues, which could cause them to converge at local maxima rather than the global maximum power point (MPP). This means that, a regular retraining on big datasets is required. This paper presents a novel hybrid MPPT algorithm that combines Extreme Gradient Boosting (XGBoost) and Vascular Invasive Growth Optimization (VIGO) to address this challenge. The exploration-exploitation conundrum that traditional optimization algorithms have is addressed by VIGO, and the convergence speed and accuracy of MPPT are improved by XGBoost. To assess its performance, the suggested approach is compared with well-known methods such as Grasshopper Optimization Algorithm (GOA), Sparrow Search Algorithm (SSA), and Particle Swarm Optimization (PSO). This comparison study shows that the hybrid VIGO-XGBoost method produces improved maximum power.

## 1 Introduction

Photovoltaic (PV) systems connected to the grid are a rapidly expanding renewable energy technology. The use of Maximum Power Point Tracking (MPPT) algorithms is essential to maximizing the amount of energy obtained from solar radiation. The PV system's operating point is dynamically adjusted by these algorithms to ensure that it runs at the voltage and current that maximizes power output (also known as the Maximum Power Point, or MPP). Due to its capacity to learn intricate non-linear relationships between PV output and environmental conditions, Artificial Neural Network (ANN) based MPPT techniques have become popular. However, one significant drawback of ANN-based MPPT techniques is that they have initialization issues. If the ANN weights are not properly initialized, the algorithm may converge at local maxima on the power-voltage (P-V) curve rather than the global MPP, which would require periodic retraining on large datasets, which could be computationally costly and impractical for practical use.

Alternative optimization strategies have been investigated recently to overcome the drawbacks of ANN-based MPPT. Swarm intelligence algorithms such as Particle Swarm Optimization (PSO) [1], Sparrow Search Algorithm (SSA) [2], and Grasshopper Optimization Algorithm (GOA) [3] have demonstrated potential in several studies. To find the best answers in difficult search spaces, these algorithms imitate the collective behaviour of natural systems, such as swarms

of insects or flocks of birds. Even though they work well, these methods sometimes have trouble striking a balance between exploitation settling on the best answer thus exploration finding new, prospective MPPs.

The paper proposes a novel hybrid MPPT algorithm that combines the strengths of two powerful techniques. Vascular Invasive growth optimization VIGO and Extreme Gradient Boosting (XG Boost). His newly created optimization algorithm presents a novel strategy influenced by the growth patterns of plants. VIGO improves the capacity to identify the global MPP by skilfully addressing the exploration-exploitation conundrum. For regression tasks, this machine learning method offers excellent accuracy and efficiency[3]. Our goal in implementing XGBoost is to increase the MPPT process's convergence speed and accuracy.

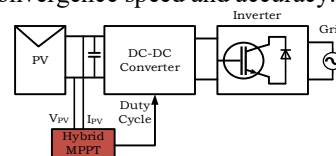


Fig. 1. Architecture of proposed system

From Fig.1. shows that, grid connected PV System whose input is fed from PV power and is employed by a hybrid MPPT algorithm. The inputs to the MPPT algorithm is PV voltage and PV current. The duty cycle of the DC-DC converter is controlled by hybrid MPPT.

## 2 Background Work

Various optimization algorithms that are based on swarm search such as Particle Swarm Optimization (PSO),

\* Corresponding author: janardhan.gu@gmail.com

Sparrow Search Algorithm (SSA) and Grasshopper Optimization Algorithm (GOA) are discussed in literature in addition to other animal herd algorithms in search of their food.

### 2.1 Particle Swarm Optimization Algorithm

To implement MPPT using Particle Swarm Optimization (PSO) algorithm, the particle position is considered as gating pulse of the dc-dc converter and PV power chosen as fitness valuation function. The larger the number of particles the more the MPPT tracking under different weather conditions [4].

The PSO algorithm works based on the following equations.

$$V_{ip}(k + 1) = \omega v_i(k) + c_{1p}r_1 (P_{best,i} - x_{ip}(k)) + c_{2p}r_2 (g_{best} - x_{ip}(k)) \quad (1)$$

$$x_{ip}(k + 1) = x_i + v_{ip}(k + 1) \quad (2)$$

Where  $x_{ip}$  is the position of particle  $i$ ,  $v_{ip}$  is the velocity of the current particle,  $k$  denotes the iteration number,  $\omega$  is the inertia weight,  $r_1$  and  $r_2$  are random variables between 0 and 1.  $c_{1p}$  and  $c_{2p}$  are coefficients.  $P_{best,i}$  is used to represent best location of the  $i_{th}$  particle and  $g_{best}$  is the best position of the particle [5]. The particles are given initial values with fixed positions in the search space of  $[D_{min}, D_{max}]$ .  $D_{min}$ ,  $D_{max}$  are minimum and maximum duty cycles of DC-DC converter. If the fitness value of a particle is best, assign it to global best so that best position of the particle is updated corresponding to maximum power. If the velocities of particles is lower than the preset value or if the highest number of iterations is completed, then the MPPT algorithm is stopped obtains global maximum power. The flow chart of PSO is shown in Fig. 2.

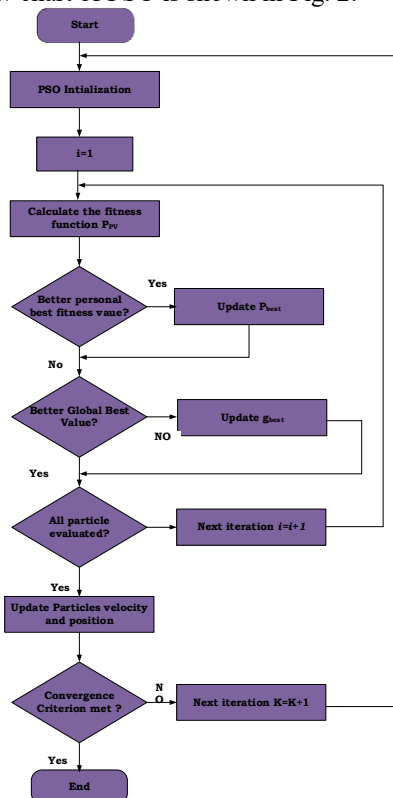


Fig. 2. Particle Swarm Optimization Algorithm

### 2.2 Sparrow Search Algorithm

Sparrow Search Algorithm initialized by a population of sparrows. The Sparrow search model establishes discoverer-joiner sparrow population. By considering the position of the discoverer based on the duty cycle of the DC-DC converter. The PV output power is considered as objective function and the foraging amount found by discoverer is regarded as output power [6]. The position of the discoverer is given by the following equation.

$$x_{id}^{t+1} = \begin{cases} x_{id}^t \cdot e^{\left(\frac{-i}{aT}\right)} R_2 < ST \\ x_{id}^t + Q \cdot L R_2 \geq ST \end{cases} \quad (3)$$

For a  $d$ -dimensional the position of  $i_{th}$  sparrow in space is  $X_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{id})$   $x_{id}$  represents the position of  $i_{th}$  sparrow in  $d$ -dimensional space. The location of the discoverer is updated by the following expression. Where  $T$  is the maximum number of iterations,  $Q$  is the random number with normal distribution and  $ST$  is between 0.5 and 1. If the  $R_2 < ST$  can be continued and there can be no danger for the discoverer sparrows. For  $R_2 \geq ST$  a predator is detected so that there will be an alarm made by one of the vigilant discoverers and all the sparrows will flew away to safe place [7].

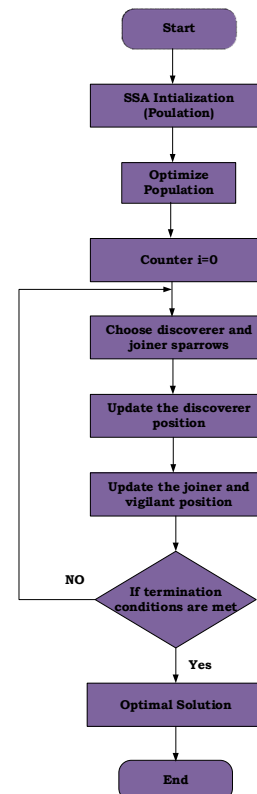


Fig.3. Sparrow Search Algorithm.

Similarly, the new position of the joiner is updated. By updating the positions of the sparrows, new optimal value is found and if the current optimal value is greater than previous value. Otherwise, continuous process is repeated. The flow chart of the algorithm is shown in Fig.3.

### 2.3 Grasshopper Optimization Algorithm

Grasshopper Optimization Algorithm (GOA) is applied for determining maximum power point due to its least oscillations in the steady state. Here the search space represents dusty cycle which varies in between 0 and 1. s s a relatively new nature-inspired metaheuristic optimization algorithm that mimics the swarming behavior of grasshoppers. The goal is to maximize this objective function to find the maximum power point (MPP) of the PV system. It's based on the principle of imitating the movement and behavior of grasshoppers while foraging for food [7].

Repeat the process until the optimization process is merged. The GOA iterates through multiple generations, with grasshoppers gradually converging towards the MPP of the PV system. Convergence is achieved when the grasshoppers can no longer improve their positions significantly or when a predefined stopping criterion is met. After convergence, the voltage value corresponding to the best-performing grasshopper represents the estimated maximum power point of the PV system. This voltage value can then be used to adjust the operating point of the PV system to maximize energy harvesting efficiency. The flow chart of Grasshopper is shown in Fig. 4.

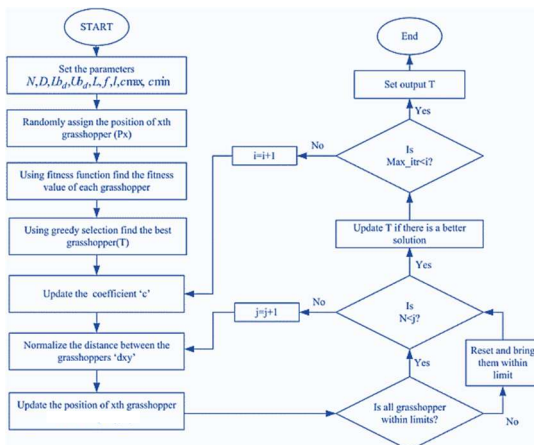


Fig.4. Grasshopper Optimization Algorithm

The position of a grasshopper optimization represents duty cycle of the DC-DC converter.

$$X_i(t+1) = c \left( \sum_{\substack{j=1 \\ j \neq i}}^N c \frac{ub_d - lb_d}{2} s(|x_j - x_i|) \frac{x_j - x_i}{d_{ij}} + \widehat{e}_g \right) + \widehat{T}_d \quad (4)$$

Where  $i$  and  $j$  stand for  $i^{th}$  and  $j^{th}$  grasshopper particles and  $d$  is the distance between them,  $t$  is the repetition index.  $ub_d$  and  $lb_d$  are upper and lower boundaries of  $d^{th}$  dimension. Equation (4) indicate the position of the grasshopper particle.

### 2.4 Proposed Hybrid MPPT Algorithm

A grid connected transformerless PV system shown in Fig.5. indicates that a hybrid MPPT algorithm is employed to trace the maximum power. The proposed hybrid MPPT is implemented y Vascular Invasive Tumour Growth Optimization technique along with XG Boost algorithm.

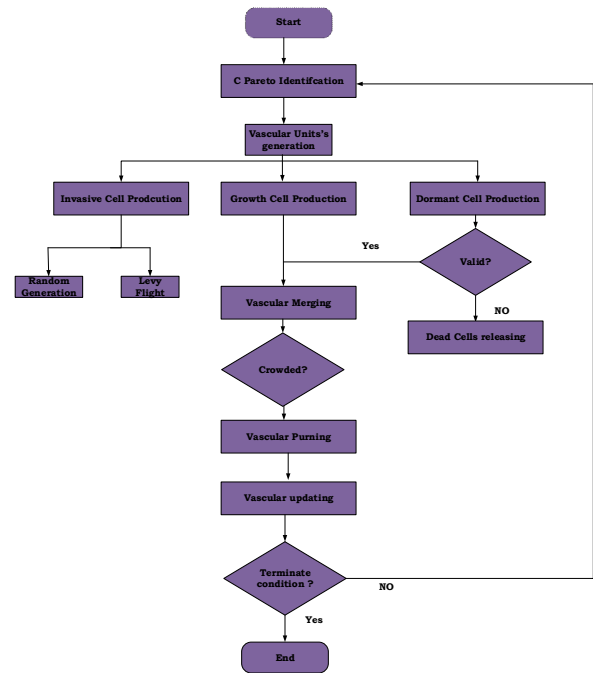


Fig. 5. Proposed VITGO Algorithm

The algorithm for vascular invasive tumor growth optimization is shown in the flowchart. It starts with Pareto detection, which is probably a multi-objective optimization method but isn't explained in detail here. It then moves on to the creation of vascular units. Circular units appear to be important structural elements all along the algorithm. They might be connected to blood vessel networks that affect cell behavior and deliver nutrients [8].

The algorithm then generates three different types of cells: dormant, growing, and invasive. Dormant cells add diversity, growing cells represent potential solutions by expanding the tumour mass, and invasive cells scour the search space. To add exploration and randomness, Levy flight, a foraging search pattern, and random generation are employed. To make sure the generated cells are within allowable ranges, a validity check may be performed. The VITGO utilizes the three population of cells. Proliferative Cells  $P_{Cells}$  which will actively divide and expand tumour. Q Cells are dormant cells which become proliferate under certain conditions.

#### 2.4.1 VITGO uses five main search strategies that resemble the growth behaviour of tumours:

$P_{cell}$  Growth: An increase in proliferative cells indicates the growth of the tumour. Development of  $I_{cell}$ : Proliferative cells have the ability to become invasive cells, which encourages searching the search space. Growth of  $Q_{cell}$ : Under some circumstances, quiescent cells have the ability to proliferate and introduce diversity. Development of  $D_{cell}$ : Restrictions in resources can cause proliferative cells to die, which regulates the population. Cells have the ability to randomly walk through the search space, which can aid in escaping local optima [9].

Finding the Maximum Power Point (MPP) in a photovoltaic (PV) system by applying the Vascular Invasive Tumour Growth Optimization (VITGO)

algorithm is an intriguing idea, but there isn't much published research on its direct application in this field. An examination of the possible advantages, difficulties, and factors is provided below:

**VITGO Exploration:** Use VITGO's exploration features to look through the PV system's I-V (current-voltage) curve. Its various search techniques (growth, random walk, and vascular units) can be used to locate potentially productive areas in and around the MPP. **Sample Point Generation:** VITGO has the ability to produce sample points, or voltage-current pairs, all along the I-V curve during its search. These points indicate possible PV system operating points.

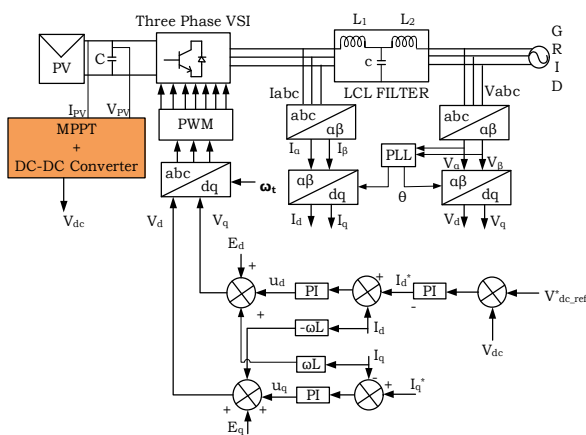
### 2.4.2 XGBoost for Local tuning [10].

**Data Collection:** A dataset of voltage, current, and corresponding power output (obtained from the PV system or a simulation model) is used to train the XGBoost model.

**Estimating the Local MPP:** With VITGO, XGBoost is able to predict the power output for each sample point. This makes use of XGBoost's capacity to figure out intricate correlations between voltage, current, and power. **Refined Search:** VITGO can concentrate its search on areas with higher predicted power output based on the predicted power from XGBoost. This local refinement facilitates a more effective convergence towards the MPP[10].

### 2.4.3 Proposed Grid Control

In addition to tracking maximum power point using hybrid MPPT technique proposed, the work also consider the implementation active power control to a three phase transformerless voltage source inverter with the as shown in Fig.



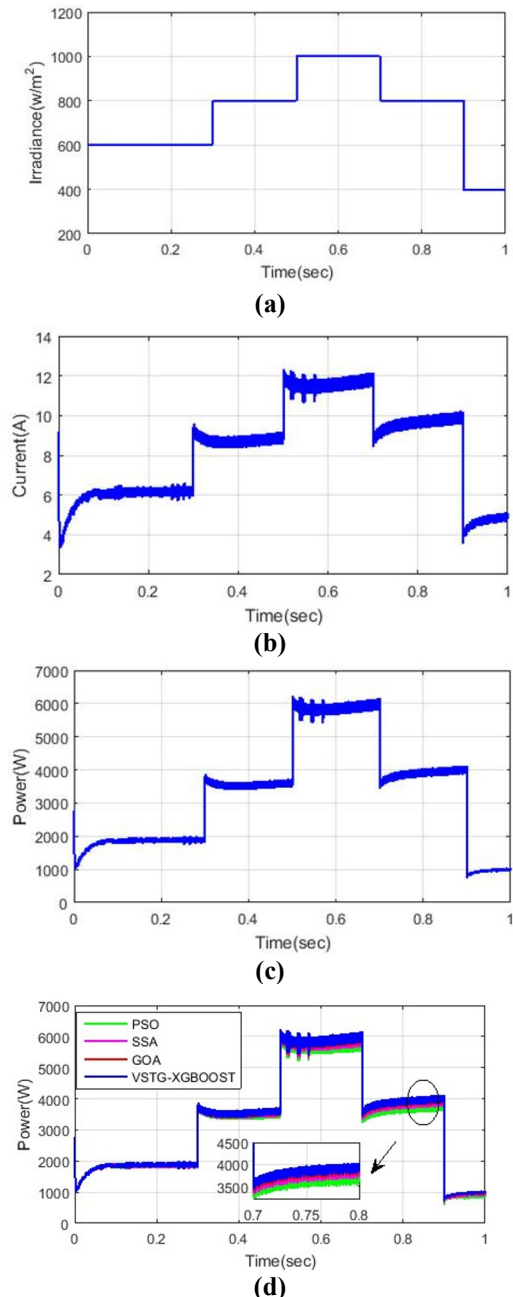
**Fig. 6.** Grid connected transformerless PV system with control structure.

A three phase VSI is controlled fed with PV output and the PV dc link is controlled by hybrid MPPT. The grid currents are tapped to determine the phase angle  $\theta$  with the help of phase locked loop (PLL). For a given DC reference voltage, the actual DC voltage compared so that the error signal fed through PI controller. The PI controller generates reference d axis current which can

be compared with actual d-axis current similarly in line with q-axis current. The d-q components of voltages are generated from respective PI controllers. By using dq to abc to dq transformation, abc control wave forms for three phase system are generated. Hence, three phase VSI is controlled.

## 3 Results

The grid connected PV system is applied with varied irradiation in the range of  $600 \text{ W/m}^2$  to  $1000 \text{ W/m}^2$ . The PV current follow the PV irradiation reaches to maximum value of 12amps as shown in Fig. 7(a) at  $1000 \text{ W/m}^2$ .



**Fig.7.** (a) Irradiance (b) PV current (c) PV Power (d) PV power outputs with different algorithms

As shown in Fig. 7.(c) the PV power indicating its value corresponding to the PV irradiance and the power value reaches to 6000 Watts. Various algorithms such as PSO, SSA and GOA are applied to the PV to determine MPPT. The PV output power determined by above algorithms is compared with the hybrid technique that combines vascular invasive tumour growth optimization technique and XG Boost technique. From Fig. 7(d), it can be concluded that proposed hybrid technique offer superior performance in reaching the maximum power.

## 4 Conclusion

The MPPT algorithms that are applied for a PV system in this paper are Particle Swarm Optimization (PSO), Sparrow Search Algorithm (SSA), and Grasshopper Optimization (GOA). The output PV power for the above algorithms is compared with the proposed vascular invasive tumour growth optimization combined with XG Boost algorithm. It is found that the power output in the proposed technique is superior compared to other mentioned algorithms.

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