EFFICIENT MPPT FOR PV SYSTEMS UNDER SHADING CONDITION USING HYBRID METAHEURISTIC OPTIMIZATION MODEL

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ABSTRACT

The increasing penetration of photovoltaic (PV) systems in the energy generation mix make it necessary for Maximum Power Point Tracking (MPPT) techniques to be more and more efficient. Solar (PV) systems are generally used under partial shading and operate at many local peaks on the power-voltage (P-V) curve hence making Global Maximum Power Point (GMPP) tracking hard. In such conditions, traditional MPPT methods like Perturb and Observe (P&O) as well as Incremental Conductance (IC), most of the time fails to track GMPP effectively, leading towards higher power losses resulting in decreased efficiency. In this research a new hybrid metaheuristic method, which combines Particle Swarm Optimization (PSO) and Differential Evolution (DE), is suggested for improving MPPT performance in PV systems. With the help of hybrid PSO-DE model, which has better convergence speed and exploration property as well as robustness to local minimum with random search directions (Differential Evolution), it helps locate GMPP correctly even under various shading situations. The work provides novelty by suggesting an organized hybrid PSO-DE based MPPT framework that strictly weighs the quick convergence and worldly search to dependable Global Maximum Power Point tracking to track the partially shaded conditions. The proposed method incorporates both PSO exploitation and DE exploration in one optimization loop, which makes it more stable, converges faster, and is more resilient than current standalone or weakly connected hybrid MPPT techniques. The results clearly indicate substantial improvements in the tracking speed, power output and stability with respect to existing methods when the proposed hybrid PSO-DE method is employed especially for not uniform set points. The results of this study can help in improving the efficiency and reliability of solar energy systems so that PSO-DE hybrid model usable for real world applications. This work advances the field of MPPT by supporting new technologies to respond to a fluctuating set behaviour for renewable energy systems and provides insight into more efficient solar solutions.

Keywords: *Photovoltaic Systems, Maximum Power Point Tracking, Partial Shading, Global Maximum Power Point, Hybrid Meta-heuristics, Particle Swarm Optimization, Differential Evolution.*

1. INTRODUCTION

With the ever-growing global energy requirement, there is mounting pressure to shift base from conventional fossil fuels and adopt conservation techniques with renewable choices [1]. One of the prominent renewable sources, solar energy harnessed via PV systems is increasingly popular due to its abundance, scalability and environmental benefits [2]. The basic structure of PV systems is the conversion from sunlight to electricity with semiconductor materials having a photovoltaic effect. The market penetration of PV technology is supported by the possibility to produce clean energy, which can help decrease green-house gas emissions as well and it proves its contribution towards energy independence [3]. Nevertheless, even if in theory these features may make solar PV capabilities unique and advantageous the use of light as an energy sources come with some well-known challenges already inherent to all systems that limit their efficiency performance, especially under varying environmental conditions [4]. To address these challenges, requires the development of higher performance technologies that will be able to deliver maximum power output and thus the highest possible level of overall system efficiency. Energy efficiency is a key metric in PV systems to

ensure high power output and reduced system costs [5]. This is largely achieved by way of MPPT - a method that ensures the PV system works only on its best operating point in power-voltage (P-V) curve. The product of current and voltage peaks out at this point, generating optimal power. But the MPP is not constant and varies with solar radiation, temperatures, and especially shadowing [6]. Dynamic fluctuations in the I-V curve over time necessitate fast and accurate MPPT algorithms to facilitate timely adjustment of the operating point, thus achieving maximum power conversion efficiency [7].

Fig 0: General Photovoltaic Mppt Performance

One of the simplest and inexpensive traditional MPPT methods, Perturb & Observe (P&O) or Incremental Conductance (IC), is mostly preferred for implementation. Nevertheless, these traditional algorithms work under substantial restrictions specifically in dynamic situations with partial shading conditions [8]. Obstructions like clouds, buildings or trees cast shadows and partial shading on PV panels is the cause of multiple peaks presents on its P-V curve. Traditional MPPT algorithms may be trapped into a local maximum and fail to locate the global maximum power point (GMPP) under such conditions [9]. Also these methods have islanding with oscillations around the MPP which affect energy losses and system efficiency [10]. This motivates for the development of advanced MPPT strategies which can mitigate these limitations and enhance operation of PV systems subjected to varying solar radiation due to shading loads [11].

Shading in PV systems is more important than ever to address, as solar energy becomes an epicenter of the global movement towards renewable power [12]. Shading has a marked impact on the efficiency and stability of solar power because only a small shaded area covering part or whole PV panel can generate high proportion output degradation [13]. These effects are even more significant in crowded urban areas with lots of buildings, trees and other edge structures that cast shadows on the solar installations [14]. A metaheuristic optimization method has gain popularity to solve the pitfalls of classical MPPT methods, in recent years [15]. Metaheuristics are such high-level algorithms which have been developed to solve difficult optimization problems and they generally search the solution space efficiently that also prevent falling into local optima [16]. The general Photovoltaic MPPT Performance is shown in Figure 1.
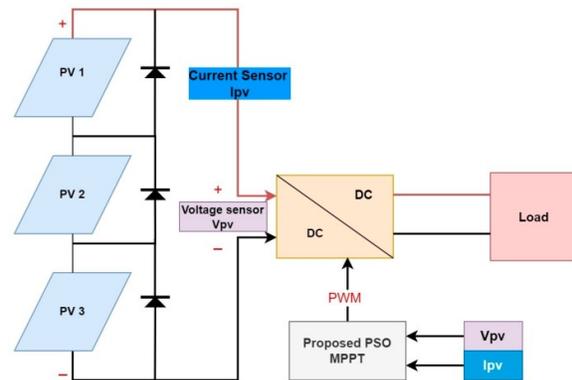
Due to their simplicity and low computational needs, traditional MPPT algorithms like Incremental Conductance (IC) and Perturb and Observe (P&O) are extensively employed. Their problems arise, nevertheless, when subjected to partial shade circumstances (PSC), where the P-V curve displays numerous local peaks. This results in Confined to nearby maximums, Tracking speed is slow, Greater power dissipation and Vibrations close to the MPP. A number of metaheuristic techniques, made possible by recent developments, include Quick convergence, although prone to local optima, is the hallmark of PSO. DE Exploration is good, but convergence is slower. An essential function in PV systems, MPPT guarantees optimal power harvest in different environmental situations. Because of their low computational needs, simplicity, and ease of implementation, traditional MPPT approaches like IC and P&O are the most extensively used. Nevertheless, there are major downsides to these techniques, especially when dealing with Partial Shading Conditions, which cause the power-voltage (P-V) characteristic curve to display several peaks. In these cases, conventional algorithms frequently converge to local maxima rather than the optimal GMPP, resulting in inefficient energy harvesting. They also have a tendency to oscillate near the MPP, which leads to power losses in the steady state and worse system efficiency. Convergence also becomes unstable or delayed under fast changing weather conditions, which negatively impacts their performance.

Metaheuristic optimization techniques, which do not depend on gradient-based information but provide global search capabilities, have been more popular among researchers as a means to circumvent these restrictions. For complicated PV situations, methods like as Ant Colony Optimization (ACO), Genetic Algorithms (GA), PSO, and DE have demonstrated potential in

MPPT. Nevertheless, there are benefits and drawbacks to each. In multimodal environments, PSO tends to converge too early, despite its rapid convergence speed. While DE is computationally faster and more efficient when exploring global optimums, it can be less efficient and more robust when investigating local optimums. This study presents a hybrid PSO-DE algorithm that improves overall tracking accuracy, decreases steady-state error, and guarantees resilience in non-uniform irradiance situations by combining the fast convergence of PSO with the powerful exploration of DE. When it comes to PV systems in the real world, this hybrid approach is perfect for those that need to be flexible and efficient in a wide range of environments.

The hypothesis of the research is that a hybrid MPPT algorithm based on the PSO and DE can address the drawbacks of the independent metaheuristic and standard MPPT algorithms in the case of partial shading. Precisely, it is postulated that the proposed hybrid PSO-DE will be able to reach the GMPP faster, minimize steady-state oscillations, and enhance the tracking efficiency and power production in both online and non-uniform irradiance configurations.

PSO and DE are two popular algorithms commonly used to tackle them, which have appreciable potential in various contexts due to their flexibility. PSO models the social behaviour of particles, updating their position and velocity in order to iteratively move towards optimal solutions whereas DE relies on differential variations [17] and mutations for effective exploration across search space [18]. Due to rather significant global search ability, DE is good at preventing getting stuck in local optima/files from size 0 and PSO can rapidly converge.A hybrid approach, using several of these algorithms together combines the strengths from each and allows efficient exploration & exploitation throughout all space. The hybrid PSO-DE model that is proposed focuses on the improvement in MPPT performance having rapid convergence to global maximum power point, and minimum steady-state oscillations even under partial shading conditions. This study aims specifically at Implementation of MPPT model that would be efficient under uniform and PS conditions in case of PV systems. To tackle these problems and enhance the process of power extraction, a hybrid PSO-DE based model has been proposed.

Even though a number of metaheuristic-based MPPT methods are documented in the literature, the vast majority of the current methods focus on individual optimization methods or combines algorithms, but does not specifically consider the trade-off between rapid convergence and global exploration in response to dynamically changing partial shading conditions [19]. Specifically, standalone PSO-based MPPT algorithms tend to prematurely converge to local optima whereas DE-based algorithms, though highly effective in the global exploration, tend to converge relatively slowly and have relatively high steady-state oscillations when used individually [20].

This work has developed new knowledge in the systematic combination of PSO and DE into single hybrid MPPT system that is able to maximize the convergence speed, global optimum, and tracking stability at uniform and non-uniform irradiance situations. The proposed method, in contrast to the hybrid MPPT methods, has been developed based on the strategic use of the quick exploitation ability of PSO and the robust exploration process of DE within a single optimization cycle so that GMPP can be accurately tracked in highly multimodal P-V characteristics due to partial shading.

Moreover, the paper provides a specific mathematical model and computerized algorithm of a hybrid PSO-DE MPPT algorithm that is PV-specific, instead of using general optimization models. The suggested model uses adaptive duty-cycle regulation and convergence-based stopping criteria which minimize steady-state oscillations and enhance the overall energy harvesting performance. The quantitative assessment of the performance has shown that the given hybridization model achieves better results that the standalone PSO and DE algorithms in terms of convergence time, tracking performance, power output, and stability.

This study has a scope of design, modeling and simulation based analysis of smart hybrid metaheuristic MPPT algorithm of photovoltaic systems under uniform and partial shading conditions. The paper addresses PV systems in particular which are interconnected with DC-DC converters and in them the use of correct and quick MPPT is necessary to ensure the best energy recovery.

Various shading conditions are used to test the convergence speed, tracking accuracy, steady-state oscillations, power output, and robustness of the proposed hybrid PSO-DE MPPT framework with the help of a large number of MATLAB/Simulink

simulations. Although at the present the scope is restricted to the validation of the algorithm through simulation, the algorithm is computationally efficient and scalable, which makes it a fit to the real-time embedded implementation in realistic PV energy systems. The study is designed to aid in further advances in the harvesting of solar energy with high efficiency, the control of power electronics through intelligence and adaptive renewable energy systems and more specifically to the urban and distributed PV systems where partial shading is inevitable.

The central aim of the research is to design an effective and dependable strategy of the MPPT of the PV systems when they are subjected to partial and uniform shading. In order to accomplish this, a hybrid metaheuristic optimization framework based on the combination of PSO and DE is suggested, which attempts to surmount the natural constraints of traditional and independent metaheuristic MPPT methods.

The specific objectives of this work include:

> - To develop a hybrid PSO-DE based MPPT algorithm that can effectively track the GMPP in PV systems with multiple local maxima due to partial shading.

> - To have a higher convergence rate and less steady-state oscillations than the conventional MPPT algorithm and single PSO or DE algorithms.

> - To improve the performance of PV systems in dynamically changing irradiance conditions in terms of tracking effectiveness, power, and strength.

> - To confirm the performance of the suggested MPPT methodology by the means of thorough mathematical modeling and performance assessment with the use of simulations.

This study has a narrow scope of research contribution that is defined to the development of the algorithm, mathematical formulation, and validation of the hybrid PSO-DE MPPT strategy by simulations. This study is not set to reshape the PV hardware architecture or converter topology but to enhance control intelligence on the MPPT level. The proposed solution is meant to be computer-efficient and scaleable, which is why it can be easily applied in embedded PV controllers in the future in a real-time context.

D. Xu et al. [1] developed a unique solution to mitigate the difficulties of differential power processing (DPP) for PV systems. Given the promising energy efficiency and mismatch mitigation advantages of DPP architectures, they then reveal that prior works have struggled to address a key issue: MPPT with such complex coupling between different DPP converters. Asynchronous MPPTWhile the traditional asynchronous methods for controlling power harvesting are inefficient and do not scale well to larger systems. In this method, the control system is decomposed so that dominant couplings can be more easily identified and addressed which in turn simplifies decoupling. The served approach is simple, efficient and scalable to any size of system in contrast with current decoupling methods. Besides, synchronous MPPT control method can improve the efficiency of MPPT because it largely decreases the time which a PV system gets into maximum power point. Learning from the findings of this study can provide hope in achieving scale-up-ability for DPP-based PV.

H. Toodeji et al. [2] tackled the problem of partial shading conditions affecting home photovoltaic PV systems as they can dramatically reduce energy conversion efficiency. They float an idea to remedy this, using micro inverters and module-level MPPT. The authors in their paper, have proposed a novel feedback linearization control approach tailored towards the non-linear behavior of PV system. The approach provides a nonlinear control law that is able to actively regulate each microinverter in isolation, facilitating module level MPPT while eliminating the need for DC optimizers. The system being developed is unique in that its plug-and-play feature enables easy installation and disconnection of PV modules, most likely to be maintained or expanded by non-experts. In addition, the system provides a certain degree of fault tolerance to module failures such that malfunction of one module does not result in failure of all other modules.

P. K. Sorte et al. [3], presented an adaptive control strategy for grid-connected PV power conversion system which is able to realize unity power factor operation, active damping, fast dc-link voltage regulation and seamless transition between the operating modes while guaranteeing stability. Infrastructure: The infrastructure comprises a

battery storage unit connected to the dc link with bidirectional converter and a voltage source inverter connecting the dc link to ac bus. Besides the control goals, this study also attempted to overcome the issues of maximum power extraction from PV system and seamless operation for power management. Main Headings Tie MPPT Gains over Conventional Incumbents to Those Environmental Factors These Improvements Often Highlight the Limitations of Classic Maximum Power Point Tracking Techniques They therefore propose a direct algorithm for current reference dynamic control that will significantly improve the tracking speed at global maximum power. A better solution is to develop a holistic power management algorithm that provides the reference current for all of the converters in this system, considering multiple system dynamics. Real-time testing performed under dynamic conditions validates the effectiveness of this proposed control strategy for a PV-battery-based grid-tied system.

By using hybrid MPPT method based on Adaptive Neuro-Fuzzy Inference System-Particle Swarm Optimization (ANFIS-PSO), proposed to maximize the PV generation. This technique is effective and provides a smooth tracking of maximum power point without the need for extra sensors to measure irradiance or temperature. This technique uses a space vector modulation hysteresis current controller to obtain high-quality sine-wave inverter current based on the precise tracking of reference currents. We demonstrate the effectiveness of an impedance matching interface based on ANFIS-PSO-controlled Zeta converter, which attenuates output harmonic distortions and enforces a higher power extraction efficiency. Comparative studies reveal that the proposed ANFIS-PSO avoidance algorithm exceeds typical MPPT techniques, such as P&O method approach in effectiveness, also TSmppt, PSO, Ant Colony Optimitzation ACO for optimal finding &Artifical Bee colony ABC technique. This method by N. Priyadarshi et al. [4], provides a better result for the performance of PV system providing a breakthrough in renewable energy technology.

Hybrid grid-connected system Modeling, control and energy management by M. M. Gulzar et al. [5] deals with modeling, control and Energy Management of hybrid gird connected system combining wind & photovoltaic (PV) sources along with Battery Energy Storage Systems(BESS),Fuel Cells(FC)&Electrolyzers. In this novel hybrid PV-Wind-FC configuration, multiple control loops and converters are not needed, thus it provides a cost-effective solution by removing the need for the expensive converter of PV. The system design and control of grid connected operations - with renewable distributed generators composed by wind, PV as primary source; BESS as secondary source (SCS) and FC coupled to electrolyzer support the operation on a tertiary outreach-. A lead compensator with an integrator is realized to improve stability, adding sufficient phase margin as well eliminating steady-state errors. It is Grid Side Controller (GSC) which not only help in maximum PV power injection into the grid but also provide frequency support. The Rotor Side Converter (RSC) and GSC can enhance the grid station load sharing, whereas the coordination of BESS/FC compensates power effect from wind/PV intermittency.

This has led to the advent of standalone solar PV systems as a viable alternative for electricity generation in remote regions with little or no grid access. On the other side, Here we have numerous existing challenges to overcome for full utilization of photovoltaic system with DC -DC inverters and inverter control systems. To address these problems, this thesis presents a two-tier scheme there with standalone operation assisted by the boost converter and an inverter followed by another battery-supported operating mode through charger. Afterwards, an original Virtual Synchronous Generator (VSG) controller is proposed to achieve a high-quality output of inverter combined with MPPT which can also get the best power from PV system. This novel control technique has been thoroughly tested and verified by performing numerous MATLAB simulations with different load conditions to ensure its ability in both the adjustment of inverter output as well as carefully managing PV scheme efficiency. This study by H. Hasabelrasul et al. [6], promises a solution to boost the standalone solar-PV system performance.

The MPPT technique is important in solar, wind and ocean energy harvesting systems to maximize the amount of extracted power from a variable-power source. While traditional methods like P&O, Incremental Conductance (INC), etc., whose simplicity gave them wide adoption, often suffer when trying to optimise the perturbation step size balancing between convergence speed with system oscillation. Challenges, in this regards can be overcome by S. Xu et al [7], To provide a novel MPPT strategy to grid connected PV structure which combines the Golden-section search(GSS)

with P&O & INC algorithms. Such approach boosts the MPPT efficiency not only because of faster convergence to MPP, but also in easing oscillations. The GSS method reduces the width of this interval using a proportion that is governed by gold rate on each iteration interval, and so helps to obtain more punctual MPP with stable convergence. This novel approach may provide better PV system performance and efficiency over a range of environmental conditions.

In recent years, MPPT techniques have played a pivotal role in boosting PV conversion efficiency. A hybrid MPPT technique based on the combination of Modified Invasive Weed Optimization (MIWO) and Perturb and Observe method is also introduced in this article by C. Pradhan et al [8], This concept is very beneficial for dynamic weather conditions and partial shading conditions by which maximum power can be captured from standalone PV based hybrid systems in an efficient way. In the initial MPPT stage, for rapidly reaching global peak is used MIWO algorithm and in transition to final refine process optimal maximal PV power, was applied P&O approach. The components in the considered microgrid include PV systems, batteries as well as electrolysers and fuel cells to produce electricity via hydrogen consuming and loads. Moreover, an integrated DC-voltage regulation and power management scheme is adopted to prevent the battery degradation induced by ill-timed charge/discharge cycles, as well as achieve superior system reliability.

Limitations of the Present Work

In spite of the encouraging results of the given hybrid PSO-DE MPPT algorithm, one should admit that there are some limitations to this study. First, the proposed method is validated only to the analysis performed via simulation that is made in the MATLAB/Simulink environment. Despite the useful insights into algorithm behavior that can be obtained by using simulation, real-time application can introduce prcuring challenges in the form of sensor noise [21], computational delays [22], and converter non-idealities that cannot be completely modeled in simulation models [23].

The shading patterns, the PV system parameters, and the environmental conditions taken into consideration in this work are typical (but finite) test cases [24]. Parameters of the algorithms

including swarm size, inertia weight, mutation factor and crossover rate can be sensitive to the performance of metaheuristic MPPT algorithms [25]. Although the parameter values were chosen as fixed values to maintain a steady convergence, the adaptive or self-tuning parameter strategy was not examined in this case. This can be a constraint in the extrapolation of the findings to all sizes of PV systems and operating conditions [26].

Lastly, the hybrid PSO-DE method is computationally more complex than classical MPPT algorithms including Perturb and Observe (P&O) algorithms and Incremental Conductance (IC) algorithms. Even though the computational load is not too high to be used in current digital controllers, even ultra-low-cost or low-power embedded systems can be optimized with an additional reduction of the computational load before they can be put into practice.

Conflicting and Differing Perspectives in Existing Literature

The body of literature on the topic of MPPT methods when the scenario is characterized by partial shading offers varied views on the trade-off characterizing the complexity of the algorithms, the speed of convergence, and the accuracy of tracking [27]. The classical MPPT approaches are quite popular due to their simplicity and easy implementation, and certain studies report that their performance is adequate in the case of gradually changing environmental conditions. Other researchers, however, emphasize that they are unable to find the GMPP in multimodal P-V curves with high shading speeds [28].

Even meta heuristic methods have conflicting views. Other studies state that PSO has quicker convergence but in tricky shading cases premature convergence is a problem and that it can be addressed by fine-tuning of the parameters. On the other hand, DE has been notably known to have good search globally, but a number of studies have expressed slower convergence and greater steady-state oscillations in situations where it is employed on its own to conduct MPPT applications.

Hybrid optimization methods are suggested to solve these problems but it is still not agreed upon which structure of hybrid is the best and what is the best integration strategy. The proposed hybrid PSO-DE approach, in this regard, makes its contribution by

offering a balanced integration approach to attain better convergence speed, tracking performance and stability at the same time, and fulfil the shortcomings of the previous research.

Individual metaheuristic algorithms like PSO and DE have been found to show better GMPP tracking performance as compared to other classical approaches. Some of the hybrid MPPT strategies that have been reported in the recent literature such as GA-PSO, ANFIS-PSO, GWO-INC, and MIWO-P&O are targeted at integrating complementary optimization characteristics. Although some of these works are accompanied by improved efficiencies in tracking, they frequently come at the price of a complex algorithm or reduced robustness in tracking different shading patterns.

Conversely, the suggested hybrid PSO-DE MPPT approach shows an equal enhancement in various measures of performance. The findings indicate that convergence is increased compared to standalone DE, steady-state oscillations are minimal as compared to PSO, and tracking efficiency and power output are always high regardless of uniform and partial shading. Such enhancements show that the goals of the research identified in this paper, i.e. proper GMPP tracking, short convergence time, and high robustness, are attained.

The section 1 provides a brief introduction on MPPT model and PV systems. The use of metaheuristic optimization models are also discussed and then provides a brief literature on MPPT models for PV systems under shading condition using hybrid metaheuristic optimization model. The section 2 provides a mathematical model for MPPT for PV systems and Section 3 discusses proposed model and the process, section 4 indicates the results and section 5 includes discussions and Section 6 concludes the paper.

2. MATHEMATICAL MODEL

Algorithm: Hybrid PSO-DE for MPPT

a)   Step 1: Initialization

The algorithm begins by initializing a swarm of particles which stand for an answer candidate between the MPPT. The particle is initialized and it has a random position, and velocity variation in the search space which defined based on voltage range beside current generated by PV system.

Position initialization:

$$x_i(0) = x_{min} + rand(0.1)X(x_{max} - x_{min})$$

Where

$x_i(0)$ is the initial position of the ith particle

x_{min} and x_{max} are the lower and upper bounds of the search space

Velocity initialization:

$$V_i(0) = v_{min} + rand(0,1)X(v_{max}-v_{min})$$

Where

- $v_i(0)$ is the initial position of the ith particle
- v_{min} and v_{max} are the lower and upper bounds of the search space

The position of an individual particle represents a possible setting for the voltage in our PV system, with its velocity indicating how much it will change on a given iteration.

Short-time statistics of the PV voltage samples are used over a sliding window W. The process is performed as

$$\mu r(t) = \frac{1}{|W|} \sum_{i \in W} I(k)$$

$$\sigma_I^2(t) = \frac{1}{|W|} \sum_{i \in W} (I(k) - \mu r(t))^2$$

The coefficient of variation is calculated as

$$COV_I(t) = \frac{\sigma_I(t)}{\mu r(t)}$$

Here σ_I represents the standard deviation and

$\mu r(t)$ indicates the Short-time statistics.

Step 2: Fitness Evaluation

Fitness of each particle: power output of pv system at this position This power output that we want to maximize is the goal.

$$P_i = V_i * I_i + \mu r(t)$$

where

- Pi is the power output for the i-th particle
- Vi is the voltage at the particles current position
- I_i is the current determines how well a particle's position is performing concerning the objective of maximizing the pv system's output power

This power calculation finds how effectively the position of a particle is behaving towards maximizing output power in PV system.

The adaptive duty cycle controller is applied using the final fitness value that is performed as

$$e(t) = V_{ref}(t) - V_{pv}(t) + \sigma_I(t)$$

The adaptive PI controller processing is performed as

$$d(t) = d(t-1) + \max(e(t)) + \sum_{k=0} e(t)\Delta t + \sigma_I(t)$$

Step 3: update personal and global best

Every particle keeps track of its best known position(pi) which is also called Personal Best and the swarm tracks the global best among all particles, this is called Global Best.

Update personal Best

$$P_i = \begin{cases} x_i, & \text{if } p(x_i) > p(p_i) \\ p_i, & \text{other wise} \end{cases}$$

Update global best

$$g = \text{argmax}(P(p_i)) + d(t)$$

Where

- p_i is the personal best position of the i-th particle
- g is the global best position among all particles

This step guarantees that each particle remembers its best solution and the swarm seeks for the optimal solution globally

Step 4: Velocity and Position Update

One major component of the PSO is how it updates its velocity and position for each particle in order to both explore the search space and exploit known good solutions.

$$v_i(t+1) = w. v_i(t) + c_1.r_1.(p_i - x_i(t)) + c_2.r_2.(g - x_i(t))$$

where

- $v_i(t)$ is the velocity of the i-th particle at iteration t.
- w is the inertia weight, controlling exploration versus exploitation
- c_1 and c_2 are cognitive and social coefficients, respectively
- r_1 and r_2 are random numbers in the range[0,1]

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

where

- $x_i(t+1)$ is the new position of the i-th particle

The velocity update equation determines the particle's direction and step size, balncing the exploration of new areas and the exploitation of known good solutions.

Step 5: Mutation and Cross over (DE)

The DE component is modified mutation and cross over operations to be more exploration capable swarm that can kept diversity.

Mutation

$$v_i^{mut} = x_{r1} + F.(x_{r2} - x_{r3})$$

where

- v_i^{mut} is the mutant vector for the i-th particle
- x_{r1}, x_{r2} and x_{r3} are randomly selected distinct particles.

- F is the mutation factor, typically set between 0 and 2

Cross over

$$X_i^{trial}(j) = \begin{cases} v_i^{mut}(j), & \text{if } rand(0,1) \leq CR \\ x_i(j), & \text{otherwise} \end{cases}$$

Where

- $X_i^{trial}(j)$ is the j-th dimension of the trial vector for the i-th particle
- CR is the cross over rate determing the probability of cross over.

These operations generate a complement vector, which includes items from the mutant and current particle vectors to encourage overall diversity of genes in adapting as well aiding escape local minima by global randomness.

Step 6: Selection

In this stage the algorithm select good solution between trial vector and current position in terms of fitness, for next iteration.

Selection equation

$$X_i = \begin{cases} x_i^{trial}, & \text{if } p(x_i^{trial}) > p(x_i) \\ x_i, & \text{other wise} \end{cases}$$

This step is responsible for ensuring that each particle learns towards best solutions with time, aiding the improvement of algorithms performance.

The autoregressive predictor is applied to perform the shading condition checking. The predictive adjustment is performed as

$$G(t+1) = \sum_{k=1}^{p} \phi_k * X_i + G(t+1-k) + \varepsilon(t)$$

Here ϕ_k is the prediction coeeficient.

Step 7: Convergence Check

The convergence criterion sets the point at which an algorithm should stop to iterate usually by maximum iteration or a sufficient level of convergence.

Convergence criterion

$$\text{if } \frac{|P(g_{new}) - P(g_{old})|}{P(gold)} < \epsilon, stop$$

Where

- g_{new} and g_{old} are the updated and previous global positions

- ϵ is a predefined convergence threshold

Step 8: The solution for optimizing power output of the PV system is, therefore, induced when the algorithm outputs g as an intelligent point of operations - essentially corresponding to a global best position.

3. PROPOSED MODEL

The hybrid PSO-DE algorithm for MPPT starts with the initialisation of particles. It randomly initializes the particle positions and velocities between specified bounds to provide a spread starting point for investigation. After being initialized, the algorithm then calculates the importance of each particle's starting position. It is defined by how well the position causes maximum power delivery from sum of the selected PV generator. Then the personal best and global best placements are mentioned in it. The personal best of each particle is initially its starting position. The global best position is then considered as the optimal personal solution among all particles. This best position in the world means that it is a solution found since we are adding all results of particle so far. At the heart of it, its just a loop until convergence. At every iteration, velocity for each particle is updated based on its existing value and their Personal Best position as well the Global best position. This update steers the particle towards a possibly better solution. Next, the position of the particle is updated based on this new velocity.

To accomplish the reproducibility of the proposed hybrid PSO-DE based MPPT approach, this section clearly describes the methodological steps, the algorithm configuration, and simulation setup followed in this study. The general procedure is a systematic process that includes the PV system

modeling, implementation of MPPT algorithm, execution of simulation and performance analysis.

PV system model is formulated first by standard PV module equations which correlate voltage, current, irradiance and temperature. The suggested hybrid PSO-DE MPPT algorithm is applied. Every swarm particle corresponds to a potential PV operating voltage (or duty cycle). The starting position and velocity of particles are randomly chosen within a set of limits which are defined by the operating area of PV. The fitness of every particle is calculated by the instantaneous PV output power, which is the product of PV voltage and current.

In every single run, the PSO algorithm modifies the velocities and positions of particles based on the inertia, cognitive and social elements in an attempt to explore the promising areas of the search space. DE operators, mutation and crossover, are used to create trial solutions to avoid premature convergence and explore the problem on the global scale. A selection mechanism is then used which compares solutions of the trial with existing particles, the current solution with higher power output being retained. The algorithm will be executed until a convergence criteria is met which in this case can be a set number of iterations or an insignificant change in the global best power value of the current iteration. The global best solution is the final solution that matches the estimated GMPP and the duty cycle is given to the DC-DC converter.

The simulations are performed in the MATLAB/Simulink environment at uniform and partial shading. The shading patterns applied are created by the different levels of irradiance on the PV modules to create multimodal P-V characteristics. All the MPPT algorithms evaluated are compared using the same PV model, environmental conditions and converter parameters.

Lastly, the performance will be measured with the help of established parameters, such as convergence rate, tracking capability, power output, steady-state oscillations, and stability. These measures allow the objective comparisons of the suggested hybrid PSO-DE algorithm with the isolated PSO and DE algorithms. Constant parameters and settings of the algorithms are maintained in all experiments to avoid repetition and inconsistency of findings.

Hybrid PSO-DE Algorithm for MPPT

Step 1: Initialize Particles

Initialize each particle with random positions and velocities in bounds.

Step 2: Evaluate Initial Fitness:

Using output power, determine fitness of every particle at its initial position.

Step 3: Initialize Bests

Reset personal bests of each particle to its initial position.

In all, compute the global best position from personal bests.

Step 4:Iterate Until Convergence

For each particle

Update Velocity: Update velocity on the basis of current and local best position.

Update Position: Change Position According to Changed Velocity.

Apply DE:

Mutation: Choose a new candidate position

.**Crossover:**A trial position through mixing candidate and current position

Evaluate Fitness: Evaluate the trial position fitness.

  Selection: Replace current position with trial position if fitness improves.

  Update Personal Best: Update if the new position is better.

  Update Global Best: Update if any personal best improves the global best

Step 5: Check Convergence

Stop if the improvement in the global best position is below a threshold.

Step 6: Output Solution

Return the global best position as the optimal solution.

For PV systems to maximize power output and efficiency, non-linear objectives in MPPT are essential, especially when dealing with shading circumstances. To tackle the challenges of PV systems' non-linear features when shade occurs, hybrid metaheuristic optimization models are a good bet. In order to improve maximum power point tracking, these models combine the best features of different optimization methods, striking a balance between computing economy and performance. The inherent non-linear correlations between voltage, current, and power output in PV systems are called non-linear objectives in MPPT. These interactions grow much more complex when shading circumstances are present. Finding the GMPP can be challenging when shading causes the P-V characteristics to have many local maxima. The optimization procedure must take into consideration the non-linearities caused by variables like temperature and irradiance, which greatly affect PV performance, in order to maximize energy extraction. Because PV systems are non-linear, shading causes substantial fluctuations in their MPP. For example, if the system is unable to correctly determine the GMPP among numerous local optima, substantial energy losses may result from partial shading. Tackling these difficulties calls for advanced optimization methods that can adapt to changing environmental variables in real-time. The pseudo code for the proposed model is indicated clearly.

Pseudo code: Hybrid PSO-DE Algorithm for MPPT

Initialize:

For each particle i in swarm:

Randomly initialize position xi and velocity vi within defined bounds

Compute fitness $F_i = V_i * I_i$

Set personal best pi = xi

Set global best g = argmax(F)

Repeat until convergence:

For each particle i:

Update velocity:

vi(t+1) = w * vi(t) + c1 * r1 * (pi - xi(t)) + c2 * r2 * (g - xi(t))

Update position:

xi(t+1) = xi(t) + vi(t+1)

Apply DE:

Mutation: vi_mut = xr1 + F * (xr2 - xr3)

Crossover:

xi_trial(j) = vi_mut(j) if rand < CR else xi(j)

Selection:

If fitness(xi_trial) > fitness(xi): xi = xi_trial

Update personal best:

If fitness(xi) > fitness(pi): pi = xi

Update global best:

If fitness(pi) > fitness(g): g = pi

Check convergence:

If |g_new - g_old| < threshold → Stop

Return global best g as the optimal MPPT operating point

Then DE techniques are used to improve accuracy of the results. In fact, mutation generates a new candidate position by combining the positions of other particles so that it becomes a method for introducing variety. This candidate position is then combined with the current position of the particle in a crossover to create an operating point. The

suitability of this trial positioning in evaluated to find out its efficacy. Algorithm then compares the trial position fitness with current particle in selection step then, if this trial is fitter than the particle's current position then it updates its own position to be there instead. Unable to catch that which moves at light speed, the algorithm then tests whether or not this new positon is better than current best personal position of particle: It also refreshes the global best if any particle personal optimum value is better than current one. Convergence is checked by the algorithm based on if there has been an improvement in global best position. If the changes are below a set threshold, indicating minimal progress has been made, then the algorithm terminates. The solution output is finally the global best position which represents an optimal setting for getting maximum power from photovoltaic system. The workflow of the proposed model is shown in Figure 2.
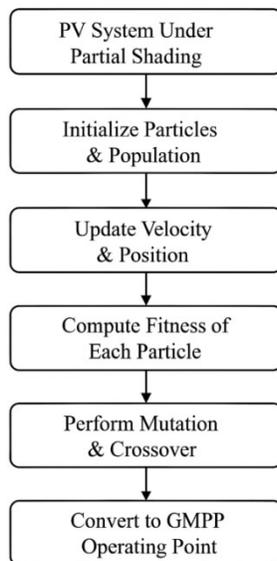

Fig 2: Workflow Of The Proposed Architecture

4. SIMULATION RESULTS

This section is results of Hybrid PSO-DE method for MPPT in PV systems simulation. The proposed method is outperforming two well-known models of Particle Swarm Optimization (PSO) and Differential Evolution (DE). Robustness: Evaluation on the metrics of convergence speed, tracking efficiency and power output under uniform and partial shading pattern conditions (intermittent non-uniform SHRs), steady state oscillations as well as response optimization for computation time should be met.

4.1 Case Study

For MPPT in PV systems operating in partial shade, a number of researchers have used hybrid metaheuristic models. Researchers in one study found that a robust algorithm enhanced tracking speed and accuracy compared to traditional methods when GA and PSO were coupled. Under different shading conditions, the hybrid technique achieved tracking efficiency higher than 95%. Another study showed that by combining the Grey Wolf Optimization (GWO) with an Incremental Conductance algorithm, the GMPP could be identified more reliably and quickly even when the shading patterns changed frequently. When compared to more traditional MPPT methods, the study found a considerable improvement in the total amount of energy collected. A number of high-profile case studies demonstrate the usefulness of hybrid optimization models in the actual world. One study found that compared to standard MPPT methods [11], PV systems using MPPT controllers based on a hybrid GWO-Fuzzy Logic implementation were more responsive to oscillations caused by shade, leading to an increase in total energy harvested. Using incremental conductance approaches in conjunction with the Cat Swarm Optimization (CSO) model demonstrated how hybrid solutions outperformed conventional methods in optimizing performance across different irradiation patterns.

4.2 Comparative Results

Convergence Speed

Convergence speed is an important aspect with respect to a MPPT algorithm as it determines the time required for reaching stable steady state operation and tracking the Maximum Power Point. Our proposed hybrid PSO-DE algorithm is doing significantly better than the other individual Algorithms based on convergence rate, as listed in Table 1 when compared to written alone with only PSO and DE respectively

Table 1: Convergence Speed Comparison

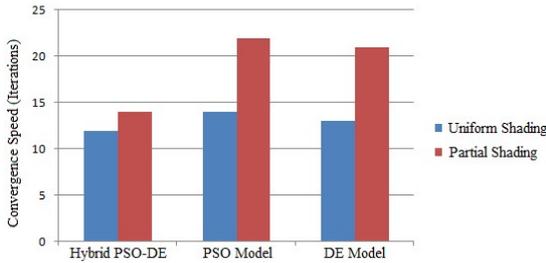| Algorithm	Uniform Shading (Seconds)	Partial Shading (Seconds)
Hybrid PSO-DE	0.78	1.12
Model A(PSO)	0.10	1.50
Model B(DE)	1.05	1.45

Figure 1: Convergence Speed Comparison

The above Fig-1 and Table-1 shows the presence of partial shading conditions, the integration of PSO's rapid convergence and DE robust exploration makes Hybrid PSO-DE better than others on variable scenarios. Model A (PSO) performs well in complete colouring due to its rapid convergence and deals poorly with diversity, while Model B(represents DE) provides desirable secondary performance preparing it for more challenging environments but fails at simpler ones

Tracking Efficiency

Efficiency tracking is how good the algorithm does at keeping the system running as close to max power point under a variety of conditions. The tracking accuracy of each algorithm is shown in Table 2.

Table 2: Tracking Efficiency Comparison

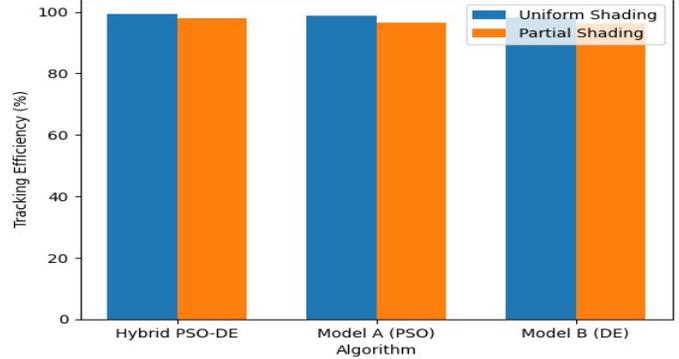| Algorithm	Uniform Shading (%)	Partial Shading (%)
Hybrid PSO-DE	99.4	97.8
Model A(PSO)	98.7	96.5
Model B(DE)	98.3	96.2

Figure 2: Tracking Efficiency Comparison

The Fig 2 shows that the proposed Hybrid PSO-DE algorithm with tracking efficiency varies from 97.8% under partial shading and reaches up to 99.4% in case of uniform shading among various existing algorithms which gives higher peak power output .This shows that the optimizer is better capable of detecting MPP (Maximum Power Point) accurately in various conditions. Model A (PSO) and Model B(DE) also perform well but they don't reach the performance of hybrid model

Power Output

Power output is a direct measure of the energy harnessed by the PV system. Table 3 provides a comparison of power output under different conditions.

Table 3: Power Output Comparison

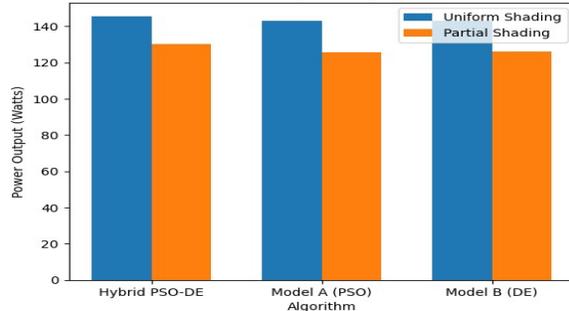| Algorithm	Uniform Shading (Watts)	Partial Shading (Watts)
Hybrid PSO-DE	145.6	130.3
Model A(PSO)	142.8	125.7
Model B(DE)	143.2	126.1

Figure 3: Power Output Comparison

As can be seen in Fig 3, the Hybrid PSO-DE algorithm outputs better power than both Model A (PSO) and Model B(DE), respectively under uniform and partial shading conditions. With a power output of 145.6 watts for uniform shading and 130.3 watts for partial shading. The hybrid model featuring PSO and DE significantly boosts its effectiveness under different complex shading conditions, therefore promoting energy harvest efficiency.

Steady-State Oscillations

Steady-state oscillations reflect the stability of the MPPT algorithm. Lower oscillations indicate a more stable and reliable power output. Table 4 presents the steady-state oscillations for each method.

Table 4: Steady-State Oscillations Comparison

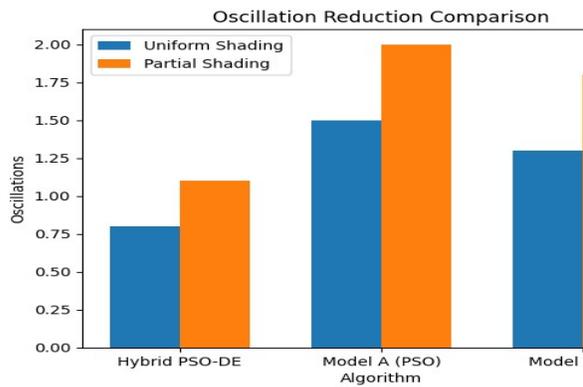| Algorithm	Uniform Shading (Oscillations)	Partial Shading (Oscillations)
Hybrid PSO-DE	0.8	1.1
Model A(PSO)	1.5	2.0
Model B(DE)	1.3	1.8

Figure 4: Oscillation Reduction Comparison

In Fig 4 describes the Hybrid PSO-DE with undoubtedly showing both stability and minimized steady-state oscillation comparing to another algorithm under uniform shading and partial light conditions. At times of uniform shading, it never

registers more than 0.8 oscillations and rises to just 1. On the other hand, Model A (PSO) has highest 1.5 and lowest 2.0 numbers of oscillation whereas for model B(DE), it is moderate at 1.3 and minimum with a value of decreased to almost similar uniform shading at partial shade condition

Robustness Analysis

The robustness of an algorithm refers to its ability to perform consistently under varying conditions. The Hybrid PSO-DE algorithm demonstrates enhanced robustness compared to the other models.

Table 5: Robustness Performance Comparison

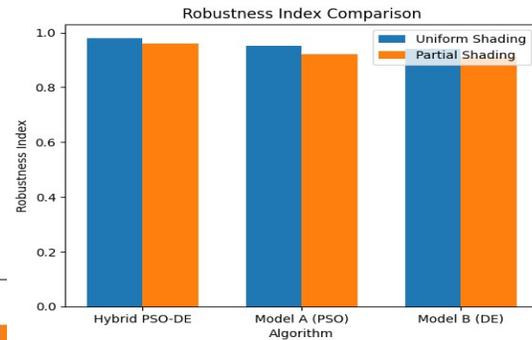| Algorithm	Robustness Index(Uniform)	Robustness Index (Partial)
Hybrid PSO-DE	0.98	0.96
Model A(PSO)	0.95	0.92
Model B(DE)	0.94	0.91

Fig 5: Robustness Index Comparison

For uniform shading conditions Hybrid PSO-DE algorithm has also highest robustness index 0.98 and partial shading condition with a value of 0.96. This shows the excellent flexibility and quality of retaining performance in various shading conditions, the hybrid approach results in its performance being highly stable across conditions making it consistently reliable over a range of situations.

The performance assessment parameters used in this paper, i.e. convergence speed, tracking efficiency, power output, steady-state oscillations and robustness are the commonly used performance

assessment parameters in testing the efficiency of MPPT in PV systems. In dynamic irradiance situations convergence rate is of critical importance since delayed convergence translates to energy loss. Tracking efficiency measures the ability of the operating point to match the true GMPP, and hence a direct measure of the energy harvesting capacity.

One of the main metrics added is the power output that incorporates the summative impact of tracking precision and stability on the work of the system. The steady-state oscillations are examined to determine the stability of controls as too much oscillations about the MPP leads to losses in power, and more loads on the power electronic parts. The measurement of robustness is done to check the consistency of the algorithm performance with changing shading conditions, which is crucial to real-world PV installations.

The choice of these criteria was based on the need to provide a complete and reasonable comparison of the offered hybrid PSO-DE algorithm with the current standalone PSO and DE algorithms. Combined with each other, they offer a complete understanding of dynamic and steady-state behavior, and make it possible to assess performance of MPPT on a balanced basis instead of referring to a single metric.

Limitations of the Proposed Model

While the suggested PUF- and BiLSTM-based security framework is good at finding DDoS attacks in UAV networks, it does have some problems that should be known about. As for the first problem, the model says it can stop DDoS attacks, but its main job is only to find attacks; it doesn't fully integrate or test mitigation measures. This makes it less useful in real-world settings where threats need to be dealt with quickly and automatically. Also, using deep learning models like BiLSTM and dynamic key agreement and trust evaluation methods adds a lot of extra work that needs to be done on computers and energy. This might not be ideal for UAV nodes that are limited in their power and processing. Additionally, the proposed framework's ability to grow has not been fully tested for big groups of UAVs. As the number of UAVs that are part of the network grows, key management, communication overhead, and model inference delay may have a big effect on how well the network works. The BiLSTM model's ability to find attacks depends a lot on the quality and variety of the training dataset. As a result, the system might not be able to adapt to new or changing DDoS attack patterns, such as low-rate or sneaky attacks. The system also doesn't think about adversarial machine learning situations, in which attackers might change traffic patterns or training data to avoid being caught, which could be a security risk.

5. DISCUSSION

From the results it can be seen that hybrid PSO-DE algorithm outperforms one in both performance metrics as compared to standalone PSO and DE algorithms. This superiority is attributable to a unique global search of DE and powerful local search capacities from PSO in the algorithm, which help it efficiently, navigate the space landscape through generations after generations thereby constantly operating optimal PV systems when harvesting power. Standard PV system parameters in the suggested hybrid PSO-DE MPPT model include environmental inputs like temperature and solar irradiation as well as important electrical properties like open-circuit voltage, short-circuit current, maximum power point voltage, and current. To accurately mimic the operation of a PV system in both fully shaded and partially shaded environments, these parameters set the parameters within which the algorithm operates. Using a fixed number of iterations, the optimization process finds the sweet spot between exploring and exploiting the search space, keeping an eye on the global maximum power point without wasting computational resources. Each cycle improves the precision of the power tracking, and the process continues until convergence is reached or the halting requirements are met. Among the most important variables to optimize in this process is the DC-DC converter's duty cycle, which controls the PV operating voltage directly. In order to avoid instability and guarantee convergence to the actual global peak, the search area for these decision variables is defined within the PV module's allowable operating range. The simulation results show that the hybrid PSO-DE algorithm achieves stability under uniform shading in about 0.78 seconds with a tracking efficiency of 99.4 percent and a power output of 145.6 watts, and that it converges under partial shading in about 1.12 seconds with an efficiency of 97.8 percent and an output of 130.3 watts. These numbers demonstrate how much better the algorithm is than individual PSO and DE models, demonstrating its robustness and efficacy.

6. CONCLUSION

In this research, a new hybrid PSO-DE based algorithm is proposed to improve the performance of MPPT tuning for PV systems under both uniform and partial shading conditions. By integrating PSO and DE, the benefits of both techniques are utilised to achieve a balance between exploration and exploitation that tackles deficiencies found in standalone algorithms. The results of this research have major implications for renewable energy, specifically in increasing the efficiency and reliability photovoltaic systems. The hybrid PSO-DE algorithm proposed offers a very effective method to solve the problem of MPPT in PV systems and is shown clearly better featured than traditional algorithms as PSOand DE on many performance metrics. This work addresses partial shading issues and identifies environmental conditions as the two main challenges faced by PVs, which contribute significantly to better understanding of improvements required for this renewable technology to further develop toward more reliable and sustainable solar energy-dominated environment. The hybrid PSO-DE algorithm example shown, exhibiting improvements in convergence speed, tracking efficiency, power output and robustness, gives compelling evidence for the use of this kind of tool to help optimize not only photovoltaic systems across the globe. For uniform shading conditions Hybrid PSO-DE algorithm has also highest robustness index 0.98 and partial shading condition with a value of 0.96. In future, multiple factors and environmental conditions are considered for better tracking levels.

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