Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 45 No. 7
July 2024

Plithogenic Neutrosophic Fuzzy Logic: Revolutionizing Solar PV with Bio-Inspired Cheetah Hunting Strategies for MPP Efficiency.

Igno Mary [1], S. Sandhiya [2*]
[1*]Assistant Professor, Department of Mathematics,
Dhanalakshmi Srinivasan University, Trichy..India
[2]Assistant Professor, Department of Mathematics,
[2]Vels Institute of Science, Technology and Advanced Studies,
Chennai, Tamilnadu

Abstract: This study investigates the performance of PV central and string arrays under uniform and partial shading conditions using a plithogenic Neutrosophic-based cheetah fuzzy logic algorithm for Maximum Power Point (MPP) optimization. The proposed cheetah-MPP techniques draw inspiration from the strategic and efficient hunting characteristics of cheetahs, employing rapid convergence, adaptability, and precision in tracking the MPP for solar PV systems. Through real-time experimental data and simulation analysis in MATLAB/Simulink, the cheetah algorithm demonstrated superior performance, achieving a maximum power tracking of 1450W with a tracking efficiency of 98.5% under uniform irradiance conditions. It also showed faster convergence and more effective power tracking under partial shading compared to traditional methods. By incorporating plithogenic Neutrosophic fuzzy-based multi-criteria decision-making (MCDM) techniques, the algorithm adeptly handles uncertainties and variabilities in solar irradiance and shading conditions, ensuring optimal PV system performance. This research opens new avenues for optimizing solar PV power generation, inspired by the adaptive and strategic hunting strategies of cheetahs.

Highlights of the work:

- **Innovative Algorithm**: Introduced a plithogenic Neutrosophic-based cheetah fuzzy logic algorithm inspired by cheetah hunting strategies for optimizing Maximum Power Point (MPP) in solar PV systems.
- **Superior Performance**: Achieved high tracking efficiency of 98.5% under uniform irradiance conditions and demonstrated faster convergence and effective power tracking under partial shading conditions compared to traditional methods.
- **Comprehensive Analysis**: Conducted both real-time experimental data collection and simulation analysis using MATLAB/Simulink to validate the algorithm's performance.
- **Handling Uncertainties**: Effectively managed variabilities and uncertainties in solar irradiance and shading conditions using plithogenic Neutrosophic fuzzy-based multi-criteria decision-making (MCDM) techniques.
- **Future Research Directions**: Opened new avenues for further exploration and optimization of solar PV power generation, encouraging future studies to enhance MPP extraction under varying environmental conditions.

Keywords: Plithogenic Neutrosophic Fuzzy Logic, Maximum Power Point (MPP) Optimization, Partial Shading Conditions, Solar PV Systems, Adaptive Hunting Strategies.

Introduction

India's journey towards renewable energy has been remarkable, driven by ambitious goals and innovative strategies[1]. As one of the world's fastest-growing economies, India faces the dual challenge of meeting its growing energy demands while mitigating environmental impact. In response, the nation has made significant strides in harnessing renewable sources, with solar power emerging as a linchpin in this transformative shift[2]. Solar power generation occupies a central role in India's renewable energy landscape, capitalizing on the country's abundant solar resources and leveraging technological advancements. The Indian government's ambitious targets, exemplified by initiatives like the Jawaharlal Nehru National Solar Mission, have propelled the rapid expansion of solar infrastructure across the nation. This concerted effort has led to substantial growth in solar capacity, with India becoming one of the world's largest solar energy markets[3]. The benefits of solar power in India extend far beyond environmental stewardship. By reducing dependence on fossil fuels, solar energy enhances energy security while mitigating the risks associated with volatile global energy markets[4]. Moreover, decentralized solar installations empower communities, particularly in rural areas, by providing access to clean and reliable electricity, thus driving socioeconomic development. Despite these successes, challenges remain, including intermittency issues and the need for robust grid integration infrastructure[5]. Nonetheless, with ongoing investments in research, development, and policy frameworks, India is poised to further capitalize on its solar potential, paving the way towards a more sustainable and resilient energy future[6].

Efficiently harnessing solar energy through solar panels involves a delicate interplay of science, technology, and optimization[7]. As the demand for renewable energy solutions escalates, maximizing the output of solar photovoltaic systems has become paramount[8]. In this pursuit, a suite of algorithms has emerged as indispensable tools, offering innovative approaches to enhance the performance and efficiency of solar panel installations. From real-time monitoring to predictive analytics, these algorithms serve as catalysts for unlocking the full potential of solar power[9]. In this introductory exploration, we delve into a curated list of algorithms driving the optimization of solar panel energy generation, illuminating their key principles, applications, and impact on shaping the future of sustainable energy[10], [11].

Achieving maximum power output from Solar-PV systems under Partial Shading Conditions (PSC) is a complex endeavor, prompting the exploration of various optimization techniques[12], [13]. Traditional methods such as Perturb and Observe (P&O) and Incremental Conductance have long been employed but struggle with accurately identifying global and local peak outputs. To address this, researchers have turned to integrating fuzzy logic (FL) with artificial neural networks (ANN), which has shown promise in improving system performance[14], [15]. However, the complexity associated with traditional Maximum Power Point (MPP) techniques has led to a shift towards Swarm Intelligence (SI) approaches. While Particle Swarm Optimization (PSO) has been utilized, concerns persist regarding its convergence rate and local search capabilities[16], [17], [18]. Recent efforts have focused on combining simulated annealing with innovative algorithms like Flower Pollination Algorithm (FPA) to enhance tracking optimization and convergence rates. Additionally, methods such as Grey Wolf Optimization (GWO) and Grouped Beetle Antennae Search (GBAS) have emerged as viable options for determining Solar-PV array structures. Hybrid approaches like Genetic Algorithm (GA)-FPA have also gained traction, emphasizing the importance of accurate modeling and steady-state operation for optimal power harvest[19], [20]. Recent studies emphasize the importance of convergence time, accuracy, and efficiency in tracking PV panels. Emerging algorithms like the plithogenic-based cheetah algorithm demonstrate greater efficiency compared to traditional methods, showing potential for both central and string architectures of PV panels.

When compared to other methods of reconfiguration, the research proposed in this study requires fewer switching networks[21]. The approach integrates each module with its plithogenic-based cheetah algorithm into the MPPT controller, resulting in higher power output compared to conventional PV string and central converter systems. In the same manner as a cheetah efficiently picks its prey while in pursuit, the plithogenic-based cheetah algorithm effectively selects the Maximum Power Point Tracking (MPPT) from solar panels by resolving Multi-Criteria Decision Making (MCDM) based on various criteria[22], [23]. This algorithm operates under the Vikor method, determining the best alternative and ranking conditions accordingly. As a result, the algorithm ensures that the maximum power is extracted from the solar panel. The research involves detailed modeling and simulations of PV array layouts under various Partial Shading Conditions (PSCs)[24], [25]. Performance evaluation of all PV array configurations is conducted, comparing numerous performance metrics. The significant contribution of this research lies in its focus on PSCs and shading patterns. It examines a 6x6 PV array under different shading and weather conditions, including center, corner, right-side end, bottom-side, diagonal, frame, and random shading conditions, as illustrated in Fig. 1 (a&b). Table 1(a) presents the outcomes under various operating partial shading conditions.

This study incorporates and validates a novel switching method to achieve efficient utilization of both the plithogenic-based cheetah algorithms. Significantly, the switch doesn't occur until the first Flower Pollination Algorithm (FPA) exploration of the global power areas. Furthermore, for an accurate comparison, the findings of the plithogenic-based cheetah algorithms are contrasted with those of recently validated alternative optimization techniques and traditional meta-heuristics. The structure of this paper is divided into the following sections. The output power of the solar energy conversion system is enhanced by using effective shade dispersion. Real-time data obtained are validated using MATLAB/Simulink (R2019a), which is employed to model the optimization approaches. Section 2 of this study outlines the literature review. Section 3 presents the proposed architecture of solar PV panels Multi-Objective Pareto Evolution (MOPE) using different algorithms, validating the optimization strategies with objective derivatives. Section 4 describes the simulation parameter results. Finally, Section 5 provides a discussion of the conclusion for PV central string architecture.

Literature survey recent study

Uniform irradiance leads to higher outcomes, while non-uniform irradiance significantly reduces the power output of a Solar-PV array[26]. The losses due to mismatching power on PV systems depend on shading patterns, physical module locations, and PV array structures, all impacting the reduction factor of PV power output. Figure 2 illustrates PV array/string modules with both regular and irregular sub-arrays. Reconfiguration procedures are commonly utilized to mitigate the effects of partial shading conditions. The proposed research aims to develop a hybrid intelligent algorithm for solar-PV systems to enhance efficiency in power point monitoring, thereby avoiding partial shadow effects and increasing PV system output power through reconfiguration techniques. Renewable energy is being promoted worldwide due to the pollution caused by fossil fuels. Solar energy stands out as one of the most important renewable energy sources, being both inexpensive and environmentally friendly. Solar photovoltaic (PV) technology has a major advantage in converting sunlight into power without disturbance, making it highly recommended and compared favorably to other renewable energy sources.

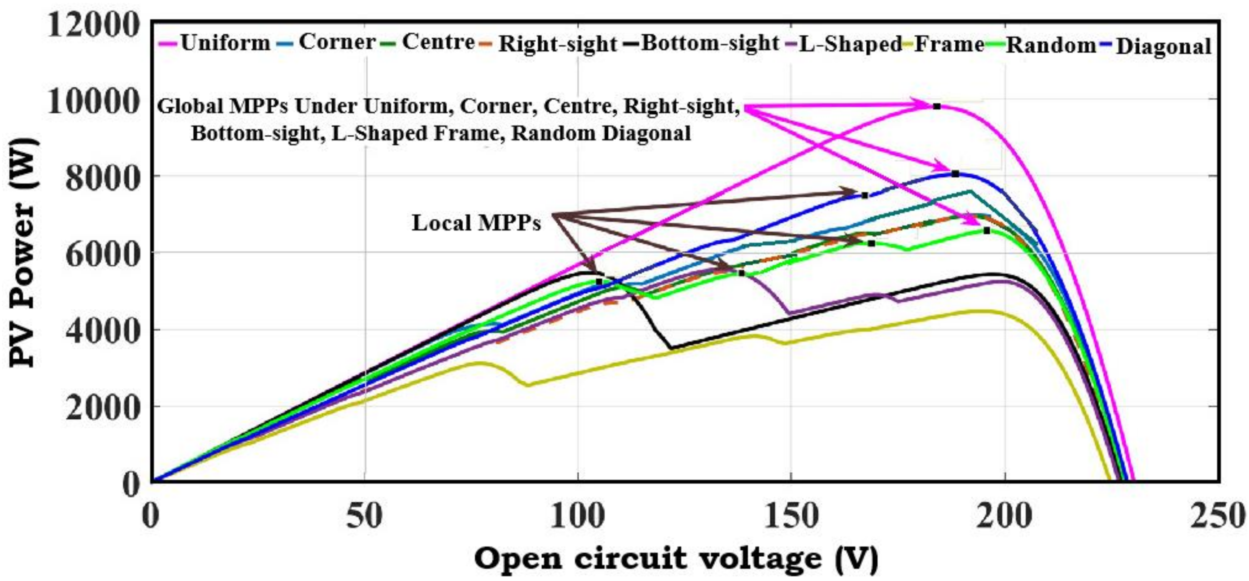

Fig.1 (b) 6*6 PV array configuration P-V characteristics curve.

Additionally, this literature review highlights a significant research gap concerning the major problem inherent in this technology, which requires the use of additional converters, MPPT controllers, and sensors. Consequently, two distinct approaches for reconfiguring DC-DC schemes, namely isolated and non-isolated, have emerged. A solar cheethah-MPP with a non-isolated switching converter is proposed as a feasible solution for various loads, alongside soft computing-based MPP techniques detailed in Table 2(b). Several non-isolated converter DC topologies have been examined with typical MPP algorithms, considering factors such as efficiency, construction, switching frequency, and losses. However, certain crucial factors such as light generation or PV current, series and diode reverse saturation current, shunt resistance, continuous diode ideality, and semiconductor energy band gap are often absent from manufacturer data sheets, complicating PV array modeling.

Multiple reconfiguration processes and strategies are explored in the recommended analysis. Static reconfiguration techniques, such as testing two-phase array configuration and unequally irradiated PV array reconfiguration methodologies for a 9X9 Total-Cross Tied PV (TCTPV) array under various Partial Shading Conditions (PSC), are presented. Modifying the physical position of modules in the TCTPV array while maintaining their electrical connections is achievable using Sudoku and advanced Sudoku patterns. Intelligent hybrid-based optimization algorithms are developed to minimize partial shading losses throughout the entire array by evenly spreading shadows. In the absence of shading, the PV array's Power-Voltage (P-V) characteristics have only one maximum power peak, whereas partial darkness causes numerous peaks. Figure 2(a) illustrates three types of solar-PV (S-PV) architectures: solar string, solar array regular, and irregular sub-array. Present PV constructions predominantly experiment with PV string type and PV array central type architecture in various applications.

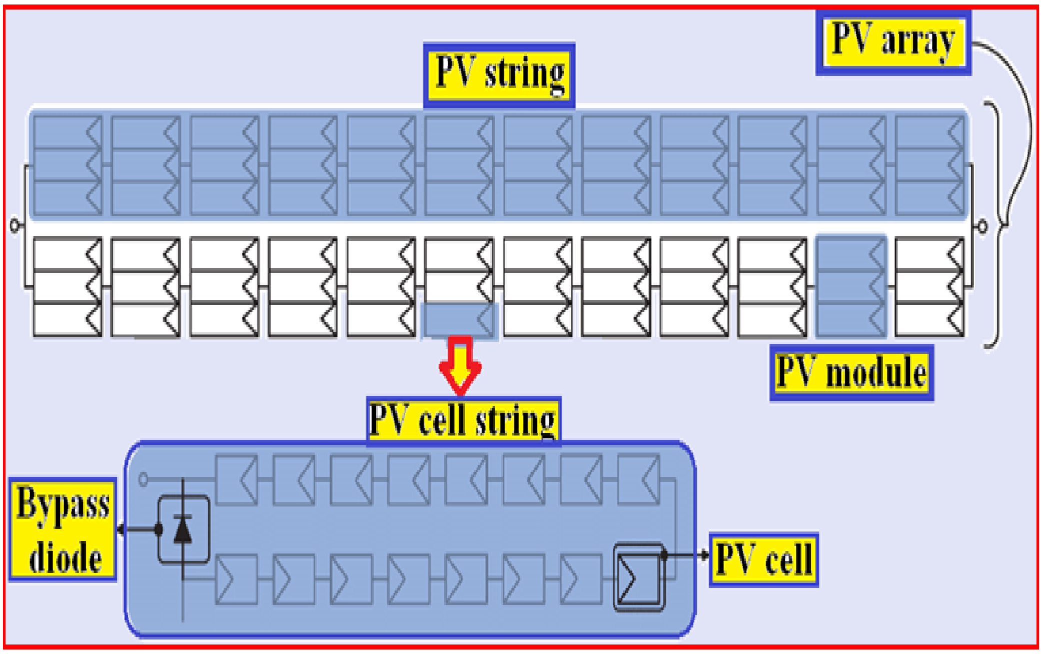

Fig.2(a) Architecture for PV string and PV array

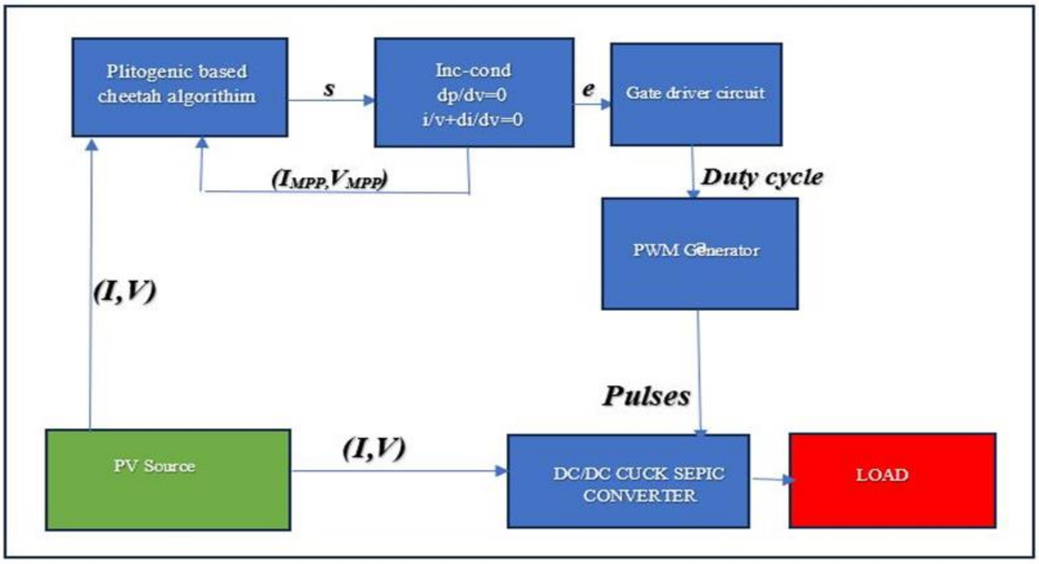

Fig.2(b) Proposed controller block diagram.

MPTT Technique	Dependency on PV Array	Sensor Type			MPP Tracking Speed	MPP Tracking Accuracy	Efficiency	Circuitry Type		Application	
		T	I	V				D	A	Grid Con-nected	Stand Alone
AI-Based SC-MPPT Techniques											
Bayesian Network	×	×	✓	✓	M	Me	H	✓	✓	✓	✓
Nonlinear Predictor	×	×	✓	✓	F	H	H	✓	✓	✓	✓
Fibonacci Search	×	×	✓	✓	F	M	M	✓	×	×	✓
Fuzzy Logic Control	✓	×	✓	✓	F	M	H	✓	×	×	✓
Artificial Neural Network	✓	✓	✓	✓	F	M	H	✓	×	×	✓
Extremum Seeking	×	×	✓		F	M	M	✓	×	×	✓
Differential Evolution	×	×	✓	✓	F	M	H	✓	×	×	✓
Soft Computing-Based MPPT Techniques											
Ant Colony Optimization	✓	✓	✓	✓	F	M	H	✓	×	×	✓
Cuckoo Search	×	×	✓		VF	H	H	✓	×	×	✓
Chaotic Search	×	×	✓	✓	F	M	M	✓	×	×	✓
Genetic Algorithm	×	×	✓	✓	F	M	H	✓	×	×	✓
Practical Swarm Optimization	×	×	✓	✓	F	M	H	✓	×	×	✓
Grasshopper	×	×	✓	✓	F	H	H	✓	×	×	✓
Memetic Salp Swarm Algorithm	×	×	✓	✓	VF	H	H	✓	×	×	✓
Dynamic Leader-based Collective Intelligence	×	×	✓	✓	VF	H	H	✓	×	×	✓
Shuffled Frog Leaping and Pattern Search	×	×	✓	✓	VF	H	H	✓	×	×	✓

T = Temperature, I = Current, V = Voltage, D = Digital, A = Analog, VF = Very Fast, F = Fast, H = High, M = Medium, L = Low.

Table.1 Comparison of MPP techniques and soft computing optimization techniques.

The recommended analysis explores multiple reconfiguration processes and strategies. Static reconfiguration techniques were employed to assess the testing of two-phase array configuration and unequal irradiated PV array reconfiguration methodologies for a 9X9 Total-Cross Tied PV (TCTPV) array under various Partial Shading Conditions (PSC). It is feasible to modify the physical position of modules in the TCTPV array while maintaining their electrical connections using Sudoku and advanced Sudoku patterns. Additionally, intelligent hybrid-based optimization algorithms are developed to minimize partial shading losses throughout the entire array by evenly spreading shadows. In the absence of shading, the PV array's Power-Voltage (P-V) characteristics exhibit only one maximum power peak, whereas partial darkness results in numerous peaks. Figure 2(b) illustrates three types of solar-PV (S-PV) architectures: solar string, solar array regular, and irregular sub-array. Currently, PV constructions predominantly experiment with PV string type and PV array central type architecture across various applications.

An intelligent approach utilizing the plithogenic-based cheetah algorithm is developed for global Maximum Power Point (MPP) tracking of a PV array under partial shade conditions[27]. This marks the first application of the plithogenic-based cheetah algorithm-MPP technique in the proposed PV string/central architecture[28]. It involves scanning a DC-DC converter's output voltage, measuring the accompanying current, calculating the output power, and then applying the plithogenic Neutrosophic-based Multi-Criteria Decision Making (MCDM) approach of fuzzy rule to estimate the MPP. This results in more effective output power for a real-time controller. This approach surpasses multiple state-of-the-art plithogenic-based cheetah-MPP algorithms in terms of tracking effectiveness, robustness, and speed. Various simulated scenarios of the plithogenic-based cheetah-MPP algorithm, validated by experimental setups, are presented, along with the closed-loop block diagram of the proposed cheetah controller as depicted in Fig 2(b). Additionally, a solar cheetah-MPP with a non-isolated switching converter is proposed as a feasible solution for various loads, alongside soft computing-based MPP techniques detailed in the literature shown in Table 1(b).

Construction of Proposed S-PV Panel

Construction of S-PV PANEL

Under a shading process, fluctuations in current from one panel to the next can lead to mismatches that complicate capturing the peak power output. PV panels often have reduced output power, making it challenging to achieve Maximum Power (MP). Various architectural approaches are examined to enhance Solar-PV panel conversion and tracking efficiency. This study focuses on central and string architectures. Specifically, between four and twenty PV solar panels are connected in series, with their output fed into a boost converter, which then supplies a DC load, as depicted in Fig.3 (a). The study tests configurations with six to twenty PV panels. In the PV string layout shown in Fig.3 (b), the PV array is divided into two strings. Each panel in a string is coupled with a DC-DC converter, enabling peak power point tracking control for each individual string. The proposed setup regulates the PV string voltage and prescribes the string current for each PV panel. Maximum Power Point (MPP) tracking is achieved between the source and load in both PV string and central configurations. Consequently, tracking efficiency in each PV string is higher compared to the central design under Partial Shading Conditions (PSC).

Fig. 4 illustrates the overall control structures for both central and string PV modules. The proposed DC converter functions intermittently within both the control and power circuits. This PV system control maintains the closed-loop system operation. By tuning the reference output voltage and input voltage with an optimization control method, the duty cycle values are adjusted based on varying irradiation conditions using the proposed optimization. The system employs four separate modules, accommodating 6 to 20 Solar-PV modules under shaded and unshaded conditions, as depicted in Fig. 5. Previously, the recommended system was implemented with an eight-module operational control output using various optimization techniques. In the proposed work, the testing has been extended to up to 20 PV array modules.

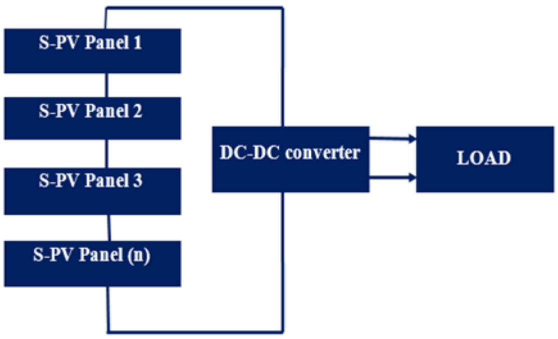

Fig.3 (a) General architecture for central

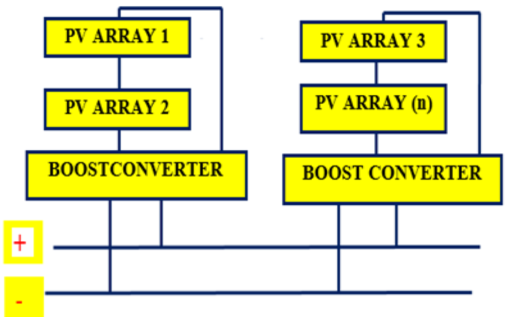

Fig.3 (b) General PV String architecture

In this proposed work, a configuration of four to twenty photovoltaic (PV) solar panels connected in series is used, with their combined output fed into a boost converter, which then supplies power to a DC load as depicted in Fig. 3(a). The study evaluates the performance of six to twenty (n) PV panels. In this setup, shown in Fig. 3(b), the PV array is divided into two strings. Each PV string has its own DC-DC converter, enabling peak power point tracking (MPPT) for each individual string. This configuration optimizes the proposed PV string voltage and prescribes the string current for each PV panel as referenced in sources. By positioning the maximum power point tracking between the source and the load in the PV string/central configuration, the tracking efficiency for each PV string surpasses that of the central design, especially under partial shading conditions.

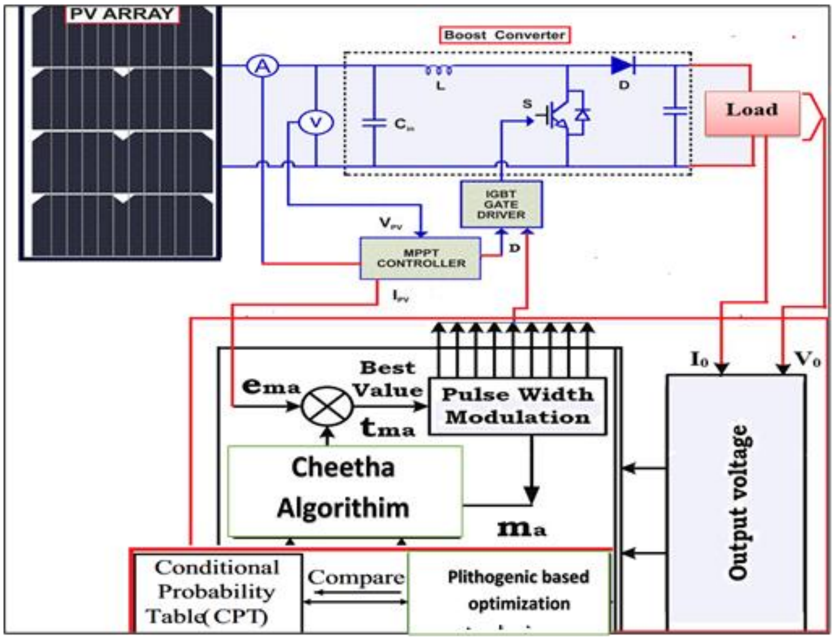

Fig.4 Overall Circuit diagram for PV array control (BFT-MPP) with FPA/GWO algorithm.

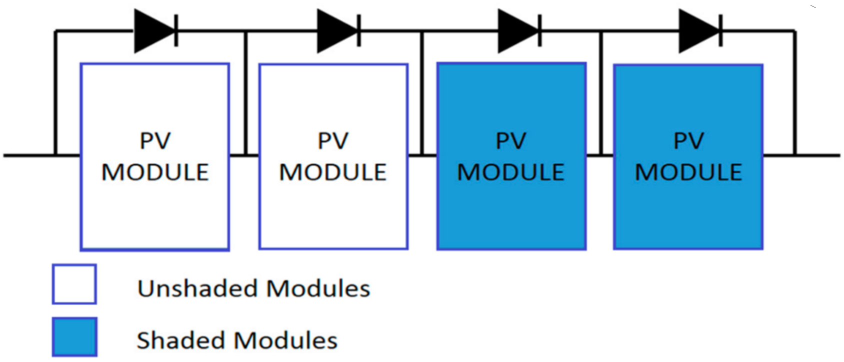

Fig.5 Proposed shaded and unshaded PV module

Figure 4 illustrates the potential overall control structures for both PV central and string array configurations (BFT-MPP) utilizing the cheetah algorithm. The proposed DC converter operates intermittently for both the control and power circuits. A closed-loop PV system control is employed, where the reference output voltage and input voltage are fine-tuned using an optimization control method. This ensures that the duty cycle values are appropriately adjusted under varying irradiation conditions. As depicted in Figure 5, the system utilizes four separate modules with 2 to 20 shaded/unshaded Solar-PV modules. Previously, the system was implemented with individual control for four or six modules using various optimization techniques. In the proposed work, the implementation extends to testing up to 20 PV array modules.

DC-DC Converter circuit Execution

Most solar PV systems utilize DC-DC converters to adjust the voltage level from the input source to the load. These converters help boost the voltage level, enabling efficient energy conversion. However, unshaded PV systems often produce lower voltage levels and exhibit instability with unpredictable output characteristics in terms of voltage-current (V-I) and voltage-power (V-P) relationships. Therefore, the Maximum Power Point (MPP) algorithm is essential for optimizing solar power tracking in both array and central PV architectures. The converter maximizes output to meet the load demand by combining MPP with different PV architectures. The primary challenge for solar PV systems is the fluctuating availability of sunlight. Various power electronic DC-DC converters are employed to address this issue and maintain a consistent output voltage to the load.

A boost converter, a type of DC-DC power converter, increases the output voltage above the input voltage of the PV system. As shown in Figure 4, this type of switch-mode power supply (SMPS) typically includes at least two semiconductor switches, such as a transistor and a diode. Additionally, energy storage devices like capacitors and inductors are used to generate maximum output. Compared to other converter circuits, conventional converters have straightforward switching strategies that are not suitable for the proposed central or string PV architectures.

Table.2 Traditional converter topology comparison

Parameters	Converter Types		
	Buck converter	Boost converter	Buck-Boost converter
V_{out} (output voltage)	V_{in}D	V_{in}1/1-D	V_{in} D/1-D
Number of Diodes	1	1	1
Number of Switches	1	1	1
Number of magnetic components	1	1	1
Efficiency	Low	Low	Moderate
Input ripple current	High	High	High

To reduce output voltage ripple, the filter act as capacitor circuit are commonly involved to the DC-DC circuit, which is produce without any harmonics of the DC power. Therefore, proposed converter comparison as shown in Table.2. A theoretical calculation of boost converter output power = Converter input power- (P_{loss}_DC-DC converter)

Converter input power = S-PV array output power = 1450W.

Therefore, Boost converter output power = (1450-40.13.) W

Hence, Efficiency of the converter estimation = (1450-40.13)/1500 = 94%

Boost converter power losses are calculate given by IGBT conduction loss, (2) IGBT Turn ON//OFF losses (3) Capacitance loss (input), (4) Capacitance loss (output), (5) Diode (D) loss, and (6) Inductor (L) loss.

- **Conduction loss**

$$Ploss_{Ron} = I_C{}^2 \times R_{on} \quad (1)$$

Where, Collector current is I_c and Ron is resistance ON condition.

- **Turn ON/OFF Loss**

$$Ploss_{trise_{tfall}} = \frac{1}{2} \cdot (trise + tfall).I_{RMS} \cdot V_{CE}.Fsw \quad (2)$$

Where, rise time (t_{rise}), fall time (t_{fall}), RMS current (I_{RMS}), Collector to emitter voltage (V_{CE}), and Switching frequency (F_{SW}).

- **Capacitance loss (Input)**

$$Ploss_{gatecharge} = \frac{1}{2}Qgtotal.V_{GE}.Fsw \quad (3)$$

Where, Q_g total is total gate charge, V_{GE} is applied gate to emitter voltage.

- **Capacitance loss (Output)**

$$Ploss_{Coes} = \frac{1}{2}Coes.V_{CE}{}^2.Fsw \quad (4)$$

Where, C_{oes} is output capacitance of the IGBT.

- **Diode (D) Loss**

$$Ploss_{diode} = I_{RMSDIODE} \times V_F \quad (5)$$

Where, RMS current through the diode($I_{RMS\ DIODE.}$) however, forward voltage of the diode (V_F).

- **Inductor (L) Loss**

$$Ploss_{inductor} = I_{RMS\_INDUCTOR}{}^2 \times R_{DC} \quad (6)$$

$$\text{Efficiency} = \frac{\text{Output Power}}{\text{Output Power} + \text{Total Losses}} \quad (7)$$

$$\text{Duty Cycle} = \frac{\text{Ton}}{\text{Ton} + \text{Toff}} \quad (8)$$

- **Boost converter losses calculation:**

I_{RMS} of IGBT = Ic of IGBT= 5A; R_{on}= 0.01Ω;trise(tr) = 68ns; tfall(tf) = 65ns; V_{CE} = 230V; Fsw = 10KHz; Q_g total-257nv;V_{GE}=15V;C_{OES}= 260pF; I_{RMS} diode value= 7A; V_F =0.7V, Inductor (I_{RMS})= 7A; R_{DC}=0.1Ω.

- $Ploss_{Ron}$ = 5^2*0.01=0.2500 W
- Ploss_trsie_tfall = 0.5*(68 x 10^{-9}+65 x 10^{-9})*(5*230)*(10 x 10^3) = 0.7647W
- Ploss_gatecharge = 0.5*257 x 10^{-9}*15*(10 x 10^3) = 0.0193W
- Ploss_Coes = 0.5*260 x 10^{-12}*230^2*(10 x 10^3) = 0.0688W
- *$Ploss_{IGBT}$ = $Ploss_{Ron}$ +Ploss_trsie_tfall+ Ploss_gatecharge+ Ploss_Coes*
  = 0.25+0.7647+0.0193+0.0688 = 1.1028W
- P_{loss}(Diode)= 7*0.7= 4.9W
- P_{loss}(Inductor)= 7^2*0.1= 4.9W
- *Ploss_converter= $Ploss_{diode}$+$Ploss_{IGBT}$+ $Ploss_{inductor}$*

Hence, the converter losses (Ploss_converter)**= 4.90+1.1028+4.90 = 10.90W.**

Plithogenic Neutrosophic based cheetah algorithm-MPP implementation

Several methods are available for tracking power in solar PV (S-PV) systems. Choosing the correct size for a PV array is the initial step toward efficient system utilization. Optimal tilting and Maximum Power Point (MPP) tracking become significant only after selecting the appropriate system size, as proper sizing minimizes initial investment. The proposed system also considers several additional factors, such as solar protection, energy conversion, source integration, and the use of MPP techniques to maximize power extraction to the load. MPP tracking is an algorithm in S-PV power converters that continuously adjusts impedance values. This adaptation occurs under varying environmental conditions, such as changes in solar irradiance and temperature, to maintain peak power or low power point output to the load. Commonly used methods include the Perturb and Observe (P&O) and Incremental Conductance (INC) techniques, which have been established practices for many years.

Plithogenic sets characterize elements by multiple attribute values, with associated relevance degrees and contradiction functions for precision[29], [30]. They generalize crisp, fuzzy, intuitionistic fuzzy, and neutrosophic sets, accommodating various degrees of membership, indeterminacy, and non-membership. Smarandache extended this notion to Neutrosophic sets, incorporating indeterminacy and lack of compatibility for handling incomplete and uncertain decision-making information[31].The theory of Neutrosophic sets, introduced by Smarandache[32], allows for the handling of "Knowledge of neural thought". Neutrosophic sets expand fuzzy logic by incorporating indeterminate membership, addressing neutral states alongside truth and falsehood. Rooted in natural language, they adapt to imprecise data, offering an alternative for decision-making in uncertain environments where traditional fuzzy sets are insufficient. Plithogenic sets characterize elements by all attribute values individually.Neutrosophic sets demonstrate strength and effectiveness in addressing challenges posed by inadequate information, uncertainty, ambiguity, and inaccuracy[33].

Cheetahs algorithm:

Cheetahs are remarkably efficient predators, employing a combination of keen senses, strategic planning, and physical prowess to choose and hunt their prey. When selecting prey, cheetahs consider their hunger level, preferring to hunt when they are sufficiently motivated but not overly exhausted. They also assess prey availability, often targeting areas with a high density of potential targets such as gazelles, impalas, and other small to medium-sized ungulates. The cheetah's acute vision allows it to spot vulnerable individuals within a herd, such as the young, old, or injured, increasing the likelihood of a successful hunt. By using stealth to get as close as possible to the selected prey, cheetahs minimize the energy expenditure required for the high-speed chase that follows. Once within striking distance, the cheetah relies on its incredible acceleration and top speed to quickly close the gap, aiming to knock the prey off balance with a powerful paw swipe before delivering a suffocating bite to the throat. This combination of careful prey selection and precise, energy-efficient hunting tactics ensures that cheetahs maximize their hunting success while conserving vital energy[34].

Unlike a cheetah that relies on instinct and physical prowess, this bio-inspired algorithm—based on a plitogenic Neutrosophic fuzzy multi-criteria decision-making (MCDM) technique—offers robust decision-making capabilities for complex problems. Specifically, it optimizes energy management for solar panel systems by evaluating various alternatives and criteria. The algorithm first assesses whether the maximum power is being generated during peak times. It then examines the impact of external weather conditions, such as rain or partial shading, and the orientation of the panels. By considering these factors, the algorithm dynamically adjusts to generate the maximum possible power for the grid, battery, and load. This method ensures efficient energy management by continuously adapting to changing environmental conditions and system requirements, thereby maximizing power output and improving overall system performance.

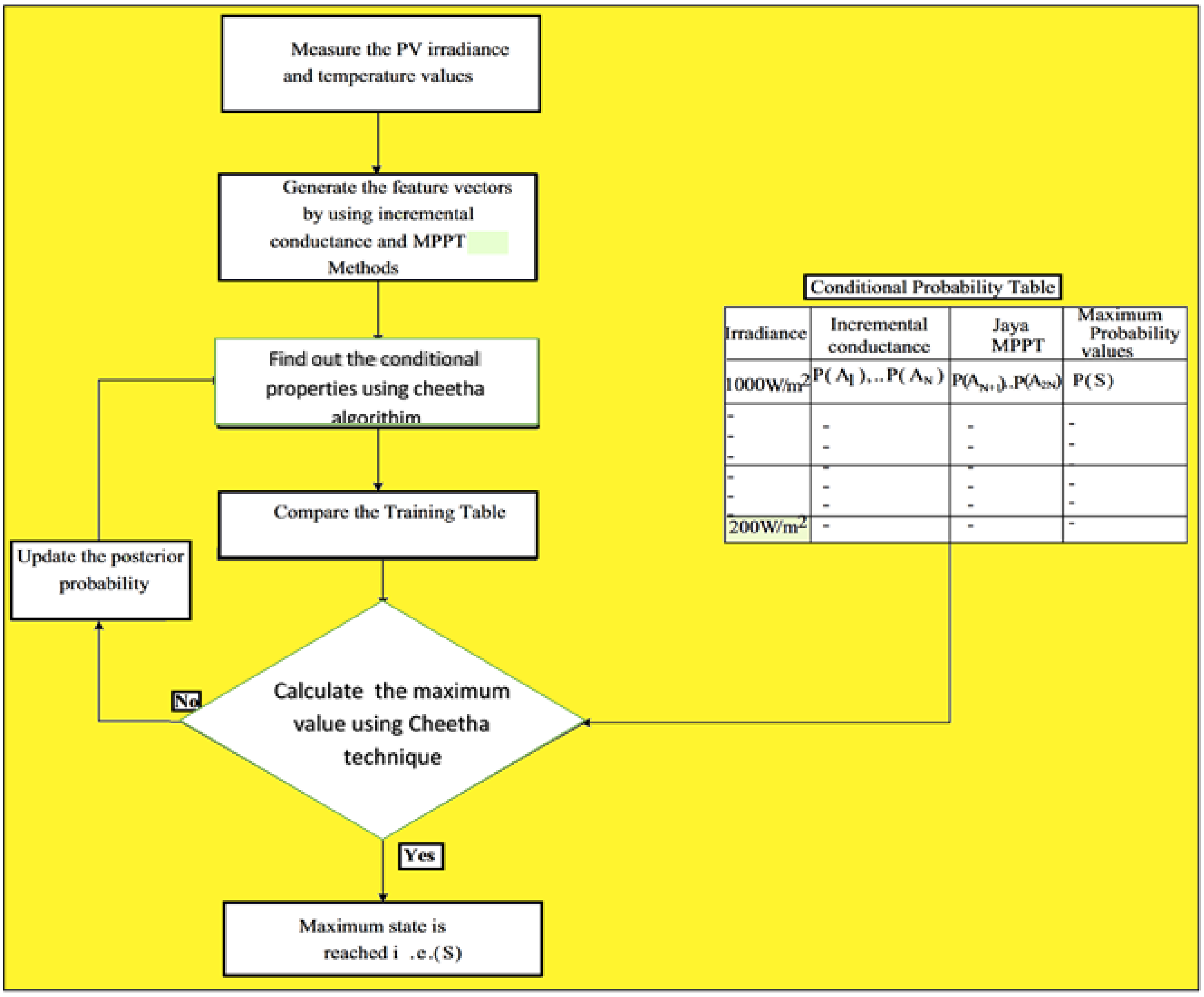

Fig.6 (a) cheetah algorithm-MPP Flowchart

A Cheetah algorithm is a powerful tool inspired by the hunting strategies of cheetahs, used for statistical fusion with joint probability distributions. The Cheetah algorithm is trained using the training data set (input, output) shown in Fig.6(a). Feature vector production is one segment of the Cheetah algorithm process. The Cheetah algorithm is a statistical method designed to improve the attainment of Global MPP under the PV array PSCs. Based on the proposal, the work focuses on the joint probability distribution of data fusion using the `plitogenic based Neutrosophic mcdm algorithms and incremental conductance. To better comprehend this, visualize a PV system with six modules. The linking series includes an input on each PV module's voltage and current combinations at 1500 W/m², and the PV system's overall open-circuit voltage will Voc must equal ŋVOCM. At this point, a Cheetah algorithm is created by observing nodes' inputs, i.e., L = a1,…….an, which are equally split into the left and right nodes a1,…,an (left nodes), and R = an+1,…,a2n. Therefore, the left nodes L = a1,...,an are given individual panel voltage information while the PV modules are operating at MPP and incremental conductance in a partially shaded environment. Similarly, the right nodes R = an+1,…,a2n are allocated input voltages acquired across individual panels while the PV system operates under comparable partially shaded conditions, implementing the Cheetah algorithm.

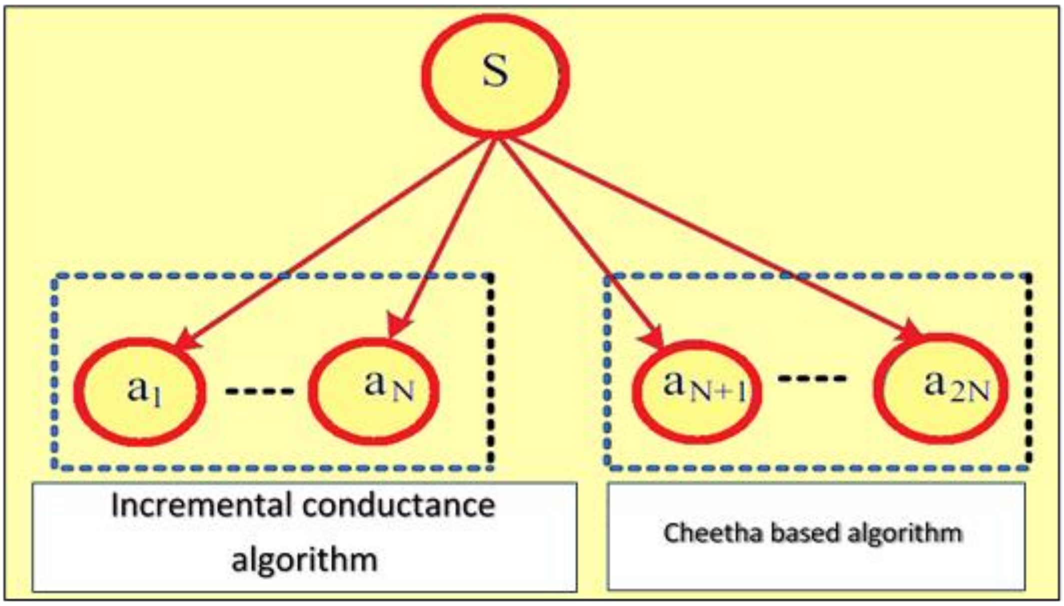

Fig.6 (b) Structure using cheetah based algorithm for MPPT data

The Global Maximum Power Point (GMPP) for both the cheetah algorithm and incremental conductance methods is identified for each sample training data set. These data sets consist of voltage and current pairs (V, I) from solar cell modules under varying irradiance and temperature conditions. The input data set includes voltage, current, and the corresponding output (GMPP). Eighty percent of the samples are randomly selected as the training data set, while the remaining twenty percent serve as the testing set. In the feature vector, if any two of the leftmost and rightmost nodes match, a "1" is inserted; otherwise, a "0" is inserted, represented as a(t) = feature vector a1(t),…..an(t), where ai(t) denotes the state of the ith node at time t. For simulation studies, a boost converter connects a PV system, consisting of four series-connected PV modules, to the loads. Table 2 should display the boost converter's settings and data values for the proposed algorithms. The proposed plitogenic-based Neutrosophic Cheetah algorithm is used to run the simulation and determine the global maximum power point (GMPP) for various potential patterns on the MATLAB/SIMULINK platform.

OPTIMIZATION APPROACH

Extracting maximum power under partial shading conditions (PSC) presents a major challenge for PV arrays and string operation. In this study, optimization methods cheetah algorithm are employed to determine the optimal duty cycle for a DC-DC converter, thereby achieving the maximum power point (MPP) from a PV array under PSC. The significance of maximum power extraction under PSC is minimal but observed.

Cheetha optimization

Cheetahs exhibit a solitary hunting behavior that relies heavily on individual prowess and strategy. They primarily hunt alone, utilizing a combination of keen senses, stealth, and exceptional speed to catch their prey. When selecting prey, cheetahs consider several parameters, including their own hunger level, the availability and density of prey, and the vulnerability of potential targets, typically focusing on smaller to medium-sized ungulates such as gazelles and impalas.

The hunting process begins with the cheetah using its acute vision to scan for vulnerable individuals within a herd, such as the young, old, or injured. Once a target is selected, the cheetah uses stealth to approach as closely as possible without being detected, minimizing the energy required for the chase. When within striking distance, the cheetah accelerates rapidly, leveraging its incredible speed and agility to close the gap quickly. The chase usually lasts no more than 20 to 30 seconds, as the cheetah aims to knock the prey off balance with a powerful swipe of its paw before delivering a suffocating bite to the throat. This methodical approach ensures that cheetahs maximize their hunting success while conserving vital energy for future hunts[35], [36].

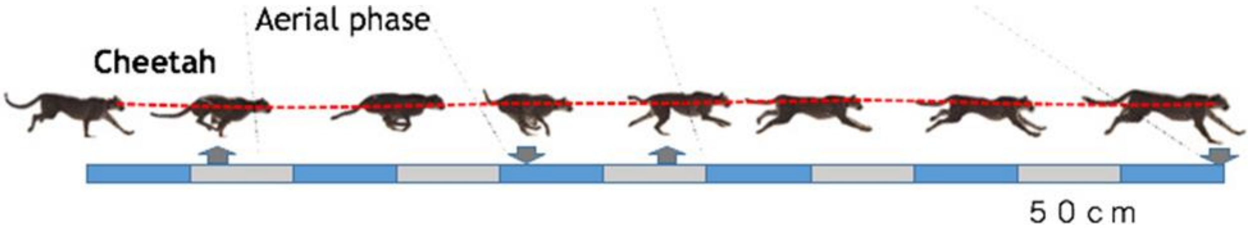

Fig.6 (c) illustrates Cheetah's hunting strategy in action, highlighting stealth, speed, and precision.

```
1. Initialize population of cheetahs randomly
2. Evaluate fitness of each cheetah in the population
3. Repeat until termination condition is met:
    4. Select alpha, beta, and delta cheetahs based on fitness
    5. Perform prey search:
        6. For each cheetah in the population:
            7. Update position based on current velocity
            8. If position is within prey detection range:
                9. Chase prey using rapid acceleration
                10. If prey caught:
                    11. Update position of successful cheetah
                    12. Evaluate fitness of caught prey
                    13. If prey is fit enough:
                        14. Consume prey and reproduce
                    15. Else:
                        16. Continue searching for prey
            17. Else:
                18. Move randomly in search of prey
    19. Update velocity of each cheetah based on alpha, beta, and
delta positions
    20. Evaluate fitness of new cheetah positions
    21. Update alpha, beta, and delta cheetahs if necessary
                22. Return best solution found
```

Fig 6 (d) pseudocode represents a simplified version of the plitogenic Neutrosophic-based Cheetah algorithm

The plitogenic Neutrosophic-based Cheetah algorithm, drawing inspiration from the hunting prowess of cheetahs, navigates through several essential stages. Initially, a population of cheetahs is randomly placed in the simulation environment. Each cheetah's fitness is then assessed based on its position and hunting performance. This process is iterated until a termination criterion, such as a maximum number of iterations, is met. Within each iteration, the algorithm selects the top-performing cheetahs—alpha, beta, and delta—guided by their fitness scores. These leading cheetahs spearhead the hunting process, mimicking the keen senses and strategic decision-making of their real-life counterparts. The prey search unfolds as each cheetah dynamically updates its position, seeking potential targets within its detection range. Upon prey detection, cheetahs engage in rapid pursuit, emulating the high-speed chases characteristic of cheetah hunts. If successful, the cheetah captures the prey, evaluates its fitness, and proceeds accordingly—either consuming it and reproducing or continuing the hunt. Throughout the process, cheetahs adjust their velocity based on the positions of the alpha, beta, and delta cheetahs, optimizing their hunting strategy. Ultimately, the algorithm concludes by returning the best solution found—a reflection of the fittest cheetah or captured prey—achieving an efficient balance of adaptation and performance in simulated hunting scenarios[37].

Table.3(a) Proposed algorithm parameter settings

Specifications	Cheetah algorithm Data
Maximum iteration number	60
Number of Decision Variables	6
Population size	15
Switching Probability	-
Stopping Criteria	100 iterations

Table.3(b) Proposed cheetah-MPP algorithm parameter

Particulars	Specifications
Cheetah algorithm	Total data set = 548, training data =90% of 528 (422), testing data = 20% of 526 (107)
Boost converter	L= 5.24 MH, C_1=C_2=10 µF , f = 20 Khz,
Incremental conductance	D initial=0.19, Delta D =0.0054
Sampling period (T_S)	For simulation, T_s=0.0030 Sec.

Throughout the entirety of the iteration process, the plithogenic Neutrosophic-based cheetah algorithm engages in simulations, receiving parameters from the PV system and meticulously analyzing them to ascertain the optimal duty cycle values. This algorithmic approach diligently seeks out the best (D) optimum duty cycle, employing the plithogenic Neutrosophic-based cheetah algorithm optimization method. This optimization process remains steadfast and operative throughout the duration of the Kth iteration process. Table 3(a & b) serves as a visual representation, outlining the parameter settings utilized within the proposed algorithm.

Algorithm inspired by the hunting behavior of cheetahs:

Step 1: Initialize the population of cheetahs (N) and determine the number of iterations (k).

Step 2: Define the objective parameter as maximizing successful hunts or prey caught.

Step 3: Assign each cheetah a role based on its hunting behavior pattern: alpha (α) as the lead hunter, beta (β) as the support hunter, and delta (δ) as the scout.

Step 4: Establish the hunting area and identify potential prey locations.

Step 5: Alpha cheetah identifies the target prey based on visual cues such as vulnerable individuals or isolated targets.

Step 6: Beta cheetahs assist alpha in stalking and closing the distance to the prey.

Step 7: Delta cheetah scouts ahead to locate additional prey or potential threats.

Step 8: Once the prey is within striking distance, alpha initiates the chase while beta provides backup.

Step 9: Delta remains vigilant for any changes in the environment or incoming threats.

Step 10: If the chase is successful, alpha delivers the final blow to immobilize the prey.

Step 11: Evaluate the success of the hunt based on the number of prey caught and adjust the hunting strategy accordingly.

Step 12: Iterate through the hunting process for the specified number of iterations.

Step 13: Monitor the overall success rate of the cheetah pack and adapt their hunting techniques based on the outcomes.

Step 14: Conclude the hunting session after reaching the maximum number of iterations or achieving the desired hunting objectives.

EXPERIMENTAL/SIMULATION RESULT & DISCUSSION

In this section, the performance evaluation of the PV central/string design is conducted through simulation models. MATLAB files were developed for analyzing the cheetah-based algorithm coding, inspired by the hunting behavior of cheetahs. These algorithms, akin to the strategies employed by cheetahs in hunting prey, are utilized to determine the total duty cycle of the converter and to attain peak power under Partial Shading Conditions (PSC). The proposed cheetah-based optimization methods emulate the agility and precision of cheetahs in tracking and capturing prey, adapting dynamically to environmental conditions. Through the implementation of these algorithms, the simulation results are obtained, shedding light on the efficacy of the proposed approach in maximizing power extraction from the PV system under varying conditions.

Table.4. Specification of PV panel

Descriptions	Values
Rated power of PV panel (W)	500W
Panel Short circuit current (I_{sc})	20A
Panel Open circuit Voltage (V_{oc})	25V
Irradiance (W/m^2)	1500 W/m^2
Current at Maximum Power (I_{mp})	16A
Number of cells per modules (n)	25

Table 4 presents the specifications of the solar panel and the suggested simulation settings. The design and implementation of uniform/PSC irradiances for the PV string unit were carried out using Matlab/Simulink 2020a software. This versatile software enabled the exploration of dynamic irradiance levels through the utilization of the cheetah algorithm optimization techniques, inspired by the hunting strategies of cheetahs. These optimization techniques, reminiscent of the adaptability and efficiency of cheetahs in their environment, were integrated into the control unit governing both the PV string and PV central units. Different levels of irradiance were simulated, resulting in varying voltage and current outputs from the PV panels, which were monitored by current and voltage sensors. The cheetah algorithm, mirroring the agile and strategic hunting behavior of cheetahs, was combined with the control system. This integration aimed to maximize power generation efficiency by dynamically adjusting the converter gate duty cycle in response to the cheetah algorithm's optimization decisions.

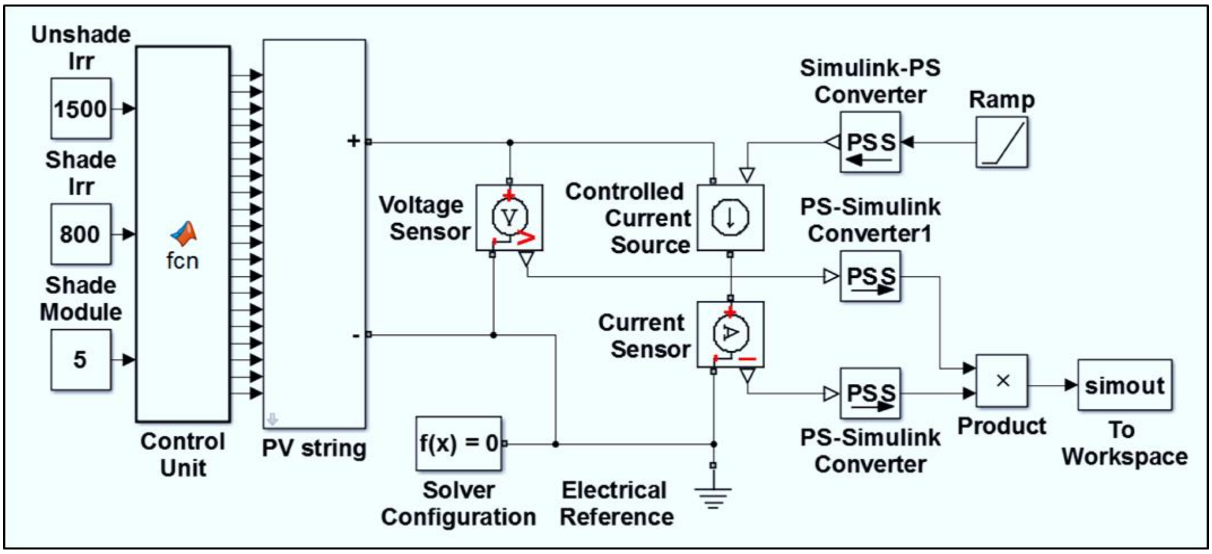

Fig.7 Matlab Simulink model of PV string architecture with uniform/PSC irradiance

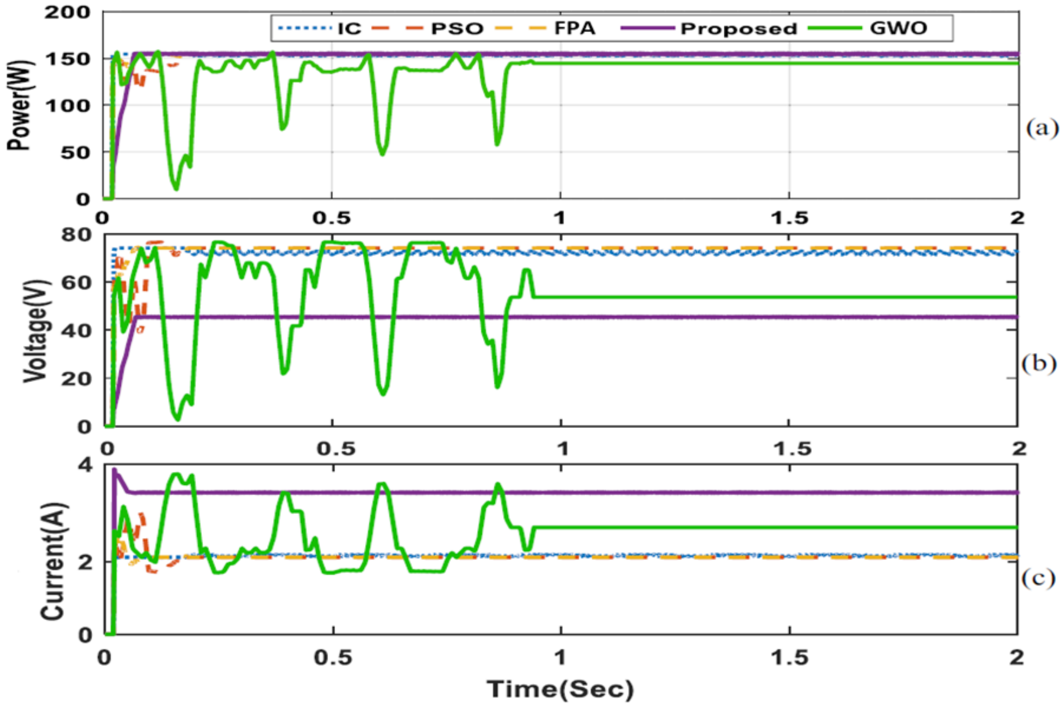

Fig.8 Comparing Global MPP under PSC PV-array output.

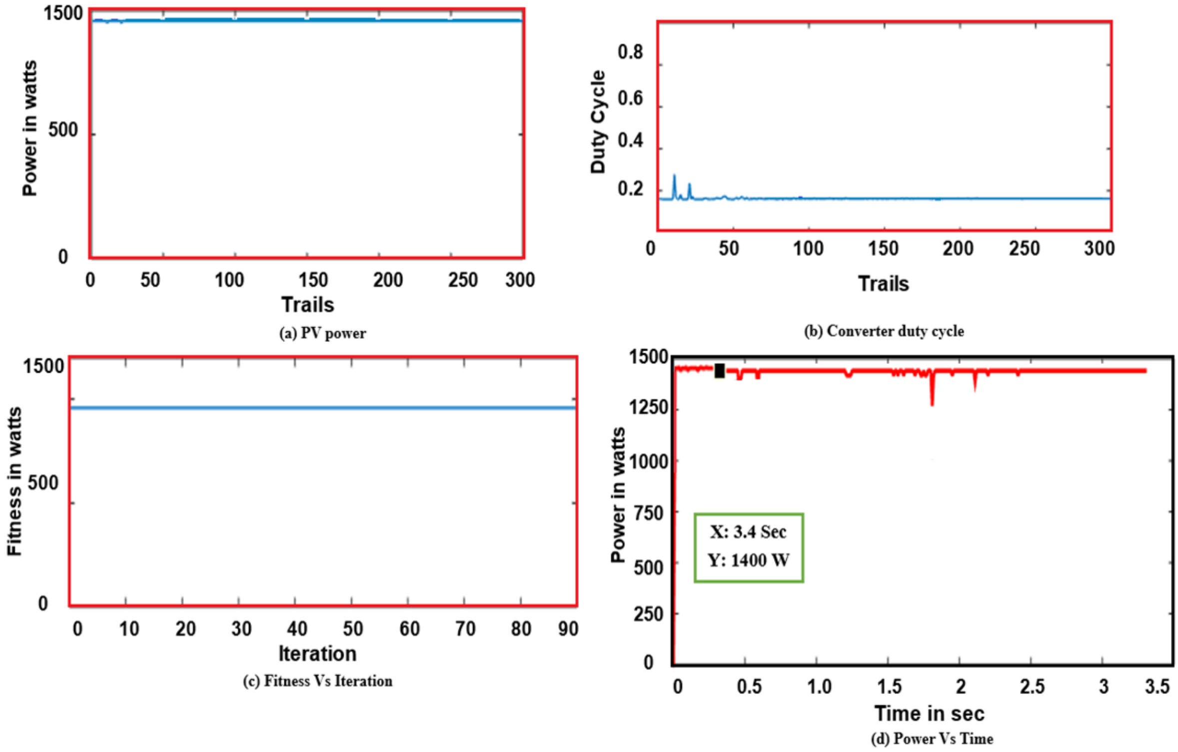

Fig.9 cheetah Matlab output for uniform irradiance

The simulation model of the central architecture is depicted in Fig. 9. Fig.10 illustrates the PV characteristics of Global Maximum Power Point (GMPP) under Partial Shading Conditions (PSC), comparing it with an existing network model. Fig.9 showcases the results of the cheetah algorithm simulation for uniform irradiances, where power extraction from the PV array is depicted under shadow-free conditions, yielding an output of 1450W. However, when a panel is shaded, only

827.3W of electricity is generated. This scenario involves four PV panels connected in series with a converter duty cycle of 0.9, with the boost converter outputs directed towards the DC load. The STC temperature remains constant at 25°C across all four PV panels, while the irradiation rates vary from 1500W/m² to 500W/m² for each panel. The simulation parameters include 200 iterations for the cheetah algorithm and 100 iterations for the cheetah algorithm. The population size for the cheetah algorithm is set at 10, resulting in simulation results without any significant deviations.

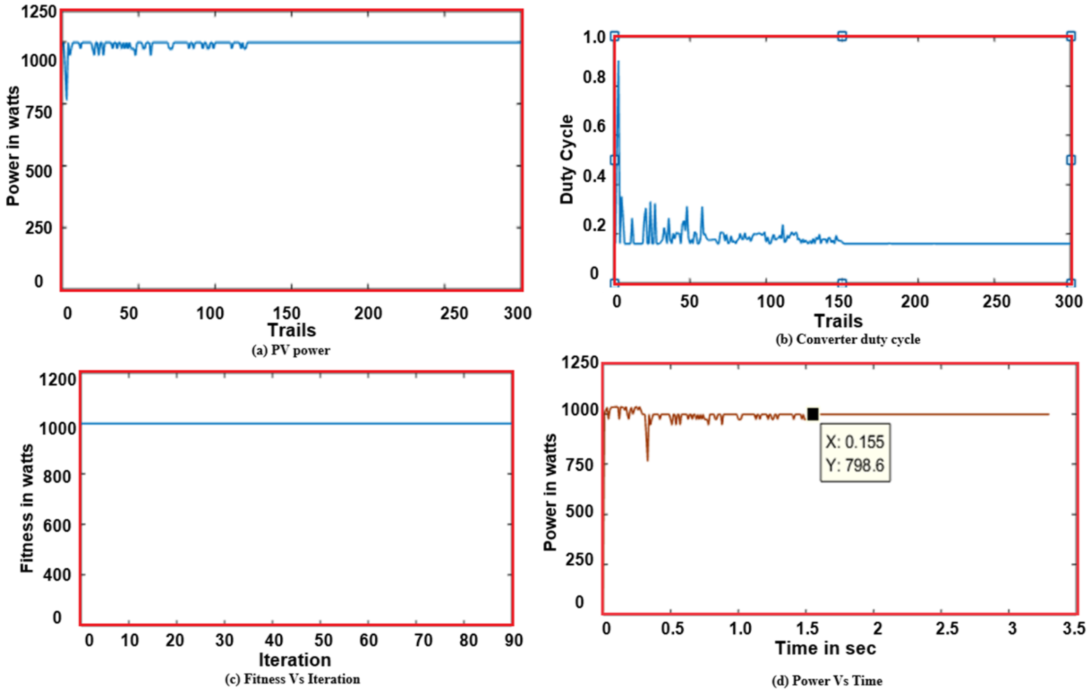

Fig.10 cheetah Matlab output for central PV configuration under shading conditions

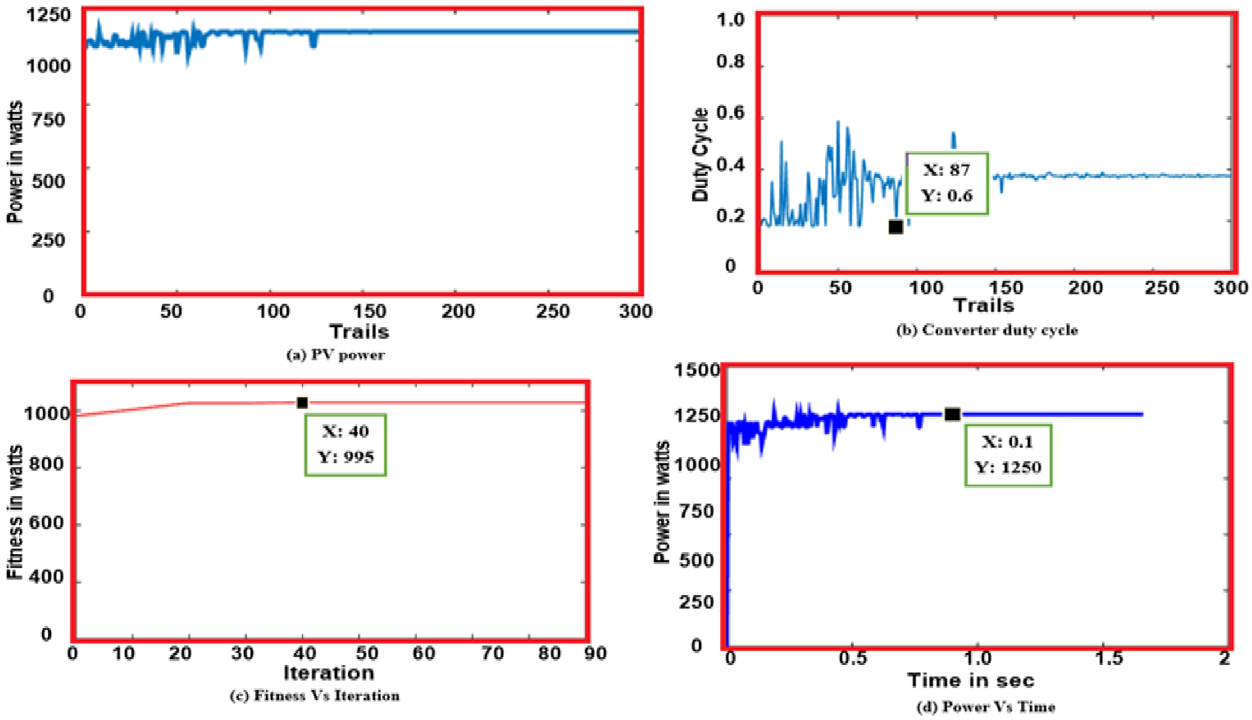

Fig.11 cheetah Matlab output for string PV configuration under shading conditions

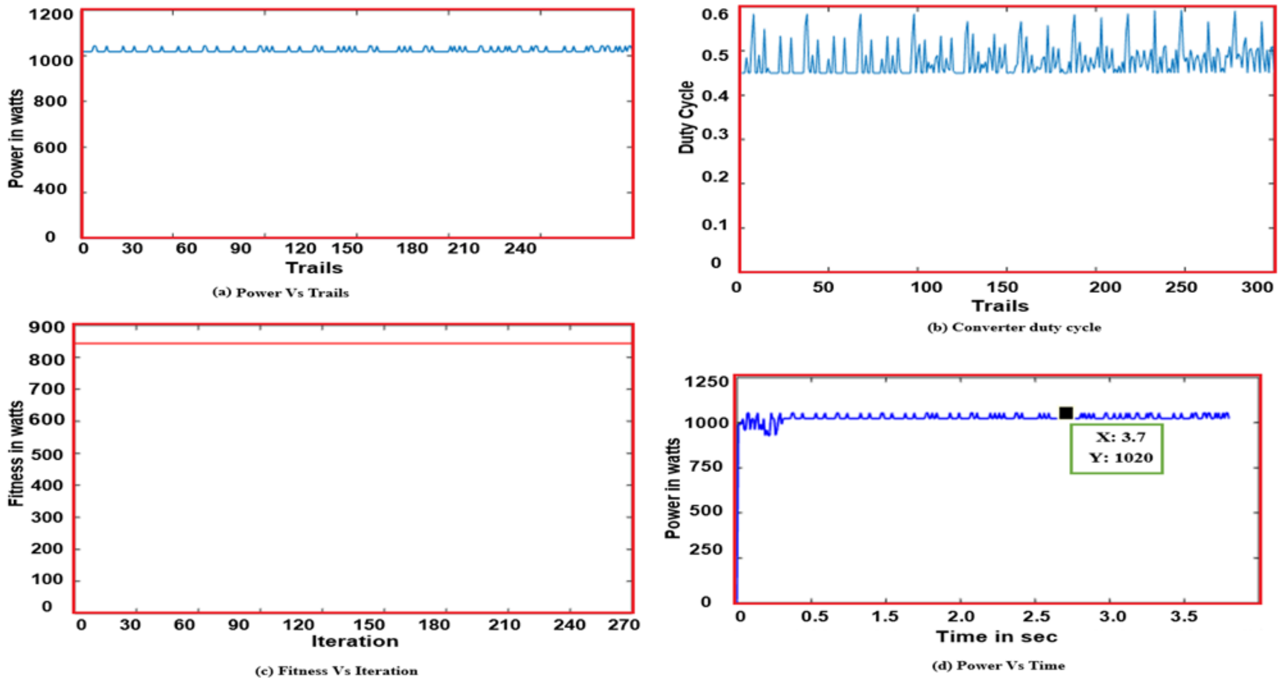

Fig.12 Cheethah Matlab output for PV string configuration under shading conditions

The cheetah algorithm simulation under shaded conditions utilizes the central architecture depicted in Fig. 12. The PV array power output is 1090W at t=0.16 seconds, as illustrated in Fig. 10(a). Fig. 10(b) shows the converter duty cycle varying from 0.3 to 0.9. Fig. 10(c) illustrates the fitness function value at 1009, and Fig. 10(d) shows the maximum output power reaching 1006W.The cheetah algorithm simulation under shaded conditions also uses the PV string architecture depicted in Fig. 12. The PV array power output is 1190W at t=0.12 seconds, as illustrated in Fig. 11(a). Fig. 11(b) shows the converter duty cycle varying from 0.21 to 0.6. Fig. 11(c) illustrates the fitness function value at 1003, and Fig. 11(d) shows the maximum output power reaching 1260W.The proposed cheetah algorithm simulation under uniform shading irradiation conditions uses the PV string architecture shown in Fig. 12. At t=0.57 seconds, the PV array module output is 1045W, with the converter duty cycle varying from 0.3 to 0.59. The fitness value of the iteration is 1003, and the maximum output power is 1260W.

Table.5 simulation output measurements of central architecture PV

S.NO	Max power (Pmax)	Algorithm types	V_{pv} (V)	I_{PV} (A)	P_{PV} (W)	V_O (V)	I_O (A)	P_O (W)	Conversion Efficiency (%)	Tracking Efficiency (%)
1	1461W	cheetah (In Uniform Irradiation conditions)	58.43	16.04	1321	59.43	15.02	1030	93.44	97.56
2	1050W	Cheetah algorithm	56.32	16.04	1201	63.02	14.72	1000	97.45	99.62

(In Central
architecture

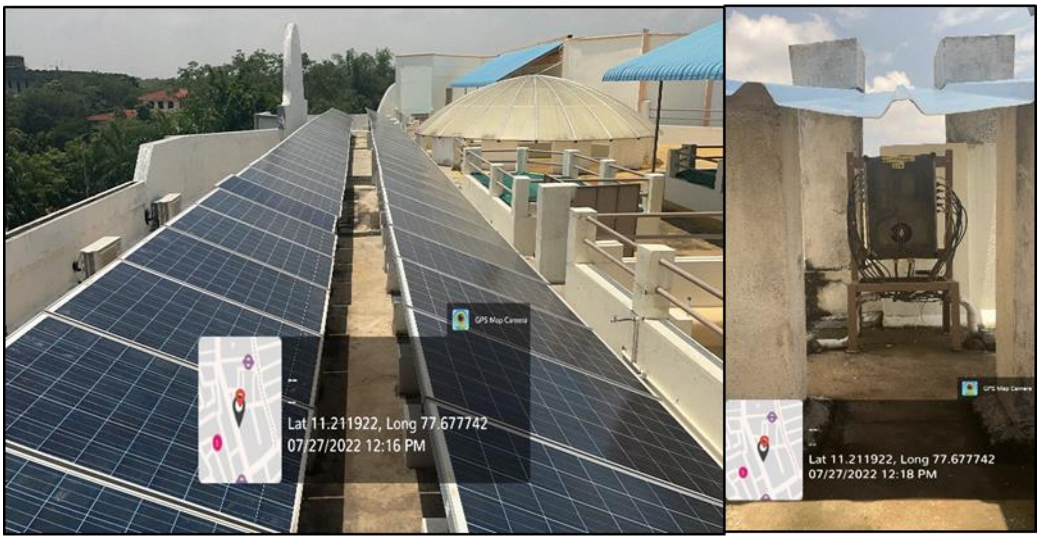

Fig.13 Real time experimental PV array central architecture

The real-time implementation of the PV array central architecture proposed in this research is shown in Fig. 15. The same parameters were used for both simulation and experimental data, with the outcome results observed and measured in Tables 7 and 8. Fig. 12(c) compares the convergence rates of several suggested optimization techniques. The highest power generated by the load is 1450W, but it does not reach a steady-state value, as depicted in Fig. 11. The outcome of the cheetah algorithm simulation for the PV central architecture under shaded operating conditions tracks the maximum power, as shown in Fig. 10. According to Table 7, the PV panel power is significantly higher compared to other optimization techniques. This comparison includes PV string architecture under uniform and partial shading conditions, showing that the cheetah algorithm outperforms other existing methods. The study highlights that PV central and string architectures using PSC/uniform shading conditions achieve better results with the cheetah algorithm compared to other optimization methods.

Table.6 Output measurements form PV string architecture under uniform and partial shading condition compared with other existing methods.

S.NO	Architecture	Algorithm type	V_{pv} (V)	I_{PV} (A)	P_{PV} (W)	V_O (V)	I_O (A)	P_0 (W)	Conversion Efficiency (%)	Tracking Efficiency (%)	Irradiance Effect
1.	Existing PV-String [ ]	BAT	51.1	11.6	1292	50	10.1	1121	86	86	Uniform / PSC
2.	PV string/ central [ ]	FPA	49.1	10.23	1301	46	14.2	960	93.62	90.52	
3.	PV string [ ]	GA-FPA	47.01	11.81	1412	46.2	14.6	960	90.1	91	
4.	PV string [ ]	GNN-MET	47	11.81		45	14.6	972	90.12	92.3	

5.	**Proposed PV-String**	FPA	56.32	13.04	1051	58.43	13.02	1251	94.44	95.56	Uniform
6.		GWO	58.43	14.04	1010	58.43	13.02	1020	95.44	96.56	
7.		GWO	56.32	13.04	785	58.63	13.03	801	96.44	98.56	PSC
8.		FPA	57.32	14.04	1201	59.73	14.06	960	97.45	95.43	

Table.7 Output measurements from PV central/string architectures using PSC/Uniform shading condition compared with other optimization methods.

S.NO	Max power (Pmax)	Architecture	Algorithm type	Convergence Time (sec)	Tracking Efficiency (%)	Irradiance
1	1350W	PV- string/ central [ ]	FPA	0.39	89	
2	1250W	PV- central [ ]	FPA	0.3762	91	
3	1350W	PV-string [ ]	FPA	0.1752	92.3	Uniform/ PSC
4	1300W	PV-string/ central [ ]	MPP	0.1565	89	
5	1200W	PV-central [ ]	MPP (P&O/INC)	0.892	90.9	
6	1000W	**Proposed PV-Central**	GWO	0.0319	95.56	Uniform
			FPA	0.0423	96.56	
7	1050W		GWO	0.1553	98.56	PSC
			FPA	0.0476	95.43	
8	1450W	**Proposed PV-String**	GWO	0.0235	86	Uniform
			FPA	0.2214	96.3	
9	1250W		GWO	0.1825	98.5	PSC
			FPA	0.2452	90.52	

Conclusion

The performance of PV central/string arrays under various uniform and partial shading conditions was investigated using a plithogenic Neutrosophic-based cheetah fuzzy logic algorithm for Maximum Power Point (MPP) optimization. The cheetah-MPP techniques incorporate methods inspired by the hunting characteristics of cheetahs. Just as a cheetah uses its speed, agility, and strategic prey selection to maximize hunting success, the cheetah algorithm employs rapid convergence, adaptability, and precision in tracking the MPP for solar PV systems.The proposed approach aims to efficiently extract maximum power from solar PV systems under various partial shading conditions by mimicking the cheetah's hunting strategy. This research involved two types of analysis: (i) real-time experimental data collected from PV panels and (ii) simulation analysis conducted using MATLAB/Simulink software. The cheetah-MPP-based converter for central/string architectures was tested under different partial shading conditions. Results show that the cheetah algorithm achieved a maximum tracking power of 1450W, with a tracking efficiency of 98.5% for the PV string design under uniform irradiance. For the proposed PV central string architecture, the power tracking was 1050W, with the cheetah-based PSC achieving a tracking efficiency of 98%. Overall, the cheetah algorithm demonstrated faster convergence and more effective power tracking under uniform and partial shading conditions compared to other existing methods. Incorporating plithogenic Neutrosophic fuzzy-based multi-criteria decision-making (MCDM) techniques into the cheetah algorithm allows for handling the inherent uncertainties and variabilities in solar irradiance and shading conditions. This method enhances decision-making accuracy, ensuring optimal performance of the PV systems by continuously adapting to changing environmental conditions, similar to how a cheetah adapts its hunting strategy based on the movement and behavior of its prey. Future researchers should further explore this approach to find more efficient ways of extracting maximum power from solar PV panels under various partial shading conditions. This work opens the door for further exploration into optimizing solar PV power generation, inspired by the effective and adaptive hunting strategies of cheetahs.

References

[1] J. R. Albert and A. A. Stonier, "Design and development of symmetrical super-lift DC–AC converter using firefly algorithm for solar-photovoltaic applications," *IET Circuits, Devices and Systems*, vol. 14, no. 3, pp. 261–269, 2020, doi: 10.1049/iet-cds.2018.5292.

[2] B. Parida, S. Iniyan, and R. Goic, "A review of solar photovoltaic technologies," *Renewable and Sustainable Energy Reviews*, vol. 15, no. 3, pp. 1625–1636, 2011, doi: 10.1016/j.rser.2010.11.032.

[3] Vinod, R. Kumar, and S. K. Singh, "Solar photovoltaic modeling and simulation: As a renewable energy solution," *Energy Reports*, vol. 4, pp. 701–712, 2018, doi: 10.1016/j.egyr.2018.09.008.

[4] D. S. Vanaja and J. R. Albert, "An Experimental Investigation on solar PV fed modular STATCOM in WECS using Intelligent controller," no. August 2020, pp. 1–27, 2021, doi: 10.1002/2050-7038.12845.

[5] A. S. Rana, M. Nasir, and H. A. Khan, "String level optimisation on grid-tied solar PV systems to reduce partial shading loss," *IET Renewable Power Generation*, vol. 12, no. 2, pp. 143–148, 2018, doi: 10.1049/iet-rpg.2017.0229.

[6] C. D. Bhos and P. S. Nasikkar, "Optimization-based maximum power extraction from solar photovoltaic system under non-uniform irradiance," *International Journal of Ambient Energy*, vol. 43, no. 1, pp. 6629–6642, 2022, doi: 10.1080/01430750.2022.2037456.

[7] B. Dhanalakshmi and N. Rajasekar, "Dominance square based array reconfiguration scheme for power loss reduction in solar PhotoVoltaic (PV) systems," *Energy Convers Manag*, vol. 156, no. October 2017, pp. 84–102, 2018, doi: 10.1016/j.enconman.2017.10.080.

[8] Manjunath, H. N. R. Suresh, S. Rajanna, S. B. Thanikanti, and H. H. Alhelou, "Hybrid interconnection schemes for output power enhancement of solar photovoltaic array under partial shading conditions," *IET Renewable Power Generation*, vol. 16, no. 13, pp. 2859–2880, 2022, doi: 10.1049/rpg2.12543.

[9] J. Prasanth Ram and N. Rajasekar, "A Novel Flower Pollination Based Global Maximum Power Point Method for Solar Maximum Power Point Tracking," *IEEE Trans Power Electron*, vol. 32, no. 11, pp. 8486–8499, 2017, doi: 10.1109/TPEL.2016.2645449.

[10] V. G. R. Kummara *et al.*, *A comprehensive review of DC–DC converter topologies and modulation strategies with recent advances in solar photovoltaic systems*, vol. 9, no. 1. 2020. doi: 10.3390/electronics9010031.

[11] J. Prasanth Ram and N. Rajasekar, "A new global maximum power point tracking technique for solar photovoltaic (PV) system under partial shading conditions (PSC)," *Energy*, vol. 118, pp. 512–525, 2017, doi: 10.1016/j.energy.2016.10.084.

[12] A. Younis, A. Bakhit, M. Onsa, and M. Hashim, "A comprehensive and critical review of bio-inspired metaheuristic frameworks for extracting parameters of solar cell single and double diode models," *Energy Reports*, vol. 8, pp. 7085–7106, 2022, doi: 10.1016/j.egyr.2022.05.160.

[13] D. Verma, S. Nema, R. Agrawal, Y. Sawle, and A. Kumar, "A Different Approach for Maximum Power Point Tracking (MPPT) Using Impedance Matching through Non-Isolated

DC-DC Converters in Solar Photovoltaic Systems," *Electronics (Switzerland)*, vol. 11, no. 7, 2022, doi: 10.3390/electronics11071053.

[14] A. A. Zaki Diab and H. Rezk, "Global MPPT based on flower pollination and differential evolution algorithms to mitigate partial shading in building integrated PV system," *Solar Energy*, vol. 157, pp. 171–186, 2017, doi: 10.1016/j.solener.2017.08.024.

[15] H. Rezk and A. M. Eltamaly, "A comprehensive comparison of different MPPT techniques for photovoltaic systems," *Solar Energy*, vol. 112, no. February, pp. 1–11, 2015, doi: 10.1016/j.solener.2014.11.010.

[16] A. Bahramipour, S. Abedi, and A. Irajpour, "Fuzzy Model of Hesitant Decision Making in Evaluating Business Plans Under Uncertainty (an Approach to Developing new Products)," *Journal of Optimization in Industrial Engineering*, vol. 16, no. 2, pp. 1–13, Jun. 2023, doi: 10.22094/JOIE.2023.1975398.2024.

[17] P. Du, B. Zhou, and M. Yang, "Carbon emission reduction contribution analysis of electricity enterprises in urban green development: A quantum spherical fuzzy sets-based decision framework," *Technol Forecast Soc Change*, vol. 200, Mar. 2024, doi: 10.1016/J.TECHFORE.2023.123181.

[18] S. K. Ramaraju *et al.*, "Design and experimental investigation on VL-MLI intended for half height (H-H) method to improve power quality using modified particle swarm optimization (MPSO) algorithm," *Journal of Intelligent and Fuzzy Systems*, vol. 42, no. 6, pp. 5939–5956, 2022, doi: 10.3233/JIFS-212583.

[19] L. Thangamuthu, J. R. Albert, K. Chinnanan, and B. Gnanavel, "Design and development of extract maximum power from single-double diode PV model for different environmental condition using BAT optimization algorithm," *Journal of Intelligent and Fuzzy Systems*, vol. 43, no. 1, pp. 1091–1102, 2022, doi: 10.3233/JIFS-213241.

[20] R. Palanisamy, V. Govindaraj, S. Siddhan, and J. R. Albert, "Experimental investigation and comparative harmonic optimization of AMLI incorporate modified genetic algorithm using for power quality improvement," *Journal of Intelligent and Fuzzy Systems*, vol. 43, no. 1, pp. 1163–1176, 2022, doi: 10.3233/JIFS-212668.

[21] J. R. Albert *et al.*, "Investigation on load harmonic reduction through solar-power utilization in intermittent SSFI using particle swarm, genetic, and modified firefly optimization algorithms," *Journal of Intelligent and Fuzzy Systems*, vol. 42, no. 4, pp. 4117–4133, 2022, doi: 10.3233/JIFS-212559.

[22] M. Keshavarz Ghorabaee, "Developing an MCDM method for robot selection with interval type-2 fuzzy sets," *Robot Comput Integr Manuf*, vol. 37, pp. 221–232, Feb. 2016, doi: 10.1016/J.RCIM.2015.04.007.

[23] A. Moghassemi, S. Ebrahimi, S. Padmanaban, M. Mitolo, and J. B. Holm-Nielsen, "Two fast metaheuristic-based MPPT techniques for partially shaded photovoltaic system," *International Journal of Electrical Power and Energy Systems*, vol. 137, 2022, doi: 10.1016/j.ijepes.2021.107567.

[24] Y. Saber, M. Abusalih, E. Bader, T. Elmasry, A. Babiker, and F. Smarandache, "Single-Valued Neutrosophic Ideal Approximation Spaces," *International Journal of Analysis and Applications*, vol. 22, pp. 26–26, Feb. 2024, doi: 10.28924/2291-8639-22-2024-26.

[25] M. B. Beverland, K. V Fernandez, and G. M. Eckhardt, "Consumer Work and Agency in the Analog Revival," *Journal of Consumer Research*, Jan. 2024, doi: 10.1093/JCR/UCAE003.

[26] D. Radojičić, N. Radojičić, and T. Rheinländer, "A comparative study of the neural network models for the stock market data classification—A multicriteria optimization approach," *Expert Syst Appl*, vol. 238, Mar. 2024, doi: 10.1016/J.ESWA.2023.122287.

[27] T. C. C. Nepomuceno, T. Agasisti, A. Bertoletti, and C. Daraio, "Multicriteria panel-data directional distances and the efficiency measurement of multidimensional higher education systems," *Omega (Westport)*, vol. 125, p. 103044, Jun. 2024, doi: 10.1016/J.OMEGA.2024.103044.

[28] L. Giese *et al.*, "Using Machine Learning for Remote Behaviour Classification—Verifying Acceleration Data to Infer Feeding Events in Free-Ranging Cheetahs," *Sensors 2021, Vol. 21, Page 5426*, vol. 21, no. 16, p. 5426, Aug. 2021, doi: 10.3390/S21165426.

[29] F. Smarandache, "Plithogeny, Plithogenic Set, Logic, Probability and Statistics: A Short Review," *Journal of Computational and Cognitive Engineering*, no. July, 2022, doi: 10.47852/bonviewjcce2202191.

[30] C. Sankar, R. Sujatha, and D. Nagarajan, "Topsis By Using Plithogenic Set in Covid-19 Decision Making," *International Journal of Neutrosophic Science*, vol. 10, no. 2, pp. 116–125, 2020, doi: 10.5281/zenodo.4011772.

[31] M. Abdel-Basset, R. Mohamed, F. Smarandache, and M. Elhoseny, "A new decision-making model based on plithogenic set for supplier selection," *Computers, Materials and Continua*, vol. 66, no. 3, pp. 2751–2769, 2021, doi: 10.32604/cmc.2021.013092.

[32] F. Smarandache, "Plithogeny, Plithogenic Set, Logic, Probability and Statistics: A Short Review," *Journal of Computational and Cognitive Engineering*, vol. 1, no. April, pp. 47–50, 2022, doi: 10.47852/bonviewjcce2202191.

[33] "An Overview of Neutrosophic and Plithogenic Theories and Applications - Florentin Smarandache, Maissam Jdid - Google Books." Accessed: Feb. 28, 2024. [Online]. Available: https://books.google.co.in/books?hl=en&lr=&id=OozmEAAAQBAJ&oi=fnd&dq=plithogenic+and+neutrosophic+&ots=P1Zr2eIpWp&sig=c6pyJA8M1hbnIS-8L4GlseAssZg&redir_esc=y

[34] K. L. Cornhill and G. I. H. Kerley, "Cheetah communication at scent-marking sites can be inhibited or delayed by predators," *Behav Ecol Sociobiol*, vol. 74, no. 2, pp. 1–10, Feb. 2020, doi: 10.1007/S00265-020-2802-9/METRICS.

[35] K. Klein *et al.*, "Visual analytics for cheetah behaviour analysis," *ACM International Conference Proceeding Series*, Sep. 2019, doi: 10.1145/3356422.3356435.

[36] K. Li, Y. N. Li, H. Yin, Y. Hu, P. Ye, and C. Wang, "Visual analysis of retailing store location selection," *ACM International Conference Proceeding Series*, Sep. 2019, doi: 10.1145/3356422.3356429.

[37] A. K. Daiy, K. Y. Shen, J. Y. Huang, and T. M. Y. Lin, "A Hybrid MCDM Model for Evaluating Open Banking Business Partners," *Mathematics 2021, Vol. 9, Page 587*, vol. 9, no. 6, p. 587, Mar. 2021, doi: 10.3390/MATH9060587.