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Intelligent Shadow Detection in Photovoltaic Panels Using Image Processing and Artificial Intelligence for Enhanced MPPT Performance

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Abstract— The process of developing in intelligent shadow detection system for solar panels using stand-alone cells and visible and infrared (RGB/IR) imaging techniques The experiment relied an reproducibility intelligence algorithms neural networks and hybrid algorithms such as ANFIS and SCFNN to analyze images and predict the effect of shadows on energy production The methodology was implemented using MATLAB and the modeling of shadow effects in maximum power point tracking (MPPT) systems were demonstrated. It has been proven that uniform shadow distribution on panel surfaces reduces energy waste and increases production efficiency. The study presents a model for reconfiguring a photovoltaic array using image analysis to track shadow movement during operation. It demonstrates the development of an intelligent system that uses imaging techniques and algorithmic analysis to improve the performance of solar panels under the influence of shadow and dust. Field experiments indicate conventional methods. It appears that dust accumulation significantly reduced the panel's efficiency. Three levels of dust density were examined, and their visual data were later analyzed through artificial neural networks (ANNs). Although the outcomes were not entirely consistent, the statistical results suggest a clear and meaningful relationship. This indicates that combining image analysis with AI enhances the system's ability to track the optimal power point and improves the overall efficiency of the photovoltaic system.

Keywords— Photovoltaic (PV) systems; partial shading; maximum power point tracking (MPPT); artificial neural networks (ANN); ANFIS; SCFNN.

1. INTRODUCTION

Solar is a stable and reliable source of energy and the most prominent [1]. Because it is a clean, environmentally friendly energy source, it can be relied upon to operate off-grid power plants and generate electricity for consumers. Despite its advantages, the system still requires occasional light maintenance, a common drawback of solar technologies. A practical approach would be to combine the photovoltaic setup with a storage battery to balance performance and reliability. In recent years, photovoltaic (PV) systems have become widely used to enhance overall energy efficiency, particularly in solar-based water applications. Still, the relatively low efficiency of some modules remains a noticeable challenge. When the user turns on the water tap in a solar heating system, the photovoltaic (PV) system is activated, a technology increasingly used to improve energy efficiency. The low module efficiency still limits the operational capacity of these PV systems [1-3]. The PV module traps and blocks solar radiation, which causes a reflection problem [4]. It seems that shading in solar systems can generally be categorized into two forms: static and variable. Static shading occurs when dust, dirt, or bird

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droppings accumulate on the panels over time, reducing light exposure. Variable shading, on the other hand, develops due to shifting obstacles, such as moving tree leaves, smoke, or the shadows of nearby buildings. To better understand these effects, dust accumulation at different levels is examined to compare the energy loss under each condition. During the process, several images are captured to represent three distinct panel states, which are later analyzed using artificial neural networks (ANNs) to estimate the extent to which dust influences system performance.

Several advanced techniques have been developed to improve maximum power point tracking (MPPT) in solar systems. Among these, control approaches using neural networks (ANNs) stand out as particularly effective. Artificial intelligence (AI)-based controllers have demonstrated strong capability to follow the MPP with precision, even when solar irradiance changes unpredictably. In comparative simulations, such control models often surpass traditional FLC and ANN-based designs in both accuracy and efficiency. On the other hand, conventional tracking methods tend to perform poorly under partial shading, underscoring the need for AI-based solutions to enhance overall system performance [2].

It seems that photovoltaic modules, as semiconductor devices, are influenced by several environmental and design factors, including module type, tilt angle, location, temperature, shading, and surface cleanliness. In desert regions, even though sunlight is abundant, the panels' performance tends to drop because of heavy dust buildup and the lack of regular rainfall. The difficulty of cleaning these surfaces is often considered the main reason behind the reduced efficiency.

Dust accumulation clearly limits the output of photovoltaic (PV) systems and reduces the energy they can generate. To achieve the highest possible electrical efficiency, each essential component of the solar panel must be evaluated carefully and under realistic conditions. System design requires selecting the most efficient PV modules using algorithms such as Maximum Power Point Tracking (MPPT). The total PV array directly affects overall system efficiency and energy production, making careful component evaluation and the selection of intelligent control technologies crucial to achieving optimal performance. Full or partial shading directly affects the photovoltaic arrays, degrading the overall system performance and reducing electrical energy production. Depending on the angle of sunlight, shadows cast by surrounding buildings and trees reduce the solar panel's output. Cloud migration also creates the same problems and imbalances in production [4].

Using MPPT and the matrix reconfiguration process [2, 7] is not capable. Gained considerable interest in the solar photovoltaic system, which produces clean and renewable electricity. Compared to other conventional sources, PV cells appear to offer pollution-free operation and to utilize abundant solar resources. Interestingly, these features may also help extend the lifespan of a PV system by maintaining a fairly stable power output. In the method proposed here, shading on PV panels can be detected in real time using a web camera. This seems to remove the need to separate the PV array from its load, which could be a practical advantage [8, 9]. The approach also appears to reduce wiring and sensor needs, cutting both cost and complexity. Once shading is detected, an algorithm adjusts the array's configuration to improve output. This makes the system more adaptable to changing shading conditions and can be applied across different PV setups. Overall, this solution improves the reliability of solar power systems in real-world situations. Next, solar photovoltaic modules are tested under high, medium, and low light intensities, depending on the light source's radiation. These technologies appear to respond better to common issues in generating output power, showing fewer deviations than earlier methods [10]. This study also provides a comparative analysis of control methods based on ANNs. These are among the more commonly used AI approaches when analyzing partial photovoltaic systems. With AI-based control systems, the maximum power point (MPP) can be tracked with high accuracy even under random variations in solar radiation intensity.

By running simulations across multiple test cases and verifying the results, it appears the proposed systems achieved better performance. Interestingly, this improvement isn't uniform; it varies depending on conditions, but overall, the results suggest a noticeable gain. This study also tries to classify random pollution factors that can significantly affect electricity production from photovoltaic modules. These factors may be captured, analyzed, and classified using artificial neural networks (ANNs). This approach provides a way to see how different environmental factors affect energy efficiency.

Several modern techniques exist to more effectively track the maximum power point. In this research, a comparative look was taken at control methods known for their ability to follow the MPP accurately, even when solar radiation changes unpredictably. Some methods seem more consistent than others, though occasional fluctuations still appear in certain scenarios.

2. Literature Review

The field of solar energy is attracting increasing attention from researchers. Lately, there's been a push to develop modern methods for estimating solar radiation, analyzing dust buildup, cooling panels, and tracking performance. Panel cooling, in particular, reflects how researchers are seeking innovative ways to improve solar system efficiency under changing conditions. Various techniques have been applied in image processing, artificial intelligence, intelligent algorithms, and even wireless sensor networks, helping increase photovoltaic efficiency and improve performance in unpredictable environments.

This research aims to take a closer, critical look at previous studies, examining how they approached problems and the results they achieved. It also seems essential to assess how well these studies addressed issues such as dust accumulation, high temperatures, and partial shading, and the effects of these factors on overall system efficiency. In doing so, it may be understood that current research builds on these earlier efforts using contemporary smart technologies such as fuzzy logic control, neural network-based energy tracking, and real-time testing of solar systems.

Cheng Yu Peng and colleagues [11] addressed improving solar cell performance under shaded conditions by designing fine-scale optical structures that reduce losses caused by metal strips. Karthikeyan and J. A. Basil Raj [12] proposed an image-processing-based method for real-time. Aziza I. Hussein and colleagues [13] developed an MPPT algorithm based on the Herbaceous Lévy method, combined with PID control, for high-precision duty-cycle tuning in smart home systems. T. L. Belahcene and colleagues [14] compared the Grey Wolf and Cuckoo Search algorithms. They found that the Grey Wolf algorithm outperforms in terms of reducing total harmonic distortion (THD) and improving response time. M. H. El-Shimy and colleagues [15] reviewed the effects of various maximum power point tracking (MPPT) techniques on the total harmonic distortion (THD) of photovoltaic systems under partial shading conditions.

Anwar and colleagues [16] also analyzed the performance of a parallel step-up converter using artificial intelligence techniques to enhance efficiency in partially shaded conditions.

On the other hand, Abdo and colleagues [17] used deep learning techniques such as DQN, DDPG, and TD3 to compare their performance in tracking the maximum power point under solar radiation variations. In contrast, Li and colleagues [18] presented an innovative approach to solar array design based on optimization techniques to improve performance under partial shading. Jaafar and colleagues [19] developed a new algorithm that achieves high speed and accuracy. Saleh and colleagues [20] developed a mechanism for rearranging photovoltaic modules using the Ken-Ken Puzzle algorithm to minimize power loss due to partial shading. Table 1 provides a comprehensive summary of the above-mentioned previous studies and compares them in terms of methods and results.

3. METHODOLOGY

Maximum power point tracking (MPPT) in photovoltaic systems is one of the most important features for extracting the maximum electrical energy from a solar system. In this work, an AI-based approach, the Adaptive Neuro-Fuzzy Inference System (ANFIS), is used. The system monitors and tracks PV panel power output across different levels of sunlight and temperature. It may be understood that the suggested approach provides a new way to design automatic control systems using Artificial Intelligence tools.

Given the plant dynamics, expected reference signals, and possible disturbances, a neural network-based controller is automatically designed. In this research, a Self-Constructing Fuzzy Neural Network (SCFNN) is developed to handle situations in which parts of the PV panels are affected by dust or shading. The SCFNN learns both its structure and its parameters online. This is done by dividing the input space and using a supervised gradient descent method guided by the adaptive delta rule. The results appear to suggest that this approach can adapt effectively even under challenging environmental conditions.

In this context, an intelligent approach based on the Adaptive Neuro-Fuzzy System (ANFIS) is employed to detect and track the generated power in MPPT systems under varying solar radiation and temperature conditions.

An optimal neural network-based controller is automatically designed to account for system dynamics, expected reference signals, and potential disturbances. The research also seeks to develop a self-forming fuzzy neural network (SCFNN) to address problems caused by dust accumulation or shading on parts of solar panels. This system performs the structure construction and parameter learning phases simultaneously and directly by partitioning the input space, using a supervised regression algorithm based on the adaptive delta law.

The ANFIS method relies on selective fuzzy logic and a specially trained neural network to display and analyze the performance of the tracking method. Within this framework, ANFIS algorithms were used to determine the optimal radiation power for the solar panel condition. The panel array was modeled using the single-diode model, the most common representation of the photovoltaic cell, as shown in Fig. 1 [21-23].

The current output of the PV cell is represented by Fig. 1 as a function:

$$I = I_{ph} - I_d - I_{sh} \tag{1}$$

The scientific problem addressed in this study is the reduced efficiency of photovoltaic systems under partial shading and dust accumulation. The research object is the photovoltaic array operating under variable environmental conditions, while the research subject is the optimization of MPPT performance using AI-based algorithms (ANN, ANFIS, SCFNN). The main aim is to enhance energy extraction efficiency, and the tasks include developing, modeling, and validating intelligent control methods for real-time power optimization.

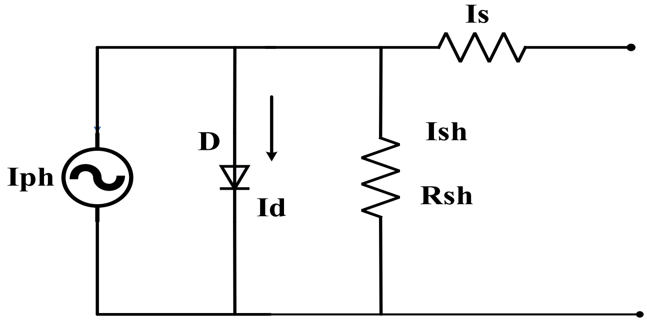

Fig. 1. Equivalent circuit of PV cell.

Table 1. Summary of the ligature review.

Author(s)	Year	Technique used	The proposed work
Cheng-Yu Peng et al.	2025	Shaded Light Trapping Solar Module	Improve ribbon shading loss using optical microstructures
G. Karthikeyan et al.	2025	Image Processing with Real-Time Reconfiguration	Enhances output using shading detection and relay switching
Aziza I. Hussein et al.	2024	Spline MPPT with PID and Levy Invasive Weed Optimization	Accurate duty cycle adjustment using LIWO for smart homes
T. L. Belahcene et al.	2024	Grey Wolf Optimization (GWO) vs Cuckoo Search (CS)	GWO shows superior THD and response time under PSC
M. H. El-Shimy et al.	2024	Comparative MPPT Techniques on THD	Analyzes the THD effects of MPPT under PSC
M. A. Anwar et al.	2023	AI-Based Interleaved Boost Converter	Performance analysis under PSC
A. A. Abdou et al.	2023	DQN, DDPG, TD3 for MPPT	Compare deep RL methods for MPPT under variable irradiance
Y. Lee et al.	2023	Optimizing PV Array in PSC	Design optimization approach for partial shading
M. Z. M. Jaffar et al.	2023	ANFIS-Based MPPT	Introduces a novel ANFIS approach for MPPT detection
K. H. Salih et al.	2021	Ken-Ken Puzzle Reconfiguration	Dynamic module arrangement for power loss reduction
Islam et al. (Current work)	2025	FCL, NN, ANFIS, and SCFNN	Proposes an AI-based MPPT method to improve response time, power extraction, under partial shading conditions in a 1400W PV system.

During the experiments, the photovoltaic array was connected to a variable resistive load using the Lucas-Nülle training system, which allows for controlling resistance values and changing load conditions to simulate real-world household and industrial systems. The variable resistors and inverter were programmed to represent different power-demand patterns, enabling the evaluation of the performance of the intelligent tracking algorithms (MPPT) under realistic, dynamic operating conditions.

3.1.1. Derating Factor

The derating factor in solar photovoltaic (PV) systems is the percentage reduction in the expected power output of a solar panel under real-world operating conditions relative to its ideal (rated or nameplate) performance. In other words, it accounts for various losses that occur in practical installations and operations. The derating factor directly affects a solar system's operational efficiency, the lower the derating factor, the higher the system's actual performance.

Purpose of Using the Derating Factor:

i. Used in simulation software such as PVsyst or SAM to understand system behavior under different conditions.
ii. Ensures a realistic estimate of the payback period and expected returns.
iii. Prevents under- or oversizing of inverters, batteries, etc.

3.1.2. Control Techniques

Controlling technologies play a crucial role in managing the maximum power point tracking process in this research. A comparative analysis was conducted between traditional control systems and an AI-based control system. The AI-based system is characterized by its superior ability to handle nonlinear situations more efficiently than conventional systems.

Fuzzy Logic Controller and ANFIS

Fuzzy Logic Controllers (FLCs) are widely used in control systems for their ability to handle non-linearities and uncertainty through rule-based, linguistic reasoning. Introduced by Zadeh in 1965, fuzzy set theory laid the groundwork for this approach. Mamdani later advanced the concept by applying it to control applications. In the proposed FLC design, the error (e) is defined as the ratio of ΔP to ΔI, and the change in error (Δe) is determined by the difference between successive error values, as shown by:

$$e(k) = \Delta P(k)/\Delta(k) \tag{2}$$

$$Increment \Delta e(k) = e(k) - e(k-1) \tag{3}$$

The FLC output is an incremental change in duty cycle (ΔD). The duty cycle is continuously regulated by this incremental change, as shown in Fig. 3.

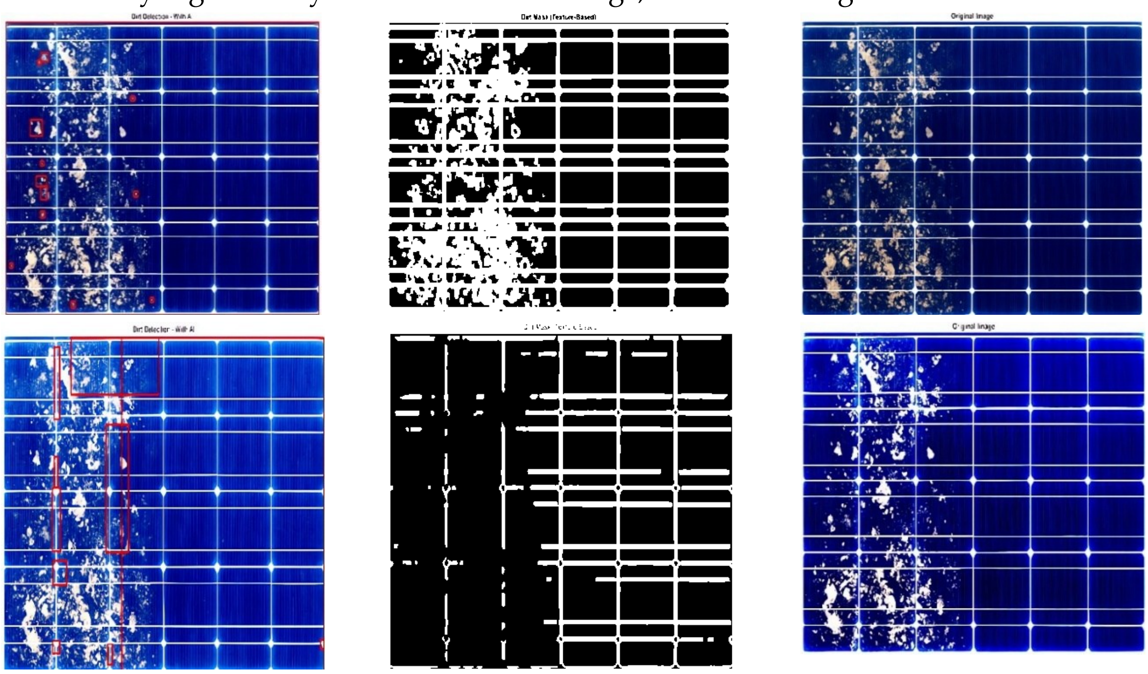

Fig. 2. Dust detection using Image processing.

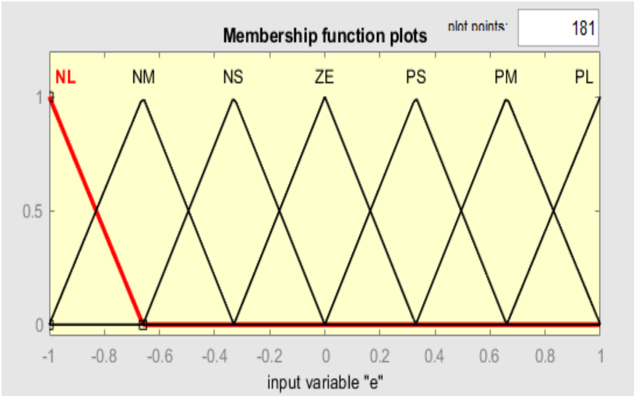

Fig. 3. Membership function of FLC.

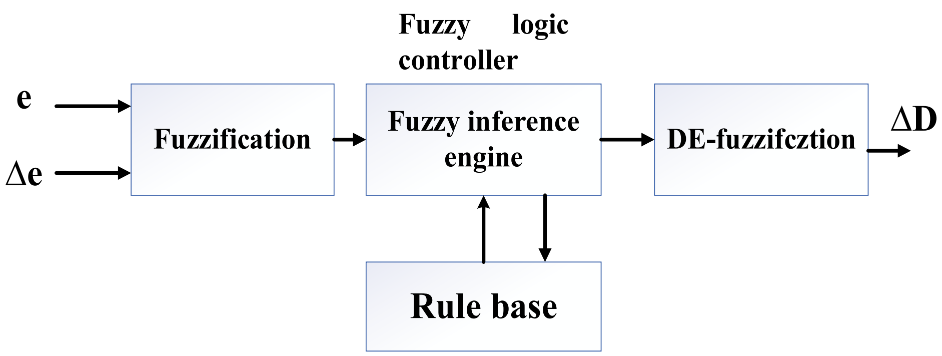

Fig. 4. A block diagram of Fuzzy Logic control (FLC).

The input and output variables were divided into seven equal fuzzy sets. These sets were named as follows: large negative, medium negative, small negative, zero, small positive, medium positive, and large positive. The results indicate that some outputs may behave unpredictably when adjacent sets overlap. In practice, this underscores the importance of carefully adjusting the membership degrees for each set; otherwise, contradictory responses may occur when using the process knowledge provided in Table 2.

Table 2. The rule base of FLC.

e/ Δe	NL	NM	NS	ZE	PS	PM	PL
NL	ZE	ZE	ZE	PL	PL	PL	PL
NM	ZE	ZE	ZE	PM	PM	PM	PM
NS	ZE	ZE	ZE	PS	PS	PS	PS
ZE	PS	PM	ZE	ZE	ZE	NM	NS
PS	NS	NS	NS	NS	ZE	ZE	ZE
PM	NM	NM	PS	NM	ZE	ZE	ZE
PL	NL	NL	NL	NL	ZE	ZE	ZE

In this work, we discuss the development of a solar cell that operates efficiently in various environmental conditions, and explore solutions to the environmental issues it faces, such as shadows or dust particles that block the panel's rays coming from the sun, and thus, a noticeable failure occurs in the panel's productivity. To address these problems, solutions were developed using tracking systems and artificial intelligence.

The system is modeled in MATLAB with a curve representing energy production over time. One factor contributing to a decrease in power is that the intensity of light falling on solar cells is affected by clouds and surrounding buildings. Mathematical models of the current and voltage of each solar cell under partial shading were developed. In effect, this means that shadows covering the cells lead to a significant decrease in power output.

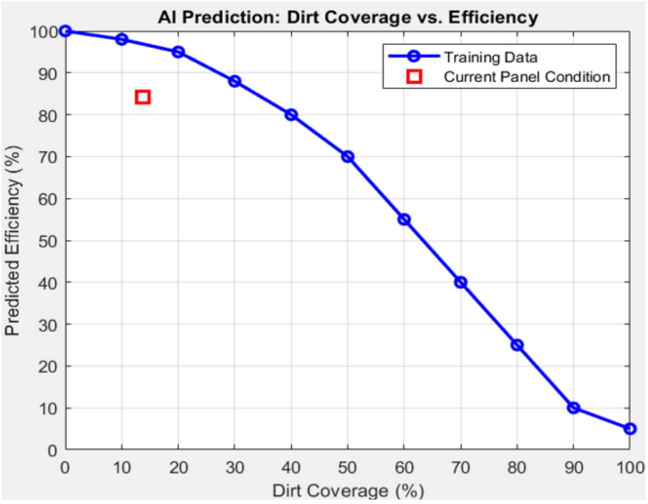

Fig. 5. AI perdition: dirt coverage vs. efficiency.

In this section, we explain the process of cleaning the solar panel and reducing its gas emissions by simulating the system using artificial intelligence to increase its productivity.

A. Artificial Neural Network Controller

Artificial neural networks have been observed to mimic the way the human brain works. They are one of the most prominent control techniques based on artificial intelligence. They can be used as a universal approach and efficiently handle nonlinearities in practical operations [11]. In this research, an artificial neural network with two neurons in the input layer, one neuron in the output layer, and ten neurons in the hidden layer were used, as shown in Fig.6. Bipolar activation functions (tanh) are used in the hidden layer. In the output layer, the activation function is linear. The network was trained using the Levenberg-Marquardt error correction algorithm with supervised learning. In practice, this means the network's performance depends heavily on layer configurations and the number of neurons.

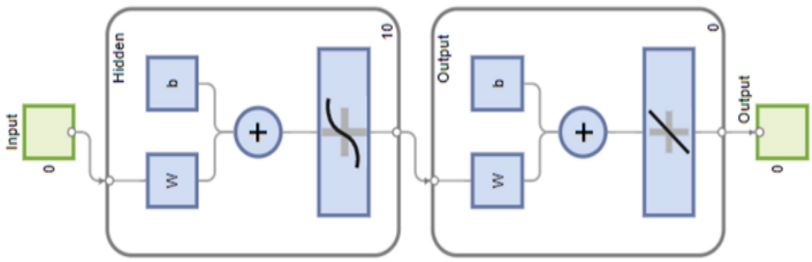

Fig. 6. Artificial Neural Network (ANN).

B. Online Learning Algorithms for SCFNN

The basic architecture of a self-configuring fuzzy neural network consists of four layers, as shown in Figs. 7 and 8: an input layer, two hidden layers, and an output layer.

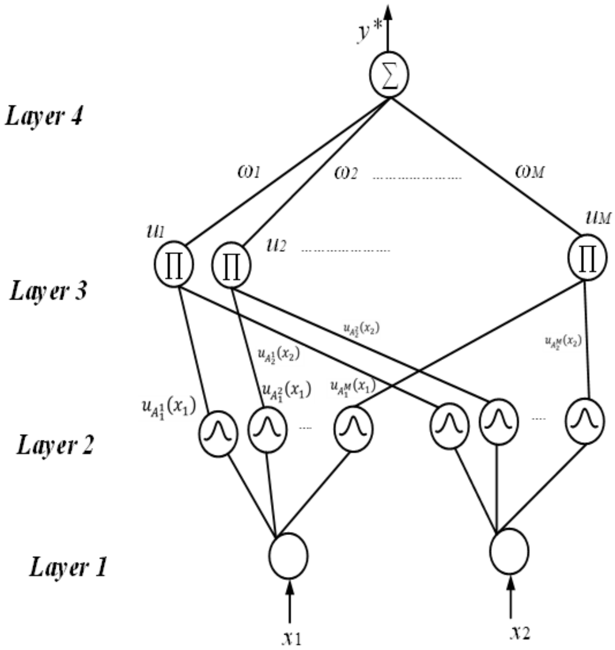

Fig. 7. Schematic diagram of SCFNN.

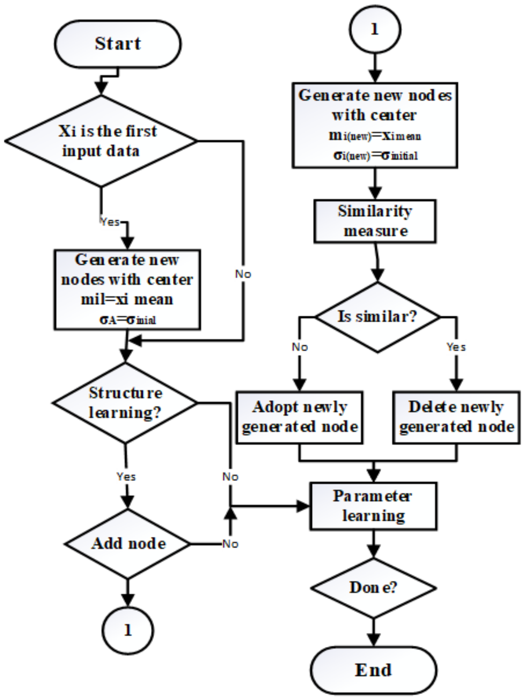

Fig. 8. Flowchart of SCFNN method.

Parameter learning employs supervised learning techniques, such as a feedback algorithm, to adjust the link weights and the membership function coefficients while minimizing a predefined energy function. Initially, the network contains only input and output nodes. Membership nodes and rules are dynamically generated during training based on incoming data.

The structure learning phase begins by checking whether structural learning is required, often based on predefined positive constants. It then decides whether to add a new membership function in the second layer and the corresponding fuzzy rule in the third layer. Each cluster in the input space represents a potential fuzzy base. The activation strength of each cluster indicates the degree to which the data belongs to the cluster and is calculated using the Eq. (4).

$$E_{max} = max_{1\leq j\leq M(t)} E\left(u\left(m_1^{(new)}, \sigma_1^{(new)}\right), u\left(m_{j1}, \sigma_{j1}\right)\right) \quad (4)$$

Losses, fill factors, Performance indicators, and tracking efficiency were observed based on various faults. In all cases, the ANFIS-based controller performs better, as shown. ANFIS is a hybrid version of an artificial neural network and a fuzzy logic unit. In practice, this gives it a performance advantage over other controllers. The current research methodology is compared with Essakiappan S' theory, which relies on an adaptive control algorithm and conductivity and voltage-current analysis to track the maximum power point. While Essakiappan's theory focuses on traditional analytical methods, this research extends the concept by integrating artificial intelligence techniques (ANN, ANFIS, SCFNN) with image analysis to detect shadows and reconfigure the solar array in real time, thereby improving tracking accuracy and stability.

4. PROPOSED SYSTEM

Figure 9 shows a block diagram of PV panel simulation using MATLAB/Simulink. Figure 10: Complete solar setup using Lucas-Nuelle system, where Fig. 10a is the wiring connection hardware and Fig. 10b is the solar panel altitude emulator. It was observed that the solar panel elevation simulator replicates the changing angle of the sun in the sky, as shown in Fig. 10b It is used to test the panel's power output. In practice, this means results may vary depending on the sun's altitude. Data: 10W polycrystalline solar module, open-circuit voltage: 22.5V, short-circuit current: 9.8A, adjustable module tilt, adjustable sun altitude, adjustable solar azimuth, 175W halogen lamp with dimming regulator. The performance of the AI-based controllers was evaluated against several criteria, including shadow losses and misalignment. Tables 3 and 4 show the specifications of the solar cell used in this work.

Table 3. Specifications of the devices used.

#	Item
1	DC-PV Output: 250 - 1000 V
2	MPP: 300 - 800 V
3	$I_{max} = 11A$
4	AC Voltage: 3 x 230, 50/60 Hz
5	Power factor=0.8
6	$I_{max} = 7A$
7	$P_{max} = 1400\ W$
8	Maximum efficiency=98.6%

Table 4. Renogy 175W Monocrystalline solar panel specifications.

Specification	Value
Maximum DC Voltage	18.9 V
Maximum DC Current	9.25 A
Maximum DC Power	175 W
Open Circuit Voltage	22.5 V
Short Circuit Current	9.8 A
Efficiency	≈19.8%
Cell Type	Monocrystalline

Dimensions	1485 × 668 × 35 mm
Weight	≈10.8 kg

5. RESULTS AND DISCUSSION

Figure 11 illustrates the relationships between voltage, current, and power under the maximum operating conditions of a solar system without shading. The pink (P-V) curve shows that the maximum power output is 1440 W at approximately 403 V and 3.57 A. The blue (I-V) curve shows that the current remains relatively stable at low voltages. Sharply declines after the maximum voltage, reflecting the natural behavior of solar cells under ideal irradiance conditions.

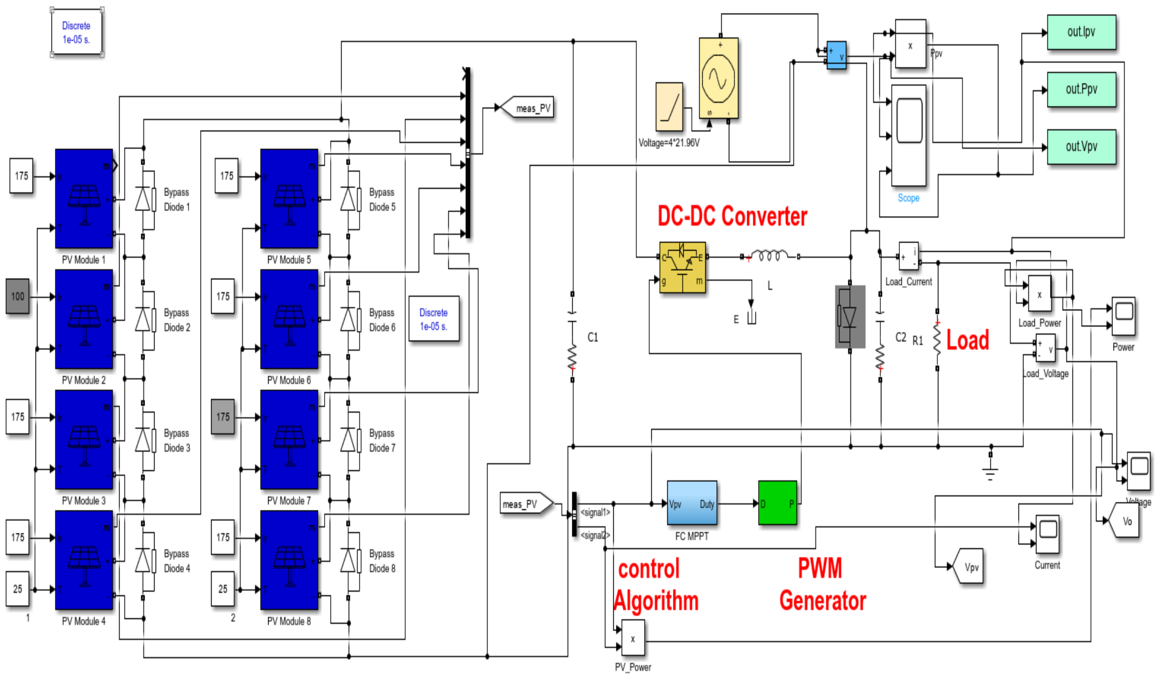

Fig. 9. Block diagram of PV panel simulation.

(a) **(b)**

Fig. 10. complete solar setup: a) wiring connection hardware; b) solar panel altitude emulator.

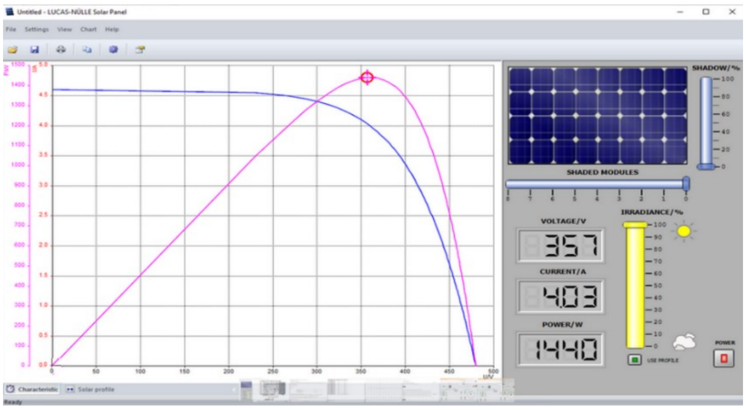

Fig.11. Power and current vs voltage using the SCADA technique.

The SCADA results show the impact of partial shading. In the ideal case with no shading or other reducing factors (Fig. 12), the maximum power was approximately 1,395 watts. With full shading (Fig. 13), the power was removed entirely. With 50% shading (Fig. 14), the power was reduced by almost half. A 30% combination with a similar reducing factor (Fig. 15) resulted in a significant drop in performance. Figure 16 shows that high shading combined with a reducing factor caused variability manifested as negative power. These results demonstrate the importance of effective tracking and shading management to maintain system operational efficiency. Figure 17 illustrates the derating case at 30% and 0% shading.

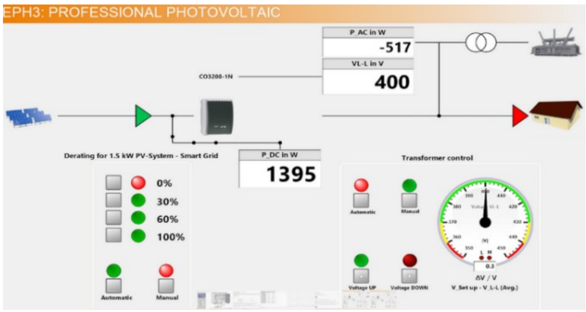

Fig.12. Derating at 0% and 0% shading.

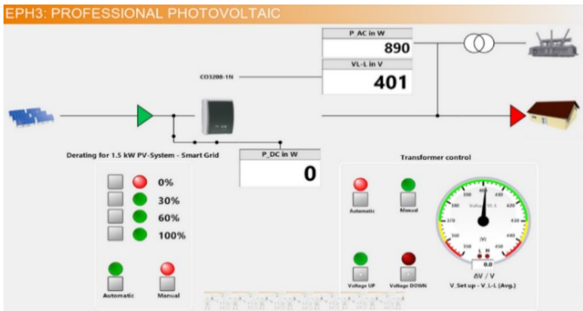

Fig. 13. Derating 0% and 100% shading.

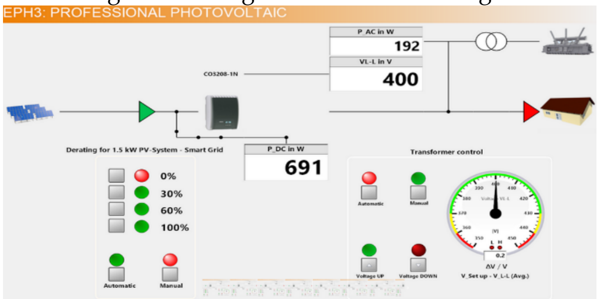

Fig. 14. Derating at 0% and 50% shading.

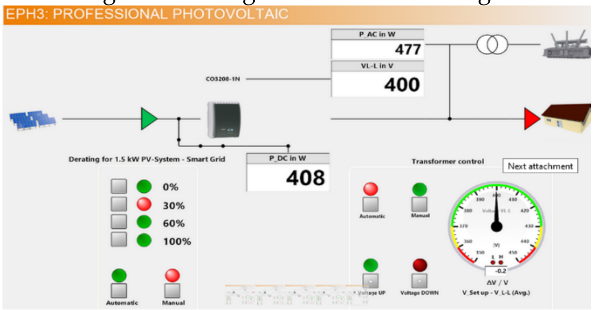

Fig. 15. Derating at 30% and 30% shading.

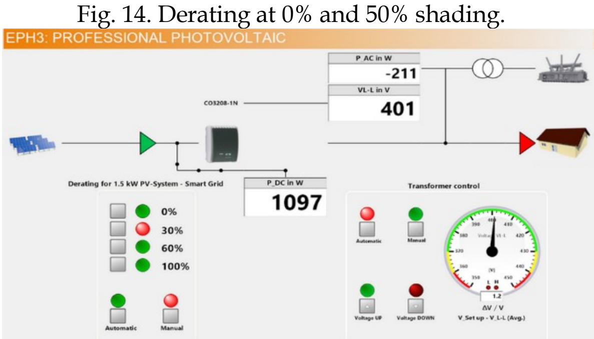

Fig. 16. Derating at 30% and 90% shading.

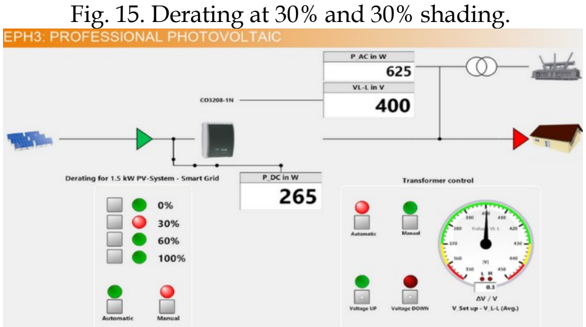

Fig. 17. Derating at 30% and 0% shading.

Figure 18 shows the relationship between the shading percentage (% shading) and the continuous control output (P_{DC}) for four derating levels. The higher the shading percentage, the more pronounced the decrease in PV system power output. At 0% derating, power drops sharply, reflecting the system's sensitivity to shading at maximum power. A 30% derating shows a similar but less severe drop, indicating better loss control .The results suggest that the 60% power-reduction case offers more stable performance than the other two cases, especially at shading levels above 50%. In contrast, the 100% reduction shows a near-horizontal line, reflecting the stability of power despite shading, but its overall value is very low. Variation between the curves highlights the importance of balancing stability and efficiency in solar system design. The intersection of the curves at shading levels between 60% and 80% indicates an optimal balance point for system performance. The reduction factor is an effective means of tuning system stability under shading conditions, even though it reduces the total power output.

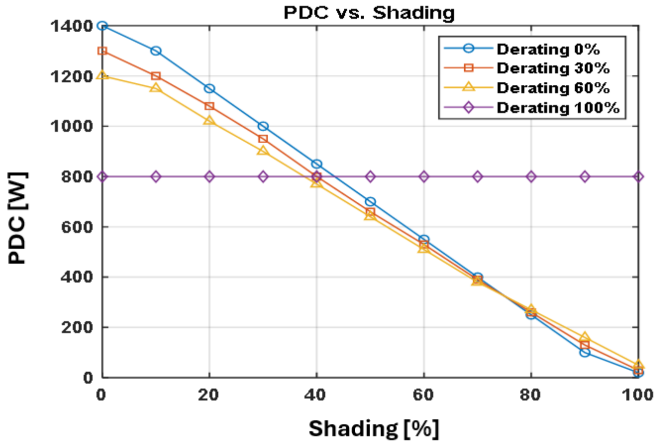

Fig. 18. The relationship between the shading percentage (% shading) and the power output (P_{DC}).

Figure 19 illustrates the relationship between the shading ratio (% shading) and the inverter output power (P_{AC}) at different levels of the step-down factor. The higher the shading ratio, the lower the inverter power in all cases. At a 0% drop, the decrease seems sharp, indicating a strong shading effect when the system is operating at maximum capacity.

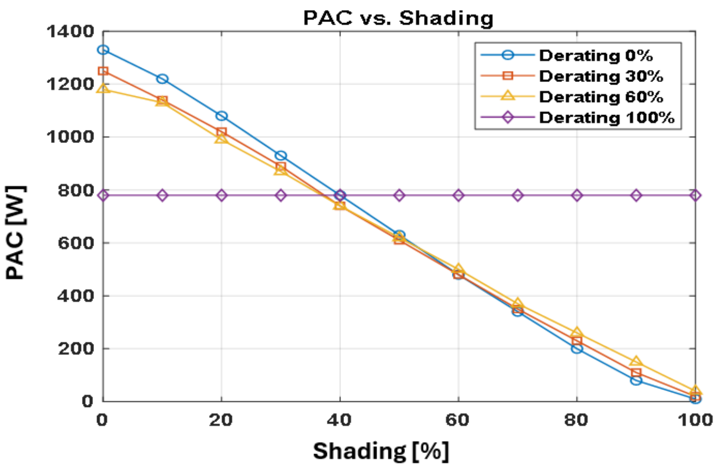

Fig. 19. The relationship between % shading and inverter output power is different for different derating levels.

At a step-down of 30% the power decline is less severe, indicating relative stability compared to the previous case. At a step-down of 60% stability improves further, and the power gradually decreases without collapsing. A 100% step-down keeps the curve nearly horizontal, keeping the output power almost constant despite shading changes. This stability at a 100% step-down demonstrates stable performance, but it indicates a loss of a portion of the total power output. The convergence of the curves at high shading ratios (80–100%) demonstrates the similarity of the systems' behavior under harsh operating conditions. The figure suggests that the inverter reacts more flexibly to shading when an appropriate step-down strategy is applied.

Figure 20 shows the relationship between the shading ratio and the overall system efficiency at different levels of the reduction factor. Efficiency here expresses the ratio of the inverter's output power to its continuous input power. (P_{AC}/P_{DC}). At 0% reduction, efficiency starts at an acceptable level and gradually declines sharply after 70% shading, until it collapses at 100%. A 30% reduction exhibits almost the same behavior, but with a lower slope, and the decline continues as shading increases. At a 60% reduction, efficiency remains relatively high up to 70% and then gradually declines. A full reduction of 100% stabilizes efficiency across shading ratios, as the constant values between P_{DC} and P_{AC} Result in misleading readings that do not reflect actual performance. The best efficiency is observed when a balance is achieved between moderate reduction and low shading. The significant drop in efficacy at 0% reduction under high shading conditions indicates substantial operational and energy losses. The figure supports the idea that adopting a moderate decrease of 30% to 60% provides the system with acceptable flexibility and stable efficiency across different operating conditions.

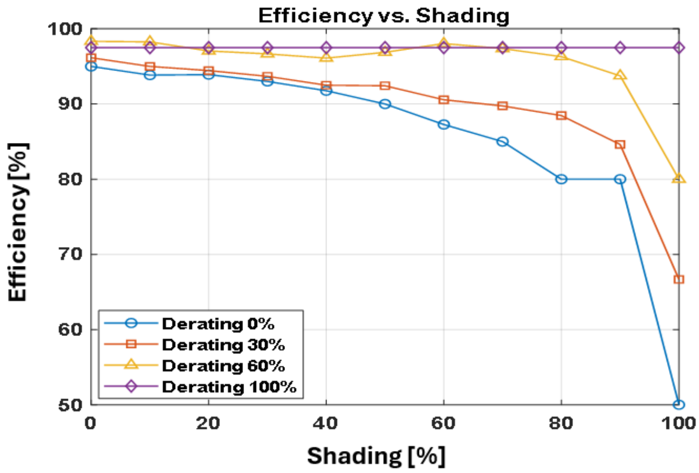

Fig. 20. The relationship between % shading and the overall system efficiency at different levels of derating.

Table 5 displays a simulation comparison of four AI-based maximum power point tracking techniques under partial shading conditions. The metrics include tracking time, steady-state error, power extracted from fluctuations around the maximum power point, and overall tracking efficiency. This translates to a total solar power output of up to 1,400 W in this scenario.

Table 5. Comparison of AI-based MPPT methods.

Method	Tracking Time [s]	Steady-State Error [%]	Extracted Power [W]	Oscillation [W]	Tracking Efficiency [%]
FCL	4.1	4.5	1267.0	±33.0	90.5
ANN	2.5	2.0	1332.8	±18.0	95.2
ANFIS	1.7	1.1	1366.4	±8.5	97.6
SCFNN	1.1	0.5	1386.0	±4.2	99.0

The SCFNN system achieves the highest trailing efficiency of 99.0%, with the lowest error and fastest response time, extracting up to 1,386 watts from a 1,400-watt system. ANFIS comes close with a powerful presentation but involves more complexity. ANN offers a good balance between accuracy and speed, while FCL performs worse but is easier to implement.

The theoretical results from the model and MATLAB simulations were compared with experimental data from the Lucas-Nülle system to evaluate the performance of the MPPT intelligent tracking algorithms. The comparison showed clear convergence between the theoretical and experimental results for tracking efficiency, response time, and extracted energy, confirming the accuracy of the mathematical model and its suitability for practical application in real-world photovoltaic systems.

6. CONCLUSION

The problem is that partial/full shadows disrupt PV system performance and confuse MPPT algorithms, resulting in significant energy losses. Early detection of shadows and their impact estimation have become operational necessities. It is concluded that combining computer vision (RGB/IR) and artificial intelligence (neural networks or hybrid algorithms such as ANFIS/SCFNN) enables quantitative shadow diagnosis and prediction of their impact on productivity with higher accuracy than traditional methods.

Core hypothesis: Homogeneous shade distribution combined with dynamic array reconfiguration reduces string heterogeneity, increases equivalent voltage/power, and improves peak power point capture. The main innovation is converting real-time visual information into an AI-driven structural electrical action (reconfiguration), i.e., moving from purely reactive MPPT to proactive structural adaptation of the array. Adopting MATLAB simulation with field-image validation provides a dual (software/practical) validation path, supporting the approach's validity in realistic shading conditions rather than just in simulation environments.

The proposed approach is understood to offer significant power increases and better consistency of the power curve under shading compared to static resampling methods on both hardware and software platforms. It is expected to reduce MPPT oscillations, shorten settling time after shadow disturbances, and improve daily energy utilization while minimizing losses at the local maximum. Performance depends on image quality, camera calibration algorithm, processing time, illumination consistency, and available interconnection architecture. That is the response time, and the array's electrical architecture may limit gains. Extending the work towards lightweight edge deep learning models, using additional spectral sensors, studying the long-term cost/benefit of rewiring, and building a benchmark dataset for motion shading.

The results indicate that the proposed configuration can be generalized to any PV Array size and that its output parameters can be improved by relocating it in physical space under various shading conditions. What is impressive is that the method does not isolate the load but instead uses a standard digital camera and MATLAB image processing techniques to detect partial shading. The camera captures images of the PV array, and real-time image processing identifies shading. The control signals generated based on the detected shading patterns energize relays that electrically reconfigure the array to maximize power output. The proposed technique will ensure the efficient operation of the PV system even under shaded conditions.

The proposed AI-based MPPT system can be practically implemented in household and industrial photovoltaic installations using standard SCADA interfaces and low-cost imaging sensors. Its integration enables adaptive reconfiguration of PV arrays, ensuring higher efficiency and reliability in real-world environments.

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