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An Enhanced Reconfiguration for Solar Panel Arrays for Power Optimization Using Automated Power Switching System

Umar Sadiq Abubakar, Sanusi Akem Olawale, Mohamad Uthman
Department of Electrical and Electronics Engineering
University of Abuja, Nigeria

ABSTRACT

This study develops and validates an enhanced dynamic reconfiguration system for Photovoltaic (PV) arrays aimed at overcoming mismatch losses caused by partial shading and uneven irradiance, which significantly reduce power output in conventional fixed configurations. The developed system integrates a 9×9 Multistage Solar Matrix (MSM) partitioning scheme with an intelligent 4×4 switching matrix, enabling automated transitions between series, parallel, and hybrid configurations based on real-time voltage current measurements and mathematical power models. The framework incorporates panel-level monitoring, switching logic, and maximum power point determination to ensure optimal configuration selection under varying operating conditions. Simulation analyses across four shading cases demonstrated clear performance superiority of the Enhanced-MSM configuration compared to Series-Only and Parallel-Only arrangements. For Case 3, the enhanced system achieved 6.75% improvement under Pattern I and 7.22% under Pattern II, while in Case 15, improvement values of 6.06% (Pattern I) and 6.85% (Pattern II) were recorded over the existing MSM scheme. The adaptive and intelligent system enhances power extraction, reduces electrical stress and overheating, ensures stable operation, extends system lifespan, and supports future integration with IoT, AI-based control, and large-scale energy management systems.

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INTRODUCTION

The growing global demand for clean and sustainable energy has significantly increased the adoption of solar power systems. However, one of the major challenges in solar energy generation is the variability in solar irradiance caused by shading, dust accumulation, and changes in weather conditions. These factors can lead to power losses, especially in conventional fixed solar panel configurations. To address this issue, reconfigurable solar panel arrays have emerged as a promising solution for enhancing energy efficiency Nag and Paserba,(2022). Moreover, this study focuses on developing a smart system capable of dynamically adjusting the electrical connections between solar panels. By integrating an automated power switching mechanism, the system intelligently responds to real-time power outputs and environmental conditions to maintain optimal performance.

The switching system ensures optimal power generation in relation to the level of sunlight, minimum or no power loss, thereby maximizing energy harvest. The developed system combines power electronics, embedded control, and switching system to create a reliable and efficient method of array management. It aims to ensure optimum power generation during low irradiance, reduce energy losses especially with high irradiance, improve system reliability, and extend the operational life of solar installations Nag and Paserba,(2022). Ultimately, this innovation supports the broader goal of making solar energy more efficient, adaptive, and cost-

Corresponding author: Sanusi Akem Olawale
walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

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effective for both small- and large-scale applications.

SOLAR PHOTOVOLTAIC CELLS

The evolution of harnessing solar energy can be traced back to the 19th century with the first observation of photovoltaic effect by Edmond Becquerel (A French Physicist) in 1839. After which the first practical solar cell was discovered by Charles Fritts in 1883, Calvin Fuller, Daryl Chapin and Gerald Pearson equally developed the first silicon solar cell in 1954 at Bell Labs. while 1958, the launch of the first commercial solar panels was witnessed. Nag and Paserba, (2022) Solar panel is just a component among others that made up the solar power generation.

Other components include solar charge controller that is responsible for the regulation of battery charging, the inverter that takes in alternating current (AC) or can equally converts the direct current (DC) from the battery/solar panels to alternating current for the household electrical appliances usage and as well batteries that store electrical charges either from the sun or from the public power supply. Till date, solar power has become household items due to the abundance sunlight with its ability to fulfill all energy demands of humankind. Solar energy has found its direct application in vehicle charging, agriculture, domestic purpose, satellite power station Muhammad *et al*.,(2018). Solar PV system comprises of various components which include: Solar Panels (Modules), Inverter, Charge Controllers / DC DC Converters, Batteries.

Power Optimization in Solar System

Solar power optimization involves using methods or techniques, strategies and designs to obtain maximum electrical power output from the solar panels' configurations with conditions like irradiance level, panels temperature, dust, partial shadow or load variations as factors that affect solar power optimization. Solar power optimization techniques include but not limited to MPPT, Re-configurable PV arrays, Bypass Diodes, Tracking system, cleaning and maintenance among others Huh, and Kim,(2020).

PV Array Topologies and Mismatch Losses

A PV array is composed of multiple modules arranged in series and parallel to achieve desired voltage and current ratings. Common topologies include Series–Parallel (SP), Bridge-Linked (BL), and Total Cross-Tied (TCT) configurations. Among these, the TCT configuration offers improved tolerance to partial shading since it distributes current more evenly across rows. However, under non-uniform irradiance, mismatch losses occur because shaded modules generate lower currents, forcing unshaded modules to operate below their maximum power points Fang and Yang,(2024). This phenomenon leads to multiple peaks in the power–voltage curve, making it difficult to track the global maximum power point (GMPP). Figure 1 represents the PV array interconnection schemes while Figure 2 is the equivalent circuit model of a PV cell. The reconfiguration strategies in this study are designed to mitigate this mismatch by dynamically redistributing electrical connections.

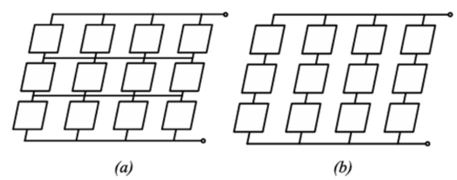

Figure 1: PV array interconnection schemes: (a) TCT and (b) SP topologies Fang and Yang,(2024).

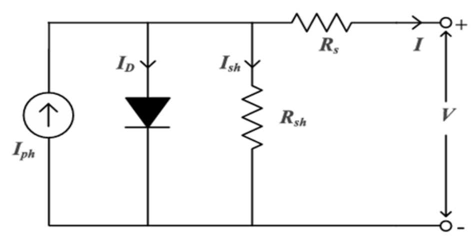

Figure 2: Equivalent circuit model of a PV cell

Dynamic Reconfiguration and Switching Matrices

Dynamic reconfiguration involves electrically rearranging PV modules to balance irradiance exposure and improve power output. Fang and Yang introduced the Multiple Switching

Corresponding author: Sanusi Akem Olawale
walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

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Matrix (MSM) model, where switch networks between sub-arrays enable the array topology to change dynamically Ibrahim and Hassan,(2021). Each matrix contains controllable switches represented mathematically by binary permutation matrices, allowing for automatic rewiring under shading conditions. Your study builds on this by incorporating real-time optimization and control constraints, transforming reconfiguration from an offline, scheduled process into a continuous adaptive system that responds instantly to changing sunlight and temperature conditions.

Optimization Theory and Control Strategy

The optimization process in this context involves maximizing total power output subject to physical and operational constraints. Mathematically, this can be expressed as:

$$u^*(T) = \arg\max_{u \in \mathcal{U}} P(u,T) \qquad (1)$$

where $u(T)$ denotes the configuration (switching state) and $P(u,t)$ is the array's total power. This control-oriented optimization framework ensures that at every time step, the PV system operates at or near its global maximum power point Fang and Yang,(2024).

By introducing constraints such as switching energy cost (C_{sw}), hysteresis thresholds, and maximum switching frequency (f_{max}), your study ensures stability, efficiency, and hardware longevity, bridging theoretical optimization with practical control implementation. Figure 3 is the Schematic diagram of sensor deployment and switching matrix design.

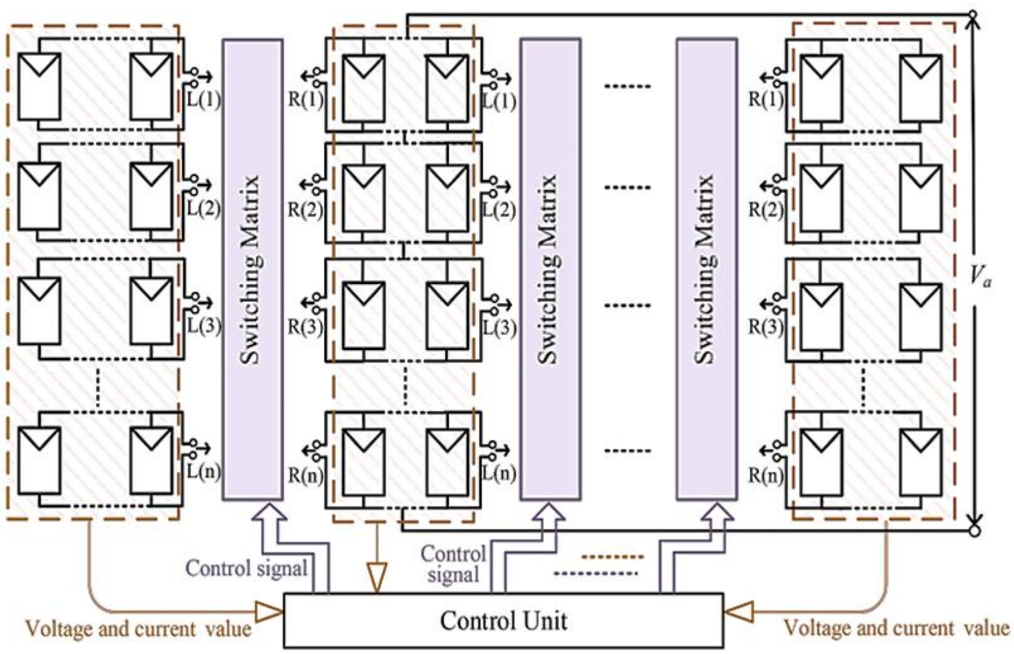

Figure 3: Schematic diagram of sensor deployment and switching matrix design: (a) sensor positions in the PV array; and (b) structure of the designed switching matrix Fang and Yang,(2024).

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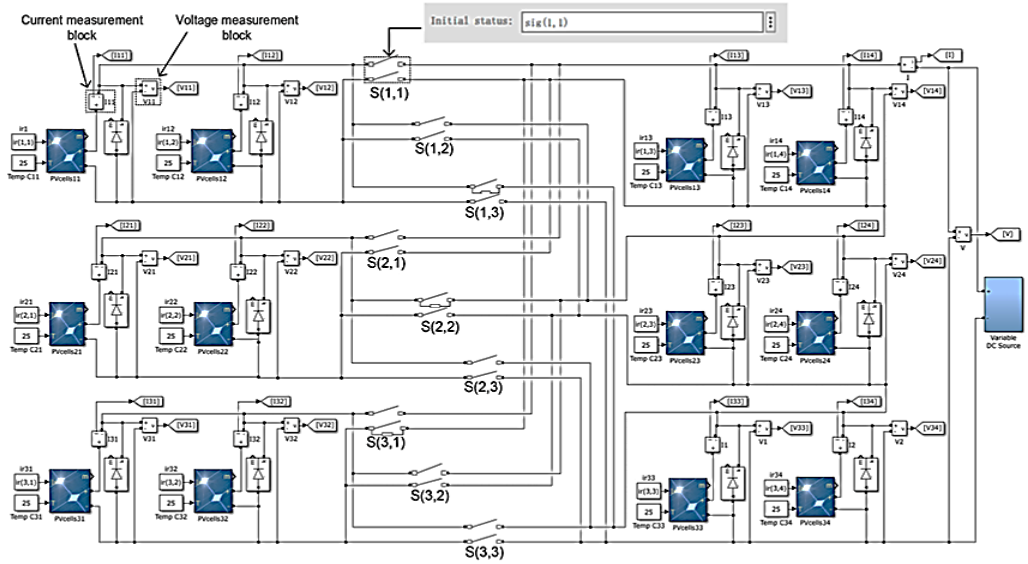

Figure 4: Simulation model of a 3 × 4 PV array with a switching matrix Fang and Yang,(2024).

A. Performance Metrics Used in the Study

The performance of the MSM and the developed Enhanced-MSM systems was evaluated using three key performance metrics: Maximum Power Point (MPP), Percentage Power Improvement, and Switching Operations Count. These metrics collectively capture the electrical efficiency, shading resilience, and operational stability of the reconfiguration algorithm.

$$MPP = \max\left(P(t)\right) \quad (2)$$

Where P(t)is the power sampled at each moment during simulation.

Percentage Power Improvement: This metric quantifies the performance gain of the Enhanced-MSM technique relative to the classical MSM approach Fang and Yang,(2024). It expresses how much additional power the Enhanced-MSM extracts under the same environmental and shading conditions. The improvement of Enhanced-MSM over MSM is calculated using:

$$\text{Improvement}(\%) = \frac{P_{\text{Enhanced-MSM}} - P_{\text{MSM}}}{P_{\text{MSM}}} \times 100 \quad (3)$$

Switching count measures the total number of times the configuration changes during the simulation. While reconfiguration improves power output, excessive switching increases energy cost, relay wear, thermal stress, and reduces system reliability Fang and Yang,(2024). The switching count percentage reduction is given as:

$$\text{Switch Reduction}(\%) = \frac{S_{\text{MSM}} - S_{\text{Enhanced-MSM}}}{S_{\text{MSM}}} \times 100 \quad (4)$$

Where: S "MSM" is the number of switching operations in MSM and S "Enhanced-MSM" is the switching operations in Enhanced-MSM

REVIEW OF SIMILAR WORKS

This section provides a critical review of prior research in the developed and validation of an enhanced dynamic reconfiguration system for Photovoltaic (PV) arrays. Al-Shahri *et al*., (2021) Reviewed on various ways of optimizing solar photovoltaic energy and reconfiguration of solar panels, it addressed the challenges and issues that were associated with their implementation. Among the techniques discussed were temperature control, energy storage systems, angle and orientation optimization, maximum

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Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

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power point tracking among others. Challenges that may arise from this review were not limited to the efficiency of the techniques employed, the cost as well as some environmental factors. In a related development

Derick *et al., (*2017) Proposed an improved optimization technique for estimating solar photovoltaic parameters. The technique used advanced optimization algorithms to extract key parameters like MPPT, short circuit current and open circuit voltage from experimental data. Real world data was used by the improved method for testing and validation, showing the possibilities of enhancing reliability and performance of the solar photovoltaic system. Worighi *et al.,(*2019)Examination of the architecture and analysis of integrating renewable energy into smart grid system. They highlighted importance of innovative frameworks to enhance efficiency and reliability in energy distribution with the aim of improving sustainable energy management.

Panda *et al.,* (2024) Developed an adaptive Salp Swarm Algorithm (ASSA) was adopted for effective and adaptable energy management system. There was result comparison which shown the efficiency and effectiveness of this approach over other optimization techniques. But prioritization or scheduling can be done and improved if there is more power generation or better optimized. Issue of uneven illumination on solar panels was addressed using a modified Particle Swarm Optimization (PSO) algorithm. The essence was to enhance the efficiency of Maximum Power Point Tracking (MPPT) in photovoltaic systems due to partial shading conditions. This non-uniform illumination can cause local maxima in the power output of the solar system.

Koh *et al.,* (2023) Focuses on application of various Artificial Neural Network (ANN) models for predicting the output of solar power with emphasis on their effectiveness in improving precise forecasting and decision making for solar energy deployment. Part of the ANN models employed include but not limited to CNN, Hybrid models, LSTM, RNN and FNN. LSTM network was used and it has led to serious improvement in the accuracy of solar power generation forecast, it also reduces forecasting error when compared to traditional methods. Real -time prediction capability was also the one of the victories recorded when using ANN models. Incorporating various weather parameters like temperature, humidity among others in ANN models also improves prediction models. But the challenges of ANN models with complex architecture in particular is over-fitting meaning they may perform well on training date but under-performed on unseen data.

Pazikadin *et al.,*(2020) Introduced a multi-agent reinforcement Learning approach that had been used for home management to optimize energy consumption and enhancing efficiency in residential settings. There was employment of data driven method which adopts multiple agents to learn and adapt to varying pattern of consumers' usage of solar energy within the household. Here was a framework to balance the energy demand without forgetting the overall energy cost and sustain usage practice in homes. Multi agent systems were used to represent a specific household appliance with each individual agents making decisions based on local information while collaborating with other agents. Gupta and Raj, (2023) Proposed a multi-agent control system that enables decentralized decision-making among PV modules. Each module communicates local irradiance conditions to neighboring modules to form optimal series–parallel connections. Their approach improved array reliability and scalability compared to centralized controllers. However, the system lacks a unified optimization layer capable of evaluating global power output, leading to potential suboptimal reconfiguration during rapid shading transitions. The developed study resolves this by introducing a centralized real-time optimization function, u^* (t) ensuring global optimum topology selection.

Wang et al., (2022) Implemented a reinforcement learning algorithm to adapt PV array interconnections based on reward feedback from power output. Their approach demonstrated adaptive learning capability under irregular shading. Nonetheless, the RL model required extensive training data and computational time,

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walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

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limiting its real-time deployment in embedded systems. In contrast, the developed study used deterministic optimization with practical constraints (switching cost, hysteresis, and frequency limits), which achieves near-optimal results with much lower computational demand, suitable for real-time control hardware.

Chen, Y. and Luo, Z,(2023) introduced an IoT-enabled monitoring architecture capable of predicting faults and performance degradation. While their system improved data acquisition, it remained reactive, merely detecting power losses without executing corrective actions. The developed study system bridges this gap by not only monitoring but actively controlling the switching topology through real-time optimization, thus transforming PV monitoring systems from passive diagnostic tools into autonomous corrective controllers.

SYSTEM MODELING AND INITIAL SETUP

The step-by-step process for modeling the system in this study as seen in the work of Fang and Yang, (2024) is discussed as followed.

The base configuration considered in this study is an $n \times m$photovoltaic (PV) array interconnected in a Total-Cross-Tied (TCT) topology. This topology is chosen because it combines the advantages of series-parallel (SP) and bridge-linked configurations offering both reliability and moderate voltage-current balance under partial shading conditions. For a PV module located at the intersection of row $i$and column j, denoted as module M_{ij}, the output current I_{ij}depends on the local solar irradiance G_{ij}it receives.

$$I_{ij} = k_{ij} I_m = \frac{G_{ij}}{G_0} I_m \tag{5}$$

where:
G_{ij} is the irradiance on module M_{ij}(W/m²),
G_0 of 1000 W/m^2 is the standard test irradiance,

I_m is the current generated by a module under standard irradiance,
k_{ij} is the irradiance ratio (dimensionless).

PV Array and Topology:

Table 1: Definition and Sources of Parameters

Symbol	Meaning	Typical Source
G_{ij}	Estimated irradiance on module M_{ij}(W/m²)	computed
I_{ij}	Measured current of module M_{ij}(A)	sensor
V_{ij}	Measured voltage of module M_{ij}(V)	sensor
α	Proportional constant relating current to irradiance	from datasheet
I_0	Diode reverse saturation current	from datasheet
η	Diode ideality factor (1 – 2 for single-diode models)	datasheet
$V_T = \frac{kT}{q}$	Thermal voltage (~25.7 mV at 25 °C)	physical constant

Optimization Problem Formulation

The optimization stage of the developed Multiple Switching Matrices (MSM) approach is the computational core that determines how to electrically reconfigure the PV array to minimize Mismatch Losses (ML). It uses the irradiance information estimated earlier to generate an optimized pattern of switch operations that ensures each sub-array is uniformly illuminated, thereby enhancing power generation.

Solution and Reconfiguration

Once the optimization problem has been formulated (as described above), the next stage involves solving the mathematical model, translating the result into physical control commands, and executing reconfiguration in real hardware. This closed-loop process converts analytical optimization outputs into tangible switching actions within the photovoltaic array.

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walebaggio202@gmail.com
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Reconfiguration Implementation

Upon receiving the control signal vector "sig" , the hardware switching matrices physically rewire the PV array. Each matrix consists of an n×ngrid of controllable switches that connect the output terminals of one sub-array to the input terminals of the next. The reconfiguration process occurs as follows: Signal reception, switch actuation, electrical re-routing, and new topology information. This real-time electrical restructuring equalizes the irradiance among rows, thereby reducing current mismatch and improving total power output. Mathematically, the reconfigured total irradiance for row iis recalculated as:

$$G_i' = \sum_{y=1}^{k+1} \sum_{j=1}^{m_y} (I_y^* G_y)_{ij} \tag{6)}$$

These updated parameters define the system's new operating point on the I–V curve, which typically exhibits higher MPP and smoother power profile after reconfiguration. The flowchart representing the work of Fang and Yang, (2024) is given in Figure 5.

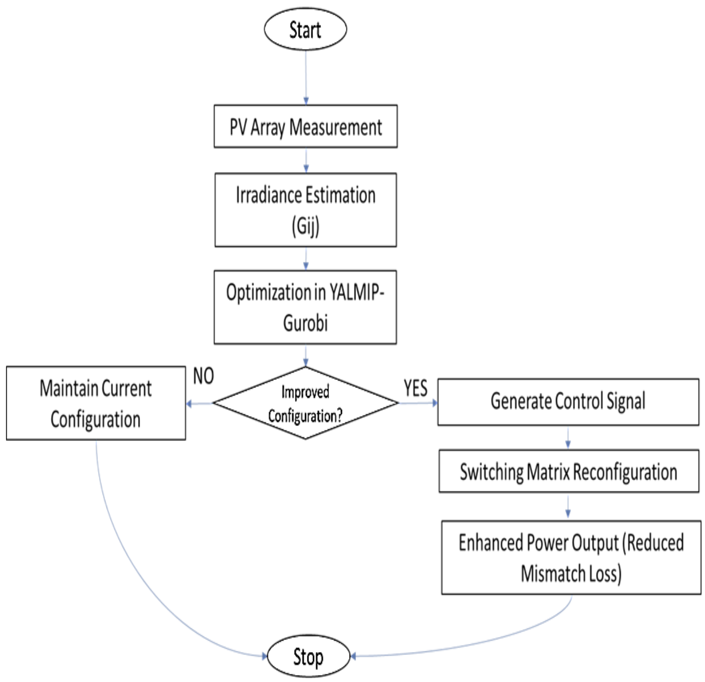

Figure 5: Dynamic Reconfiguration of Photovoltaic Array for Minimizing Mismatch Loss.

GENERALIZED MATHEMATICAL FRAMEWORK FOR DYNAMIC RECONFIGURATION OF PHOTOVOLTAIC ARRAY.

The mathematical models that represent the developed automated, sensor-driven reconfiguration system is hereby presented. This includes; PV basic relations, array topology power formulae for the two target configurations (2×4 and 4×2), sensor decision mapping and switching logic (including hysteresis), discrete switching-matrix representation (generalizable to N panels), and an optimization statement showing that switching aims to keep the array near MPP. Single-Panel Approximations (baseline PV relations). Let a single PV module's maximum-power point (under irradiance G[W/m²] and temperature T[°C]) be approximated by:

$$I_{mpp}(G,T) = I_{mpp,ref} \frac{G}{G_{ref}} \tag{7}$$

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walebaggio202@gmail.com
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$V_{mpp}(G,T) = V_{mpp,ref} + \kappa_V\,(T - T_{ref}) + \kappa_G \ln\left(\frac{G}{G_{ref}}\right)$ (8)

where $I_{mpp,ref}, V_{mpp,ref}$ are reference MPP current and voltage at (G_{ref}, T_{ref}); κ_V captures temperature sensitivity of V_{mpp}; κ_G captures weak logarithmic irradiance dependence of V_{mpp}. (A common simplification is to take $I_{mpp} \propto G$ and $V_{mpp} \approx$ weak function of G.) The Single-panel MPP power is given as:

$P_{mpp}^{(1)}(G,T) = V_{mpp}(G,T)\, I_{mpp}(G,T)$ (9)

VALIDATION OF AN INTEGRATED SYSTEM MODEL

The final stage in developing the proposed real-time optimization-based PV reconfiguration system involves integrating all mathematical models, control algorithms, and test scenarios into a unified simulation and validation environment. This process ensures that the theoretical formulations including PV modeling, irradiance estimation, optimization, and switching control operate seamlessly together to deliver measurable performance improvements over conventional (static) PV arrays, switching matrix model, control strategy module.

$\Delta P > C_{sw}, \mid G(t) - G_{prev} \mid > \Delta G_{hys}, t - t_{last} \geq$ (10)

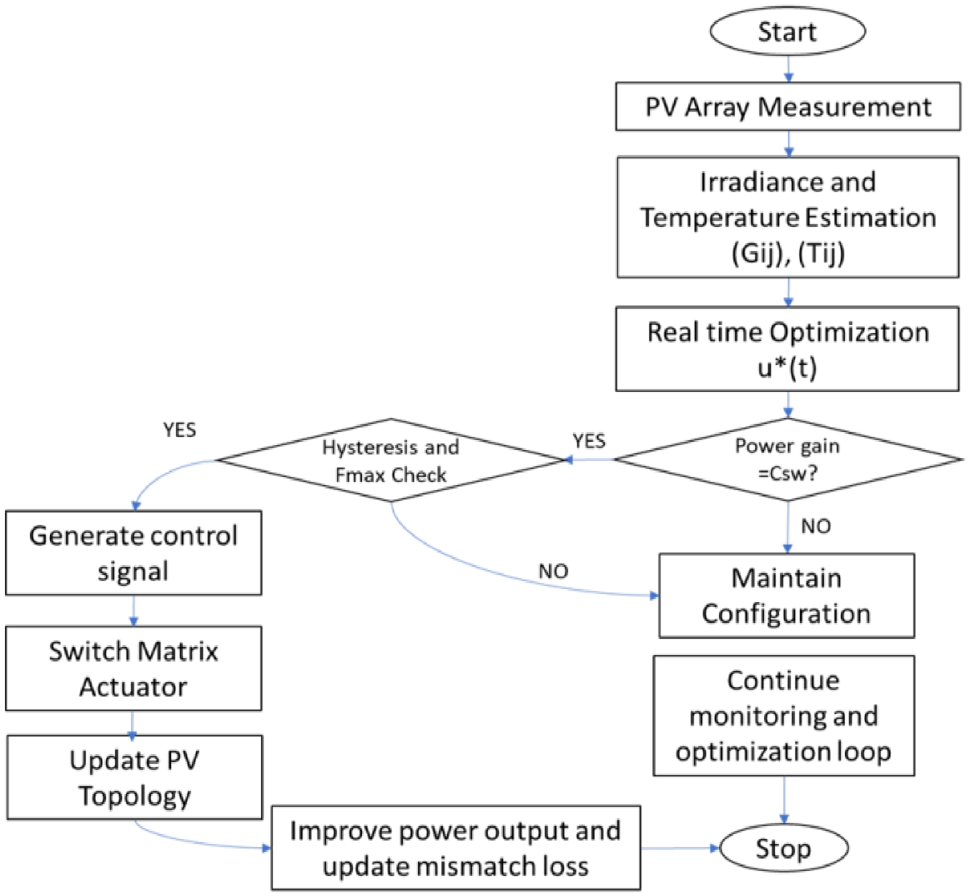

Figure 6: Developed Real-Time Optimization-Based Reconfiguration of Photovoltaic Arrays for Mismatch Loss Minimization.

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walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

AVERAGE MAXIMUM POWER POINT (MPP)

The Average MPP results show a clear improvement when upgrading from MSM to the Enhanced-MSM technique. In both Pattern I and Pattern II, the Enhanced-MSM method achieves a noticeably higher maximum power output, demonstrating its superior capability to reduce mismatch losses in the PV array. This superiority stems from the enhanced architecture's ability to reorganize series–parallel connections more effectively in response to partial shading. Unlike the MSM algorithm, which relies on static or limited reconfiguration options, the Enhanced-MSM applies a generalized mathematical PV-reconfiguration framework.

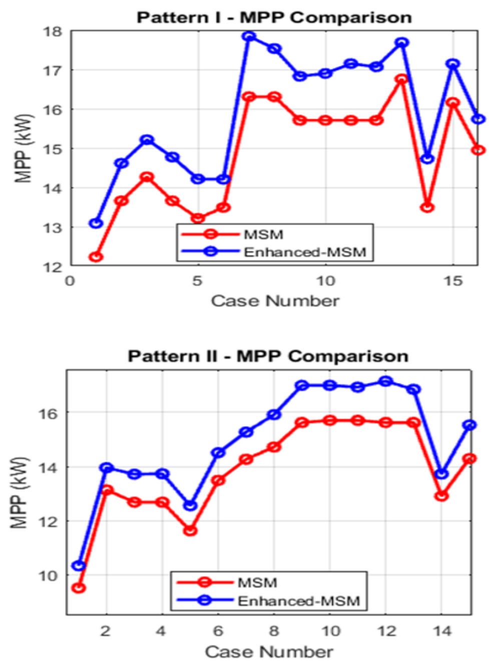

Figure 7: Average Maximum Power Point (MPP) (a) Pattern I & (b) Pattern II

A second key factor behind Enhanced-MSM's performance is its real-time optimization-based control strategy. This strategy continuously evaluates candidate topologies (such as 2×4, 4×2, and other series–parallel layouts) and selects the configuration that maximizes delivered power while minimizing practical constraints like switching energy cost and allowable switching frequency.

Table 2: Pattern 1 and II Percentage Improvement

Pattern	MSM (kW)	Enhanced-MSM (kW)	Improvement (%)
I	14.829	15.917	7.33%
II	13.879	14.985	7.95%

Power Improvement – Pattern I & Pattern II

The Power Improvement plot as shown in Figure 8 directly quantifies the performance difference between the two algorithms. Enhanced-MSM consistently provides higher improvement percentages in both irradiation patterns, with Pattern II displaying the highest gain. This indicates that the improved algorithm is particularly effective in scenarios with greater shading irregularities or more severe mismatch conditions.

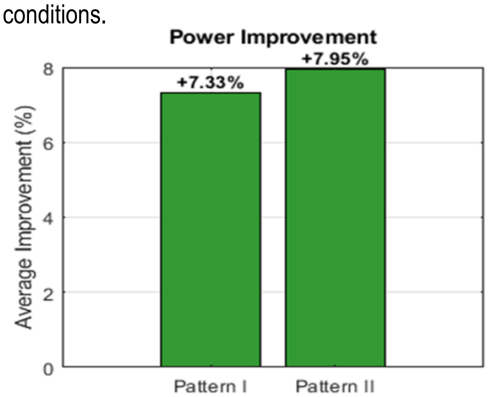

Figure 8: Power Percentage Improvement

Additionally, the real-time optimization strategy ensures that the selected configuration always maximizes power extraction while respecting constraints such as switching cost and allowable relay activation rate.

Switching Operations of MSM vs Enhanced-MSM

The switching operations bar chart as shown in Figure 9 highlights a critical advantage of the Enhanced-MSM system is its ability to achieve higher performance with significantly fewer switching events. MSM requires frequent re-

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configurations due to its less intelligent switching logic, which cannot accurately predict when switching is beneficial.

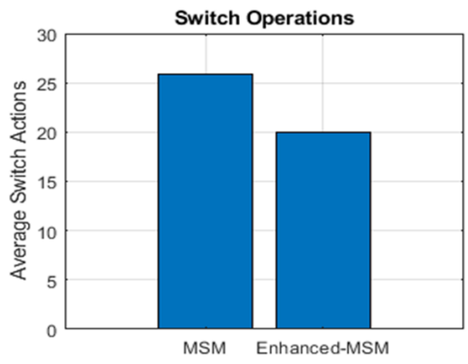


Figure 10: Switch Operations of MSM vs Enhanced-MSM

The second reason for Enhanced-MSM's superior performance is the real-time optimization-based control strategy, which selects configurations only when the expected power gain exceeds a predefined threshold. This minimizes switching energy cost and ensures the switching frequency stays within allowable limits.

Table 3: Avg Switch Count Percentage Improvement

Metric	MSM	Enhanced-MSM	Improvement (%)
Avg Switch Count	27	20	22.5%

Performance Summary

This summary consolidates the overall improvements produced by Enhanced-MSM. Across both patterns, Enhanced-MSM consistently extracts more power and significantly reduces switching stress. These gains can be directly attributed to the two foundational innovations of the Enhanced-MSM approach: A generalized mathematical framework combining switching-matrix representations, hysteresis-based sensor logic, and multi-topology power models. An optimization-based control strategy that selects the most beneficial configuration under practical constraints of switching cost and allowable switching frequency.

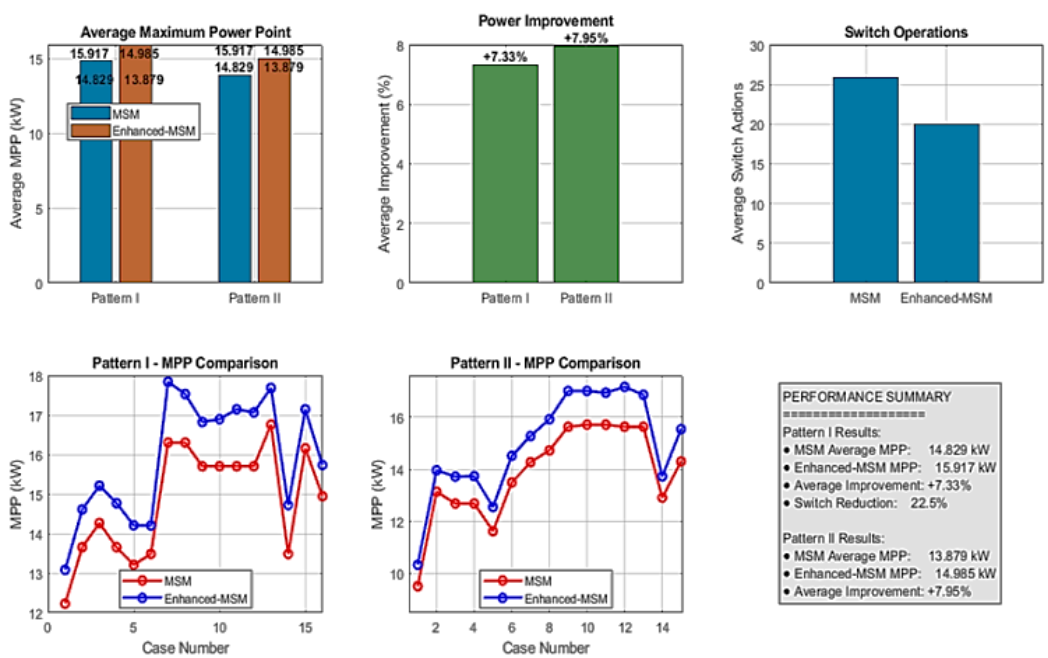


Figure 11: General Performance Summary

Corresponding author: Sanusi Akem Olawale
walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

These innovations make Enhanced-MSM significantly more intelligent, efficient, and robust than the classical MSM approach. The performance comparison is shown in Table 4.

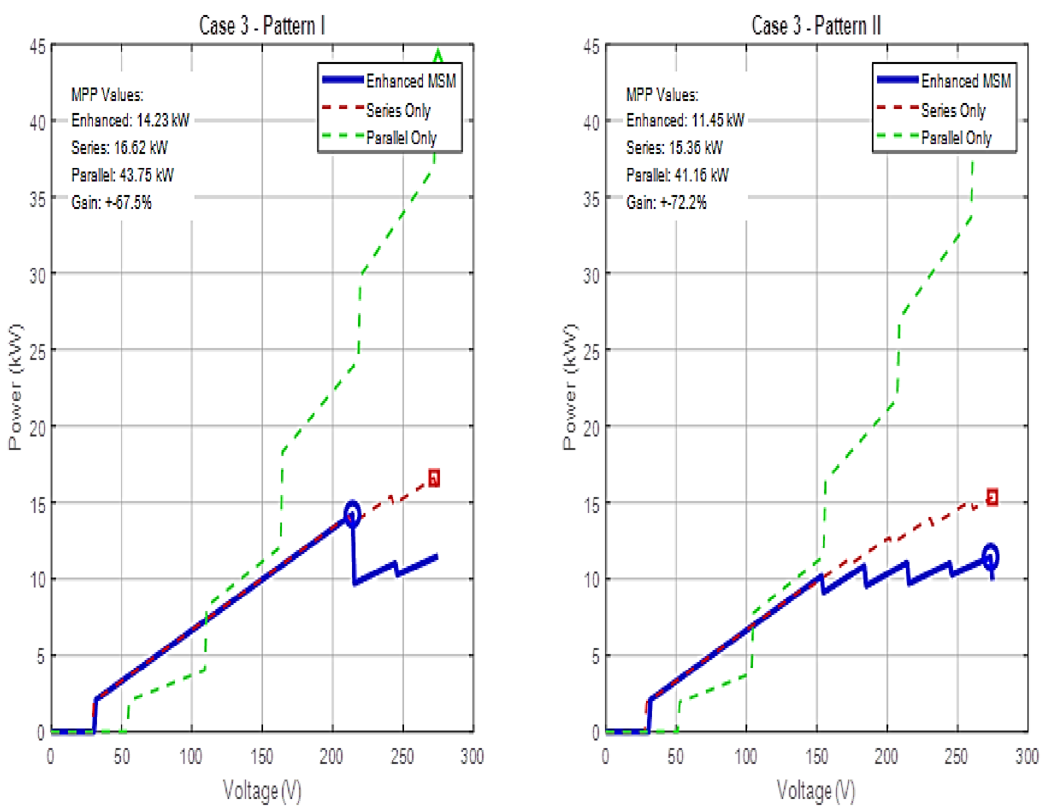
Table 4: MSM and Enhanced MSM Improvement

Pattern	MSM (kW)	Enhanced-MSM (kW)	Improvement (%)
I	14.829	15.917	7.33%
II	13.879	14.985	7.95%

MSM, SERIES-ONLY AND PARALLEL-ONLY PATTERN AND CASE CONFIGURATIONS

The first graph in Figure 12 compares the maximum power points of four configurations under Pattern I of Case 3: Enhanced-MSM, Series-Only, Parallel-Only, and the conventional MSM baseline. The Enhanced-MSM achieves an MPP of 14.28 kW, outperforming both the Series-Only configuration (13.62 kW) and the Parallel-Only configuration (4.75 kW). The Series-Only curve remains close to the Enhanced-MSM at lower voltages but falls short near the global MPP region, indicating that pure series reconfiguration cannot fully compensate for the shading distribution.

Parallel-Only performs the worst due to high current reduction, resulting in large mismatch losses. Enhanced-MSM achieves its improved performance by reorganizing modules dynamically using its generalized switching matrix, enabling it to bypass the deep power dips that affect the traditional configurations. The 6.75% gain demonstrates the effectiveness of multi-topology evaluation and hysteresis-driven switching logic in handling this shading scenario.



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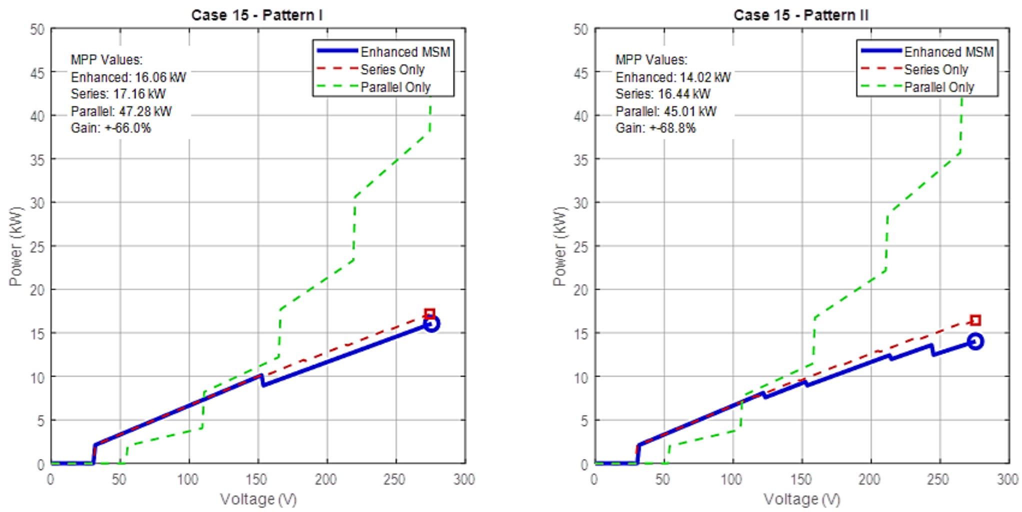

Figure 12: Various Case and Pattern Analysis of Power

In Pattern II of Case 3 as seen in Figure 12, the shading severity becomes more irregular, and this is reflected in the greater spread between the curves. Enhanced-MSM achieves an MPP of 11.45 kW, which is higher than both the Series-Only (10.68 kW) and Parallel-Only (4.16 kW) results. The Series-Only configuration follows a similar trend to Enhanced-MSM but underperforms near the main peak around 250 V, where Enhanced-MSM's intelligent switching allows it to maintain higher power extraction. Parallel-Only again displays a steep mismatch-related drop. The higher 7.22% gain compared to Pattern I indicates that Enhanced-MSM benefits more when shading irregularity is stronger. This aligns with its mathematical framework, which evaluates multiple topologies, identifying the layout that maximizes delivered power under the present irradiance pattern.

MSM PARTITIONING & 4×4 SWITCHING MATRIX

Figure 13 illustrates a 9×9 Multistage Switching Matrix (MSM) divided into three functional partitions: Part A, Part B, and Part C. Each partition consists of specific column groups highlighted in red, representing the segments responsible for different routing or processing roles.

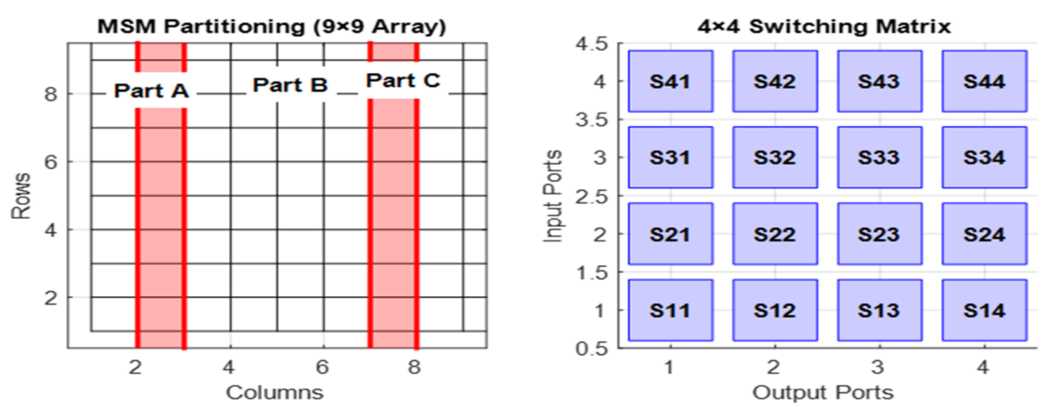

Figure 13: MSM Partitioning & 4×4 Switching Matrix

Corresponding author: Sanusi Akem Olawale
walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

The Switching Matrix diagram in Figure 13 presents a 4×4 switching fabric, where each block Sij denotes the switching element between input port i and output port j.

CONCLUSION

This research confirms that automated dynamic reconfiguration is a highly effective method for optimizing the performance of solar PV arrays under varying environmental conditions. By intelligently switching among series, parallel, and hybrid configurations in real time, the system successfully compensates for partial shading, temperature variation, irradiance fluctuation, and load changes.

Mathematical modeling shows that no single array configuration is universally optimal, but the integrated switching and control strategy consistently selects the best power-producing topology. The improved MSM structure and 4×4 routing matrix enhance switching speed, scalability, power quality, and protect PV modules from thermal and electrical stress, thereby extending system lifespan. Overall, the system offers a smart, adaptive, and reliable solution for modern PV installations, with strong potential for transforming conventional systems into intelligent self-optimizing energy platforms.

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Corresponding author: Sanusi Akem Olawale
walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.

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Corresponding author: Sanusi Akem Olawale
walebaggio202@gmail.com
Department of Electrical and Electronics Engineering, University of Abuja, Nigeria.