



REVIEW ARTICLE

A Systematic Review for Reconfiguring Photovoltaic Arrays under Conditions of Partial Shading

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| Article Info. | Abstract |
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| <i>Article history:</i> Received 20 February 2024 Accepted 21 May 2024 Publishing 30 June 2024 | In the rapid progress towards sustainable energy systems Photovoltaic (PV) systems are notably susceptible to power losses and gaining hotspots due to partial shading, a pervasive issue that significantly diminishes power output. This article presents a systematic review of more than seventy up-to-date relevant articles that are involved in PV array reconfiguration, and their strategic response to combat the detrimental effects of partial shading. These studies were meticulously chosen for their relevance to current PV array practices, their methodological robustness, and the reliability of their empirical or simulated results. The provided analysis is a multi-dimensional assessment of these methods, considering factors such as array size, complexity, execution speed, merits, demerits, acquired parameters, and alongside, validation methods employed. A significant finding from this review is the emerging preference for reconfiguration techniques that blend static and dynamic elements, particularly those employing meta-heuristic algorithms, over purely dynamic approaches. The article presents a comprehensive reference for and a lucid primer in the domain of PV array reconfigurations. |
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1. Introduction

The worldwide pursuit of sustainable energy answers has spurred big research into optimizing PV structures. Amid this progress, a persistent obstacle confronted with the aid of PV arrays stays partial shading—a tricky mission arising using diverse factors such as building, dust, clouds, or different obstructions [1]. Partial shading outcomes in widespread discounts in power output, substantially impairing the general efficiency of PV installations [2]. This phenomenon has sparked immoderate inquiry because of its big effect on the sun's electricity era. The importance of addressing this issue cannot be overstated because it at once influences the feasibility and effectiveness of sun strength as a probable electricity delivery in diverse settings. Researchers have endeavored to increase the techniques to mitigate the losses and decorate energy harvesting from PV systems. Among the one's techniques, static and dynamic reconfiguration techniques have emerged as pivotal improvements within the realm of solar electricity engineering [3]. This paper delves into PV array reconfiguration methods, aiming to provide comprehensive information on the existing techniques, their methodologies, benefits, and barriers. By severely comparing these strategies, this examines objectives to contribute valuable insights that no longer simply improve the expertise of sun electricity engineering but additionally provide realistic answers for optimizing PV systems, thereby fostering the extensive adoption of sustainable electricity assets. The escalating call for sustainable power answers has accentuated the need for maximizing the effectiveness of photovoltaic structures. However, the continual partial shading poses a sizable risk to the performance of PV arrays. Shadows solid by surrounding systems or natural elements cause abrupt fluctuations in irradiance, main to voltage mismatches and in the end decreasing the general electricity output. These fluctuations, if now not addressed effectively, can result in full-size strength losses, hindering the seamless integration of sun strength into the grid. This pressing issue necessitates innovative answers to ensure constant and reliable energy from PV installations. To bridge this hole, the exploration of static and dynamic reconfiguration strategies has received promise. Static reconfiguration includes a set arrangement of PV modules to limit shading results, while dynamic reconfiguration adapts the array configuration in real time to optimize strength technology underneath various shading conditions. Investigating the effectiveness of those strategies is essential for devising practical, scalable, and economically possible answers to decorate the overall performance of PV structures, making them extra resilient in the face of partial shading demanding situations. These studies adopt a complete analysis of these reconfiguration techniques, shedding light on their capacity to revolutionize the sphere of solar power engineering and pave the way for sustainable electricity solutions globally [4-8].

| Nomenclature & Symbols | | | |
|------------------------|---|--|---|
| AAR | Adaptive Array Reconfiguration | PSC | Partial Shading condition |
| ABC | Artificial Bee Colony | PSO | Particle Swarm Optimization |
| AEJSA | Adaptive Evolution Jelly Fish Search Algorithms | RLS | Recursive Least Squares |
| AI | Artificial Intelligence | RMPPT | Reconfigure Maximum Power Point Tracking |
| ASO | Atom Search Optimization | S | Series |
| AVOA | African Vulture Optimization Algorithms | SAOS | Sudoku And Optimal Sudoku Optimization |
| BL | Bridge Linked | SDM | Single Diode Model |
| COA | Coyote Optimization Algorithms | SDQ | Swarm-Based Double-Q Learning |
| DCQL | Divide And Conquer Q-Learning Algorithms | SOA | Seagull Optimization Algorithms |
| DDM | Double Diode Model | SP | Series Parallel |
| DPSC | Dynamic Partial Shading Condition | SPV | Solar Photovoltaic |
| DPVAR | Dynamic Photovoltaic Array Reconfiguration | TCT | Total Cross-Tied |
| EAR | Electrical Array Reconfiguration | TDM | Triple Diode Model |
| FLC | Fuzzy Logic Control | V _m | Voltage At Max PowerPoint |
| GA | Genetic Algorithms | V _{oc} | Open Circuit Voltage |
| GMPP | Global Maximum Power Point | ΔP | Power Loss Due to Mismatch |
| GOA | Grasshopper Optimization Algorithms | Symbols | |
| HC | Honey Comb | a ₁ , a ₂ , and a ₃ | Ideality Factor to D1, D2, and D3 respectively |
| HBM | Honey Badger Method | I _{D1} | Current Flowing through the diode |
| HHO | Harris Hawks' Optimization | I ₀₁ | Represents The Leakage Current of diode D1 |
| HPSO | Hybrid Particle Swarm Optimization | I ₀₂ | Congestion Current |
| IE | Irradiation Equalizer | I ₀₃ | Leakage Current of D3 |
| Imp | Current At Max Power Point | | Current Flowing Through the Parallel Resistance |
| KCL | Kirchhoff's Current Law | I _p | Resistance |
| LMPP | Local Maximum Power Point | I _{PV} | Current Produce by The PV Cell |
| MHHO | Modified Harris Hawks' Optimization | I _{irr} | Current Source |
| MLI | Multi-Level Inverter | N _s | Total No. Of Series-Connected Cells |
| MOGWO | Multi-Objective Gray Wolf Optimizer | PV | Photovoltaic |
| MPP | Maximum Power Point | q | Charge Of an Electron |
| MPPT | Maximum Power Point Tracking | R _p | Shunt Resistance |
| MS | Magic Square | R _s | Series Resistance |
| Pmax | Maximum Power Output | T | Temperature of the Cell (Kelvin) |
| POA | Pelican Optimization Algorithms | V _{PV} | Photovoltaic Voltage |
| | | V _T | Thermal Voltage |

2. General Background Theory

2.1 Photovoltaic Model

It is essential to model a PV module to analyze the behavior and performance of the module within a solar PV system. However, due to the non-linear properties of PV systems, accurate PV modeling presents several challenges. To simulate the performance of the PV array, it has been necessary to make use of three different models: the single diode model (SDM), the double diode model (DDM), and the triple diode model (TDM). The SDM is favored above these other models because of its straightforward nature, straightforward design, and low number of factors involved. [9]. The equivalent circuit diagrams of the three PV models are presented in Fig. 1. The series resistance R_s , the shunt resistance R_p , and the current source I_{irr} make up the SDM. They are linked antiparallel to the diode D_1 in the circuit. In a similar vein, the DDM and TDM models each include two or three diodes, depending on which type they are [9]. By applying Kirchhoff's current law (KCL) to the PV models' equivalent circuits, one can estimate the amount of current that is generated by the PV models. The SDM is the model with the fewest moving parts and the most widespread application, while the DDM and TDM both provide more accurate results [10, 11]. However, the need for more accurate models is not always evident, as the SDM can still provide satisfactory results in many cases [11]. The expression delineating the total current generated by the single-diode PV model is as follows:

$$I_{PV} = I_{irr} - I_{D1} - I_p \quad (1)$$

The equation describing the current in a PV source, denoted as I_{irr} , involves the components I_p and I_{D1} , representing the current flowing through parallel resistance and the diode, respectively. By substituting the values of I_{D1} and I_p into the equation, a more refined and academic expression for the current can be derived.

$$I_{PV} = I_{irr} - I_{01} \left(\exp \left(\frac{V_{PV} + I_{PV} R_s}{a_1 V_t} - 1 \right) \right) - \left(\frac{V_{PV} + I_{PV} R_s}{R_p} \right) \quad (2)$$

Within the parameters of this discussion, the variable V_t denotes the thermal voltage and can be interpreted as $\frac{N_s k T}{q}$, when k -stands for Boltzmann's constant, T signifies the temperature of the cell in Kelvin, q denotes the charge of an electron, N_s represents the total number of series-connected cells, a_1 represents the ideality factor, and I_{01} represents the leakage current of diode D_1 .

$$I_{PV} = I_{irr} - I_{01} \left[\exp \left(\frac{q(V_{PV} + I_{PV} R_s)}{a_1 k T} \right) - 1 \right] - I_{02} \left[\exp \left(\frac{q(V_{PV} + I_{PV} R_s)}{a_2 k T} \right) - 1 \right] - \frac{(V_{PV} + I_{PV} R_s)}{R_p} \quad (3)$$

In the given scenario, I_{PV} represents the current produced by the PV cell, while I_{o1} and I_{o2} denote the diffusion and congestion currents, respectively. Additionally, a_2 represents the ideality factor of diode D2. The mathematical expression representing the current in the three-diode model can be articulated in a more refined and scholarly manner.

$$I_{PV} = I_{irr} - I_{o1} \left[\exp \left(\frac{q(V_{PV} + I_{PV}R_S)}{a_1 kT} \right) - 1 \right] - I_{o2} \left[\exp \left(\frac{q(V_{PV} + I_{PV}R_S)}{a_2 kT} \right) - 1 \right] - I_{o3} \left[\exp \left(\frac{q(V_{PV} + I_{PV}R_S)}{a_3 kT} \right) - 1 \right] - \frac{(V_{PV} + I_{PV}R_S)}{R_p} \quad (4)$$

In this context, I_{o3} signifies the leakage current of diode D3, while a_3 represents the ideality factor associated with the diode. The information provided can be expressed in a more polished and scholarly manner [5] and the Structure of the reconfiguration technique can be seen in Fig. 2.

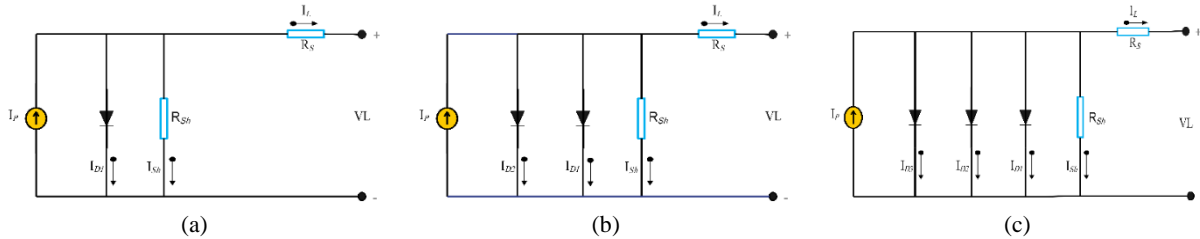


Fig. 1. PV models with the following equivalent circuits: (a) SDM, (b) DDM, and (c) TDM [9].

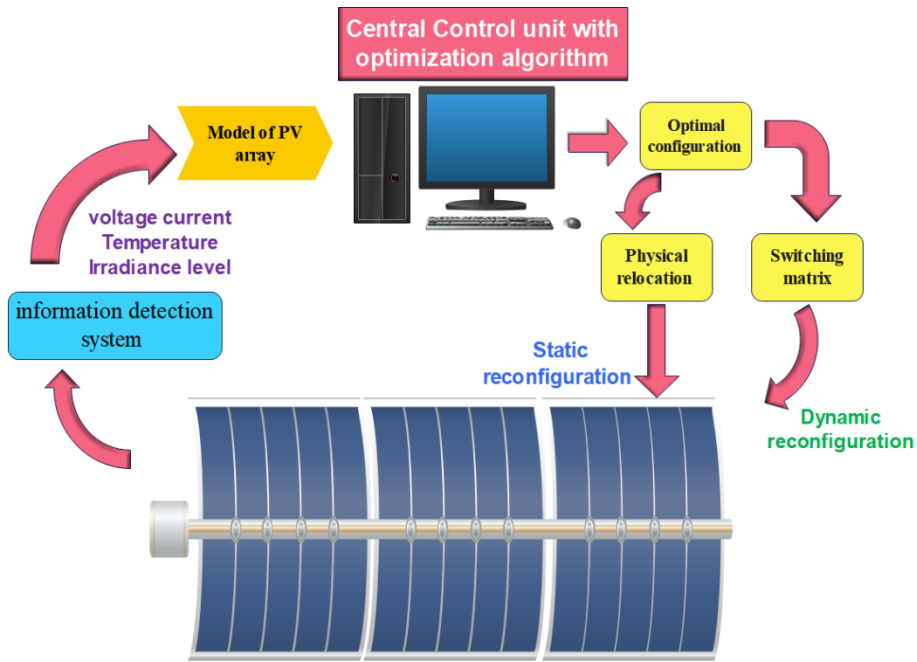


Fig. 2. Structure of reconfiguration technique.

2.2. Problem Statement

Optimizing solar PV systems underneath partial shading conditions remains a vital challenge inside the renewable strength landscape. Partial shading, as a result of environmental elements consisting of clouds or buildings, ends in uneven energy distribution across PV arrays, resulting in decreased performance and electricity generation. Existing studies have added diverse reconfiguration strategies, including Sudoku algorithms, Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and hybrid techniques, to mitigate these effects. However, there is a fragmented know-how of those strategies' comparative effectiveness, limitations, and realistic applicability. A comprehensive review is essential to synthesize existing knowledge, identify gaps, evaluate emerging technologies like hydrogen energy integration, and assess the economic feasibility of these solutions. This paper aims to systematically analyze and compare these strategies, providing valuable insights for researchers, engineers, and policymakers striving to enhance solar energy systems' efficiency in real-world, partially shaded environments [6, 7, 12-14].

2.3 Mitigating Partial Shading Effects Using Basic Interconnection Schemes

Partial shading refers to the condition where only a part of a PV solar panel is exposed to sunlight, while the relaxation is shaded, both using nearby items, clouds, or other obstructions. This phenomenon drastically influences the performance of sun energy structures. When even a small part of a sun panel is shaded, it could lead to a considerably lower energy output due to the mismatch in the contemporary-

voltage traits of the shaded and unshaded cells. The primary detrimental results of partial shading on sun panels are the decline in total energy output, a drop in efficiency, and the formation of hotspots. Partial shading leads to a discrepancy in sunlight absorption in a number of the cells inside a panel, resulting in a choppy generation of electrical. This unevenness can cause the "opposite bias effect," where shaded cells switch roles, consuming instead of generating power, therefore diminishing the overall energy output and the electricity production capability of the PV gadget. Additionally, partial shading can initiate reverse biasing. This takes place while a shaded cell, receiving much less mild, acts as a resistance in the circuit, growing the voltage throughout itself. This increased voltage can push the cell into a reverse bias state, interfering with energy technology and reducing the sun panel's overall efficiency. Besides efficiency loss and energy reduction, partial shading can also cause hotspots at the sun panel. These hotspots develop when shaded cells enter a reverse-biased state and start dissipating power as heat. Continuous exposure to these hotspots can damage the sun cells, doubtlessly main to lasting impairment of the panel's performance. This not only impacts the efficiency of the man or woman panel but can also compromise the whole PV system's durability. To mitigate the outcomes of partial shading, diverse techniques, which include bypass diodes, most power point tracking (MPPT) algorithms, and careful gadget design, are hired. Bypass diodes are incorporated into sun panels to provide alternative paths for the current to skip shaded cells, stopping opposite biasing and minimizing strength losses. MPPT algorithms optimize the working point of the solar panels, making sure that they operate at their highest strength output even underneath partial shading situations. Proper gadget layout, which includes the format and orientation of panels, can also decrease shading effects and decorate typical efficiency [15, 16]. In the literature [17, 18], researchers mentioned fundamental PV array interconnection configurations as shown in Fig. 3, which might be series (S), series-parallel (SP), total cross-tied (TCT), honey-comb (HC), and bridged-linked (BL). Specifically, the BL, TCT, and HC designs have been proposed to mitigate shading effects, offering alternatives to the conventional SP setup. From these configurations, TCT has been emphasized for its superior power conversion efficiency under prolonged shading scenarios. Within various PSC scenarios, the TCT design is recognized for its outstanding performance in power extraction, albeit not always achieving the maximum potential power.

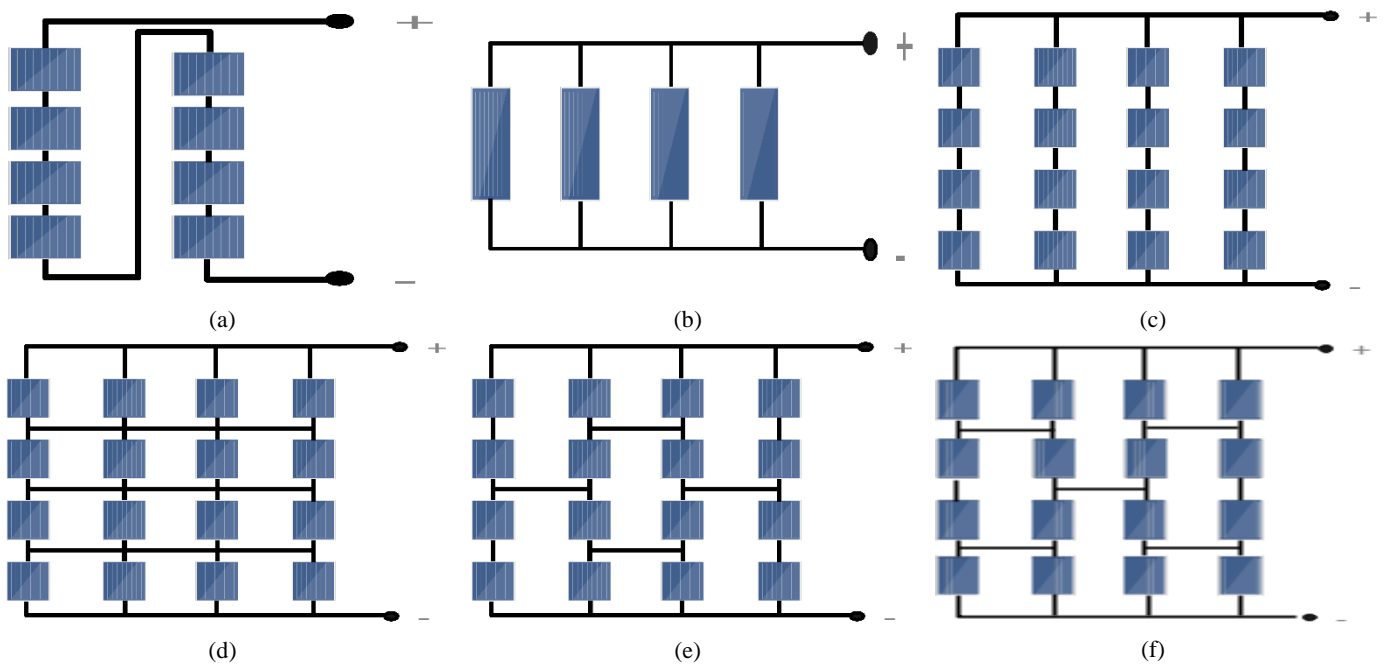


Fig. 3. The fundamental linking configurations for PV arrays include (a) Series (b) Parallel (c) SP (d) TCT (e) BL and (f) HC. [19]

3. PV Reconfiguration Techniques

Hence, strategies for PV array reconfiguration have been proposed to optimize power yield in the face of variable irradiance. The primary aim of these reconfigurations is to modify the currents in different electrical circuits and to adjust the solar PV panels' position, either electrically or physically, to cater to the changing irradiance conditions [7, 20, 21], these reconfiguration methodologies fall into two distinct types as shown in Fig. 4.

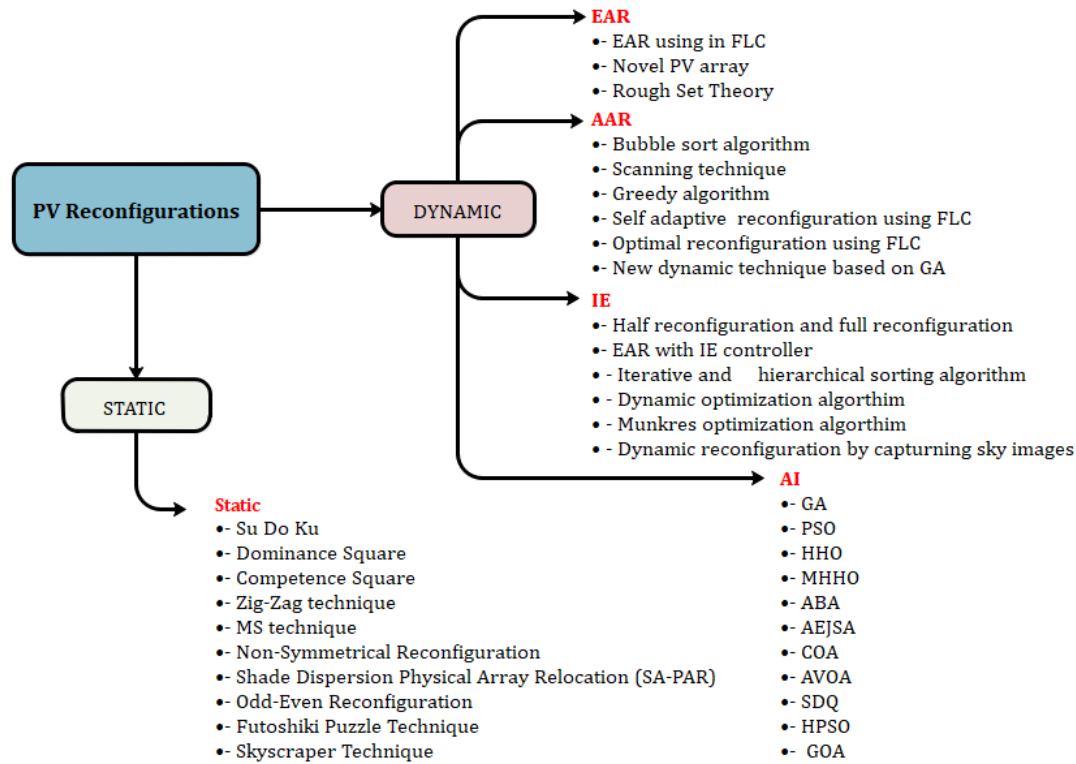


Fig. 4. PV array reconfiguration techniques.

3.1. Static Reconfiguration

Static reconfiguration involves altering the physical layout of PV panels while keeping the electrical connections constant. This method aims to minimize shading impact by strategically rearranging panel positions in the array regarding electrical connection, thereby optimizing energy absorption. Static reconfiguration techniques, such as Total-Cross-Tied (TCT) configurations, have been widely explored to enhance power generation under partial shading conditions. These approaches are particularly advantageous in scenarios where altering electrical connections is impractical or cost-prohibitive [7]. Static reconfiguration techniques, such as Su Do Ku [22], Dominance square [23], competence square [24], zig-zag technique [25], Magic-Square [26], non-symmetrical reconfiguration techniques [27], shade dispersion physical array [28], puzzle-based reconfiguration technique [29], and skyscraper technique [30].

3.2. Dynamic Reconfiguration

Dynamic reconfiguration stands out by modifying the electric connections between photovoltaic (PV) panels while maintaining their physical association intact. This method dynamically alters the wiring to adapt immediately to modifications in shading styles, as a consequence enhancing the system's universal overall performance and making sure efficient energy production even under variable shading conditions. Dynamic reconfiguration employs sophisticated algorithms and control systems, PV arrays to modify to environmental shifts rapidly. This paper conducts an in-depth evaluation of both static and dynamic reconfiguration strategies that can be used to counter the detrimental consequences of partial shading on PV arrays. It delves into the foundational principles, strategies, benefits, and boundaries of those techniques, aiming to provide an in-depth comprehension of their realistic application and effectiveness. Furthermore, this overview significantly assesses the real-world implementation challenges of each static and dynamic reconfiguration technique, highlighting the current research efforts being dealt with to overcome these challenges, as referenced in [4, 7]. As the world accelerates toward renewable energy adoption, an in-depth understanding of static and dynamic reconfiguration approaches is paramount. By illuminating the intricacies of these techniques, this paper contributes to the growing body of knowledge in solar energy engineering, paving the way for more efficient and resilient PV systems in the face of partial shading challenges. The analysis encompasses configurations characterized by distinct properties. The fundamental formats, namely series-parallel SP, Total Cross Tied (TCT), and bridge-link interconnection are explained in [31, 32]. Modules are connected in series using the SP setup, whereas rows are correlated using parallel connections. The TCT calls for the parallel connection of modules as well as the correlation of setups in series. On the other hand, BL entails the joining of ties that go across junction rows [20, 21].

Dynamic reconfiguration techniques are classified into four types which are electrical array reconfiguration (EAR), Irradiation equalization (IE), Adaptive array reconfiguration (AAR), And Artificial Intelligence (AI).

Electrical Array Reconfiguration (EAR): EAR method adjusts PV panels using switches for insulation and current control [33], but needs a robust monitoring system for efficiency. Such as:

- Fault detection scheme: The scheme identifies and rectifies module faults using IMP, VMP, and aging data, optimizing switch operation and shade mitigation as explained in Fig. 5 [34].
- circular array data structure :[35] The study introduces a reconfiguration method for PV arrays based on the circular array data structure, enhancing efficiency under partial shading, validated by simulations.

- Rough-Set theory [36]: This method extends set theory, focusing on extracting and formulating rules from data sets, and has emerged with the growth of computational capabilities.

Irradiation equalization (IE): reconfiguration explores techniques for PV module reconfiguration based on the irradiation equation (IE) to optimize power generation during shading. Methods include connecting shaded panels to unshaded rows, utilizing switching matrices, and employing algorithms to maximize power output. These approaches aim to reconstruct the IE, ensuring efficient PV array reconfiguration under varying shading conditions [37-41].

Adaptive array reconfiguration (AAR): The proposed adaptive reconfiguration scheme uses a switching matrix in solar PV arrays to reduce shadow impact, optimizing power output with a control algorithm. such as:

- bubble sort algorithm [42]: Bubble sort rearranges a list by repeatedly swapping adjacent elements, effective for small data but less so for large sets.
- scanning techniques [43]: Scanning techniques involve systematic methods for data analysis and area examination across various fields like computing and medical imaging.
- greedy algorithm [44]: Greedy algorithms make the optimal choice at each stage, aiming for the overall best outcome, but may not always yield the most effective solution in complex scenarios.
- Self-adaptor using FLC [45, 46]: A self-adaptor with FLC modifies its behavior using fuzzy rules, efficiently handling imprecise or complex data.
- dynamic techniques based on GA [47]: Dynamic techniques using Genetic Algorithms evolve solutions through biological-like processes, effectively tackling complex problems.

Artificial Intelligence (AI): methods reconfiguration techniques such as:

- GA [47]: Genetic Algorithms are optimization methods based on evolutionary principles, using natural selection and genetic variation to solve intricate problems.
- PSO [48]: PSO is a nature-inspired computational approach where particles in a group move through a search space, leveraging their own and neighbors' experiences to find optimal solutions.
- GOA [49]: GOA, mimics grasshopper behavior to find optimal solutions for complex problems through population movement and communication patterns.
- MHHO [50]: This is a variant of the Harrier Hawk Optimization algorithm, utilizing the hunting behavior of harrier hawks to optimize complex problems.

4. Methodology and Literature Review

In this complete evaluation, our investigation delved into the world of photovoltaic (PV) array reconfiguration strategies amidst partial shading conditions. Our exploration started with a focused literature search through outstanding databases, including Scopus, IEEE Xplore, and the Web of Science. By utilizing a meticulously selected array of key phrases, we ensured the inclusion of developments from the past three years, thereby encapsulating the current progressive strides in the field.

From a preliminary pool of approximately seventy-four assets, our choice system changed into governed with the aid of a rigorous set of criteria. These criteria had been crafted to appraise the methodological soundness and thematic pertinence of every publication. This filtration system yielded a core of 31 papers (static and dynamic) that withstood our stringent evaluation. It is those pick-out works that we subjected to an in-depth examination to parent their innovative techniques and solutions to the crucial challenges posed by partial shading on PV arrays. Each method delineated in the selected literature was juxtaposed within a comparative framework. This framework is designed to elucidate every technique's performance, applicability, and contribution to mitigating the effects of partial shading. The synthesis of this evaluation aimed to provide a lucid comprehension of modern-day PV array reconfiguration strategies. Upholding educational integrity was a cornerstone of our review system. This commitment entailed a scrupulous interest in the right quotation practices, ensuring that everyone's references were appropriately and ethically recounted. Publications that fell short of our hooked-up benchmarks for clarity and substance were unequivocally excluded, for that reason keeping an investigative narrative that resonates with our objectives.

The 25 papers (dynamic) that met our exacting standards will go through an in-depth exam within this section. This vital analysis is structured to deepen the understanding of the state-of-the-art PV array reconfiguration strategies, offering a basis for future academic endeavors in this domain. The study in [51] investigated Sudoku and Optimal Sudoku (SAOS) Reconfiguration Techniques for improving electricity in 9x9 PV arrays beneath partial shading. While solar electricity is considerable and powerful, its efficiency can be lessened with shading. The TCT model, generally used for maximizing electricity, has barriers beneath shaded situations. Using MATLAB simulations, the observer determined that the Sudoku and SAOS methods may surpass the TCT version's overall performance in such eventualities. However, those strategies want in addition refinement. The research also highlighted demanding situations in reconfiguration and the blessings of tools like multilevel inverters (MLI) and maximum energy point techniques (MPPT) in shaded conditions. While the authors in [7], introduced a reconfiguration technique the use of improved hybrid particle swarm optimization (HPSO) for general-move-tied PV arrays dealing with strength loss from partial shading. The goal changed to discover quality reconfiguration schemes to boost power, shop electricity, and decorating efficiency. The proposed HPSO blends genetic algorithm concepts and balanced local and global search capabilities. When compared, this method outperformed others, optimizing power, especially for both square and non-square matrices and reducing mismatch loss. It produced smoother P-V curves. However, the technique had downsides: it needed switches and sensors, added costs, and had unused hardware in uniform irradiance situations.

A novel swarm-based double Q-learning (SDQ) [52] method was combined with a hydrogen energy storage system for optimizing PV array configurations under partial shading conditions (PSC). This method aimed to reduce mismatch loss, power fluctuations, and regulation costs. When coordinated with hydrogen storage, the system cut regulation costs and boosted overall profits. Simulations on a 10x10 PV array showed SDQ reduced costs by around 89.22% and turned profit margins from negative to positive under varied PSC. However, this study was based on simulations, and real-world testing is needed. The paper didn't fully address SDQ's optimal conditions or its adaptability, suggesting avenues for future research.

Moreover, a study in [53] conducted a comparison of a new two-step GA-based PV array reconfiguration technique with other strategies to combat the effects of partial shade on PV plants. Partial shading reduces energy output and creates power-voltage curve inconsistencies. The proposed method, based on a Genetic Algorithm (GA), aimed to change only the electrical connections of the PV panels without altering their physical locations. Testing in MATLAB/SIMULINK, using four shading patterns, showed this method surpassed others, including TCT, CS, SuDoKu, two-phase array, PSO, and MHHO in increasing energy output under shade. However, the study's limitations weren't specified, so consulting the full publication is advised for a holistic view.

A detailed study presented the effects of partial shading on PV arrays in [54]. It also proposed a solution combining reconfiguration with a Reconfigurable Maximum Power Point Tracking (RMPPT) algorithm. This method, validated using a reconfigurable PSO algorithm, improved the PV array's output power by at least 7.2% under real-world conditions, outperforming traditional methods like Perturb and Observe and PSO-based MPPT. By spreading shading throughout the PV array, it significantly reduced mismatch power loss, showing increased power generation compared to static configurations like MS-EC. However, the study didn't explicitly mention the method's limitations or challenges in practical applications, suggesting areas for further research.

A study in [55] emphasized the want to optimize photovoltaic array configurations due to partial shading issues that arise with prolonged use. A particular objective function becomes delivered, combining power optimization with transfer movement optimization. This technique boosted power output while decreasing switch matrix movements, simplifying management and increasing tool lifespan. An enhanced Pelican Optimization Algorithm (POA) was used, yielding a 30% strength increase, mainly underneath short and wide shadow situations. This approach provided the best power while minimizing switching, proving its effectiveness in opposition to partial shading challenges on PV arrays. However, they have a look at particularly targeted theoretical optimization, suggesting that real-world trying out is vital for practical software. Similarly, in [56] the authors brought a method for reconfiguring PV arrays underneath partial shade, using the African vulture's optimization algorithm (AVOA). Compared to other strategies and metaheuristic optimizers, AVOA confirmed advanced searchability, balancing exploration and exploitation whilst having low computational complexity. Simulations showed that AVOA handed different strategies in power generation and convergence fees. Yet, there were constraints, like relying on an unmarried goal characteristic and desiring real-world trying out. Overall, the AVOA technique can improve PV systems underneath partial shade, promoting extra sustainable and green renewable power answers. In addition, [57] research added the coyote optimization algorithm (COA) as a solution to redecorate PV arrays to combat partial shadowing challenges. Partial shadowing causes considerable power loss in PV arrays. The COA-primarily based technique aimed to optimize PV module connections to reinforce the array's maximum energy (GMP). Results confirmed this method outperformed others like TCT and Su Do Ku in electricity extraction and efficiency. COA became tested under numerous shadow patterns and proved powerful. However, it had shortcomings like sensitivity to preliminary parameter values and local optimal solution confinement. Further studies became advised to refine COA and widen its programs in renewable power. This examination contributes to creating extra efficient renewable electricity systems. Nevertheless, another study [58] evolutionary Pareto optimization algorithms have been investigated for bi-objective PV array reconfiguration under partial shading situations. The researchers found that these algorithms may want to gain comparable or higher maximum power output than traditional techniques without optimization. Furthermore, the variety of switches required was substantially decreased, imparting better operational flexibility below various irradiation conditions. However, the particular boundaries or demanding situations confronted throughout the research have been now not explicitly unique in the extracted sections. Furthermore, in [59], the authors supplied a look at the performance enhancement of PV device configurations below partial shading situations using the MS approach. The study diagnosed key metrics such as strength and temperature that needed to be taken into consideration while designing PV machine configurations. The studies presented in this have a look at giving realistic insights that could enhance the performance and effectiveness of photovoltaic (PV) structures in actual-life applications. However, the look at stated sure boundaries, together with an oversight of different factors that would affect PV's overall performance. In evaluation, all other studies exact in supply in [60] sought to introduce an advanced Runge Kutta optimizer geared toward improving the global optimization of PV systems under partial shading. The findings indicated that this new optimizer exceeded other algorithms in performance and precision. Nevertheless, this has a look at had its limitations, consisting of relying on a specific version of PV gadget and presuming a uniform distribution of sun irradiance.

Moreover, in a comparable vein, research in [61] explored the performance of various PV array configurations below dynamically changing partial shading. The examine observed that SuDoKu and Total-Cross-Tied reconfiguration techniques had been superior to traditional configurations in energy output. However, this observation was confined to simplified dynamic partial shading conditions (D-PSC) and recommended in addition studies to evaluate the impact of real D-PSC on homes and the efficacy of different reconfiguration strategies. This study is especially treasured for those looking to enhance the power output of PV structures below dynamic partial shading.

In [62] researchers targeted reconfiguring solar photovoltaic (SPV) arrays using the artificial bee colony (ABC) algorithm to optimize performance in part shaded conditions. This has a look at contributing to the frame of knowledge on optimizing PV system overall performance through array reconfiguration beneath partial shading. Multiple connection kinds, along with series, parallel, and overall-cross-tied, had been evaluated, with the TCT connection proving the maximum efficiency. The ABC set of rules outperformed other strategies, together with the genetic set of rules. However, the research had obstacles due to the optimization hassle's complexity and the SPV array's size. The findings supplied massive insights into SPV device layout and optimization, pushing a renewable strength technology. Future work might discover this technique's scalability for larger, more complex SPV arrays.

In a comparative analysis [63] the grasshopper optimization approach (GOA) and particle swarm optimization set of rules (PSO) had been assessed for reconfiguring non-uniformly shaded sun arrays. Both efficaciously improved energy output and the PV curve's overall performance. However, the grasshopper technique slightly outperformed in decreasing mismatch losses and elevating the fill factor. Despite those findings, the examination became confined to the usage of the handiest shading pattern and lacked real-world checking out. Overall, the studies brought price to the literature on optimizing PV systems under uneven sunlight conditions.

In [64], a continuous reconfiguration framework for sun arrays was delivered to optimize the below variable partial shading. Utilizing heuristic methods, the framework aimed to optimize the performance of the extensively used TCT configuration in conditions with changing cloud cover. A principal accomplishment was the reduction in switching activities, particularly benefiting the efficiency of Dynamic PV Array Reconfiguration (DPVAR). However, the research diagnosed key challenges in DPVAR, such as the unpredictable nature of shadows and practical concerns with shading emulators. While these paintings signified an advancement in sun gadget efficiency underneath partial shading, they emphasized the need for similar exploration to cope with diagnosed understanding gaps. While in [65] the authors introduced a technique to optimize sun photovoltaic (SPV) systems dealing with uneven irradiation, in particular from partial shading. They utilized power-voltage (P-V) characteristics to identify multiple strength peaks, extensively the global maximum power point (GMPP) and local maximum power point (LMPP). To enhance shade distribution across the PV array, they proposed a reshuffling technique for the PV

modules. A giant focus was on the Butterfly Optimization Algorithm (BOA) as a solution to achieve higher GMP during partial shading conditions. Its efficacy was validated through simulations and experiments. However, they take a look at examples that lack real-world utility and state obstacles, such as the need for accurate PV array modeling and the inherent complexity of the optimization process. Also in [66] a unique reconfiguration technique for photovoltaic arrays below partial shading conditions using a fuzzy logic-based approach. The proposed technique has been proven experimentally on a small TCT dynamic PV array of 11 modules with three relays. The outcomes showed that the fuzzy logic-based approach improved the performance of the array under partial shading conditions. Additionally, a value-powerful irradiance estimator based on Recursive Least Squares (RLS) was proposed and compared to different estimators. The RLS-based estimator provided high precision and reduced investment costs.

The experimental validation of the proposed technique showcased its advantages over other estimators in terms of reduced estimation error and enhanced accuracy. However, its primary hindrance became its suitability, especially for small-scale photovoltaic (PV) arrays. This requires similar research to confirm its performance in larger PV array setups. In addition, the study referenced as [67] introduced an algorithm designed to optimize the real-time energy output in photovoltaic structures with Total-Cross-Tied (TCT) interconnections. This algorithm was tailored to reduce electricity losses because of mismatches in contemporary and voltage. The research meticulously mentioned the development of this method, after which it benchmarked its performance against that of the SuDoKu and genetic algorithms. This comparative evaluation was essential in underscoring the new set of rules' performance and efficacy in enhancing the overall performance of PV structures under various conditions. The results revealed stronger current-voltage (I-V) and energy-voltage (P-V) curves with this novel method, suggesting a capacity growth in energy output by up to 30% for PV arrays. However, the take look no longer addresses positive real-world implementation demanding situations, inclusive of the environmental influences, scalability of the set of rules, and its cost-effectiveness, which are critical factors within the realistic utility of such technology. Further research is wanted to deal with those gaps and validate the algorithm's sensible application. In [68], a study was added to the Adaptive Evolutionary Jellyfish Search Algorithm (AEJSA) to optimize PV array configurations during partial shading conditions. The AEJSA aimed to cope with unusual problems with current algorithms, which includes settling for inferior nearby optima. Tested on a 15x15 TCT PV array, it confirmed faster convergence and advanced performance than different techniques. Real-world hardware-in-the-loop checks confirmed its practical efficacy, yielding a marked electricity output improvement below shading. However, the examination was restrained by using the dimensions of the PV array examined and a constrained set of rules comparisons. Future studies might increase this by way of assessing larger arrays and numerous shading contexts. Likewise, in [69] the authors introduced the Honey Badger Method (HBM), a singular reconfiguration method for photovoltaic arrays aimed at minimizing the effect of shading. By addressing troubles like failing modules and partial shade, which are Hinder Optimal Power Generation, this has a look at proposed a unique objective function to optimize array configuration below shading situations. The findings recommended that this technique may want to significantly boost electricity output compared to the traditional collection-parallel setup. Using nine×9 and 10×8 collection-parallel PV arrays, the look at assessed energy financial savings and payback periods over day by day and yearly periods, revealing potential long-time period benefits. However, the reliance on simulated data and the dearth of actual-international trying have been recognized as barriers. Meanwhile in [70], the authors proposed the usage of regularized Deep Neural Networks to rewire connections in photovoltaic arrays, aiming to enhance sun energy efficiency. Specifically, the take a look at work on 4 PV topologies: SP, BL, HC, and TCT. The novel technique yielded about an 11% improvement in power when implemented in a 5x5 array. The consequences, benchmarked against conventional algorithms like Support Vector Machines and XGBoost, confirmed the deep neural network method achieving eighty-one.1% accuracy. The primary constraint of the method discussed earlier is its dependence on simulated data, underlining the significance of undertaking real-world checks for greater conclusive validation. In a separate study, indicated in [71] researchers developed the Seagull Optimization Algorithm (SOA) to maximize power extraction from partly shaded photovoltaic (PV) arrays. This looks focused on figuring out the greatest reorganization of the PV array's switching matrix to decorate strength output efficiency. The SOA's performance turned into evaluated using numerous indicators, such as strength development, mismatching energy loss, fill factor, and the percentage of power loss, as compared with other strategies. The findings underscored the SOA's superiority in strength era and performance, particularly in mitigating partial shading's impact on PV electricity production. The widespread locating from the observation was the SOA's superior performance in contrast to different techniques. However, the study's cognizance of a single photovoltaic (PV) array length and a confined array of shading styles raises questions about the generalizability of the effects. Furthermore, in reference [72], a method for PV array reconfiguration was delivered, which makes use of the Divide and Conquer Q-Learning (DCQL) algorithm to correctly deal with the problems springing up from partial shading. This technique took advantage of Q-Learning, a form of unsupervised synthetic intelligence getting to know, which lets the machine analyze and adapt based on its environment, disposing of the need for large historical statistics or prior information. The superior DCQL technique included special elements which include action, fitness feature, and action, and employed the divide principle to boost up the reconfiguration system at the same time as minimizing computational. Although this approach confirmed its ability to enhance the efficiency of PV structures, its complexity and the requirement for extra great environmental checking out have been diagnosed as key boundaries.

In another study [73], researchers explored a PV array reconfiguration strategy using Atom Search Optimization (ASO). This technique became mainly geared toward decreasing the effect of partial shading on the formation of hot spots in PV arrays. By evaluating the brand-new technique to four previous techniques, the use of mismatch loss, fill factor, and popular deviation as assessment metrics, it was found to be superior in performance, velocity, and reliability. The research hired a transferring cloud shadow mode on a 9x9 PV array, indicating the ability to overall performance upgrades in part-shaded environments. However, the Act's scope changed to be limited to a particular PV array type and shading condition, suggesting the need for broader testing. Finally, a study [74] introduced the multi-goal grey wolf optimizer (MOGWO) for optimizing PV systems below shaded conditions, in particular in 9x9 configurations. Aiming to balance current and voltage mismatches, MOGWO confirmed marked efficiency improvement whilst compared to standard techniques like SuDoKu and TCT. MOGWO yielded smoother I-V and P-V curves with fewer inflexion factors, and simulations hinted at an ability 30% electricity output boost. However, future research should address these to validate MOGWO's complete applicability in real eventualities.

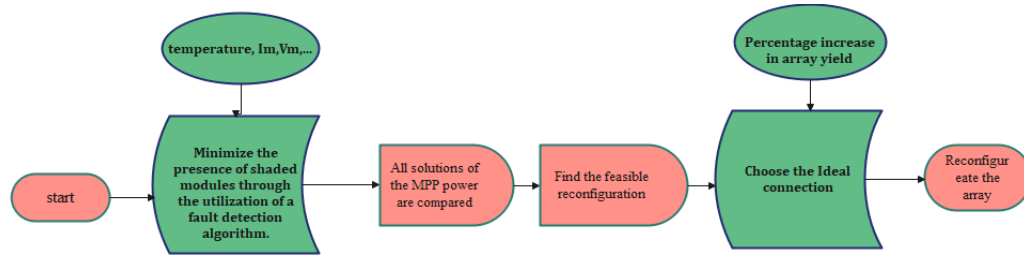


Fig. 5. Reconfiguration technique according to fault detection [34].

5. Results and Discussion

A more detailed exploration and evaluation of various static and dynamic reconfiguration methods for the PV array can be presented in Table Table 1 and Table 2, respectively. These tables are a comprehensive repository in which different techniques used under partial shade conditions are compared. Each method is thoroughly described, highlighting its approach, advantages, limitations, speed, complexity, and real-world applications. Based on the above, the best methods are explained by delving into the nuances of each redesign process. These tables provide readers with a comprehensive understanding of the methodologies, enabling them to make informed comparisons and derive useful insights. Fig. 6 shows comparisons between the methods in terms of configuration type, matrix size, years, level of complexity, and speed. After examining the different reshaping strategies evaluated, dynamic reshaping techniques are useful in improving strength in shading situations. The methodology based on optimization algorithm, HBM, HPSO, and SDQ optimization are practical methods to provide the most satisfactory optimal solution according to the method speed and matrix size.

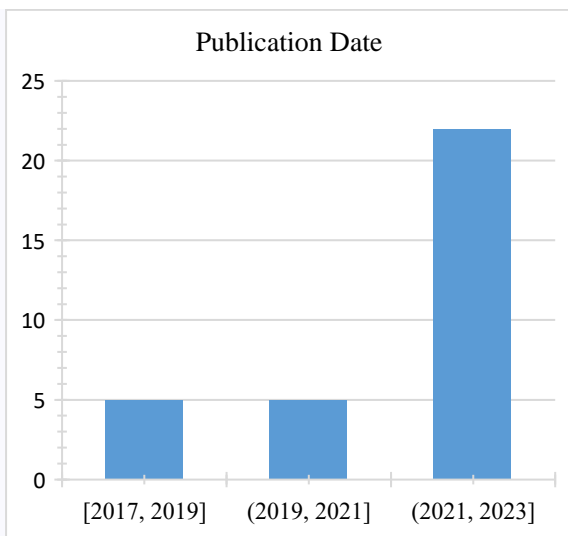
Table 1. Comparison among the various static reconfiguration methods.

| Technique | Year | Configuration | Array Size | Execution Complexity | Validation Used | Acquired Parameters | Execution Speed | Merits/demerits | Ref. |
|---------------------------------|------|------------------|------------|----------------------|---------------------------|--|-----------------|---|------|
| SuDoKu | 2023 | TCT, SP, BL, &HC | 5×5 | Low | Simulation | Improved P-V characteristics | Fast | <ul style="list-style-type: none"> Execution is straightforward. Modules in the first column remain stationary. | [22] |
| Dominance square | 2017 | TCT | 5×5 | High | Simulation | Increased uniformity in row currents, reduced mismatch losses | Medium | <ul style="list-style-type: none"> Row current disparities are minimal. Inappropriate for extensive PV systems. | [23] |
| Competence square | 2018 | TCT | 9×9 | High | Simulation | Optimized power output, smoother P-V curves. | Fast | <ul style="list-style-type: none"> Straightforward to implement. Conductor loss is significant. | [24] |
| Zig-zag technique | 2017 | TCT | 4×3 | High | Simulation | Increased efficiency, and fewer inflection points on I-V curves. | Medium | <ul style="list-style-type: none"> Applicable in all sizes. Limited flexibility. | [25] |
| Non-Symmetrical Reconfiguration | 2022 | TCT | 9×9 | Medium | Simulation + Experimental | Improved P-V characteristics | Fast | <ul style="list-style-type: none"> Execution is straightforward. Shadow dispersion is inadequate. | [27] |
| Ken-Ken | 2021 | TCT | 4×4 | Medium | Simulation | less power loss | Medium | <ul style="list-style-type: none"> Avoid LMPPs Inadequate shade spread in PSC. | [29] |
| skyscraper technique | 2019 | TCT | 9×9& 5×5 | High | Simulation | Improve P-V characteristic | Medium | <ul style="list-style-type: none"> Significant power enhancement Prone to premature convergence. | [30] |
| MS method | 2021 | TCT& SP | 5×5 | Medium | Simulation + Experimental | Improved I-V characteristics , increased array efficiency | Medium | <ul style="list-style-type: none"> Energy dissipation is negligible. Applicable to symmetric matrices | [59] |

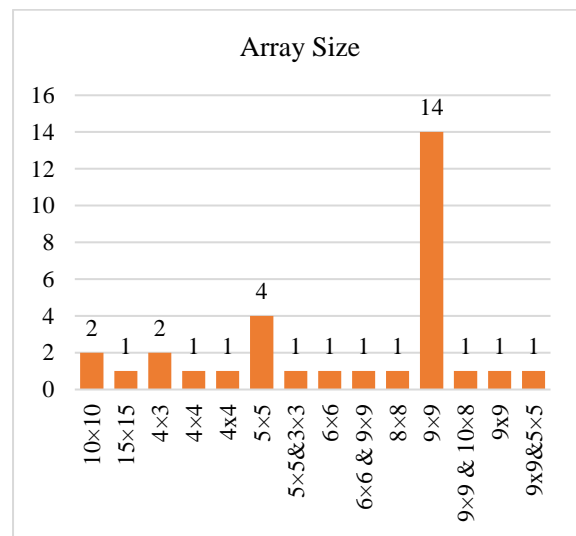
Table 2. Comparison among the various dynamic reconfiguration methods.

| Technique | Year | Configuration | Array Size | Execution Complexity | Validation Used | Acquired Parameters | Execution Speed | Merits/demerits | Ref. |
|--|------|---------------|------------|----------------------|---------------------------|---|-----------------|--|------|
| SAOS | 2022 | TCT | 9×9 | High | Simulation + Experimental | Increased max power output, Reduced shading impact. | Medium | <ul style="list-style-type: none"> • Boosted performance efficiency. • Potential for Scalability issues. | [51] |
| Improved HPSO | 2023 | TCT | 4×3 | Low | Simulation | Increased uniformity in row currents, reduced mismatch losses | Fast | <ul style="list-style-type: none"> • Optimization improvement. • Increased demand for computing. | [7] |
| SDQ | 2023 | TCT | 10×10 | Medium | Simulation | Optimized power output, smoother P-V curves. | Fast | <ul style="list-style-type: none"> • Improved learning efficiency. • Susceptible to exact data fitting. | [52] |
| Two-step GA | 2021 | TCT | 9×9 | Medium | Simulation | Increased efficiency, and fewer inflection points on I-V curves. | Medium | <ul style="list-style-type: none"> • Boosts power output. • Overly reliant on weight coefficient. | [53] |
| RMPPT | 2023 | TCT | 6×6 | Medium | Simulation | Improved electrical characteristics, and higher energy yield. | Medium | <ul style="list-style-type: none"> • Flexible performance. • Intricate setup. | [54] |
| Improved POA | 2023 | TCT | 10×10 | Medium | Simulation + Experimental | Improved P-V characteristics, higher energy yield. | Fast | <ul style="list-style-type: none"> • Optimization enhancement. • Possible equilibrium challenge. | [55] |
| AVOA | 2022 | TCT | 9×9 | Low | Simulation + Experimental | Improved efficiency and reliability | Fast | <ul style="list-style-type: none"> • Search effectiveness. • Specific use limitation. | [56] |
| COA | 2020 | TCT | 9×9 | Medium | Simulation + Experimental | Greater fill factor and less power loss | Medium | <ul style="list-style-type: none"> • Adaptive versatility. • Variable convergence. | [57] |
| Pareto optimization algorithms | 2022 | TCT | 9×9 | Moderate | Simulation | Improved power extraction | Medium | <ul style="list-style-type: none"> • Varied solutions. • Elevated processing needs. | [58] |
| Modified Runge Kutta optimizer | 2022 | TCT | 9×9 | Medium | simulation + experimental | Enhanced P-V characteristics across different shading patterns | Fast | <ul style="list-style-type: none"> • Improved optimization. • Possible precision constraints. • Enhanced Efficiency | [60] |
| Advanced ABC Algorithm | 2023 | TCT | — | Medium | simulation + experimental | optimized power output. | Fast | <ul style="list-style-type: none"> • Prone to parameter reliance. | [62] |
| PSO and GOA | 2023 | TCT & SP | 8×8 | Medium | simulation | Detailed electrical parameters (VOC, ISC, Vmp, Imp, P_MML, FF_PL) for enhanced optimization | Medium | <ul style="list-style-type: none"> • Consistent and effective • Extensive computational data. | [63] |
| Continuous Reconfiguration Framework for Photovoltaic Array under Variable Partial Shading Conditions. | 2022 | TCT | 9×9 | Medium | simulation + experimental | More consistent irradiance capture, reduced switching activities | Medium | <ul style="list-style-type: none"> • Real-time adjustment. • Possible complexity. | [64] |
| BOA | 2022 | SP & TCT | 6×6 & 9×9 | high | simulation + experimental | Improved P-V curve performance, more efficient power generation | Medium | <ul style="list-style-type: none"> • Fewer control parameters, and fast computation. • Intricate search methodology. | [65] |
| Fuzzy logic-based | 2021 | TCT | 4×4 | Low | experimentally validated | more efficient power generation | Fast | <ul style="list-style-type: none"> • Adaptive decision process. | [66] |

| reconfiguration method | Year | Method | Array Size | Complexity | Validation | Characteristics | Speed | Advantages | Disadvantages | Reference |
|---|------|---------------------|------------|------------|---------------------------|--|--------|-----------------------------|-------------------------------------|-----------|
| New Simplified Algorithm for Real-Time Power Optimization | 2022 | TCT | 9×9 | Low | simulation + experimental | Potentially improved power output and efficiency | Medium | • Effective loss reduction. | • Possible complexity. | [67] |
| AEJSA | 2023 | TCT | 15×15 | Medium | simulation + experimental | I, V and P characteristic values of each module | Medium | • Consistent and effective. | • Prone to local optima entrapment. | [68] |
| HBM | 2023 | SP | 9×9 & 10×8 | Low | simulation + experimental | Enhanced I-V and P-V characteristics, more efficient energy conversion | Fast | • Robust | • Potential solution constraints. | [69] |
| Regularized deep neural network | 2023 | SP, BL, HC, and TCT | 5×5 | Medium | simulation | Accounting for wiring losses, optimized power output. | Medium | • Improved generalization. | • Higher computational demand. | [70] |
| SOA | 2023 | TCT | 9×9 | Medium | simulation + experimental | Improved I-V and P-V characteristics, efficient power optimization | Fast | • Effective exploration. | • Specific algorithmic focus. | [71] |
| DCQL | 2023 | TCT | 9×9 | Medium | simulation + experimental | I, V and P characteristic values irradiance and short circuit currents. | Fast | • Enhanced efficiency. | • Potential partitioning drawbacks. | [72] |
| ASO | 2023 | TCT | 9×9 | Medium | experimentally validated | Enhanced I-V and P-V characteristics, quick adaptation to shading | Fast | • Diverse applicability. | • Possible convergence challenge. | [73] |
| MOGWO | 2022 | TCT | 9×9 | High | simulation | Detailed row current analysis, dynamic output power optimization, and voltage management under shading | Fast | • Minimizes mismatch loss. | • Intricate search process. | [74] |



(a)



(b)

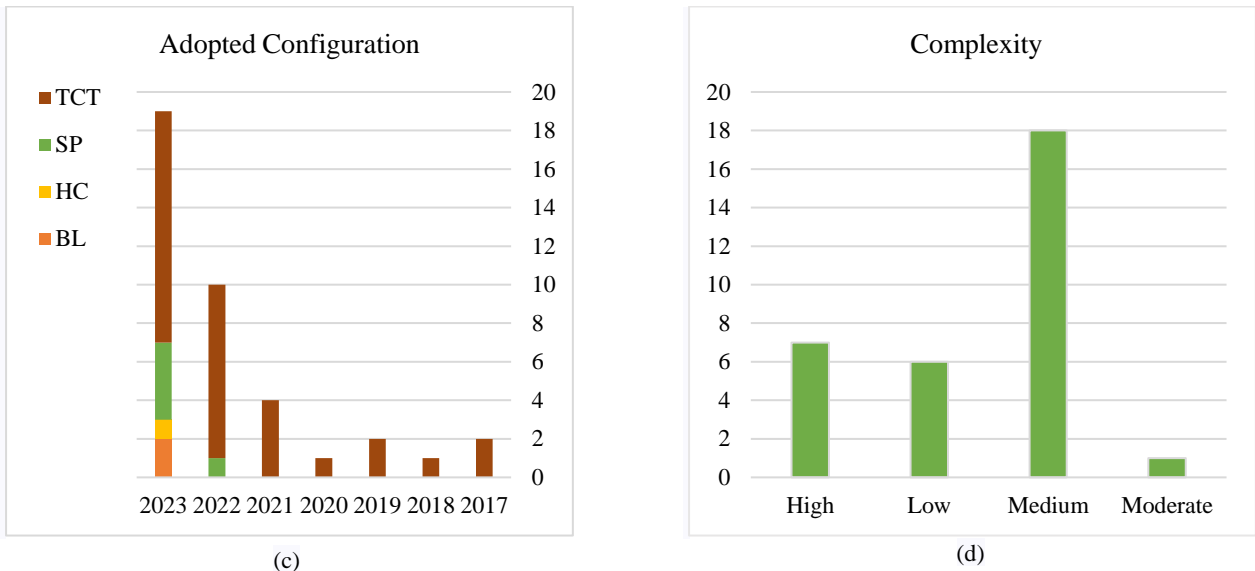


Fig. 6. Indices about the reviewed articles in a) histogram for the publication date, b) adopted PV array sizes, c) adopted configurations, and d) the complexity of the used methods.

6. Conclusion

In this systematic review, more than seventy up-to-date relevant articles involved in the photovoltaic (PV) array reconfiguration techniques highlighted their pivotal role in augmenting the efficiency of PV systems amidst the challenges posed by partial shading. Through a detailed analysis of static and dynamic reconfiguration strategies, including exploring cutting-edge methods such as the TCT, HBM, HPSO, and SDQ optimization, our study sheds light on the diversity and effectiveness of contemporary approaches designed to optimize the PV system's performance. Notably, the rigorous selection and review process, encompassing 31 of the initial 74 sources identified, was meticulously structured around criteria that emphasize execution speed, execution complexity, and overall effectiveness. However, this article's results are based on results collected under different experimental environments and different processors' speeds; for that, the authors recommend the researchers reevaluate these methods using the same shading patterns, the same experimental conditions, and the processor's speed.

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