

Research article

An energy-first reconfiguration of PV Array for Multi-MPPT systems considering inverter clipping under partial shading

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Abstract: Impacts of partial shading and non-uniform irradiance in photovoltaic (PV) strings, and thus, arrays, can be mitigated by Array reconfiguration (ARC). On the other hand, the power clipping and the saturation of a PV inverter can lead to energy losses in grid-connected systems with limited maximum power point trackers (MPPTs) in their inverters. However, most ARC researchers focus on mismatched-oriented reconfiguration approaches that minimize the mismatch in each PV string to make them almost uniform. These conventional approaches aim to optimize the proxies, not the final alternating-current (AC) yield energy. Therefore, we proposed a string-level energy-first ARC method based on an Acceleration-Enhanced River Formation Dynamics (AE-RFD) algorithm. The proposed method directly maximized the delivered energy while maintaining current constraints and MPPT power limits. The proposed energy-first framework optimized the array configuration at the grid-tied inverter interface, maximizing delivered energy of multi-inputs and AC-side clipping constraints. A real grid-tied PV system of 15 kVA, 6 strings, and 3 MPPTs was utilized first to evaluate the proposed method with disturbed irradiance conditions for different MPPT architectures and a second benchmark PV system of 24 strings and 8 MPPTs. Our simulation results confirmed the effectiveness of the proposed method by demonstrating energy gains exceeding 5.5% with significant clipping reduction and enhancing the mismatch index. Comparisons with the ARC that is based on particle swarm optimization (PSO), Genetic Algorithm (GA), and Differential Evolution (DE) indicated that the proposed AE-RFD-based method exhibits improved robustness and stable convergence behavior.

Keywords: energy optimization; MPPT; array reconfiguration; partial shading; river formation dynamics

1. Introduction

The employment of grid-connected photovoltaic (PV) systems is growing steadily in developing countries for residential, commercial, and industrial applications. However, in such environments, non-uniform solar irradiation is a common operating condition related to compact layouts and surrounding obstructions. Partial shading, cloud cover, dust, hedges, and nearby trees can cause electrical mismatches between PV strings, leading to a significant reduction in inverter power, especially when multiple strings are assembled at the same maximum power point tracker (MPPT) [1,2]. Hence, the traditional configuration of fixed strings-to-MPPT is often not optimal under realistic operating conditions. However, the layout of the PV array, which consists of several strings that are connected in parallel, can be reconfigured to mitigate the effect of non-uniform irradiance and to enhance the performance of the PV system under partial shading [3,4].

The reconfiguration of PV arrays under partial shading has been widely studied as a software-level mitigation technique [5]. Early studies proposed reducing mismatch losses based on static electrical configurations such as series-parallel and total cross-tied structures. On the other hand, recent studies of ARC are optimization-based ARC approaches that employ metaheuristic algorithms such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and Differential Evolution [6–9]. Those optimization-based ARC algorithms dynamically adapt PV interconnections under complex shading patterns.

A comparative study of MPPT techniques emphasizing the impact of control strategies under varying environmental conditions have been introduced in [10]. The researchers in [10] simulated and assessed the energy extraction of four MPPT algorithms. Nevertheless, these researchers do not address system-level reconfiguration under inverter constraints or clipping conditions. Furthermore, the researchers in [11] demonstrated the importance of detailed performance analysis in multi-MPPT PV systems. They proposed a string- and MPPT-level DC-side performance assessment based on monitored data for demonstrating the significance of component-level analysis in detecting underperformance of the strings [11]. However, such approaches focus mainly on performance evaluation rather than active optimization or reconfiguration strategies. Most ARC methods primarily minimize mismatch or maximize output power at the level of DC array [12,13]. Despite their effectiveness, those methods often assume unconstrained or ideal MPPT operation. Nevertheless, grid-connected PV systems with limited MPPT ports suffer from inverter saturation and power clipping.

While such approaches can mitigate scattered string currents, they are loss-oriented and do not explicitly account for system-level constraints such as inverter clipping or MPPT operating limits. Consequently, minimizing mismatch does not necessarily maximize delivered energy at the inverter, particularly in multi-MPPT systems under power-limited conditions. Moreover, many ARC techniques are module-level reconfiguration methods, which are not efficient in large-scale systems or rooftop installations [14,15]. In contrast, the proposed methodology adopts an energy-based strategy, where the optimization objective is the maximization of delivered AC energy. Thus, the combined effects of mismatch reduction, inverter clipping mitigation, and MPPT constraints are inherently captured for providing a more system-relevant performance metric.

Motivated by the above limitations, we propose an energy-first string-level ARC approach

utilizing the River Formation Dynamics (RFD) optimization algorithm, which has proven its ability to solve many technical problems [16,17]. The proposed method targets the research gap by providing a practical solution that considers the MPPT power limits and prioritizing delivered energy rather than mismatch alone. This shift from mismatch-driven optimization to energy-driven optimization constitutes a key pillar of the proposed ARC framework.

In the next section, we introduce the mathematical formulation of the PV yielded energy and the modeling of ARC under the shading effect. Moreover, modeling of the AE-RFD and how to adopt it for achieving the objective function of the energy-first ARC are investigated. The simulation results of two case studies are presented in Section 3 with discussions of the performance of the proposed method in large-scale PV systems. Conclusions and recommendations are provided in Section 4.

2. The proposed method of array reconfiguration

2.1. Formulation of the energy-based ARC

In the ARC problem, the PV strings are reassigned to the inverter inputs to maximize the supplied energy, resulting in a discrete optimization task. The objective function, hence, is defined as the negative of the delivered power, augmented by a small regularization term representing string-level mismatch and penalty terms enforcing MPPT current limits and feasible reconfiguration. The proposed formulation aims to prioritize energy maximization as the dominant optimization objective. The proposed energy-based ARC problem is formulated as an energy-maximization task under realistic inverter constraints, and expressed as:

$$\max \sum_{m=1}^{N_{\text{MPPT}}} \min \left(\sum_{s \in \mathcal{S}_m} P_s, P_m^{\max} \right) \quad (1)$$

The terms of the objective function are as follows:

1) N_{MPPT} represents the number of MPPT trackers. For instance, $N_{\text{MPPT}} = 3$ for an MPPT of three independent inputs or channels.

2) m refers to the MPPT index, where $m \in \{1, 2, \dots, N_{\text{MPPT}}\}$ represents the m th MPPT of the inverter.

3) s is the PV string index, where $s \in \{1, 2, \dots, N_s\}$ identifies an individual PV string, each consisting of several series-connected PV modules. Thus, $\mathcal{S}_m$ indicates the set of strings assigned to MPPT m where the subset of electrically connected strings is $\mathcal{S}_m \subset \{1, \dots, N_s\}$ after reconfiguration. The ARC decision variable determines these sets.

4) P_s represents the DC power of string s . The instantaneous DC power is a function of irradiance, temperature, and shading/soiling conditions. The P_s is evaluated in this study based on measured or simulated irradiance profiles for each timestep.

5) $\sum_{s \in \mathcal{S}_m} P_s$ is the total DC power at MPPT m and represents the aggregated DC power from all strings connected to MPPT m . This is the power that would be available if the MPPT were unconstrained.

6) $P_m^{\max}$ refers to the maximum power capacity of MPPT m . The power limit of each MPPT is restricted to the inverter hardware and thermal electrical constraints and leads to power clipping when the DC power exceeds $P_m^{\max}$.

7) **min**($\cdot$) operator is the MPPT saturation model that ensures the physical feasibility of the delivered power from MPPT m . The behavior of the inverter is modeled as:

$$P_{m,\text{delivered}} = \begin{cases} \sum_{s \in \mathcal{S}_m} P_s, & \text{if } \sum P_s \leq P_m^{\max} \\ P_m^{\max}, & \text{if } \sum P_s > P_m^{\max} \end{cases} \quad (2)$$

which explicitly captures DC-to-AC power clipping.

8) Finally, the outer summation $\sum_m$ refers to the Total system's power delivered by all MPPTs.

It is important to highlight that the proposed formulation directly optimizes the delivered AC energy, which is critical in multi-MPPT systems. Moreover, the conventional array reconfiguration techniques rely on mismatch minimization as the primary objective. In such cases, the configuration that minimizes mismatch cannot ensure optimal delivered energy. Therefore, the proposed objective function is designed to prioritize energy extraction at the inverter output while implicitly accounting for mismatch, clipping, and operational constraints within a unified optimization framework.

2.2. The modified algorithm of River Formation Dynamics

The optimization algorithm of RFD is employed in this paper to solve the resulting combinatorial optimization problem. RFD is a population-based metaheuristic technique inspired by natural erosion and deposition processes of river streams. In this algorithm, altitude guides the candidate solutions through probabilistic local transitions [17,18]. In this study, RFD operates on string-to-input permutations, ensuring feasible array reconfiguration while efficiently exploring the solution space.

The algorithm simulates how streaming water reduces altitudes to form a river moving from the source to the destination, i.e., from high altitude mountains to zero altitude (sea level) where the global solution is achieved [19]. In its route, the riverbed is eroded by a water stream in a steep while depositing sediment on flat paths.

Similar to the other nature-inspired techniques, the major steps of the RFD algorithm include: an initialization stage, a searching best path stage, and the stopping criterion. First, a flat environment is assigned for all vertices in the system assuming the same altitudes. The source nodes and the number of iterations are selected to start unleashing the water drops. Second, the erosion of the adjacent nodes/vertices initiates path formation where the drops create a new gradient. The steep gradient facilitates propagating the erosion along the river channel. Then, a new group of drops maintains this routing process. The probability of water drops to select the next adjacent vertex is formulated as follows [18,19]:

$$P(x) = \begin{cases} \frac{\text{Gradient}(i,j)}{\sum_{l \in n(i)} \text{Gradient}(i,l)}, & \text{if } j \in N_K(i) \\ 0, & \text{if } j \notin N_K(i) \end{cases} \quad (3)$$

where N_K represents the set of graph's nodes. The decreased gradient of the $(i-j)$ path is found as:

$$\text{Gradient}(i,j) = \frac{\text{altitude}(i) - \text{altitude}(j)}{\text{distance}(i,j)} \quad (4)$$

The erosion process is the process to preserve the path seeking process toward the zero-altitude level. As shown next, the erosion rate increases when the altitude decreases:

$$Erosion_{i,j} = altitude_{i,j}^k - altitude_{i,j}^{k+1} \quad (5)$$

The best path is chosen over iterations based on the accumulated altitudes of the chosen path. Consequently, the low-cost path has the best performance as it reaches the sea faster than that of the higher latitudes. Therefore, the rate of the accumulated erosion evaluates the process.

Although the RFD was proposed in 2008 for solving optimization problems [19], no researcher has adopted it in solving the ARC problem. The reason is that ARC is based mainly on a discrete permutation search with strict feasibility constraints, whereas the conventional RFD lacks a dedicated mechanism of permutation encoding and feasibility preservation. Thus, a severe local minimum can be caused by partial shading conditions. Therefore, the objective function of the ARC is implemented in this paper using an enhanced RFD. The process is evaluated by the accumulated erosion and accumulated gradient. Hence, the proposed ARC is achieved using the AE-RFD, which stimulates the moving of water drops from a higher altitude to a lower altitude, while an altitude memory biases future movements.

In the proposed AE-RFD, each drop maintains an acceleration state $a \geq 0$ that accumulates only when the improvement rate increases, i.e., when the current gradient is steeper than the previous gradient. The conceptual illustration of the modified RFD is shown in Figure 1.

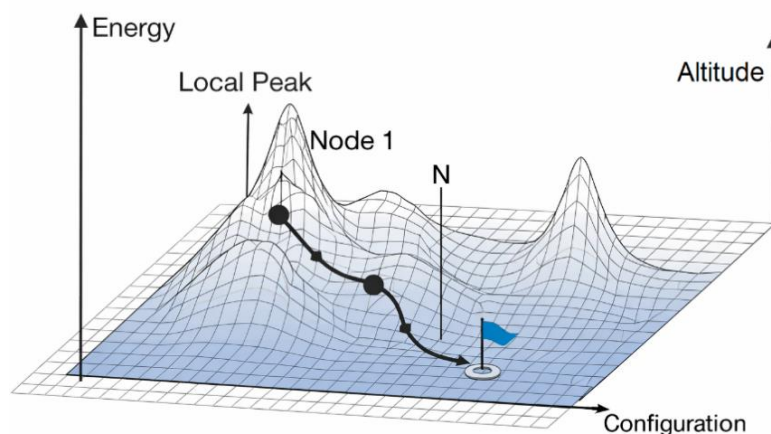


Figure 1. Illustration of the search-landscape of the AE-RFD optimization algorithm.

The improvement magnitude is defined based on J_k , which is the cost at step k along a drop trajectory:

$$\Delta J_k = J_{k-1} - J_k \quad (6)$$

Thus, the acceleration update is formulated as:

$$a_k = \begin{cases} \min(a_{\max}, a_{k-1} + k_a(\Delta J_k - \Delta J_{k-1})), & \Delta J_k > \Delta J_{k-1} \\ a_{k-1}, & \text{otherwise,} \end{cases}$$

where $k_a > 0$ controls acceleration accumulation and $a_{\max}$ covers growth. Primarily, a_k increases only when the algorithm experiences a stronger convergence than in the previous step, enabling an

adaptive move toward exploitation when descending efficiently.

The search behavior is regulated with the assistance of a_k by increasing the selection probability, expanding the candidate neighborhood, slightly increasing erosion rate, and thereby boosting successful assignments. The resulting algorithm improves convergence stability for large combinatorial ARC problems while preserving its exploration capability. The AE-RFD, thus avoids sticking in local minima as the stream successes in exceeding obstacles by leveraging the erosion rate and thus accelerates the gradient as well.

2.3. The ARC problem using AE-RFD

In the proposed optimization algorithm of AE-RFD, each configuration is associated with an altitude value proportional to the optimization objective. For the proposed energy-first ARC formulation, the altitude of a solution ($\mathbf{x}$) is defined as:

$$H(\mathbf{x}) = J(\mathbf{x})$$

where $J(\mathbf{x})$ is the energy-first objective function of Eq (1). Hence, optimization is written as a minimization of an artificial cost or altitude.

$$\max f(\mathbf{x}) \Leftrightarrow \min J(\mathbf{x}) = -f(\mathbf{x}) + \text{regularization}$$

$$J(\mathbf{x}) = -\sum_{m=1}^{N_{\text{MPPT}}} \min \left(\sum_{s \in \mathcal{S}_m(\mathbf{x})} P_s, P_m^{\max} \right) + \lambda_{\text{mis}} \Phi_{\text{mis}}(\mathbf{x}) + \lambda_{\text{pen}} \Phi_{\text{pen}}(\mathbf{x}) \quad (7)$$

Based on the ARC problem, AE-RFD operates on string-to-input permutations, ensuring feasible reconfiguration while efficiently exploring the solution space. Compared with other metaheuristics techniques, AE-RFD offers strong exploitation capability through altitude memory while maintaining exploration via probabilistic path selection.

Each candidate in the AE-RFD-based ARC solution is encoded as a permutation vector:

$$\mathbf{x} = [x_1, x_2, \dots, x_{N_s}]$$

where:

- $x_s \in \{1, 2, \dots, N_{\text{in}}\}$ denotes the inverter input assigned to string s ,
- N_s is the number of PV strings,
- N_{in} is the number of available inverter inputs.

The permutation constraint includes: Each string is connected to only one inverter input; and each input is connected to one string to guarantee electrically feasible configurations.

Each RFD-generated configuration is associated with an artificial altitude value related to the optimization objective. The maximization objective is transformed into an equivalent minimization problem as the RFD is a minimization-based algorithm.

This is achieved by an artificial altitude function that is equivalent to the negative delivered power augmented by regularization and penalty terms. Thus, minimizing this altitude is equal to maximizing the delivered energy. Although the optimization variable assigns strings to inverter inputs, delivered power is evaluated at the MPPT level. Each inverter input is therefore mapped to its corresponding MPPT, and the set $\mathcal{S}_m$ includes all strings connected to inputs associated with MPPT m . To sum up

the analogy:

- The Node represents assignment of one string-to-input (which is a full configuration path).
- The Edge is a neighbor move (by swapping two strings, or reinserting one string).
- The Path equals to the sequence of accepted best solutions over iterations.

3. Case studies and results

In this section, we evaluate the energy-first ARC using AE-RFD under the MPPT-limited method. The performance is inspected using: (i) delivered energy per day, (ii) sum of curtailed power due to MPPT constraints (clipping proxy), and (iii) sum of intra-MPPT current variances (a mismatch proxy). The crucial understanding is that maximizing energy yield under MPPT limits may increase mismatch while improving net energy by reducing clipping. The tests are implemented using MATLAB. Two PV systems, different in size and configurations, are utilized to the evaluation of the proposed approach.

3.1. The PV system of the 6-string array

A real grid-connected PV array of 72 PV modules grouped by six strings to provide a 15 kVA to an office building of the Renewable Energy Center in Baghdad, Iraq [20,21] is employed. The PV array is interfaced with the inverters as follows: (i) three MPP trackers, and (ii) two MPP trackers with three DC inputs per MPPT (thus, six inputs for six strings each case). Figure 2 illustrates the schematic configuration of the investigated 6-string PV system for the case of 3-MPPT. Each MPPT receives power from three string inputs. The second scenario considers a 2-MPPT configuration with three inputs per MPPT. The case studies employ synthetic disturb irradiance to systematically evaluate the proposed ARC under controlled partial-shading conditions, enabling mitigation of clipping impact through string reassignment.

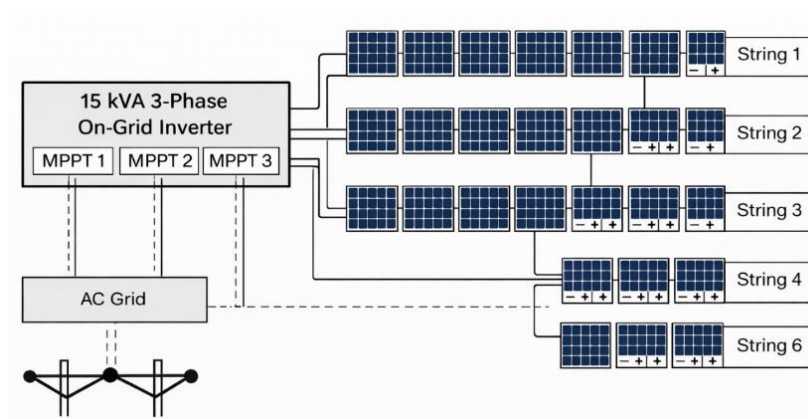


Figure 2. Schematic diagram of the 6-string array test system.

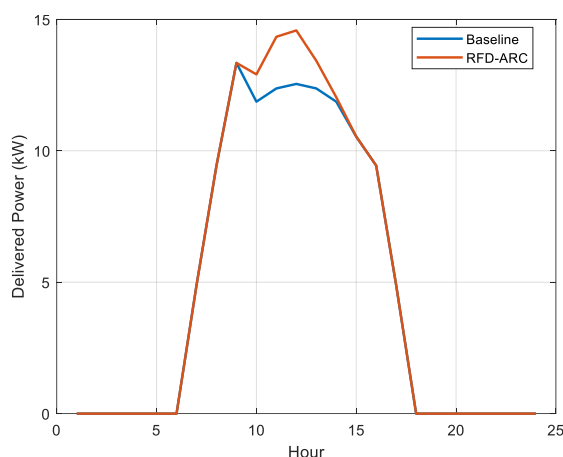
Based on this configuration, Table 1 summarizes the key performance indicators for the two scenarios under time-varying disturbed irradiance conditions. The proposed energy-first ARC increases the delivered daily energy in both configurations.

Table 1. The daily energy for the baseline and optimized configuration of the 6-string system.

Scenario	Baseline Energy (kWh)	Optimized Energy (kWh)	Energy Gain (%)	Mismatch Sum: Base → Optimized (kWh)	Clipping Sum: Base → Optimized (kWh)	Clipping Reduction (%)
3-MPPT, 2 inputs/MPPT	115.29	120.04	4.12	18.54 → 71.74	4.88 → 0.14	97.2
2-MPPT, 3 inputs/MPPT	113.53	119.79	5.51	5.97 → 36.08	6.64 → 0.38	94.2

The improvement is more noticeable in the 2-MPPT configuration (which is the selected one to the installed real system) since multiple strings share the same MPPT power limit. Hence, reassigning strings to balance the MPPT-level power reduces clipping more effectively. The clipping is reduced by about 94%, resulting in a 5.51% energy gain in the case of two MPPTs. The mismatch proxy sum increases, on the other hand, which is expected because the objective prioritizes delivered energy and enables mismatch when it helps avoid MPPT saturation. It can be observed that configurations with slightly higher mismatch may still achieve higher energy yield. This is due to the reduced clipping losses as the power distribution across MPPTs is improved. Hence, mismatch minimization alone cannot guarantee optimal delivered energy in multi-MPPT configurations.

Additionally, the results in Table 1 are illustrated in the following figures, where Figure 3 shows the comparison between the delivered power of baseline architecture to that delivered by the ARC based on AE-RFD for the 2-MPPT inverter. Figure 4 displays the clipping gain of applying the proposed methodology (94.2% for 2 MPPTs), and Figure 5 thereby indicates mismatch gain of energy yield comparing to the base case (around five times that of the baseline).

**Figure 3.** Case of 2-MPPT: Delivered power profile over 24 hours (baseline vs. optimized).

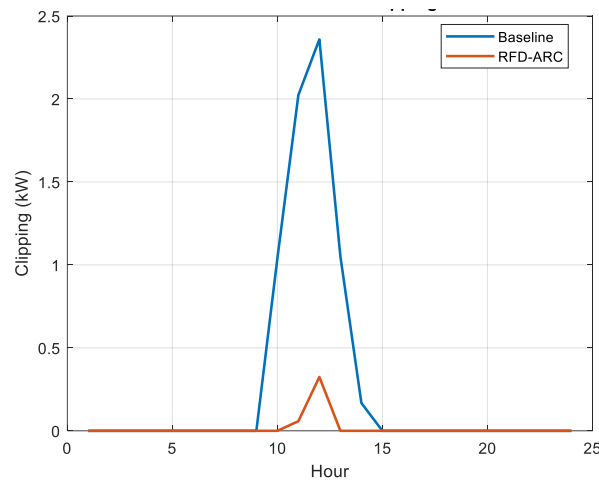


Figure 4. 2-MPPT case: Reducing MPPT daily clipping proxy (baseline vs. optimized).

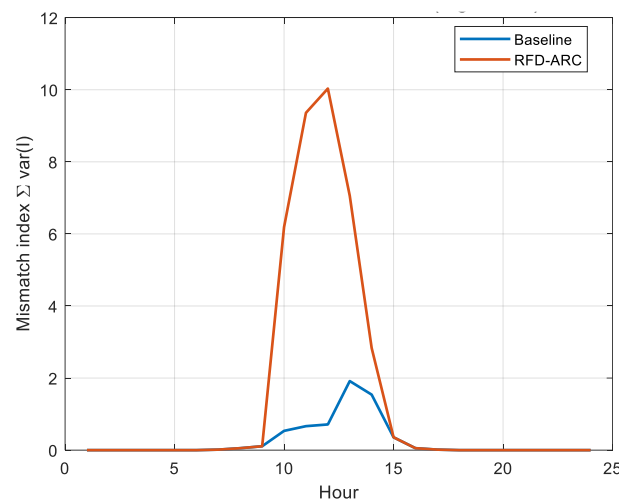


Figure 5. 2-MPPT case: Daily mismatch proxy and trade-off between mismatch and energy yield.

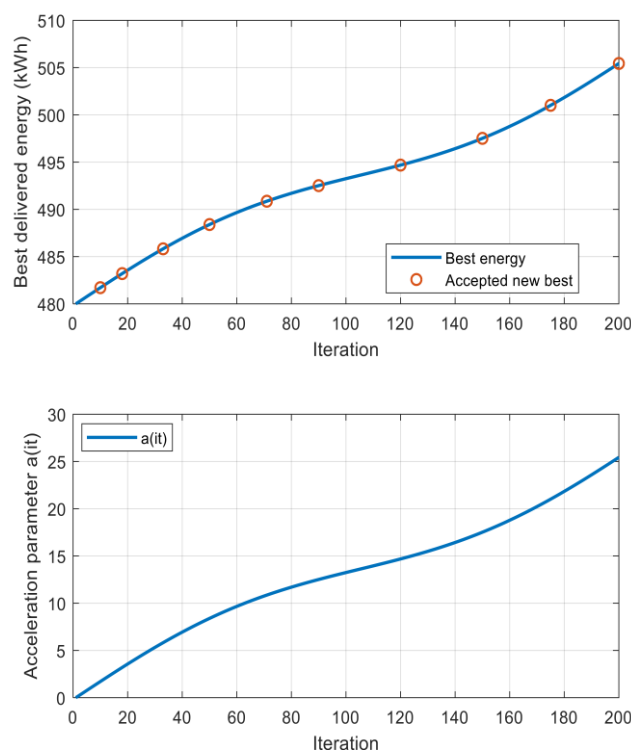
3.2. A large-scale PV system (24 strings, 8 MPPTs)

To examine the scalability, a large-scale 60-kVA PV benchmark with 24 strings and 8 MPPTs (three inputs each) is simulated using a standard time-varying shading pattern set. Table 2 summarizes the main simulation and AE-RFD parameter settings used for the investigated large-scale case study. In a representative moving cloud-band scenario, the AE-RFD improves the delivered energy from 488.78 kWh to 505.91 kWh (i.e., 3.5% gain) while reducing the clipping proxy from 42.56 kWh to 25.44 kWh (with 40.2% reduction). These results indicate that the energy-first ARC framework remains effective with increasing the system size and combinatorial search space.

Table 2. Principal system characteristics and AE-RFD parameter settings for the 24-string system.

PV Strings	Number of MPPTs	Inputs/MPPT	Peak Power (kVA)	Population size	Maximum Iterations	Final $a(i_t)$
24	8	3	60	40	200	25

Figure 6 presents the iterative improvement of the delivered-energy objective during the ARC optimization process using the proposed AE-RFD method for the studied large-scale 8-MPPT system. The best delivered energy progressively improves during the accepted string-reassignment process, reaching 505.91 kWh within 200 iterations. The acceleration accumulation gradually increases throughout the iterative optimization process and reaches approximately 25 near the final iteration.

**Figure 6.** Iterative evolution of the delivered-energy objective (upper) and the acceleration accumulation of the AE-RFD-based ARC (lower) for the 8-MPPT system.

Since the ARC problem is formulated as a discrete combinatorial reconfiguration problem, a perfectly smooth monotonic trend is not expected in the iterative evolution shown in Figure 6. Instead, the delivered-energy improvements occur incrementally through accepted string-to-MPPT reassignment updates during the AE-RFD optimization process.

Beyond the energy gain and clipping results discussed above, the following figures provide further illustration, starting with Figure 7, which compares the delivered power of baseline configuration to that delivered by the ARC based on AE-RFD for an 8-MPPT inverter, 24-string array.

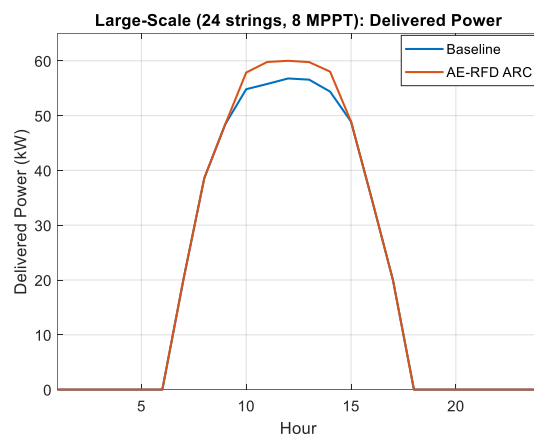


Figure 7. Delivered power improvement for 24 strings 8-MPPT system using AE-RFD-based ARC.

Figure 8 demonstrates the clipping proxy of the proposed configuration versus the base topology (42.2% for 8 MPPTs). Figure 9 illustrates the improvement in mismatch index of the 24-strings system and comparing it to the base case (around three times the base case mismatch). Last, Figure 10 shows selective strings profile of representative disturbance using synthetic irradiance conditions and controlled partial-shading scenarios.

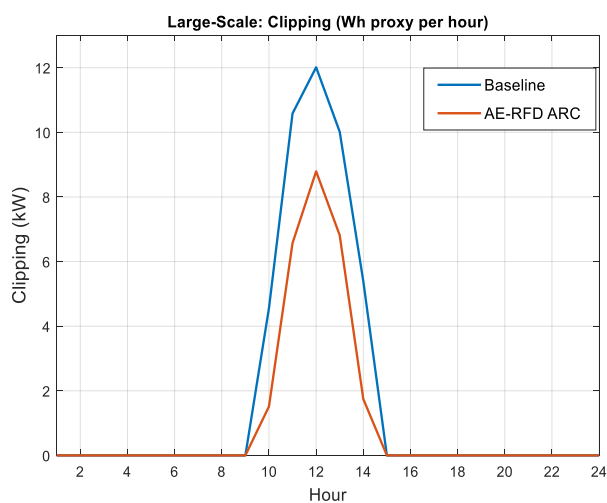


Figure 8. Clipping proxy per hour of the baseline vs. the proposed ARC for the 24 strings system.

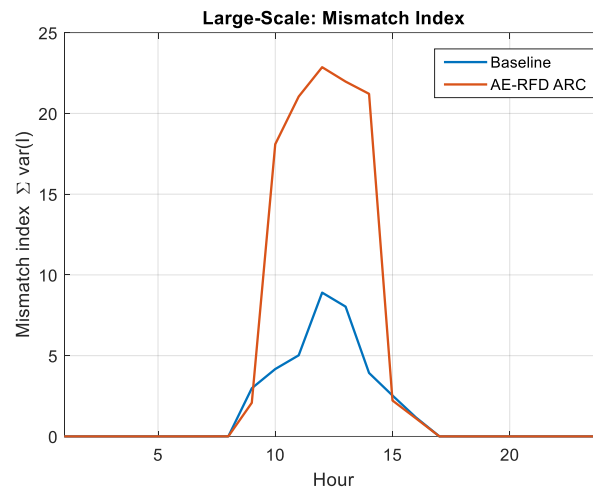


Figure 9. Enhancement of the Mismatch index of the 24-strings 8-MPPT using the proposed ARC.

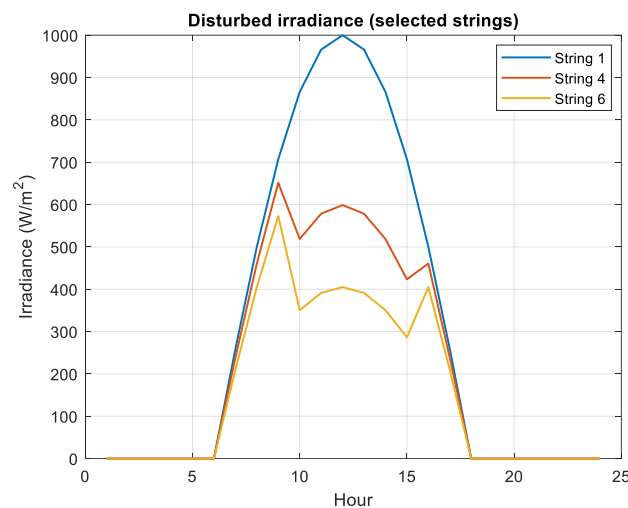


Figure 10. Representative disturbed irradiance profiles of selected shaded PV strings.

Overall, the results confirm that (i) energy-first ARC is most beneficial under MPPT-limited architectures where clipping dominates, and (ii) RFD-based solvers can discover high-yield string-to-input assignments. The increase in mismatch after optimization is an expected consequence of prioritizing delivered energy under MPPT limits.

3.3. Comparative evaluation with benchmark optimization algorithms

In addition to the yielded energy performance, the convergence and physical interpretability of the proposed AE-RFD-based method are involved in the following comparison results. The matrix arrangement of the eight MPPTs with their three inputs based on the proposed ARC methodology is shown in Figure 11. The obtained mapping represents the final snapshot for the reassignment process of the iterative AE-RFD-based optimization.

Furthermore, Figure A1 displays the mapping of 24 strings arrangement over the eight MPPTs and their three inputs where the baseline configuration indicates the ordinary assignment of the strings versus inputs. On the other hand, Figure A2 provides further information to the evolution string-MPPT reassignment by AE-RFD from the first iteration to the final assignment.

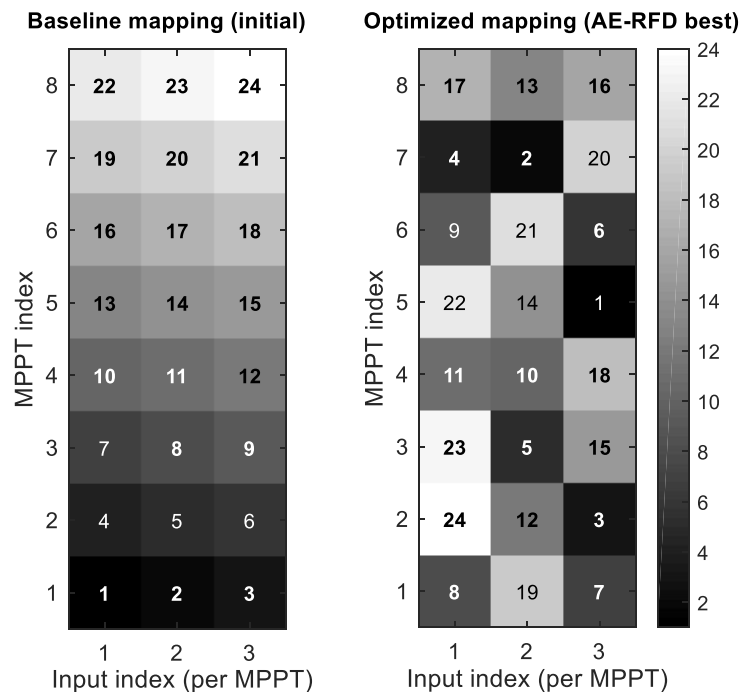


Figure 11. Mapping the ARC for the 8-MPPT, 24-string system (left, baseline sequential configuration vs. right, AE-RFD optimized).

In the mapping configuration, the ARC using AE-RFD can be directly linked to the gradient descent (and erosion mechanism) of the underlying optimization framework, providing clearer physical interpretability compared with conventional population-based optimization techniques.

The effectiveness of the AE-RFD-based energy-first array reconfiguration is additionally assessed by comparing its performance to a PSO-based ARC under identical operating constraints. The convergence profiles of the PSO and AE-RFD are shown in Figure 12. The convergence characteristic of the AE-RFD is smoother and more stable than that of the PSO, although PSO reaches a similar minimum energy cost under the investigated conditions. This behavior is associated with the combinatorial nature of the ARC problem, where the improvements occur incrementally through beneficial string reassignment patterns.

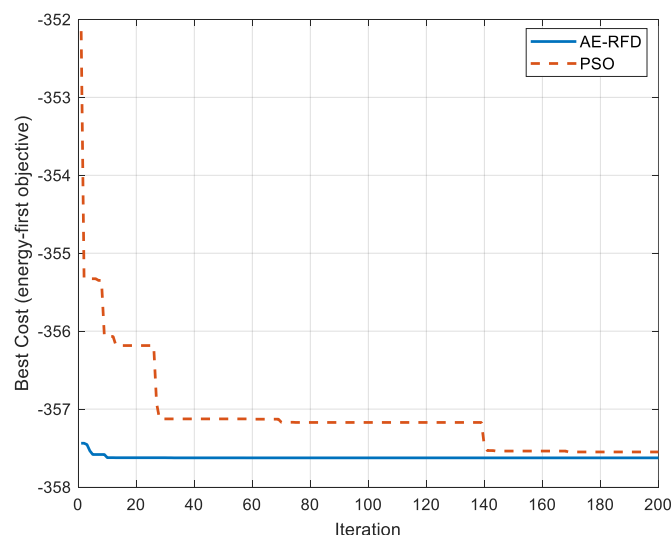


Figure 12. The convergence of AE-RFD vs. PSO for the ARC problem of 8-MPPT system.

Figure 12 reflects the gradient-driven search mechanism of the AE-RFD over the energy search landscape, which is consistent with the river formation analogy. In addition, the standard deviation of best cost for the AE-RFD is 0.0238, which is lower than that of the PSO (0.6128), highlighting improved convergence consistency.

To further evaluate the effectiveness of the proposed AE-RFD-based ARC, additional comparisons with conventional benchmark optimization methods, including Genetic Algorithm (GA) and Differential Evolution (DE), are conducted under identical operating conditions and objective-function settings. As shown in Figures 13–15 and summarized in Table 2, GA-ARC and DE-ARC approaches improve the delivered energy relative to the baseline configuration.

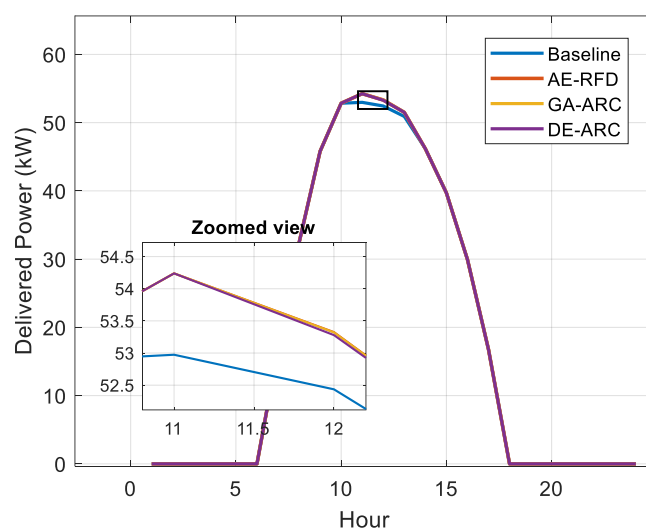


Figure 13. Delivered-power comparison of the baseline, AE-RFD-, GA-, and DE-based ARC configurations for the investigated 24-string system.

AE-RFD achieves the highest delivered energy (439.473 kWh), followed closely by GA (439.468 kWh), while DE reaches 439.426 kWh under the same conditions. On the other hand, AE-RFD mitigates clipping losses, whereas DE retains a small residual clipping value of 0.047 kWh.

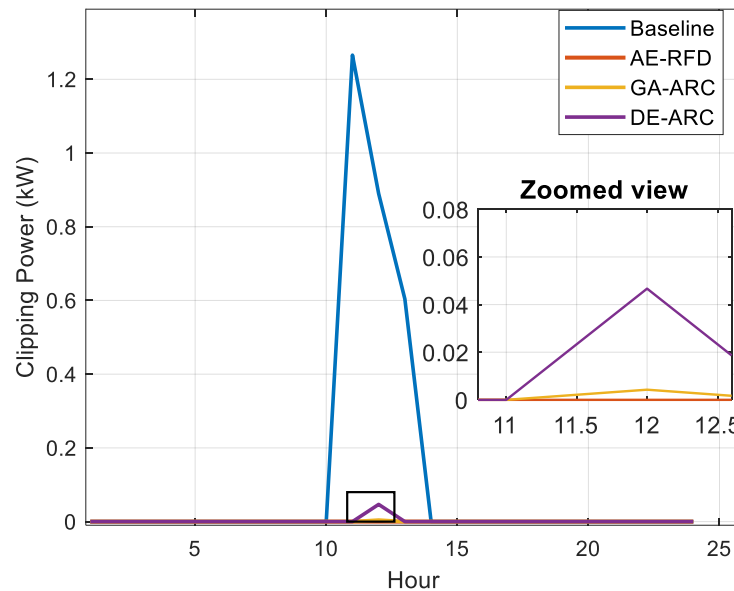


Figure 14. Clipping-power comparison of the baseline, AE-RFD-, GA-, and DE-based ARC configurations with zoomed view of the residual clipping region.

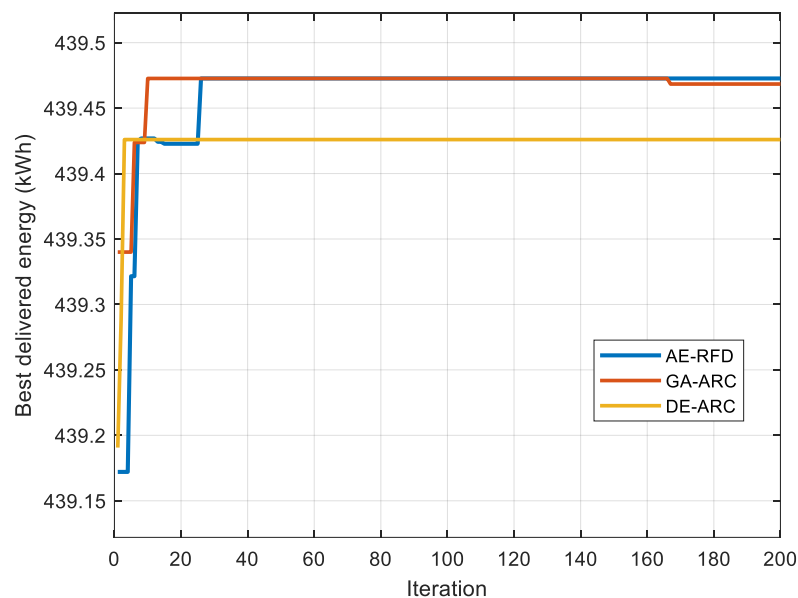


Figure 15. Iterative evolution of the best delivered energy for AE-RFD, GA, and DE under identical ARC operating conditions.

Overall, the comparative results demonstrate consistent improvement in delivered energy and clipping mitigation across the investigated ARC optimization approaches. Table 3 summarizes the corresponding quantitative performance metrics.

Table 3. Daily performance comparison for the investigated 24-string large-scale system.

Method	Delivered Energy (kWh)	Energy Gain (%)	Clipping Loss (kWh)
Baseline	436.714	—	2.759
AE-RFD-ARC	439.473	0.632	0.000
GA-ARC	439.468	0.631	0.004
DE-ARC	439.426	0.621	0.047

4. Conclusions

In this paper, we present an energy-first ARC approach for grid-connected PV systems, in which the objective function of the array's reconfiguration is formulated based on the delivered energy under MPPT power constraints, rather than conventional mismatch-only methods. An AE-RFD algorithm is developed to solve the combinatorial optimization problem over the ARC search space.

The proposed AE-RFD enables faster convergence toward high-energy configurations while maintaining solution feasibility. The ARC problem is modeled to explicitly account for multi-MPPT inverter limits, clipping effects, and string-level reassignment, making the formulation directly relevant to practical PV installations.

Simulation case studies are conducted for small-scale (6 strings) and large-scale (24 strings, 8 MPPTs) PV arrays under irradiance disturbance and shading scenarios. In the results, the proposed energy-first AE-RFD-ARC consistently reduces MPPT clipping losses and achieves up to 5.5% improvement in daily delivered energy compared with baseline fixed configurations, with significant clipping gain by 94.2% and 40.2% for 6-string and 24-string systems, respectively. The mismatch indices are also improved. Graphical visualization of the reconfiguration process indicates the evolution of string–MPPT assignments and confirm the algorithm's ability to adaptively redistribute power across the available MPPT channels. Comparing this with other optimization techniques such as PSO, GA, and DE confirm the effectiveness and convergence stability of the proposed AE-RFD-based methodology for the investigated large-scale PV system. The smoother iterative behavior, significant clipping mitigation, and physical interpretability may make AE-RFD more favorable for large-scale ARC applications.

In future, the proposed framework will be extended to include real-time reconfiguration constraints, considerations of switching-frequency, and hardware-in-the-loop validation for large-scale PV systems under dynamic partial-shading conditions.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Conceptualization: Hatim Abood; Methodology: Hatim Abood, Balasim Hussein, Waleed Al-Jubori; Software: Hatim Abood; Validation: Hatim Abood, Balasim Hussein; Formal analysis: Hatim Abood; Investigation: All authors; Data curation: Hatim Abood; Writing—original draft preparation: Hatim Abood; Writing—review and editing: All authors; Visualization: All authors. All authors have read and agreed to the published version of the manuscript.

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Appendix

Illustrative maps for the configuration of the 24-string 8-MPPT system to support understating the performance of the optimization algorithm.

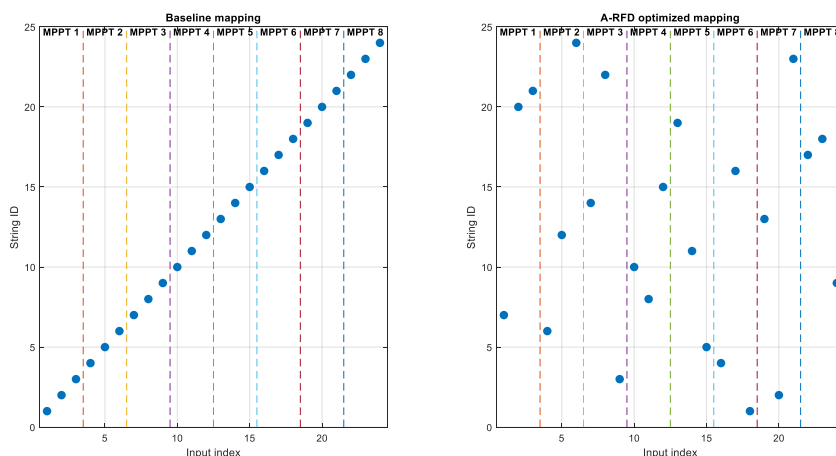


Figure A1. Distribution of the AE-RFD-based configuration of the 24-string system over the MPPT inputs (baseline vs. optimized).

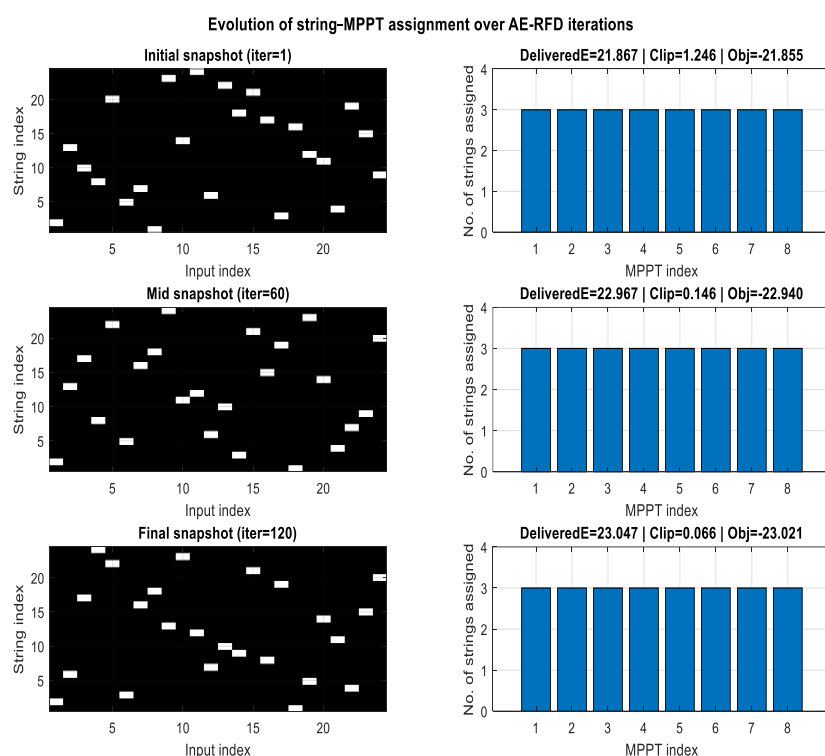


Figure A2. Evolution of string-MPPT assignment over the iterations of the AE-RFD algorithm (24-strings PV system).



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