Multi-Objective Design and Optimization of Grid-Connected Photovoltaic Power Plants Considering Real-World Constraints

Angelo Raeli
Dept. of Energy
Politecnico di Milano
Milan, Italy
angelo.raeli@mail.polimi.it

Marco Mussetta
Dept. of Energy
Politecnico di Milano
Milan, Italy
marco.mussetta@polimi.it

***Abstract*—The optimal design of utility-scale photovoltaic (PV) plants involves complex trade-offs between maximizing energy production and minimizing Capital Expenditures (CAPEX). This paper proposes the use and integration of a Multi-Objective Evolutionary Algorithm (MOEA) framework utilizing the well-known Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to optimize the electrical and geometrical configuration of grid-connected PV systems with geographical and orographical contraints. An automated workflow is introduced, integrating MATLAB for the optimization logic, PVsyst for detailed carrier-grade energy simulations considering real-world environmental features and constraints, and AutoHotkey for interface automation. The methodology is applied to a real-world 26.6 MWp case study in Southern Italy. Two scenarios are analyzed: one reflecting historical market conditions and one reflecting modern pricing and bifacial technology trends. Results demonstrate that the proposed algorithm identifies configurations that dominate the actual project design in terms of Pareto optimality. Furthermore, the study highlights how recent market shifts significantly impact the optimal selection between monofacial and bifacial tracking systems.**

***Index Terms*—Multi-Objective Optimization, NSGA-II, Photovoltaic Systems, PVsyst, Evolutionary Algorithms, Power Engineering.**

I. Introduction

The global transition towards renewable energy has placed utility-scale photovoltaic (PV) systems at the forefront of electricity generation strategies. As indicated by international forecasts, solar PV is expected to become a leading technology by 2030 [1], in particular to address and increasing penetration of fast-charging electric vehicles (EVs), which will require a seamless integration with large PV energy production plants and storage systems. However, designing large-scale plants requires addressing non-linear trade-offs between competing objectives: minimizing Capital Expenditures (CAPEX) while maximizing Annual Energy Production (AEP).

Traditional heuristic methods often fail to navigate the complex search space created by the interaction of numerous design variables (e.g., pitch, tilt, layout configuration, inverter sizing) and site-specific constraints [2], [3]. Consequently, Computational Intelligence (CI) techniques, specifically Evolutionary Algorithms (EAs), have gained prominence for their ability to solve such multi-objective optimization problems (MOPs) [4].

While previous studies have applied EAs to PV sizing, a gap remains in effectively bridging robust optimization algorithms with industry-standard simulation software. Many academic models rely on simplified mathematical approximations of PV yield, ignoring complex phenomena like near-shading losses on uneven terrain or specific inverter clipping behaviors and open-data [5]. Indeed, even if the most common shading and yield approximations in the scientific literature are simplified methodologies, however, simpler shading approximations are commonly used since detailed phenomena are not entirely accounted for even in industry-grade frameworks due to 3D simplifications and uniform shading factors [6] . On the other hand, similar, detailed shading approaches has been explored in the literature [7].

This paper bridges this gap by proposing a fully automated optimization framework that couples *NSGA-II* (implemented in *MATLAB*) with *PVsyst*, the industry standard for bankable PV simulations [8]. The interaction is mediated by *AutoHotkey* to handle the GUI-based batch processing of PVsyst [9].

The methodology is validated against a real-world case study: an already existing 26 MWp plant in Southern Italy. We analyze two scenarios to assess how technological evolution (specifically the rise of bifacial modules) shifts the Pareto-optimal front. In fact, while it is clear that, by technological advancement, a much better solution can be achieved, the reported results will also allow to understand if the currently existing solution could be transformed to one of the preferred solution under the technological advancements. Recent studies on *Innovation Path* may discover a series of systematic and small changes to get the target optimal solution from the current solution [10].

II. Methodology and Workflow

The optimization process follows a cyclic workflow designed to generate a set of Pareto-optimal solutions, as reported in Figure 1. The framework integrates three distinct software tools:

1) *MATLAB* hosts the NSGA-II algorithm [11], manages population initialization, genetic operators (crossover, mutation), and fitness evaluation.
2) *PVsyst* performs detailed batch simulations to calculate the Annual Energy Production (AEP) considering site topography and shading.
3) *AutoHotkey* acts as middleware to automate the interaction with PVsyst's user interface, enabling iterative batch simulations without human intervention.

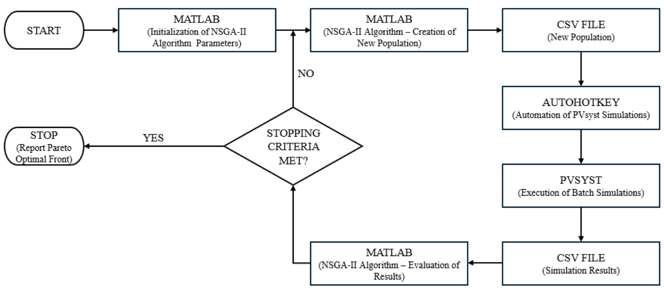

Fig. 1. Flowchart of the considered workflow.

A. The NSGA-II Implementation

The optimization core utilizes the NSGA-II algorithm due to its efficiency in handling MOPs through fast non-dominated sorting and crowding distance mechanisms [11].

The process begins with the initialization of a random population of N individuals. Each individual represents a unique system configuration vector $\vec{x}$. In each generation, offspring are created using binary tournament selection, intermediate crossover, and Gaussian mutation.

B. Automated Simulation Loop

A critical contribution of this work is the automation of PVsyst. As illustrated in the system workflow, MATLAB generates a population and writes the design variables to a CSV file. AutoHotkey scripts then trigger PVsyst to read this CSV, execute the 'Batch Mode' simulation, and write the energy outputs to a result CSV. MATLAB reads the results to compute the objective functions for the current generation.

III. Case Study

The methodology was applied to a ground-mounted PV plant under construction in the considered region in Southern Italy. The site spans approximately 48 hectares with a hilly topography, as shown in Figure 2, thus introducing some demanding orographical constraints, which are specifically to be addressed and satisfied by the proposed multi-objective optimization approach.

In particular, although the selected site is largely free from constraints that could impede the construction of the photovoltaic plant, however, overhead high-voltage power lines traverse parts of the area, requiring careful planning to minimize shading and interference with the modules.

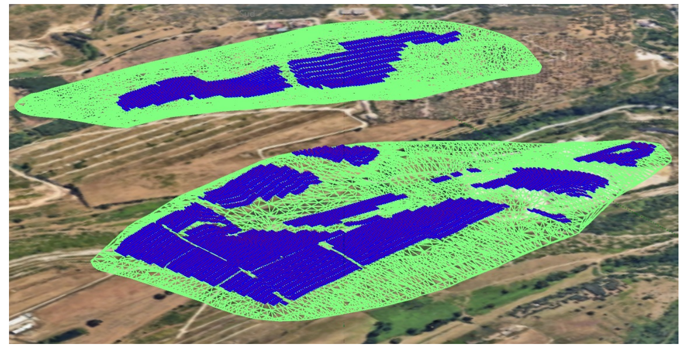

Fig. 2. Spatial layout of the considered photovoltaic plant modeled in GIS.

The site features a hilly topography with variable slopes of up to 27% and terraced sections, which have been considered in the layout design.

A. Reference Plant

The "Current System Design" (CSD) serves as a benchmark. It features:

- Capacity: 26.596 MWp.
- Technology: Monofacial modules (575 Wp), Single-axis trackers (1P layout).
- Inverters: 8 Central Inverters.

B. Scenarios

Two scenarios were simulated to evaluate robustness against market changes:

- *Scenario 1 (Historical)*: Uses component costs and module technologies (575W/605W) from the initial design phase (approx. 2022-2023). Bifacial modules are significantly more expensive than monofacial.
- *Scenario 2 (Modern)*: Uses current market data (2024-2025). Includes higher power modules (660W/690W) and reflects the sharp price drop in bifacial technology and tracking structures [12].

IV. Problem Formulation

The optimization problem is defined as the minimization of two conflicting objectives subject to m constraints.

A. Decision Variables

The study considers 8 decision variables ($\vec{x} = [x_1, ..., x_8]$) for both fixed-tilt and single-axis tracking systems:

- x_1: Tilt angle (Fixed) or Rotation Limits (Tracker) [deg].
- x_2: Azimuth angle (Fixed) or Backtracking strategy (Tracker).
- x_3: Pitch (inter-row distance) [m].
- x_4: Modules per string (series connection).
- x_5: Number of strings (parallel connection).
- x_6: Number of inverters.
- x_7: Module layout (e.g., 1P, 2P, 3L).
- x_8: PV Module type (selection from the database).

B. Objective Functions

1) Maximize Energy Production: Since NSGA-II is a minimization algorithm, the energy objective is formulated as:

$$\min f_1(\vec{x}) = -E_{batch}(\vec{x}) \cdot k_{corr} \tag{1}$$

Where E_{batch} is the grid-injected energy calculated by PVsyst, and k_{corr} is a corrective factor derived from detailed 3D shading simulations to account for complex topography not fully captured in batch mode.

2) Minimize CAPEX: The cost function includes variable costs (dependent on module count, structure type, cabling) and fixed costs (civil works, grid connection):

$$\min f_2(\vec{x}) = C_{mod} + C_{struct} + C_{elec} + C_{fixed} \tag{2}$$

Cost parameters were derived from real EPC contracts associated with the case study.

C. Constraints

Beyond the complex topographical and orographical constraints to be considered by means of proper modeling through Geographical Information Systems (GIS), to ensure the feasibility and practicality of the photovoltaic system configurations, several constraints have been defined in the optimization problem. These constraints address technical and physical aspects of the system, ensuring that the solutions align with the requirements of the plant project. The specific constraints are detailed below:

- Inverter Voltage: $V_{OC}(-10°\text{C}) \leq V_{max}^{inv}$ and $V_{MPP}(45°\text{C}) \geq V_{min}^{inv}$.
- Inverter Current: $I_{DC} \leq I_{max}^{inv}$.
- Power Ratio: $0.8 \leq P_{DC}/P_{AC} \leq 1.2$.
- Grid Limit: Active power injection $\leq$ 36 MW (limited by HV transformer).
- Capacity: $P_{peak} \geq 26$ MWp.
- Land Area: The total occupied area must not exceed the usable site surface ($A(\vec{x}) \leq A_{max} = 263,000 m^2$).

V. Results and Discussion

A. Algorithm Validation (Scenario 1)

The optimization was first performed under historical conditions to validate the model against the CSD.

The results obtained for the tracking systems are presented in Figures 3 and 4: it can be observed that the current system configuration (highlighted by the green diamond) lies slightly to the left of the Pareto front in the monofacial case and slightly below the front in the bifacial case, yet still follows the same trend as the latter.

This indicates that for the monofacial tracking configuration, the algorithm identified solutions that outperform the current design in terms of both cost and energy production. In contrast, for the bifacial system, since the algorithm was constrained to explore only configurations with a minimum installed capacity of 26 MW (limit applied to all system types), the lowest achievable annual energy production with bifacial modules is approximately 49.5 GWh. As a consequence, no solutions

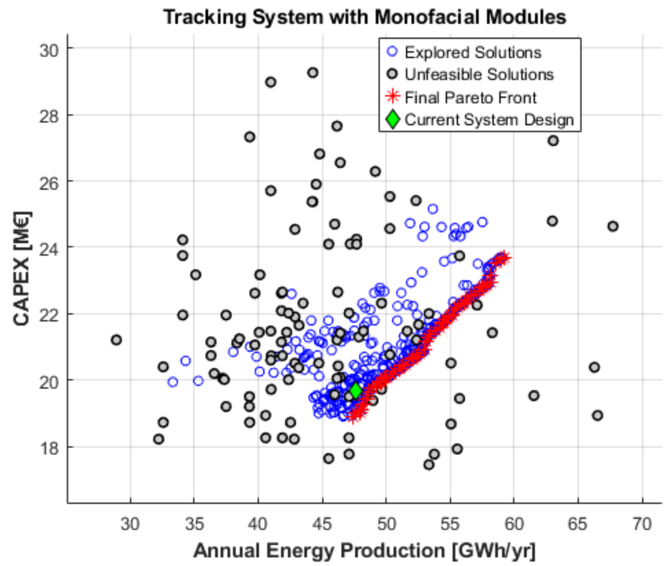

Fig. 3. Results for the tracking photovoltaic systems: Costs and energy productions for monofacial modules.

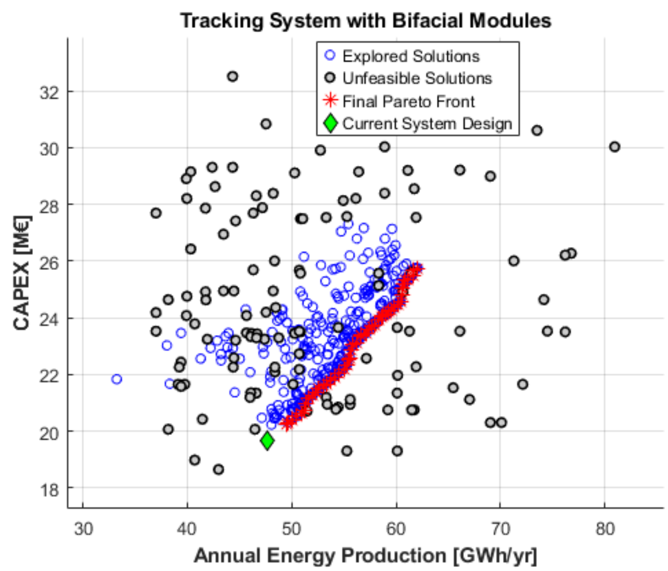

Fig. 4. Results for the tracking photovoltaic systems: Costs and energy productions for bifacial modules.

were found that match the lower energy output of the current system while also offering reduced costs, making a direct comparison unfeasible within the defined search space. However, as shown in Figure 4, bifacial tracking systems consistently display a less favorable cost-energy trade-off compared to their monofacial counterparts. For this reason, it was not necessary to extend the analysis to configurations with capacities below 26 MW. If bifacial systems had proven to be more efficient, a specific investigation could have been conducted with a less restrictive power constraint to allow a direct comparison with the existing system. Furthermore, the choice to impose a minimum capacity of 26 MW is in line with the general objective of this

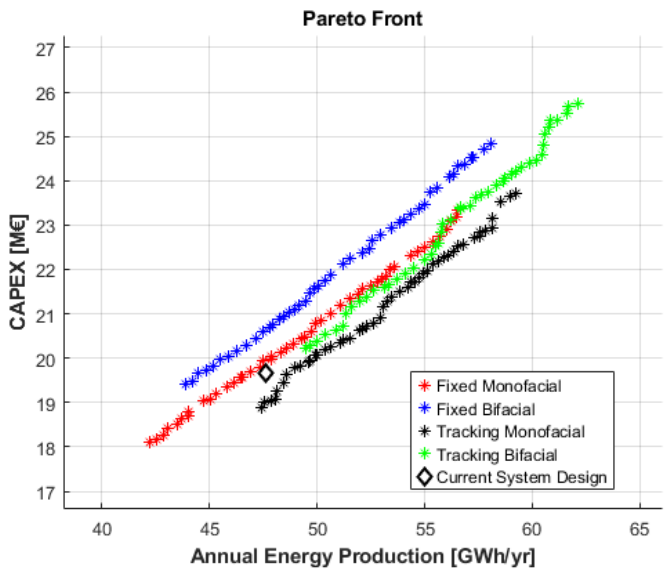

Fig. 5. Pareto fronts for Scenario 1. The 'Current System Design' is dominated by the optimized Monofacial Tracking solutions.

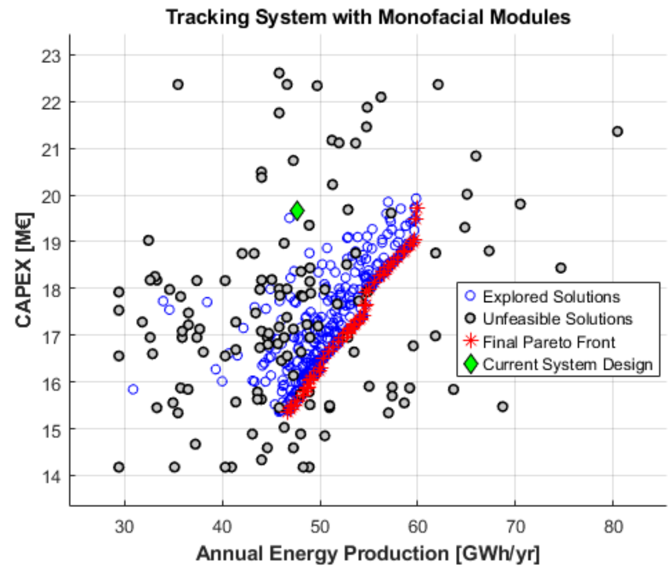

Fig. 6. Results for the tracking photovoltaic systems: Costs and energy productions for monofacial modules.

study, which is to explore system configurations that maximize land utilization and ensure scalability, key requirements in the design of utility-scale photovoltaic plants.

Figure 5 summarizes the Pareto fronts for fixed and tracking systems.

The CSD (indicated by the green diamond) lies dominated by the Pareto front generated for the *Monofacial Tracking* system. This confirms that the algorithm successfully identified configurations with superior trade-offs (higher energy or lower CAPEX) compared to the manual design.

In Scenario 1, the optimization shows that *Monofacial Tracking* systems provided the best Hypervolume (HV = 119.02) compared to Bifacial Tracking (HV = 109.43). This aligns with historical data where the premium cost of bifacial modules outweighed the generation gains. The fixed-tilt systems were consistently outperformed by trackers.

The optimal configuration identified (ID 4) reduced the specific energy cost (EUR/kWh) by 3.87% compared to the CSD, achieving 48.05 GWh/yr with a CAPEX of 19.08 Meur.

B. Impact of Technological Evolution (Scenario 2)

Scenario 2 introduces modern pricing and high-efficiency modules.

Figures 6 and 7 illustrate the shift in optimal solutions. From the Pareto fronts and hypervolume trends shown, it is immediately evident that in the second scenario the system costs are significantly lower. This reduction is primarily due to technological advancements, increased market maturity, and government incentives supporting energy efficiency. Both Pareto fronts lie well below the current system configuration, meaning that all the solutions identified are characterized by lower Capital Expenditures (CAPEX). Notably, the front corresponding to bifacial modules (Figure 7) is entirely shifted to the right with respect to the current design, in terms of energy

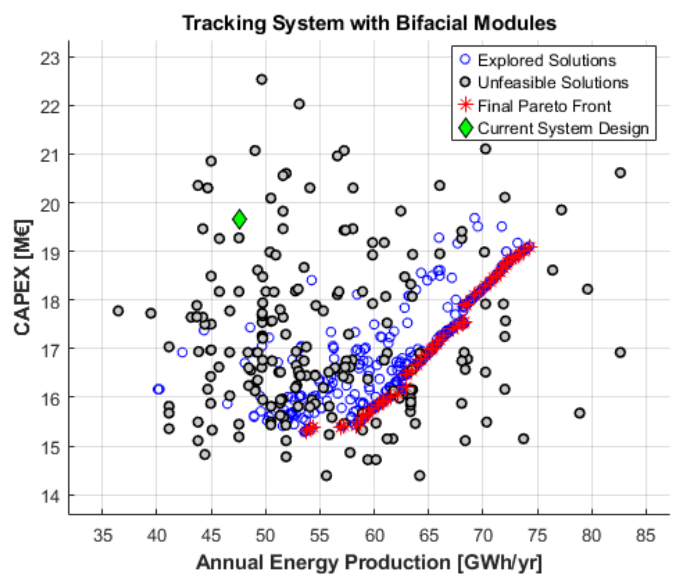

Fig. 7. Results for the tracking photovoltaic systems: Costs and energy productions for bifacial modules.

production, indicating that every bifacial con5— figuration on the Pareto front yields a higher annual energy output. Therefore, in this scenario, almost all Pareto-optimal solutions outperform the current system in both objectives simultaneously, with all bifacial configurations clearly demonstrating superiority in terms of both cost and energy production.

Figure 8 summarizes the Pareto fronts for fixed and tracking systems.

A definitive inversion of the trend is observed. Due to the cost reduction of bifacial modules (now comparable to or cheaper than monofacial per Wp due to incentives), the *Bifacial Tracking* system emerges as the absolute global optimum.

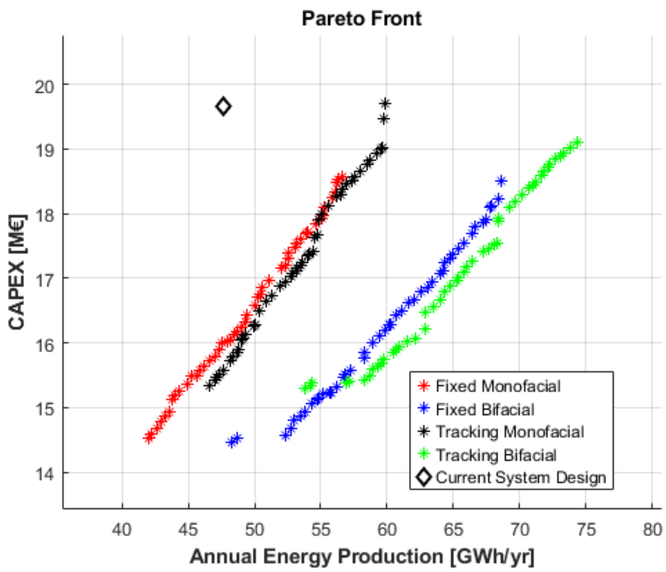

Fig. 8. Comparison of Pareto fronts in Scenario 2. Bifacial tracking systems now dominate the solution space.

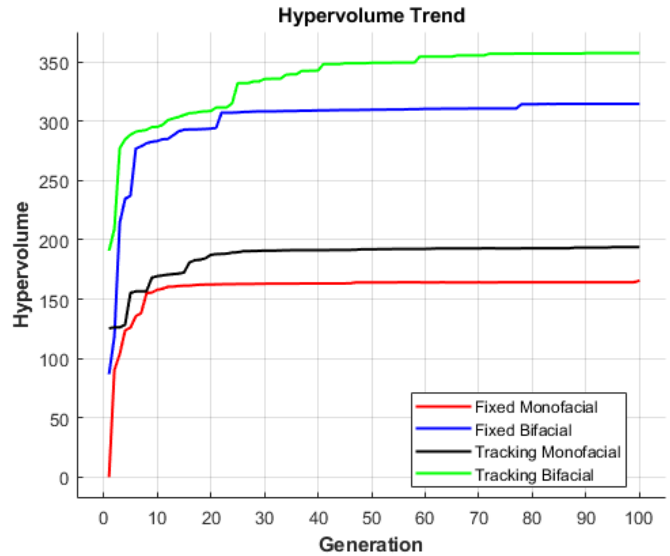

Fig. 9. Hypervolume trends for Scenario 2. The Bifacial Tracking system shows superior convergence and solution space coverage.

The Pareto front for Bifacial Tracking is shifted significantly to the right (higher energy) and downwards (lower CAPEX). Key findings from Scenario 2 include:

- *Bifacial Dominance*: Even *fixed* bifacial systems outperformed *tracking* monofacial systems in terms of energy yield, a result driven by the high efficiency of 690 Wp modules.
- *Specific Cost*: The optimal bifacial tracking solution achieved a specific energy cost of 0.262 EUR/kWh, a dramatic reduction compared to the 0.413 EUR/kWh of the original design in Scenario 1 context.
- *Backtracking*: Interestingly, the optimization consistently disabled backtracking. On the specific hilly topography of the considered site in Southern Italy, standard backtracking algorithms caused excessive yield losses that outweighed the shading losses they were meant to prevent.

C. Hypervolume Analysis

The convergence of the algorithm was monitored using the Hypervolume indicator. As shown in Fig. 9, the algorithm achieves convergence within 100 generations. The significant gap between the Bifacial Tracking curve (Cyan) and others in Scenario 2 quantifies the technological advantage gained.

D. Final result

As a result, the final configuration selected for detailed simulation was taken from the Pareto front of the tracking bifacial system, using the same criterion adopted in the first scenario – *i.e.*, selecting the solution with an installed capacity close to that of the current system design, and the lowest specific energy cost. Table I presents the main configurations from the Pareto front of bifacial tracking systems with an installed power close to that of the current system design. Among them, the selected configuration is highlighted – ID 12.

VI. Conclusion

This paper presented a multi-objective optimization framework for PV plant design, integrating evolutionary computation with bankable simulation tools. The application to the real-world Italian case study demonstrated that the NSGA-II based approach effectively identifies design configurations that minimize CAPEX and maximize energy production, outperforming manual engineering designs.

The comparative analysis reveals that optimal design choices are highly sensitive to market conditions. While monofacial systems were optimal under historical pricing, the modern scenario dictates a decisive shift toward bifacial tracking technologies. The proposed tool allows developers to rapidly re-evaluate project feasibility as market parameters fluctuate, ensuring robust investment decisions.

Future developments will include the integration of Operational Expenditures (OPEX) into the objective functions and the inclusion of battery energy storage systems (BESS) sizing.

Acknowledgment

This study was partially carried out within the EVFLEX (Solutions for the flexibility of electric vehicles in the grid) project (ID: MI_FAE_00360), funded by the Italian Ministry of the Environment and Energy Security (MASE) under the ”Mission Innovation 2.0” framework.

References

[1] IEA Renewables, “Analysis and forecast to 2030,” International Energy Agency, Paris, 2024.

[2] T. Kerekes, E. Koutroulis, D. Séra, R. Teodorescu and M. Katsanevakis, “An Optimization Method for Designing Large PV Plants,” in *IEEE Journal of Photovoltaics*, vol. 3, no. 2, pp. 814–822, April 2013, doi: 10.1109/JPHOTOV.2012.2230684

TABLE I

OPTIMAL CONFIGURATIONS FROM THE PARETO FRONT OF BIFACIAL TRACKING SYSTEMS. THE CHOSEN SOLUTION (ID 12) IS HIGHLIGHTED.

ID	Rotation Limits [°]	BT [On/Off]	Pitch [m]	Modules in Series	Strings in Parallel	Number of Inverters	Layout Type	Module Type	Energy [GWh/yr]	CAPEX [M €]	Power [MW]	Ratio [€/kWh]
7	±45.00	2	5.00	27	1417	7	1	2	58.702	15.498	26.40	0.264
8	±35.00	2	5.00	28	1383	7	1	2	58.925	15.593	26.72	0.265
9	±45.00	2	5.00	27	1440	7	1	2	59.290	15.646	26.83	0.264
10	±45.00	2	5.00	28	1397	7	1	2	59.523	15.686	26.99	0.264
11	±45.00	2	5.00	28	1406	7	1	2	59.746	15.746	27.16	0.264
12	**±45.00**	**2**	**5.00**	**28**	**1384**	**8**	**1**	**2**	**60.434**	**15.845**	**26.74**	**0.262**
13	±45.00	2	5.00	28	1391	8	1	2	60.728	15.892	26.87	0.262
14	±40.00	2	5.00	28	1398	8	1	2	60.941	15.938	27.01	0.262
15	±40.00	2	5.00	28	1411	8	1	2	61.478	16.025	27.26	0.261

[3] Roberto S. Faranda, Hossein Hafezi, Sonia Leva, Marco Mussetta, and Emanuele Ogliari, “The optimum PC plant for a given solar DC/AC converter,” in *Energies*, vol. 8, no. 6, pp. 4853–4870, 2015, doi: 10.3390/en8064853.

[4] P. A. Vikhar, ”Evolutionary algorithms: A critical review and its future prospects,” *2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC)*, Jalgaon, India, 2016, pp. 261–265, doi: 10.1109/ICGTSPICC.2016.7955308.

[5] M. Mussetta, ”Data Collection, Analysis and Optimization in Prosumer Buildings: A Case Study with an Open Dataset,” *2025 10th International Conference on Applying New Technology in Green Buildings (ATiGB)*, Danang, Vietnam, 2025, pp. 745–750, doi: 10.1109/ATiGB66719.2025.11142074.

[6] E.D. Chepp, F.P. Gasparin, A. Krenzinger, “Accuracy investigation in the modeling of partially shaded photovoltaic systems,” in *Solar Energy*, vol. 223, no. 15, pp. 182–192, July 2021, doi: 10.1016/j.solener.2021.05.061.

[7] C. Silva, S. Mendes, L. Negrete, J. López-Lezama, N. Muñoz-Galeano, “Optimizing Photovoltaic Generation Placement and Sizing Using Evolutionary Strategies Under Spatial Constraints,” in *Energies*, vol. 18, no. 8, p. 2091, 2025, doi: 10.3390/en18082091.

[8] PVsyst. Pvsyst: Photovoltaic software for professionals, 2025. URL https://www.pvsyst.com/.

[9] AutoHotkey Community. Autohotkey: Automate everything with scriptable hotkeys, 2025. URL https://www.autohotkey.com/.

[10] A. Khan and K. Deb, “Gradual Innovative Transitional Solutions Improving Current to a Desired Target: Innovation Path,” in *IEEE Transactions on Evolutionary Computation*, vol. 30, no. 1, pp. 378–392, Feb. 2026, doi: 10.1109/TEVC.2025.3552685.

[11] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, ”A fast and elitist multiobjective genetic algorithm: NSGA-II,” in *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, April 2002, doi: 10.1109/4235.996017.

[12] Baliozian, P., et al. “The international technology roadmap for photovoltaics and the significance of its decade-long projections,” *37th European PV Solar Energy Conference and Exhibition*, vol. 7, p. 11, 2020.