BACKTRACKING 3D: A NOVEL APPROACH TO CONVENTIONAL BACKTRACKING ALGORITHMS FOR IMPROVED PV PERFORMANCE IN COMPLEX TERRAINS

J. Tomás Villalonga Palou, D. López Dalmau, H. Mirandona López, C. Javier Lopes Gomes, C. Rossa
[1]SUNVEON
calle del Musgo, 2, 1B, Madrid, Spain. 28023

Backtracking strategies are widely used in photovoltaic (PV) plants to reduce shading, but they become ineffective on the irregular terrains typical of large-scale installations. Slope-aware approaches improve performance but rely on simplified terrain models, which fail to represent the diverse slopes of real PV layouts. As a result, current methods remain limited in mitigating shading losses, reducing irradiance capture, and lowering overall energy yield. To overcome these limitations, an innovative tracking strategy based on Machine Learning is proposed to optimize the performance of PV plants in complex terrains.

Keywords: backtracking strategies, irregular terrain, backtracking 3D, machine learning, shading losses

1 INTRODUCTION

Backtracking strategies are widely applied in tracking photovoltaic (PV) plants, to prevent mutual shadings between generators, especially during the early and late hours of the day[1]. In modern PV plants, which can cover areas as vast as a small city and reach installed powers in the gigawatt range[2], the inherent irregularity of the terrain makes conventional backtracking algorithms ineffective, as they fail to completely eliminate shading and consequently reduce the yield potential. In this sense, significant advancements have been made by incorporating slope-aware backtracking strategies[3], [4], [5], [6]. However, these tracking approaches assume a generalised terrain model, either flat or with a uniform slope, whereas real PV layouts are often installed in complex terrains made up of a wide variety of slopes, which limits the effectiveness of these methodologies in reducing the yield penalty due to near shadings. In this context, this work presents an innovative tracking strategy that accounts for the specificity of different zones within the plant site, based on a novel, multi-zonal clustering-based tracking strategy for photovoltaic plants in complex terrains (BT3D).

2 METHODOLOGY

2.1 The approach

The proposed methodology begins by dividing the plant site into distinct clusters, enabling a more granular and accurate representation of the landscape. This is achieved through machine learning techniques, specifically Ward’s Hierarchical Clustering, which groups areas with similar terrain characteristics. The clustering is performed independently of the size or location of each zone within the plant—meaning that distant zones with comparable properties are treated similarly. This approach provides a precise characterization of the terrain, marking a significant departure from conventional methods that typically assume a uniform or gently sloping surface. Each cluster is assigned a specific transposition model (including bifaciality) and a coordinated tracker movement strategy, allowing for precise adaptation to local terrain slope and solar position. The rotation is determined by both the cross-axis slope of the terrain section and the representative axis tilt of the trackers in the selected cluster, as illustrated in Fig. 1

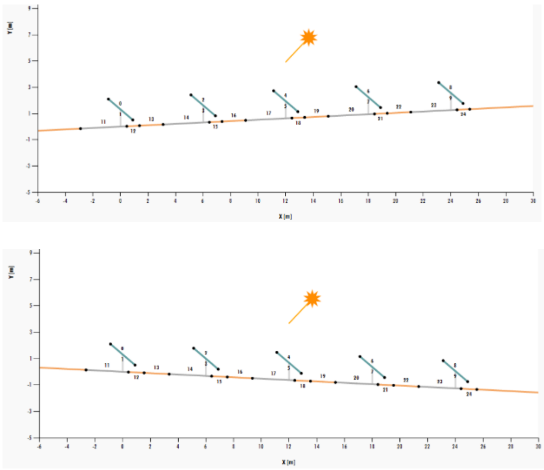

Figure 1: Cluster detail

This strategy optimizes tracker orientation according to the specific conditions of each zone, substantially reducing the negative impact of electrical shading on the PV plant’s final energy yield. In addition, it improves irradiance capture and minimizes shading losses compared to conventional backtracking, which applies a single transposition model to the entire plant. In contrast, the proposed method assigns each cluster its own transposition value. This targeted approach is particularly relevant because it maximizes energy yield by adapting tracker orientation to local conditions, a key factor for efficient PV plant operation.

Under overcast conditions, the methodology further accounts for terrain heterogeneity at the cluster level. Within each cluster, the tracker rotation angle is optimized to maximize captured irradiance using Brent’s method, a derivative-free numerical algorithm well suited for efficiently finding the optimal tilt. The search range spans from the standard tracking angle to the flat position (0º) and is adjusted by a slope-dependent margin, shown in equation 1:

$$\theta_{margin} = -\gamma \cdot \max(0, \cos\psi) \quad (1)$$

where γ is the cross-axis slope angle and ψ is the angular difference between the solar azimuth and the slope aspect. This correction enables each cluster to progressively compensate for terrain slope when aligned with the solar vector. By allowing clusters to operate independently, the methodology contributes significantly to improving the overall energy yield of the plant.

2.2 Validation

The method is validated through simulations and compared with conventional backtracking, evaluating the increase in production in five real PV plants, located in Spain. Moreover, the predictability of the methodology, coupled with its significantly lower computational cost than other algorithms available in the market and literature (due to the group-based clustering behaviour), ensures compatibility with common simplifications in desktop software solutions, such as shading tables. The proposed approach offers a computationally efficient alternative to ray-tracing methods, which, while accurate, are computationally intensive (requiring 10,000 to 100,000 times more computing power) and impractical for conventional computers[7].

2.3 Brent's Algorithm

Brent's method [8] is a deterministic, derivative-free optimization algorithm designed to identify a local minimizer of a continuous function $f: [a, c] \to \mathbb{R}$ over a bounded interval $[a, c]$ known to contain at least one minimizer. The method achieves both efficiency and robustness by adaptively combining inverse quadratic interpolation (IQI) and golden-section search (GSS). At each iteration, three abscissae are maintained—x (the current best estimate), w (the second-best point), and v (the point before w)—which define a quadratic polynomial interpolating $(v, f(v))$, $(w, f(w))$, and $(x, f(x))$. The candidate minimizer x_p is obtained by solving $P'(q) = 0$, yielding the closed-form update:

$$x_p = x - \frac{(x-w)^2(f(x)-f(v))-(x-v)^2(f(x)-f(w))}{2[(x-w)(f(x)-f(v)-(x-v)(f(x)-f(w))]} \qquad (2)$$

This step is accepted only if xp lies strictly within $[a, c]$ and is numerically stable, ensuring meaningful progress. Otherwise, the method reverts to a GSS step, in which the next candidate is computed as:

$$x_g = x \pm \varphi(c - x), \varphi = \frac{\sqrt{5}-1}{2} \approx 0.618 \qquad (3)$$

This strategy shrinks the interval by a fixed ratio regardless of smoothness. After each new evaluation, the bracketing triplet (a, b, c) is updated to preserve the condition $a < b < c$ and $f(b) < min(f(a), f(c))$. Convergence is declared when the interval width satisfies $|c - a| < x_{tol}$ or when function values stagnate such that $|f(x\_new) - f(x)| < \varepsilon$. By blending the superlinear local convergence of IQI with the global reliability of GSS, Brent's method ensures robust minimization performance and is widely regarded as a standard in one-dimensional optimization.

2.4 Ward's Hierarchical Clustering Algorithm

Ward's method is an agglomerative hierarchical clustering [9] procedure that constructs a nested partition of a dataset by iteratively merging clusters. Unlike linkage criteria based on pairwise distances, Ward's method employs a minimum variance principle, selecting at each step the pair of clusters whose merger induces the smallest possible increase in the total within-cluster sum of squares. This criterion leads to compact and homogeneous clusters, making the method particularly suitable for exploratory data analysis.

Let clusters A and B contain nA and nB observations with centroids $\bar{x}_A$ and $\bar{x}_B$, respectively. The increase in the total within-cluster sum of squares resulting from their merger is:

$$\Delta(A, B) = \frac{nAnB}{nA+nB} \parallel \bar{x}_A - \bar{x}_B \parallel^2 \qquad (4)$$

where $\|\cdot\|^2$ denotes the squared Euclidean norm. At each iteration, the pair (A, B) that minimizes $\Delta(A, B)$ is selected for fusion.

Algorithmic procedure

1. **Initialization:** Each of the N observations forms a singleton cluster.
2. **Iteration:** For all candidate pairs(A, B), compute $\Delta(A, B)$ and identify the minimizing pair.
3. **Update:** Replace clusters A and B by their union, update centroids and distances, and decrease the cluster count by one.
4. **Termination and interpretation:** The process continues until the desired number of clusters k is obtained, where k is specified according to the analytical objectives.

3 RESULTS AND DISCUSSION

Fig. 2 shows the distribution of the clusters considered at one of the analysed plants, which has an installed capacity of 51 MW. For this specific plant, the number of clusters is equal to 40.

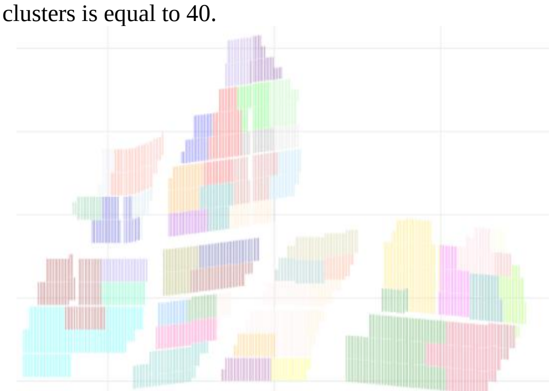

Figure 2: Multi-zonal cluster

Fig. 3 shows a heat map of the results for the same plant, comparing the 3D backtracking algorithm methodology (BT3D) with the traditional methodologies - standard tracking (ST) and conventional backtracking (BT) - during the early and late hours of the day, which are more prone to higher amounts of shading.

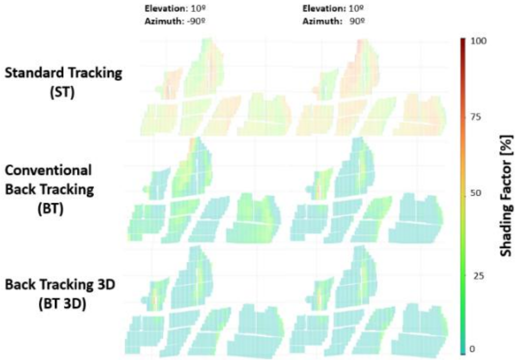

Figure 3: Shading factor heatmap

It should be noted that these specific results drawn from the analysed plant are equally representative of the other PV plants, without loss of generality. This is supported by the annual results for total energy accumulated by the strings, considering the different tracking strategies analyzed in Table I and Table II.

Table I: Strings total cumulative energy per plant. ST, BT and BT3D stands for standard tracking, conventional backtracking and backtracking 3D, respectively

		Total Cumulative Energy (Strings) per year [GWh]		
		Tracking Strategy		
Plant	**P[MW$_p$]**	**ST**	**BT**	**BT3D**
PV1	5.12	12.3	12.47	12.65
PV2	50.00	123.84	124.91	126.54
PV3	47.15	114.03	114.87	116.51
PV4	36.52	86.37	86.75	89.17

Table II: Comparison between standard strategies and the proposed strategy. ST, BT and BT3D stands for standard tracking, conventional backtracking and backtracking 3D, respectively

		Tracking Strategy Improvement	
Plant	**P[MW$_p$]**	**BT3D vs ST**	**BT3D vs BT**
PV1	5.12	2.85%	1.44%
PV2	50.00	2.18%	1.30%
PV3	47.15	2.17%	1.43%
PV4	36.52	3.24%	2.79%

The results indicate that the total energy accumulated by the strings using the BT3D strategy improves consistently, with an average gain of approximately 2.6% compared to ST and 1.7% compared to BT across the analysed plants. This increase in production is mainly attributed to the lower incidence of shading, which reduces both direct irradiance losses and the number of submodules affected by partial shading. As a representative case, Fig. 4 depicts the climate-dependence gain applying the proposed methodology for PV4.

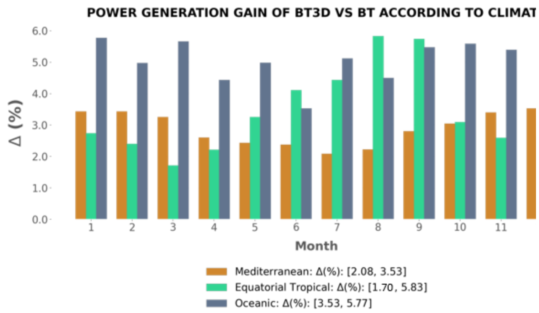

Figure 4: Climate-dependent power gain: BT3D vs BT

By analyzing the performance of the PV4 photovoltaic plant across diverse climates highlights the significant impact of geographical location on the energy output of the proposed algorithm. The results reveal substantial monthly gains in energy production, ranging from approximately 1.7% to 6%, depending on the climate. These improvements arise from the combination of detailed terrain modelling and the algorithm's ability to maximize captured irradiance under varying climate scenarios. This effect is further illustrated in the daily plots shown in Fig. 5, Fig. 6 and Fig. 7, which demonstrate the BT3D model's marked performance advantage over the BT model under specific weather conditions.

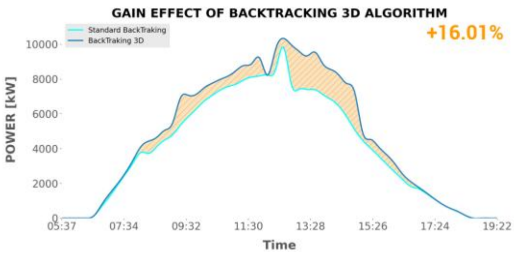

Figure 5: Typical overcast day – Equatorial tropical climate

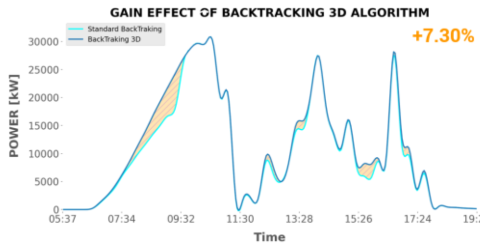

Figure 6: Typical clear to partialy cloudy day – Oceanic climate

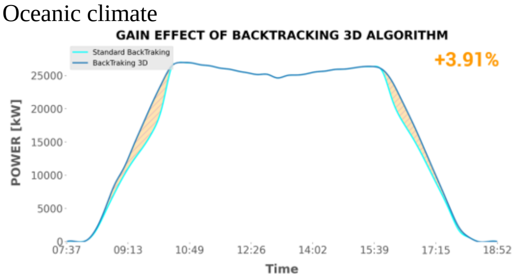

Figure 7: Typical sunny day – Mediterranean climate

4 CONCLUSIONS

The detailed terrain representation achieved through clustering improves the accuracy of incident irradiance calculations, resulting in a 1.7% increase in string production compared to conventional backtracking (BT) and a 2.6% increase compared to standard tracking (ST). This improvement is particularly relevant, as accurate irradiance estimation is essential for optimizing PV plant design and operation, especially in challenging terrains.

In addition, the BT3D model demonstrates substantial performance improvements over the BT model under specific climatic scenarios, with gains ranging from 1.7% compared to BT to 6% compared to ST.

The predictable tracker behavior within each cluster also makes the proposed methodology compatible with commonly used simplified shading solutions, such as Shading Tables. This compatibility enables efficient integration with existing design tools while reducing computational burden, thereby facilitating the practical implementation of the method in real-world PV plant design and assessment.

Furthermore, the proposed method offers a computationally efficient alternative to traditional ray-tracing techniques, requiring 10,000 to 100,000 times less computing power. This efficiency not only overcomes significant computational limitations but also broadens accessibility, making the approach suitable for a wider range of users and projects.

5 ACKNOWLEDGEMENTS

C.R. is partially supported by Torres Quevedo Grant No. PTQ2023-013183, funded by the Agencia Estatal de Investigación from the Spanish Ministry of Science. Most of the data used is available on the NREL web page, and the authors would like to thank them for it.

6 REFERENCES

[1] E. Lorenzo, L. Narvarte, and J. Muñoz, ‘Tracking and back-tracking’, *Progress in Photovoltaics: Research and Applications*, vol. 19, no. 6, pp. 747–753, Sep. 2011, doi: 10.1002/pip.1085.

[2] V. Shaw, ‘World’s largest solar plant goes online in China’, PV Magazine. Accessed: Jan. 29, 2025. [Online]. Available: https://www.pv-magazine.com/2024/06/06/worlds-largest-solar-plant-goes-online-in-china-2/

[3] K. S. Anderson and A. R. Jensen, ‘Shaded fraction and backtracking in single-axis trackers on rolling terrain’, *Journal of Renewable and Sustainable Energy*, vol. 16, no. 2, Mar. 2024, doi: 10.1063/5.0202220.

[4] K. Anderson and M. Mikofski, ‘Slope-Aware Backtracking for Single-Axis Trackers’, Golden, CO, 2020. [Online]. Available: https://www.nrel.gov/docs/fy20osti/76626.pdf.

[5] L. Perez *et al.*, ‘Comparison of tracking algorithms for photovoltaic systems on irregular terrains’, in *40th European Photovoltaic Solar Energy Conference and Exhibition (EU PVSEC)*, 2023, pp. 1–4. [Online]. Available: https://www.researchgate.net/publication/374387385

[6] E. Cooper, K. Anderson, and D. Riley, ‘Performance Improvements Through Advanced PV Backtracking on Uneven Terrain’, *IEEE J Photovolt*, pp. 1–7, 2025, doi: 10.1109/JPHOTOV.2025.3558254.

[7] A. Asgharzadeh *et al.*, ‘A Benchmark and Validation of Bifacial PV Irradiance Models’, *Conference Record of the IEEE Photovoltaic Specialists Conference*, no. July, pp. 3281–3287, 2019, doi: 10.1109/PVSC40753.2019.8981272.

[8] R. P. Brent, *Algorithms for Minimization without Derivatives*, vol. 1. Englewood Cliffs, New Jersey: Prentice-Hall, 1973.

[9] J. H. Ward, ‘Hierarchical Grouping to Optimize an Objective Function’, *J Am Stat Assoc*, vol. 58, no. 301, pp. 236–244, Mar. 1963, doi: 10.1080/01621459.1963.10500845.