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Enhancing agrivoltaic synergies through optimized tracking strategies

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ABSTRACT. Agrivoltaic systems offer innovative solutions to pressing global challenges such as climate change, renewable energy production, and food security. Specifically, horizontal single-axis tracker agrivoltaic systems can mitigate agricultural yield losses through optimized tracking strategies that balance light distribution between crops and solar panels. This paper presents a methodology for dynamically optimizing solar panel positioning to meet the varying light requirements of crops. Simulations are conducted for a case study of an agrivoltaic system in an apple orchard in southwestern Germany. Conventional shading strategies for apple orchards, based on agronomic experience and hail nets, are challenged, and specific irradiance targets for regional apple varieties are proposed, expressed in W/m^2 or $Wh/m^2/day$. Unlike estimated relative shading percentages, these absolute targets facilitate optimization and ensure consistent light availability, addressing issues related to weather variability. The analysis, focusing on tree light availability, is performed using the custom-developed tool APyV. Results indicate that 91% of the target irradiation for apples can be achieved in the simulated year with tailored PV control, resulting in a moderate 20% reduction in electrical yield. Periods when apple light requirements are not met are identified, highlighting the limitations of crop-based optimization. These findings provide valuable guidance for future optimizations that better balance electrical yield with agronomic effectiveness.

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Keywords: agrivoltaics; optimization; horizontal single-axis tracker; light-sharing; apple orchards

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1 Introduction

Agrivoltaic systems, which integrate solar power plants into agricultural systems, offer an innovative solution to the land use conflict between agriculture and the production of renewable energy. They also alleviate crop water stress and provide protection against extreme weather events, playing a critical role in the global energy transition.[1] Agrivoltaics can also provide ecosystem services, such as pollinator habitat and forage production. Graham et al.[2] found benefits for ecosystems characterized by water scarcity. Partial shade plots showed an increase in the number of flowers and a delay in blooming, which is particularly beneficial for late-season pollinators. As for grasslands, when the limiting factor is water, studies have found that the impact of solar panel shading does not alter their productivity.[3,4] Solar panels have also been found to benefit from agrivoltaic applications, showing increased energy efficiency over croplands thanks to the microclimate created underneath them.[5]

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However, the shared dependence on sunlight for electricity generation and crop development creates a potential light-sharing competition. In this context, optimization becomes crucial to increase the efficiency and the agrotechnical potential of agrivoltaics.[6] Research on design optimization has been extensive. Reasoner and Ghosh[6] classified design optimization into two main categories: approaches focused on system layout and those based on engineering optimization, the former being the most mature. Optimum designs can be achieved by changing various parameters, such as photovoltaic (PV) density, row spacing, the placement pattern of the solar panels, the height, and the orientation of the system. The results depend on the location and the crop studied and are often quantified through the land equivalent ratio parameter, a measure of the overall efficiency of the system.

Dupraz et al.[7] and Oleskewicz et al.[8] investigated the effect of different array densities, and Tahir et al.[9] found that half-density systems can increase productivity by 24%. Perna et al. evaluated the optimal design in terms of light homogeneity[10] and showed through modeling the positive effects of checkerboard arrangements. In addition, Campana et al.[11] and Riaz et al.[12] focused on the optimization of vertical systems for different crops in Sweden and Pakistan, respectively. More recently, innovative methods for finding the best system layout have been developed, such as a genomic optimization for greenhouse systems by Isied et al.[13] and a numerical procedure for techno-economic optimization by Costa et al.[14]

With horizontal single-axis tracking (HSAT) agrivoltaic systems, an additional degree of freedom can be leveraged to further optimize light management through novel control algorithms. The idea was already suggested in 2011,[7] but it started to attract attention relatively recently. In the last years, companies started developing control strategies specifically for agrivoltaics. Axial AgriTracker[15] optimizes sunlight and shade periods to enhance crop growth through a specialized electronic system and innovative control programs that choose between tracking and anti-tracking options. Solargik[16] developed Solargik's Orchestration Master Application, a comprehensive Supervisory Control and Data Acquisition system that centrally manages solar arrays with cloud-based monitoring, balancing crop sunlight needs, and energy production using integrated crop models, sensor data, and proprietary tracking algorithms. Sun'Agri[17] adjusts solar panels prioritizing only crop needs using ad-hoc algorithms based on plant growth patterns, intraday weather forecasts, temperature and humidity sensors, plant growth sensors, and farmer's objectives.

In the literature, few studies have investigated the combination of backtracking and anti-tracking over different time spans. For example, Valle et al.[18] and Riaz et al.[19,20] developed specific tracking strategies aimed at shading plants during midday while minimizing light reduction in the morning and late afternoon, across the different seasons. Although these approaches led to increased biomass production, they significantly decreased electricity generation. Knapp et al.[21] proposed an ecovoltaic approach for managing solar trackers, which involves positioning them parallel to the sun's rays in the morning and perpendicularly in the afternoon. This strategy benefits grasslands by maximizing light availability when photosynthesis rates are highest while providing shade during periods of water stress, thus reducing evapotranspiration.

When developing tracking algorithms specifically for crops, it is necessary to take into account the varying needs of plants throughout the cropping season.[18,22] There are critical phases in a plant's development that require full sunlight, whereas other phases can tolerate or even benefit from more shade, allowing for increased electricity production during these periods. Grubbs et al.[23] identified critical phases of the maize growing season by analyzing the correlation between irradiation obtained through multi-physics simulation and the agricultural yield measured on the field. Then, they optimized the light distribution in the system, optimizing anti-tracking during those time frames. Thus, the strategies found are based on the alternation between standard tracking and anti-tracking rather than on an optimization of the tracker's position.

This paper presents a methodology for the development of dynamic and customized light management strategies tailored to different crop requirements expressed in terms of required solar radiation. Although light interception is not the only agronomic parameter relevant to crop development, it is critical for photosynthetic processes along with carbon assimilation and soil moisture uptake. In addition, light quality, intensity, and duration profoundly affect a number of agronomic traits, including fruit ripening, coloration, and overall quality, which in turn influence marketability and consumer preferences. The flexible approach developed adapts to different crops and to their different seasonal needs. For some varieties, requirements can be determined through simulations using crop models such as Expert-N,[24] WOrld FOod STudies (WOFOST),[25] and Decision Support System for Agrotechnology Transfer.[26] For specialty crops, where such models do not exist, requirements may be determined empirically through consultation with agronomic experts or through ad-hoc developed models. For example, Chopard et al.[27] developed a decision support system for grapevines and apples based on water, energy, and carbon balances, able to guide agricultural practices and solar panel steering.

In this study, the developed methodology is applied to a specific agrivoltaic pilot in Nussbach, West Germany, which is part of the "Modellregion Baden-Württemberg" project.[28] The system is installed in an apple orchard, and as apple cultivation represents almost 70%[29] of the total fruit cultivation area in Germany, it represents an important example that could lead to insights for the scaling up of agrivoltaics. Previous studies by Juillion et al.[22,30] provided useful insights in defining critical phases for apple development. Under standard tracking, flowering intensity at the shoot scale was reduced, highlighting the importance of minimizing shading during this period. However, hail and frost protection resulted in a higher number of fruits.

The proposed optimization, to produce reliable and repeatable results, needs to work with absolute light requirements. Thus, this paper proposes foundational photosynthetically active radiation (PAR) values for optimal fruit development and quality obtained from empirical deduction during decades of agronomic practice. In particular, rough shading values as provided by hail protection nets have been used as general guidelines for shade tolerance. Observations and data from existing practices are used to obtain an optimized tracking strategy for the specific system and layout analyzed. These preliminary findings will then be tested and validated in field conditions to assess their practical applicability and impact. The importance of this work lies in its potential to provide a detailed understanding of light's role in apple crop development, which can inform more precise and effective agronomic practices.

2 Methodology

The methodology developed is structured around six key steps, as shown in Fig. 1. This approach is designed to be versatile, allowing the crop requirements to be defined in several ways, thus making it adaptable to different applications. In addition, by modifying the three main external data inputs, the methodology can be applied to diverse agrivoltaic facilities and locations.

First, all relevant data needed for the simulation, including weather data, are collected. The daily weather data are then clustered based on global horizontal irradiation (GHI) for each month to enhance computational efficiency. Simulations are then performed using APyV,

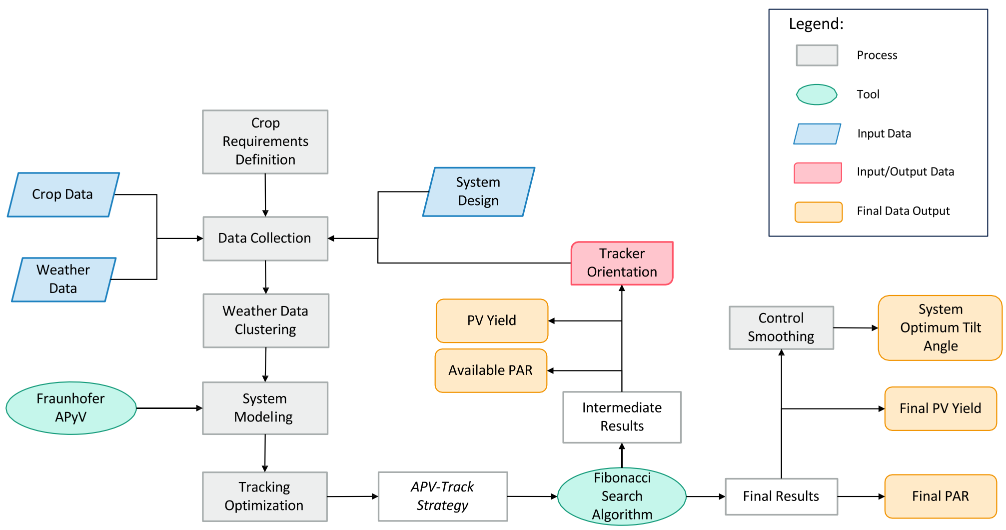

Fig. 1 Flowchart of the simulation and tracking optimization methodology, with its six core steps, and the relevant inputs and outputs.

a Python-based tool developed by the agrivoltaics group at Fraunhofer ISE, which uses radiance's backward ray tracing techniques. This method is chosen over the view factor method because of its higher accuracy, a crucial factor for complex agrivoltaic systems.[31–34]

Finally, tracking optimization is performed to find the optimal tilt angle of the system at each time step. This angle is iteratively integrated into the simulation loop to compute the relevant outputs: PV yield and PAR available for the crops. The process concludes when the objective function reaches its minimum, yielding the final results. The last step is function smoothing, essential for developing a realistic tracking strategy suitable for field implementation, minimizing excessive movements of the panels, and reducing wear and tear of the motors.

In Secs. 2.1–2.6, the focus shifts to an in-depth analysis of the specific case study under investigation. Each step of the methodology is explained in detail, highlighting the simulation parameters, the input data used, and the resulting outputs for this particular system. The aim is to provide a thorough understanding of the processes and considerations involved, ensuring that the methodology is transparent and reproducible. As the study is focused on the crop needs, the focus is only on the cropping season, thus on the months from March to September, excluding the winter season from the analysis.

2.1 Crop Requirements Definition

Photosynthetically active radiation is a critical factor in crop carbon fixation and corresponds to the visible light spectrum, with wavelengths ranging from 400 to 700 nm. PAR can be quantified as energy per unit of time and area or as a photon flux, known as photosynthetic photon flux, which is more relevant because photosynthesis is a quantum process. The relationship between the rate of photosynthesis, in terms of oxygen evolution, and the irradiance received by the plant is represented by the light response curve, which is unique to each plant species and weather conditions. This curve highlights the light saturation point, the intensity level above which the rate of photosynthesis remains constant. For apple leaves, this saturation point is 1000 $\frac{\mu\text{mol}}{\text{m}^2\cdot\text{s}}$, whereas, for the whole canopy, it is 1700 $\frac{\mu\text{mol}}{\text{m}^2\cdot\text{s}}$ due to shading effects.[35–38]

The knowledge about the shade tolerance of apple trees comes from the use of anti-hail nets, and the Agricultural Technology Center, Landwirtschaftliches Technologiezentrum (LTZ), based on its extensive experience in apple cultivation, has provided PAR reduction thresholds for the apple varieties in the Nussbach field: Bonita, Belle de Boskoop, and Topaz. Table 1 outlines the requirements for the different months of the cropping season. Sprouting begins in March, and excessive shading should be avoided to prevent delays in the budding process. Shoot growth continues in April until the onset of flowering. During this period, vegetative growth can be stimulated by providing red light in the morning and afternoon. The cell division and flowering phase in May is critical as carbohydrate assimilation is vital during this period. Thus, May has the lowest acceptable PAR reduction rate, and the blue light of the midday sun should be prioritized to maximize photosynthetic performance. Higher shading rates can be tolerated in June and July. Heat reduction during this month can improve fruit quality, reduce evapotranspiration stress,

Table 1 PAR requirements for apples in terms of tolerable percentage reduction, for the different months of the cropping season.

Month	PAR reduction (%)
March	40
April	30
May	25
June	30
July	30
August	25
September	30

and protect against sunburn. The second critical phase of fruit development is ripening. During August and September, the trees must be exposed to adequate radiation to ensure proper fruit coloration. Although these shade reduction values provide initial guidelines, it is clear that relative shading targets expressed in percentage are inadequate for optimization pathways that require absolute value inputs. However, these values nevertheless provide a starting point for apple tree light targets.

Every crop has a unique spectral efficiency function that shows how its sensitivity varies with photon wavelength and energy. However, it is common to give equal weight to all photons between 400 and 700 nm. Using this approximation, PAR values can be calculated as

$$\mathrm{PAR}\left[\frac{\mu\mathrm{mol}}{\mathrm{m}^2 \cdot \mathrm{s}}\right] = 2.016 \cdot \mathrm{G}\left[\frac{\mathrm{W}}{\mathrm{m}^2}\right], \tag{1}$$

where G is the solar irradiation.[39]

Given the above equation, applying the reduction rates to the PAR or to the solar radiation leads to the same results; therefore, the second approach is adopted because solar radiation is the main output of the simulations performed. In this study, the shift from relative to absolute requirements is obtained by performing a light simulation for the apple orchard and applying the PAR reduction rates provided by LTZ to the irradiation reaching the surface of the trees, obtaining $\mathrm{Irr}_{\mathrm{target}}$.

Table 2 summarizes the results of the target daily light integral (DLI) of irradiance for the months of the growing season, with daily values obtained from a 15-min time integration of the calculated irradiance. The values reported in the table already include the tolerated PAR reduction.

As the PAR thresholds proposed by LTZ are based on long-term experience and expertise, a light simulation was performed for the apple orchard only, for a year with weather conditions given by the average between 1994 and 2014. This approach mitigates the effects of the progressive increase in GHI by excluding the most recent years.

2.2 Data Collection

The selection of weather data is the first critical step in performing light simulations and evaluating the distribution of solar radiation within the system. For this particular case study, the Solargis database was used because it provides high-resolution data at 15-min intervals, achieved through a combination of meteorological models and satellite technology. The Solargis dataset provides a comprehensive time series spanning over 35 years.[40] The data are obtained for Nussbach, 48° 32′ 16.8″ N, 8° 01′ 01.2″ E. The year 2019 was chosen for the simulation because it is characterized by a GHI value that is close to the long-term average for the specific location in Germany.

Table 2 Absolute requirements expressed in terms of DLI for the different months of the cropping season. The results take into account the tolerated PAR percentage reduction.

Month	Daily received PAR ($\mathrm{kWh/m^2/day}$)
March	1.17
April	1.85
May	2.04
June	1.84
July	1.75
August	1.75
September	1.21

Table 3 Simulation parameters for: (a) the apple orchard, (b) the modules, and (c) the PV system.

(a)	
Row orientation	N - S
Row-to-row distance	3.5 m
In-row distance	1 m
Tree height	3.5 m
Foliage height	3 m
Max tree diameter	1.4 m
Trunk diameter	0.1 m
(b)	
Cell type	Half-Cut
Technology	N-TOPCon
Num cells	108
Length	1.134 m
Height	1.722 m
Bifaciality	80%
Efficiency	21.3%
(c)	
Azimuth	39 deg
Pitch	3.5 m
Hub height	2.8 m
Modules per row	27
Num rows	5

In addition, detailed design parameters of the agrivoltaic system are required. These include the characteristics of the orchard (Table 3a), the technical specification of the modules used (Table 3b), and the layout of the PV system (Table 3c). The orchard characteristics include row spacing, intra-row spacing, and orientation. The values are chosen based on a typical spindle production system that is very common in Germany.[41–43] The solar panel parameters include details such as the module type, which corresponds to the pitch, clearance height, and azimuth. The module data are taken from the datasheet of the module used in the pilot project: the Suntech STP415S-C54, half-cell N-TOPCon bifacial module. The tilt angle of the solar panels is dynamically and iteratively adjusted by the optimization workflow before each simulation run.

2.3 Weather Data Clustering

The clustering divides the days into distinct groups that reflect varying weather conditions, providing a comprehensive representation of weather variability. These categories have been chosen to correspond to specific points in the monthly GHI distribution, which is assumed to follow a normal distribution. This approach serves two purposes. First, as mentioned in Sec. 2, it allows for a reduced number of simulations while still allowing for extrapolation of annual behavior. Second, as GHI is often the easiest variable to measure in the field, this choice facilitates the practical implementation of different tracking strategies for each cluster based on the measured or forecast irradiation.

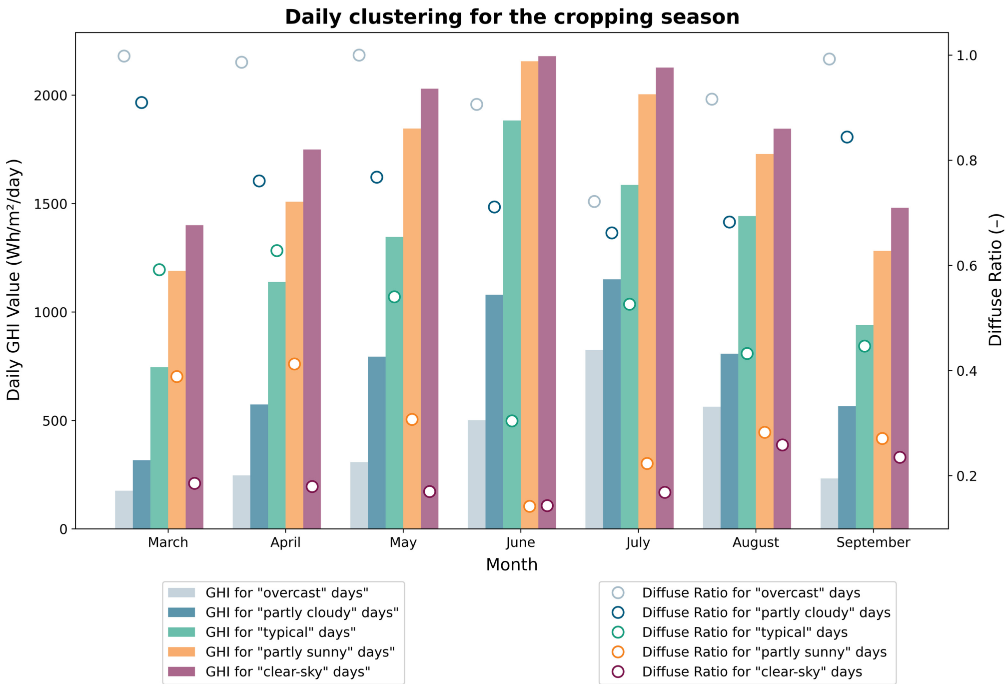

Fig. 2 Daily global horizontal irradiance (GHI) values (left *y*-axis) and diffuse ratio (DR) (right *y*-axis) for the selected five categories of days during the cropping season, spanning from March to September. The different clusters allow us to analyze a spectrum of weather conditions, ranging from "overcast" days, characterized by high DR and low GHI, to "clear-sky" days, which exhibit the opposite conditions of low DR and high GHI.

"Overcast" days are characterized by a GHI equal to the monthly mean minus two standard deviations, and a diffuse ratio (DR) above 0.9. As the DR (represented on the right *y*-axis of Fig. 2) is the ratio between diffuse horizontal irradiation (DHI) and GHI, it means these days are characterized by a predominance of clouds and diffuse irradiation. Conversely, "clear-sky" days are defined by a GHI at the opposite end of the spectrum, equal to the monthly mean plus two standard deviations. As direct normal irradiation (DNI) prevails during these days, the DR shows values lower than 0.3. For each month of the cropping season, the most representative, or "typical" day, is selected based on the median GHI, providing a robust selection less influenced by outliers. The diffuse ratio of typical days varies from 0.3 and 0.6 depending on the predominant weather conditions of the month considered. Intermediate weather conditions are also accounted for by including "partly cloudy" and "partly sunny" days, characterized by a GHI equal to the monthly mean minus or plus one standard deviation, respectively. Figure 2 summarizes the characteristics of the simulated days and thus the daily cumulative GHI value and the DR.

2.4 System Modelling and Light Simulation

APyV is based on the concept of light simulation with a special focus on agrivoltaic applications. Its core features are similar to those of bifacial_radiance[44] with added functionality for agrivoltaics, system optimization, and bankability analysis. Advanced ray tracing techniques are used to evaluate the distribution of solar radiation and its impact on both the photovoltaic panels and the underlying crops. Among the novelties of the tool are the automated design optimization of agrivoltaic systems based on some key performance indicators, the interface with different crop models, and the integrated simulation of specialty crops. The simulation always starts with the creation of a detailed three-dimensional radiance scene, and when the application involves crops such as apples and vines, these can be directly introduced in the scene using ad hoc developed methods. This allows direct calculation of the light received by the crop and a more accurate simulation of its impact on the overall agrivoltaic system.

For the apple model, a custom 3D representation was developed consisting of a cylindrical trunk in the center and the leaves randomly distributed around it, following a prolate ellipsoid surface.[45] The leaves are represented by small opaque triangles of a suitable material selected from the radiance databases.[46,47] The same database was used to select the trunk material. To realistically mimic the light response of a real apple tree, the leaf gap, which allows partial penetration of sunlight, was adjusted and calibrated for different stages of tree development using field measurements performed by Casadesús et al.[48] The final values range from 75% to 40%.

Virtual measuring points, or sensors, are strategically placed in the scene where the irradiance needs to be evaluated. As shown in Fig. 3(a), the sensors are placed around the main relevant surfaces of the tree. With reference to the figure, these are the east, the top, and the west surfaces. It should be noted that these surfaces are only one of the possible ways to approximate the surface of the tree. The analysis of the irradiation between the trees is neglected in the study due to the high shading caused by the small distance between the trees of the row in this particular design. The sensor points are then averaged to give a measure of $\mathrm{irr}_{\mathrm{right}}$, $\mathrm{irr}_{\mathrm{top}}$ and $\mathrm{irr}_{\mathrm{left}}$ in $\mathrm{W/m^2}$. The final key result is the irradiance received by the tree $\mathrm{irr}_{\mathrm{avg}}$, obtained as the average of the irradiance hitting the tree surfaces. This value can be multiplied by the area of the trees and the total time of exposure to give a measure of the total energy received by the canopy.

PV modules and their substructures are also modeled, with cell-level resolution, depending on the relevant input parameters. Although this feature may seem redundant for this application, it is critical to have this functionality in APyV when simulating semi-transparent modules in agrivoltaic systems. Sensors are then placed on each cell to more accurately represent the distribution across the panel surface. These values are then averaged to give a measure of the plane of array irradiance in $\mathrm{W/m^2}$. Given the total installed power and the efficiency of the modules, it is then possible to estimate the total PV yield.

As can be seen in Fig. 3, the radiance scene also includes a representation of the natural horizon, obtained from PVGIS.[49] The ground albedo was set to 0.2, which is typical for grassland.[50] The sky was generated according to the Perez model,[51] which uses DNI, DHI, and sun position as input. The latter is calculated using the PVlib library.[52] Once the albedo, the sky, and the system are included in the scene, the light simulation is started, and the irradiance is calculated for the selected sensor points.

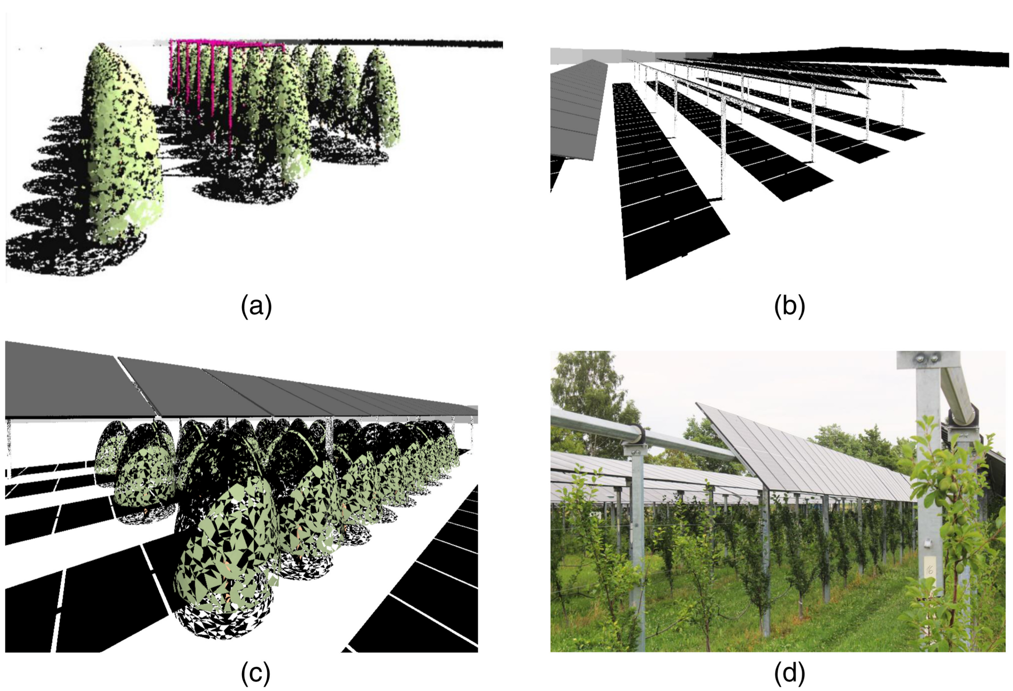

Fig. 3 Renderings of the different radiance scenes created: (a) reference scenario with an apple orchard and light simulation sensors in violet, (b) PV system with torque tube and relevant substructure, and (c) BaseCase scenario: a combination of PV system and apple orchard. Last, a picture of the pilot project in Nussbach (d).

Several simulations are performed:

- The reference scenario includes only the apple orchard in the radiance scene. It allows us to evaluate the irradiance distribution on the trees without the influence of the solar panels.
- The BaseCase scenario where PV and apple trees are combined. This enables the analysis of the impact of the panels on the tree when a standard backtracking strategy is followed.
- The optimized scenario, where the tracking of the solar panel is optimized according to the specific needs of the apple trees.

2.5 Tracking Optimization

The innovation introduced by APV-Track, the optimized tracking algorithm developed, is the inclusion of the sensitivity of the crop to shade at different stages of development. The objective function is as follows:

$$\mathrm{obj}_{\mathrm{APV}} = \min(|\mathrm{Irr}_{\mathrm{avg}} - \mathrm{Irr}_{\mathrm{target}}|). \tag{2}$$

The search space is mono-dimensional because the only relevant variable is the tilt angle of the solar panels. The search is confined to a limited range, specifically between the backtracking position, where the PV panels are perpendicular to the sun with adjustments for relative shading, and the anti-tracking position, where they are parallel to the sun's rays

$$\mathrm{space}_{\mathrm{APV}} = [\mathrm{Tilt}_{\mathrm{backtracking}}; \mathrm{Tilt}_{\mathrm{antitracking}}]. \tag{3}$$

The objective function is generally unimodal as there is a unique point at each time step where the average irradiation received by the trees is closest to the target value. For some specific locations of the sun, the function has two identical minima and can thus be considered unimodal in a given interval. Given these characteristics and the computational cost of the simulation, a Fibonacci search algorithm was chosen. The optimization process begins by calculating the smallest Fibonacci number greater than or equal to the width of the search space. The algorithm then uses these Fibonacci numbers to determine positions within the array for comparison. At each step, the target value is compared with the element at the calculated position, and based on the result, the search area is reduced by moving to either the left or right segment. This process is repeated until the target value is found or the search area is exhausted.

Compared with binary search or other elimination techniques, Fibonacci search ensures a balanced search with fewer element accesses.[53] Other techniques were evaluated, such as Bayesian optimization, which could not accurately predict the optimal solution within reasonable running times, and brute force optimization. Compared with the latter, the Fibonacci algorithm reduces the time needed to optimize a single day to one-sixth.

2.6 Function Smoothing

Due to the variability of the weather, the output of the optimization function exhibits significant discontinuities, resulting in abrupt changes in the tilt angle. Implementing such a control algorithm in the system is challenging for two main reasons. First, the rotation speed of the trackers is limited and can vary significantly, ranging from 10 to 40 deg/s.[54] Second, rapid angular changes lead to excessive wear and tear on the motors. Even if such swift movements were technically feasible, they would ultimately threaten the longevity of the motors. To address this issue, it was decided to take the sequence of optimal tilt angles and apply a one-dimensional Gaussian filter to render the function smoother and more amenable to real-world trackers. This technique is commonly used in image processing and is effective in reducing fluctuations while preserving critical features of the function. The implementation used the gaussian_filter1d function from the SciPy library. To achieve the desired level of smoothing, a sigma value of 2 was selected, which allows for a compromise between reducing abrupt changes and maintaining the integrity of the tilt angle adjustments.

3 Results

A digital twin is created for a pilot in Nussbach, Western Germany, part of the "Modellregion Agri-PV Baden-Württemberg" project. Figure 4 shows the daily solar radiation received by the trees, with a breakdown for the different surfaces analyzed. The results are presented here for the

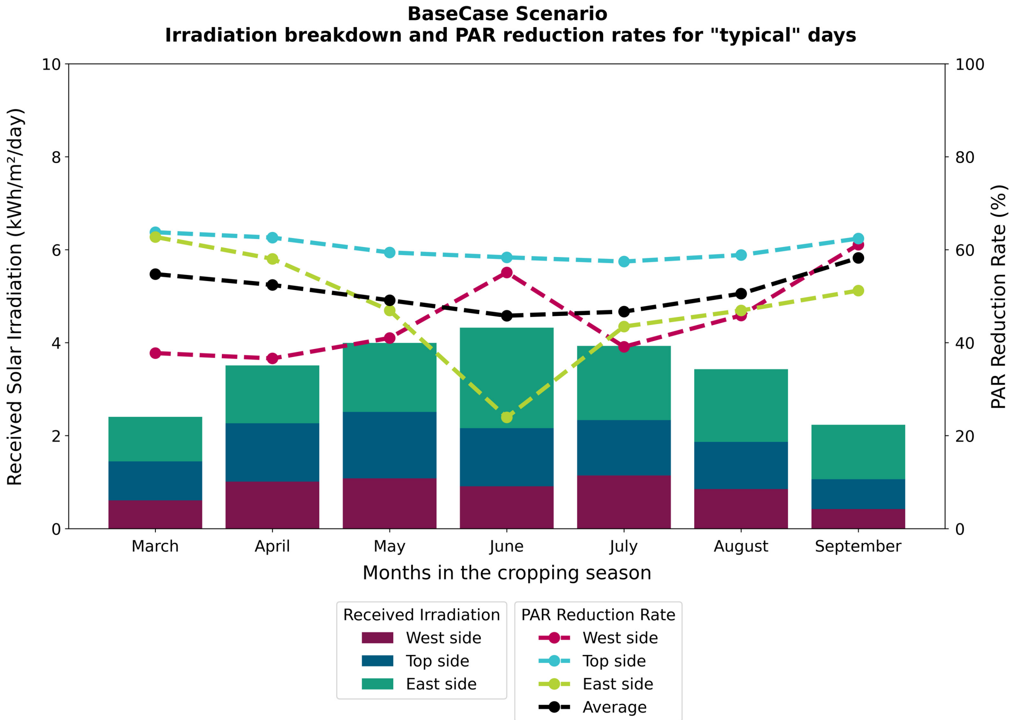

Fig. 4 Breakdown of the irradiation received by the apple orchard on the analyzed tree surfaces (west, top, and east) in the BaseCase scenario. The right y-axis represents the corresponding PAR reduction rate plus the average trend. The results are shown for each "typical" day of the months of the cropping season.

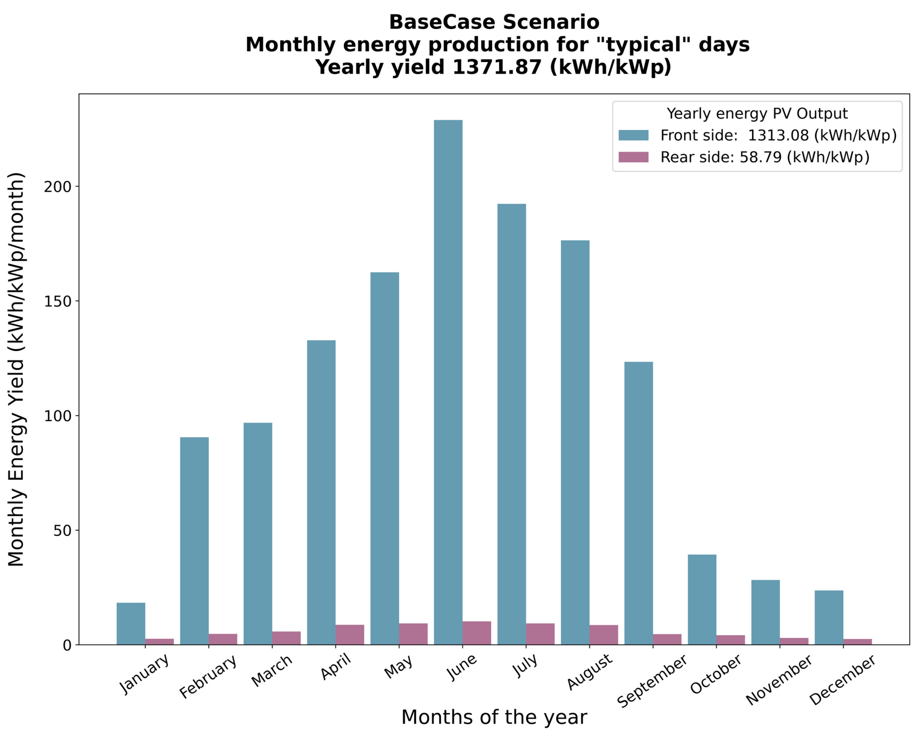

Fig. 5 Monthly energy yield for the front and rear sides of the PV. The results are reported for the "typical" days of every month of the year, for the BaseCase scenario. Yearly values are indicated in the title and legend.

"typical" days of each month of the cropping season and show the significant impact of PV on the apple orchard in terms of light reduction. Compared with the reference scenario, the installation of solar panels following a backtracking strategy leads to an average PAR reduction rate of ∼50% for the trees. Due to the design of the system, which has an azimuth of 39 deg, most of the solar radiation is received on the east side. As expected, the largest reduction in available light occurs on the top side.

The electricity production in this scenario is shown in Fig. 5. Approximating each month to its "typical" day gives a total PV yield of 1372 kWh/kWp. Although the front side is almost unchanged, the rear side is reduced by 48% due to the presence of the apple trees. Such a high reduction is observed due to the relatively low clearance height, which is necessary to limit investment costs and protect the crop. Consequently, the bifacial gain is also greatly reduced.

The optimized scenario calculates the optimal tilt angle of solar panels every 15 min. This sequence is then smoothed to obtain APV-Track, a more practical control strategy that can be easily implemented in the field, minimizing excessive wear and tear on the motors. As illustrated in Sec. 2, the main outputs of the simulation are the irradiation received by the apple trees, calculated as the average of the irradiation on the tree surfaces (east, west, and top), along with the PV yield. In the following pages, the results are presented for three characteristic days:

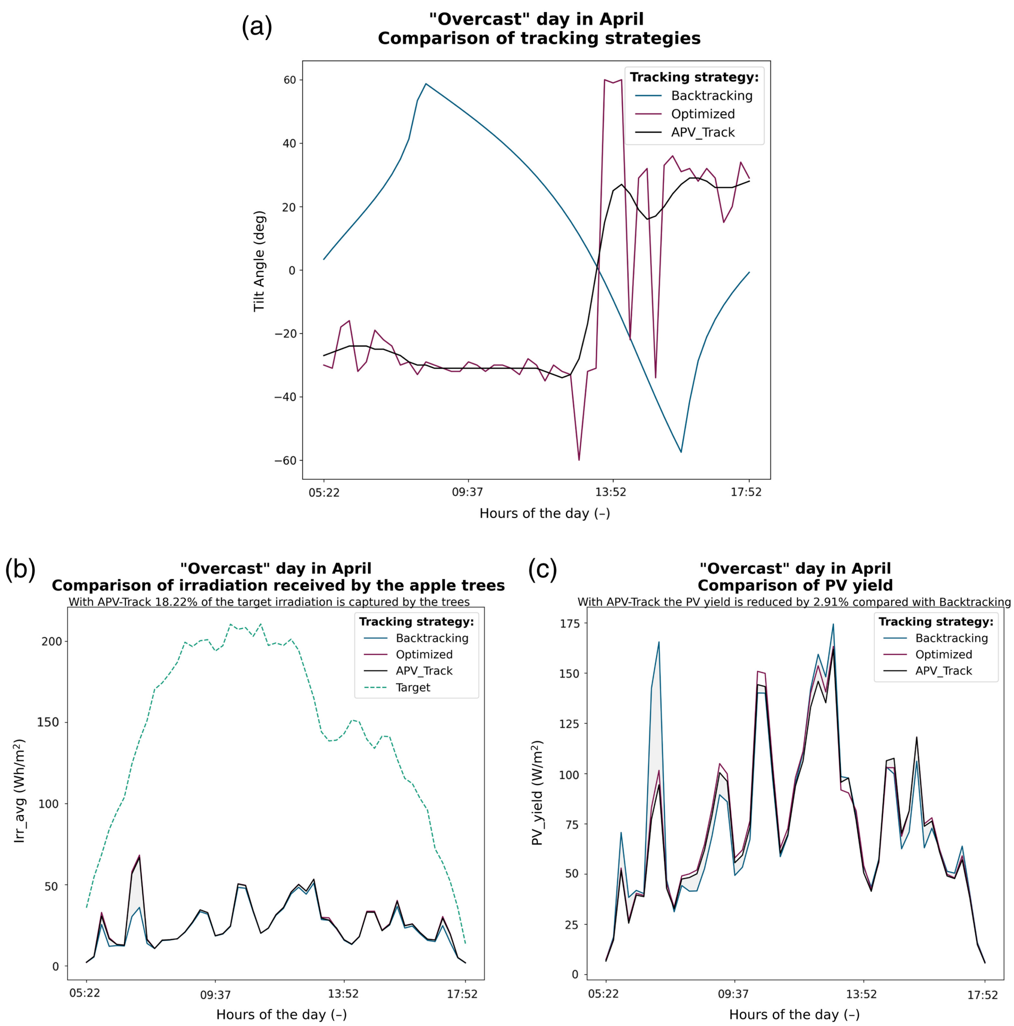

Fig. 6 Key results for the "overcast" day of the month of April. Panel (a) reports a comparison of the tracking strategies, with the backtracking in blue, the optimized routine in red, and the final APV-Track in black. The corresponding average irradiation received by the apple trees is illustrated in panel (b) with the same color scheme and the addition of the targeted irradiation in green. Finally, panel (c) shows the comparison of the PV yield with the different control algorithms.

"overcast," "clear-sky," and "typical." This selection allows for an analysis of the control algorithm's performance under varying weather conditions. Intermediate days, such as "partly sunny" and "partly cloudy," are omitted from this phase because they represent mixed weather conditions and do not provide significant additional insights for this analysis. However, these days have been simulated as they are essential for accurately reconstructing yearly performance. For the sake of conciseness, detailed results are only provided for April; the results from other months show similar trends across different weather conditions and are summarized later in this section.

Figure 6 presents the results for the "overcast" day in April. The first plot, Fig. 6(a), compares the different tracking strategies. The blue line represents the standard backtracking strategy for the case study location, whereas the red line indicates the output of the optimization, showing the sequence of tilts intended to minimize the difference between target irradiation and the actual irradiation received by the trees. As mentioned earlier, although this approach is designed to provide the apple trees with the precise light they need, such frequent adjustments would cause significant wear and tear on the motors. This can be clearly observed in the plot, where the red line appears quite discontinuous. Consequently, the last line, colored in black, represents APV-Track, the refined tracking strategy obtained by smoothing the optimized approach. It can be seen that the limited solar radiation on this day requires significant deviations from the backtracking

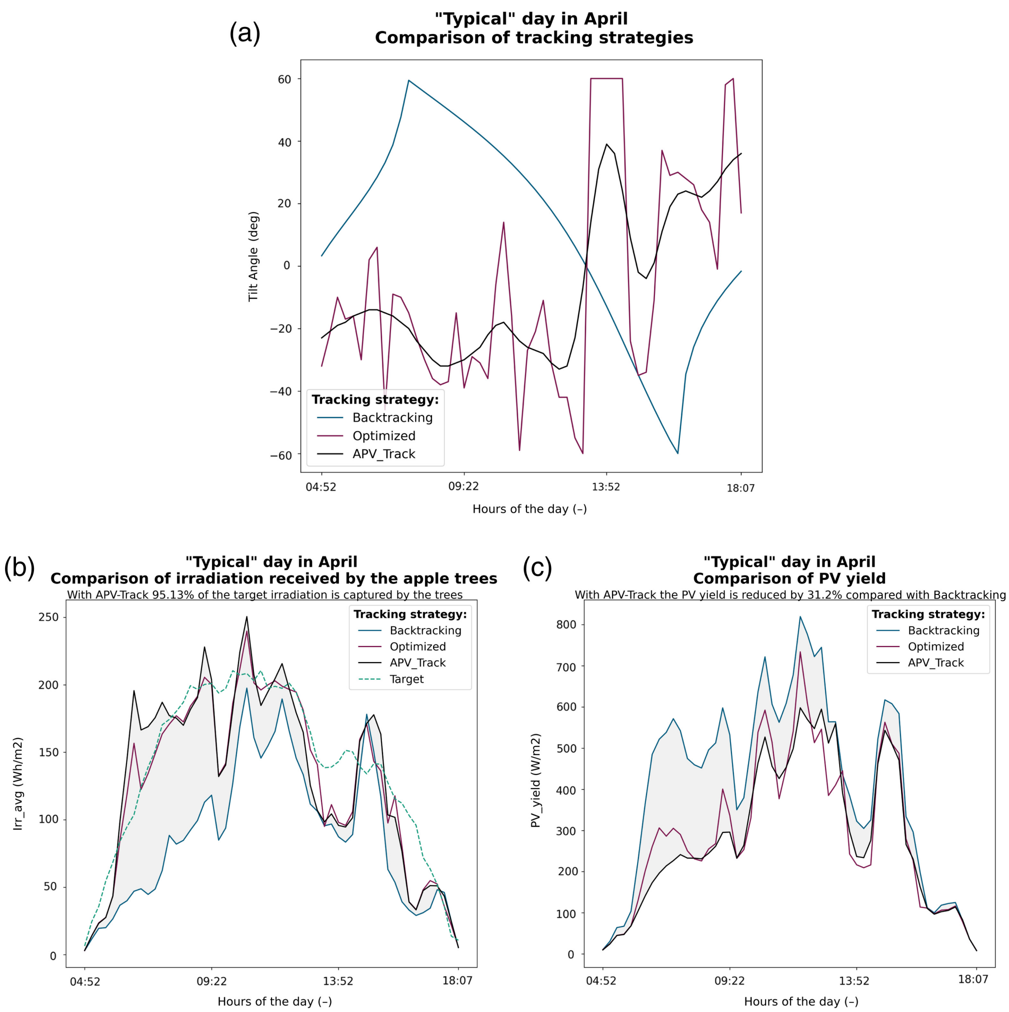

Fig. 7 Key results for the "typical" day of the month of April. Panel (a) reports a comparison of the tracking strategies, with the backtracking in blue, the optimized routine in red, and the final APV-Track in black. The corresponding average irradiation received by the apple trees is illustrated in panel (b) with the same color scheme and the addition of the targeted irradiation in green. Finally, panel (c) shows the comparison of the PV yield with the different control algorithms.

angles, resulting in a control strategy very similar to anti-tracking. However, despite these significant deviations, only minor improvements over standard backtracking can be achieved. As shown in Fig. 6(b), only 18% of the target irradiation can be achieved for this day. Furthermore, due to the diffuse nature of the irradiation on this completely cloudy day, positioning the panels to align with the sun's rays has minimal impact on the PV yield, resulting in a 3% reduction, as illustrated in Fig. 6(c).

On the "typical" day in April, the diffuse ratio is 60%, with variable weather conditions throughout the day, including both sunny intervals and periods of increased cloud cover. During sunny moments, the optimized panel positioning closely matches the backtracking tilt, whereas, during cloudier conditions, the optimal tilt corresponds to the anti-tracking tilt, as shown in Fig. 7(a). Due to the smoothing applied in the control algorithm, there are instances where the irradiation received by the trees does not match the optimal values. For example, in the morning, Fig. 7(b) illustrates an excess of solar radiation because APV-Track uses lower tilt angles than those determined by optimization. However, the overall performance throughout the day allows the trees to receive 95% of the target irradiation. In the graph, the area shaded in light gray indicates the irradiation gain resulting from the deviation of the solar panels. It is evident that during periods of predominantly direct solar radiation, even small deviations from the PV optimum can lead to significant yield losses. For this specific day, adhering to the APV-Track

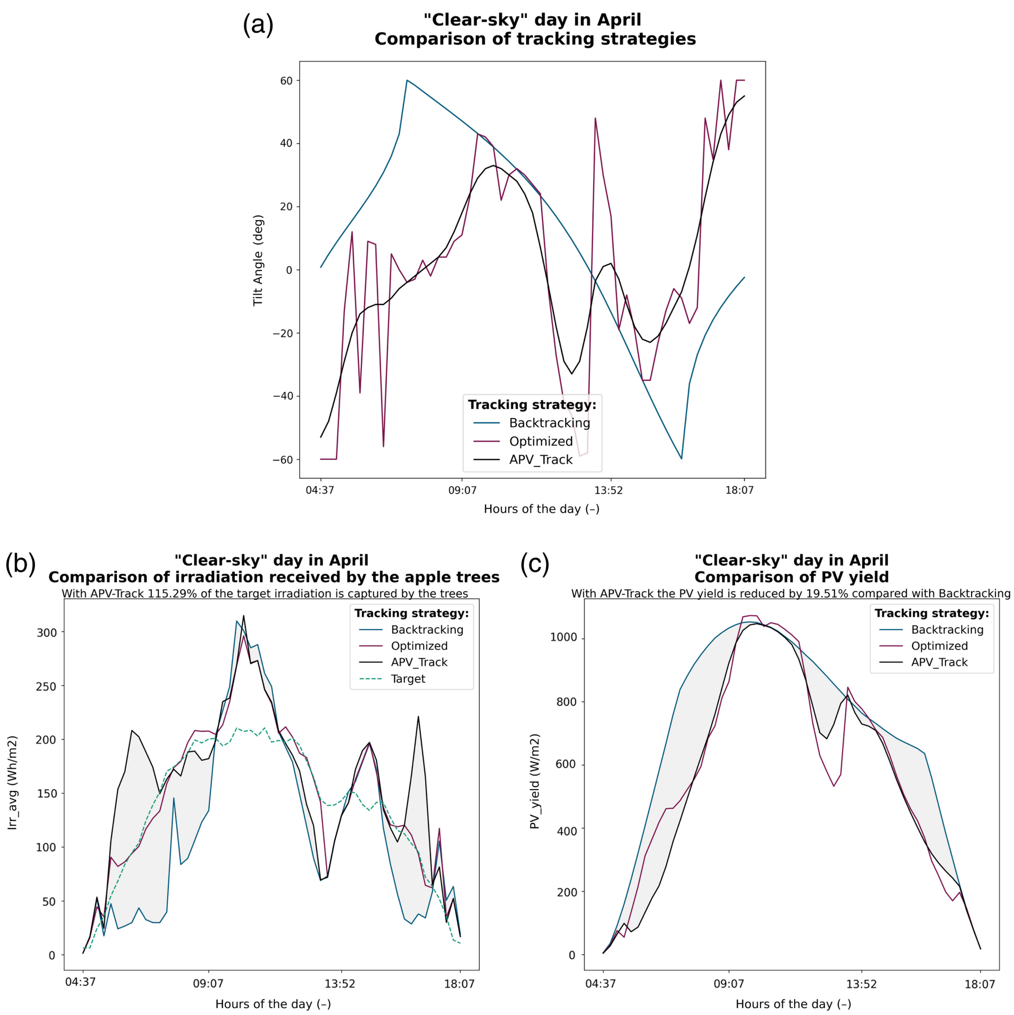

Fig. 8 Key results for the "clear-sky" day of the month of April. Panel (a) reports a comparison of the tracking strategies, with the backtracking in blue, the optimized routine in red, and the final APV-Track in black. The corresponding average irradiation received by the apple trees is illustrated in panel (b) with the same color scheme and the addition of the targeted irradiation in green. Finally, panel (c) shows the comparison of the PV yield with the different control algorithms.

strategy results in a loss of 31% of the PV yield. The difference between the yield with the backtracking strategy and the yield with APV-Track is highlighted in light gray.

Finally, for a "clear-sky" day, a more frequent alignment with the backtracking strategy can be observed (Fig. 8). This positioning helps to ensure that the panels are perpendicular to the sun, effectively blocking excess radiation and avoiding sunburn and excessive evapotranspiration. Identifying these time steps is crucial to avoid losing a significant contribution to the PV yield. If a predefined tracking strategy based on the alternation of backtracking and anti-tracking were

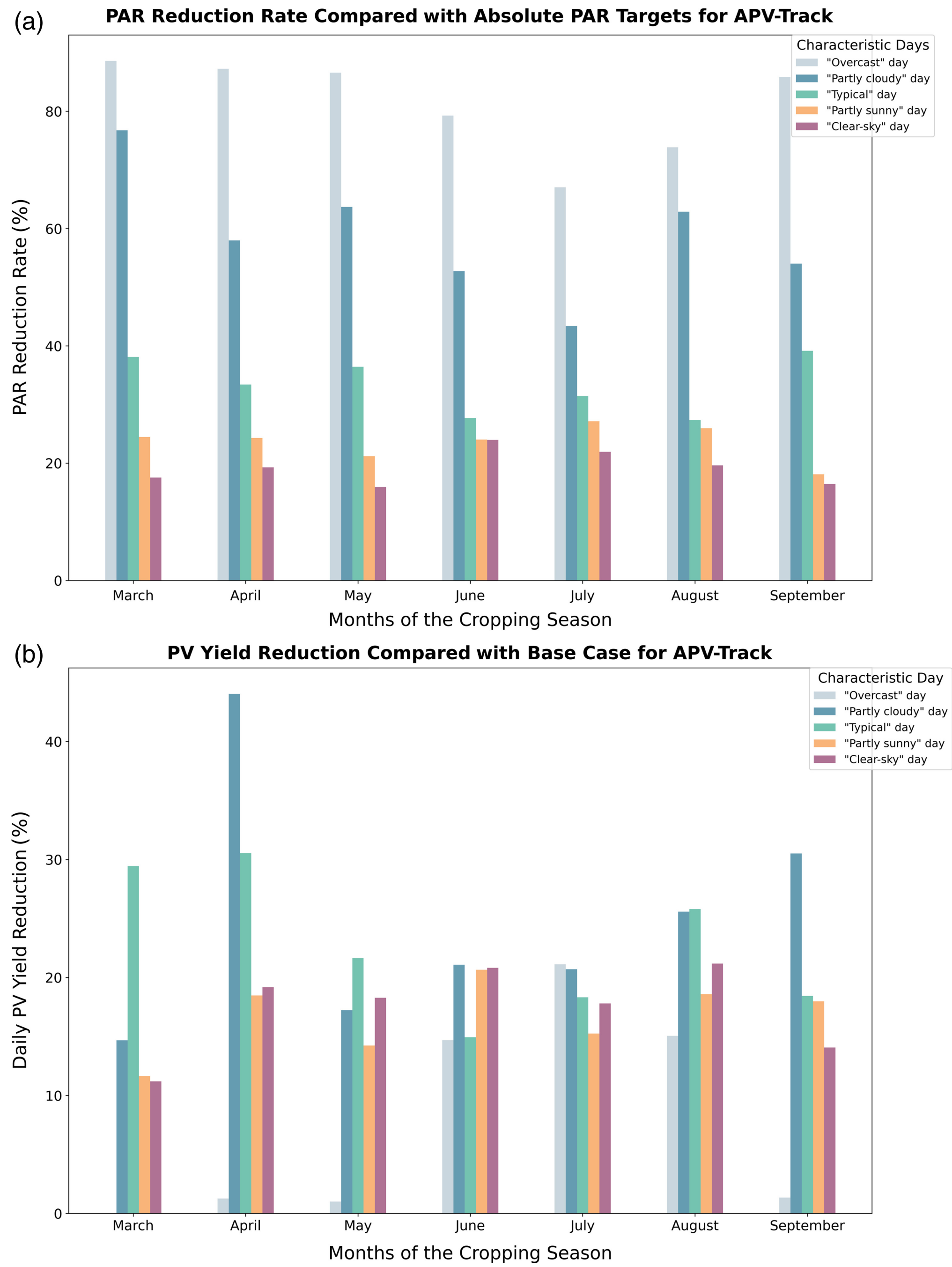

Fig. 9 Summary of the main results obtained with APV-Track. These graphs compare the performance of the algorithm over different weather conditions and thus characteristic days, for each month of the cropping season. Panel (a) shows the rates of reduction in photosynthetically active radiation (PAR) alongside the target values, whereas panel (b) illustrates the rates of reduction in photovoltaic yield.

used, then this information would be lost, leading to an excessive penalization of electrical production. As fewer deviations from the backtracking tilt are required, compared with the "typical" day, a smaller reduction in photovoltaic yield can be observed in Fig. 8(c). However, due to the abundance of sunlight during this day, despite the APV-Track strategy, there is an excess of solar irradiation available for photosynthesis, amounting to 115% of the target value.

Figure 9 summarizes the results of APV-Track over the different months and characteristic days of the cropping season. Figure 9(a) focuses on the trees and shows the comparison of the PAR reduction rates under different weather conditions with the target rates for each month. On "clear-sky" and "partly sunny" days, values below the target are achieved due to the abundance of sunlight, whereas the most representative days of the months of the cropping season are often within 10% of the desired threshold. On "overcast" days, on the other hand, it is impossible to keep within the desired reduction: moving the solar panels does not have much effect because diffuse irradiation prevails. Figure 9(b) is dedicated to the other key player of agrivoltaics systems and shows the daily reduction of PV yield, compared with the BaseCase scenario. Consistent with what was observed in the daily results analysis, the impact for "overcast" days is generally quite small, except in the summer months, when even the most cloudy days have a low diffuse ratio and deviating from the PV optimum quickly reduces the yield.

4 Discussion and Conclusion

This paper presents a comprehensive methodology consisting of six key steps to create a digital twin of an agrivoltaic system and optimize the solar panels tracking strategy to meet the needs of the underlying crops. Simulations are performed using APyV, which allows the integration of a calibrated tree model into a ray-tracing environment to accurately compute the solar radiation distribution. An important aspect of this study is the introduction of preliminary absolute targets for crop requirements. These are derived from agricultural best practices and from the use of anti-hail nets and are typically expressed in relative terms as a percentage of tolerated shade. However, communicating crop requirements as a percentage reduction in PAR can lead to inconsistencies and inaccuracies in the light management as the target can vary greatly depending on the initial weather conditions. When the requirements are expressed as $\mathrm{W/m^2}$ or $\mathrm{Wh/m^2/day}$, the tracker control system has a fixed reference point and can dynamically optimize the position of the solar panels according to the current weather conditions. To the best of the authors' knowledge, this concept has not yet been addressed in the literature, but these absolute targets are necessary to optimize the entire system, including PV yield considerations.

The results are presented from a specific case study within the "Modellregion Baden-Württemberg" project, which integrates solar panels into an apple orchard. Relevant inputs are collected from the system, and simulations are performed for five days per month, clustered to represent weather trends. The effectiveness of the methodology and the tailored tracking algorithm is quantified by comparing the annual sums of the target DLI with the actual values achieved. For the specific application, crop, and simulated year (2019), the targeted annual DLI is 351 $[\mathrm{kWh/m^2}]$, whereas the achieved DLI is 319 $[\mathrm{kWh/m^2}]$, indicating that 91% of the target irradiation is successfully achieved. In contrast, a backtracking strategy would provide only 67% (234 $[\mathrm{kWh/m^2}]$) of the required light to the trees.

The strength of the dynamic strategy lies in its ability to identify periods of low irradiation, during which APV-Track may not meet the target, as well as periods of high irradiation during which panel positioning can be maintained close to the electrical optimum. Because the absolute daily irradiation targets are based on average weather conditions, meeting them on cloudy days with initially low solar radiation is a challenge. On average, only part of the target irradiation is achieved with "overcast" conditions during the cropping season, ranging from 18% to 47%. As shown for the month of April, even a strategy close to anti-tracking often results in minimal increases in irradiation due to high diffusivity. This characteristic should be leveraged to optimize the positioning of the solar panels and implement a diffuse tracking strategy during such weather conditions to increase the PV yield without compromising the underlying crops. The gains from this optimization could partially offset the yield losses associated with APV-Track, which amount to 20% for the simulated year, a figure comparable to the findings of Grubbs et al.[23] The most significant PV yield reductions occur on "typical" and "partly cloudy" days, with average daily reduction rates of 23% and 25%, respectively. Meanwhile, "clear-sky" days require less deviation from the backtracking strategy, and even small angle adjustments can substantially impact PV yield due to the predominance of direct solar radiation, so the average daily reduction rate for these days is 17.5%.

4.1 Limitations and Further Developments

It is important to acknowledge that this study has some limitations. The calculation of light availability for the trees focuses solely on the irradiation received on a virtual plane in front of the tree models, which may not accurately represent the light intercepted by a complex three-dimensional leaf network. However, this approach allows efficient comparisons among different agrivoltaic systems.

In addition, the consideration of incident irradiance alone does not provide a comprehensive view of the consequences of the proposed tracking strategy. For a complete evaluation, it would be essential to understand the effects on the water and soil relations.[42] Although this work is primarily concerned with optimizing the distribution of solar radiation within agrivoltaic systems, assumptions can be made based on current results and relevant literature. Changes in panel orientation affect the availability and distribution of light, which in turn alters the microclimate beneath the solar panels. Key variables affected include air and soil temperature and humidity. Existing studies indicated that shading by solar panels can lead to increased humidity and decreased air temperature, and similar outcomes are anticipated in this application. For example, Adeh et al.[55] found that the heterogeneous shading created by the agrivoltaic system resulted in increased soil moisture. This in turn led to a threefold increase in water use efficiency. Juillion et al.[22] monitored the microclimate in an apple orchard with HSAT over three cropping seasons and measured a decrease in air temperature of 4 deg and an increase in relative humidity of 14%.

The literature on soil-related effects is less abundant, making it more challenging to assess potential impacts. Armstrong et al. conducted a comprehensive review highlighting specific land management practices and conditions that can enhance carbon uptake in grasslands.[56–58] However, few studies have provided measurements of soil moisture.[55] Furthermore, a comprehensive assessment should consider additional factors not included in this study. For example, wind distribution significantly influences soil and air moisture and temperature, requiring fluid dynamics simulations for a thorough analysis. In addition, precipitation patterns and the impact of solar panels on water distribution, including potential dripping edge effects on soil, should also be investigated.

Currently, the presented digital twin is based on a robust three-dimensional representation of the system and a solid simulation methodology but still uses historical weather data. Future developments of this study envisage several modifications. First, it is essential to enable real-time operation of the tracking control system, which will require the establishment of an interface with the monitoring platform. Relevant sensors will be carefully selected to monitor both solar irradiance and plant health, providing valuable feedback for dynamic adjustments. This capability will enable various objectives, including crop protection during extreme weather events, when combined with forecasting and nowcasting techniques, namely, high-resolution forecasts for the near future. In the event of heavy rain or light hail, the solar panels can be moved to the stowed position. Another extreme weather event predicted to increase is drought, and agrivoltaics has also shown its potential in reducing the effects of drought in semi-arid grasslands.[4] The economic assessment carried out by Cuppari et al.[59] found that agrivoltaic systems can reduce the financial risks associated with extreme weather events, thanks to income diversification and crop protection.

In addition, different objective functions are being evaluated to take into account both PV and crop yield. This development follows on from the current work, which highlights moments when agrivoltaic tracking is crucial, as well as instances when it is not feasible, allowing PV yield to be prioritized. The current study is an important step in understanding the suitability of the proposed absolute targets and the response of apple trees to shading rates. However, this initial approach results in a significant reduction in the electricity yield of the system, which could challenge the overall economic performance of the agrivoltaic project without incentive structures. It is therefore critical to consider the overall performance of the system. Given the complexity of the multi-objective function designed for this case, efforts are underway to enhance computational efficiency by integrating neural networks in place of the ray tracer.

In conclusion, given the importance of agrivoltaics in the energy transition and the benefits that HSAT offers in this application, tailored tracking strategies are becoming increasingly relevant. Effective control of panel positioning can help preserve agricultural yields while adhering to the yield loss thresholds required to access subsidies, ultimately improving the viability of agrivoltaic systems. Despite the limitations identified, this study lays a strong foundation for future research that is already underway. The proposed absolute targets and control strategy will be field tested in Nussbach during the 2024/2025 season, contributing to a deeper understanding of the impact of agrivoltaic systems on apple orchards and the surrounding environment. This research will either confirm or challenge existing assumptions and will contribute significantly to the body of knowledge in this field.

Disclosures

The authors state that none of the work presented in this study may have been influenced by personal ties or any known conflicting financial interests.

Code and Data Availability

The data that support the findings of this article are not publicly available due to confidentiality. They can be requested from the author at maddalena.bruno@ise.fraunhofer.de.

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