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A New Methodology for Estimating the Potential for Photovoltaic Electricity Generation on Urban Building Rooftops for Self-Consumption Applications

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Highlights:

Urban PV solutions utilize city rooftops to address energy challenges.
The Roof-Solar-Max method optimizes photovoltaic panel placement in urban areas.
Significant energy potential aligns with substantial power needs in cities.
Policy insights and grid surplus solutions provide valuable guidance for policymakers.
The research promotes cleaner and more sustainable global energy solutions.

What are the main findings?

- The Roof-Solar-Max method successfully optimizes the placement of photovoltaic (PV) panels on urban rooftops, significantly increasing energy generation potential.
- The methodology demonstrated that PV energy generation in the urban district studied can exceed the local electricity demand by more than six times, highlighting the feasibility of surplus energy contribution to the grid.

What is the implication of the main finding?

- This approach offers a practical and scalable solution for urban planners to maximize the use of rooftop spaces, facilitating the widespread adoption of renewable energy in cities.
- By utilizing surplus energy through grid integration, the method can contribute to national energy systems, reduce reliance on non-renewable sources, and promote sustainability.

Abstract: As the world increasingly embraces renewable energy as a sustainable power source, accurately assessing of solar energy potential becomes paramount. Photovoltaic (PV) systems, especially those integrated into urban rooftops, offer a promising solution to address the challenges posed by aging energy grids and rising fossil fuel prices. However, optimizing the placement of PV panels on rooftops remains a complex task due to factors like building shape, location, and the surrounding environment. This study introduces the Roof-Solar-Max methodology, which aims to maximize the placement of PV panels on urban rooftops while avoiding shading and panel overlap. Leveraging geographic information systems technology and 3D models, this methodology provides precise estimates of PV generation potential. Key contributions of this research include a roof categorization model, identification of PV-ready rooftops, optimal spatial distribution of PV panels, and innovative evaluation technology. Practical implementation in a real urban setting demonstrates the methodology's utility for decision making in the planning and development of solar energy systems in urban areas. The main findings highlight substantial potential for PV energy generation in the studied urban area, with capacities reaching up to 444.44 kW. Furthermore, implementing PV systems on residential rooftops has proven to be an effective strategy for reducing CO_2 emissions and addressing climate change, contributing to a cleaner and more sustainable energy mix in urban environments.

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1. Introduction

Solar energy is increasingly recognized worldwide as a sustainable energy source. As aging energy grids and rising fossil fuel prices pose challenges, photovoltaic (PV) generation systems are emerging as a promising solution to address both fossil fuel scarcity and global climate change [1]. The increasing adoption of renewable energy systems has driven numerous studies aimed at optimizing PV system designs across various contexts, from high-rise residential buildings to complex urban structures. For instance, research on sustainable energy designs in high-rise buildings in China [2] and advanced simulations for urban PV under partial shading in Europe [3] underscore the adaptability needed for different environmental conditions. Additionally, performance assessments in hot climates, such as in Egypt [4], and the potential for PV systems in predominantly hydropower-driven energy contexts, like Norway [5], expand our understanding of PV integration across diverse climatic and socioeconomic scenarios. Recent studies in Spain and Algeria have further explored optimized energy management and the economic feasibility of grid-connected PV systems in residential and medium-consumption settings, highlighting both the benefits of energy independence and the need to lower costs [6,7].

As PV systems gain traction in residential and commercial settings, it becomes imperative to accurately assess the solar energy potential available for electricity generation [8]. Building roof structures constitute a significant portion of the global solar energy potential [9]. Integrating solar panels on rooftops is considered an effective means of harnessing PV energy [10–12]. Nevertheless, determining the optimal size and layout of these systems on rooftops presents a challenge due to factors like building shape, location, and the surrounding environment [13,14]. Current methodologies often overlook these factors, resulting in imprecise estimations [15]. This study addresses this challenge by proposing an innovative approach, introducing an algorithm known as Roof-Solar-Max. This algorithm considers solar panel orientation, size, and rooftop shape. By leveraging advanced Geographic Information Systems (GIS) technology and 3D models, precise and dependable estimates of PV generation potential on rooftops can be obtained [16,17]. Advances in the accurate evaluation and optimization of PV systems on urban rooftops have been significantly enhanced by novel algorithms and reconfiguration techniques. For example, the "northern goshawk" optimization algorithm has been introduced to adapt PV arrays to variable conditions, minimizing power losses and improving system efficiency [18]. Similarly, recent simulation and optimization methods applied in different urban contexts demonstrate the effectiveness of using multi-objective and multivariate techniques to optimize distributed generation integration, thus reducing operational costs and improving system reliability [19]. Moreover, techniques like path analysis and remote sensing have been utilized to assess the impact of meteorological variables on vegetation indices, providing insights for urban planning to maximize green space cooling effects and improve environmental conditions in cities [20,21]. Few studies have comprehensively considered all these factors, leading to less accurate estimations [22].

This literature review underscores the increasing interest in utilizing rooftop surfaces of buildings as an essential resource for estimating PV energy potential and comprehending the state of PV system development. This understanding holds utmost importance in shaping sustainable planning strategies within a global context marked by aging energy grids and escalating fossil fuel costs. Remote sensing (RS), referred to as teledetection, emerges as a versatile technology capturing surface data across diverse temporal and spatial scales, extending its applicability to various facets of PV system development. In reference [1], the authors present an extensive literature review, spotlighting the advancements of RS technology across various stages of PV system development, which encompass PV potential estimation, PV array detection, monitoring, fault diagnosis, and other interdisciplinary domains where RS has showcased its value.

Furthermore, as mentioned in [8], a proposition combines LiDAR (Light Detection and Ranging) datasets with GIS to assess PV potential. This approach, pivotal for urban planning and future energy policies, scrutinizes diverse mechanisms to encourage installing PV systems on publicly accessible rooftops. In the context of [11], an innovative method for evaluating large-scale rooftop solar energy potential leverages global solar irradiance data from solar-GIS and building polygons. Moreover, incorporating LiDAR (light detection and ranging) and advanced wide field sensor 3D (AW3D) measurement data within a GIS framework refines the estimation process, accounting for rooftop slope and azimuth to yield precise results.

In [9], the authors introduce an integer mixed-integer programming (MIP) model tailored for sizing PV systems on flat rooftops. This model optimizes net present value (NPV) and generates multi-azimuth layouts while accommodating practical considerations such as shadow mitigation and rooftop accessibility. Examining the Chinese city of Shenzhen's potential for PV energy in residential buildings concerning electrical consumption, as addressed in [23], involves an analysis of urban morphology's influence on solar irradiance received by individual buildings. Similarly, ref. [24] focuses on Nanning, China, providing insights into optimal PV system installation options on various rooftop types and estimating electricity generation potential alongside performance assessment.

In the realm of deep learning-based methods, ref. [25] introduces an approach for constructing three-dimensional building models from high-resolution satellite images to estimate PV potential. This methodology employs two convolutional neural networks and enhancements to the DeepLabv3+ architecture. In [10], the authors present a methodology for assessing solar irradiance resources and PV integration potential in residential buildings across different climatic zones in China. The findings underscore rooftops as the primary choice for integrated PV system installation (BIPV). The research in [13] delves into the design and feasibility evaluation of PV-integrated systems on rooftops and facades, aiming to meet the energy demand of residential buildings within an academic campus. It investigates various residential typologies categorized based on constructed area and the occupants' historical energy consumption. Within the context of integrating PV systems into historical urban structures, as explored in [26], potential and limitations are examined, particularly in the context of smart cities and positive energy districts. The study extends recommendations and principles for assessing visual impact and selecting suitable solutions.

In line with [27], efforts concentrate on estimating solar energy potential from satellite images through deep learning-based segmentation techniques. Various convolutional neural network architectures are evaluated to enhance accuracy, considering factors such as the average PV panel inclination. On a different note, ref. [28] introduces a hierarchical geospatial technique founded on open-source data to estimate potential PV energy production across several cities in Nepal. Meanwhile, ref. [29] provides comprehensive maps illustrating Lebanon's solar rooftop footprints and potential. This is accomplished by employing deep learning-based instance segmentation and a PV panel placement algorithm. A highly efficient procedure for assessing PV potential on rooftops, offering a spatial resolution of 1 m, is outlined in [29]. This method is applicable at a regional scale, demanding minimal computational resources. Furthermore, ref. [15] proposes an optimal planning strategy for distributed PV systems at the municipal level, focusing on high-density cities.

Lastly, ref. [30] introduces an economical approach for assessing PV potential on rooftops, as demonstrated through a case study on Fernando de Noronha Island, Brazil. Moreover, ref. [31] devises a method to estimate the spatial distribution of energy generation potential on rural rooftops, drawing upon publicly accessible satellite images. Despite the strides made in assessing rooftop PV potential, notable gaps persist, such as the lack of consideration for diverse user-profiles and rooftop typologies across different buildings. Current methodologies often oversimplify PV system design without factoring in precise rooftop geometries and their impact on system efficiency. Additionally, there exists a dearth of accurate data regarding the location and capacity of PV energy systems on rooftops, thereby limiting estimation precision. These gaps underscore the pressing need for more precise research integrating rooftop morphology and user behavior into PV potential assessments [32].

Despite advances in assessing the potential for photovoltaic (PV) energy generation on rooftops, there are significant gaps that still need to be addressed. For instance, many studies overlook the diversity of user profiles and the specific typologies of rooftops across different buildings, which can substantially influence the feasibility and efficiency of PV installations. Studies such as [8,10] highlight the importance of tailoring PV systems to distinct user needs and structural roof designs; however, these factors remain underexplored in many current models. The lack of consideration for these variables can lead to suboptimal system designs that do not fully leverage the available rooftop space or meet the diverse needs of users effectively.

Current approaches often simplify the design of PV systems by disregarding the precise geometry of rooftops and how it affects system efficiency. For example, the work in [9] presents a general model for rooftop PV design, but does not integrate detailed geometric factors that influence performance, such as roof angles and shading patterns. Similarly, refs. [16,31] point out that, while rooftop solar assessments provide essential data for PV placement, they rarely incorporate comprehensive spatial analysis or adaptability to different rooftop shapes, which can cause inaccuracies in energy production estimates. This simplification limits the potential for maximizing energy generation on irregular or multi-angled rooftops, a limitation that our model seeks to address by integrating geometric considerations directly into the PV layout optimization process.

Furthermore, there is a shortage of precise data on the exact locations and capacities of rooftop PV systems, which significantly restricts the accuracy of potential assessments. For instance, ref. [1,15] discuss the challenges in gathering accurate, high-resolution data on rooftop PV installations, noting that existing databases are often outdated or lack sufficient detail. Studies such as [21,27] attempt to map rooftop solar capacities, but the absence of granular data on PV system specifications and installation sites results in broader estimation errors. Efforts like those in [29,32] advocate for enhanced data collection frameworks to capture site-specific details and system configurations, emphasizing the role of advanced imaging technologies and geospatial tools to improve assessment accuracy. These gaps underscore the critical need for more precise research that thoroughly integrates roof morphology and user behavior into PV potential estimation, enabling more reliable and customized system designs.

This study addresses the knowledge gaps identified in the literature, providing valuable contributions to the field of solar energy generation potential assessment through PV panels in urban environments. Leveraging an innovative methodology backed by prior research, our work presents the following key contributions:

- Roof Categorization Model: We have developed a roof categorization model that enables precise classification of urban rooftops into four main orientations: north, south, east, and west. This detailed characterization lays the foundation for a rigorous estimation of available rooftop area, essential for installing commercial PV panels.
- Identification of PV-Ready Roofs: Using satellite imagery and advanced image segmentation techniques, our study effectively identifies roofs suitable for PV panel installation. Furthermore, we accurately calculate the usable area on these roofs, providing a solid basis for estimating annual solar energy production.
- Optimal Spatial Distribution of PV Panels: We introduce an innovative approach for the optimal distribution of PV panels on identified rooftops. This method considers space constraints based on the dimensions of commercial panels, thereby maximizing the efficiency of solar energy generation at each location.
- Innovation in Evaluation Technology: Our primary innovation lies in integrating image segmentation technology with precise methods for calculating the potential

PV panel installation area. This combination offers an advanced and accurate tool for assessing the solar energy potential in urban environments.

- Practical Application in a Real Urban Setting: We verify the feasibility of our method by implementing it in a real-world urban environment. These practical applications demonstrate the utility of our approach in real-world scenarios and its ability to guide the planning and expansion of solar energy systems in urban areas.

In summary, this study significantly contributes to advancing the assessment of PV energy generation potential in urban environments. Our comprehensive and accurate methodology, supported by cutting-edge technology and innovative calculation methods, positions itself as a valuable tool for decision-making in the planning and development of solar energy systems in urban areas, effectively addressing previously identified knowledge gaps in the literature. The remainder of this paper is organized as follows: Section 2 addresses the problem statement, Section 3 presents the implementation of the Roof-Solar-Max algorithm, Section 4 details the case study, Section 5 discusses the results and provides a discussion, and Section 6 concludes the paper.

2. Problem Statement

This study aims to optimize the arrangement of PV panels on urban rooftops to maximize electricity production. The methodology is divided into four interconnected stages, as shown in Figure 1. In the first phase, contiguous rooftop segments are identified, considering their various orientations. To achieve this, a combination of QGIS (Version 3.38.0 "Grenoble") and a custom MATLAB (From version 2015b onwards) program is employed. Using QGIS, high-resolution orthophotographs are imported and georeferenced to ensure that rooftop data align accurately with real-world coordinates. The georeferencing process employs QGIS's built-in tools, using control points to match the imagery with known geographic locations. Rooftop areas are then defined and segmented manually based on orientation (north, south, east, and west), without the use of pre-built algorithms or plugins.

Subsequently, a custom image processing routine in MATLAB is developed, which includes filters such as grayscale conversion and edge-smoothing techniques. This enables the identification of rooftops and the precise delineation of the contours of each rooftop segment. No existing MATLAB functions from the literature were used; instead, the routines were specifically designed for this study. Key parameters, such as edge detection thresholds and smoothing factors, were carefully adjusted to ensure accurate rooftop boundary detection.

Once rooftops are identified, suitable areas for PV panel installation are determined. Solar irradiance is uniformly distributed across the rooftop area; hence, a finite set of potential panel locations is determined. This calculation is based on area, angles, and georeferenced locations to find the optimal arrangement of each panel and the maximum number that can make up PV arrays on each rooftop. To illustrate the applicability of this methodology, a case study based in an urban district in a high-altitude equatorial city is used.

With the suitable areas defined, annual solar irradiance is calculated using real data from a nearby meteorological station. These data, obtained from the Micro-Grid Laboratory at the University of Cuenca, Ecuador [33], include solar irradiance records for the year 2022, with a 1 s resolution, averaged to an hourly scale.

Finally, an innovative algorithm is developed to address the complexity of irregular polygons that may appear in the structure of urban rooftops. The algorithm adapts to any geometric configuration and aims to find the optimal orientation and ideal location for PV panel placement. Unlike previous approaches, this algorithm is guided by three essential criteria:

- Comprehensive coverage: Each panel must remain within the limits of the rooftop polygon, avoiding uncovered areas.
- Geometric compatibility: Each panel must fit the corresponding rooftop segment.

- No overlap: Adjacent panels must not overlap, ensuring a realistic and feasible design of PV installations. Conflict zone parameters are also incorporated to prevent interference in the panel placement within an array.

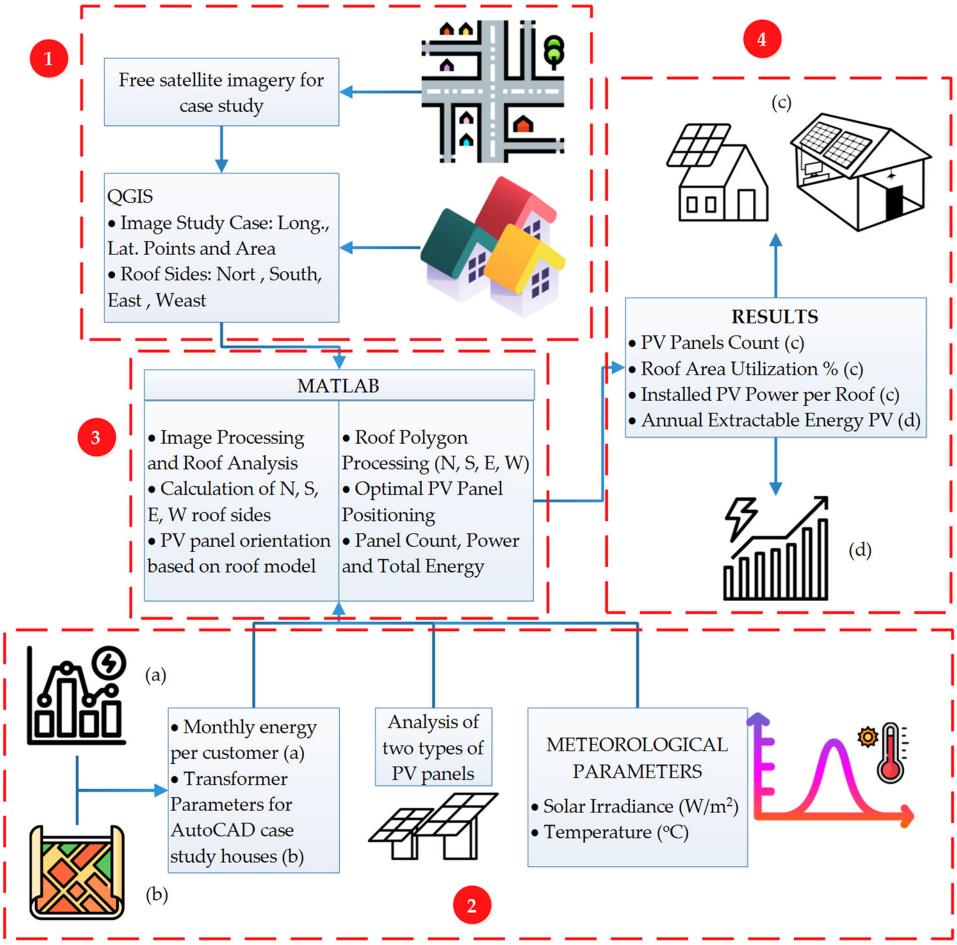

Figure 1. Graphic representation of the integrated four-stage methodology, which involves identifying roofs and their segments, determining suitable areas for photovoltaic (PV) panel installation, calculating annual solar irradiation, and applying an innovative algorithm tailored for irregular polygonal structures.

3. Implementation of the Roof-Solar-Max Algorithm

The Roof-Solar-Max algorithm, designed to optimize the placement of photovoltaic panels on rooftops, aims to determine the ideal geospatial arrangement of PV panels on rooftops to maximize their electricity generation. Its operation is explained in detail below:

3.1. Roof-Solar-Max Algorithm Flowchart

Figure 2 provides an overview of the proposed method. The process begins by defining different geographical zones on the rooftops based on their orientation: north, south, east, and west.

Subsequently, data from the variables defining each rooftop polygon (identification number, area, latitude, and longitude) are separately extracted for each geographical area and its geospatial characteristics. The physical dimensions (height and width) of the PV panel and its electrical variables (voltage, current, and power) are established. Using geospatial visualization functions, the proposed Roof-Solar-Max algorithm visualizes each geographical area and delineates the corresponding rooftop polygons using geospatial visualization functions. Calculations are then performed to determine the optimal number of PV solar panels that can fit within each geographical area, and the results are visualized.

After processing all geographical areas, the program aggregates and computes the data to obtain general information about the arrangement of PV panels on each rooftop. The algorithm also ensures that the number of panels is even, simplifying the configuration of panel arrays in series and parallel to maximize installed power in each case. Finally, voltage, current, and power values are calculated for the PV panel array using specific functions and divisible options based on the number of panels calculated per rooftop.

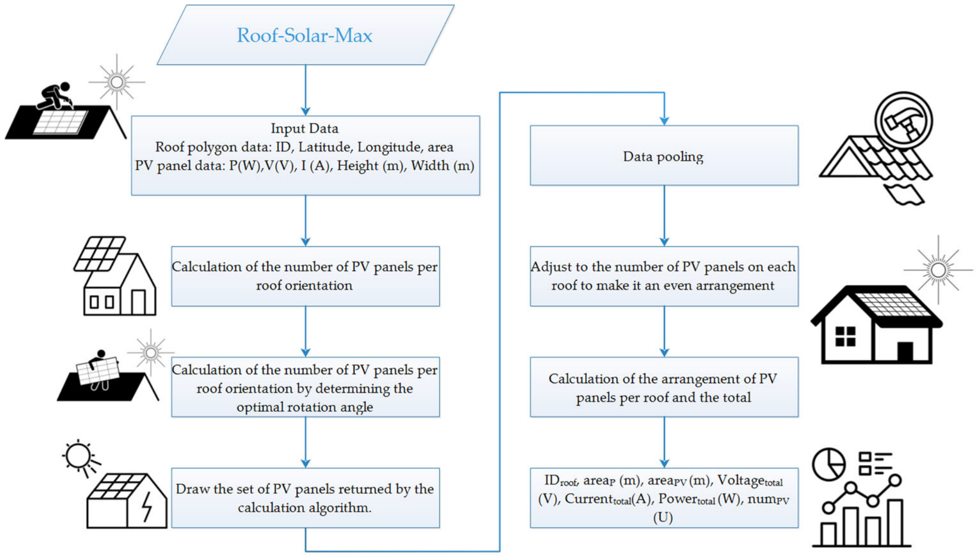

Figure 2. Proposed flowchart for optimal PV panel placement considering rooftop morphology.

3.2. Optimal Placement of Photovoltaic Panels

This section provides a detailed explanation of the computational implementation of the Roof-Solar-Max algorithm, designed to optimize the arrangement of PV panels within geographic polygons. Through calculations and geometric transformations, the algorithm aims to find the best placement for the panels, maximizing their effective area of occupancy and avoiding overlaps. It also includes functions to aggregate data and search for divisible options for the PV panel array's layout and configuration. This approach has the potential to enhance the efficiency of solar system distribution in rooftop spaces, thereby maximizing solar energy harvest. A key preprocessing step in the algorithm involves converting geographic coordinates (latitude, longitude) into a local Cartesian coordinate system using the East-North-Up (ENU) projection based on the WGS 84 reference ellipsoid. This transformation is implemented with the "geodetic2enu" function from MATLAB's Mapping Toolbox, ensuring precise geometric calculations in meters. The origin of the ENU system is defined as the first point in the dataset, allowing all transformations and calculations to be performed in a localized frame of reference. This ensures the accuracy required for defining polygon boundaries, optimizing panel placements, and avoiding overlaps. The pseudocode of the algorithm is presented below:

1. Definition of Calculation Function: A central function is established to process geo-referenced coordinates of polygons (which will later accommodate the PV panels) on rooftops. Its objective is to optimize the geometric division of the found areas to ensure the proper distribution of PV panels on the rooftops.
2. Processing of Rooftop Polygon Coordinates: Geographic coordinates are converted to local East, North, Up (ENU) coordinates. Polygon objects are created from these coordinates for further analysis.
3. Calculation of Rooftop Polygon Boundaries: Polygon boundaries in terms of minimum and maximum ENU coordinates are determined, which are essential for the optimal placement of PV panels.

4. Search for the Best Angle: The angle that maximizes the placement of PV panels without overlaps is sought, evaluating rotation matrices.
5. Iteration over Rooftop Polygon Vertices and PV Panel Calculation: A sweep is performed within the polygon's vertices, identifying suitable points for PV panel placement that meet the established conditions. Rotated PV panels are then evaluated, and those without overlaps are counted.
6. Update of the Best Solution: The maximum number of non-overlapping PV panels and the corresponding angle are recorded.
7. Final Iteration and Visualization: Rotation transformations are applied to the PV panels and checked if they meet the placement criteria.
8. Coordinate Conversion and Storage: Rotated PV panels are converted to geographic coordinates and stored in a data structure.
9. Calculations and Storage of Final Results: The quantity of PV panels placed on each rooftop polygon is stored for energy analysis.
10. Search for Optimal Divisible Options: A function that searches for the optimal array layout based on the number of PV panels, voltage, and current for inverter sizing is provided.

The algorithm's pseudocode is presented in Appendix A for a more detailed understanding and potential practical implementation.

4. Case Study

The data collection methods and criteria for selecting the study area were carefully designed to ensure the accuracy and relevance of our findings. To identify and delineate usable areas on the rooftops of the urban district, a high-resolution orthophoto was acquired from the city council's public website. Using QGIS, the orthophoto was georeferenced, and rooftop segments were identified based on their orientation (north, south, east, and west). A custom MATLAB routine was then used for image processing, applying color filtering and grayscale techniques to delineate rooftop contours and create polygons for analysis precisely. This approach did not rely on pre-built algorithms, emphasizing reproducibility through custom-developed methods.

The duration of the data collection process spanned the entire year of 2022. This year was chosen specifically because the nearby Micro-Grid Laboratory provided a comprehensive and consistent set of solar irradiance data, with measurements taken at 1 s intervals and averaged hourly. These high-resolution data were crucial for accurately modeling the solar energy potential of the rooftops. However, a key challenge was obtaining satellite images of sufficient quality to ensure precise rooftop identification, an issue we managed by using the best available data sources.

The study area was strategically selected for its proximity to the Micro-Grid Laboratory and the availability of high-quality meteorological data since 2017. Additionally, transformer ID 33443 was chosen because it provided complete and reliable billing and energy consumption records for all connected households, obtained from the utility company's website. These records included real data on energy usage and installed power, allowing for a robust comparison between energy demand and the solar energy potential.

To mitigate potential biases, we ensured that the sample included a diverse range of residential rooftops, representative of the typical urban architecture in the region. This diversity enhances the applicability of our results to other similar urban areas. By integrating accurate meteorological and electrical data, our methodology offers a comprehensive and practical framework for urban energy planning, providing valuable insights for implementing sustainable energy solutions.

4.1. Study Area Description

The city of Cuenca is in the Azuay province of Ecuador at latitude 2°53′00″ South and longitude 79°00′00″ West, situated at an average altitude of 2500 m above sea level. The selected study area is an urban district with consumers from a medium to high socioeconomic stratum (high demand). The selected district is situated near the Micro-Grid Laboratory at the University of Cuenca, where there is a meteorological station, and its records will serve as input for the proposed methodology.

4.2. Solar Irradiance Levels in the Study Area

Solar irradiance in Cuenca is significantly high due to its proximity to the Earth's equator. The average annual global horizontal solar irradiation is high (see Figure 3). This provides excellent potential for PV generation in the region. Figure 4 presents an overlay of daily solar irradiance curves throughout 2022 observed in Cuenca. Each color in the figure represents the solar production of a single day, with the overlay combining 365 curves to highlight the high variability of the solar resource in this Andean mountainous region. The figure highlights two distinct solar irradiance profiles: Type I, which represents periods of low variability with relatively stable irradiance levels, and Type II, indicating periods of high variability with significant fluctuations in daily solar irradiance. These profiles provide a comprehensive view of the dynamic nature of solar resources at the study site, underscoring how irradiance levels can shift substantially over short periods. This understanding is critical for readers, as the energy performance calculations in subsequent sections rely on an annual energy analysis that, while offering a broader overview, may mask the effects of short-term PV output variability. The irradiance data recorded over 2022 will serve as the input for the energy calculations within the proposed methodology, establishing a realistic foundation based on the actual solar resource variability at the site.

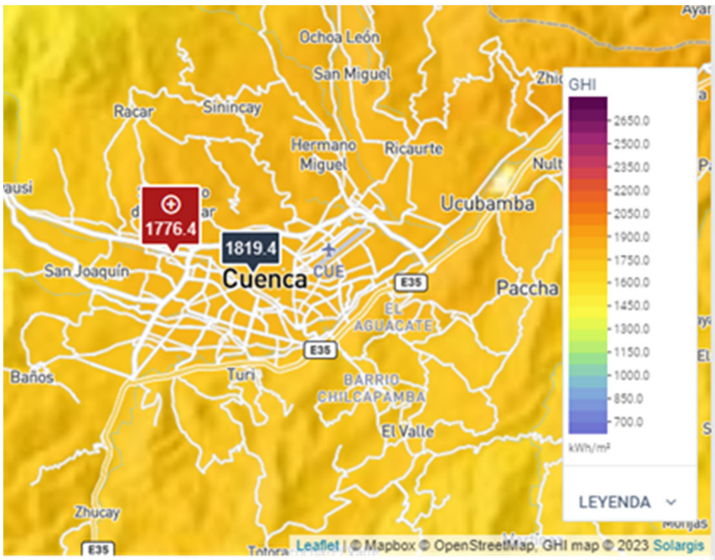

Figure 3. Annual global horizontal solar irradiance map in the study area (highlighted in red)—Cuenca, Ecuador [34].

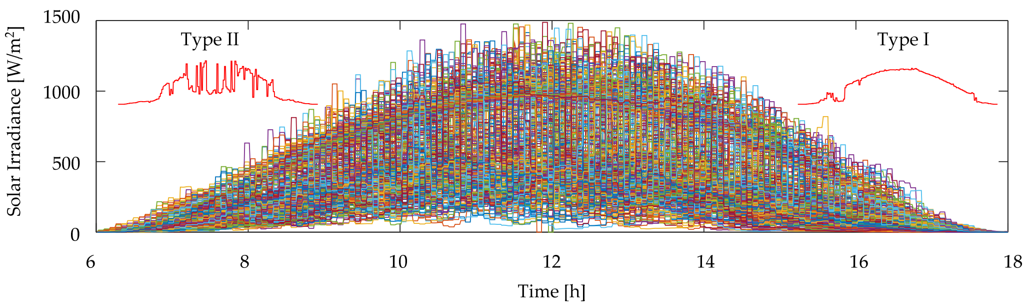

Figure 4. Annual solar irradiance curve (year 2002) with identification of type I and type II patterns, recorded by a meteorological station at the Micro-Grid laboratory, University of Cuenca.

4.3. Electrical Infrastructure in the Study District

Figure 5 illustrates the map of the chosen study district, delineating its boundaries and the electrical supply infrastructure. Within this context, a distribution transformer is identifiable and linked to a specific primary feeder owned by the distribution company responsible for supplying electricity within the city. This publicly accessible information, available at [35], served as the basis for an extensive examination of the number of subscribers connected to this transformer. Additionally, monthly consumption data for each subscriber were consulted to acquire precise and dependable information to underpin this analysis. This initial procedure is of paramount importance, ensuring that the subsequent calculation process accurately reflects real-world conditions.

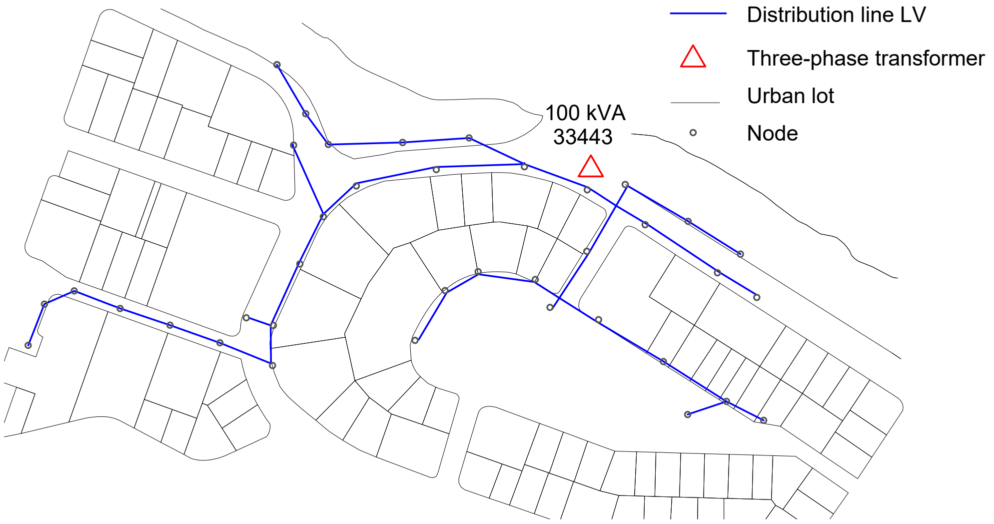

Figure 5. Selected urban district for study and existing distribution system. Illustration compiled from information sourced from [35].

4.4. Energy Consumption in the Study District

Based on the data from [35], it was determined that the distribution transformer was supplying a total of 23 consumers. Figure 6 presents a sample of actual consumption records from residential users within the considered district. In our study, we have access to the annual records of each of the remaining 22 consumers obtained from the public information source.

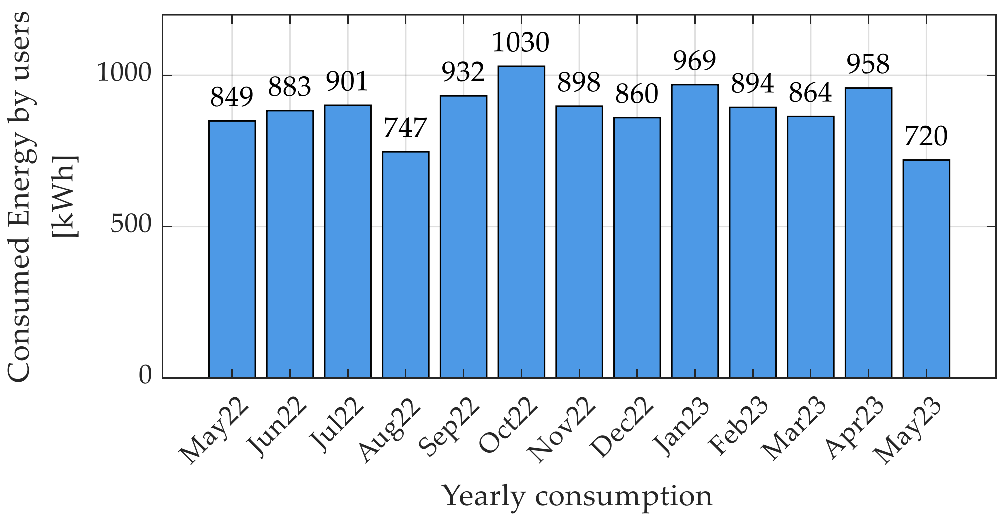

Figure 6. Annual energy consumption exhibited by one of the subscribers [35].

4.5. Identification of Usable Rooftop Areas

To identify and delineate usable areas on the rooftops of the urban district, an orthophoto of the area of interest was acquired from the city council's public website [36], as shown in Figure 7. This figure illustrates each of the steps taken to identify rooftops and the areas available for PV panel installation. In Figure 7a, the original orthophoto of the district is displayed. Subsequently, through image processing (color filtering and grayscale usage), it was possible to highlight the rooftops of the residential area, as seen in Figure 7b. Next, a MATLAB routine was implemented to delineate and create polygons over the identified rooftops. Georeferencing of the image allowed for the determination of rooftop orientations (north, south, east, and west) and their respective areas, categorizing them into four categories represented by different colors: rooftops facing north were shown in green, south-facing rooftops in yellow, east-facing rooftops in blue, and west-facing rooftops in orange (see Figure 7c).

(**a**)

(**b**)

Figure 7. *Cont.*

(c)

Figure 7. Rooftop identification through image processing: (**a**) original orthophoto of the study district, (**b**) initial filtering highlighting available rooftops (based on shape and height), and (**c**) rooftop delineation and segmentation using georeferenced polygons. Color coding indicates the cardinal orientation of the rooftops (green for north, yellow for south, blue for east, and orange for west).

4.6. Validation of Rooftop Areas

Furthermore, an examination of the resulting image of the study district was conducted, where 23 residences belonging to the previously mentioned distribution transformer were manually selected. This process was carried out using the open-source GIS tool QGIS. It allowed for the verification of rooftop areas and validation of accuracy using OpenStreetMap, following the methodology employed by [28].

4.7. Selection of Photovoltaic Panel Models

This study considers two commercial PV panel models: the A-250P and the A-335P GS, whose main specifications are detailed in Table 1. These models were chosen based on their availability in the Micro-Grid laboratory, for which there is a six-year historical performance record.

Table 1. Main specifications of the two PV modules considered in this study.

PV Module Specification	A-250P	A-335P GS
Efficiency (%)	15.35	17.26
Area [m^2]	1.62	1.94
Dimensions (height, wide) [m]	1.645×0.99	1.956×0.992
Maximum Power Voltage (Vmp) [V]	30.35	37.7
Open Circuit Voltage (Voc) [V]	37.62	46.5
Maximum Power Current (Imp) [A]	8.45	8.89
Short Circuit Current (Isc) [A]	8.79	9.51
Maximum Power (Pmax) [W]	250	335

4.8. Application of the Algorithm and Energy Balance Calculation

With all the primary information generated up to this point, the algorithm proposed in Section 3 was applied to achieve a spatial and realistic distribution of PV panels on the various identified rooftops. Additionally, it provides an estimate of energy production from these panels. Finally, by comparing the generation data with the consumption of each building, a net energy balance calculation could be performed.

5. Results and Discussion

5.1. Case 1: Distribution of A-250P PV Panels on Rooftops in the Urban District

Figure 8 illustrates the outcome of applying the Roof-Solar-Max algorithm to achieve an optimal distribution of A-250P PV panels on rooftops. The algorithm provides georeferenced positions for the polygons constituting each of the PV arrays correctly placed on the rooftop. PV panels (colored in red) are distributed in four orientations: green for north, yellow for south, blue for east, and orange for west. This color notation is also applied in Figures 9 and 10. Considering the cardinal orientation of panels on rooftops allows for more reliable numerical results when assessing the PV energy potential from each of them.

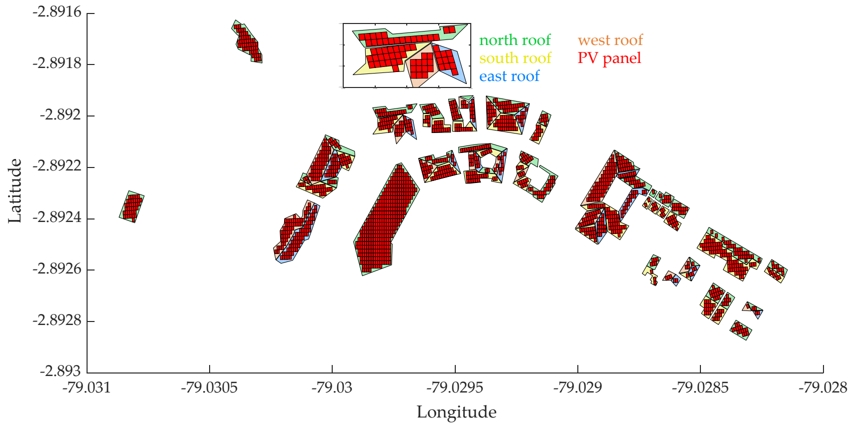

Figure 8. Optimal distribution of A-250P PV panels on rooftops using the proposed application (case 1).

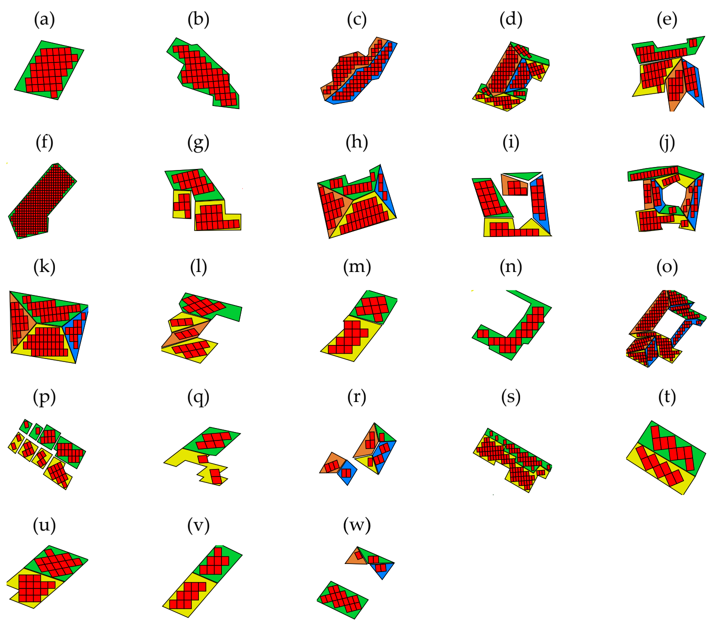

Figure 9. Detailed view of the 23 rooftops identified by the algorithm and optimal distribution of a-250P PV panels (case 1).

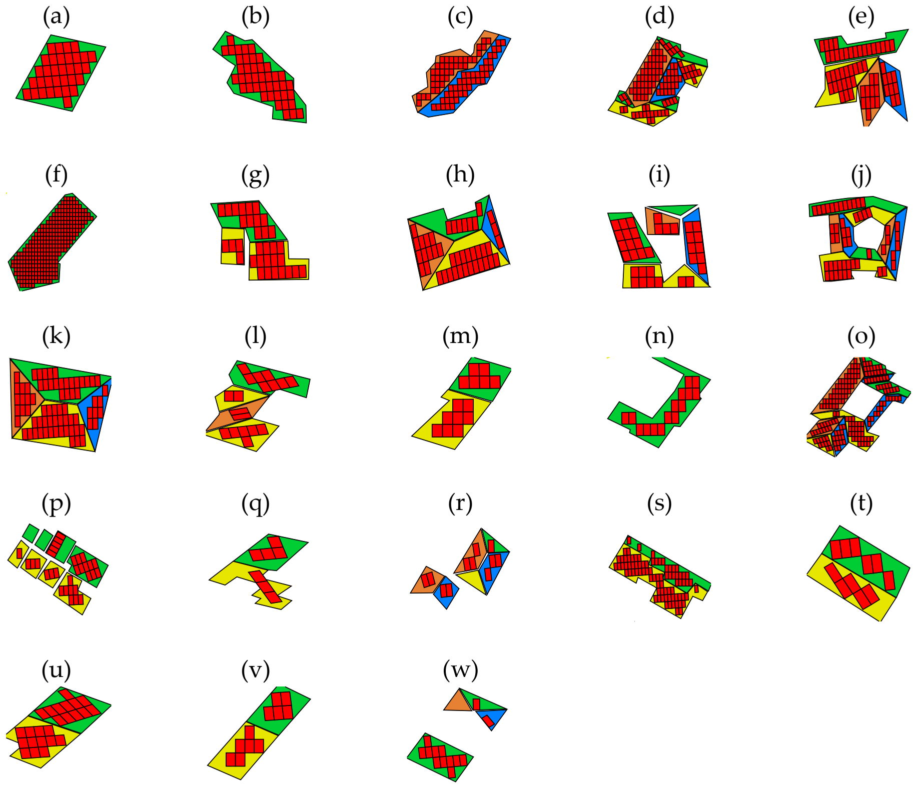

Figure 10. Detailed view of the 23 rooftops identified by the algorithm and optimal distribution of A-335P GS PV panels (case 2).

Figure 9 provides a close-up view of the results generated by the proposed algorithm. In the illustration, each of the 23 analyzed rooftops is assigned a code to facilitate reference in the calculations presented in the subsequent sections. It is important to note that the Roof-Solar-Max algorithm ensures that no PV panel extends beyond the rooftop's polygon area or overlaps with other PV panels, thus ensuring a realistic distribution and maximizing the utilization of the available area.

Considering the capacity of each of the 1574 panels organized by the algorithm, this distribution achieved a PV solar potential of 393.5 kW in the studied district. Table 2 provides a detailed summary that includes the number of PV panels used per rooftop, the percentage of area utilized, and the total installed PV power. This breakdown highlights the effectiveness of the PV panel arrangement in harnessing solar potential in the district.

Table 2. Comparison of results between PV panels A-250P and A-335P GS: number of panels, area used, and installed power.

Roof	Roof Area [m^2]	Number of PV Solar Panels [u]		Percentage of Usable Area Used by PV Panels [%]		Installed Solar PV Power [kW]	
		A-250P (Case 1)	A-335P GS (Case 2)	A-250P (Case 1)	A-335P GS (Case 2)	A-250P (Case 1)	A-335P GS (Case 2)
(a)	91	38	32	68.01	68.23	9.5	10.7
(b)	121	50	42	67.3	67.35	12.5	14.1
(c)	274	102	80	60.62	56.65	25.5	26.8
(d)	359	128	102	58.07	55.13	32	34.2

Table 2. *Cont.*

Roof	Roof Area [m^2]	Number of PV Solar Panels [u]		Percentage of Usable Area Used by PV Panels [%]		Installed Solar PV Power [kW]	
		A-250P (Case 1)	A-335P GS (Case 2)	A-250P (Case 1)	A-335P GS (Case 2)	A-250P (Case 1)	A-335P GS (Case 2)
(e)	190	66	56	56.57	57.19	16.5	18.8
(f)	684	364	298	86.67	84.54	91	99.8
(g)	102	36	32	57.48	60.87	9	10.7
(h)	160	56	42	57.00	50.93	14	14.1
(i)	119	42	34	57.48	55.44	10.5	11.4
(j)	231	66	50	46.53	42.00	16.5	16.8
(k)	245	88	70	58.49	55.44	22	23.5
(l)	89	24	18	43.92	39.24	6	6
(m)	59	18	14	49.68	46.04	4.5	4.7
(n)	72	22	14	49.76	37.73	5.5	4.7
(o)	573	224	170	63.66	57.57	56	57
(p)	155	46	30	48.33	37.56	11.5	10.1
(q)	44	8	6	29.61	26.46	2	2
(r)	73	14	10	31.23	26.58	3.5	3.4
(s)	288	102	80	57.68	53.90	25.5	26.8
(t)	56	14	10	40.71	34.65	3.5	3.4
(u)	84	30	24	58.16	55.44	7.5	8
(v)	55	16	10	47.38	35.28	4	33.4
(w)	70	20	12	46.53	33.26	5	4
Total	4194	1574	1236	60.80	57.17	393.5	444.4

5.2. Case 2: Distribution of A-335P GS PV Panels on Urban Rooftops

In order to assess the effectiveness of the proposal when using a slightly larger commercial panel model, the Roof-Solar-Max algorithm was executed with the data of the A-335P GS PV panel.

Figure 10 presents the optimal distribution of PV panels achieved using the algorithm in this case study. The results demonstrate that, in this instance, panel distribution respected the predefined polygons and their boundaries on each of the 23 rooftops while avoiding panel overlap. In total, the proposed algorithm effectively distributed a total of 1236 panels, resulting in a total installed power of 444.4 kW. Furthermore, Table 2 provides a comparative summary that encompasses the number of PV panels used, the percentage of rooftop area utilized for PV panel placement, and the total installed power per rooftop. This comparative presentation highlights the differences between the case studies, offering a clear view of the specific outcomes for each.

In Figure 11, a detailed comparison of the results obtained using the Roof-Solar-Max algorithm is presented between the PV panel models A-250P and A-335P GS. Figure 11a displays the number of PV panels to be placed on each rooftop, Figure 11b illustrates the percentage of rooftop area utilized for PV panel placement, Figure 11c highlights the total installed power capacity on the rooftops, and finally, Figure 11d presents the PV power per square meter installed on the rooftops. These four components of Figure 11 provide a clear visualization of the differences between the two models and their impact on the number of panels and the total installed power capacity in the study area.

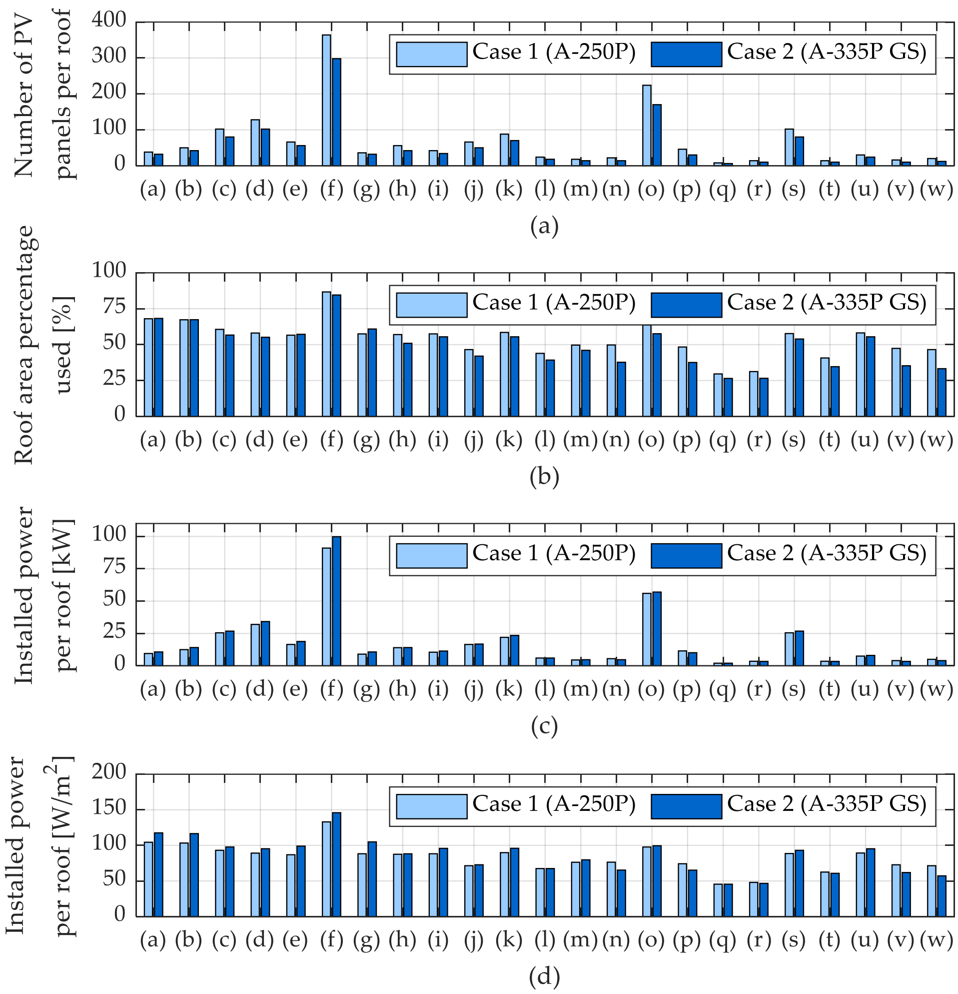

Figure 11. Comparison of numerical results obtained with the proposal's implementation for the two case studies: (**a**) total number of PV panels assigned per rooftop. (**b**) Rooftop area utilization percentage, (**c**) installed nominal power per rooftop, and (**d**) installed nominal power per square meter of rooftop.

5.3. Comparison of Methodology and Algorithm Results

During the literature review, studies such as [19,20,26] were identified, which address the installation of PV panels on rooftops while considering the surface area. However, these approaches often align the panels at the top of the roof without considering the optimal rotation angle. In contrast, our proposal aims to maximize the placement of PV panels by finding this optimal angle, resulting in a higher installed capacity and more significant PV energy production.

With the methodology we propose (see Figure 12), a total of 1575 PV panels were installed for case 1, and 1236 for case 2 (see Figure 12a). This translates to average installed capacities of 393.5 kW and 444.4 kW, respectively (see Figure 12b). In contrast, applying the methodology proposed in [30] resulted in 1166 PV panels for case 1 and 1004 for case 2, with average installed capacities of 291.5 kW and 336.34 kW, respectively. The study in [30] employed the ArcGIS Solar Radiation toolset, a widely recognized method in urban PV modeling applications. This toolset was calibrated using the diffuse proportion and atmospheric transmissivity values derived from the Global Solar Atlas, ensuring reliable annual irradiation modeling even in the absence of ground-based meteorological data, as demonstrated for Fernando de Noronha Island. This demonstrates the effectiveness of our methodology, as it provides comparable results while offering an innovative and flexible framework for PV placement optimization.

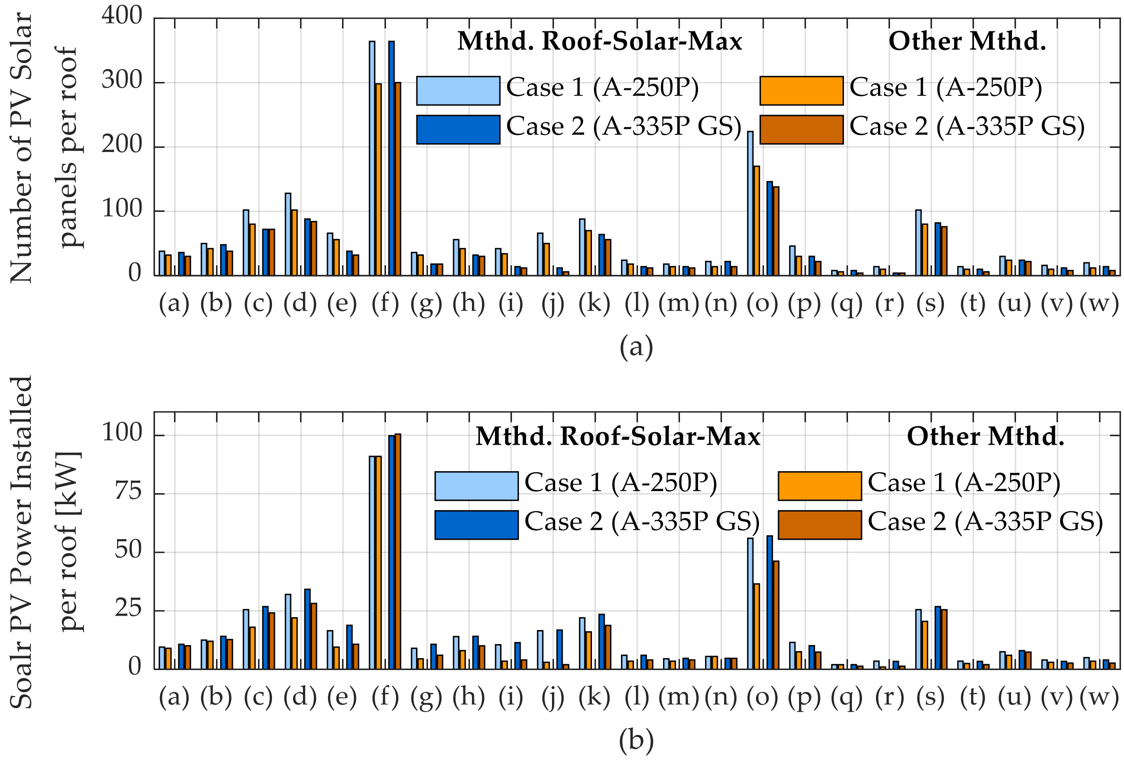

Figure 12. Comparison of methodologies for the two case studies: (**a**) total number of PV panels assigned per rooftop, (**b**) nominal installed power per rooftop.

Furthermore, when analyzing the same solar profile, our methodology yielded an annual energy generation of 521.214 MWh compared to the 366.902 MWh obtained by the existing method, confirming the higher efficiency of our proposal (see Figure 13).

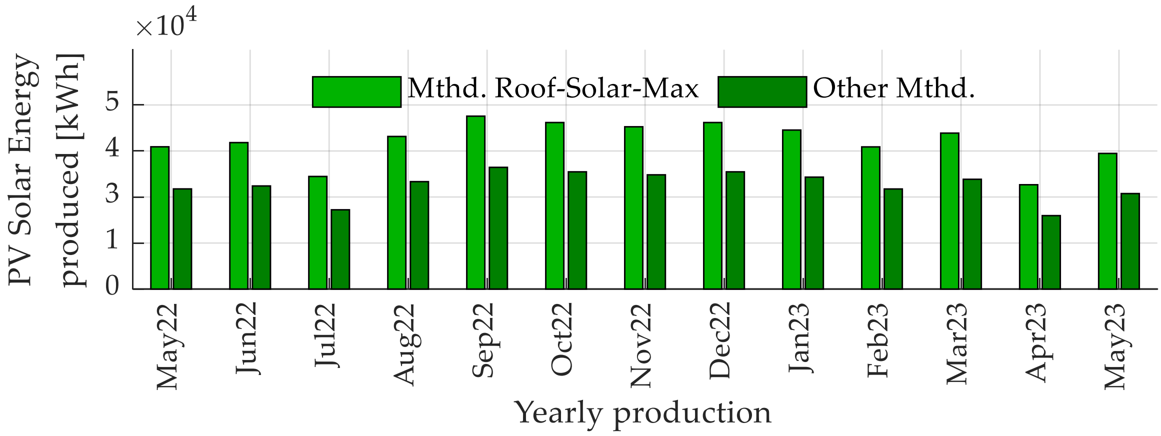

Figure 13. Comparison of energy production between proposed and existing methodologies.

Despite the demonstrated effectiveness of our methodology, several limitations should be noted. Firstly, our analysis relies on freely available satellite images, which, while useful, are limited in quality and resolution. This can hinder the precise identification of usable rooftop areas, introducing a margin of error in surface delineation and, consequently, in the energy generation potential calculation.

Secondly, the images used are in 2D, which prevents the assessment of building heights and the shadows cast by surrounding structures and the panels themselves. This limitation affects our ability to account for the impact of shading on energy efficiency.

Additionally, our program currently lacks the capability to accurately identify the material of each rooftop or assess its structural robustness to support the weight of PV panels. Satellite imagery does not provide detailed information about roof construction materials or structural integrity, posing a challenge for ensuring safe and suitable installation.

Another limitation lies in the algorithm's performance when dealing with irregular rooftop geometries. While the methodology effectively identifies and categorizes rooftop polygons and optimizes panel placement at a district-wide scale, it may leave certain rooftop areas underutilized, particularly in irregularly shaped rooftops: see roofs in Figure 9m,q,t,v and Figure 10m,n,q,t,v. The algorithm balances maximizing the usable area with practical constraints such as geometric compatibility, avoiding overlaps, and maintaining energy efficiency, but this may result in some low-utilization rooftops. Future refinements could involve a secondary optimization step that identifies rooftops with a low "Roof Area Percentage Used" and applies more detailed adjustments to improve panel coverage in these cases. This refinement step could achieve results closer to manual placement, enhancing the overall utilization of complex rooftops.

Lastly, our methodology focuses on optimizing the rotation angle of the panels on the rooftop to maximize the number of panels that can be installed without exceeding the roof boundaries. However, it does not address the optimization of the tilt angle of the panels, which is crucial for maximizing solar energy capture. Optimizing the tilt angle could further enhance energy generation, but falls outside the scope of this study.

These limitations highlight the need for future work that incorporates high-resolution data or three-dimensional models, such as those obtained through LiDAR, to improve the accuracy of usable surface evaluations and optimize both the placement and tilt of solar panels. Additionally, improvements to the algorithm's adaptability to irregular rooftop geometries could significantly enhance its utility and precision, especially when applied to individual buildings within urban districts.

5.4. Annual Net Energy Balance of Residential PV Systems

The proposed algorithm optimizes the distribution of a finite number of commercial PV panels per rooftop, providing the immediate nominal capacity to be installed on each rooftop (Figure 11c). Given the absence of height data for each rooftop, it was not feasible to calculate an optimal tilt angle for each PV panel. Therefore, we utilized historical irradiance data from a nearby meteorological station, which featured PV panels installed at a fixed tilt angle of 5 degrees facing north. This approach ensured consistent energy potential calculations. With this information and the consumption records of each user residing in the buildings, the proposed methodology calculated the annual net energy balance. The results of this calculation are presented in Figure 14a details the annual monthly consumption of the set of buildings within the district under study, while Figure 14b displays the annual total consumption per building. These data were then compared with the maximum energy that can be extracted from the PV panels installed in the study area, calculated based on historical irradiance data recorded at a nearby meteorological station, as shown in Figure 15.

Effective rooftop optimization leads to energy overproduction, indicating the need to consider a change in the initial transformer and the possibility of feeding excess energy back into the distribution grid for economic benefits. The algorithm results in an annual PV energy potential generated by the PV panels on the rooftops of the study district that exceeds local demand, surpassing it by more than 6.7 times the total electricity requirement, meeting the maximum energy demand for each building.

The total nominal power of the PV panels in the proposed cases for the network of all buildings is 393.5 kW (case 1) and 444.4 kW (case 2), with an average annual energy production of 521.214 MWh. However, since the system has been designed to extract the maximum amount of energy with the placement of PV panels, there is an annual surplus of 443.5 MWh on average compared to the measured annual residential energy consumption, which can be injected into the grid to supply additional households.

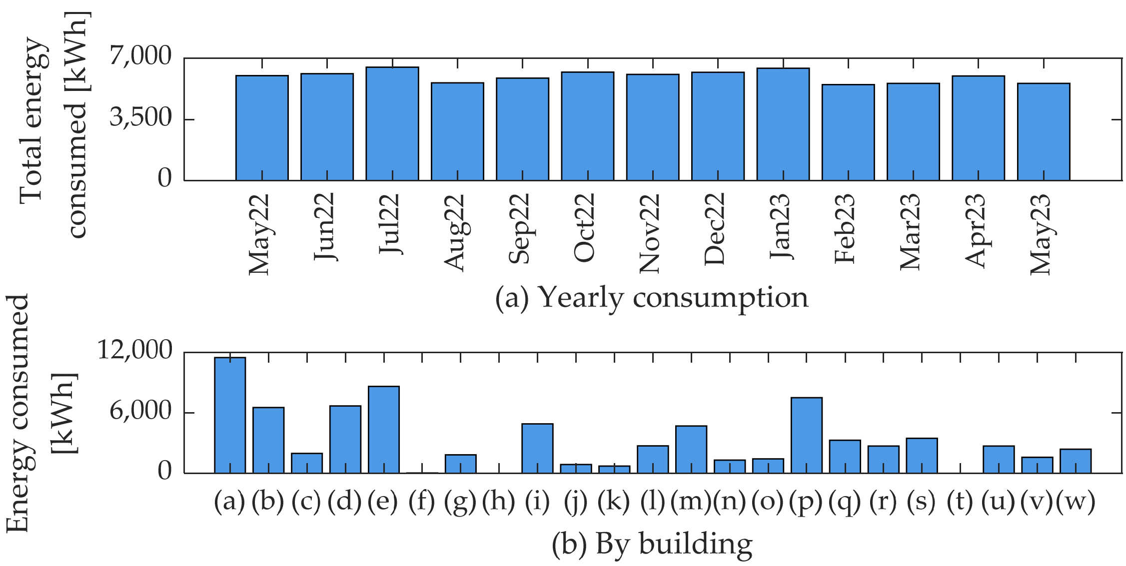

Figure 14. Expected household energy balance: (**a**) monthly energy consumption for all buildings and (**b**) annual energy consumption per building.

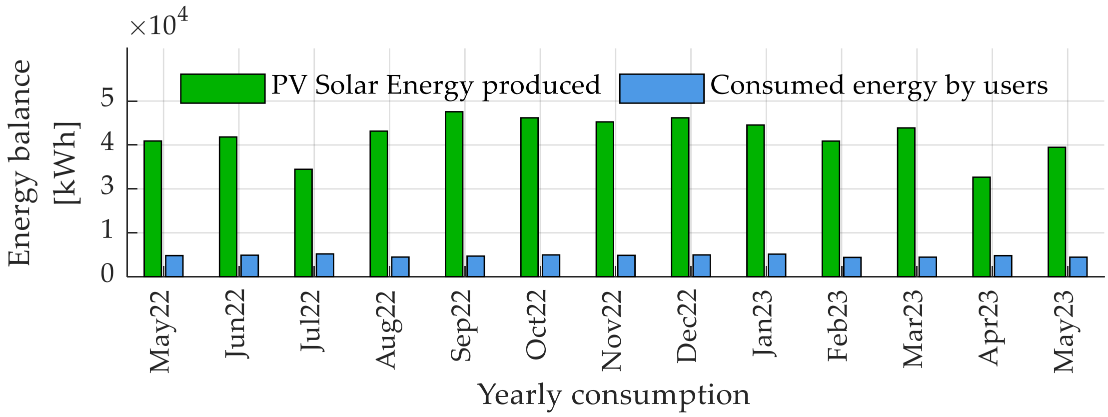

Figure 15. Surplus energy potential compared to monthly building consumption in the case study.

Despite the encouraging results, it is essential to recognize that implementing large-scale PV systems in residential environments presents technical, economic, and regulatory challenges. Appropriate policies and financing are needed to promote the adoption of PV energy, and it is crucial to involve the community and the government in the transition to sustainable and accessible solutions. The study also highlights the importance of considering aspects such as excess production stored in batteries, installation costs, net gains, and payback time as part of a more comprehensive analysis of the feasibility of large-scale solar projects in similar contexts.

6. Conclusions

This study successfully introduced the Roof-Solar-Max method, designed to optimize the placement of PV panels in urban environments to maximize solar energy production. This work reached several key conclusions: The Roof-Solar-Max method demonstrated its effectiveness by enabling an efficient distribution of PV panels on urban rooftops while ensuring maximum energy production and avoiding overlap and shadows. This approach is globally applicable and relies on globally available solar irradiance data and building polygons. However, it is important to acknowledge the limitations of using freely available satellite imagery, as quality and resolution can vary. This variability may affect the precision of rooftop material identification, structural assessments, and energy production estimates. Additionally, while the algorithm effectively optimizes panel placement at a district-wide scale, its performance on rooftops with irregular geometries may result in certain areas being underutilized. Future refinements could include a secondary optimization step to improve coverage on low-utilization rooftops and achieve results closer to manual placement. Future studies should consider employing higher-resolution data sources, such as LiDAR or 3D models, to enhance the accuracy of these calculations and further improve the algorithm's adaptability to complex rooftop shape.

Significant potential for PV energy generation in the study area has been identified, reaching up to 44.44 kW in case 2. This highlights the viability of PV energy as an important and practical source of electricity in urban settings. The implementation of PV systems on residential rooftops has proven to be an effective strategy for reducing CO_2 emissions and addressing climate change. While effective, our method does not incorporate tilt angle optimization, which could further enhance energy capture. Future research should explore combined optimization techniques for both tilt and rotation angles, addressing variations in solar incidence and shading.

In light of the findings from this study, significant implications emerge for policymakers aiming to facilitate the transition to sustainable energy systems in urban areas. The Roof-Solar-Max methodology offers a robust framework for maximizing PV energy generation on rooftops, an insight that is directly applicable to policy decisions in urban planning, renewable energy integration, and carbon reduction strategies. Policymakers could leverage these findings to enact guidelines that encourage or mandate the installation of PV systems on residential and commercial rooftops, especially in high-density urban areas where rooftop space is abundant yet underutilized. For instance, local governments could implement incentive programs, such as tax reductions or subsidies, for building owners who incorporate PV installations based on optimized layouts like those outlined in this study. Furthermore, the data-driven approach of Roof-Solar-Max, which utilizes real-time GIS and solar irradiance data, can underpin zoning regulations that promote sustainable rooftop designs and dictate specific spatial requirements for PV panels to maximize energy production and economic viability. The research underscores the value of using empirical data to inform decisions regarding the scale and placement of renewable energy systems, which could influence regional energy policies aimed at reducing dependency on fossil fuels and enhancing grid resilience. Additionally, by demonstrating the feasibility of surplus energy generation and its potential to feed back into the distribution grid, the study offers a clear framework for developing policies around energy-sharing programs or grid-interactive residential PV systems, which could be particularly valuable in urban districts. Policymakers can adopt these insights to shape effective regulations that incentivize solar investments, streamline permitting processes, and set standardized criteria for rooftop PV systems. Moreover, the method's adaptability to different urban contexts is promising, but it should be tailored for unique urban environments with specific architectural and climatic conditions. Extending the model to include variable demand patterns and fluctuating electricity prices could enhance its practical utility. The exploration of surplus energy generation on the studied rooftops opens the possibility of injecting this excess energy into the electrical grid, which could translate into economic benefits and promote greater diversification of energy sources.

In considering the long-term impact of these findings, it becomes clear that this research can serve as a foundation for sustainable policy evolution, adapting to technological advances and future energy needs. To maximize the practical applications of Roof-Solar-Max, policymakers are encouraged to foster collaboration with essential stakeholders—such as community leaders, energy providers, and research institutions—to create an inclusive framework that promotes feedback and shared responsibility in PV implementation efforts. By involving communities, governments can enhance public support, while partnerships with research organizations and private sectors can drive the incorporation of emerging technologies, thus ensuring that policies remain forward-looking and resilient. Future studies could extend this work by developing adaptive PV designs tailored to variable seasonal demand or by exploring advanced energy storage solutions for managing surplus generation. Such continuous improvements would enhance both the Roof-Solar-Max methodology and the data-informed policies it supports, ensuring that urban energy strategies contribute to lasting sustainability and economic resilience across cities and regions.

This research also holds broader implications for sustainable urban development and energy policy. By maximizing solar energy production on rooftops, cities can reduce greenhouse gas emissions and harness economic opportunities from feeding excess energy into the grid, supporting the global transition toward renewable energy. The model can be adapted to address variable demand patterns, fluctuations in electricity prices, and other factors such as shading for future research. Improving the quality of energy generated by grid-connected PV systems is also a potential area for enhancement.

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Nomenclature

Acronyms

AW3D	Advance wide Field Sensor 3D
BIPV	Building Integrated Photovoltaics
CCTIB	Centro Científico, Tecnológico y de Investigación Balzay
ENU	East-North-Up
FPN	Feature Pyramid Network
GIS	Geographic Information System
GRASS	Geographic Resources Analysis Support System
LiDAR	Light Detection and Ranging
LOD3	Level of Detail 3
MIP	Mixed Integer Programming
PSPNet	Pyramid Scence Parsing Network
PV	Photovoltaic
QGIS	Quantum GIS
RS	Remote Sensing
VPN	Net Present Value

Latin letters

E	Energy
GWh	Gigawatt-hour
I	Current
kVA	Kilovolt-ampere
kW	Kilowatt
kWh	Kilowatt-hour
m	Meter
m^2	Square meter
No.	Number
P	Power
V	Voltage
W	Watts

Symbols

°C	Degrees Celsius
$	Dollar
%	Percentage

Symbology

$width_{PV}$	Width of photovoltaic panels
$height_{PV}$	Height of photovoltaic panels
lon_p	Longitude of the polygon
lat_p	Latitude of the polygon
Id_p	Polygon identification
$area_p$	Area of the polygon
x_{meter}	Polygon coordinates in meters (x-axis)
y_{meter}	Polygon coordinates in meters (y-axis)
x_{min}	Minimum x-coordinate of the polygon
x_{max}	Maximum x-coordinate of the polygon
y_{min}	Minimum y-coordinate of the polygon
y_{max}	Maximum y-coordinate of the polygon
θ	Initial angle of PV
θ_{new}	Optimal angle of PV
x	Number of x-coordinates within the polygon
y	Number of y-coordinates within the polygon
x_{PV}	x-coordinates of the PV panel
y_{PV}	y-coordinates of the PV panel
R_θ	PV panel rotation angle
$x_{PV_{rotated}}$	Rotated x-coordinates of the PV panel
$y_{PV_{rotated}}$	Rotated y-coordinates of the PV panel
num_{PV}	Number of PV panels
max_{PV}	Maximum number of PV panels
$lat_{PV_{new}}$	New latitude of the PV panel
$lon_{PV\,new}$	New longitude of the PV panel
Id_{PV}	PV panel identification based on the polygon
$area_p$	Usable area of the polygon

Appendix A. Pseudocode for the Roof-Solar-Max Algorithm

This appendix contains the pseudocode for the Roof-Solar-Max algorithm, which was developed to optimize the distribution of PV panels on rooftops, ensuring maximum energy production and efficient use of rooftop space. The pseudocode provides a high-level overview of the steps involved in the algorithm, making it easier to understand and replicate the methodology used in this study.

Pseudocode

Calculation function to determine the optimal angle for maximizing the number of photovoltaic panels on each roof

1. Input Data
1.1. Constant data: $width_{PV}$, $height_{PV}$, lon_p, lat_p, Id_p, $area_p$
2. Conversion of georeferenced units for the roof polygons in the four orientations (north, south, east, and west)
2.1. Given (lon_p, lat_p) coordinates of a roof polygon, convert them to (x_{meter}, y_{meter})
3. Calculate the limits of the roof polygon
3.1. $(x_{min}, x_{max}, y_{min}, y_{max}) = (min(x_{meter}), max(x_{meter}), min(y_{meter}), max(y_{meter}))$
4. Search for the best rotation angle (θ_{new}) for the PV panels
4.1. Iterate over angles (θ) between 0 and 180 degrees to find the best angle for the most PV panels
4.2. Iterate over points within the polygon limits
4.2.1. $x = (x_{min} : width_{PV} : x_{max} - width_{PV})$
4.2.2. $y = (y_{min} : height_{PV} : y_{max} - height_{PV})$
4.3. Define the coordinates of the vertices of the PV panel within the vector x_{PV}
4.3.1. $x_{PV} = \begin{bmatrix} x & x + width_{PV} & x + width_{PV} & x \end{bmatrix}$
4.3.2. $y_{PV} = \begin{bmatrix} y & y & y + height_{PV} & y + height_{PV} \end{bmatrix}$
4.4. Rotate the vertices of the PV panel using the rotation matrix
4.4.1. $R_\theta = \begin{bmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{bmatrix}$
4.4.2. $\begin{bmatrix} x_{PV_{rotated}} & y_{PV_{rotated}} \end{bmatrix} = R_\theta * \begin{bmatrix} x_{PV} \\ y_{PV} \end{bmatrix}$
4.5. Check if the number of PV panels found is greater than the current maximum
4.5.1. If $num_{PV} > max_{PV}$
4.5.2. $max_{PV} = num_{PV}$
4.5.3. $\theta_{new} = \theta$
4.5.4. End
4.5.5. $R_{\theta_{new}} = \begin{bmatrix} cos(\theta_{new}) & -sin(\theta_{new}) \\ sin(\theta_{new}) & cos(\theta_{new}) \end{bmatrix}$
4.6. Rotate the vertices of the PV panel with the best angle
4.7. $\begin{bmatrix} x_{PV_{rotated}} & y_{PV_{rotated}} \end{bmatrix} = R_{\theta_{new}} * \begin{bmatrix} x_{PV} \\ y_{PV} \end{bmatrix}$
4.8. Check if the rotated panel PV is completely inside the roof polygon
4.9. If all $(x_{PV_{rotated}}, y_{PV_{rotated}})$ inside the roof polygon (x_{meter}, y_{meter})
4.10. Convert coordinates from meters to original geodetic coordinates
4.10.1 $(lat_{PV_{new}}, lon_{PV\,new}) = convert\_coordinates(x_{PV_{rotated}}, y_{PV_{rotated}})$
4.11. Draw the panel PV in the original geodetic coordinates
4.11.1 $draw(lat_{PV_{new}}, lon_{PV\,new}, 'red')$
4.11.2 $num_{PV} = num_{PV} + 1$
4.12. End
5. Output information
5.1. Id_{PV}, $area_p$, num_{PV}, $lat_{PV_{new}}$, $lon_{PV\,new}$

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