Report on Solar Potential Prediction using Image Segmentation and Structured Data

Report

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Abstract

Solar panels are a cost-effective solution for generating energy in a carbon-free manner. However, not every roof is suitable for installing solar panels. Architecture and location heavily affect the viability of such systems. Predicting this solar potential of a roof is traditionally a labor-intensive process requiring on-site measurements. Automating this process and scaling it up is a difficult challenge. Here, we will introduce a solution proposed by de Barros Soares et al. [1] and discuss it.

Introduction

In the European Union (EU) alone, rooftops make up an estimate area of $7935\,\mathrm{km}^2$ [2]. Much of this area could be used to install solar panels and help feed demand for renewably generated energy. Before installing solar panels, it is useful to estimate how much energy they could produce. This is referred to as a roof's solar potential [1] and is a crucial task. Locally, to determine the viability and economic efficiency of solar panels. Globally, it could also help yield a guess of how much solar energy could contribute to overall energy production capabilities. An estimate of solar potential on a per-country basis of EU members states is illustrated in Figure 1. It highlights the solar potential in central and southern Europe.

Traditionally, a roof's solar potential is estimated by performing measurements of roof geometry, considering its geographic location, and architecture of surrounding buildings or vegetation [3]. While more recently, geographic information systems (GIS) play an increasingly large role in guiding solar development, much of the process is still labor- and time-consuming. Thus, solar potential estimation on a large scale remains challenging.

Machine learning offers promising capabilities to increase the magnitude on which solar potential estimation can be performed. However, due to limited and complex data, it is not a trivial problem. A solution is proposed by de Barros Soares et al. [1]. They incorporate structured data and existing knowledge as an inductive bias to a method that combines machine learning, algorithmic, and analytical methods. In this work, we will introduce their approach, discuss it, and propose further enhancements to it.

Related work

Freitas et al. [3] present an overview of approaches combining algorithms and GIS modeling to estimate solar potential in densely populated urban environments. They compare different numeric

[1] The term technical potential is used interchangeably in this work. It refers to what is 'technically' possible without economical considerations.

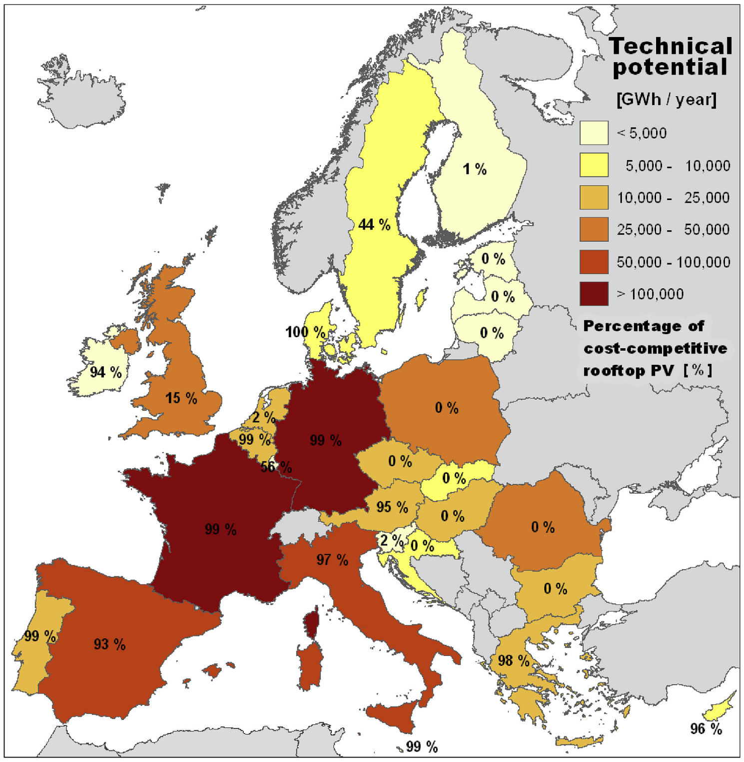

Figure 1: Technical solar potential in $\mathrm{GWh/year}$ across EU member states. The percentages indicate the share of cost-effective solutions accounting for energy prices and the cost of capital. Most countries in central and southern Europe show high technical solar potential exceeding $25\,000\,\mathrm{GWh/year}$. A large east-west divide in cost-effectiveness can clearly be observed. France and Germany have high potential and high cost-effectiveness making them primary targets for installing solar panels. The figure is taken from Bódis et al. [2].

solar radiation algorithms and data sources ranging from 2d maps to high-resolution 3d models of urban scenes. In their survey, they find that major factors limiting these approaches include poor data quality and the difficulty of validating models.

[2] use high-resolution satellite data and statistical information to produce an estimate of solar potential across the whole EU. They also include economical calculations in their method to estimate viability of solar installations. However, their method only yields estimates for wider areas and not for individual rooftops.

Early approaches incorporating machine learning are proposed by Ouammi et al. [4] and Sözen et al. [5]. They use rudimentary neural network architectures and focus on Moroccan and Turkish territory respectively. Similarly, Assouline et al. [6] focus on Switzerland and use random forests for their predictions.

With project sunroof, the technology company Google has proposed an approach that offers fine-grained solar potential estimation for individual rooftops within the United States and Puerto Rico. From Google Maps data, they find rooftop outlines using a (not further specified) deep learning method. They then estimate rooftop geometry and use historical weather data to predict the solar potential [7].

Further private sector endeavors include joint effort between the companies Otovo and In Sun We Trust that offer a product similar to Project Sunroof but only serve France [8]. Other existing products focus on small areas or only produce solar potential estimates on-demand [8, 9].

Lee et al. [10] propose a data-driven method that mostly relies on widely available satellite data. They estimate roof topology directly from this imagery using image segmentation architectures. They then use further public data of solar irradiance to estimate solar potential. They validate their method by comparing it to a precise but expensive LIDAR-based approach. Their method can be applied in a wide variety of settings.

Several other approaches leveraging sophisticated deep learning methods are proposed for solar potential estimation [11, 12] or solar irradiance mapping [13, 14, 15].

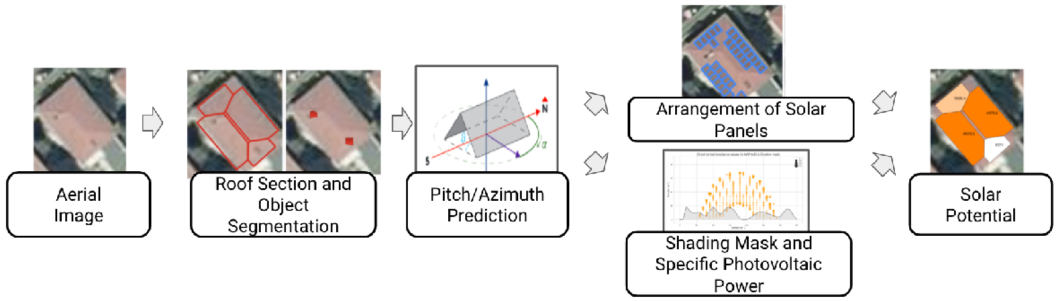

Figure 2: Modular pipeline consisting of segmentation, geometry estimation, panel layout, shading estimation, and eventual solar potential estimation. The figure is taken from de Barros Soares et al. [1]

Method

With the challenges of large-scale solar potential for individual rooftops established and several related proposed methods presented, we will use this section to explain the method proposed by de Barros Soares, Andrieux, Hell, Lenhardt, Badosa, Gavoille, Gaïffas, and Bacry [1] in detail. Its major steps are illustrated in Figure 2.

Segmentation of Aerial Imagery

Given satellite imagery, de Barros Soares et al. [1] first identify suitable roof spaces. This includes finding roof and more precisely, sections of roofs where solar panels can be installed. This means omitting ridges or occupied roof spaces. Therefore, they segment into the categories background, usable segments, and ridges. A second model with the same architecture segments roof objects and predicts a map for classes like chimney, window, and others. They use two different models to achieve this. [1]
To extract features from raw images, they use a ResNet backbone [16] with 34 residual blocks.
Inspired by U-Net [17] they store features along the layers during encoding the input. When decoding the features they progressively concatenate these kept features with upsampled ones that match in dimension. This ensures that information from input images is not lost and the model rather has to learn a difference function to the input image as opposed to a whole new image. Satellite imagery is particularly rich in structural information, such as sharp and straight outlines of roofs or roads, making this U-Net style architecture very applicable.
To train the model, de Barros Soares et al. [1] use labels obtained from GIS data and manually annotated images from the French cities of Bordeaux, Brest, Montpellier, and Strasbourg.

Estimating Roof Geometry

Once they obtain the segmentation maps, where roof space suitable for solar panel installation, is denoted as a specific class, de Barros Soares et al. [1] predict pitch and azimuth of such areas. This gives information about the geometry of the roof.
The pitch of a roof segment refers to its slope. This plays a crucial role for solar potential since roofs that are either completely flat or vertical might be less beneficial than moderately sloped ones. de Barros Soares et al. [1] regress on the normalized pitch. For this, they use a simple linear regression algorithm [18]. Additionally,de Barros Soares et al. [1] use a random forest algorithm [19] to predict roof inclination where features, such as roof type, material, and shape, or the height of the building are known. The training data is obtained again from 3d models of the five French cities.
The azimuth refers to the orientation of the roof from a bird's view perspective. This is obviously important as i.e. on the northern hemisphere south-facing segments might receive more solar radiation than otherwise oriented ones.
de Barros Soares et al. [1] compute the azimuth analytically. For this, they make the simplifying assumption that roof segment orientations can be assigned one of four classes which are the elements

of a cyclic 90° rotation group. This allows them to treat it as a classification problem to which the solution can be obtained in closed form.

Optimal Panel Arrangement

Based on the predicted roof section that is suitable for solar panel installation and its predicted geometry, de Barros Soares et al. [1] compute the maximum number of panels that can be installed. Given the simple rectangular shape of solar panels, they are able to apply a greedy algorithm to the problem. The algorithm's primary aim is to fit as many panels of a fixed size to a roof segment. It accounts for objects occupying rooftop space, mandatory distances between panels and roof edges, and overlapping.

Shading Estimation

A roofs shading depends on factors such as surrounding vegetation and buildings, its location and geometry, and meteorological factors. To compute the shading, a roof segment is objected to, de Barros Soares et al. [1] use the SkyViewFactor software [20] to obtain data on how much light could reach the panels theoretically. This information is refined further using the R-package shadow [21]. Additionally, de Barros Soares et al. [1] use digital elevation models and projected shadow computations using a QGIS extension [22, 23] to produce a second shading mask per panel. de Barros Soares et al. [1] then combine the two shading masks for a final shading prediction.
Using the shading information, they predict photovoltaic power $\mathrm{PV}_{\mathrm{DC}}$. This is converted to $\mathrm{PV}_{\mathrm{AC}}$ considering losses that might occur in converters or other system components. This value summed up over the span of a year forms $\mathrm{PV}_{\mathrm{out}}$.

Solar potential prediction

Finally, de Barros Soares et al. [1] compute solar potential based on estimated number of solar panels and $\mathrm{PV}_{\mathrm{out}}$. Additionally, $\mathrm{P}_{\mathrm{max}}$ is required. This value depends on the solar panel itself and can be treated as a constant. The resulting equation is

$$\textit{solar potential}(\mathrm{kWh/year}) = N_{\textit{modules}} \cdot \mathrm{P}_{\mathrm{max}} \cdot \mathrm{P}_{\mathrm{out}}$$

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Discussion

With their proposed methods, de Barros Soares et al. [1] are able to estimate solar Potential for a great number of roofs. Their method relies heavily on manual data wrangling and steps are performed separately. Training is not done in an end-to-end manner.
While evaluation is possible on hold-outs of the respective datasets, it is difficult to verify whether the datasets' distribution matches the real world. As a sanity check, de Barros Soares et al. [1] test whether south-facing roof segments have higher solar potential than north-facing ones and find that this is indeed true. Moreover, they find that east and west-facing segments do not significantly differ in solar potential, which is expected.
Since the proposed method relies so heavily on different data sources it is not trivial to scale to other areas, where a lot of the data used might not be available. Also, architecture or zoning differs from the French cities the method was trained on. In, for example, Asian cities, flat roofs are much more common which might cause bad segmentation results. Also, roof objects like air conditioners that are not so common in central Europe, might not be identified correctly in that case.
For segmenting the roof sections, de Barros Soares et al. [1] report a pixel accuracy of $77\,\%$. This is a very good value given the challenging task. It should be noted that de Barros Soares et al. [1] do not report mean intersection over union scores (mIoU) which is a more common metric in the image segmentation literature [24]. The pixel accuracy for roof objects is only $30\,\%$. We hypothesize that making the simplifying assumption that there are just two classes for this task, either rooftop object or background would result in a higher pixel accuracy as more capacity in the model's filters could be dedicated to making the distinction between the two.
Further, we hypothesize that using a unified architecture for segmenting would bring performance benefits. As rooftop segment and rooftop object are mutually exclusive, sharing weights might yield

a performance increase and faster convergence. A single segmentation model would then produce segmentation maps with classes rooftop segment, ridge, rooftop object, and background.
As de Barros Soares et al. [1] are likely using cross-entropy as segmentation loss, this approach might also enable a cleaner learning signal as there are no overlapping labels.
Another interesting approach to explore might be to use a rotation equivariant segmentation model. Applying convolutional filters at different orientations could enable further weight sharing. The utilized remote sensing data is particularly suitable for this as the top-down perspective results in the same class of objects occurring in the data, rotated in different ways [25]. A rooftop is a rooftop, no matter how it is rotated.
This might also prove useful for the downstream task of azimuth prediction. If the orientation value is kept throughout the segmentation model, it might not be necessary to discretize it into a classification task but it might be possible to regress on a continuous value.
de Barros Soares et al. [1] state that the segmentation step of the pipeline was particularly challenging [26]. The downstream tasks are more rigid and offer less room for errors. They also report good evaluation results for those.

Conclusion

de Barros Soares et al. [1] propose a method to predict solar potential from satellite imagery and other data such as elevation maps and 3d models. These data are used in separate steps of a pipeline consisting of machine learning models, algorithmic, and analytical steps.
They demonstrate that their method is able to estimate the solar potential of rooftops albeit for selected areas only. We argue that while their method is unlikely to scale beyond the domain it is trained on without further manual labeling, there is potential for more generalization. The modular nature of the pipeline makes it flexible and individual parts might be usable for a wide range of scenarios. Moreover, a more streamlined segmentation model could yield better results for downstream tasks.

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