Predicting the Solar Potential of Rooftops 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 panel. Architecture and location heavily effect the viability of such systems. Predicting this solar potential of a roof is traditionally a labour intensive process requiring on site measurements. Automating this process and scale it up is a difficult challenge. Here, we will introduce a solution proposed by de Barros Soares et al. [1], review it, and compare it to other approaches.

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. Predicting how much energy a roof could produce once panels are installed. This is referred to as a roofs solar potential and is a crucial task. Locally, to determine the viability and economic efficiency of solar panels. Globally, it could also help producing a guess of how much solar energy could contribute to overall energy production capabilities.
Traditionally, a roofs 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 labour 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 inductive bias to a method that combines machine learning and analytical methods.

Related work

Freitas et al. [3] present an overview of approaches combining algorithms and GIS modeling to estimate solar potential in dense urban environments. They compare different numeric 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 installing solar. However, their method only yields estimates for areas and not for specific

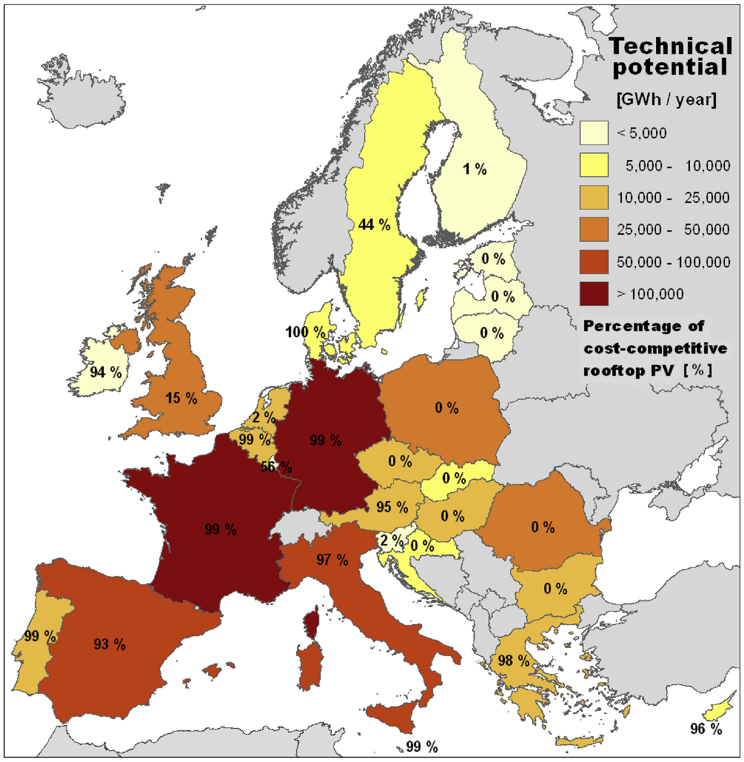

Figure 1: Technical solar potential in $\mathrm{GWh/year}$ across EU member states. The percentages indicate the share of cost effective solutions accounting for energy prices and cost of capital. Most countries in central and southern Europe show high technical solar potential exceeding $25\,000\,\mathrm{GWh/year}$.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

rooftops.
Similar and very early approaches are proposed by Ouammi et al. [4] and Sözen et al. [5] who use rudimentary neural network architectures and focus on Moroccan and Turkish territory respectively. 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 a cooperation 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 offer 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 radiance 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].

Method

With the challenges of large-scale solar potential for individual rooftops established and several related proposed methods established, 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. The major steps are illustrated in Figure 2.

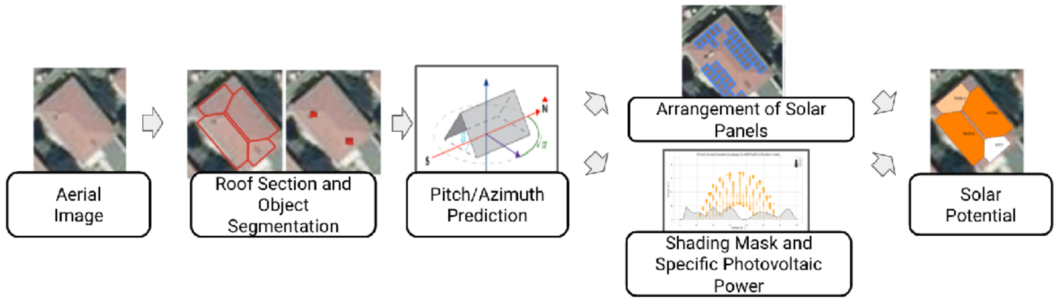

Figure 2: The figure is taken from de Barros Soares et al. [1]

Segmentation

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, sections, ridges. A second model with the same architecture segments roof objects and predicts a map for classes like chimney, window, or 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 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.
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.

Geometry

Once they obtain the segmentation maps where roof space suitable for solar panel installation is denoted as specific class, de Barros Soares et al. [1] regress on pitch and azimuth of such areas. This gives 3d information about the roofs geometry.
They 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 a moderately sloped one. 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 it analytically. For this, they make the simplifying assumption that roof segment orientations can be assigned on 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.

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 pannels that can be installed. Given the simple rectangular shape of solar panels, they are able 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 to roof edges, and overlapping.

Shading

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 coverters 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 $\mathrm{PV}_{\mathrm{out}}$. Additionally, $\mathrm{P}_{\max}$ is required. This value depends on the solar panel itself and can be treated as a constant. The resulting equation is

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

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Discussion

With their proposed methods, de Barros Soares et al. [1] were able to estimate solar Potential for the entire area of mainland France. Their method relies on a lot of manual data wrangling and steps are performed separately. Training is not done in an end-to-end manner.
While evaluation the is possible on a hold out of the respective datasets, it is difficult to verify wheter the dataset's distribution match 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, further indicating that the predictions are as 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 required and i.e. 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.
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. However, 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 further 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 used 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 [24]. A rooftop is a rooftop, no matter how it is rotated.
This might also proof 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.
While de Barros Soares et al. [1] state that the segmentation step of the pipeline was particularly challenging [25], the many steps of their proposed method offers space for errors at each step. However,

training a concatenated model to regress on solar potential from raw image input might impractical. However, it would be interesting to compare

Conclusion

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