INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH
D. A. Widodo et al., Vol.12, No.4, December 2022

Study of Solar Photovoltaic Potential and Carbon Mitigation in University Buildings

Djoko Adi Widodo*‡, Nur Iksan*, Riana Defi Mahadji Putri*, Anggraini Mulwinda*

*Department of Electrical Engineering, Faculty of Engineering, Semarang State University, Indonesia

(djokoadiwidodo@mail.unnes.ac.id, nur.iksan@mail.unnes.ac.id, riana.dmp@mail.unnes.ac.id, anggrainimulwinda@mail.unnes.ac.id)

‡ Corresponding Author; Djoko Adi Widodo, Department of Electrical Engineering, Faculty of Engineering, Semarang State University, 50229, Indonesia

Tel: +62 812 2541 733, djokoadiwidodo@mail.unnes.ac.id

Received: 27.10.2022 Accepted: 14.11.2022

Abstract- Capturing solar radiation through photovoltaic deployment on the rooftop of buildings not only produces clean energy but also plays an important role in mitigating carbon dioxide emissions. Semarang State University in Indonesia expanding solar energy until 2021 has installed 260 kWp rooftop solar photovoltaic in 8 buildings. Gradually, the rooftop photovoltaic portfolio is being improved to realize the vision of the green campus. It is important to conduct a quantitative assessment of the power generation potential of rooftop photovoltaics to formulate a policy on effective electricity production integration. The objective of this study is to predict the potential for rooftop solar photovoltaic exploration and the potential for mitigating carbon dioxide emissions. The method used was the combination of a deep learning approach and aerial photography of an unmanned aerial vehicle. It was found that of the 40 tallest building units, the available roof area was approximately 26,645 m^2. The average monthly irradiation was 5.63 kWh/m^2/day. Energy potential per year: 8,671.1 GWh (m-Si); 7,234.4 GWh (p-Si); 4,427 GWh (a-Si); and 7,414.3 GWh (CdTe). Based on local emission factors, the mitigation potential per year was: 7,199,468.9 tons of CO_2 (m-Si); 6,000,536.3 tons of CO_2 (p-Si); 3,674,417.7 tons of CO_2 (a-Si), and 6,153,902.9 tons of CO_2 (CdTe). The findings of the study are dedicated to university management to design and manage roof photovoltaic systems reliably and economically.

Keywords Solar irradiation, deep learning, unmanned aerial vehicle, carbon mitigation, photovoltaic.

1. Introduction

Meeting the increasing demand for electrical energy from new and renewable energy-based sources can help reduce CO_2 emissions in the atmosphere and protect the environment. Solar energy is the most promising source of electricity for residential, commercial, and industrial applications. Solar energy is considered to be one of the sustainable energy sources that can meet future energy needs [1–3]. A study highlights that the earth receives about 1.8 1011 MW of power from solar radiation instantly [4]. Solar energy converted into electricity has proven to be technologically robust, scalable, and geographically dispersed and has great potential as a source of sustainable energy [5, 6]. Solar photovoltaics can significantly help buildings increase energy self-sufficiency and cost-effectively reduce environmental emissions [7].

The need for a change and a sustainable transition to a low-carbon emission society is a vision widely promoted in Higher Education Institutions. In this context, Semarang State University, Indonesia, which has intended to realize the vision of becoming a Green Campus, was chosen as a case study in this study. By 2022, this institution has installed rooftop solar photovoltaic systems in 8 buildings with a total capacity of around 260 kWp. The installation of these photovoltaic systems aims to reduce the use of electricity from conventional fossil fuel power plants which have negative impacts on the environment. Most of the day, significant solar resources are available in the campus area. According to the Meteorology, Climatology, and Geophysics Agency, the average monthly air temperature reaches 21°C to 36°C in 2021. However, until now there has never been a comprehensive study of solar energy potential on the roofs of all buildings. However, the output power of rooftop solar photovoltaics is highly uncertain due to local meteorological factors. Many parameters affect the generation of electricity from solar power, but solar insolation is the main component [8–10]. Therefore, it is necessary to identify the potential for rooftop solar photovoltaics so that it can be utilized for sustainable electricity generation planning to meet daily electricity needs. On the other hand, the main problem and challenge in the production of solar energy is the intermittent volatility of photovoltaic power generation due to the dynamics of weather conditions [11]. In particular, variations in temperature and radiation can have a major impact on the quality of electric power produced.

Estimating the solar potential of an area usually requires knowledge of the availability of a suitable area for the installation of photovoltaic panels (geographical potential), the availability of solar insolation (physical potential), the ability or efficiency of certain technologies in converting solar energy into electricity by considering technical limitations (technical potential), and costs associated with solar panels uses for energy generation (economic potential) [12, 13].

Studies related to roof geometry and physical features are used to evaluate the impact of rooftop solar photovoltaic system installations. The approach developed is based on a slope using Light Detection and Ranging (LiDAR) data, building footprint data, Geographic Information System tools, and aerial photography [14]. Evaluation of the potential for rooftop solar energy in an area requires information on the availability of the appropriate area concerning aspects of solar insolation, orientation, slope, and shade [15, 16]. Geographic Information Systems (GIS), such as orthophotos and digital surface models (DSM) are important elements in determining the ideal roof area. There are several techniques used to obtain GIS data; manned aerial sensor methods, such as Light Detection and Ranging (LiDAR), and manned ground methods, such as terrestrial laser scanning or satellite imagery. Using manned aerial platforms, such as LiDAR and satellite imagery, is time-consuming and expensive. GIS data can be obtained by flying an unmanned aerial vehicle (UAV) which is now increasingly being adopted directly by researchers from various disciplines [17]. UAV photogrammetry has very similar accuracy to Real Time Kinematic Global Positioning System data. So it is possible to use UAVs to obtain photogrammetric data for map making, surveys, and several other engineering applications with the advantages of low cost, time conservation, and minimum fieldwork [18]. Aerial images obtained from unmanned aerial vehicle technology are an alternative approach for investigating the roof area of a building [19].

Solar radiation data has an important role as it provides information about all the energy that comes to earth, which is needed for the utilization, planning, and design of solar power plant. These data are not available from all locations, so different climate variables were used to estimate solar radiation. The solar radiation level parameter directly affects the energy output and efficiency of the photovoltaic system [20, 21]. There are several methods to predict the value of solar radiation at a location, one of the deep learning-based methods that are widely implemented is the Recurrent Neural Network. RNNs are a type of neural network that exploits the sequential nature of the input data. RNNs can predict random input sequences due to their internal memory. Internal memory can store information about previous calculations [22]. RNN is used to model time-dependent data and gives good results in time series data, which has proven successful in several application domains [23]. Application of deep learning techniques for horizontal daily solar irradiation estimation shows a good performance [24, 25]. Another study also used deep learning techniques to estimate hourly, daily, and yearly solar radiation [26].

Based on research studies that have been reviewed, this study highlighted (i) the roof surface area of the tallest building in the campus area; (ii) the solar insolation level of the campus area for a certain period. The objective of this study is to estimate the potential for solar photovoltaic energy of the tallest rooftop for various types of photovoltaic technology and the potential for carbon dioxide that can be reduced. This paper is prepared as follows: section 2 introduces the data set used in this study, section 3 describes the methodology for the prediction of the rooftop photovoltaic potential and the estimation of carbon dioxide mitigation, section 4 presents the results and a step-by-step analysis of the estimation process at each stage, and section 5 presents the conclusions and provides views for the follow-up development of the rooftop solar photovoltaic system of the University building.

2. Materials

2.1. Description of Building Sample

The location of this study was the campus area of Semarang State University, Central Java Province, Indonesia. This institution occupies an area of approximately 157 hectares. Geographically, the coordinates are between 6°50'-7°10' south latitude and 109°35' - 110°50' east longitude.

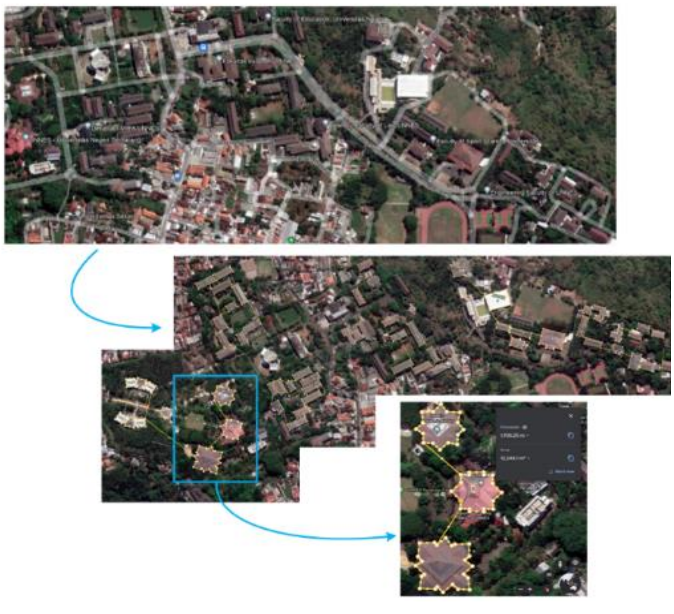

Fig 1. Google Earth Image of Semarang State University

Figure 1 shows land and buildings in the campus area based on Google Earth Imagery. From site observations, there are 94 buildings with various types of area sizes and heights. The location of the building is 11 work units, consisting of eight faculties and three centers. Detail location name of each building is shows in Table 1.

The tallest building in each location is used as a sample in this study. Based on the survey of all locations, it was identified that there were 40 units of three-story buildings. The surface of the roof area of the tallest building was considered ideal because it was not blocked by plants and trees around the building. Almost all the roofs of the tallest buildings receive sunlight all the time from morning until afternoon. Because the roof area was not blocked by trees throughout the day, they can be used as options to be studied.

Information on the roof area of the building is useful for estimating the potential for solar power that can be captured from the rooftop solar photovoltaic system. Installation of photovoltaic panels on the roof is very good for generating solar energy [27, 28]. Because of these considerations, the roof of the tallest building was very appropriate for study. But it should be noted that not every roof surface is fully accessible for the installation of photovoltaic panels. Generally, the roof surface of the building is used for the placement of exhaust air chimneys, water storage tank, communication antennas, and outdoor air conditioning units.

2.2. Daily Solar Irradiation

This study used local area global horizontal irradiance data obtained from the NASA Surface Meteorology and Solar Energy database. The total amount of radiation calculated for a given location or area was referred to as global radiation [29]. Figure 2 presents a daily global radiation graph consecutively from January 1 2017 to December 31 2021. In one year there were 365 variations of daily global radiation data, and for 5 years there were 1,825 variations of data. The variability of this radiation value was the interest of this study.

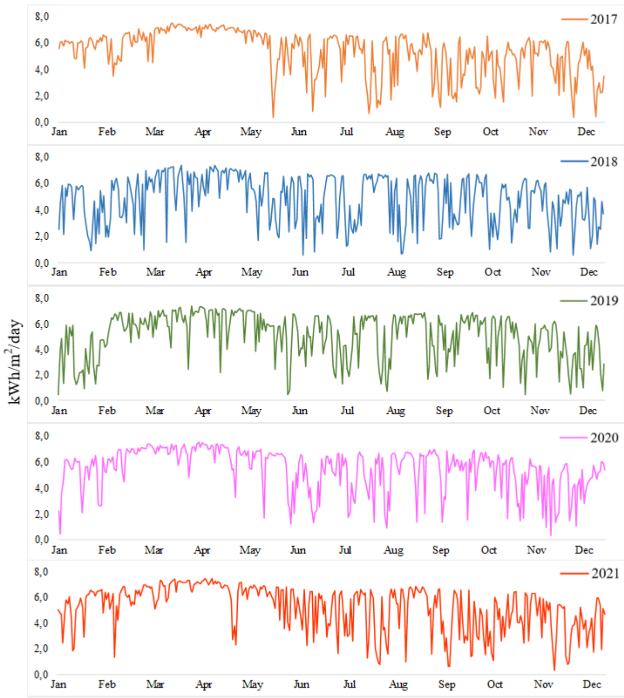

Fig 2. Horizontal Surface Insolation in 2017–2021

3. Methodology

This study estimated the rooftop solar photovoltaic potential in the campus area and carbon dioxide emissions mitigation. The study framework is illustrated in Figure 3, the rooftop solar photovoltaic potential was based on the variable of physical, geographical, and technical potentials, which adopts related studies [30, 31]. The variables of physical potential based on solar insolation reflect the energy received from the sun by the roof of the University building. The variables of geographic potential are variables that reflect the location or area where solar energy can be captured and used for photovoltaic deployment. The variables of technical potential are related to the conversion of solar energy received by the photovoltaic roof area into electrical energy using the technical characteristics of photovoltaic technology or photovoltaic efficiency and performance. Our assessment of rooftop solar photovoltaic potential combines deep learning with aerial photo processing of unmanned aerial vehicles. Assessment of emission reductions from the use of renewable energy sources is by considering the total rooftop solar

Table 1. Description of the three-story building

Building location	Number	Orientation	Roof of facing
Faculty of Education	5	Peaked Buildings	North and south
Faculty of Art Language	5	Peaked Buildings	East and west
Faculty of Social Sciences	4	Peaked Buildings	North and south
Faculty of Mathematics and Natural Sciences	5	Peaked Buildings	East and west
Faculty of Engineering	5	Flat Building	Facing the sky
Sports Science Faculty	4	Peaked Buildings	North and south
Economics Faculty	3	Flat Building	Facing the sky
Law Faculty	3	Peaked Buildings	North and south
Research Center Building	2	Flat Building	Facing the sky
Library Center Building	2	Peaked Buildings	East and west
Rectorate Center Building	2	Peaked Buildings	East and west

photovoltaic electricity production and the emission factors of the area where the photovoltaic system is installed.

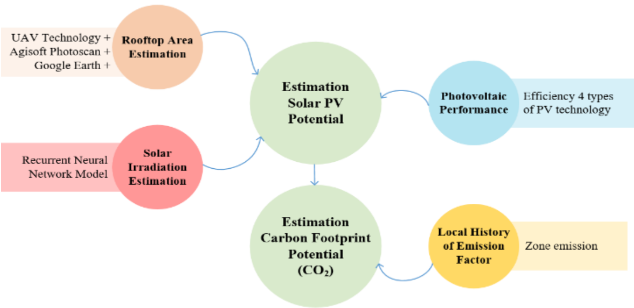

Fig 3. Forecasting framework for photovoltaic and CO_2 mitigation potential

Solar photovoltaic systems use photovoltaic cells that convert solar irradiation into electric power. Factors that affect rooftop photovoltaic electricity productivity are the placement and orientation of the roof, roof design, roof slope, type of photovoltaic, and performance. The rooftop photovoltaic potential mainly depends on the efficiency of the photovoltaic modules used to generate solar electricity [32, 33]. Thus, it is important to choose a solar panel with high efficiency and the best performance. The efficiency and performance factors of different types of photovoltaic panels vary according to the manufacturing technology and materials used. Table 2 summarizes the efficiency and characteristics of different types of photovoltaic panels to illustrate various scenarios of solar power generation. The electrical energy output of a photovoltaic solar panel is given by Equation 1 [34]:

$$E_{pv}\,(kWh\,) = E_{sol}\,(\,kWh\,.m^{-2}\,)\;x\;A\;(m^2)\;x\;\eta_{pv}\;x\;\eta_{pcu} \quad (1)$$

Where in E_{pv} is the output energy of the solar photovoltaic panel in one hour and E_{sol} is the incoming solar energy, in one hour, in one unit area; A is the area of the panel; η_{pv} is the photovoltaic panel efficiency value; η_{pcu} is the efficiency of the power conditioning unit including the inverter. For this analysis, the monthly average solar insolation value was calculated. Therefore, generation estimation from rooftop solar photovoltaic systems was carried out hourly, for a typical day of each month of the year. So, Equation (1) is modified to Equation (2):

$$\textstyle\sum_{N_{sh}} E_{pv}\,(\,kWh\,) = \sum_{N_{sh}} E_{sol}\,(kWh\,.m^{-2}\,)\;x\;A\;(\,m^2\,)\;x\;\eta_{pv}\;x\;\eta_{pcu} \quad (2)$$

Wherein N_{sh} is the number of hours of effective sunlight. Annual energy output takes into account the number of hours of sunlight in 365 days effectively. Emission reduction potential was found by considering the weighted average emission factor of 0.83 in 2019 in Central Java Province, Grid Jamali. Weighted average emission factor data was provided by the Ministry of Energy and Human Resources. The total emission of reduced CO_2 is derived by Equation (3).

$$C = \textstyle\sum_{Nsh} E_{pv}\;x\;\;WAE \quad (3)$$

Where in C is tons of CO_2 per MWh, $\sum_{Nsh} E_{pv}$ is the total annual electrical energy from solar photovoltaic generated in MWh, and WAE is the weighted average emission factor.

Table 2. Overview and comparison of four different types of PV technologies

PV Technology	Module efficiency (%)	Panel output (W)
m-Si	21.5	350
p-Si	15.06	245
a-Si	19.8	250
CdTe	17	320

3.1. Rooftop Area Estimation

The installation of a photovoltaic panel considers radiation slope and roof area available on each roof surface. Before installing solar panels on the roof of a building, it is necessary to assess the location where solar panels to be placed. This can significantly improve the panel performance. In the Northern Hemisphere, roofs facing south have more direct sunlight. On the other side, in the southern hemisphere, roofs facing north receive more direct sunlight. Thus, the angle of orientation of the roof determines the actual solar generation output. The flat roof and low angle of inclination receive sunlight for about 8–10 hours, regardless of its orientation. However, if the inclination angle is greater than 20°, the orientation of the building affects the hours of sun exposure in the photovoltaic surface area because some parts of the photovoltaic surface can be shaded by the roof structure itself [35, 36].

This study analyzed the roofs of all the tallest buildings, which were three-story buildings. The roof area received sunlight without being blocked by trees. Based on Google Earth imagery and a physical survey of the building, all samples of the roofs of three-story buildings were grouped into several sub-areas. The procedure for determining the sub-area and estimating the roof area is shown in Figure 4.

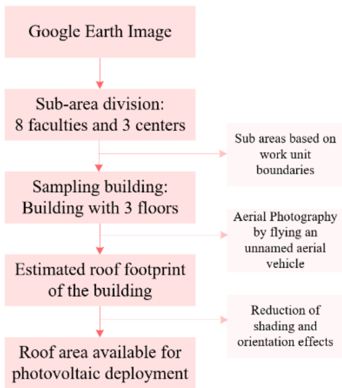

Fig 4. Identification of building samples and estimation of roof area

After choosing a sample of the roof of the building, then an unmanned aerial photo was taken for the assessment of the roof area. We flew a DJI Mavic 2 Zoom drone equipped with a camera at a height of 50 meters. Many photo sets were used to create as many as 40 models of the roofs of three-story buildings. All models of the roof of these buildings were taken from a platform that corresponds to a predetermined area. The model of the building roof was explored using the Agisoft Photoscan Professional tool to get the total roof area (AT). Thus, AT represents the potential of the roof footprint of the study sample used in the calculation. The available roof area was effective for installing photovoltaic panels (Apv) and it was expressed by Equation (4), after considering the reduction of the shading factor and the orientation of the building.

$$Apv = AT * Fo * Fs = AT * 0.5625 \quad (4)$$

In this case, AT is the total roof area obtained from the model explored with Agisoft Photoscan Professional. Fo and Fs are respectively the orientation factor and the shading factor. Fo and Fs were estimated by considering the condition of the buildings in the study area. From the physical survey of buildings, it was identified that around 25% of the buildings had flat roofs (Rflat = 0.25). Flat-roof buildings did not experience a reduction in the roof area and were not affected by the orientation of the building (Oflat = 1). On the other hand, there are 75% of the buildings are peaked roofs buildings or have slope roofs (Rpeaked = 0.75). The buildings were considered to have a roof area suitability of 50% for photovoltaic installation (Opeaked = 0.5). So by considering the orientation of the roof of the building, the orientation factor (Fo) can be calculated using the following approach [32, 37]:

$$Fo = Rflat * Oflat + Rpeaked * Opeaked$$
$$= 0.25 * 1 + 0.75 * 0.5 = 0.625 \quad (5)$$

The next factor that must be taken into account for mitigating the roof area is the shading factor. Based on the site survey, it was seen that there was no roof area of the buildings that were used for water storage tanks and other uses. The roof area of the three-story building was also not covered by the shade of trees and nearby buildings. Considering these various factors, Equation (6) can be used to calculate the shading factor.

$$Shading\ Factor\ (Fs) = 0{,}9 \quad (6)$$

The orientation factor (Fo) and the shading factor (Fs) have been estimated by considering the physical condition of all the sample buildings in the study area.

3.2. Solar Irradiation Estimation

This section provides an assessment of the potential for solar irradiation available in the campus area located in Semarang City, Central Java province, Indonesia. The variability of solar radiation depends on the time scale. This irradiation value is very important because it can predict the energy generated from the exploration of rooftop solar photovoltaic systems. This physical potential is defined as the global solar radiation on the earth's surface for each time step.

Figure 5 illustrates daily global radiation from 2017 to 2022. The variability of the daily radiation value was highlighted to obtain the predicted daily radiation value. Since the data structure was time series data, the daily solar radiation assessment adopted a deep learning approach.

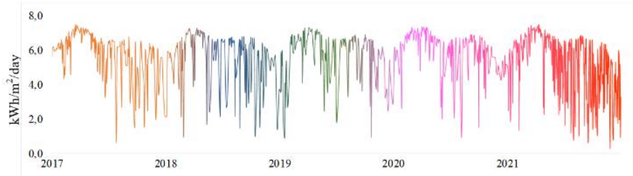

Fig 5. Local area daily solar irradiation variation pattern

A recurrent neural network (RNN) is a deep learning architecture that is widely used to process sequential data. An iterative neural network model is a type of neural network that exploits the sequential nature of the input data. The algorithm of this model adheres to the iteration principle. The input data is fed to the network one by one and the nodes in the network store their state at a one-time step and use it to inform the next time step. Unlike classical neural networks, RNNs use temporal information from input data, which makes them more suitable for time series data. The typical structure of a repetitive neural network, x_t , is data inputted at time t. The black box obtaining input from other neurons in the previous time step x_{t-1}, s_t is a hidden state in the time step t and is the "memory" of the network. s_t calculated based on the previous hidden state and the input in the current step. s_t captures information about what happened in all the previous time steps and is given by Equation (7).

$$s_t = g\ (U_{xt} + W_{st-1}) \quad (7)$$

Output in step t is y_t. To predict the next sequence in the time series, it will be a probability vector in the time series. Function g is usually a nonlinear activation function as the hyperbolic tangent (Tanh). RNNs share the same parameters (U, V, W) across all steps performing the same task at each step, only with different inputs.

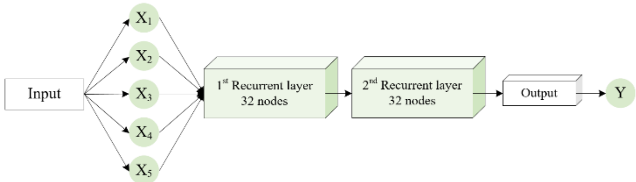

Fig 6. RNN architecture for irradiation prediction

The iterative neural network architecture shown in Figure 6 was applied to predict daily solar irradiation. The configuration consisted of 5 input sizes, 1 output size, 2 hidden layers, 32 hidden sizes, 21 sequence lengths, 16 batch sizes, and root-mean-squared error criteria. The imported dataset was 1825 daily irradiation average data. To become multivariate, time-series data was divided into quarters in a year. Outlier data were interpolated. For prediction purposes, the portion for training data was determined to be 80% and 20% for testing data. The form of iterative neural network data was NSF, which defined the amount of data, the sequence value, and the number of features. In this context, the sequence value was specified as 21, thus the array into train data (N, S, F) was (69, 21, 5) and test data (N, S, F) was (17, 21, 5).

4. Result and Analysis

4.1. Estimated Building Roof

Traces of the roof area of the building throughout the sample locations or sub-areas have been obtained. After the gross roof area was calculated, a reduction must be made to the roof area considering the effects of shading and building orientation. The available roof area for photovoltaic panel deployment is summarized in Table 3.

Table 3. Description of the roof area of the three-story building

Sub-area or work unit	Building	Total (m^2)	Available (m^2)
Faculty of Education	5	2.120	954,0
Faculty of Art Language	5	8.546	3,845.7
Faculty of Social Sciences	4	6.295	2,832.8
Faculty of Mathematics and Natural Sciences	5	7.726	3,476.7
Faculty of Engineering	5	7.214	3,246.3
Sports Science Faculty	4	5.962	2,682.9
Economics Faculty	3	2.872	1,292.4
Law Faculty	3	2.279	1,025.6
Research Center Building	2	3.698	3,328.2
Library Center Building	2	2.345	1,055.3
Rectorate Center Building	2	6.456	2,905.2

The total sample buildings were 40 building units. All of these sample buildings were three-story buildings which were the tallest in the campus area. The available roof area was chosen by considering the reduction of the orientation and shade factors in each sample building. Building orientation was obtained by considering the slope of the roof on each building. Buildings with a slope of up to 10 degrees were considered flat roofs because they did not need a reduction. While the roof of the building with a slope of 25 degrees or more needed a reduction from the orientation factor. Reduction of the shading factor for sloping roof buildings was not necessary because there was no reserved area in each building. While, for flat roof buildings, the reduction of the shading factor was calculated because there was a reserved area used for building support, such as outdoor air conditioning units.

This study showed that the trace of the roof area of the entire sample was 55,513 m^2 and the roof area available for photovoltaic deployment was 26,645 m^2. Based on the traces of the roof area of the sampled buildings, it was known that not all roof areas were suitable for deploying photovoltaic panels as solar power plants. The results of this study estimated that only 47.9% of the trace of the roof area of the entire three-story building was available for photovoltaic panel deployment. Compared to the campus area of 157 hectares, equivalent to an area of 1.57 million m^2, it showed that the portion of the roof area of the building studied in the study was relatively small.

4.2. Estimated Solar Radiation

Figure 7 shows the average monthly irradiation of the local area obtained from the prediction results using a repetitive neural network. Irradiation potential in each month was in the range of 3.9–6.7 kWh/m^2. The average monthly irradiation was 5.6 kWh/m^2. The highest irradiation potential occurred in March and April, while the lowest irradiation occurred in December. From these predictive findings, it can be a motivation to utilize solar energy in the local campus area. In Indonesia, the average intensity of solar radiation that falls on the surface area was around 4.8 kWh/m^2 every day. Thus, the campus area has a significant solar energy potential compared to the national area.

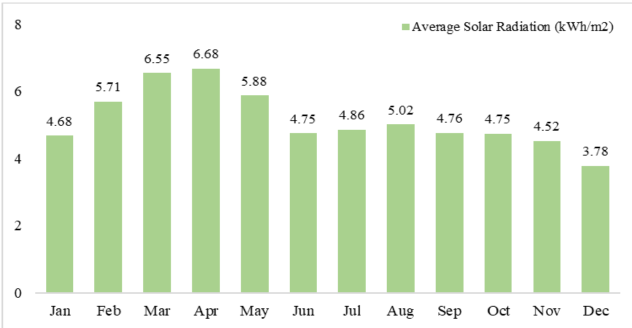

Fig 7. Average of solar irradiation prediction

Data on the availability of solar irradiation in a place is very important for planning solar power plants. These data are used to estimate the potential energy output of photovoltaic deployment. Photovoltaic solar technology is capable of converting to electricity both direct irradiation and diffuse irradiation. However, not all regions have available irradiation maps or solar insolation maps. Capturing this unexploited solar radiation will not only improve the total mix of energy but also reduce emissions of greenhouse gases that degrade the environment.

4.3. Estimated Rooftop Solar Photovoltaic Potential

After obtaining the roof area available for photovoltaic deployment in all sub-areas or work unit locations, the photovoltaic power potential can be calculated. This study found the monthly electrical energy potential as shown in Figure 8 for different types of photovoltaics. From the estimation, it was found the electrical energy per year of 8,671.1 GWh (m-Si); 7,234.4 GWh (p-Si); 4,427 GWh (a-Si); and 7,414.3 GWh (CdTe). Thus, it is crucial to choose a solar panel with high efficiency and the best performance.

Fig 8. Monthly roof photovoltaic potential of all building samples

Rooftop photovoltaic deployment can play an important role in the transition to low-carbon energy systems. Until now, the lack of data on building and environmental aspects has impeded accurate estimation of the photovoltaic potential of the local area. The case study on the roof of the University building provides an overview of the scenario of rooftop photovoltaic-based electricity generation. Many variables require estimation through various approaches to obtain a measurable photovoltaic output.

4.4. Estimated Carbon Dioxide Emissions

The potential for mitigating carbon dioxide emissions was obtained based on the photovoltaic potential of the solar roof. The chart in Figure 9 shows the estimated mitigation potential based on the historical emission factors of the local area. This emission mitigation potential result was obtained from the use of photovoltaic roofs in all sample buildings. From the estimates made in this study, mitigation potential per year was: 7,199,468.9 tons of CO_2 (m-Si); 6,000,536.3 tons of CO_2 (p-Si); 3,674,417.7 tons of CO_2 (a-Si); and 6,153,902.9 tons of CO_2 (CdTe).

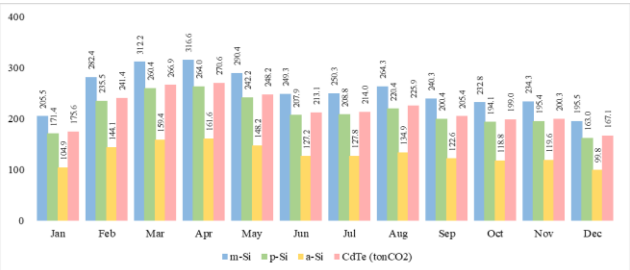

Fig 9. Monthly carbon dioxide potential of all building samples

The description of the mitigation potential displayed provides information that photovoltaic panels with high efficiency and performance provide a proportionally high CO_2 mitigation potential. The estimation results showed that the installation of photovoltaic panels on the roofs of University buildings can help slow down the pace of climate change.

4.5. Rooftop Photovoltaic Potential and CO_2 Mitigation in University Sub-Area

The potential for clean energy and carbon dioxide mitigation in each building in the campus area has been identified. The identification results are presented in the chart of Figure 10. From the description, it can be seen that the greatest potential for clean energy and CO_2 mitigation from photovoltaic was generated by the roof of the building of the Faculty of Mathematics and Natural Sciences with a net energy of mono-crystalline PV of 13,260 GWh/year and CO_2 mitigation potential of 1,100,604 tons of CO_2/year. The potential map of each sub-area or work unit is useful as a material for planning the deployment of photovoltaic panels in each building.

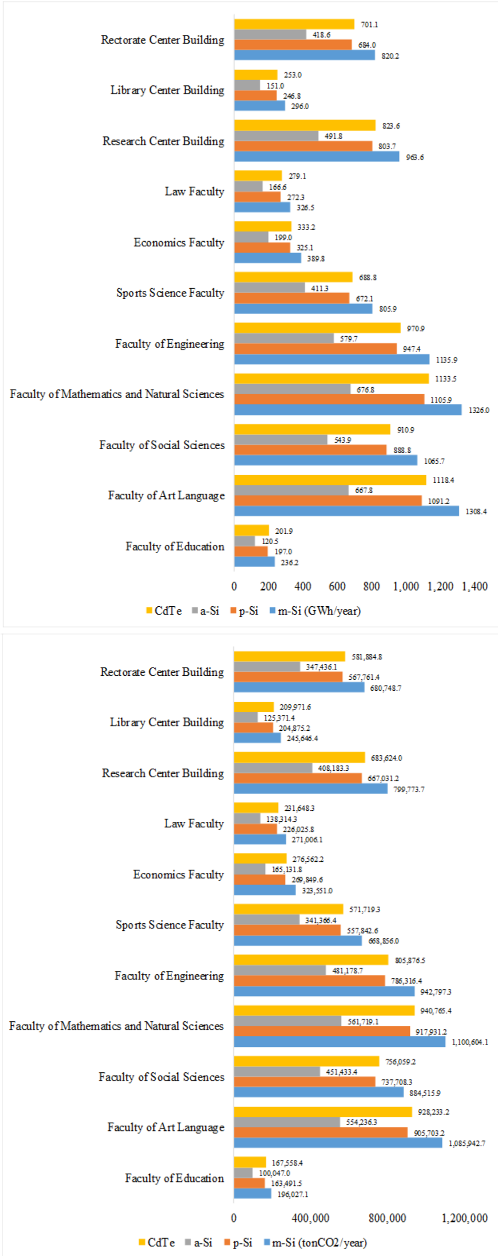

Fig 10. Rooftop photovoltaic potential and CO_2 mitigation in sub-area

4.6. Photovoltaic Comparison with Clean Energy Potential and CO_2 Mitigation Potential

This study has succeeded in comparing the performance of 4 types of photovoltaics widely used to produce clean energy. The different characteristics and efficiency of each photovoltaic used produce different net energy outputs.

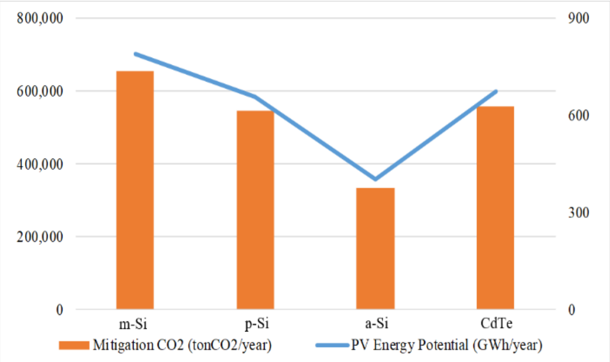

Fig 11. Average monthly energy potential and CO_2 mitigation

The description of Figure 11, shows that photovoltaic types of mono-crystalline, poly-crystalline, amorphous silicon, and cadmium telluride were used on the roof area of the University building. The chart shows that the potential for clean energy generated from photovoltaic systems was directly proportional to the potential for carbon dioxide mitigation. Mono-crystalline photovoltaic had the largest clean energy potential and carbon dioxide mitigation potential, followed by cadmium telluride photovoltaic.

5. Conclusion

Assessment of the power generation potential from rooftop photovoltaics is very important to create a policy on solar power production integration. This study highlighted the roof of the tallest buildings and solar insolation in local areas. The objective of this study is to predict the potential for rooftop solar photovoltaic exploration and the potential for mitigating carbon dioxide emissions. The method used in this study combined a deep learning approach and aerial photography of an unmanned aerial vehicle. Based on the study on the 40 tallest buildings, it was found a roof area of approximately 26,645 m^2 with an average monthly irradiation of 5.63kWh/m2/day and energy potential per year of 8,671.1 GWh (m-Si); 7,234.4 GWh (p-Si); 4,427 GWh (a-Si); and 7,414.3 GWh (CdTe). Based on local emission factors, it can provide mitigation potential per year of: 7,199,468.9 tons of CO_2 (m-Si); 6,000,536.3 tons of CO_2 (p-Si); 3,674,417.7 tons of CO_2 (a-Si) and 6,153,902.9 tons CO_2 (CdTe). These findings are dedicated to university management to design and manage rooftop photovoltaic systems reliably and economically.

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