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# Towards deep learning methods to improve photovoltaic prediction and building decarbonization in benchmarking study

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**Abstract.** High energy demand, energy transition, energy consumption control are challenges for the future, especially for Building Integrated Photovoltaic (BIPV). There is a great potential to harvest large amounts of photovoltaic (PV) energy on horizontal and vertical surfaces. However, this high potential is often hindered by the slow deployment of these panels, the complex integration into existing buildings, and the possible complex interactions between different factors, such as visualization and active projection of buildings in the decarbonization process. Building Information Modeling (BIM) offers complete and real generative building data that is used in our deep learning methods. Indeed, there is currently no framework for design linking photogrammetry, BIM and PV for BIPV. In this work, we propose artificial learning models, such as Deep Learning, to predict PV energy production for BIPV decarbonization. We determined the optimal prediction of PV production by testing and evaluating different models on a building case study. We compared the PV power generation prediction results with 3D simulation software for solar architecture.

## 1. Introduction

Fossil fuels have been the subject of controversy for the past few years, and it has become clear that the best alternative would be the use of renewable energies to reduce the amount of carbon released. With the increasing popularization of PV panels, several studies demonstrate the effectiveness of these panels for an efficient energy transition and significant carbon neutrality. According to the International Energy Agency Photovoltaic Power Systems Programme (IEA-PVPS) report of 2022 [1], the total business value in the PV sector is estimated to be 190 billion dollars in 2021. The design of PV systems is still a challenge due to the complexity of the parameters to be considered. Salimzadeh, N. et al. proposed a study in which they developed a parametric model to generate a set of solutions on panel configuration and layout to find the best panel layout for optimal production [2]. However, the arrival of Building Information Modeling (BIM) has made it much easier to integrate photovoltaic panels and their layout into buildings. In this sense, Ning, G et al. have implemented a BIM-based tool that is much more powerful than some of the most widely used PV tools and manual methods for PV design that improves the efficiency of the design by up to 265%, and increases energy production by 36.1%[3]. With the help of BIM, we can also improve the layout of photovoltaic panels in buildings. Vahdatikhaki, F et Al. propose a PV optimization model using a generative approach to the layout of PV modules[4]. However, artificial intelligence models make it easier to predict photovoltaic energy and improve its production. Alomari, M. et al., used models such as ANN, Levenberg-Marquardt (LM) and Bayesian Regularization (BR) algorithms to correlate timing with produced PV power for forecasting, in advance, in real time, temperature and solar irradiation [5]. According to Zhou, Y. et al., to ensure the transition to carbon neutrality in buildings, it is necessary to combine artificial intelligence and renewable systems to ensure

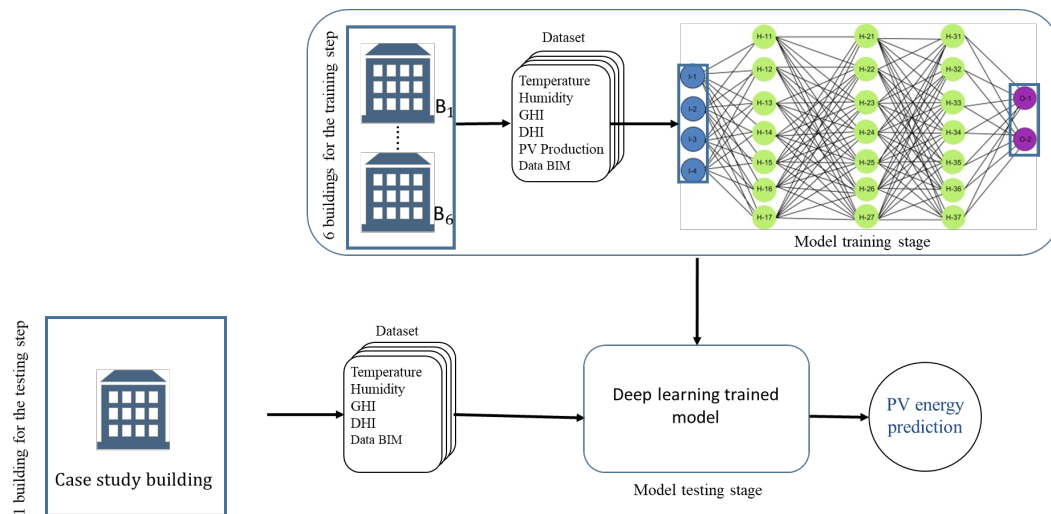


robustness, reliability, automation and flexibility [6]. We can combine Geographic Information Systems (GIS) with machine learning (ML) to estimate PV energy prediction at the national level. Using this method, Walch, A. et al., showed that Switzerland could obtain an annual production of  $24 \pm 9$  TWh, representing 43% of the national electricity demand in 2018, if 50% of the Swiss roofs were covered with PV panels [7]. According to Ahmed, R. et al. the best performing approaches are ANN and CNN or their hybrid forms [8]. However, Jouane, Y. et al., proposed a study of PV power prediction on a residential building, in France [9]. This study shows that the RF had the best performance followed by the ANN, compared to the other models studied. Like most technical methods, AI approaches also have their shortcomings for the prediction and optimization of renewable energy performance [10]. As a result, difficulties may be encountered in practical applications [11]. With the complexity of integrated systems, prediction or optimization would seem difficult with a single AI approach, because the objective function is complex [10]. The 3D modeling process is an essential step in BIPV design. There are several tools and techniques available for this, such as photogrammetry. According to Polo, J et al. [11], photogrammetry enables the 3D shape of an object to be accurately and reliably recovered. It identifies the spatial positions of all the object's features (shapes and colors). We therefore used photogrammetry in our study to recover the point clouds of our building and integrate them into our artificial learning model. In order to maximize the use of renewable energies to finally achieve carbon neutrality, decarbonization processes are beginning to develop in buildings. It can be estimated and quantified in BIPV through a life cycle analysis (LCA) and the potential for integration of PV panels into buildings. Toosi et al. [12] showed that the application of a BIPV-TES coupled system can reduce CO<sub>2</sub>eq emissions by 21.42% over the life cycle of the building. Therefore, we propose in this paper a prediction method based on artificial learning models such as Convolutional Neural Network (CNN), photogrammetric points cloud and some BIM data. This method gives us the energy prediction of the PV production and gives us the estimation of building decarbonization.

## 2. Scientific methodology

### 2.1. Working principle method description

We propose a new PV prediction method for the decarbonization of existing buildings by using a deep learning model to predict the PV energy production of buildings with an accurate energy prediction to enable efficient decarbonization. This approach uses information of buildings, such as building orientation and localisation, and information about windows surface and usable surface facade coming from BIM data. Thus, we combine these data with deep learning models to predict PV production energy. The idea of our proposed methodological approach is to use 3D photogrammetric point clouds for building modelling and then merge this data with the BIM ones for our deep learning (DL) models as shown in figure 1. Indeed, the working principle is to compare more artificial learning models to choose the best, in order to test it on a case study building to estimate its potential PV production on its facades and so its decarbonization. Initially, we are going to experiment our models on seven BIPV buildings, the training and the test will be done on their basis. We will then choose the most efficient model out of the eight proposed, which will be tested on a case study building of the engineering school CESI. The latter will undergo all the PV prediction method with the photogrammetric capture in point clouds transformed into BIM data for our database then we add to our database such as the climate and irradiance data, so we will test our study building to predict potential PV energy production as schematized in figure 1. Finally, we will use its results to compare with those made with PV sizing software and thus evaluate the building decarbonization. The artificial deep learning models that we will test in our approach are Artificial Neural Network (ANN) and Convolutional Neural Networks (CNN). For comparison, we include machine learning (ML) models like Linear Regression (LR), Bayesian Regularization (BR), Random Forest (RF), Adaptive Boost (AdaBoost), Decision Tree (DT) and Support Vector Regression (SVR). All models will be defined in detail in the next section.



**Figure 1.** The architecture of the proposed methodological approach

## 2.2. Machine & Deep learning models

Machine learning uses input data to train models to make predictions. Several classical ML models have been associated with energy prediction [9], and we have chosen to include them in our results for comparative purposes. Among the ML models we have used are Linear Regression (LR), Bayesian regularization (BR) Random Forest (RF), Adaptive Boosting (AdaBoost), Decision Tree (DT), Support Vector Regression (SVR) and Artificial Neural Network (ANN). In contrast, deep learning is a sub-domain of ML that can be identified as a machine learning technique with several layers of simple, scalable computational elements. Deep learning is generally performed using a stack of layers called a neural network, and CNN is considered a subcategory of artificial neural networks. In this work, we will present results from both types of learning, classical machine learning and deep learning using convolutional neural network (CNN) stacks [13]. The latter is one of the most widely used algorithms, particularly in image processing [14,15]. The CNN architecture consists of 4 layers: the convolution layer, the clustering layer, the ReLU correction layer and the fully connected layer. However, it is little discussed for the decarbonization of BIPV through the prediction of PV energy production.

## 3. Results and discussion

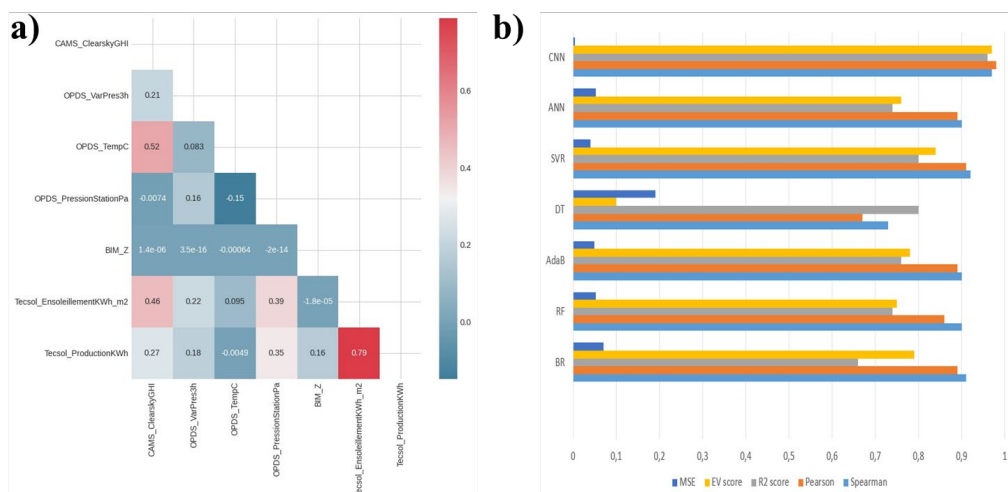
### 3.1. Studied BIPV

In this work, we exploit the daily PV power generation data of six residential properties located northeast of the city of Strasbourg in FRANCE, 48°34' 31" north, 7°46' 17" east, in the Grand Est region. The PV generation capacity is about 14 kW with 65 multicrystalline silicon PV panels and an area of about 112 m<sup>2</sup>, covering about half of the south facade of each building. The PV production capacity of the BIPV system was measured in hours and collected in a database.

### 3.2. Data and Preprocessing

The input dataset for developing our deep learning models is built on the basis of climate data, continuous atmospheric composition information containing historical meteorological data, and building BIM model characteristic data. These data come from the National Solar Radiation Database (NSRDB), Copernicus Atmosphere Monitoring Service (CAMS), Open Data Soft (OPDS) and European PV Geographical Information (PVGIS). Twenty meteorological parameters, 9 solar irradiation parameters and ten BIM parameters were used as predictors. These parameters are DNI: diffuse normal irradiance, DHI: diffuse horizontal irradiance, GHI: Global horizontal irradiance, outdoor temperature (T), relative humidity (RH), pressure (P), barometric trend type TB, precipitable water (PW), wind direction (WD), wind speed (WS), average wind speed every 10mn, and 3h pressure variation. Other BIM data are also added to the database for further customization of building characteristics such as

building facade area, window size, latitude, longitude and elevation. All meteorological variables consist of data collected daily. Before committing to a raw use of the data in our different models, we start by pre-processing all these variables in order to keep only the most relevant, such as the irradiance parameters (GHI and DHI), with a resolution of 1 day. The first general correlation of all the parameters is presented in figure 2a. Indeed, this first correlation tells us more about the weight of the coherence and the influence between the variables. To analyse the degree of correlation between the production of PV energy and the meteorological parameters and the BIM data of the building we will use the path analysis method which will serve to reduce the size of the database by analysing the influence of independent variables on the dependent variables. Thus we can select for example among the irradiance parameters the Clearsky data of GHI. This will allow us to select the variables by degree of influence to integrate them into the ML models and therefore we will only keep the parameters with a correlation greater than 0.2 as shown in the figure 2a. However, the elimination by degree of influence of certain parameters can influence the effectiveness of the models, thus the method presents in its approach the limitations compared to the target in the PV prediction of the building. In order to evaluate the performance of our models, we used evaluation metrics such as coefficient of determination ( $R^2$ ), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE) [10]. In Figure 2b, the results of various machine learning techniques are presented in terms of different scores and errors. The training model was fed with 6413 samples as input data, out of which 80% (8016 samples) were used for training and the rest were used for validation and testing purposes. The model error includes Spearman, Pearson,  $R^2$  score, MSE, and EV score. The results indicate that SVR and CNN models are much more accurate than other models, with an  $R^2$  score of 96% and a Pearson coefficient of 98%, indicating their close proximity to actual production values.



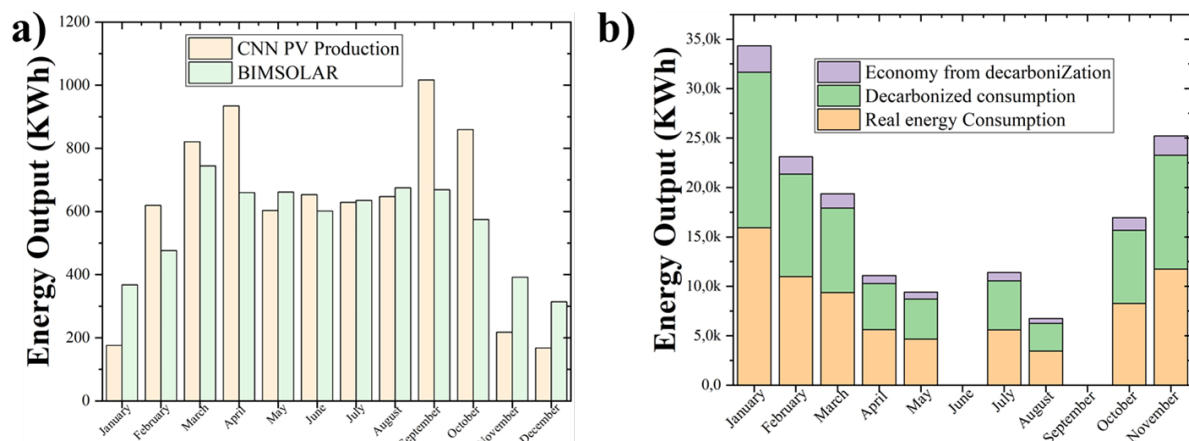
**Figure 2.** a) Correlation matrix between the meteorological variables used in the deep learning models. b) Results of the tested machine learning models.

### 3.3. Building case study

In this part we are going to test our new PV prediction method on a building case study of the engineering school CESI located in Strasbourg in FRANCE. In the first step we collect aerial photogrammetric images of the building and its environment to have the 3D design in point clouds by using a drone with photographic acquisition. Then we performed another process of cleaning and segmentation of facade point clouds in order to select the southern facade; we do not address this part of the study in this paper. Our photogrammetric data will be used to complete our final input database. The second step is to experiment our CNN model in the case study building to visualize the capacity of the PV power production through the medium term prediction for an installation of panels on the facade. The last part is to evaluate the decarbonization of the building with respect its actual energy consumption. The results of our new PV prediction method of the building gave the results exposed in the figure 3. We observe that the PV prediction results of the building correspond to the projection of the 3D PV sizing software



BIMSOLAR as shown in figure 3a. This means that our algorithmic CNN model was able to predict consistently with what we may have as PV power generation. Furthermore, to complete the analysis of these PV prediction results, we wanted to estimate the decarbonization of this study building by calculating the impact of PV energy on CO<sub>2</sub> reductions. The scenario with and without integration of PV panels in the Building has been carried out by H. A. Toosi [16]. They estimate that for roof PV panels, the total CO<sub>2</sub>eq emissions of the building can be reduced by 11.04%, which is equivalent to 17.91 t CO<sub>2</sub> eq avoided over the 30-year building life. However, in our case, the PV panels are arranged in the facade with a large occupation of the surface. Indeed, in our case, our method consists in taking into account the forecast CNN photovoltaic production of this building and its actual consumption of primary energy in kWhpe/year. Thus, the building will consume 9% less energy than today if it had been equipped with panels equivalent to the PV power predicted by our CNN model. In terms of decarbonation savings, this represents 5.1%. Finally, we found that the greenhouse gas (GHG) impact would increase from 6350 to 3704 kgeqCO<sub>2</sub>/m<sup>2</sup> SU.year, indicating a decarbonization of more than 40%, as shown in figure 3b. Finally, we believe that this new method allows us to provide a new projection in the prediction of PV production in a BIPV building use case, with the best possible decarbonization depending on the configuration of the panels on the facade.



**Figure 3.** (a) comparison between CNN model predictions and BIMSOLAR. (b) Real and decarbonized energy consumption with PV prediction by CNN model.

#### 4. Conclusion

In this article, we have proposed a new approach to address the decarbonization process of building integrated photovoltaics (BIPV) through a rapid estimation of PV production. The method uses artificial intelligence (AI), photogrammetry and building information modeling (BIM). The results of our study demonstrate that the deep learning model accurately predicts PV panel production for the BIPV test building, which closely matches subjective panel efficiency. Our innovative approach not only makes it possible to accurately estimate photovoltaic energy potential, but also facilitates the optimization of decarbonization efforts by predicting PV production.

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