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Geospatial Graph Attention Network for High-Resolution Building Facade Photovoltaic Potential Prediction

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Abstract

Accurately predicting the photovoltaic (PV) potential of urban building facades plays a crucial role in the development of photovoltaics. This study proposes an innovative building facade PV potential prediction method based on the Geospatial Graph Attention Neural Network (GGAT). Compared to traditional methods, this approach considers the differences in solar radiation intensity at various heights of the building facade, enabling more precise identification of areas with higher PV potential on the facade. The study focuses on buildings in the Manhattan area of New York City and employs Rhino software and the Ladybug Tools plugin to conduct building solar radiation simulations, obtaining high-quality training data. During the modeling process, the concept of building height stratification is introduced, dividing the building facade vertically into 10 equal-height layers, with each prediction point representing the average solar radiation intensity within that height range. Experimental results indicate that GNN-based algorithms (especially GGAT) outperform traditional machine learning algorithms in predicting solar radiation on building facades. GGAT integrates geospatial features and graph attention mechanisms, enabling more accurate prediction of solar radiation on building facades. Solar radiation intensity exhibits significant differences both in the vertical direction of the building facade and in the horizontal direction (between census tracts). The stratified modeling method can reveal these differences, providing more comprehensive and detailed information for analyzing the PV potential of building facades.

1 Introduction

The world is facing increasingly severe energy crises and global warming issues, necessitating effective measures to address these challenges (Ahmed et al. 2022). As a major consumer of urban energy and a primary source of greenhouse gas emissions, buildings play a crucial role in achieving sustainable urban development and low-carbon transition. By installing solar photovoltaic (PV) systems on buildings, we can fully utilize clean and renewable solar energy resources for power generation, reducing buildings' reliance on fossil fuels and effectively lowering carbon emissions during building operations (Brown et al. 2024). This not only helps mitigate global warming but also makes significant contributions to achieving low-carbon transition and climate change goals in cities.

Building PV systems can be generally classified into two main categories based on their installation locations: rooftop PV systems and facade PV systems (Petter Jelle, Breivik, and Drolsum Røkenes 2012). The former involves installing solar panels on the rooftops of buildings, utilizing the roof space for power generation. This approach is relatively simple to install, does not occupy additional land resources, and does not affect the main structure and appearance of the building. Rooftop PV systems are suitable for various types of buildings, such as residential, commercial, and industrial buildings. On the other hand, facade PV systems integrate solar panels into the exterior walls of buildings, forming a building-integrated photovoltaic (BIPV) curtain wall. This approach not only generates electricity but also serves as a decorative material for the building's exterior, enhancing its aesthetic value.

Accurately predicting the installable area for PV systems on buildings is of great significance for the promotion and application of PV systems (Tian, Ooka, and Lee 2023). The size of the installable area directly determines the capacity of PV systems that can be installed on buildings, which in turn affects the power generation potential and economic benefits of the PV systems. By accurately assessing the installable area of buildings, we can determine the PV power generation potential of buildings and provide a basis for formulating PV system promotion policies and targets. Therefore, developing efficient and accurate methods for predicting the installable area of PV systems is of crucial practical significance for promoting the large-scale application of PV systems in urban buildings.

2 Related works

To gain a comprehensive understanding of the current research status and progress in building PV potential prediction, this study conducts a literature review and analysis based on two categories: rooftop PV potential and facade PV potential (Gassar and Cha 2021).

2.1 Rooftop PV Potential Prediction

Rooftops are ideal locations for installing PV systems, making rooftop PV potential prediction a research hotspot. Due to the relatively easy accessibility of building rooftop data and the simplicity of rooftop PV system installation, this area has received widespread attention, and research methods and techniques have become increasingly mature (Fakhraian et al. 2021).

For example, Singh et al. (Singh and Banerjee 2015) proposed a method for estimating the rooftop PV potential of a region, using Mumbai as a case study. Utilizing publicly available data, GIS analysis, and PVSyst simulation, they estimated the building footprint area ratio and available rooftop area ratio while considering factors such as irradiance, temperature, and tilt angle. The results showed that Mumbai's PV potential was 2190 MW with a capacity factor of 14.8%, capable of meeting 12.8-20% of the daily average demand and 31-60% of the early peak demand. With the development of big data and artificial intelligence technologies, some researchers have begun to explore the use of advanced algorithms for assessing rooftop PV potential. Zhong et al. (Zhong et al. 2021) proposed a general framework for estimating urban-scale rooftop solar PV potential using publicly available high-resolution satellite imagery. They developed a deep learning-based method for automatic extraction of rooftop areas. To address the labor-intensive issue of training rooftop extraction models, they developed a spatial optimization sampling strategy. In a case study in Nanjing, China, the manual cost of preparing the training dataset was reduced by approximately 80%, and the robustness of the extraction model was improved. The total rooftop area in Nanjing was 330.36 square kilometers, with an estimated potential installed capacity of 66 GW and an annual power generation of approximately 49,897 GWh in 2019.

In summary, rooftop PV potential prediction has been widely studied, with research methods and techniques continuously evolving and improving. From early GIS and remote sensing technologies to recent machine learning and deep learning methods, researchers have been exploring new approaches to enhance the accuracy and efficiency of rooftop PV potential prediction. These research findings provide important theoretical foundations and technical support for the planning, design, and promotion of rooftop PV systems.

2.2 Facade PV Potential Prediction

Compared to rooftop PV systems, the potential prediction of facade PV systems has received relatively less attention (Catita et al. 2014). However, with the development of BIPV technology, the application prospects of facade PV systems are becoming increasingly broad. In recent years, more and more studies have begun to focus on facade PV potential prediction and have proposed various novel methods and techniques.

Some studies utilize three-dimensional building models for simulation to assess the power generation potential of facade PV systems. For example, Brito et al. (Brito et al. 2017) used a digital surface model obtained from LiDAR measurements and typical meteorological year data to calculate the PV potential of two typical case studies in Lisbon, Portugal, and compared it with the estimated local electricity demand. The results showed that the rooftop and facade PV potential exceeded the local non-base load demand and could meet 50-75% of the total electricity demand. Considering the solar potential of facades, PV generation could meet the electricity demand during winter noons. Economic analysis revealed that installing PV only on rooftops could result in a payback period of less than 10 years, while a 50-50 split between rooftops and facades would yield a payback period of 15 years. Additionally, Liu et al. (Liu et al. 2023) proposed an innovative method that, for the first time, utilized publicly available satellite imagery and vector maps to construct 3D building models for rural areas and precisely assessed the solar PV potential of rural rooftops and facades. The method was validated using two real 3D village models and on-site solar radiation measurements. The case study showed that south-facing and north-facing rural rooftops, as well as south-facing and west-facing facades, had the highest PV potential grades. North-facing rooftops with a slope of 30° accounted for 32.7% of the total rooftop solar PV potential and should not be neglected in future assessments. The method is cost-effective and can accurately assess rural solar PV potential at both micro and macro scales, contributing to the promotion of rural renewable energy penetration.

From the above review, it is evident that the existing assessment methods for facade PV potential still have some shortcomings. First, they often treat the entire facade as a whole, ignoring the differences in solar radiation intensity at different positions on the facade due to shading from surrounding buildings. This simplified approach may lead to biased assessment results and underestimate the actual PV potential of facades. When the facade is treated as a whole, the contribution of local high-radiation intensity areas may be averaged out, resulting in the entire facade exhibiting a lower average radiation level, masking the PV potential at specific positions on the facade. Second, most high-precision studies have a small spatial scale, and their assessment methods and conclusions may be difficult to generalize to the urban scale. These studies are often based on a limited sample of buildings and may not fully consider the complexity and diversity of the urban environment. Therefore, the existing research results may have limitations in guiding the formulation of facade PV policies at the urban level.

2.3 Objective

To address the aforementioned shortcomings, this study proposes a more refined urban-scale building facade PV potential assessment method that can evaluate the solar radiation intensity at different heights of each building's facade. Compared to traditional methods, this novel approach takes into account the differences in radiation intensity at various heights on the facade, enabling more accurate identification of facade areas with higher PV potential. This method can optimize the economic viability of PV systems by avoiding unnecessary costs associated with installing PV systems in low radiation intensity areas.

3 Methodology

In urban environments, predicting the PV potential of building facades is a complex and challenging task. Building facades are often subject to shading from surrounding buildings, resulting in significant differences in solar radiation intensity at various positions on the facade. Therefore, considering the influence of surrounding buildings on the target building is crucial when predicting PV potential. Traditional methods often struggle to effectively capture the complex spatial relationships between buildings, but Graph Neural Networks (GNNs) (Scarselli et al. 2008) provide a new perspective for addressing this issue.

GNNs can abstract buildings as nodes in a graph structure and represent the spatial relationships between buildings through edges. By propagating and aggregating information on the graph, GNNs can aggregate the features of surrounding buildings onto the target building, thereby more comprehensively considering the impact of the surrounding environment on the target building's PV potential. However, in real urban scenarios, the influence of surrounding buildings on the target building is often imbalanced. For instance, buildings that are closer in proximity, larger in volume, or taller in height may have a more significant shading effect on the target building, while the influence of buildings that are farther away or smaller in volume is relatively weaker.

To address this issue, we introduce the Graph Attention Network (GAT) model (Veličković et al. 2018). Unlike conventional GNNs, the GAT model can adaptively adjust the influence weights between different buildings through an attention mechanism. Specifically, the GAT model calculates an attention coefficient based on the features of buildings (such as height, volume, etc.) to measure the relevance between different buildings. Surrounding buildings that have a greater impact on the target building will be assigned higher attention weights, while those with lesser influence will be correspondingly weakened. In this way, the GAT model can more accurately capture the complex spatial relationships between buildings, thereby improving the accuracy of PV potential prediction.

Furthermore, considering the uniqueness of the building facade PV potential prediction problem, we have innovated and extended upon the GAT model. We observed that, in addition to the features of the buildings themselves, many other geospatial features have a significant impact on PV potential, such as distance and azimuth angle. To fully utilize this geospatial information, we propose a novel model called the Geospatial Graph Attention Neural Network (GGAT). In the GGAT model, we incorporate more geospatial features into the calculation of attention coefficients, enabling the model to simultaneously consider building features and geospatial features, thereby more comprehensively characterizing the PV potential of building facades.

3.1 Building Solar Radiation Simulation

Acquiring high-quality training data is a crucial step in the study of building facade PV potential prediction. To train our proposed GGAT model, we require solar radiation intensity data for building facades. However, directly measuring the solar radiation intensity of every building facade in real-world scenarios is extremely difficult and expensive. To address this issue, we employ building solar radiation simulation methods to generate training data. First, we create three-dimensional models of the buildings in the study area using Rhino software. Next, we perform building solar radiation simulations in Rhino using the Ladybug Tools plugin. During the simulation process, we divide the building facades into multiple grids and calculate the solar radiation intensity received by each grid at different time points. After the simulation is complete, we export the solar radiation intensity data for each grid and associate it with the corresponding building. Through this approach, we obtain a dataset containing building IDs, grid IDs, timestamps, and solar radiation intensities.

3.2 Building Height Stratification

Accurately estimating the solar radiation intensity at different positions on building facades is crucial in predicting PV potential. Traditional methods often treat the building facade as a whole and only calculate the average solar radiation intensity. However, in reality, due to factors such as shading from surrounding buildings and differences in sky view factors, the solar radiation intensity at different heights of the building facade may vary significantly. To more precisely predict the PV potential on facades, we propose a stratified modeling approach.

Our method is based on the following assumption: positions at the same height on the building facade receive the same solar radiation intensity. This assumption simplifies the lighting conditions of the building facade, ignoring horizontal differences and focusing on vertical variations. Although this simplification may introduce some errors, it greatly reduces computational complexity, enabling us to perform building facade PV potential prediction more efficiently. Specifically, we divide the facade of each building vertically into 10 equal layers, with each layer approximately 10% of the total building height. Through this stratification approach, we obtain 10 facade prediction points for each building, with each prediction point representing the average solar radiation intensity within that height range (Figure 1). Compared to traditional holistic modeling methods, our stratified approach can more finely characterize the vertical lighting differences on building facades, thereby improving the accuracy of PV potential prediction.

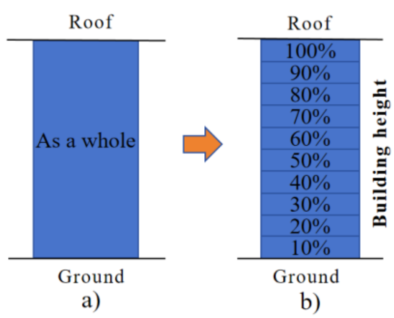

Figure 1. A brief diagram of the traditional method and our stratification method.

4 Results and Discussion

To validate the effectiveness of the GGAT model, we selected buildings in the Manhattan district of New York City (NYC) as the research object. It includes approximately 45,000 buildings in total. To further enrich the dataset, we also introduced other common features of Manhattan buildings, such as building density, building shape coefficient, average height of surrounding buildings, etc. These features were obtained from the NYC open data website or can be derived by analyzing the three-dimensional building models. By combining these geospatial features with the solar radiation intensity data, we obtained a more comprehensive and rich training dataset.

4.1 Model performance comparison

Table 1 presents a performance comparison of six different algorithms in predicting solar radiation intensity and total radiation on building facades. These six algorithms are divided into two main categories: traditional machine learning algorithms and GNNs based algorithms. In the traditional machine learning algorithms, this study selected gradient boosting decision trees (GBDT), random forest, and deep neural networks (DNN). These three algorithms have been widely applied in many fields and can serve as benchmarks for comparison. In the GNNs algorithms, we selected graph convolutional networks (GCN), GAT, and GGAT. GCN and GAT are two models that have received extensive attention in the field of graph learning in recent years, while GGAT is a model specifically designed for the task of predicting solar radiation on building facades based on GAT.

From the experimental results, the three GNNs algorithms generally outperform the traditional machine learning algorithms. Whether in the task of predicting radiation intensity (RMSE and R-Squared metrics) or total radiation, the performance of GCN, GAT, and GGAT is better than GBDT, random forest, and DNN. This indicates that by introducing graph structures and attention mechanisms, GNNs algorithms can better model the spatial relationships between buildings, thereby improving prediction performance. Among the three GNNs algorithms, the GGAT model proposed in this study achieves the best performance. Compared with GCN and GAT, GGAT has significant advantages in both RMSE and R-Squared metrics for predicting radiation intensity and total radiation. This demonstrates that GGAT can more accurately predict the solar radiation on building facades by integrating geospatial features and graph attention mechanisms.

Table 1. The model performance on building facade solar irradiation predictions.

		Facade			
		Irradiation intensity		Total radiation	
		RMSE	R-Squared	RMSE	R-Squared
Machine learning	GBDT	0.7539	0.5181	1.0456	0.6912
	Random forest	0.6653	0.6063	0.9407	0.7500
	DNN	0.7347	0.5199	1.1035	0.6561
GNNs	Graph Convolutional Network (GCN)	0.6451	0.6340	0.8803	0.7932
	Graph attention network (GAT)	0.5945	0.6837	0.8213	0.8425
	GGAT (our work)	0.5774	0.7067	0.8005	0.8635

4.2 The distribution of solar irradiation intensity

Figure 2 and Figure 3 illustrate the spatial distribution of solar radiation intensity on building facades in the Manhattan area at the census tract level, comparing the differences between two modeling approaches: treating the building facade as a whole (traditional method) and stratifying by height (the method proposed in this study).

In Figure 2, the color of each census tract represents the average solar radiation intensity of all building facades within that tract. It can be observed that the solar radiation intensity exhibits significant spatial heterogeneity across the Manhattan area, with tracts in the southern and northern parts generally having higher radiation intensity compared to those in the central part. This may be related to factors such as building height, density, and street orientation. Figure 3 shows the distribution of solar radiation intensity under 10% building height stratification. Each row represents a height layer, from bottom to top: 0-10%, 10-20%, ..., 90-100%. It can be seen that as the height increases, the solar radiation intensity of each tract gradually increases, with colors transitioning from yellow to red. This indicates that the difference in radiation intensity along the vertical direction of the building facade is very significant.

By comparing Figure 2 and Figure 3, we can conclude that the traditional holistic modeling approach ignores the difference in radiation intensity along the vertical direction of the building facade, while the stratified modeling approach can reveal this difference. The solar radiation intensity of building facades not only varies significantly in the horizontal direction (between census tracts) but also in the vertical direction (building height). Therefore, it is necessary to comprehensively consider these two dimensions. The stratified modeling approach provides more comprehensive and fine-grained information for analyzing the PV potential of building facades, which helps to formulate more precise PV deployment strategies.

Overall, these two figures intuitively showcase the spatial distribution characteristics of solar radiation intensity on building facades in the Manhattan area and highlight the advantages of the stratified modeling approach compared to traditional methods. This provides important references for subsequent building PV potential assessment and planning.

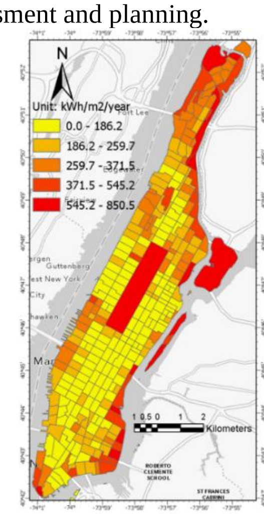

Figure 2. The distribution of facade irradiation intensity at the census tract-level (facade considered as a whole).

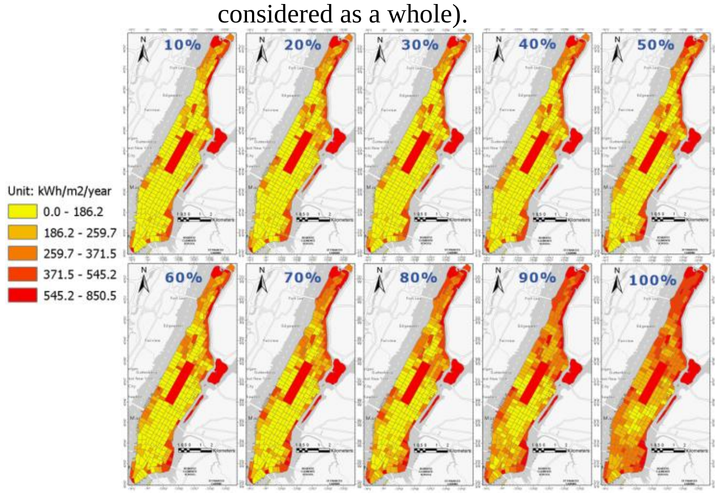

Figure 3. The census tract-level distribution of irradiation intensity when the facade is stratified.

5 Conclusions

The study proposes an innovative building facade PV potential prediction method based on the GGAT model. By incorporating geospatial features into the graph attention network, the GGAT model can more comprehensively characterize the complex spatial relationships between buildings, thereby improving the accuracy of PV potential prediction. Experimental results demonstrate that the GGAT model outperforms traditional machine learning algorithms and other GNN algorithms in predicting solar radiation intensity and total radiation on building facades. This provides a new perspective for utilizing graph learning techniques to address problems related to urban building PV potential prediction.

Furthermore, this study introduces the concept of stratified modeling for building facades. By dividing the building facade vertically into multiple equal-height layers and predicting the average solar radiation intensity of each layer, we can more precisely depict the vertical lighting differences on building facades and reveal information overlooked by traditional holistic modeling methods. Experimental results show that the solar radiation intensity on building facades exhibits significant differences not only horizontally (between census tracts) but also vertically (building height). The stratified modeling approach can provide more comprehensive and detailed information from these two dimensions, offering important references for subsequent building PV potential assessment and planning.

In summary, the stratified modeling method based on the GGAT model proposed in this study provides a new solution for predicting building facade PV potential at the urban scale. This not only helps improve prediction accuracy and optimize the economic viability of PV systems but also provides an important basis for formulating more precise PV deployment strategies. Future research can further expand the GGAT model by incorporating more geospatial factors and exploring more efficient and intelligent building PV potential assessment methods. Meanwhile, applying this method to different cities and climatic conditions can verify its universality and robustness.

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