Location Planning for Solar Power Generation Using Artificial Intelligence

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Overview

To reduce greenhouse gas emissions, governments around the world have enacted policies and targets to encourage renewable energy deployment. For example, China aims to reach 560 GW of solar capacity by 2025 and 804 GW of solar capacity by 2030 (253.4 GW of solar capacity in 2020) [1]; the United States targets to power 5 million American homes with community solar projects by 2025, which requires 700% growth of current capacity (3.3 GW of solar capacity in 2020)[2].

Renewable energy has grown exponentially in Taiwan in the past decade—especially solar power growing from 0.035 GW in 2010 to 5.817 GW in 2020. The government rencently published "Taiwan's Pathway to Net-Zero Emissions in 2050", aiming to increase the share of renewables in the country's electricity generation to 60-70%[3]. For solar power, the goals are to deploy 20 GW by 2025, add 2 GW of solar power capacity annually from 2026 to 2030, and expand the capacity to 40 ~80 GW by 2050. The cumulative installed solar capacity has reached 7.9 GW by the end of 2021, accounting for the largest share across all sources of renewables in Taiwan. Given that 12.1 GW of solar capacity will be added in the coming years, prioritizing the appropriate locations for solar panel deployment to maximize its capacity utilization becomes an urgent issue.

The actual output of a solar panel depends on a variety of factors, including climate, environmental, and geomorphological characteristics. Despite being challenging, predicting long-term (i.e., month or year) solar power generation precisely by region is crucial to optimal location planning for solar deployment. With a specific focus on Taiwan, this paper is offered as a contribution toward assessing the long-term solar power generation potential using artificial intelligence techniques.

Methods

Artificial intelligence, with its ability to identify patterns or functions in complex, massive datasets, has been widely applied in many practical applications such as face recognition, language recognition, handwriting recognition, and has had great impacts on our daily life. Various machine learning techniques, particularly Recurrent neural network-Long Short Term Memory (RNN-LSTM), were proposed to forecast solar power generation using historical time series data [4][5][6].

In this study, we use three artificial intelligence methods to forecast solar power generation by region in Taiwan: eXtreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), and RNN-LSTM. XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework; MLP contains several layers of input nodes connected as a directed graph between the input and output layers; RNN-LSTM consists of a cyclic memory cell and three types of gates (input, forget, and output gates), which allows information to persist.

Regarding the model inputs, we first choose ten meteorological factors based on the previous studies[6][7][8][9]: station pressure (hPa), temperature (°C), relative humidity (%), wind speed (m/s), precipitation (mm), sunshine hours (hour), sunshine rate (%), global radiation (MJ/m^2), daily maximum UV index (0~15), cloud amount (0 ~10). Then we conduct Pearson correlation coefficient and Spearman's rank correlation coefficient analysis to find out whether there is an insignificant feature among these factors. The model output is the solar capacity factor, which is a ratio of actual power generated by a plant divided by its maximum output.

In this work, the historical meteorological data is collected from the Central Meteorological Administration in Taiwan[10], from 2017 to 2021 with the daily resolution. The installation capacity and solar power generation are gathered from the Taiwan Power company[11]. Because the locations associated with the meteorological data are different from those of the solar power plants, we apply the Kriging interpolation method to estimate the values of the selected training features in the plant locations using a linear combination of observations.

To evaluate the loss of the predicted results, we calculate different commonly used metrics including mean squared error (MSE), root-mean-square error (RMSE), normalized root-mean-square error (nRMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R squared).

Results

Correlation coefficient analysis

The relationships between solar power generation and the selected ten meteorological parameters are examined by using the historical data in Taiwan from 2017 to 2020 (i.e., a total of 32,345 sets of data). The correlation coefficient analysis results (Table 1) suggest that station pressure and wind speed are insignificant features (i.e., the absolute value of correlation coefficient is less than 0.1), thus being dropped from our training data.

Table 1. Pearson and Spearman's rank correlation coefficient

Relationship	Pearson correlation coefficient	Spearman's rank correlation coefficient
Solar power/ Station pressure	0.02	-0.07
Solar power/ Temperature	0.34	0.36
Solar power/ Relative humidity	-0.27	-0.28
Solar power/ Wind speed	-0.03	0.03
Solar power/ Percipitation	-0.23	-0.35
Solar power/ Sunshine hours	0.63	0.66
Solar power/ Sunshine rate	0.61	0.62
Solar power/ Global radiation	0.64	0.66
Solar power/ Daily maximum UV index	0.35	0.39
Solar power/ Cloud amount	-0.45	-0.51

AI model prediction results

XGBoost, MLP, and LSTM models are trained and tested using 2017~2021 dataset (i.e., a total of 41,679 sets of data: 80% for training, 20% for testing). Different evaluation metrics are used to measure the performance of the prediction models and summarized in Table 2. We find that LSTM model gives the best performance for all the measurements except for MAPE; that is because MAPE produces infinite values when the actual values are close to zero—which is a common occureence in renewable energy.

Table 2. Comparison of the AI-based models testing results in performance evaluation

	XGBoost	MLP	LSTM
	Test dataset	Test dataset	Test dataset
MSE	0.0012	0.0012	0.0010
RMSE	0.0345	0.0343	0.0315
nRMSE	0.1093	0.1087	0.1001
MAE	0.0260	0.0264	0.0240
MAPE	0.3418	0.3455	0.3571
R squared	0.6988	0.7021	0.7475

Conclusions

This study presents three AI models for predicting the daily solar power capacity factor output of potential solar PV systems at new sites. Such models can help support the power deployment strategy and feasibility analysis when the meteorological data—global radiation, sunshine hours, sunshine rate, cloud amount, daily maximum UV index, temperature, precipitation, and relative humidity—are available. To improve the predictive accuracy, satellite data is being collected for better meteorological data quality and other AI models such as Transformer will be explored.

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