Solar Power Generation Forecasting via Multimodal Feature Fusion (Student Abstract)

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Abstract

Solar power generation has recently been in the spotlight as global warming continues to worsen. However, two significant problems may hinder solar power generation, considering that solar panels are installed outside. The first is soiling, which accumulates on solar panels, and the second is a decrease in sunlight owing to bad weather. In this paper, we will demonstrate that the solar power generation forecasting can increase when considering soiling and sunlight information. We first introduce a dataset containing images of clean and soiled solar panels, sky images, and weather information. For accurate solar power generation forecasting, we propose a new multimodal model that aggregates various features related to weather, soiling, and sunlight. The experimental results demonstrated the high accuracy of our proposed multimodal model.

Introduction

With escalating concerns regarding global warming, the emphasis on solar power generation and the consequent need for accurate forecasting has markedly increased. However, forecasting solar power generation faces two significant challenges due to the outdoor installation of solar panels. The first challenge is panel soiling; when exposed to the natural environment, solar panels accumulate various types of soiling, such as bird droppings or dirt, which can significantly reduce power generation efficiency. The second challenge involves weather changes. As sunlight travels through the atmosphere, various weather conditions can diminish its intensity before it reaches solar panels, consequently reducing the amount of solar power generated.

Existing studies have addressed these challenges separately. For example, Mehta et al. proposed the DeepSolarEye model, which uses panel images and weather factors to forecast power loss, soiling location, and soiling type. However, the exact amount of solar power generation could not be determined because the reduction in power generation was considered a classification problem. Nie et al. proposed the Stanford University Neural Network for Solar Electricity Trend (SUNSET) model that forecasts solar power generation using sky images. Although the SUNSET model extracts sunlight-related features from sky images, it cannot respond to solar power generation changes due to the solar panel's condition. In other words, existing studies have proven that weather-, soiling-, and sunlight-related features influence solar power generation. However, responding to solar power generation reduction is challenging because existing studies fail to consider various environmental factors.

This paper proposes a novel multimodal model for forecasting solar power generation. The main challenge in model construction is the dataset. For this, we collected a CBNU-SolarPower dataset containing images of clean and soiled solar panels, sky images, and weather information. As far as we know, this is the first multimodal dataset collected for forecasting solar power generation. In addition, we propose an ensemble network architecture to fuse multimodal features that represent soiling, sunlight, and weather extracted from the CBNU-SolarPower dataset. The experimental results indicate that the proposed model significantly improves forecasting accuracy when combining weather, soiling, and sunlight information.

Proposed Method

Data collection. A solar power generation testbed was constructed at the Chungbuk National University campus in Cheongju, South Korea. Data related to solar power generation, panel soiling, and sky images were collected from the testbed. Specifically, we employed the following strategies to collect the multimodal data. First, the solar panel images were collected weekly from March 22 to May 24, 2023. Image collection was conducted at 1-minute intervals during 9:00-10:30 AM, 1:30-3:30 PM, and 4:30-6:00 PM time slots. Each cycle was repeated several times during the collection period. The cycle consisted of artificially changing the shape and amount of soiling for a minute and leaving it in natural condition for three minutes. It is important to note that the soiling on the panels was artificially created by considering various factors related to the Korean environment. Consequently, 2,317 solar panel images were collected with bird droppings, pine pollen, plastic bags, sand, and shadow soiling. We used the Computer Vision Annotation Tool (CVAT) to annotate the soilings on the solar panels manually. Second, sky images were collected using a camera installed near the solar panels. Third, weather information related to temperature, humidity, wind speed, and solar

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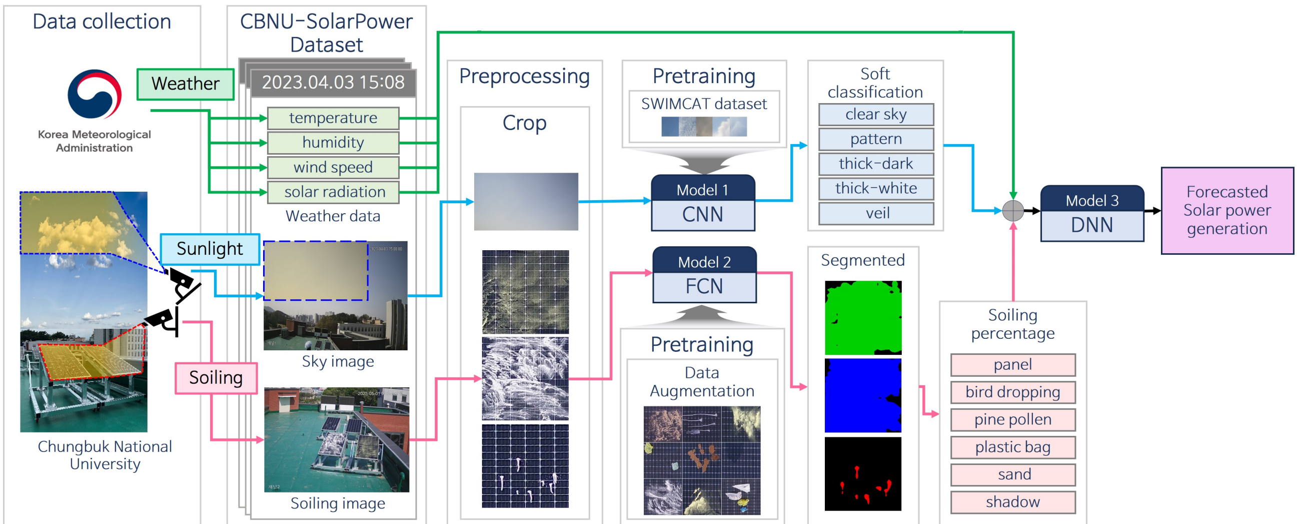

Figure 1: The overall proposed model is divided mainly into three modalities: 1. weather, 2. soiling, and 3. sunlight. Later, all modalities are aggregated, and Model3 DNN performs solar power generation forecasting.

radiation was collected from the Korea Meteorological Administration for the same period as solar panel images (i.e., from March 22 to May 24, 2023).

Modalities. The purpose of each modality is to extract features related to soiling and sunlight using the CBNU-SolarPower dataset. To achieve this purpose, we first removed the image background to highlight the solar panel and sky. Then, we train the proposed model using pre-processed images. Specifically, we use Fully Convolutional Network (FCN) (Long, Shelhamer, and Darrell 2015) extracted soiling-related features from solar panel images. FCN calculates the percentage of classes in each image using a segmented mask image. It is important to note that the accuracy of soiling segmentation of the FCN model was 71.2% in terms of mean Interaction over Union (mIoU). Second, we used Convolutional Neural Network (CNN) to detect cloud formations in the sky by extracting sunlight-related features from sky images. For this, we used the Singapore Whole Sky IMaging CATegories Database (SWIMCAT), which is a cloud classification benchmark dataset (Dev, Lee, and Winkler 2015), for model training. As a result, the model detected the following categories of cloud formation: clear sky, patterned clouds, thick dark clouds, thick white clouds, and veil clouds.

Aggregation and Forecasting. We concatenated the data obtained from each modality and fed the result results into the Deep Neural Network (DNN) to forecast solar power generation.

Performance Evaluation

Training details. Each model uses a single NVIDIA Quadro RTX 6000 GPU. Table 1 lists the hyperparameters yielding the highest performance of our proposed models. Each dataset was divided into 70% training, 20% validation, and 10% testing sets for model learning.

	CNN	FCN	DNN
Optimizer	Adam	SGD	RMSprop
Loss function	CrossEntropy	CrossEntropy	MSE
Learning rate	0.001	$10e^{-14}$	0.001
Epoch	500	100	1000
Momentum	N/A	0.99	0.0
Weight decay	N/A	0.0005	N/A
Batch size	32	4	4

Table 1: Hyperparameters of each model

Modalities	***R*^{2}*(%)***	***RMSE***	***MAE***
Weather	50.54	57.70	46.66
Weather+Soiling	75.26	40.80	30.67
Weather+Soiling+Sunlight	**81.79**	**35.01**	**25.44**

Table 2: Result of experiments

Result. Table 2 shows the experimental results in terms of R^2, Root Mean Square Error ($RMSE$), and Mean Absolute Error (MAE). From the table, we can observe that the forecast accuracy notably increases by 24.72% and 6.53% when adding a modality to the concatenation. This supports the need to consider various environmental factors for forecasting.

Conclusion and Future Work

This study proposes a new multimodal method for forecasting solar power generation. Features related to weather, soiling, and sunlight were extracted from the CBNU-SolarPower dataset. Although the proposed model is strong for various environmental variables, data collection is expensive. In the future, we plan to conduct research to recognize weather conditions through solar panels.

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