

이중 SGRU-DCNN 기반 태양광 발전 예측

Dual Stream Hybrid Model for Solar Power Forecasting

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Abstract

Solar power generation provides significant environmental and economical advantages, in comparison to nuclear and fossil fuel. Although, due to the unpredictable and intermittent patterns in the data, it is difficult to forecast power generation effectively. Therefore, in this study, we proposed stacked Gated Recurrent Units (SGRU) and deep Convolutional Neural Networks (DCNN) for power generation forecasting. Initially, data preprocessing strategies are applied such as imputing missing values and data normalization, to convert the raw input data into refined format. The proposed dual SGRU-DCNN is then used to learn temporal pattern via SGRU and spatial pattern via DCNN, followed by a feature fusion layer, where the outputs vectors of both networks are integrated into a single representative feature vector and fed to fully connected layers for final forecasting. Furthermore, the effectiveness of the SGRU-DCNN is evaluated via two benchmarks where the SGRU-DCNN achieved optimal performance among state-of-the-art (SOTA) architectures.

Keywords: *Solar power prediction, stacked GRU, Deep CNN, Dual stream network*

1. Introduction

Global climate change and financial collapse are major concerns associated to energy generation via fossil fuels[1]. Power consumption worldwide has been increasing by 2% annually, primarily relying on nuclear and fossil fuels, resulting in a significant rise in Greenhouse Gas (GHG) emissions [1]. Fossil fuel-based energy generation also leads to an energy crisis and natural hazards, such as resource depletion and environmental pollution, negatively impacting human lives [2]. Consequently, governments are prioritizing the exploration of renewable energy resources to overcome the drawbacks of fossil fuel-based generation. Solar power generation is a particularly viable solution compared to nuclear and fossil fuel-based methods due to its clean, green, and naturally replenished characteristics. However, the uncertainty patterns in solar power generation data pose stability challenges to power systems, especially when integrating solar energy on a large scale. To solve certain problems, effective renewable power generation forecasting is the sole solution to decline the uncertainty, which is

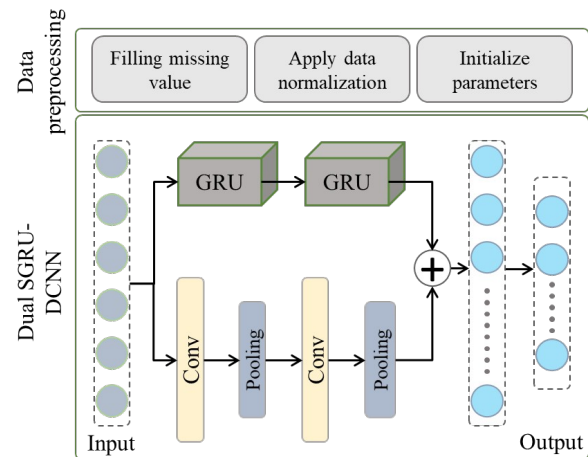


Figure 1. The high-level framework of dual SGRU-DCNN.

significant for management, planning and energy systems operation [3]. Several techniques have been employed in literature for effective power forecasting [4]. Among those, the hybrid techniques have exhibited superior performance and achieved SOTA results, these techniques include CNN-RNN [4], CNN-LSTM [3], Convolutional LSTM (CLSTM) [5], and LSTM-CNN [1]. However, the recent literature is focused on developing hybrid models based on stacked layers for solar power forecasting where historical data on solar power have a limited number of patterns which is difficult to acquire spatiotemporal information at a time via stacked layer phenomena. Therefore, we

employed a dual SGRU-DCNN architecture for power forecasting, where the dual stream mechanism enables the model to extract spatiotemporal features from historical data at the same time. The output streams of these networks are then concatenated and fed to dense layers for final forecasting. Additionally, we compared the proposed SGRU-DCNN via two benchmarks and achieved the lowest error-rate as compared to SOTA methods.

2. THE PROPOSED METHOD

The high-level framework of this study is given in **Figure 1**. Initially, preprocessing techniques are applied to refine the data. The refined data are then parallelly fed to dual SGRU-DCNN architecture to extract spatiotemporal patterns. Followed by a fused layer, which concatenates the output streams of networks in a single representative and transfers to the dense layers for final forecasting. The dual mechanism enables the model to acquire both spatiotemporal features at the same time from the historical data. In addition, the SGRU-DCNN can deal with irregular complex patterns and can acquire uncertain information from solar power generation data.

3. Experiment result

The effectiveness of the proposed model is evaluated using two benchmarks: DKASCASA-2, and DKASCASA-1B. The solar power plants in DKASCASA are currently operational and collect the data with a resolution of five minutes. The DKASCASA-2 was installed in 2010 with a production capacity of 26.5 kW. Similarly, the

Table I. Technical details of each dataset.

Dataset	Specificati	Value
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	on	
DKASCASA-2	Manufacturer	Eco-kinetics
	Duration	8-24-2010 ~ 8-22-2020
	Resolution	5 minutes
DKASCASA-1B	Manufacturer	Trina
	Duration	8-14-2013 ~ 7-1-2021
	Resolution	5 minutes

DKASCASA-1B was established in 2009 with a generation capacity of 23.4 kW. The technical and statistical information of these datasets are tabulated in **Table I**. Furthermore, the difference between the actual value and the observed value

Table II. Comparative analysis over DKASCASA datasets.

Dataset	Method	MSE	MAE	RMS E
DKASCASA-2	CNN	0.2653 7	0.4095 4	0.51 5
	GRU	0.1270 9	0.1807 4	0.35 7
	LSTM	0.1621 1	0.2316 8	0.40 3
	SGRU-DCNN	0.0469 5	0.1417 3	0.21 7
DKASCASA-1B	CNN	0.2920 4	0.3759 8	0.54
	GRU	0.2440 3	0.2837 2	0.49 4
	LSTM	0.1904 5	0.3077 3	0.43 6
	SGRU-DCNN	0.0268 8	0.1219 8	0.16 4

of SGRU-CDNN and other DL methods are calculated based on MSE, MAE, and RMSE. The models were executed using a Core i7 processor (32GB RAM), GeForce RTX 1080 GPU (16GB RAM), and Windows 10 OS with Python version 3.6 using Keras with TensorFlow backend.

3.1. Comparative analysis

In this section, various experiments are

conducted using DL models including CNN, GRU, and LSTM, before choosing the proposed SGRU-DCNN, where the performance of each model is

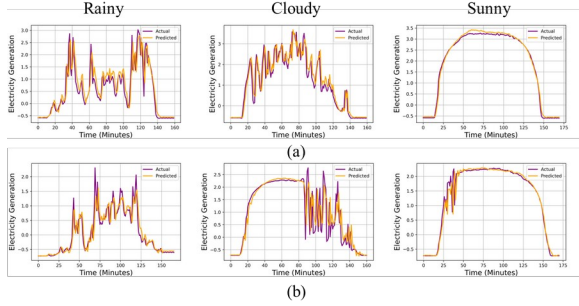


Figure 2. SGRU-DCNN model performance for different days over (a) DKASCASA-2 and (b) DKASCASA-1B.

given in **Table II**. The experimental results demonstrated that the DL-based requires further improvement in terms of evaluation metrics. The dual SGRU-DCNN achieved a minimum error value for both datasets, which is 0.04695, 0.14173, and 0.217, of MSE, MAE, and RMSE, respectively, for DKASCASA-2. Similarly, the SGRU-DCNN achieved 0.02688 MSE, 0.12198 MAE, and 0.164 RMSE error values over DKASCASA-1B. And Figure 2 illustrates the visual results of our proposed network for different days.

3.2. Comparison with SOTA methods

The proposed dual SGRU-DCNN is compared with

CNN-LSTM [3], LSTM-CNN [1], and WPD-LSTM [2]

Table II. Comparison with SOTA methods.

Method	RMSE	MAE
CNN-LSTM [3]	0.693	0.294
LSTM-CNN [1]	0.621	0.221
WPD-LSTM [2]	0.2357	-
SGRU-DCNN	0.164	0.12198

using RMSE and MAE as presented in **Table III**. In this study, the experimental results illustrate that the dual SGRU-DCNN outperformed and achieved the lowest error

values: 0.164 RMSE and 0.121 MAE. In summary, the proposed dual mechanism effectively integrates temporal and spatial information using SGRU and DCNN, respectively. This integration enhances model performance compared to hybrid techniques, which may have less optimized fusion of spatial and temporal features. The Dual Stream architecture excelled in power generation forecasting, due to its separating relevant information, enhancing feature extraction, and enabling multi-modal fusion. These advantages lead to effective forecasts.

4. Conclusions

In this study, we proposed a dual SGRU-DCNN architecture for solar power forecasting and evaluated its performance using benchmark datasets. Extensive experiments are performed over different DL-based approaches before choosing the SGRU-DCNN. In addition, we also conducted a comparative analysis with different SOTA techniques where the SGRU-DCNN achieved better performance comparatively. In the future, we plan to explore new technologies in the domain of energy such as probabilistic forecasting, incremental learning, and active learning, to forecast power production more effectively.

Acknowledgment

This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (2021R1A2B5B02087169).

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