Development of an Intelligent IoT Platform for PV Power Plant Monitoring and Control

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***Abstract*—PV power plants are a promising renewable energy source nowadays. However, due to the highly stochastic properties of renewable energy, monitoring and controlling PV power plants is not an easy task, especially when having to monitor and control multiple PV power plants at the same time. With the help of recent developments in IoT platforms and AI technology, a monitoring system can be developed to solve the issues. An IoT platform that utilizes a web server to monitor and control multiple PV power plants is implemented and presented. LSTM and BiLSTM models are also developed to produce day-ahead PV power generation forecasting by using weather data. The trained model is implemented in the web server, and the BiLSTM achieves a 9.67% forecast error when compared to measured PV power generation data.**

***Index Terms*—IoT platform, PV power plant, monitoring system, forecasting.**

I. Introduction

PV power plants generate electric energy by converting sunlight's radiation into electricity. Naturally, renewable energy, including solar radiation, is highly stochastic. The energy intensity is always changing. The volatility of the solar radiation energy increases the difficulty of controlling and predicting the generated power. Hence, a complex and sophisticated control method is required to effectively operate the PV power plant and achieve maximum results.

In contrast to non-renewable energy sources, which use a turbine to generate electric energy in alternate current (AC), a PV power plant generates energy in direct current (DC), which the power grid cannot use directly. Therefore, the generated energy is stored in a battery for a while. An inverter is also used to convert the stored energy into AC, ready to be consumed by the grid. Many components are incorporated into the PV power plant, and each component needs to be monitored to improve the effectiveness of the system control.

PV technology is expected to be the major world electricity source and is important for future power systems [1]. The usage of PV technology is crucial to transforming the electricity sector, where radical energy and digital transitions are required to achieve a decarbonized future [2]. Radical energy transitions can lead to higher utilization of renewable energy and minimize the share of non-renewable energy.

To achieve these goals, sophisticated monitoring, operation, and maintenance strategies are required. With the improvement of modern PV plants, they are able to generate an enormous amount of data. Hence, a data-driven operation and maintenance method is more favorable because the generated data is highly valuable and can be processed further to provide meaningful information. The extracted information is useful to improve the PV plant's performance, increase efficiency, and maintain PV plant safety.

Recently, the fields of artificial intelligence (AI), cloud computing, and the internet of things (IoT) have grown vastly. The growth of those technologies enables the establishment of enhanced PV power plant monitoring systems. The AI model can be utilized to monitor faults or abnormalities in PV power plants [3]–[5]. Besides, PV power plant forecasting is also possible by using an AI model [6]–[9].

In this paper, the implementation work of the national PV power plant monitoring system is presented. The monitoring system is developed to remotely monitor and control multiple PV power plants that are separately located in a distant location. The IoT platform architecture to establish the monitoring system is presented. Also, an AI model is being developed to predict PV power generation. The day-ahead PV power generation prediction is useful to improve the quality of decision-making.

II. System Overview

A. IoT Platform

In this work, an IoT platform is developed to monitor multiple PV power plants. The monitored PV power plant is located in a separate location, with each PV power plant located in a different city in South Korea. In each PV power plant, hundreds of PV panels are equipped, including an energy storage system (ESS), a power conditioning system (PCS), and a weather station. The IoT platform should be able to collect data from each PV power plant, store all the data in a database, and provide an analysis based on the collected data.

From each PV power plant, the sampling time is set to one minute, meaning that every minute the monitoring system will receive thousands of data points from each PV power plant. Receiving a huge amount of data at the same time may slow the server's performance. Therefore, in this work, a three-tier IoT platform is utilized. Instead of using only one server, in a

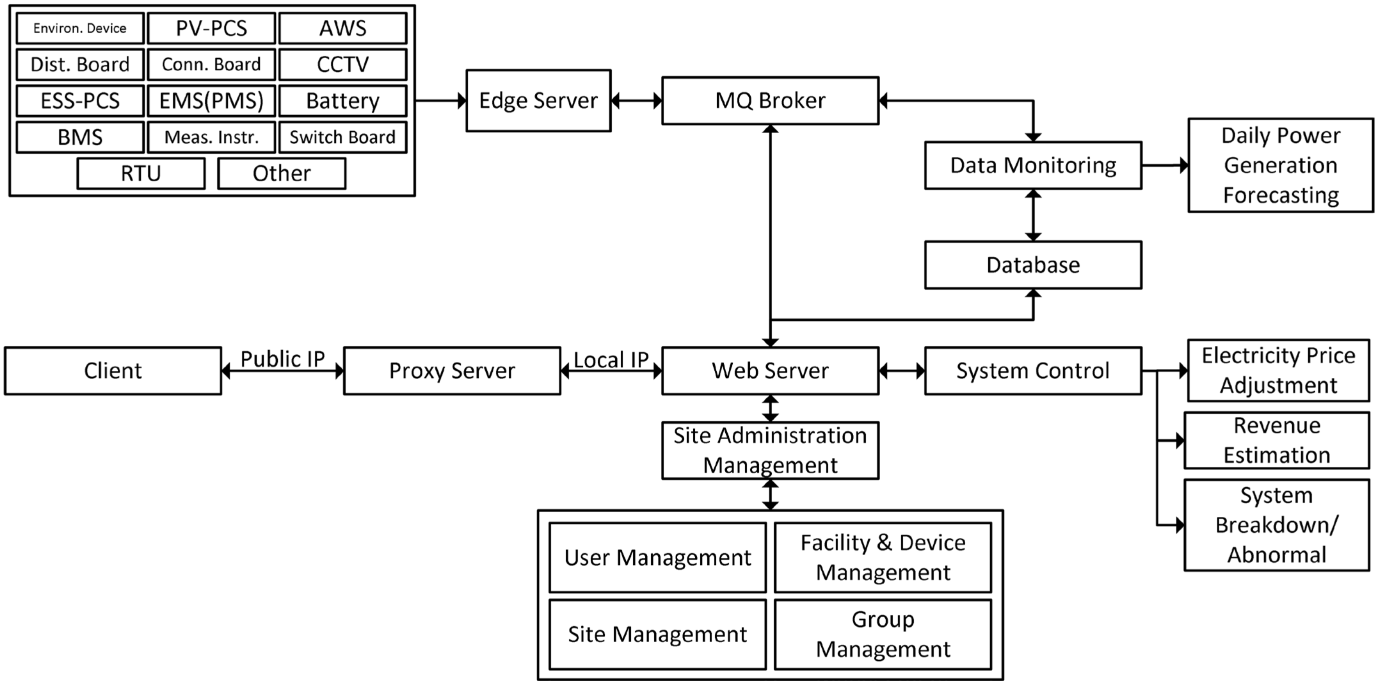

Fig. 1. Architecture of the developed IoT platform for monitoring the PV power plant.

three-tier IoT platform, an edge server is utilized and located between the device layer and the cloud server.

Generally, an edge server is located near the device layer or data source. By using edge servers, the latency in data transmission can be minimized. More importantly, the edge server can reduce the load on the cloud server. In this work, the edge server is located in each PV power plant, where each PV power plant has one edge server. All sensors in the PV power plant will send the data to the edge server. On the edge server, the data is stored in the local database and relayed to the cloud server. Also, on the edge server, an AI model is developed to perform day-ahead PV power generation prediction.

As depicted in Fig. 1, The edge server receives data from all sensors in the PV power plant. Then, the edge server communicates with the cloud server by sending the data to the message queuing (MQ) broker that is located on the cloud server. MQTT is utilized as the MQ broker in this work. MQTT has a publish-subscribe work mechanism that eases communication between the edge and cloud servers.

On the cloud server, a web server is used to orchestrate the system. The web server is developed using the Flask framework, which uses the Python programming language. The web server coordinates all functions to monitor and control the PV power plant. The client request to monitor and control the PV power plant is handled by the web server. The coordination of the edge server is also controlled by the web server.

The web server also performs site administration management, which includes the following functions:

- User management: control the web server's user access and classify the user types.
- Site management: manage and control the settings of each PV power plant connected to the monitoring system.
- Facility & device management: manage the sensors and devices installed in each PV power plant.
- Group management: manage the user access based on the group of PV power plants.

System control functions are also developed on the web server. The system controls provide the following functions:

- Electricity price adjustment: manually adjust the system electricity price to support energy trading.
- Revenue estimation: based on the electricity price and forecasted PV power generation, the revenue can be estimated and is useful for energy trading.
- System breakdown/abnormal: monitor abnormalities in each connected PV power plant and provide notification when abnormalities occur.

A database system is crucial to the development of the IoT platform because it stores all data related to the operations of multiple PV power plants. MariaDB was chosen to be the database in this work due to its excellent features. The database stores all collected sensor data from all connected PV power plants. Besides that, the database also stores data related to user management and device management.

By developing a web server for the IoT platform, easier operation and maintenance of the monitoring system can be achieved. Only by accessing the web server on the cloud server, the client monitor and control the edge server, sensors, and devices that are installed in each PV power plant.

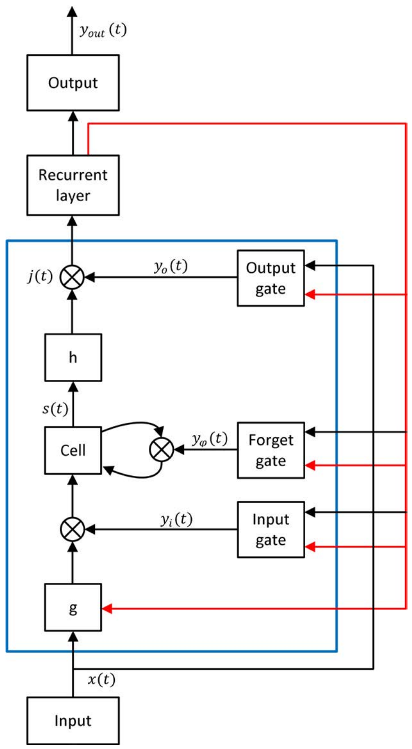

Fig. 2. Architecture of the LSTM model for day-ahead PV power generation forecasting.

B. Day Ahead PV Power Generation Forecasting

The developed monitoring systems are expected to support automatic energy trading with the power grid. Therefore, day-ahead PV power generation forecasting is important to help with decision-making in energy trading. By knowing the future generated power, a decision about whether to keep the generated electricity in the ESS or sell it to the power grid becomes easier.

To generate day-ahead PV power generation forecasting, a long short-term memory (LSTM) model and bidirectional LSTM (BiLSTM) are utilized, as shown in Fig. 2. The PV power generation is largely affected by the weather in the surrounding area of the PV power plant. The solar radiation intensity, cloud position, and cloud size could affect the generated power. Therefore, to develop the forecasting model, weather data is used as input. The weather data is acquired from the Korean Meteorological Agency (KMA) through API access. Every hour, the web server queries the weather data API to retrieve the latest weather data in each PV power plant area.

Because the real weather data measurement from KMA is available up to *D-1*, current-day measured weather data cannot be acquired. Hence, additional input of forecasted today's weather data is utilized where the forecasted weather data is also retrieved from the KMA. As such, the LSTM and BiLSTM models have an input dimension of 10, where 5 is from *D-1* measured weather data and another 5 is from today's forecasted weather data. The features used from measured and forecasted weather data are temperature, humidity, solar irradiance, cloud, wind speed in x direction, and wind speed in y direction. Meanwhile The length of the input is 24, which represents each hour in a day.

The input of LSTM and BiLSTM, which is shaped as (10, 24), is used to train the LSTM and BiLSTM models to produce next-day hourly PV power generation. Hence, the output of the LSTM model is in the form of (1,24), which expresses each hour in a day. To train the LSTM model, the real data of generated PV power is utilized for each PV power plant.

Fig. 3. Screen of the monitoring system of multiple PV power plants in South Korea.

III. Implementation Results

A. IoT Platform

The IoT platform is developed based on the architecture shown in the previous section. As depicted in Fig. 3, a monitoring screen for national PV power plant generation power is shown. The screen shows cumulated PV power plant generated power from PV power plants that are located in the same province.

The IoT platform has been successfully developed to the point where it is able to retrieve data from all connected PV power plants in real-time. The PV power plant will send new data every one minute, and hence the screen in Fig. 3 is updated every one minute. Fig. 3 also shows that the developed IoT platform is able to manage data from multiple PV power plants and process them together to produce a summary of multiple PV power plant operations. As such, the operator of the PV power plant will be able to monitor and operate multiple PV power plants at the same time.

B. Day Ahead PV Power Generation Forecasting

The LSTM and BiLSTM models are developed using TensorFlow and the Python programming language. For training, the LSTM and BiLSTM models are trained by using the PV power generation and weather data in 2021 for each PV power plant, for a total of 8760 data points. Before using the dataset in training, preprocessing is performed on the dataset.

Previously, in 2021, the PV power generation data was not collected using the IoT platform, causing several missing data points in the dataset. Hence, preprocessing to fill the missing data points is performed by using the nearest interpolation method. Then, the dataset is normalized and scaled into values between -1 and 1. After that, the dataset is transformed into a sliding window format with a length of 24 for the input and output sequences.

After the model training, the trained LSTM and BiLSTM models are retrieved. In training, the performance of the model is measured by the following metrics:

TABLE I
MODEL PERFORMANCE

Model Name	MSE	RMSE	MAE	MAPE	R^2
LSTM	0.0197	0.1404	0.0880	1.7615	0.96
BiLSTM	0.0192	0.1387	0.0757	0.5799	0.988

From Table 1, it shows that the LSTM and BiLSTM models have a promising performance to generate PV power generation forecasts for the day ahead. Based on Table 1, the performance of BiLSTM is better than LSTM in all metrics. Then, the BiLSTM model is chosen and applied to the developed web server to perform real-time day-ahead PV generation forecasting by using the real-time retrieved data. The result is shown in Fig. 4.

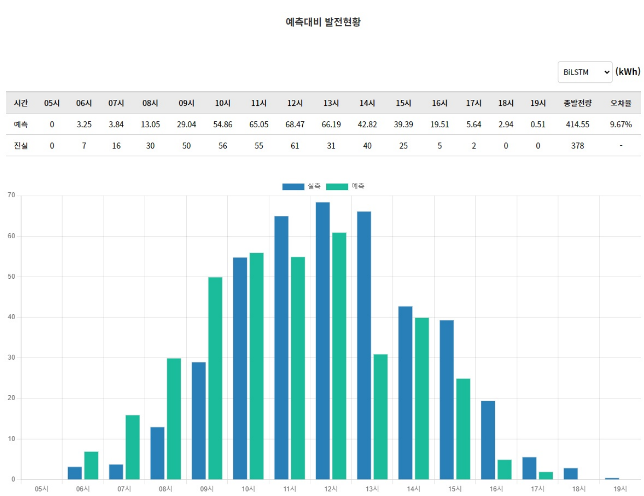

Fig. 4. Real time PV day ahead PV power generation forecasting results.

As shown in Fig. 4, the BiLSTM model successfully performs day-ahead PV power generation forecasting by using real-time PV power generation and weather data. The forecasted PV power generated by BiLSTM is compared with the measured PV power generation. As a result, the total forecast error generated by the BiLSTM is 9.67%, which is relatively small and still acceptable.

IV. CONCLUSION

In this paper, an IoT platform to monitor multiple PV power plants that are located in distant locations is presented. The developed IoT platform includes multiple functionalities to ease the operator's operation and maintenance of the PV power plant. Two AI algorithms, LSTm and BiLSTM, are developed to generate PV power generation forecasts based on weather data. The BiLSTM performs better than the LSTM and is used in the implementation to generate forecasting based on real-time data. The BiLSTM results in 9.67% forecast error compared to the measured PV power generation.

In the future, more types of AI models will be used to perform forecasting. Additionally, the AI model will also be used to perform real-time anomaly detection in each connected PV power plant.

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