Multi-Layer RNN-based Short-term Photovoltaic Power Forecasting using IoT Dataset

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***Abstract*—Photovoltaic power fluctuation in daytime is one of critical problems for the efficient and stable operation of the smart grid. To respond the PV power fluctuation resulting from weather change, the short-term PV power forecasting algorithm using multi-layer RNN is proposed in this paper. It consists of multiple RNN layers using power and meteorological data which are collected by on-site IoT (Internet of Things) sensors. Experimental results showed that the accuracies of the short-term PV power prediction of 5 minutes and 1 hour later using 3 RNN layers with 12 time-step were 98.02% and 96.58% based on the normalized RMSE, respectively. These experimental results confirmed that the proposed short-term prediction algorithm using multi-layer RNN model was applicable to respond the short-term PV power fluctuation.**

***Index Terms*—photovoltaic power, PV forecasting algorithm, multi-layer RNN, IoT (Internet of Things)**

I. Introduction

The use of fossil fuels has long been regarded as one of major causes of environmental pollution. According to the International Energy Agency (IEA), electrical energy is supplied 31.8% by petroleum, 28.1% by coal, 21.6% by natural gas, 4.9% by nuclear power and 13.6% by renewable energy, resulting in 81.5% of the total energy supplied by using fossil fuels [?]. Recently, the renewable energy has attracted attentions as a substitute for fossil fuels, since it does not make any pollution to the environment. Among many renewable energy sources, solar energy is currently the most promising renewable energy source as a substitute for fossil fuels, since solar energy is relatively inexpensive compared with other renewable energy sources.

As the portion of PV power in the total electrical energy has increased, the electrical power supply and demand curve has changed [?]. Since the PV power reaches the maximum at noon and then decreases till the evening, a lot of power demand in the day time could be responded with PV power. However, PV power generation is influenced by the weather fluctuation. This PV power fluctuation caused by the day-time weather change penetrates to the power grid, resulting in the short-term mismatch between the power demand and supply and the instability of the power grid. As the PV power systems are deployed more and more, it increases the threat of grid stability due to PV power fluctuations. It becomes more significant to quickly respond the short-term PV power fluctuation in order to improve the stability and efficiency of the grid operation [?], [?].

The short-term prediction of PV power generation becomes significant for the fast respond to the PV power variation [?]. To forecast PV power generation, the statistical approaches such as ARMA (Auto-Regressive Moving Average) [?] and ARIMA (Auto- Regressive Integrated Moving Average) [?] have been studied using historical data. Furthermore, the machine learning method has been showed superior to the statistical method, given large datasets [?]. To improve the short-term prediction of PV power, several neural network models have been proposed, such as the gray prediction model [?], BP-ANN model [?], the radial basis function (RBF) network [?], and so on [?], [?]. Recently, the online sequential extreme learning machine with forgetting mechanism has been introduce to the short-term PV power prediction [?]. However, even though the online trained data for a prediction were for 48 hours before, the weather prediction model was required as an input, which requiring a large amount of computation. In this paper, we propose the short-term PV power prediction model using onsite PV and meteorological data.

In this paper, we propose the forecasting short-term power generation based on the multi-layer recurrent neural network (RNN) to respond quickly in changing suddenly power demand pattern. The proposed multi-layer RNN to forecast the short-term PV power generation utilizes the on-site weather information, since PV power is affected by weather fluctuation. Internet of Thing (IoT) sensors are installed in the PV generation system to collect real-time data such as the generated PV power as well as the weather information. In this study, we choose a module temperature, a solar radiation, an ambient temperature, a wind speed, and a humidity. The proposed multi-layer RNN consists of 3 RNN layers including layer normalization units. For the further optimization of the predication accuracy and learning speed, we apply the decayed learning rate and gradient clipping method. For experiments, we perform two short-term predictions for PV power generation to respond the weather fluctuation: PV power prediction 5 minutes and 1 hour later. The experimental results showed that the short-term prediction accuracies using the normalized Root Mean Square Error (nRMSE) were 98.02% for 5 minutes later and 93.75% for 1 hour later using 3 layer RNN.

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This paper is organized as follows. The photovoltaic power generation system with IoT is presented in section II. In section III, the short-term PV power forecasting algorithm based on multi-layer RNN is proposed. The experimental data, the performance evaluation and experimental results are discussed in section IV, and then the conclusion remark is given in section V.

II. Photovoltaic Power Generation System with IoT Sensors

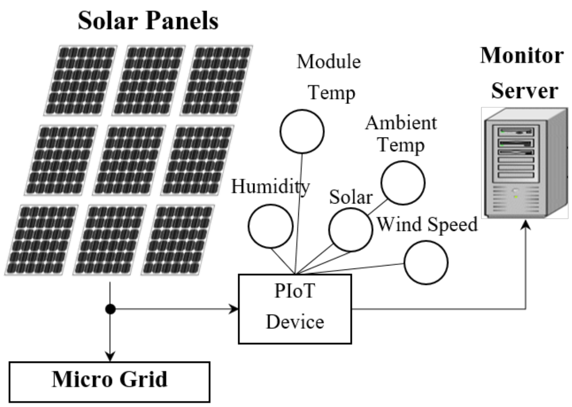


Fig. 1. Photovoltaic power system with IoT sensors.

PV power system generates electricity using solar radiation but is affected by weather changes. Therefore, to forecast the short-term PV power generation, real-time photovoltaic power data as well as weather information are significant. The weather information, provided by various weather information providers such as Korea Meteorological Administration (KMA), can be gathered easily through the internet. However, this weather information is not suitable for forecasting short-term power generation because it is announced after a certain time by observing the weather at intervals of at least one hour. In addition, since the weather data is collected based on a meteorological observation at a certain area, it is difficult to indicate the accurate weather condition of the PV system [?]. In this paper, we propose a real-time data acquisition system using IoT sensors as shown in Figure 1 in order to gather PV data as well as weather information in real time. The DC current and voltage of the PV power generation system are measured to observe power generation data. Also, there are five IoT sensors installed: solar radiation, air temperature, humidity, wind speed, and module temperature. The IoT data measured in real time are transmitted to the monitor server.

III. Multi-Layer RNN-Based Short-Term Power Forecasting

A. The review of RNN

The general artificial neural network (ANN) consists of independent inputs and outputs each other. In general, it has been known that the ANN is not suitable for applications with time-series data since their inputs and outputs of time-series applications are interdependent. For time-series applications, the recurrent neural network (RNN) [?] is proposed as shown in Figure 4. Unlike ANN, an RNN unit takes in input its previous hidden state and the current input, and outputs a new hidden state, as shown in Figure 2. The backpropagation though time (BPPT) algorithm [?] is used for the RNN training, which is described as a dashed line in Figure 2.

The hidden state h_t at time t can be calculated as follows, where the current input is x_t, the recurrent hidden state is h_{t-1} at time $t-1$, σ is the sigmoid function (or other non-linear function like hyperbolic tangent and the rectified linear function) and W and U are the weight matrices and b is the biases:

$$h_t = \sigma(Wx_t + Uh_{t-1} + b) \tag{1}$$

$$y_t = Wh_t \tag{2}$$

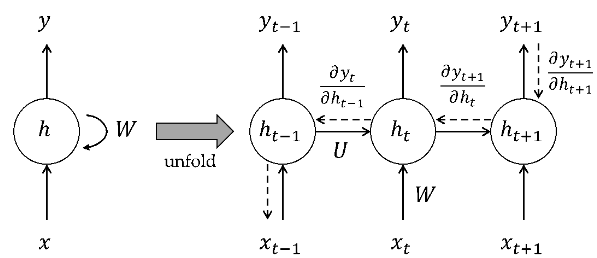


Fig. 2. The structure of the recurrent neural network.

B. Multi-layer RNN-based Short-term PV Power Prediction

To forecast short-term PV power generation, we propose a multi-layer RNN algorithm as shown in Figure 3. To build a multi-layer RNN model, there are three processes: training, valid, and test process. In the training process, multi-layer RNN model is trained using the training dataset. During the training process, the valid process evaluates the performance of the trained deep RNN model every epoch by predicting PV power generation with the valid dataset. After finishing the training process, the test process evaluates the performance of the multi-layer RNN model using the test dataset. The valid and test process are same process, even though they use different datasets.

The proposed multi-layer RNN model takes in input data measured by IoT sensors, which are a PV power, a solar radiation, a module temperature, an ambient temperature, a humidity, and a wind speed in the on-site, in order to predict the short-term PV power generation. The time-series sequenced data are collected periodically by IoT sensors. Before feeding into the model, the pre-process step is applied. At first in the pre-processing stage, long sequence data are formatted by sampling data with an interval requested by short-term prediction model to fit their input format. In the next step, the input data are normalized with the environmental parameters. In general, a photovoltaic system has the maximum capacity to generate electrical power. Also, other environmental parameters have some range of variations according to the weather statistical information. Based on the statistical information, the normalization of input data is computes as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

where x is an input vector, x_{norm} is the normalized input vector x, x_{max} is the maximum value of x, and x_{min} is the minimum value of x. Input normalization helps to improve the performance and execution time of the training process.

The proposed multi-layer RNN model is trained with back-propagation using an Adam optimizer [?] to minimize the prediction loss. Furthermore, the decayed learning rate method is used in the training optimization stage. Also, the gradient clipping is applied in order to limit the magnitude of the gradient. After using the training optimizer to complete the training, the inference model is built and is used to short-term predict PV power generation. Since the data normalization is applied to valid and test dataset in the pre-processing stage, the predicted output should be denormalized to compare with the measured PV power.

IV. Experiment Results

The proposed model is based on the PV power data as well as the on-site weather information instead of the weather forecasting data in the wide area. In this paper, the PV power and weather IoT data were collected from the PV power platform, which was installed on the roof the Engineering Building in Konkuk University, Seoul, Korea. The DC voltage and current generated from the PV panels and the weather data such as sun radiation, module and ambient temperature, humidity, and wind speed were collected from the IoT sensors every 5 minute. For the experiment, the whole data was divided 3 sets: training, valid, and test set, the ratio of which is 3:1:1.
60 20 20
The experiments were performed on the Nvidia Tesla P100 server. The basic training parameters were shown in Table I.

TABLE I
Train Parameters

Paramenter	Value
Learning Rate	0.01
Layers	3, 5, 7
Epochs	10000
Time steps of RNN	12, 24

We performed the training until the end of training epochs and saved the model of the smallest validation test loss during the training. We report the average result for 10 repeated tests using two models: a training model at the end of training epochs and the smallest loss model in validation tests. To evaluate the performance of the prediction in the test sets, nRMSE (normalized Root Mean Square Error) [?] with respect to the maximum capacity of PV system are used as follows:

$$nRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{(\tilde{P} - P)^2}{P_m}} \tag{4}$$

where $\tilde{P}$ is the prediction power, P is the measured power, and P_m is the maximum capacity of the PV power. The nRMSE can be represented as percentage (%) since the normalized power, varying from 0 to 1, is used as an input.

TABLE II
Results of the very short-term prediction error by varying the number of RNN time steps

Time Steps	nRMSE
12	0.019769
24	0.020955
48	0.037106

We designed two experiment sets for short-term prediction: the PV power prediction 5 minutes and 1 hour later. To make the efficient short-term prediction model, we performed experiments by varying the number of time steps of RNN. Table II showed the results varying the number of time steps in the short-term prediction 5 minutes later. As shown in Table II, the prediction of 12 time-step had the smaller prediction error than ones of 24 or 38 time-step.

Table III and IV showed the error of short-term prediction 5 minutes and 1 hour later by varying the number of RNN layers. RNN with 3 layers had the best prediction result and as the number of layers increases, the prediction performance was degraded a little. Since the training and inference time increase as the number of RNN layers, we chose the RNN with 3 layers for overall experiments in the short-term prediction. The accuracy of short-term PV power prediction 5 minutes and 1 hour later were 98.02% and 93.75%, respectively, using 3-layer RNN with 12 time steps.

TABLE III
Results of short-term prediction 5 minutes by varying the number of RNN layers

RNN Layers	nRMSE
3	0.020367
5	0.020679
7	0.020895

Figure 4 reported the prediction results of PV power after 5 minutes for 3 different weathers using 3 RNN layers, 12 time-steps of RNN, and the sampling interval with 5 minutes. Figure 5 showed that short-term PV prediction 1 hour later for 6 consecutive days varying weather condition. Even though weather changed to cloudy or rainy day, Figure 5 and 6 showed the proposed model had the stable prediction results.

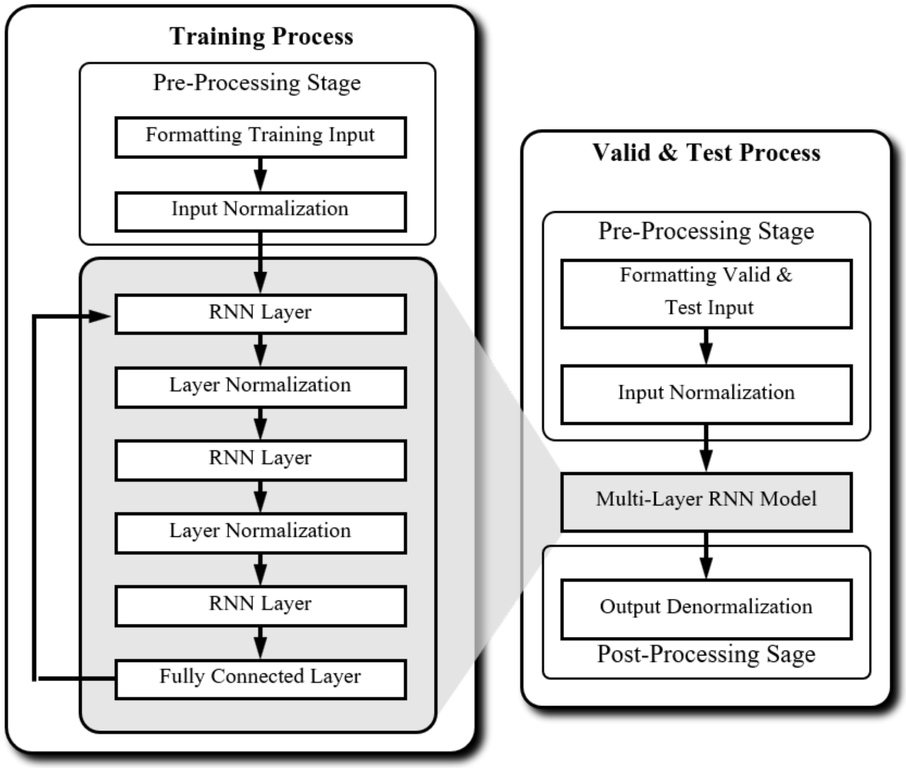
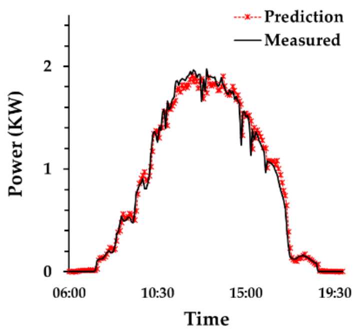
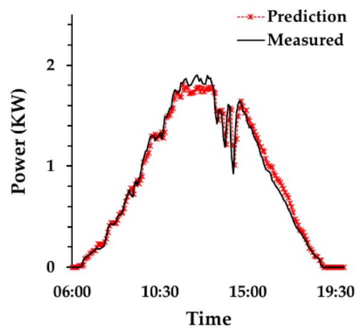


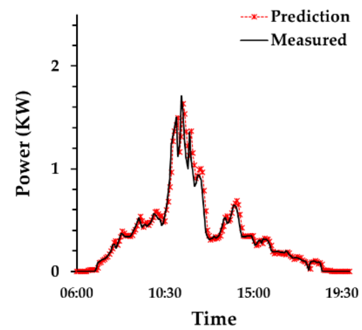
Fig. 3. The proposed Multi-Layer RNN system to forecast PV power generation.



(a) after 5 minutes on Sunny



(b) after 5 minutes on Cloudy



(c) after 5 minutes on Rainy

Fig. 4. The result of forecasting PV power generation after 5 and 15 minutes (Layer=3).

TABLE IV
RESULTS OF SHORT-TERM PREDICTION 1 HOUR LATER BY VARYING THE NUMBER OF RNN LAYERS

RNN Layers	nRMSE
3	0.062429
5	0.066030
7	0.073382

V. CONCLUSIONS

In this paper, the multi-layer RNN-based the short-term forecasting algorithm of PV power was proposed, in order to respond to the PV power fluctuation. The proposed short-term forecast algorithm of PV power generation is designed based on a multi-layer RNN using IoT data including the selected meteorological data. The designed multi-layer RNN consists of one input layer, one output layer and three hidden layers. The output layer is connected the fully connected layer. For efficient learning, the pre-processing module samples the data and converts the input data into sequence data. The sequence inputs are normalized, and its outputs are denormalized to make training faster and to reduce the chances of getting stuck in local optima. To evaluate the proposed short-term PV power forecasting algorithm, the PV power system with IoT sensors was installed on the rooftop of the engineering

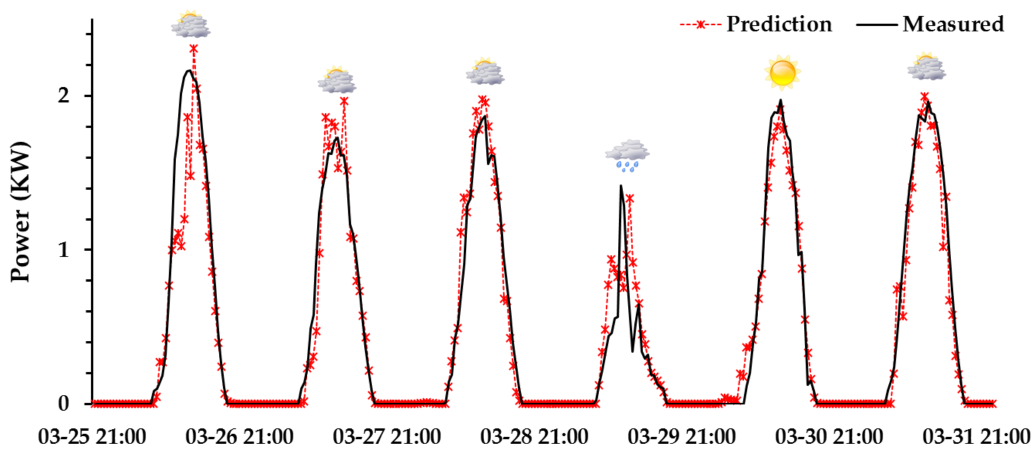


Fig. 5. The very short-term forecasting results of PV power generation for 6 days (RNN layers=3, time steps = 12, sampling interval = 30 minutes).

building in Konkuk University. The data was collected every 5 minutes. To evaluate the prediction accuracy, nRMSE was used as the performance metrics. Various cases of experiments were performed according to the number of hidden layers, sampling data interval and the time steps of a deep RNN. Experimental results showed that the prediction accuracy was the best when it consists of three hidden layers. In the experiments using the very short-term forecasting algorithm with 3 RNN layers and 12 time-steps in each RNN layer, the prediction accuracies were 98.02% and 93.87% for the PV power prediction 5 minutes and 1 hour later, respectively. To improve the short-term PV power prediction, we will develop another feature sets like a cloud image and dust sensors and apply the new deep learning algorithms in the future. Furthermore, based on the short-term prediction algorithm, we will develop the method to detect the abnormality of the PV power system.

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