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Design of Short-term Forecasting Model of Distributed Generation Power for Solar Power Generation

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Abstract

Background/Objectives: For efficient PhotoVoltaic (PV) power generation, computing and information technologies are increasingly used in irradiance forecasting and correction.

Methods/Statistical Analysis: Today the majority of PV modules are used for grid-connected power generation, so solar generation forecasting that predicts available PV output ahead is essential for integrating PV resources into electricity grids. This paper proposes a short-term solar power forecasting system that employs Neural Network (NN) models to forecast irradiance and PV power.

Results: The proposed system uses the weather observations of a ground weather station, the medium-term weather forecasts of a physical model, and the short-term weather forecasts of the Weather Research and Forecasting (WRF) model as input. To increase prediction accuracy, the proposed system performs forecast corrections and determines the correction coefficients based on the characteristics and temperature of PV modules. The proposed system also analyzes the inclination angle of PV modules to predict PV power outputs.

Conclusion/Application: In the future, the proposed forecasting system for solar power generation resources will be further refined and run in real environments.

Keywords: Distributed Power Generation, Forecasting System, Photovoltaic Power Forecasts, Solar Energy, Wind Power

1. Introduction

Forecasting systems for the interconnection of distributed power resources predict the expected output of wind and solar power using meteorological forecast models. Such systems are essential for linking wind and solar power facilities to an electric power grid system[1,2]. The fundamental technologies for such forecasting systems are meteorological forecasting methods. In addition, the optimization technology that aims to achieve the highest possible prediction accuracy is also significant. The same forecasting systems can be used in different countries but the real challenge lies in adjusting them to the meteorological conditions of a specific region[3–5].

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Inaccurate forecasting of future power output has often caused low energy conversion efficiencies and high operational costs in existing renewable energy facilities. In traditional base-load power stations, such as coal- or gas-fired thermal power stations, it increases the time and cost required for re-activation. Power generation forecasting systems with a low prediction error rate increase return on investment and extend the application domains in which forecasted information can be utilized. The wide adoption of power forecasting systems contributes to increasing power productions, thus decreasing the required number of backup power facilities[6,7].

PV power has gained a lot of attention lately. It is considered as an alternative for fossil fuels that have been widely used all over the world. In particular, the field of solar generation forecasting that predicts the power output of PV modules for look-ahead periods is rapidly evolving. Another field of interest is determining the optimal location of PV module installations based on the distributions of the solar radiation obtainable at the Earth's surface. Along with irradiance, ambient temperatures can be used to predict the power outputs of PV modules.

This paper proposes a short-term forecasting system that predicts future irradiance and PV power using NN models. The proposed system uses the weather observations of a ground weather station, the medium-term weather forecasts of a physical model, and the WRF-based short-term weather forecasts as inputs to its forecast models. To increase forecast accuracy, the proposed system performs corrections of the forecasting results. That is, it sets the correction coefficients for the preliminary irradiance forecasts by examining the characteristics and temperature of PV modules. The proposed system also examines the inclination angle of the installed PV modules to produce accurate PV power forecasts (Table 1).

The rest of the paper is organized as follows. In Section 2, solar power generation and its forecasting technologies are discussed. Section 3 presents the proposed short-term forecasting system for PV power generation. Section 4 evaluates the performance of the proposed system by analyzing the accuracy (error rates) of its predictions. Finally, conclusions are given in Section 5.

2 Related Works

2.1 PV Power Generation

Solar photovoltaic systems transform solar energy into electric power. Semiconductors (e.g., silicon-N or silicon-P solar cells) that exhibit the photovoltaic effect convert solar radiation into direct current electricity[1,8,9]. PV power generation employs solar panels (PV modules)

Table 1. Global status of photovoltaic generation forecast models

Division	Approach	Grid, Time	Prediction Model
University of Oldenburg, German ECMWF-OL	sky model and statistical model Combination	ECMWF* - 0.25°°x 0.25° - 3 hours	Global models, the post-processing
Bluesky, Austria a) SYNOP b) BLUE	a) cloud cover predicted by meteorologists b) BLUE: a statistical model	for b) GFS+ - 1° x 1° and 0,5°x 0.5° - 3 hours and 6 hours	
Meteocontrol, Germany MM-MOS	Model Output Statistics of Meteomedia GmbH	ECMWF* - 0.25°x 0.25° - 3 hours	
Cener, Spain CENER	The model output through continuously updated	Skironx/GFS+ - 0.1°x 0.1° - 1 hour	Mesoscale numerical model and post-processing
Ciemat, Spain HIRLAM-CI	Statistical correction	AEMET-HIRLAMx - 0.2°x 0.2° - 1 hour	
Meteotest, Switzerland, WRF-MT	Calculated by the average model	WRFx/GFS+ : - 5 km x 5 km - 1 hour	Mesoscale numerical model
University of Jaen, Spain WRF-UJAEN	Direct Model Output	WRFx/GFS+ - 3 km x 3 km - 1 hour	

composed of a number of solar cells, and PV modules can be grouped together as an array of connected modules to provide any level of power requirements.

The power output of a PV facility is a function of the power output of a PV array with the incoming solar radiation that varies over time. Equation 1 is used to calculate the average power output of a PV array.

$$P_{pv,\,ave} = \int P(S) f(S) ds \tag{1}$$

In Equation 1, P(S) is the power output of a PV array and f(S) is the probability density function. The energy conversion efficiency of a PV array is not fixed but varies depending on changes in irradiance. The PV efficiency is usually described as the ratio of the power output of a PV array to the irradiance per unit. Increases in the PV efficiency remain almost constant when a certain amount of the irradiance, denoted as K_C, has been reached.

The power output (P_{PV}) of a PV array is proportional to the irradiance (G_t) obtainable at a certain time (τ). Equation 2 and 3 are used to compute P_{PV}.

$$P_{pv}(\gamma) = \frac{\eta_C}{K_C}(G_t)^2, 0 < G_t < K_C \tag{2}$$

$$P_{pv}(\gamma) = \eta_C \cdot G_t, G_t < K_C \tag{3}$$

The power output of a PV generation system is computed using Equation 4.

$$P_{pv,ave} = P_{PV}(\gamma) \cdot A \cdot Y_P(kWh) \tag{4}$$

In Equation 4, $P_{pv}(\gamma)$ is the power output of a PV array in kilowatts (kW) and A is the surface area of the PV array in square meters (m^2). Y_P is the operation time of the PV generation system in hours (hour).

2.2 PV Power Generation Forecasting Technologies

Rapidly depleting fossil fuels and escalating energy consumption have increased interest in renewable energy sources. In South Korea, PV installations are increasing continuously[10,11]. For an efficient use of PV power and the management of the electricity grid, research has been conducted on the development of solar power forecasting systems. Such systems predicts the future power output of a PV facility by considering the probability distribution function of irradiance in connection with PV facility's location, solar cell efficiencies and PV system design parameters. Some solar power forecasting methods consider ambient temperatures as well as irradiance[12]. Another key research area in PV power generation is to find the optimal geographical location for a solar power plant by investigating the distributions of the irradiance in different areas[13–15].

Among the existing solar forecasting tools, the one developed in Denmark predicts the future power output of a PV generation site by taking into account the site's actual PV production output obtained via remote monitoring. It provides solar power forecasts every 15 minutes and up to 3-day ahead. Its error rate is 38-60% for 1 to 72 hour ahead forecasting. Its forecast error rates decrease to the range of 8-15% in clear days[4,7].

3. Proposed Short-term Forecasting System

This section describes the proposed NN-based forecasting system that produces short-term PV power forecasts for interconnected electricity grids.

3.1 Overview

The proposed PV power forecasting system uses NN models to produce short-term predictions of the incoming solar radiation. In the proposed system, the change patterns of irradiance are determined based on the latitude and longitude of the forecast target and the Sun's altitude that varies according to the day and time. Irradiance can be locally influenced by cloudiness and the atmosphere's conditions.

In general, irradiance is less fluctuating than wind velocity, and it is determined by the Sun's altitude and meteorological conditions than by time series characteristics. Hence, the proposed system does not consider time series characteristics. The NN model of the proposed system performs short-term irradiance forecasts with factors related to the Sun's altitude and meteorological variables related to weather conditions.

To build NN models, the historical weather data from a ground weather station spanning over a 3-year period, from 2010 through 2012, were used. The used weather data were measured every hour at Jeonju Weather Station. The considered meteorological variables are irradiance, wind speed and direction, temperature, humidity and barometric pressure. In the NN model, the dependent variable is the irradiance (W/㎡), and the independent variables are the date and time of forecasting, temperature, wind speed and direction, humidity, and barometric pressure. Other variables of the NN model are the weather data weighted by the month of forecasting and the short-term forecasts (e.g., wind direction, temperature, humidity, barometric pressure, etc.) from the short-term physical forecast model.

Figure 1 shows the overall process of the NN model that generates short-term irradiance forecasts. As the operation of the proposed forecasting system continues, the short-term predictions and the actual measurement data regarding irradiance are accumulated. The accumulated data can be used to continuously refine the statistical model (i.e.,NN) of the proposed system, thereby increasing prediction accuracy. In particular, accumulating the irradiance data that are measured at a PV power generation site enables the forecasted power output of the site to be more accurate.

The NN model of the proposed system combines the auto-regressive integrated moving average (ARIMA) and neural networking techniques. The weather observations from the ground weather station and the medium-term weather forecasts from the physical model are used as the input of the NN model. In addition to these two input sources, the WRF model is run separately to produce short-term weather forecasts. This weather forecast information, produced every 5 minutes, is also fed into the NN model. As shown in Figure 1, the initial forecasting of irradiance is performed using the ARIMA model, and then the output of the ARIMA model is applied to the NN model, producing a final short-term forecast of irradiance.

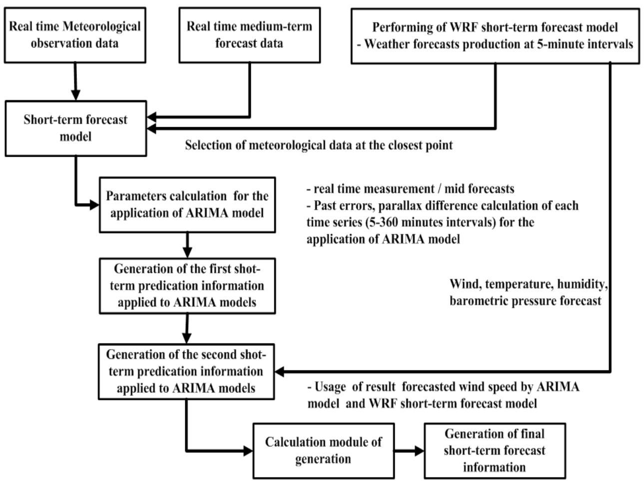


Figure 1. Process of the short-term prediction model.

3.2 Forecasting Procedure of the NN Model

Figure 2 presents the steps of producing short-term irradiance forecasts using the NN model. The change patterns of irradiance are determined based on the latitude and longitude of the forecast target and the Sun's altitude that varies according to the date and time of forecasting. The irradiance can be locally influenced by cloudiness and the atmosphere's conditions.

3.3 Algorithm for PV Power Output Forecasting

3.3.1 Determining the Weights

The NN model of each month realized using the weather data from Jeonju Weather Station has seven hidden layers, as shown in Figure 3. The weights for the constant term (bias) and the seven layers are calculated in between the input and hidden layers and in between the hidden and output layers. The detailed operations of running the NN model, such as standardization and activation function computing, are not different from the NN model for short-term wind speed forecasting.

3.3.2 Forecasting of PV Power Output

The proposed system predicts future solar generation outputs using the weather forecasts of the PV power generation site. Figure 4 shows the procedure of generating

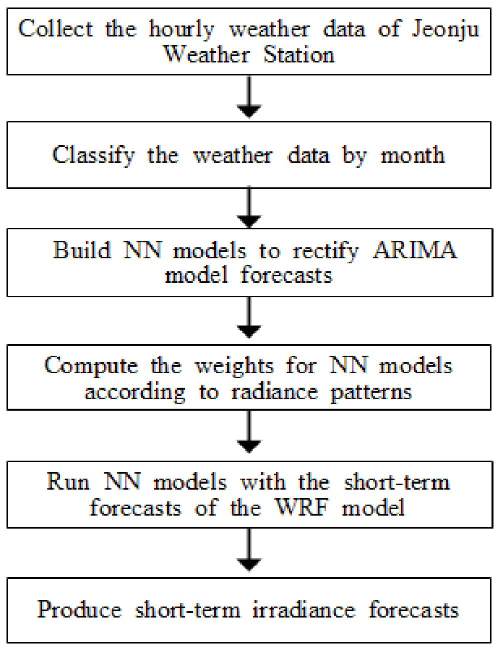


Figure 2. Forecasting procedure of the NN model.

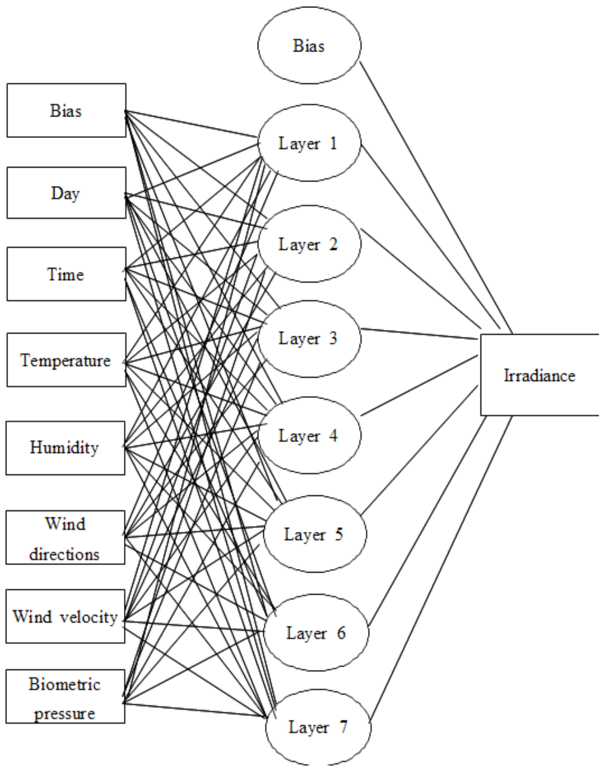


Figure 3. Structure of the NN model.

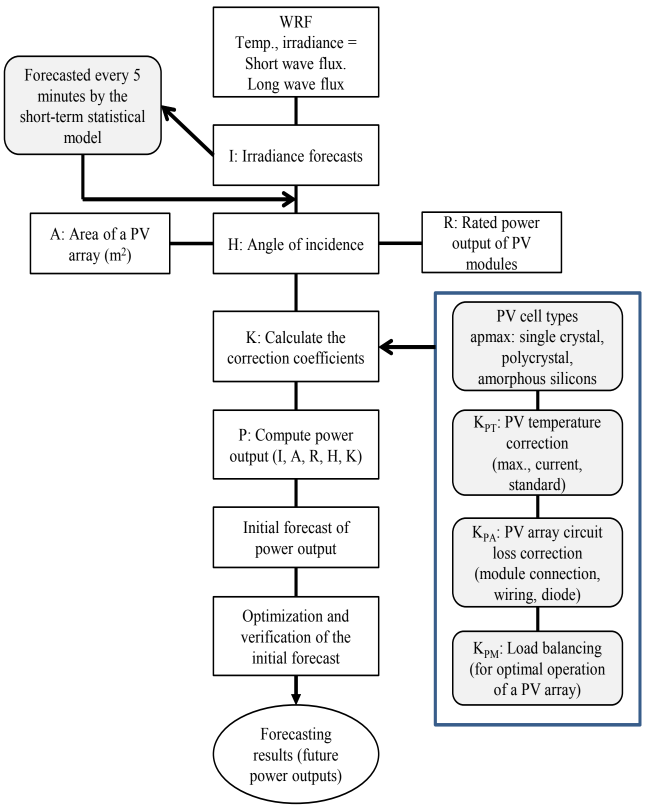


Figure 4. Algorithm for generating PV power forecasts.

short-term PV power forecasts. The forecasts of irradiance used to predict solar generation outputs are generated every 5 minutes. In addition to irradiance forecasts, the total surface area of the PV modules, the angle of incidence, the rated power output of the PV modules and the correction coefficients are considered in computing future power outputs. The correction coefficients are determined based on the characteristics and temperature of PV modules.

3.3.3 Correction of Irradiance Forecast Errors

A static-mounted PV array is generally installed at an angle of 30° to maximize its electricity production. The proposed system forecasts irradiance on the assumption that the PV array is at a straight angle. This necessitates correction allowing for PV array's inclination. This task requires tracing the movement of the Sun, computing the angle of solar panel to the Sun, and adjusting the forecasted irradiance with regard to PV array's angle of inclination.

Solar PV installations can be classified into two types: static-mounted and tracking systems. In the static-mounted, the inclination of a PV array is fixed. Tracking systems move PV panels to follow the Sun, so their inclination changes according to the movement of the sun. The proposed system identifies the angle of the plane of the PV array to the Sun in different PV installation types and performs irradiance corrections with the identified angle.

The proposed system uses the Solar Position Algorithm to trace the Sun's path across the sky. The solar altitude and azimuth angle vary according to the seasons and the time of the day.

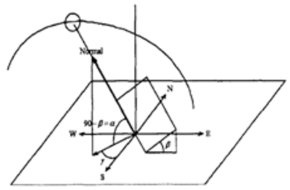
The inputs of the Solar Position Algorithm are time and location. In the input parameter of time, the format of date (year, month, day) and time (hour, minute, second) is used. In the location parameter, the latitude and longitude of a target are given. With the input data, the Sun's angular altitude (αS) and azimuth angle (γS) are calculated, as shown below (Figure 5).

$$a_S = \sin^{-1}(\sin L \sin\delta + \cos L \cos\delta \cos\omega) \tag{5}$$

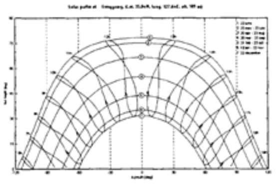
$$\gamma_S = \sin^{-1}\left(\frac{\cos\delta \sin\omega}{\cos a_S}\right) \tag{6}$$

3.3.4 Correction of PV Module Temperature

The output of a silicon solar cell decreases by 0.5% as its temperature increases by 1°. Suppose that the standard temperature is 25°. If the temperature of a 1MW solar module is 50°C, the output decreases by 12.5%, i.e., (50–25)°C × 0.5% = 12.5%. Hence, the obtained output is only 875kW, decreased by 125kW. Due to this overheat problem, more PV electricity is produced in spring and autumn than in summer (Figure 6).



(a) Sun's azimuth and altitude angles



(b) Annual changes in the azimuth and altitude angles

Figure 5. (a)The sun's azimuth and elevation angle (b) the annual change in the sun's azimuth and elevation angle.

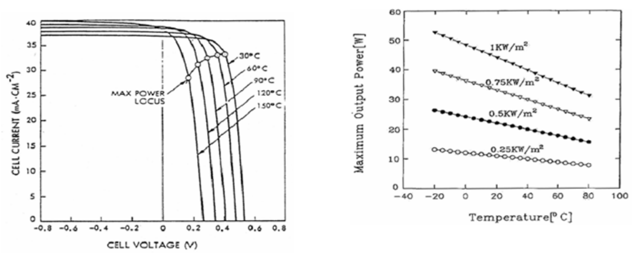


Figure 6. Correlation of PV module temperature with irradiance and power output.

To estimate the PV module surface temperature, its correlation with ambient temperatures and irradiance is analyzed. The existence (or non-existence) of the cooling system is also considered in the correlation analysis. The energy conversion efficiency of a PV module decreases as the temperature of the PV module increases, and the solar power generation is nearly proportional to the irradiance. The proposed forecasting system performs PV module temperature corrections to yield accurate solar power forecasts.

Equation 7 represents the computation of power output that includes the correction of PV array temperatures.

$$P_m(t) = P_m \times Q \times [1 + \alpha(t - 25)] \tag{7}$$

In Equation 7, $P_m(t)$ is the maximum power in the operational condition and P_m is the rated power (i.e., the temperature is 25°C and the irradiance is 1kW/m²). Q is the corrected irradiance (kW/m2) of a certain PV module inclination. t is the PV module surface temperature (°C) computed using the forecasted irradiance and temperature. α is the output temperature coefficient given in the PV manufacturer specifications.

4 Evaluation of the Proposed System

4.1 Irradiance Forecasting Accuracy

To evaluate the proposed system, the irradiance data were collected from the weather observations of Jeonju Weather Station spanning over a one-year period (January 2012-December 2012). The measured weather data corresponding to the forecasting time horizons were inputted as a validation dataset over which forecasts are performed and verified. It was observed that the output (the forecasting results and their error rates) of the proposed system varies depending on the accuracy of the medium-term weather forecasts given as input.

As shown in Table 2, the average irradiance forecasted by the NN model is 287W/m². It differs from the measured value (297W/m²) by 10W/m². The lowest MAPE is 21% in May and the highest MAPE is 33% in April, with the average MAPE of 27%. In terms of RMSE, the lowest is 75W/m² in January and the highest is 167W/m² in April, with the average of 107W/m².

Table 2. Forecasting of irradiance by the NN model

Month	Actual value (W/m²)	Predicted value (W/m²)	MAPE(%)	RMSE (W/m²)
1	232	234	25	75
2	295	288	28	106
3	311	301	26	113
4	385	334	33	167
5	397	394	21	111
6	357	357	24	119
7	300	299	24	97
8	309	277	33	141
9	287	276	24	94
10	299	317	21	85
11	207	204	31	89
12	188	161	33	86
Avg.	297	287	27	107
Min.	188	161	21	75
Max.	397	394	33	167

4.2 Correction of Irradiance Forecast Errors

Deviations between the forecasted and measured irradiance are highest around noon during which irradiance is most intense. Table 3 shows correction values for NN model outputs, i.e., short-term irradiance forecasts. The range of irradiance measures is equivalently partitioned into a series of smaller ranges differing by 5W/m^2, and correction values of each of the partitioned ranges are given on a monthly basis.

Table 3. Correction values for short–term irradiance forecasts (%)

Irradiance (W/m^2)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0 ~ 5	15.5	4.9	−0.1	0	0	−0.1	0	0	1.1	−0.9	−0.1	0.9
5 ~ 10	21.5	180.2	−33.4	587	99.9	−0.1	−13.2	0	73.8	−41.7	−18.3	114.7
10 ~ 15	−11.2	124.3	−58.5	456.1	8	18.8	−43.3	10.3	44.7	−49	−14.4	44.1
15 ~ 20	−56.9	108.1	−51.8	174.1	−63.9	−11.7	−28.3	98.6	−11.5	−45	128	−6.2
20 ~ 25	−21	74	−21.8	7.7	−32.8	25.9	−30	105	−21.2	−9	27.8	10.3
25 ~ 30	−29.6	177.7	−12.4	29	−49.5	−42.8	−30	88.4	7.1	−22.7	55.6	66.1
30 ~ 35	5.1	99.5	16	44.8	−24.7	−24.1	−28.1	146	8.5	−16.4	31.2	90.1
35 ~ 40	−11.6	16.9	−2.5	−2.2	−29.9	0.8	4.8	93.5	−8.8	−10	32.5	39.3
40 ~ 45	10.4	47.3	35.5	30.2	−44.3	−1.6	−11.8	80.1	−17.4	17.8	49.7	70.3
45 ~ 50	−14.5	26.7	23.4	−16.9	12.3	−1.2	−7.8	49.6	−14.7	−28.6	18.5	139.3
50 ~ 55	4.5	82.6	−15.2	2.2	−7.5	−32.9	1.4	72.5	−7.9	−3.2	29.5	2
55 ~ 60	−26.7	62.7	18.8	83.3	−30.5	−3.4	−25.9	−20.4	21.3	−19.2	39.2	49.5
60 ~ 65	−2.3	29.9	10.7	44.3	−4.4	26.2	30.7	−18.3	−0.4	45.6	36.6	66.2
65 ~ 70	−0.3	−1.7	47.5	39.4	−14.7	−9.1	4.8	20.9	42.3	−4.7	53.4	70.9
70 ~ 75	−28.9	−20.3	28.3	33.4	11.4	−5	−12.9	49.4	25.6	−0.3	17.8	27.5
75 ~ 80	−2.5	13.3	21.4	6.9	6.2	53.5	−11.4	7	11.2	32.9	67.5	7.3
80 ~ 85	−11.1	17.4	−2.3	60	13.5	1	−1.4	−27.8	26.9	−2.9	16.3	27.9
85 ~ 90	6.3	−12.1	30.3	72.2	−16.6	39.8	−1.7	−31.4	46.2	−12.5	68.4	32.4
90 ~ 95	−6.5	5.6	−44.3	12.2	7.8	23.6	−1.6	27.6	18.3	32.6	35.5	21.6
95 ~ 100	−10.2	8.2	128.8	78.4	−16	−21.9	40.5	34.8	64.8	−25.4	16.4	104
100 ~ 105	−2.2	14.2	5.9	−1	−0.9	−7	−6.2	34.7	17	13.3	11.2	10.1
105 ~ 110	−15.3	3.5	42.7	11.5	46.9	8.3	−18	−30.6	64.4	54.7	22.9	13.9
110 ~ 115	17.8	2.8	28.9	−38.4	27	−4.5	29.4	5.8	−10.8	12	37.6	−4.9
115 ~ 120	−4	6.7	−25.1	47	39.5	16.4	46.4	34.6	14.6	−17	6.9	15.2
120 ~ 125	−2.6	−44.1	5.9	26.6	−16.1	−4.6	37.8	15.5	13.7	25.9	16.6	−26.6
125 ~ 130	−38.8	44.7	−32.8	97.2	6.6	−11.3	11.1	−9.9	50.9	−4.4	16.3	2.7
130 ~ 135	11.4	8.2	35.8	49.1	16.8	−6.1	107.4	39.5	−19.7	32.8	29.9	46.7
135 ~ 140	−18.2	−17.9	9.8	52.5	9.5	4.9	63.6	36.4	43.1	−21.9	23.9	10.2
140 ~ 145	18.2	−17.9	17.1	59.9	42.4	162.6	−3.1	39.9	55.6	−2.2	−11.2	45.9
145 ~ 150	5.6	−29.1	−13	8.2	−18.5	20.8	−11.2	−9.4	−3.9	9.1	30.2	40.4
150 ~ 155	42.7	7.6	−20.7	−17.6	22.2	−4.4	−28.7	11.9	10.2	39.5	−22.2	−6.5
155 ~ 160	−22.2	23.6	−18	17.8	54.5	35.3	−19.9	−15.2	−8.5	37.6	5.2	17.2
160 ~ 165	4.9	−29.9	−46.9	24.3	−1	53.9	6.1	−33.6	11.1	32.6	20	36.2
165 ~ 170	31.3	8.4	1.8	7.7	−17.5	12.2	43.1	−11.9	18.1	17.1	20	10.1

Continued

Table 3. (*Continued*)

Irradiance (W/m²)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
170 ~ 175	−4.8	37.9	−35	−29.7	−4.2	0.9	−9.9	28.7	−16.6	18.4	41.2	30.7
175 ~ 180	18.5	22.6	18.1	−38.2	4	8.2	10.4	−2.1	11.8	19.7	7.1	4
180 ~ 185	19	−23.9	−20.5	65.2	−17.6	40.9	9.9	−14.8	4.8	17.7	53.3	15.6
185 ~ 190	−5.3	13.6	43.7	−6.8	21.7	67.3	23.4	−42.2	15	−44.1	2.8	41.8
190 ~ 195	3.1	20	24	37	31.5	35.9	−21	29	−13.5	4.3	−14.9	3.2
195 ~ 200	1.5	34.2	−15.7	67.5	32.2	13.6	−6.9	−35.8	7.7	41	−8.5	2.6
200 ~ 205	21.9	51.4	−6.4	33.8	21.2	3.1	13.4	−19.4	−20.2	−9.7	5.6	8.2
205 ~ 210	−7.3	−8.1	9.7	−23.2	13	51	−10.3	−28.8	−24.9	−4.4	3.5	−3.1
210 ~ 215	8	−12.8	40.2	11.6	−24.5	−37.2	−4.1	24.7	−2.8	25.3	3.4	−18
215 ~ 220	3.4	9.5	−21	−10.3	24.2	23.5	−10.6	15.3	4.8	25.6	43	9.3
220 ~ 225	11.7	1.6	−2	66.6	−14.4	14.2	−7.9	14.6	16.9	−14	7.7	−22.6
225 ~ 230	−7.1	12	33.4	54.8	4.2	−8.3	39.9	−10	4	−24.7	31.5	17
230 ~ 235	22.8	13.8	−49.6	−20.5	−5.2	−10.1	14	−0.9	−62.7	17.7	21.5	14
235 ~ 240	35.9	41.9	−21.5	32.1	17.3	27.8	−13.9	7.2	−7.5	7.7	21	−7.3
240 ~ 245	3.3	25.9	25.9	15.8	3	6.9	29.6	41.3	−25.4	7.4	19.5	1.4
245 ~ 250	19	−5.4	−14.9	2.7	−14.9	−4.4	15.5	0.8	23	−9.8	−11.2	−12.8
250 ~ 255	−3.1	2.6	30.4	−24.5	6.5	31.5	−18.2	−17.5	24.4	−9.6	14.4	8
255 ~ 260	1	−17.3	−11.2	21.6	1.4	37.1	−17.4	−21.6	−0.7	−5.1	−24.6	26.1
260 ~ 265	−24.6	31.2	17.5	−36	30.7	−4.7	3.3	−36.4	33.2	18.5	−7.4	−7
265 ~ 270	−2.2	−6.8	−6.8	2	−1.6	50.3	−14.1	−4.7	−30.2	−20.9	4.5	−11.9
270 ~ 275	16.7	18.8	16.9	30.4	−14.4	6.3	18.6	18.4	−9.2	5.1	−1.4	−20.7
275 ~ 280	−1.2	−0.1	−43.1	9.5	−1.8	−6.7	−21.4	60.9	−15.7	9.8	−12.4	−12.3
280 ~ 285	7.9	31.6	−18.4	−19.8	13.8	23.2	−0.2	8.6	44.1	−15.2	−18.8	−9.2
285 ~ 290	6	−23.3	36.6	5.4	−26.7	−11.4	11.8	44.7	−6	17.1	7.2	−23.6
290 ~ 295	−7.2	6.6	5.7	6.8	4.4	−16.7	−3.5	−9.7	14.7	4.3	27.1	10.3
295 ~ 300	18.7	−0.1	26.4	46.5	40.7	−14.7	−15.1	24.5	18.8	−9.6	9.1	11

Table 3 shows the irradiance forecasts produced by the NN model with and without corrections. The forecasted average irradiance without correction is 287W/m², with the average MAPE of 27% and the average RMSE of 107W/m². In the corrected case, the forecasted average irradiance is 293W/m², with the average MAPE of 25% and the average RMSE of 98W/m². That is, irradiance forecasts passing through corrections match more closely to the measured irradiance. The average MAPE decreases by 2% and the average RMSE decreases by 9W/m². The forecast accuracies are improved for all forecast time horizons.

The correlation of the forecasted and measured irradiance values was analyzed. For all look-ahead periods, the coefficient of determination (R2) is above 0.85, indicating that they are highly correlated.

4.3 Measured Irradiance Data

The measured irradiance used to verify the forecasted irradiance was collected from the weather observations of Jeonju Weather Station over a month (July 1st, 2012-July 31th, 2012). This weather station is located in the Jeonbuk province where there are several PV power sites. In addition to the measured irradiance from Jeonju Weather Station, the power outputs of two solar power sites, Cheonil Buan Photovoltaic Power and NRE Buan Photovoltaic Power, were used to evaluate the irradiance prediction accuracy of the NN model.

The correlation of the irradiance of Jeonju Weather Station with the solar generation outputs of Cheonil Buan Photovoltaic Power and NRE Buan Photovoltaic Power was analyzed. This was to examine the correlation between the irradiance of Jeonju and the irradiance of the other areas where the two PV power sites are located. It was determined that the irradiance of Jeonju Weather Station has the representative characteristics of the irradiance of the two PV sites. Thus, the measured irradiance of Jeonju Weather Station and the forecasted irradiance of Cheonil Buan Photovoltaic Power and NRE Buan Photovoltaic Power were compared to evaluate the accuracy of the NN model.

4.3.1 Cheonil Buan PV Power's Irradiance Forecasts

The irradiance of Cheonil Buan Photovoltaic Power was forecasted using the irradiance of Jeonju Weather Station. The forecasted average irradiance was about 435-467W/ m^2, differing from the measured irradiance (300W/m^2) by 135-170W/m^2. The error rate is 51.4% for 6-hour ahead, 55.4% for 24-hour ahead, and 60.1% for 48-hour ahead. The time series analysis showed that sudden irradiance changes caused, for example, by clouds cannot be predicted properly but the forecasted and measured irradiance data show overall similar patterns (Table 4).

4.3.2 NRE Buan PV Power's Irradiance Forecasts

In the irradiance forecasts of NRE Buan Photovoltaic Power, the average irradiance is about 437-476W/㎡. This is higher than the measured irradiance (300W/㎡) by 137-176W/㎡. The error rate is 53.5% for 6-hour ahead, 53.9% for 24-hour ahead, and 59.4% for 48-hour ahead. The time series analysis results are the same as those of Cheonil Buan Photovoltaic Power. That is, it is difficult to accurately predict sudden changes in irradiance but the overall pattern of the predicted irradiance is similar to that of the measured irradiance (Table 5).

Table 4. Cheonil Buan PV Power's irradiance forecasts

	Jeonju Weather Station	6-hour ahead	24-hour ahead	48-hour ahead
Avg. irradiance (W/m^2)	300.23	454.88	435.37	467.28
RMSE (W/m^2)	-	252.92	255.77	272.38
NMAE (%)	-	51.4	55.4	60.1

Table 5. NRE Buan PV Power's irradiance forecasts

	Jeonju Weather Station	6-hour ahead	24-hour ahead	48-hour ahead
Avg. irradiance (W/m^2)	300.23	466.42	436.92	475.81
RMSE (W/m^2)	–	257.81	252.18	267.29
NMAE (%)	–	53.5	53.9	59.4

5 Conclusion

(1) As the demand for energy rapidly grows, ways to integrate wind and solar power resources to electricity grids are required. This paper proposes a short-term forecasting system that forecasts irradiance and PV power using the forecasted weather data of a PV power site.
(2) To predict future solar power outputs, the proposed system analyzes the inclination angle of PV modules and identifies the correction coefficients based on the characteristics and temperature of PV modules. The NN model of the proposed system forecasts irradiance using the meteorological observations from a weather station and the medium-term weather forecasts produced by the physical model.
(3) In the correlation analysis of the forecasted and measured irradiance, R2 was over 0.85 for all look-ahead periods, indicating a high correlation between the two data. In the future, the proposed forecasting system for solar power generation resources will be further refined and run in real environments.

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