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Estimating hourly profiles of insolation based on weekly weather forecast

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Abstract: In this paper, the authors present a simple procedure of estimating weekly profiles of insolation for photovoltaic (PV) power generation output of a roof-top PV system. The model is based on the historical data of solar insolation and weather conditions. Weather conditions are classified into representative patterns such as sunny, cloudy, and rainy, and corresponding hourly profile of insolation is obtained as the most likely values under each weather condition. The system uses the text weather forecast and the probability of precipitation information as input to obtain the estimated weekly profile of insolation. From the results presented here it is shown that such a simple profile can be useful for rating the storage batteries and scheduling electric vehicle charging to better utilize the PV-generated electricity.

Keywords: Solar Photovoltaic Power Generation, Insolation, Weather Patterns, Probability of Precipitation, Regression

1. Introduction

Energy-efficient houses equipped with photovoltaic panels on their rooftops are being designed and implemented around the world for greenhouse gas emission reductions [1]-[2]. The sustainable energy house may also have an electric water heater as regulating load, an electric vehicle for charging and discharging electricity [3], some storage batteries, and a fuel cell or other combustion engine-based generators for adverse weather conditions and thermal energy supplies. Such renewable energy-based houses are usually connected with utility grid for backup power, but the residents/owners may be interested in minimizing the electricity purchases due to high cost.

Because human lifestyle has cyclic patterns, such as daily, weekly, and seasonal variations, operating household energy supply systems in an efficient manner requires a good planning, whereas PV output changes due to weather and seasonal conditions [4].

By estimating the profile of PV output for the week ahead in advance, it enables the efficient use of the PV-generated energy, saving the backup fuel or electricity cost, and potentially reducing the chances of excess PV output adversely flowing into the utility grid at a critical peak time.

Forecasting PV generation output is an extensively studied topic in recent years [5]-[8]. Many sophisticated forecasting systems are proposed, particularly aimed at utility-scale applications which aim at wide-area coverage and accuracy requirement for reserve power planning. For residential PV systems, however, the forecasting procedure must be as simple as possible, because this is one of the many functions of the home energy management system, and the information available for the residential users are not much in detail.

In this paper, the authors propose a simple estimation procedure of weekly insolation (solar radiation energy received on the ground) based on the statistical analysis of historical data of insolation and weather conditions. Weather conditions are classified into most-likely patterns under the simple category of sunny, cloudy, and rainy, and representative hourly profile of insolation is obtained from the most likely values of each pattern. The system uses, along with the text weather forecast, the probability of precipitation information as input to enhance the accuracy of the estimation. The (near) real-time information is assumed to be available from a local meteorological agency web site or be delivered by a digital data broadcast (such as a sub-signal on a digital television) in some areas.

2. The Procedure of PV Output Profile Estimation

2.1. Analysis of Historical Weather Data

First, we analyzed historical data of weather conditions publicized by the local meteorological agency [9]. Hourly insolation data are normalized by the monthly maximum value to remove the effect of the Sun angle (Hereafter, these normalized values are represented in "per unit," or p.u. for short, following the practice of power system engineering). Fig. 1 shows the monthly maximum insolation averaged over the past years in Tokyo area where the effect of rainy season is observed in June/July period.

The description of the past weather conditions are expressed in plain text such as "sunny" and "rain," as summarized in Table I. The users of such information need to know the reality in terms of insolation. In an earlier paper of the authors [10], cluster analysis was applied to the daily insolation data along with the hours of sunshine in the same day. The results justified the general categorization of the weather descriptions with three overlapping clusters. Now, the weather patterns in each general category are detailed to reflect the variable reality of weather forecast. (There are more variations of actual text description but these are integrated into the description of forecasted weather conditions which appear most-frequently.)

Next, weather conditions included in the identified three clusters are analyzed closely. Based on the hourly insolation data we obtain the mean of insolation patterns under the different weather conditions such as shown in Fig. 2. However, as observed in the insolation histogram of "cloudy" weather in Fig. 3, insolation varies over a wide range, and it is not always practical to use the mean as the representative value.

Therefore, we use the probability of precipitation (PoP) values as additional information for modifying the statistically most likely values [11-12]. By regression analysis on the probability of precipitation given in the weather forecast and the actual maximum insolation values occurred on the same days, the multipliers to modify the estimated insolation are identified.

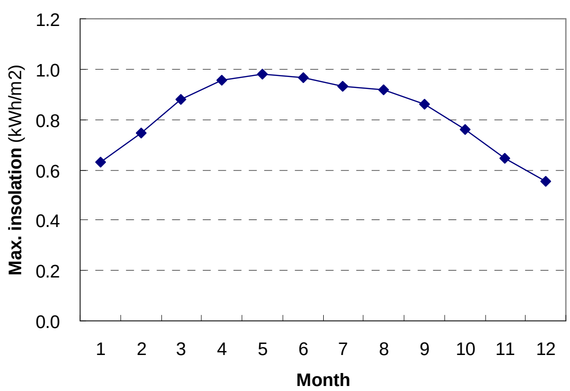


Figure 1. *Monthly maximum insolation.*

Table 1. *Description of weather conditions*

Category	Pattern	Description
Sunny	S1	Sunny
	S2	Sunny with cloudy periods
	S3	Sunny with rainy periods
	S4	Sunny later cloudy
	S5	Sunny later cloudy periods
	S6	Sunny with later rainy periods
	S7	Cloudy with sunny periods
Cloudy	C1	Cloudy
	C2	Cloudy later sunny
	C3	Cloudy later sunny periods
	C4	Cloudy later chances of rain
	C5	Cloudy later with rainy periods
	C6	Cloudy with chances of rain
	C7	Cloudy with rainy periods
	C8	Cloudy later rain
Rainy	R1	Rain later cloudy
	R2	Rain later sunny
	R3	Rain with cloudy periods
	R4	Rain

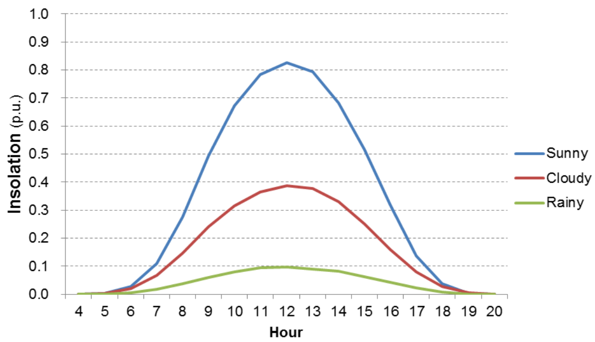


Figure 2. *Typical daily insolation patterns under different weather conditions.*

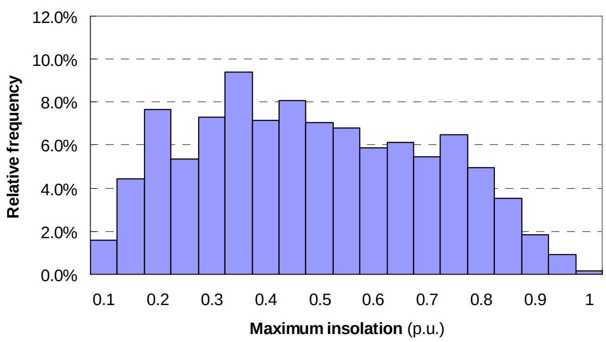


Figure 3. *Histogram of maximum insolation under cloudy weather.*

2.2. A Model to Generate Weekly insolation patterns

With the parameters obtained in the above analysis, we can generate the estimated insolation for the target day based on the weather forecast including the probability of precipitation as follows:

$$i(t) = I_m^{\max} \cdot i_w(t) \cdot p_c \quad (1)$$

where

t hour of day (t = 4, 5, …, 20)
I_m^{max} monthly maximum insolation [kW/m^2] (m = 1, 2, …, 12)
$i_w(t)$ mean value of normalized insolation at hour t in the forecasted weather condition w
p_c multiplier based on the probability of precipitation for the weather category c.

Fig. 4 shows the identified hourly insolation patterns (i_w) under the different weather conditions. Based on the pattern of the most likely insolation under the particular season (I_m^{max}) and weather (w), probability of precipitation (p), the insolation profile is estimated. The expected PV-generated electricity can be estimated, using the insolation profile, together with such factors as the PV system rating, panel direction, tilt angle, and ambient temperature. (These factors are calculated for different regions and made public as standard data by research agencies such as [13]).

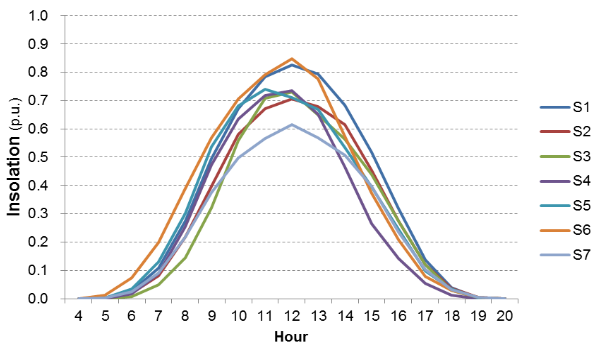
2.3. Identifying Modifiers by Probability of Precipitation

In the proposed model (1), the maximum insolation value is modified by the multiplier (p) depending on the probability of precipitation. To identify the modifiers, we applied a statistical analysis on the maximum insolation and the PoP data. Fig. 5 shows the histograms of the insolation under different weather conditions and PoP values. Data observed in the day when the forecast was incorrect were removed from this analysis. By regression analysis, as illustrated by Fig. 6, we have identified the multipliers for different weather categories. Note that PoP values are given in discrete values such as 10% or 20% in the forecast.

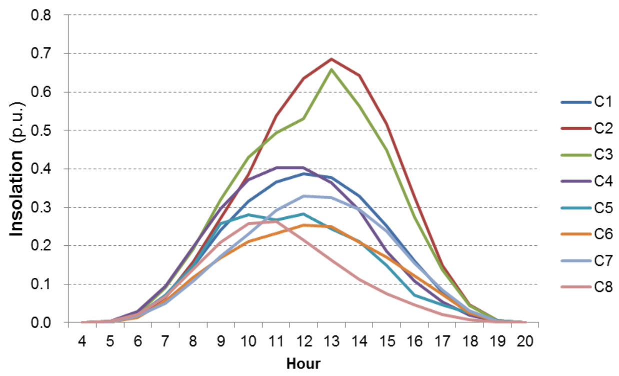
3. Estimation Examples and Evaluation

3.1. Weather Data Analysis

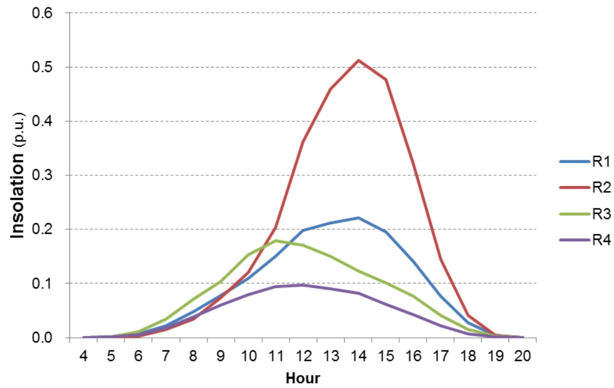
From the weather conditions recorded in downtown Tokyo, for the period from the year 2000 to 2012, the insolation data are classified into several patterns within general weather conditions, sunny, cloudy, and rainy, and mean curves for each weather conditions are identified as shown in Fig. 4.



(a) Hourly insolation patterns under sunny category



(b) Hourly insolation patterns under cloudy category



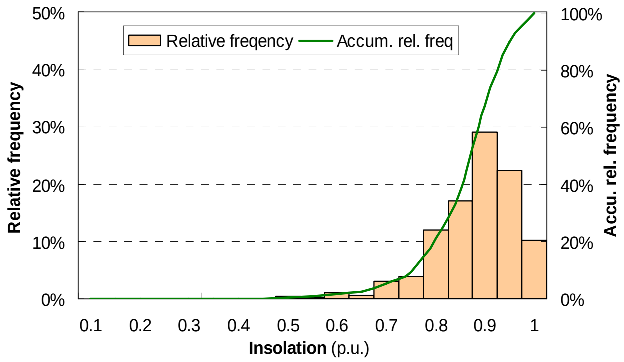
(c) Hourly insolation patterns under rainy category

Figure 4. *Detailed hourly insolation patterns under different weather conditions.*

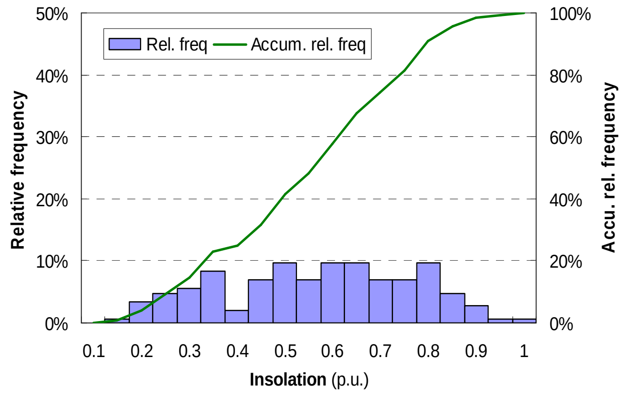
In each weather condition, the most likely insolation values are obtained for each daylight hour of the day from 4 am to 20 pm. Also, by the regression analysis of the actual insolation records versus the probability of precipitation given in the weather forecast, the multipliers to modify the estimated insolation are identified as above.

3.2. Weekly Profile Estimation and Evaluation

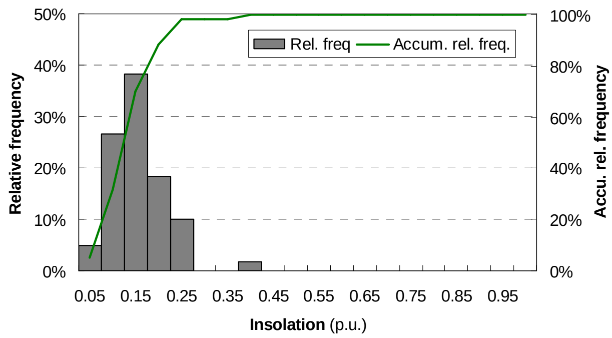
We have tested the weekly profiles of insolation generated by the model (1) based on the weather forecast information for seven consecutive days starting with a randomly selected day in different seasons of the year 2013. Fig. 7 shows typical profiles generated for the four seasons of the year. Table 2 compares the tested weather conditions including the probability of precipitation (PoP), and summarizes the root-mean-squared (RMS) errors and the mean absolute errors (MAE) of the weekly profile compared with the actual measurement of insolation for the target days in 2013.



(a) Max. insolation on sunny days (PoP=0%)



(b) Max. insolation on cloudy days (PoP<20%)



(c) Max. insolation on rainy days (PoP>70%)

Figure 5. *Histograms of daily maximum insolation under different weather conditions and different PoP values*

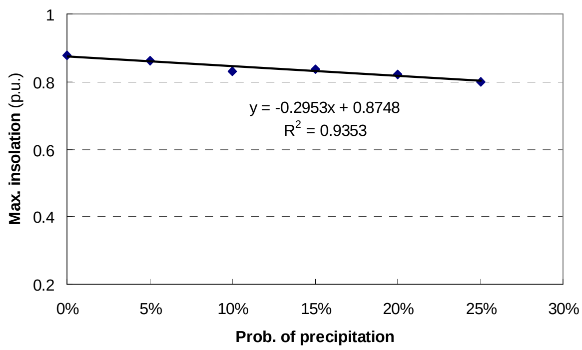
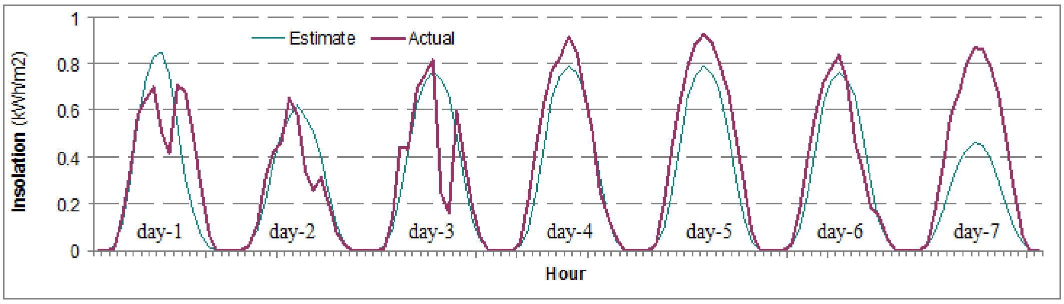


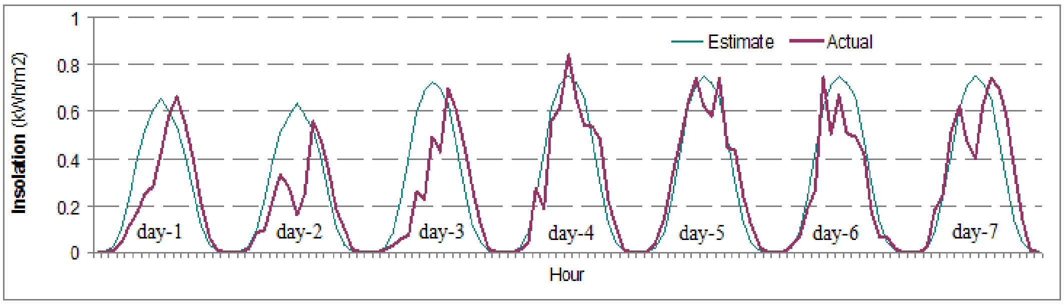
Figure 6. *Regression applied to find the maximum insolation under sunny day and PoP=0.*

Table 2. *Summary of weather conditions and errors on the insolation profiles.*

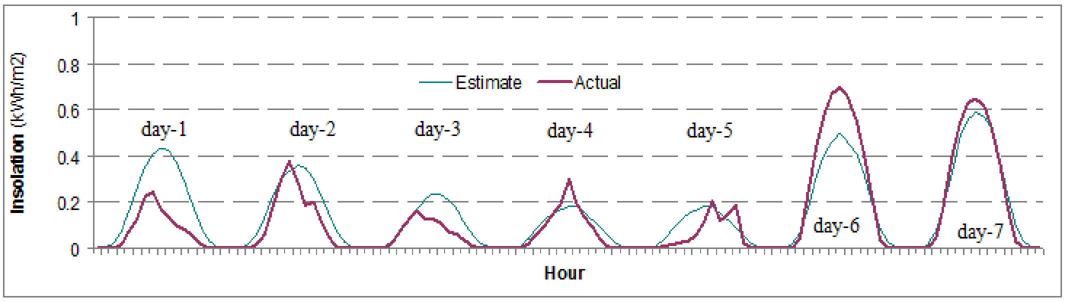
Season	Dates	Forecast	PoP	Actual weather	Errors
	2013/4/9	Sunny later cloudy	5%	Sunny	RMS: 0.1568
	2013/4/10	Cloudy with sunny periods	40%	Sunny	MAE: 0.1005
	2013/4/11	Sunny with cloudy periods	20%	Sunny with later rainy periods	
Spring	2013/4/12	Sunny with cloudy periods	10%	Sunny	
	2013/4/13	Sunny with cloudy periods	10%	Sunny	
	2013/4/14	Sunny with cloudy periods	20%	Sunny	
	2013/4/15	Cloudy	40%	Sunny	
	2013/7/30	Cloudy with sunny periods	20%	Cloudy	RMS: 0.1427
	2013/7/31	Cloudy with sunny periods	30%	Cloudy	MAE: 0.0974
	2013/8/1	Sunny with cloudy periods	30%	Cloudy later sunny periods	
Summer	2013/8/2	Sunny with cloudy periods	20%	Cloudy	
	2013/8/3	Sunny with cloudy periods	20%	Cloudy with sunny periods	
	2013/8/4	Sunny with cloudy periods	20%	Cloudy	
	2013/8/5	Sunny with cloudy periods	20%	Sunny with cloudy periods	
	2013/10/22	Cloudy	15%	Cloudy	RMS: 0.0837
	2013/10/23	Cloudy	40%	Cloudy	MAE: 0.0545
	2013/10/24	Cloudy with chances of rain	70%	Cloudy with rainy periods	
Fall	2013/10/25	Cloudy with rainy periods	70%	Cloudy with rainy periods	
	2013/10/26	Cloudy with rainy periods	70%	Rain later cloudy	
	2013/10/27	Cloudy with sunny periods	30%	Sunny	
	2013/10/28	Sunny with periods of cloudiness	20%	Sunny	
	2013/12/24	Sunny with cloudy periods	5%	Sunny	RMS: 0.0548
	2013/12/25	Sunny with cloudy periods	20%	Sunny	MAE: 0.0401
	2013/12/26	Cloudy later chances of rain	50%	Cloudy	
Winter	2013/12/27	Cloudy later chances of rain	50%	Cloudy with chances of rain	
	2013/12/28	Sunny with cloudy periods	20%	Sunny	
	2013/12/29	Sunny with cloudy periods	20%	Sunny	
	2013/12/30	Sunny with cloudy periods	20%	Sunny	



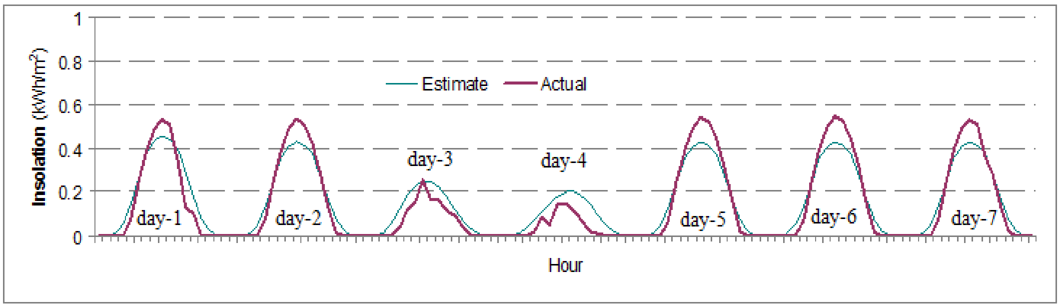
(a) Spring



(b) Summer



(c) Fall



(d) Winter

Figure 7. *Comparison of PV output profiles.*

Similar tests are done for the entire weeks of the year 2013. Table 3 compares the tested models with three basic categories of weather conditions versus detailed models including the probability of precipitation (PoP). It summarizes the root-mean-squared (RMS) errors for the weekly profile averaged over the entire weeks of 2013. It seems that these error values indicate that the estimates are not badly off the target because the standard deviation of maximum daily insolation is about 0.21 p.u./day for the most variable cloudy days. Major errors are caused by incorrect weather forecasts, which turned out to be less than 80% accurate [14-15]. The PoP modifier is particularly effective on the model using the detailed weather patterns.

Table 3. *Summary of errors on the weekly insolation profiles in year 2013.*

Model	Basic patterns		Detailed patterns	
	PoP n/a	PoP incl.	PoP n/a	PoP incl.
RMS errors	0.1287	0.1259	0.1287	0.1202

4. Conclusion

In this research, we supposed an energy-efficient house equipped with solar photovoltaic (PV) panels, and have developed a simple estimation procedure of weekly insolation profile for the PV output to be used in the home energy management system. Although the resultant accuracy may not be as good as other sophisticated systems, the proposed system uses the text information of public weather forecast, which is commonly available to household users.

The profiling procedure is simple and it can be implemented by lookup tables with stored parameters. The results obtained here can be applied, for example, to the ratings of PV panels and energy storage systems for the energy-efficient house and the schedules of electric vehicle charging by the residential PV-generated electricity.

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