

Photovoltaic Power Curtailment with Forecasting and Unit Commitment Scheduling: A Study on the Kanto Region in Japan

Joao Gari da Silva Fonseca Junior¹, Yuki Nishitsuji¹, Yusuke Udagawa¹, Takashi Oozeki², and Kazuhiko Ogimoto¹

¹ Institute of Industrial Science, The University of Tokyo, Tokyo (Japan)

² National Institute of Advanced Industrial Science and Technology, Tsukuba (Japan)

Abstract

Photovoltaic, PV, power generation is reaching unprecedented levels of penetration in many power grids around the world. Such trend is forcing utilities and transmission system operators to rethink the traditional ways to schedule the operation of their power generators. In this study we investigate the impact of day-ahead forecasts of PV power on the unit commitment scheduling of a regional power system. To do that we assumed a scenario of 33 GW of PV installed in the Kanto region in Japan, and that PV power can be curtailed. Using day-ahead forecasts of PV power, we generated daily unit commitment scheduling for one year, and compared them with those generated with a forecast without error. Annually, the amount of power curtailed based on the day-ahead forecasts differed in 1% of the amount required when a perfect forecast was used. Nevertheless, day-ahead forecast errors caused an increase 1.7% of the generators fuel costs (a significant value for cost). Day-ahead forecast errors also caused a need of curtailment in months when the relation between power demand and PV power generation by itself would not require it, such as June and July. Finally, the detection of PV curtailment based on day-ahead forecasts had a positive predictive value (precision) of 73%, but a true positive rate (hit rate) of 32%. Such results are mainly explained by the poor performance of the forecasts on spring and summer in Kanto, indicating a specific period when the forecast error should be improved.

Keywords: Photovoltaic Power, Day-ahead Forecasting, Power System Simulation, Curtailment of Power.

1. Introduction

Scenarios of high penetration of photovoltaic, PV, power generation on power grids are becoming reality in many places around the world. Such growth is causing transmission system operators (system operators hereinafter) to search for new ways to operate their systems so that PV, and renewable energy systems in general, can be smoothly integrated with conventional power generators. To support such integration process, measures such as construction of better transmission lines, storage solutions, demand response measures, etc., should also be taken to prepare power grids and power systems to high levels of renewable energy penetration. The implementation of such measures, however, require considerable investments, and long periods. Thus, in markets where the penetration of renewable energy is growing sharply short-term measures must be taken to support renewable while long-term measures are being implemented. One of such short-term measures is curtailment of renewable power generation.

In Japan, a rapid growth of PV systems associated with limited interconnection capacity between balancing areas caused the government to authorize, since April of 2016, utilities to curtail PV power without quantity or period limitation whenever they judge its generation will affect the stability of the power grid. However, to do that the utilities must inform PV systems owners one day ahead of the time that their PV system's power generation should be curtailed. This rule makes the use of day-ahead forecasts of PV power an essential condition in the operation of PV systems in Japan. Unfortunately, day-ahead forecasts of PV power are not always accurate. Thus, it is necessary to evaluate the impact that forecast errors will have on the effective curtailment of PV power, and on the overall operation of power systems. In technical literature many studies focus on the unit commitment side of the problem, including the development of stochastic or probabilistic unit commitment planning that can integrate uncertainty of renewable energy system's power forecasts (Lowery and O'Malley, 2012), (Wang et al, 2011), (Peng and Jirutitijaroen, 2009), (Ikeda et al, 2012). Nevertheless, studies that evaluate directly the impact of forecast errors of PV system's power generation on its curtailment and on unit commitment planning are still scarce.

Our research group has been investigating the general effects of different kind of PV and wind power forecasts and the use uncertainty information regarding such forecasts in modeling the operation of power grids (Udagawa et al, 2016, 2017a, 2017b). In this study our objective is to clarify the direct relation between day-ahead forecast inaccuracies and errors on curtailment of PV power. Specifically, we investigate such relation in a scenario of high penetration of PV power and when its curtailment is regarded as a routine to deal with PV power fluctuations. To provide realistic results, 30-minute UC scheduling for the region of Kanto in Japan, considering also a scenario for the distribution of power generators installed in the area by 2030, was done for a period of one year. The UC scheduling used day-ahead forecasts of PV power and the expected power demand for each day of the period studied. The impact of the forecast error on curtailment of PV, was also evaluated using as reference a second UC scheduling done with PV forecasts without errors. Such scheduling represents an ideal or perfect one as it is based on zero errors forecasts. Comparing both UC scheduling we analyze how forecasts affect the annual amount of power curtailed, if it is properly detected one day ahead of time, the annual running costs of the power generators, and other characteristics of the regional power system in different time scales.

2. PV Power Forecasting and Uncertainty Estimation

To forecast regional PV power generation a method developed by Fonseca et al., 2015a was used. With this method first insolation in 6 points locations within the Kanto area were forecasted hourly one day ahead of time. Point insolation values were used to obtain the regional yield, which then was converted to regional PV power generation. This calculation procedure was repeated for each targeted hour within the period studied. A brief description of the data and methods used are described in the following paragraphs.

The forecasts of insolation were done for each hour using as input data numerical weather prediction data of the Japan Meteorological Agency. Namely, data from the grid-point value meso-scale model, GPV-MSM, developed by Saito et al., 2006, were used. From the data set related with this model, air temperature, relative humidity and cloudiness in 3 levels were retrieved and used as input data of the forecasts of insolation. In its most recent version the GPV-MSM provides data with a lead time of up to 39 hours ahead of time, with a spatial resolution of 5 km by 5 km in Japan and surroundings. For the day-ahead forecasts data released at 12 h, Japan Standard Time, of the day preceding each targeted day were used as input. The targeted hours to be forecasted were within 5 h and 20 h of each day. Thus, the insolation and PV power forecasts were done one day ahead of time with a lead time varying from 17 hours to 33 hours. Besides the GPV-MSM variables the theoretical horizontal plane extraterrestrial insolation of each hour targeted was also used as input data of the forecasts. Finally, regarding the data used in the PV forecasts, they correspond to the fiscal year of 2013, April to March, and the forecasts were interpolated to 30-minute values to perform the UC scheduling calculations.

To make the forecasts a machine learning technique known as support vector regression was used. The support vector regression technique converts the learning problem as an optimization procedure, and the relation between the input and output variables is modeled through a linear fit in a high-dimensional space. The original problem is mapped to a high-dimensional space with kernels. Thus a kernel function has to be chosen and set as part of the problem. In this study the Gaussian kernel was used. The specific support vector regression technique used was the ν -support vector regression, which was developed by Schölkopf et al., 1998, implemented in part of the LibSVM library (Chang et al., 2001) for the R language.

Before being used in the training stage, the support vector regression algorithm has to have its configuration parameters set. The configuration parameters in this case were set with an ensemble based approach also described in Fonseca et al., 2015a. Regarding the training data, each set of 16 hours characterizing one day-ahead forecasts was done with a support vector regression model trained with data of the 60 days preceding the targeted day of the forecasts. Thus a unique forecast model for each day forecasted was developed.

Once an insolation forecast for a given hour and day is done for each of the 6 point locations within Kanto area, the regional value was obtained with an upscaling procedure, regarding the regional yield as the average value of the 6 point forecasts as showed in Eq. 1. Once the regional insolation forecast is obtained for a given hour, its value is converted to regional PV power following the formulation suggested by JISC8907 standard to calculate PV power from insolation. In this formulation all non-linearities and losses involved in insolation to PV power are represented by a performance ratio factor as showed in Eq. 2.

$$H_{rf} = \frac{1}{N} \sum_{n=1}^N H_{p(n)} \quad (1)$$

$$P_{rf} = P_{ins} \cdot \frac{H_{rf}}{G_s} \cdot K \quad (2)$$

In Eq. 1 H_{rf} is the regional insolation forecasts, in kW/m², calculated for a given hour based on the insolation forecast H_p of N points within the target region. This regional insolation forecast is used in Eq. 2 with the PV installed capacity P_{ins} , in kW, the insolation in standard conditions G_s , regarded as 1 kW/m², and a performance ratio K , set as 0.8, to calculate the PV power forecast.

To make the UC scheduling with the model described in section 3, besides the deterministic forecast of PV power generation at a given time, it is also necessary to have information about the uncertainty of such forecast. If such information is not available, uncertainty could be represented by a margin of variation from the forecasted value, such as 10% or 20% of it. In this study, for each forecast value of day-ahead regional PV power generation, the uncertainty of it was estimated via prediction intervals. The prediction intervals for the forecasts of PV were calculated using a method we proposed in Fonseca et al, 2015b. In this method, past forecasts are used to estimate the prediction intervals of a target forecast. Basically, this is done in 3 steps. First, past forecasts are selected from a database of forecasts for the region based on how similar their input data are to those of the target hour. Once a set of past forecast is formed, their error is calculated and it is assumed that its distribution follows a Laplacian distribution. Finally, through the maximum likelihood method the best Laplacian distribution that fits the data is selected. Prediction intervals for any forecast are then calculated using the selected distribution. Details about the calculation of prediction intervals for PV forecasts are in Fonseca et al., 2015b. Prediction intervals for the PV forecasts with confidence level of 90% were used in the UC scheduling.

3. Power System Scheduling Model

The operation of power systems in Japan is executed by different system operators depending on the region of the country. Each system operator must schedule the use of their power generators in different time frames so that power demand is always properly and timely supplied. At the day-ahead time frame, the use of power generators available to the operator is planned so that total operational costs required to supply demand of power are minimized under constraints that guarantee all security of supply requirements and the balance between supply and demand of power are met. After that, in intra-day and real-time operation the use of the generators follow dispatch strategies with the similar objectives.

At day-ahead level, one way of scheduling power generators of a region is known as unit commitment, UC, scheduling. In this study we used an UC scheduling model developed by Udagawa et al, 2016. This model minimizes the fuel, CF , and start-up, CS , costs of a set of n thermal power generators in a given area necessary to meet the expected power demand of the 24 hours of the next day in each t , 30-minute intervals (Eq. 3). In Eq. 3 pSt is a binary variable (0 or 1) indicating if generator n is going to be started or not at time t . The fuel costs are calculated based on the power output of each power generator considering partial load efficiency and series of constraints that ensure that power demand will be met and that secondary regulation control reserves of power will be available in real time operation of the power system.

Detailed description of the basic model and its constraints are available at Udagawa, 2016. The development of specific constraint conditions model PV curtailment was presented in Udagawa, 2017b. In this section only the main constraints are presented. The constraint in Eq. 4 ensure that power demand forecast d_t^{fd} , in MW, is met by power provided by n thermal power generators $p_{n,t}$, by m hydro-pumped power generators ($g_{m,t}$ for generated power and $h_{m,t}$ for consumed power) and by PV power after curtailment, pv_t . The constraint in Eq. 5, guarantees that PV power after curtailment is always equal to or smaller than the amount forecasted, pv_t^{fd} , (as it is a day-ahead scheduling). Constraints in Eq. 6 to Eq. 11, ensure that the thermal generators operate within their maximum and minimum operation loads at any time, mxT_n , mnT_n , allowing for reserves of secondary regulation control, for each power generator. For example, the constraint in Eq. 6 controls the upward spinning reserves, Eq. 7 the downward spinning reserves, and Eq. 8 controls the maximum amount allowed for upward secondary control regulation reserve. Finally, Eq. 9 guarantees that the operation of the power generator does not exceed its maximum capacity and E.q 10 and Eq. 11 control downward secondary control regulation reserves. These constraints also ensure that at any given time there will be always power reserve available to deal with the forecast error up to a margin given by the superior and inferior prediction intervals, pv_t^{fu} and pv_t^{fd} provided with the forecasts.

$$\text{Minimize} \quad \sum_{t=1}^T \sum_{n=1}^N (CF_{n,t} + CS_{n,t} \cdot pSt_{n,t}) \quad (3)$$

Subject to

$$\sum_{n=1}^N p_{n,t} + \sum_{m=1}^M (g_{m,t} - h_{m,t}) + pv_t \geq d_t^f, \forall t \quad (4)$$

$$pv_t \leq pv_t^{fd} \forall t \quad (5)$$

$$\sum_{n=1}^N (\bar{p}_{n,t} - p_{n,t}) \geq 0.05 d_{Dmax}^{fd} + \max(pv_t - (pv_t)^{fd}, 0), \forall t \quad (6)$$

$$\sum_{n=1}^N (p_{n,t} - \underline{p}_{n,t}) \geq 0.05 d_{Dmax}^{fd}, \forall t \quad (7)$$

$$pWk_{n,t} \cdot mxT_n \cdot (1 - blT_n) \leq \bar{p}_{n,t}, \forall t, \forall n \quad (8)$$

$$\bar{p}_{n,t} \leq pWk_{n,t} \cdot mxT_n, \forall t, \forall n \quad (9)$$

$$pWk_{n,t} \cdot (mnT_n + mxT_n) - \bar{p}_{n,t} \leq p_{n,t}, \forall t, \forall n \quad (10)$$

$$p_{n,t} \leq \underline{p}_{n,t}, \forall t, \forall n \quad (11)$$

In Eq. 5, Eq. 6, Eq. 7, Eq. 8, Eq. 9, Eq. 10 and Eq. 11, $\bar{p}_{n,t}$ is the maximum power output of a thermal generator n at time t discounting its secondary regulation control reserve margin. The symbol $\underline{p}_{n,t}$ is the minimal power output of a thermal generator n at time t , discounting its secondary regulation. In Eq. 6 $pWk_{n,t}$ is a binary decision variable indicating if thermal generator n is online or not at time t , and blT_n is the maximum amount of secondary regulation reserve that can be provided by a thermal generator, and it is expressed as a ratio of the generator's maximum power output. Constraints that allow for the determination of the optimum number of power generator needed to provide necessary secondary regulation reserve are also inserted in the optimization model. They are described in in Udagawa et al, 2016.

It was assumed in this model that up to 5% of the maximum operation loads of online thermal generators are regarded as reserve for secondary regulation control reserves. For pumped hydro power the maximum values were 16.5% when generating power and 10% when pumping up water to the reservoir. Moreover, only 11 pumped hydro-power plants were regarded as capable to provide LFC reserve in pumping mode as not all of them have this capability. Pumped hydro power efficiency values were set with values from 60% to 70% depending of the plant. These values are regarded as typical values for the area studied and are also based on Udagawa et al, 2016.

In the UC scheduling calculation, PV power generation is used also to determine the necessary power reserve to deal fluctuations of power in real-time operations. Curtailment of PV will be scheduled then, whenever it is not possible to allocate enough power reserve to deal with PV power fluctuations at a feasible cost. The required reserve of power as having the magnitude of the prediction intervals of the forecasts of PV with a confidence level of 90% plus the power demand fluctuation. Every time, for any given operation time, power reserve required to cover forecasted PV and associated prediction intervals reach physically unfeasible values or has cost beyond acceptable values, curtailment of PV is scheduled.

Depending on how curtailment is applied in practice, different interpretations of the effects of the forecast errors can be done. We assumed, that when curtailment request signal is sent one day ahead of the time to a PV system owner, it sets in the power conditioning system, PCS, of the PV system a maximum output value allowed at a given hour. This value is fixed and based on the capacity of the PCS. Thus, if a curtailment request is issued at a given hour, and less insolation than forecasted is realized (yielding less PV than the maximum allowed), no curtailment of PV is done.

4. Target Region and Simulated Scenario Description

The Kanto region in Japan was the target area of the study. It is where Tokyo is located. It is the region with the highest regional power demand in Japan. The regional power system comprising power generation, transmission, distribution is operated by TEPCO power utility, although the market is currently in the process of being liberalized. Besides Kanto area, TEPCO operates also in parts of the prefecture of Shizuoka and Yamanashi. In this study we considered the whole area operated by TEPCO as Kanto area, so that the real balancing area could be better simulated. Regarding power generators installed in Kanto region, a scenario for 2030 regarding their configuration and installed capacity based on the study of Ogimoto et al., 2012 was used. The assumed values for number of generators, their type and capacity are in Table 1.

Tab. 1: Characteristics of the power plants simulated for Kanto region power system.

Type of Generator	Number of Generators	Installed Capacity (GW)
Coal	15	9.6
LNG	57	22.1
Oil	20	10.8
Hydro Pump Storage	52	13.68
Nuclear and Hydro	Assumed as providers of base load	13.1

A scenario of high penetration of PV was also assumed. Such scenario is based on a study published by New Energy and Industrial Technology Development Organization, NEDO (2010), investigating the possibility of 100 GW of PV power penetration in Japan by 2030 (NEDO, 2014). Based on this value, we considered PV installed capacity as following the ratio between each region and the national annual power demand. Doing that, in a scenario of 100 GW for Japan and if PV is deployed proportionally to the area power demand, Kanto area should have 33.1 GW of PV power installed, which was the scenario simulated.

To simulate real operation conditions of the power system in Kanto, power demand and weather forecast data of the region were used. Power demand data for 1 year, from April 2013 to March 2014, for Kanto region, with a temporal resolution of 30 minutes were used. Accordingly, weather data of the same period was used to yield the insolation and PV power forecasts. Forecast of insolation for 6 points within Kanto area were done one-day ahead of time, from 5h to 20h of each target day. The insolation forecasts were done hourly due to the temporal resolution of the weather data used as input of the forecasts. Thus a simple interpolation procedure was applied using values of two consecutive hours to obtain 30 minute forecasts. This procedure was only applied after the regional forecast of PV power was calculated. The names and approximate location of the 6 places within Kanto for which insolation forecasts were done and, from which the regional yield was estimated, are in Table 2. In each location there is a weather measurement station of the Japan Meteorological Agency.

Tab. 2: Location of the 6 points within Kanto for which forecasts of insolation were done.

Location	Utsunomiya	Maebashi	Kofu	Tsukuba	Choshi	Tokyo
Latitude	36.54 N	36.40 N	35.66 N	36.05 N	35.73 N	35.68 N
Longitude	139.87 E	139.06 E	138.55 E	140.13 E	140.85 E	139.76 E

5. Results

In Fig. 1 four annual values of the day-ahead forecast errors are presented. The root mean square error, $RMSE_n$, mean absolute error, MAE_n and mean bias, $Mbias_n$, were calculated hourly and normalized by the total rated PV power assumed to be installed in the region. To offer a extra measurement of the accuracy of the forecasts the mean absolute percent error $MAPE_n$ is also provided. In this case, it was calculated in daily fashion and normalized by

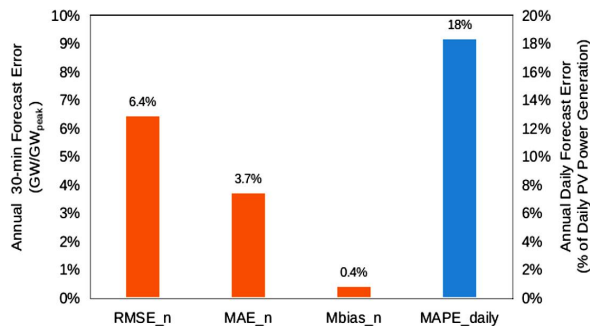


Figure 1: Regional PV Power Forecast Errors for Kanto.

average PV power generation (also daily). The values in Fig. 1 indicate that the accuracy of the regional day-ahead forecasts for Kanto had usual values found for this kind of forecast in Japan (Fonseca et al, 2014).

One way to assess the impact of the day-ahead forecast errors showed in Fig. 1 on the UC scheduling of Kanto's power system is to compare the performance of a UC scheduling based on such forecasts with the performance of one based on a forecast without error (a perfect forecast). In Table

3, we present the annual amount of PV curtailed, fuel cost and curtailment period that both kinds of UC scheduling would yield. The results in Table 3 indicate that annually the total amount of PV curtailed, when each kind of forecasts was used, was near to 5% of total PV generated.

Tab. 3: Scheduling of PV curtailment and Running Cost of Kanto Power System in 1 Year based on a UC using day-ahead forecasts, and a UC using a perfect forecast (without forecast errors).

Forecast	PV curtailment scheduled (% of total PV power generated)	Generators' Fuel Cost (10 ⁹ JPY)	Curtailment Period (% of total 30m intervals*)	PV Curtailment MAE _n (scheduled vs. total PV surplus) (% of average PV Power generated*)
Day-ahead	4.90	715.7	18.3	7.2
Perfect	4.96	703.7	13.0	--
Variation	-1.2%	+1.7%	+41%	--

*Within the period of PV forecasts (1 year from 5h to 20h).

Regarding the forecast error, its impact in the annual PV curtailed was relatively small; when day-ahead forecasts were used in the UC the annual PV scheduled to be curtailed was 1.2% lower than the amount that would be curtailed if perfect forecasts were used. On the other hand, looking at the curtailment period at Table 3, when day-ahead forecasts were used, curtailment was scheduled to happen for a longer period than it should reaching 18.3% of the time in the year studied (against 13% of the case when perfect forecasts were used). Thus, the forecast error caused scheduling of PV curtailment in hours when it was not necessary, and also insufficient scheduling of curtailment in the hours when it was necessary. The impact of the forecast error also caused an increase of 1.7% of the power systems fuel cost. Although this value seems small, as its unit is 10⁹ JPY it has considerable impact in the operation cost of the system. Such increase of the operation cost is related with how the thermal and hydro pump power generators are used to satisfy the residual power demand in the day-ahead forecast based and perfect forecast based UC. It represents the impact of having to maintain reserve power to deal with the forecast error.

Finally, the cost of the forecast error can be expressed as the mean absolute error of PV power scheduled to be curtailed when compared with the total PV power surplus at each hour. Table 3 shows that, in average, 7.2% of the average annual PV power generated (in GW) was wrongly curtailed. In the cases that PV curtailment errors were negative, more PV than scheduled was curtailed, yielding higher economic and energy losses to owners of PV systems than expected. When the error was positive less PV than scheduled was curtailed (due to less PV generation than forecasted). Although, in this case some PV systems' owners will have less economic losses than expected, there will be losses due to issuing unnecessary PV curtailment requests.

In Fig. 2 the amounts of PV scheduled to be curtailed monthly with the the real forecast based UC and with the one based on a perfect forecast are presented. Because the day-ahead forecasts contain errors, when using them to curtail PV power, two other quantities will appear besides the scheduled PV curtailment. The first one is the actual curtailment of PV power, and it is a direct consequence of the way curtailment was applied (section 3). It represents the difference between actual PV power surplus and PV power scheduled to be used in the power grid, when curtailment was scheduled to happen. The second quantity is the required curtailment of PV. It represents the actual PV curtailment (black dotted line in Fig. 2) plus the PV surplus that must be curtailed but it was outside the hours in which PV curtailment was scheduled to happen. In the case of a perfect forecast both quantities disappear.

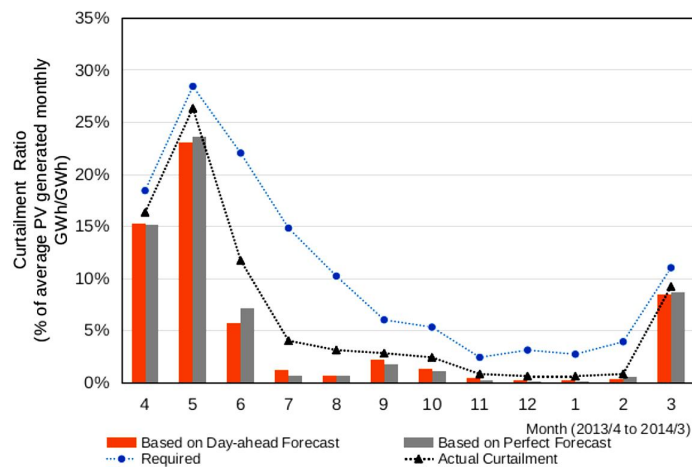


Figure 2: Monthly PV power curtailment ratio in Kanto using real day-ahead forecasts and perfect ones.

The results in Fig. 2 show that if there were no forecast errors, the months when PV would be strongly curtailed would be April and May, and at a lower level March and June. In spring in Kanto, insolation is almost as high as summer but power demand is lower than in winter and summer. In such conditions even using the conventional

power generators at their minimum loads would not be enough to prevent considerable curtailment of PV for the scenario studied. On summer, higher power demand reduces considerably the need for curtailment of PV. The result would be July and August with low PV curtailment as showed by day-ahead and perfect forecast based UC scheduling results in Fig. 2. Nevertheless, what happens is different due to the forecast error. The curtailment required item in Fig. 2 indicates that from June to August between 10% to 25% of the average PV generated in these months should be curtailed if day-ahead forecasts with errors were used. Moreover, in June the required curtailment was more than 2 times higher than the actual one. That result indicates that in June there were many hours in which there was surplus of PV power but there was no scheduling for its curtailment. These hours, in which curtailment happened, were not regarded as such one day ahead of the time.

A forecast error of the PV generation expected at a given hour can cause a difference between PV scheduled to be curtailed, the actual amount curtailed and the required amount to be curtailed. If such PV generation is underestimated, for example, the required curtailment of PV will be higher than the scheduled and the actually curtailed PV power. The result will be an unexpected surplus of PV that the power utility will have to deal with in a short period of time during the operation day. The results in Fig. 2, show that such unexpected surpluses of PV can occur even in months with high demand of power such as July and August.

To better understand the relation between the day-ahead PV power forecast error and the difference between actual PV curtailed and required curtailment in Fig. 2, in Fig. 3 we plotted the monthly PV forecast mean absolute errors and their respective mean biases.

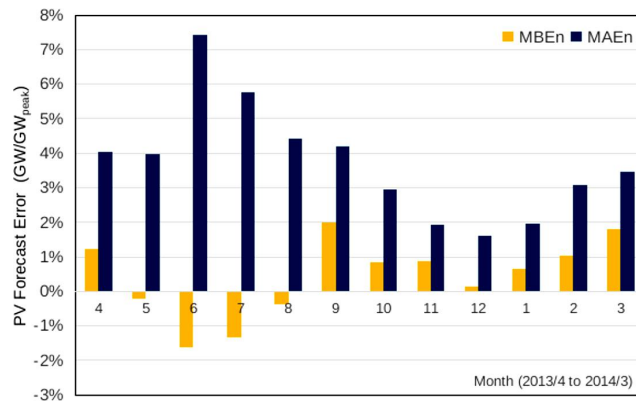


Figure 3: Monthly day-ahead PV power forecast mean absolute errors and mean biases of Kanto region.

The results in Fig. 3 show that June and July had the PV power forecasts with the highest mean absolute errors of the period studied. Furthermore, these two months also had not only negative biases but also the lowest ones of the period. These two characteristics indicate that in many hours in those months, the PV forecasts underestimated significantly the PV generated. As a consequence, the associated UC scheduling in this period did not curtail enough PV, yielding the behavior presented in Fig. 2.

Continuing the comparison between the curtailment of PV scheduled with day-ahead forecasts with the one curtailed with a perfect forecast, Fig. 4 shows the direct relation between both curtailment values throughout the period studied. A linear fitting is also plotted with the respective coefficient of determination. The value of coefficient of determination indicates that in general there was good agreement between both variables. It shows that 83% of the variance of the curtailment scheduled with a perfect forecast was explained by the curtailment scheduled with the day-ahead forecast. A particularly good relation between both variables is observed when curtailment of PV was higher than 10 GW. In this range, scheduled curtailment based on day-ahead forecasts of PV was usually similar to the one based on a perfect PV forecast. The lower the curtailment of PV based on day-ahead forecasts, the higher was the largest deviation from the curtailment value based on perfect

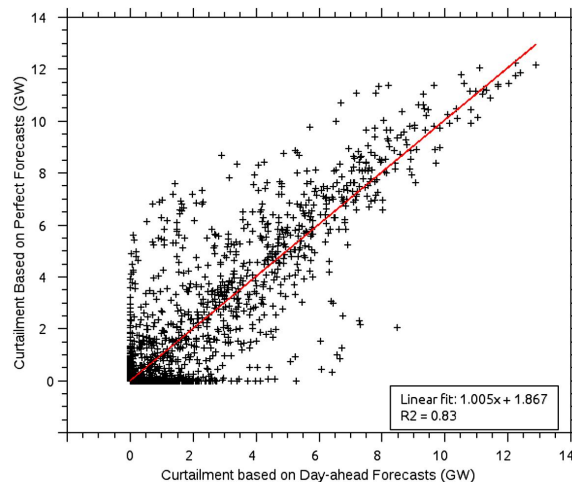


Figure 4: Curtailment of PV based on a perfect forecast versus curtailment of PV based on day-ahead forecasts for Kanto region.

forecasts. For example, when 2 GW of PV were scheduled to be curtailed with day-ahead forecasts, their errors caused a deviation of almost 6 GW from the value that would be curtailed if perfect forecasts were available. For this specific hour, the forecast of PV power generation greatly underestimated the amount actually of PV generated.

Besides the fuel cost of the power system and the error of the amount of PV curtailed, another effect of the day-ahead PV power forecast error on PV curtailment, regards the identification of the hours in a day when curtailment of PV should be applied. If PV curtailment is scheduled to happen at a given hour and due to the real amount generated, it is found that such curtailment was not necessary, this is an hour when curtailment was wrongly scheduled. The opposite, no curtailment scheduled but actually required, is also a scheduling error. To verify the effects of the forecast error from this point of view, Table 4 contains a contingency table of the hours (counted as two 30m time intervals) of the period studied with and without curtailment; the precision and hit rate achieved in the same table.

Table 4: Hours with PV curtailment based on day-ahead forecasts of PV for Kanto region in 1 year.

		Required		Precision (AC/(AC+AB))
		Yes (A)	No (B)	
Based on day-ahead Forecasts	Yes (C)	1517	552	73.3%
	No (D)	3161	6085	
Hit rate (AC/(AC+AD))		32.4%		

The precision indicates how reliable was the PV curtailment scheduling based on day-ahead PV forecasts, when it indicates that in given hour curtailment will happen. According to this parameter, curtailment scheduling based on day-ahead forecasts had a good level of reliability; in 73% of the hours that curtailment was forecasted, it was actually required. The accuracy (ability to identify correctly the hour with and without PV curtailment) of the scheduling based on day-ahead forecasts was slightly lower than its precision, reaching 67.1%. Nonetheless, the corresponding hit rate was low, indicating that most of the hours of the period studied in which curtailment was required, it was not detected. The low detection of curtailment hours is associated with forecasting less PV power than the actual value. Additionally, in months with negative bias the difference between scheduled curtailment and required one was considerable. We infer from these results that, even though the bias of the day-ahead forecasts, in Fig. 1 and Fig. 3, were not particularly high, reducing even further the forecasts' bias may improve PV curtailment scheduling.

Comparing with a perfect forecast, the curtailment scheduling based on day-ahead forecasts actually yielded more hours of curtailment, Table 3. This result seem to contradict the results of low hit rate in Table 4. However, when should keep mind that the day-ahead error affected the occurrence of curtailment itself, by scheduling curtailment in the wrong hours and by not scheduling it in the right ones. This wrong scheduling generated a need for curtailment that would not exist if a perfect forecasts were used. Therefore, reducing the day-ahead error of the forecasts should cause a reduction of item AD and BC in Table 4, and a proportional increase on item BD.

Besides the error regarding the amount and hours of PV curtailed, the error and uncertainty of the day-ahead forecasts also have an important effect on the way different conventional power generators are scheduled to be used. To show this effect, in Fig. 5 we plotted the UC scheduling with day-ahead forecast and with a perfect forecast. The plots represent the respective UC scheduling in a day in which the forecast of PV power strongly underestimated the the actual PV generation.

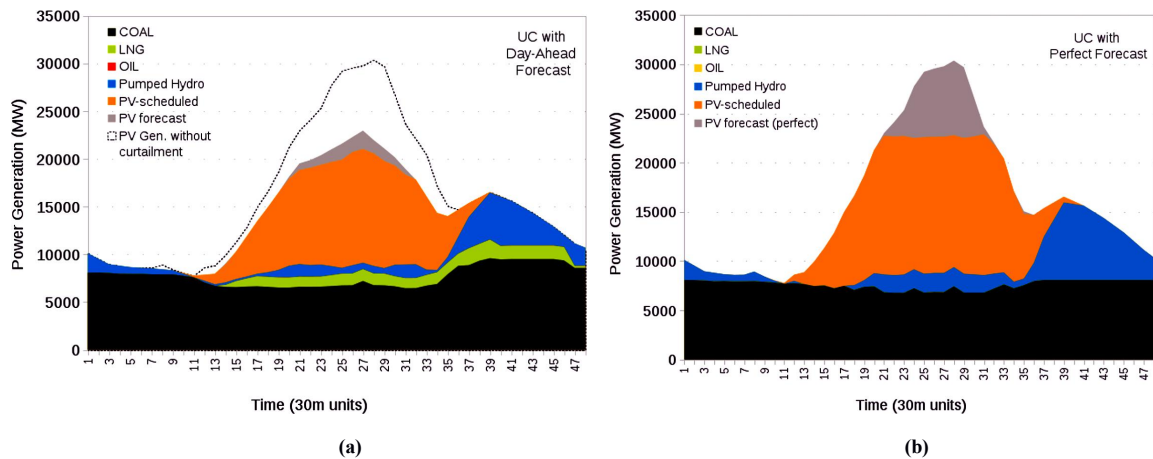


Figure 5: UC scheduling of a day (June 2nd) based on day-ahead (a) and on perfect (b) forecasts of PV power generation for Kanto.

The UC scheduling based on day-ahead forecasts, in Fig. 5(a), shows that almost all of the PV generation forecasted was scheduled to be used, with small amounts pumped hydro and LNG, which are used to provide secondary regulation frequency control and to compensate for the uncertainty associated with the forecasts. Coal provides the remaining amount of power to meet the demand. Still, looking at the PV power generation in Fig. 5(a) one see that PV power generation greatly exceeded the forecasted amount even with the part scheduled to be curtailed. For example, looking at the dotted line in Fig. 5(a) at 13h30 (point 27 in the plot), 21 GW of PV were scheduled to be used from a forecast of 23 GW. The amount generated after curtailment was 27 GW, resulting in extra 6 GW of unscheduled PV power that will be curtailed. The economic loss for PV systems' owners will be in this case considerably higher than expected. On the other hand from point 11 to 20 and from point 32 to 35 no PV was scheduled to be curtailed and thus the surpluses generated at those hours will have to be dealt with in the intra-day operation to avoid frequency and instability problems on the power grid. In these hours unscheduled PV power curtailment occurs, something that could be avoided reducing the error of the forecast used.

In the UC scheduling based on a perfect forecast, the power generators are used differently. First, due to the lack of uncertainty of the perfect forecast and high amounts of PV power, LNG generators do not need to be used at all and pumped hydro increase its contribution on the total power generated. Moreover, in this case, from 9h to 16h, the maximum amount of PV the grid can absorb is scheduled, near to 22.5 GW, and the remaining PV generation is curtailed. The total amount scheduled to be curtailed in this day with the perfect forecast use was near to 50 GWh against 14 GWh with the day-ahead forecast. Although more PV is scheduled to be curtailed with the perfect forecast, considerably more PV is also used compared with the curve in Fig. 5(a) and no surplus of PV will have to be dealt with in intra-day operations. Moreover, although only 14 GWh of PV were scheduled to curtailed with the day-ahead forecast, in reality the actual curtailment reached by using the respective UC scheduling 94.7 GWh, considerably higher than what would be curtailed with a perfect forecast.

6. Conclusions

The objective of this study was to investigate the use of day-ahead forecasts of PV power in the unit commitment scheduling of a regional power system, and its effects of the scheduling of PV power curtailment. A comparison with a UC scheduling based on perfect forecasts showed that monthly, the use of the day-ahead approximates well the amount of PV power that should be curtailed with a perfect forecast.

Nevertheless, the day-ahead forecast errors had some important effects on UC scheduling and PV power curtailment. Annually, it caused a more expensive scheduling of power generators, and curtailment for longer periods than necessary and in the wrong hours. Additionally, although the monthly PV scheduled to be curtailed based on both UC scheduling were similar, the day-ahead forecast error caused a surplus of PV power generation that has to be curtailed in situations when insolation and power demand conditions would not justify curtailment. June and July were examples of when such cases occurred. In those months there was a negative bias of the day-ahead forecasts, which explain in part the poor detection of the hours when PV curtailment should happen. Thus, one potential measure to reduce such poor detection of curtailment is to further reduce the day-ahead forecast bias, particularly in spring and summer and in the hours when PV should be curtailed.

From the results we conclude that when using day-ahead forecasts of PV in the UC scheduling problem, the forecast error will cause not only affect the fuel cost of the power generators, but it will also yield a considerable

amount the PV surplus that will have to be dispatched or curtailed in intra-day operations. Thus, further measures to improve day-ahead forecast accuracy and to integrate PV forecast error in the UC modeling should be investigated to reduce PV curtailment and to support higher penetration of PV power in the power grid in Japan.

Finally, It should be mentioned that improvements on forecasting techniques are not the only way to deal with the problem of curtailment. Unoptimizing the tilt of PV panels, improved interconnections, demand response, and other measures can be applied together to reduce the need for curtailment of PV in a scenario of high penetration. The compound effect of all these measures together is an interesting topic that also should be investigated in further studies.

Acknowledgment

This study was funded by the New Energy and Industrial Technology Development Organization in the Project Mitigation Technologies on Output Fluctuations of Renewable Energy Generations in Power Grid.

References

- Chang, C.-C., and Lin, C.-J., 2001, LIBSVM : a library for support vector machines.
- Fonseca Jr., J.G.S., Oozeki, T., Ohtake, H., Shimose, K., Takashima, T., Ogimoto, K., 2014. Characterizing the Regional Photovoltaic Power Forecast Error in Japan: A Study of 5 Regions. *IEEJ Transactions on Power and Energy* 134.
- Fonseca Junior, J.G.S., Oozeki, T., Ohtake, H., Takashima, T., Ogimoto, K., 2015a. Regional forecasts of photovoltaic power generation according to different data availability scenarios: a study of four methods. *Prog. Photovolt: Res. Appl.* 23, 1203–1218. doi:10.1002/pip.2528
- Fonseca Jr., J.G.S., Oozeki, T., Ohtake, H., Takashima, T., Kazuhiko, O., 2015b. On the Use of Maximum Likelihood and Input Data Similarity to Obtain Prediction Intervals for Forecasts of Photovoltaic Power Generation. *Journal of Electrical Engineering & Technology* 10, 1342–1348.
- Ikeda, Y., Ikegami, T., Kataoka, K., Ogimoto, K., 2012. A unit commitment model with demand response for the integration of renewable energies, in: 2012 IEEE Power and Energy Society General Meeting. Presented at the 2012 IEEE Power and Energy Society General Meeting, pp. 1–7. doi:10.1109/PESGM.2012.6344788
- Lowery, C., O'Malley, M., 2012. Impact of Wind Forecast Error Statistics Upon Unit Commitment. *IEEE Transactions on Sustainable Energy* 3, 760–768. doi:10.1109/TSTE.2012.2210150
- NEDO, 2014. White Paper on Renewable Energy Technologies - 2nd Edition, 'in Japanese'.
- Ogimoto, K., Ikeda, Y., Kataoka, K., Ikegami, T., Oozeki, T., 2012. Flexibility of Japan's Power System to Accommodate PV Penetration in 2030, 27th European Photovoltaic Solar Energy Conference and Exhibition.
- Peng, X., Jirutitijaroen, P., 2009. A probabilistic unit commitment problem with photovoltaic generation system, in: TENCON 2009 - 2009 IEEE Region 10 Conference. Presented at the TENCON 2009 - 2009 IEEE Region 10 Conference, pp. 1–6. doi:10.1109/TENCON.2009.5396186
- Saito, K., Fujita, T., Yamada, Y., Ishida, J., Kumagai, Y., Aranami, K., Ohmori, S., Nagasawa, R., Kumagai, S., Muroi, C., Kato, T., Eito, H., Yamazaki, Y., 2006. The Operational JMA Nonhydrostatic Mesoscale Model. *Monthly Weather Review* 134, 1266–1298. doi:10.1175/MWR3120.1
- Schölkopf, B., Bartlett, P., Smola, A., and Williamson, R., 1998, Support Vector Regression with Automatic Accuracy Control, *Proc. ICANN98 Perspect. Neural Comput.*, pp. 111–116.
- Udagawa, Y., Ogimoto, K., Oozeki, T., Ohtake, H., Ikegami, T., Fukutome, S., 2016. Development of Unit Commitment Model Considering Confidence Intervals of Photovoltaics Forecast and Analysis of a Large Scale Power System. *IEEJ Transactions on Power and Energy* 136, 484–496. doi:10.1541/ieejpes.136.484
- Udagawa, Y., Ogimoto, K., Fonseca Junior, J. G. S., Ohtake, H., Fukutome, S., 2017, Economic Impact of Photovoltaic Power Forecast Error on Power System Operation in Japan, in: 12th IEEE PowerTech Conference. Presented at 12th IEEE PowerTech Conference, Manchester, UK.
- Udagawa, Y., Ogimoto, K., Fonseca Junior, J. G. S., Ohtake, H., Fukutome, S., 2017, Analysis of Photovoltaic

Power Yield Curtailment in Day-ahead Unit Commitment, in: *IEEE Transactions on Power and Energy*, 137, 7, pp. 1-10. doi:10.1541/ieejpes.137.1

Wang, J., Botterud, A., Bessa, R., Keko, H., Carvalho, L., Issicaba, D., Sumaili, J., Miranda, V., 2011. Wind power forecasting uncertainty and unit commitment. *Applied Energy* 88, 4014–4023. doi:10.1016/j.apenergy.2011.04.011.