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SOLAR PV POWER INTERMITTENCY AND ITS IMPACTS ON POWER SYSTEMS – AN OVERVIEW

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ABSTRACT: Although solar photovoltaic (PV) systems are environmentally friendly, policy makers and power system operators have concerns regarding the high penetration of these systems due to potential impacts of solar power intermittency on power systems. Understanding the nature of this intermittency is important to make informed decisions regarding solar power plants, size and location, transmission and distribution systems planning, as well as thermal generation units and electricity markets operations. This article presents a review of solar PV power characteristics and its impacts on power system operation.

Keywords: Solar PV power; Intermittency; Power system operation; Reserve requirements.

تذبذب الطاقة الكهروضوئية وآثارها على أنظمة الطاقة الكهربائية ـ نظرة عامة

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الملخص: على الرغم من أن أنظمة الطاقة الشمسية الكهروضوئية (PV) صديقة للبيئة ، إلا أنه توجد بعض المخاوف لدي صناع القرار ومشغلي أنظمة الطاقة الكهربائية بشأن الآثار المحتملة لتذبذب انتاج أنظمة الطاقة الشمسية الضوئية على عمليات تشغيل نظم الطاقة الكهربائية. ولذالك فانه من المهم فهم طبيعة هذا التذبذب من أجل اتخاذ قرارات مستنيرة بشأن حجم محطات توليد الطاقة الشمسية وموقعها ، وكذلك تخطيط شبكات النقل والتوزيع ، فضلاً عن وحدات التوليد الحرارية وعمليات أسواق الكهرباء. تقدم هذه المقالة عرض لخصائص الطاقة الشمسية الكهروضوئية وتأثيراتها على تشغيل نظم الطاقة الكهربائية.

الكلمات المفتاحية: الطاقة الشمسية الكهروضوئية؛ تشغيل نظم الطاقة الكهربائية؛ تذبذب الأنتاج؛ الأحتياطي الدوار.

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1. INTRODUCTION

Solar photovoltaic (PV) systems experienced a tremendous increase in installed capacity in the past decade. According to the 2019 REN21 Renewables Global Status Report, the global solar PV installed capacity increased from 17 GW in 2008 to 505 GW in 2018 as shown in Fig. 1. About 100 GW solar PV capacity was added in the year 2018. This rapid growth of solar PV system deployment is attributable to several factors such as PV technology improvements, cost reduction, as well as policies and regulations promoting the use of renewable energy resources (REN21 2019).

Solar PV power is environmentally friendly and can be used to extend fossil fuel reserves' life. However, the implications of intermittent nature need to be examined. Intermittency of solar PV power affects the balance between supply and demand. When supply-demand balance is not maintained, power system frequency deviates from steady state values; consequently, system stability and reliability are jeopardized (Kundur, Paserba *et al.* 2004). Although it is technically possible to integrate a large amount of intermittent renewable-based facilities in power systems, higher penetration levels result in more challenges to power system stability and reliability. These challenges are quantified using intermittency integration costs (Albadi and El-Saadany 2010). In general, the impacts of intermittent renewable-based generation facilities on power systems are due to two factors: variability and uncertainty (Ummels, Gibescu *et al.* 2007; Albadi and El-Saadany 2011).

Understanding solar power variability is necessary to make informed decisions regarding energy policy, solar energy conversion system design, transmission system planning, thermal generation units' operation, and efficient electricity market operations (Sengupta, Xie *et al.* 2018). This paper presents a state-of-the-art review of solar PV power variability and its impacts of power systems.

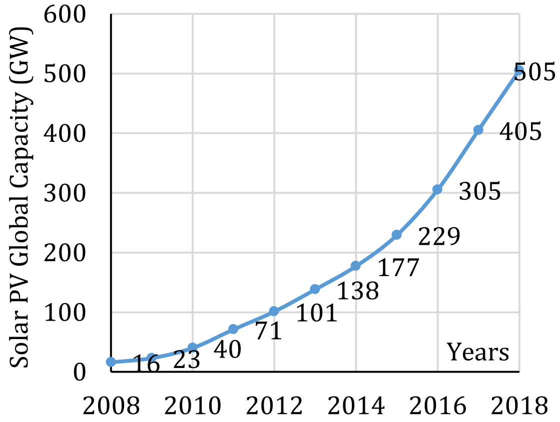

Figure 1. Global solar PV installed capacity.

This introduction is followed by presenting the characteristics of solar PV power output in section 2. Section 3 presents the impacts of PV power intermittency on power systems. Section 4 discusses the lessons learned from PV integration studies. The main conclusions are summarized in section 5.

2. CHARACTERISTIC OF SOLAR PV OUTPUT

To highlight the variability aspect of solar PV power, Fig. 2 presents a typical clear sky solar PV system output based on ground measurements and recorded load data of the Main Interconnected System (MIS) of Oman on 1 January 2015 (Albadi 2017, OPWP 2019). As seen from this figure, even with a clear sky and its variation, there is a challenge to power system operator. As seen from Fig. 2, solar PV power output is not correlated with the load requirements. This mismatch poses a challenge to power system planner and operators.

Figure 3 presents the intermittency nature of solar PV power caused by passing clouds. The presented PV power data are based on recorded 1-minute solar irradiation data (OPWP 2019).

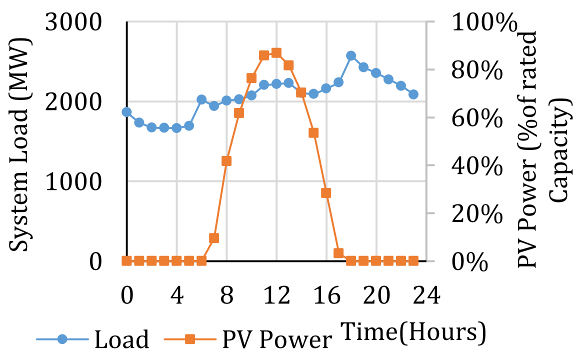

Figure 2. Manah site solar PV system output (clear sky) and recorded MIS system load data on 1 January 2015.

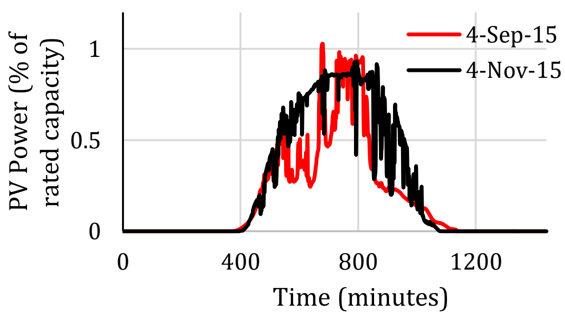

Figure 3. Manah site 1-minute PV power output data for 2 days in 2015 (passing clouds).

Variability is defined as the step changes from one averaging interval to the next one. There are two types of solar irradiance and PV plant output variabilities: deterministic and stochastic. The former variability is related to the position of the Sun whereas the latter is related to clouds. The output of different PV plants can be accurately calculated for a clear sky; therefore, the deterministic variability between different plants located in the same geographical area is highly correlated and its smoothing effect is very limited. However, stochastic variabilities caused by passing clouds on a single PV plant are severe and their implications on power system operation can be substantial. The magnitude of stochastic variabilities can be obtained from the difference between the PV system(s) output power during a sunny day and a cloudy day.

2.1 Solar PV Variability Statistical Representation

Mathematically, variability is defined as the step changes from one averaging interval to the next one. To quantify the variability of an intermittent source of power, step changes of its average output is evaluated over different intervals (Hoff and Perez 2012). For example, considering availability of 1-minute data (P_{1m}), the 5-minute step changes ($\Delta P_{1m}^{\bar{5}}$) are obtained by calculating the average output for every 5-munite interval ($P_{1m}^{\bar{5}}$), and then evaluating the changes between the calculated 5-minute data (Hoff and Perez 2012).

$$P_{1m}^{\bar{5}}(t) = \frac{1}{5}\sum_{i=1}^{5} P_{1m}(t+i) \quad (1)$$

$$\Delta P_{1m}^{\bar{5}} = P_{1m}^{\bar{5}}(t) - P_{1m}^{\bar{5}}(t-5) \quad (2)$$

The standard deviation (σ) of step changes is used to quantify variability over relevant timeframe. For the example of 5-minute data, it is calculated using the following formula (Elsinga and van Sark 2015):

$$\sigma_{\Delta P_{1m}^{\bar{5}}} = \sqrt{V(\,\Delta P_{1m}^{\bar{5}})} \quad (3)$$

where V is the variance.

Considering a normal distribution of variations, 3σ represent 99.7% confident interval that data (step changes) will be within. However, considering a flat tail distribution, the 99.7 confidence interval requires more than 3σ.

The variability of the aggregate PV power that can be estimated is affected by correlation between different PV plants and between aggregate PV power and system load. To quantify the trends between time series measurements at two sites, correlation coefficient is used as an index. At value of 1.0, both sites have simultaneously the same trends. When the value is less than 0.25, the correlation is considered to be weak (Brouwer, Van Den Broek *et al*. 2014). For weak and uncorrelated variabilities, the combined variability (σ_{12}) of two sites can be found using individual site variabilities (σ_1 andσ_2) as described by the following formula.

$$\sigma_{12} = \sqrt{(\sigma_1)^2 + (\sigma_2)^2} \quad (4)$$

2.2 Variability Smoothing through Aggregation

Aggregating the output of different PV systems can reduce negative implications. The negative implication of intermittency is highly dependent on smoothing effect due to geographic diversity of these resources (Mills 2010). There are different levels of smoothing effect as discussed below:

2.2.1 Smoothing effecting of aggregate solar irradiance data

Although clouds can cause substantial changes in solar irradiance in a single site as shown in Fig. 3, aggregating the output of several different solar irradiance meters reduces aggregated sites solar irradiance variability. This effect exists because clouds are diverse in nature as their sizes and shapes are changing and they do not cover different sites at the same time.

The authors in Jayaraman and Maskell (2012) used 1-second data to study temporal and spatial variations of solar irradiance in Singapore. The study demonstrated that the global horizontal radiation variability is caused by direct beam radiation variabilities and that diffused radiation variability is very limited. The authors in Projects 2015 used 5 second averaged irradiation data from 9 sites located within 0-15 km radius from central location. The authors concluded that combined irradiance is substantially less variable compared with a single site. For example, the step changes of the measured irradiance at a single site exceeded 500 W/m^2. However, when the measured irradiance at the nine sites were combined, step changes were below 140 W/m^2 and mostly below 100 W/m^2. In addition, the authors of Projects 2015 concluded that both geographical dispersion and number of sites contributes to reducing solar irradiance variability. However, spatial dispersion smoothing effect is less important than increasing the number of sites for the considered timeframe (5 seconds).

In Murata, Yamaguchi *et al.* (2009), the authors demonstrate that the measured solar irradiation in Japan is uncorrelated for 1-minute time-scale when the geographical distance between them is more than 50-100km. For the 20-minute time-scale, the correlation coefficient quickly decreases to 0.1 as the distance increases (Murata, Yamaguchi *et al*. 2009).

Similarly, the authors in Mills (2010) used 1-min solar irradiance data of 23 sites in the Southern Great Plains in the USA to study aggregation effect. The study reported that single site 1-min to 180-min variability can exceed 60% of the clear sky insolation. Moreover, aggregating the solar irradiance of five sites close to each other show that 99.7% of the 15-min and shorter time scales variabilities did not exceed 25% of the expected clear sky output. Additionally, the 99.7% of the 15-min and shorter time scales variabilities did not exceed 10% of the clear sky output from 100 sites with 20 km spacing, as shown in Fig. 4 (Mills 2010). These conclusions are based on measurements of solar irradiance data; therefore, they are considered to be conservative compared to actual aggregated PV power output variability.

In Perez, Lauret *et al*. (2018), the authors studied the temporal and spatial variabilities of solar radiation in Kenya using hourly solar irradiation Meteosat satellite derived data of 0.05°×0.05° grids in longitudes and latitudes. The authors reported that GHI measurement in a location can be used to represent an area of 1,225 km^2 in most areas of Kenya. Moreover, in the central and western highlands, the area is increased to 5,625 km^2. The authors reported that DNI spatial variability is twice that of GHI. Regarding inter-annual variability. The authors concluded that obtaining a representative year of solar irradiation in Kenya, 5.5 and 7-year data are required for GHI and DNI respectively.

The authors in Luiz, Martins *et al*. (2018) used one-year of 1-min resolution ground-based irradiance data measured at three sites to analyze the intra-day solar irradiance variability. The surface solar irradiance variability was evaluated using visible satellite images of cloud cover in different Brazilian climate zones. The study concluded that generally humid months have more variability than dry months. In addition, dry locations experience more short-timescales variability than more humid locations.

Willemsen (2016) studied temporal, spatial and the impacts of wind characteristics of short term solar intermittency using 5-seconds data from 200 PV systems in Utrecht, the Netherlands. To quantify PV power output variability, the author used clearness index and delta clearness index. Clearness index is defined as the ratio of the measured global horizontal irradiance to the modeled clear sky irradiance at a horizontal level at a given time. The study concluded that the variation of irradiance between sites becomes independent if the separation distance is 100 meter for 5 seconds data.

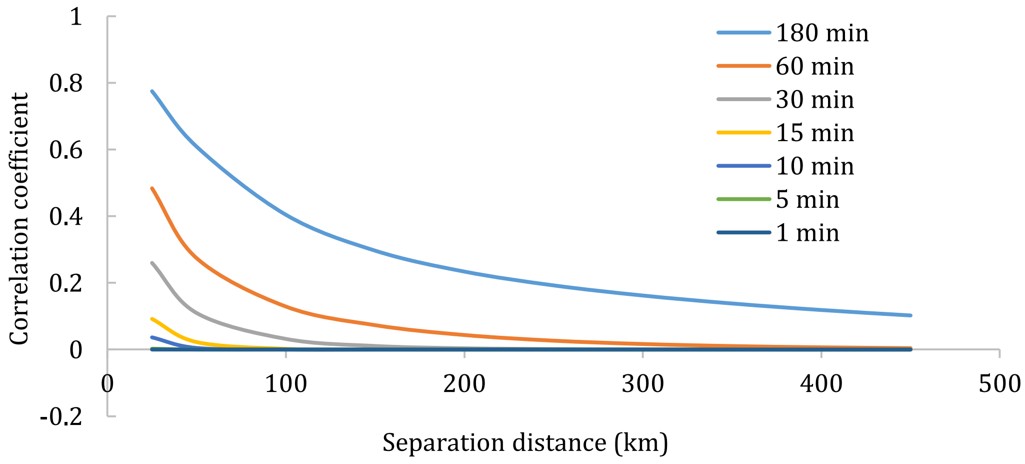

Figure 4. Correlation of stochastic solar irradiance variabilities (Mills 2010).

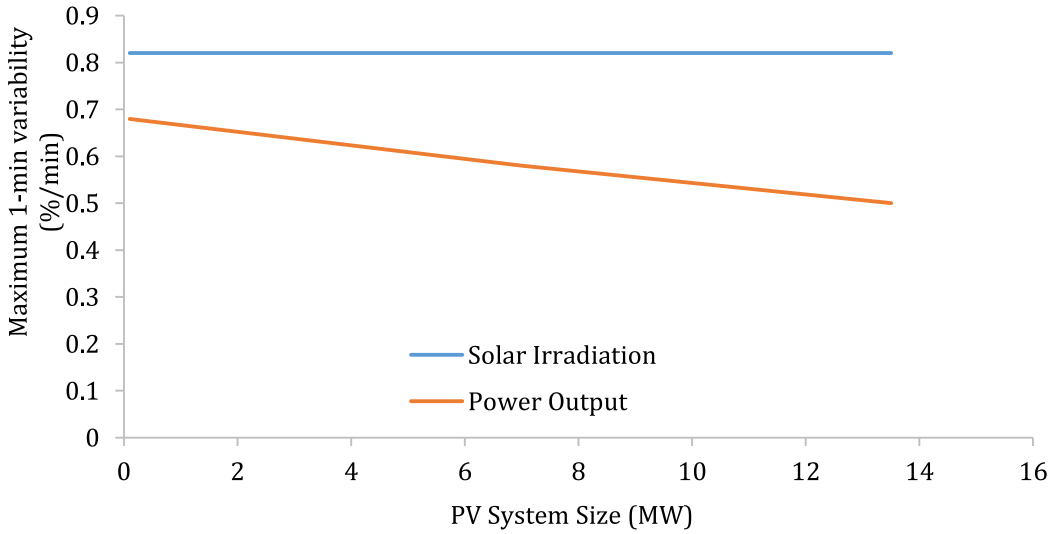

Figure 5. Maximum 1-min variability of a 13.2-MW PV plant on a highly variable day (Mills 2010).

2.2.2. Smoothing effect of within a single PV plant

In general, solar irradiance variabilities are more severe than power output variability (Projects 2015). This smoothing effect is a function of the plant size and the timeframe. In general, larger PV plants have better smoothing effect than smaller plants (Lew, Brinkman *et al*. 2013). The authors in Mills (2010) conducted measurement analysis of a multi-kW PV plant and showed that the sub-minute power output variabilities are lower than the corresponding solar irradiance variabilities. For a multi-MW power plant, similar smoothing effect is observed in sub 10-minute power output variabilities. Figure 5 below presents a linear curve fitting for data presented in (Mills 2010).

2.2.3. Smoothing effect of aggregate PV plants output

The geographic diversity of PV plants decreases the probability of cloud fronts covering different PV plants at the same time. This smoothing effect has been observed (Wiemken, Beyer *et al*. 2001). Experience from PV plants performance in Germany showed that normalized 5-minute output variability at one site may exceed 50%, whereas the normalized variability from 100 PV sites was within 5% of installed capacity (Wiemken, Beyer *et al*. 2001). The power output variabilities of PV plants 20 km and 50 km apart are considered uncorrelated for 15-min and 30-minute or shorter time-scales, respectively. To obtain uncorrelated 60-min power output variability, sites should be at least 150 km apart (Mills 2010).

Elsinga and van Sark (2015) used the standard deviation of 25 PV systems power output 1-minute data to quantify variability in and around Utrecht, the Netherlands. The authors concluded that the power output of different PV systems becomes uncorrelated after a certain decorrelation length. For the full year data of the system understudy (100 km^2), the decorrelation length was found to be 0.34, 2.6, and 5.0 km, for 1, 5, and 15-minute timeframes, respectively.

If the outputs of an N-number of PV power plants are considered uncorrelated, the aggregated output variability is reduced by $N^{-0.5}$.

It can be concluded that the correlation of output variabilities between different PV plants installed at different locations is a function of both a dispersion area and relevant time-scale. Less correlation is achieved over shorter time scales variability and broader geographical dispersion areas. Additionally, the speed of the clouds affects this correlation (Lave and Kleissl 2010; Hoff and Perez 2012).

2.2.4 Smoothing effect of load and other energy resources variabilities

The study in (Projects 2015) considered the effect of 10 MW additional solar PV capacity on net load variability of a 55 MW islanded system having 4 MW existing PV capacity. The authors concluded that the net load variability caused by additional 10MW dispersed PV plants (9x1.1MW) was very similar to the original load variability. This result is attributed to the fact that aggregated load variabilities are not highly correlated to aggregated PV power variability. In addition, the authors in (Energy 2010; Halamay, Brekken *et al*. 2011) concluded that aggregating different energy resources reduces the overall variability of the renewable-based power output.

In *Koivisto, Das et al*. (2019), the authors used time series simulation of wind and solar generation to analyze the variability and uncertainty of intermittent renewable power. The study concluded that increasing intermittent renewable power capacity in future Nordic and Baltic countries is not expected to cause a significant increase in the hourly ramp rates of net load. The mean value of net load decreased for all studied scenarios. Moreover, the standard deviation of the net load is expected to have a slight and notable increase for in 2030 and 2050 scenarios, respectively. The authors concluded that with more geographical dispersion and mix of different renewable energy technologies, the standard deviation of the net load deceases significantly.

3. IMPACTS OF SOLAR PV POWER INTERMITTENCY ON POWER SYSTEMS

In general, the intermittency of solar PV power can negatively affect power system operation in different aspects. These effects could be either local or system wide depending on installed PV capacity, load profile, flexibility of dispatchable generation units, and system network.

3.1 Power Quality

Fluctuation solar irradiation a specific location results in fluctuating solar PV power output. This fluctuation, in turn, can cause power quality distortion such as flicker and overvoltage at that location or feeder (Trindade, Ferreira *et al*. 2017). Voltage variations caused by variable PV power could be slow (steady) variations during sunny days, in which the voltage at the point of common coupling increases with the power output. In addition, fast (transient) voltage variations occur on partly cloudy days as a result of passing clouds (Lew, Miller *et al*. 2010). This voltage variations could affect the tap changers and voltage regulators (Trindade, Ferreira *et al*. 2017). In addition, cloudy conditions can increase harmonic distortion levels caused by PV systems as reported in Varma, Rahman *et al*. (2016). The degree of power quality distortion caused by PV systems is a function of the characteristics of cloud transients, the size of PV system, the stiffness of the point of common coupling, and the inverter used.

3.2 Power Flow and System Losses

The fluctuating output of solar PV systems changes the power flow; therefore, it affects system losses.

This effect is a function of the size and location of solar PV facilities. Even if PV systems are allocated optimally for certain load and solar conditions, fluctuating output of PV systems will change losses. (Albadi, Al-Hinai *et al*. 2013, Albadi, Al-Mashaikhi *et al*. 2015). In general, power system losses are expected to decrease when PV systems are distributed and located in load centers, and vice versa.

3.3 Cycling and Ramping of Thermal Generation Units

High variability of PV power output could result in increased net load variability. This can increase cycling (turning ON/OFF) of thermal-based generation units (Albadi and El-Saadany 2011). Increased cycling results in increased wear-and-tear costs as well as increased emissions. The study in Lew, Brinkman *et al*. (2013) concluded that while the additional cycling costs caused by wind and solar power are minimal ($0.14–0.67 /MWh), the fuel cost reductions are substantial ($28–$29/MWh). In addition, the authors concluded that the increased cycling due to renewable energy caused a negligible impact on the CO2, NOX, and SO2 emissions reductions from renewable energy. Moreover, the increased ramping requirements of the net-load might result in dispatching generators that have high ramping capabilities regardless of marginal cost. This is of special importance when load ramping up/down requirements are opposite PV power variability.

3.4 Operating Reserve

Operating reserve is required to balance short-term demand fluctuations. As the penetration of intermittent PV power in a power system increases, operators would require more operating reserves to maintain supply-demand balance (Halamay, Brekken *et al*. 2011, Dowell, Hawker *et al*. 2016). Additional uncertainty and variability caused by intermittent generation resources over time scales shorter than the starting time of fast-start generation units must be balanced using spinning reserve. However, adding more spinning reserve capacity results in more units operating at sub-optimal operating points with higher marginal costs (Ortega-Vazquez and Kirschen 2007).

Depending on study assumptions and system operator procedures, different integration studies address reserve requirements in presence of intermittent solar PV power differently (refer to Fig. 6). Earlier studies considered a constant amount as a reserve requirement for the whole year based on load and/or intermittent renewable power (Energy 2010, Halamay, Brekken *et al*. 2011). Recent studies considered variable hourly requirement to reflect expected load and intermittent power variability (Tabone, Goebel *et al*. 2016).

Two approaches are used to determine the reserve requirements: n-sigma and heuristics. In n-sigma approach, reserves are defined to be equal to a given number of forecasting error standard deviation (Halamay, Brekken *et al*. 2011). If the probability distribution function of the forecasting error is Gaussian, this method gives a confidence level for reserve requirements. For example, specifying the reserve to be 3-sigma (3σ) implies a 99.73% confidence level. As extreme variabilities occur more than what Gaussian function predict, some studies use heuristics approaches to quantify reserve requirements. For examples, the authors in Lew, Brinkman *et al*. (2013) set regulating reserves to cover 1% of the load and 95% confidence level of the 10-minute load and renewable power forecast errors, respectively. Load following reserve is set to cover 70% of the 60-minute renewable power forecast errors. In Tabone and Callaway (2015), Tabone, Goebel *et al*. (2016), Markov chain modeling is used to predict variability and uncertainty of PV systems for reserve requirement calculation.

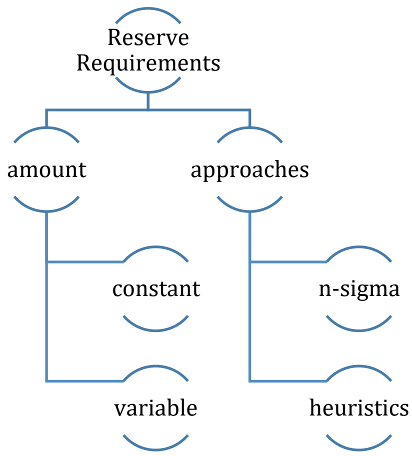

Figure 6. Reserve Requirements.

4. LESSONS LEARNED FROM PV INTEGRATION STUDIES

4.1 Extreme PV Power Variabilities Timings

Reserve is of special importance during extreme events that include the steepest net load ramps, the minimum net load, and the biggest forecast errors. As PV power variability is dominated by known deterministic (diurnal) changes, its reserve requirements should be based on stochastic (weather) component of solar variability (Ibanez, Brinkman *et al*. 2012). Extreme solar power variability is attributed to the known daily position of the sun in the sky (sun rise/set) not from fast-moving clouds.

4.2 PV Geographical Dispersion

The authors of Tabone, Goebel *et al*. (2016) demonstrated that locations of utility-scale PV systems play an important role on regulation and load following reserve requirement in California's power system considering additional 12GW PV capacity. When the PV capacity is geographically dispersed, additional reserve requirements are less than 0.05%

and 1.2% of installed PV capacity, for regulation and load following, respectively. These requirements increase to 0.2% and 5.6% for the centralized scenarios. In Tabone, Goebel *et al*. (2016), load following reserve is defined as the difference between hourly and 5-min schedules, whereas regulation reserve is the difference between actual net-load and the 5-minute schedule.

4.3 PV Power Impacts on System Stability

It is unlikely that PV power will change contingency reserves (Brouwer, Van Den Broek *et al*. 2014). This conclusion stands because the loss of supply resulted from a single contingency at the largest infeed will likely continue to be larger than that resulted from a contingency at single PV plant. The authors in Miller, Shao *et al*. (2014) studied transient stability and frequency response of the Western Interconnection with high wind and solar penetration. The authors concluded that the Western Interconnection can meet transient stability and frequency regulation objectives with high levels of wind and solar generation.

However, in the context of small and islanded grids, high PV power penetration level can change the required contingency reserves. For example, if the solar PV power becomes low due to a passing could, the frequency of the system will drop below frequency ride-through limit of PV inverters and they might disconnect simultaneously. This simultaneous loss of inverters can create a large loss of generation.

4.4 Factors Affecting Intermittency Costs

To quantify the impact large solar PV power in a specific system, the following aspects need to be considered.

- Characteristics of solar PV power output: PV power output is a function of both solar irradiation characteristics and geographical dispersion of PV production facilities.
- System load and PV power output profiles: Highly correlated load and PV power profiles results in lower integration costs. Storage and demand response options can reduce net load variability.
- Conventional generation units and transmission system characteristics: Flexible generation units such as natural gas-based power plants can accommodate increased net load variability better than other large units such as coal-fired or nuclear plants.
- Electricity market design: The market design influences the reserve required to accommodate variable PV power. For example, forecasting errors and reserve requirements are lower when generation scheduling is done more frequently.

5. CONCLUSION

The wide-scale integration of solar PV power might bring concerns regarding PV output variability and its challenges to power system operation. Although the solar irradiation measured at a specific site experience drastic change during cloudy days, a smoothing effect exists with aggregated measured data from multiple sites. In addition, because solar irradiation data at a specific site is based on one point of very small area, the output of a PV plant that covers hundreds of meters at that site is less variable than the measured solar irradiation. Moreover, field experiment shows that the output variability of aggregated PV plants output is much smaller than that of a single PV plant. Fortunately, extreme aggregate solar power variability is attributed to the known daily position of the sun in the sky not from fast-moving clouds. To quantify the system-wide impacts of PV power, reserve requirements to address intermittency are to be quantified. Studies show that geographical dispersion of PV power facilities is important to reduce reserve requirements. In addition, extreme solar power variability of geographically distributed PV power is attributed to the known daily position of the sun in the sky not from fast-moving clouds. The intermittency integration costs of PV power can be determined by calculating the difference between overall electricity cost with and without PV power. This integration cost is system specific and is affected by several factors such as the characteristics of solar PV power output, correlation between load and PV power output profiles, characteristics existing generation units' and transmission system, as well as the design of electricity market.

CONFLICT OF INTEREST

The author declares no conflicts of interest.

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