An empirical approach to frequency droop characterization from utility-scale photovoltaic plants operation in a power system

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Abstract
PV plant power excursions can have adverse implications on grid frequency. This phenomenon is observable due to inherently uncertain cloud transients across a local PV plant. Hence, provision of decision-based controllers for centralized power inverters becomes imperative for supporting local grid operations. Such controllers can be improved to better counteract minutes-based PV power deviations from its stable equilibrium. Thus, grid frequency deviations require further investigation at PV plant point of interconnection to the grid. In this research, single and spatially distributed utility-scale PV plants operation is studied on a real-time power system simulator, under fast-changing meteorological conditions at different PV site loading levels ($P_{PV-ref}$). Software-in-the-loop Monte Carlo simulation is conducted and an empirical approach is proposed for characterizing minutes-based variations in grid frequency originating from PV plant operation, that is, power fluctuations at different $P_{PV-ref}$. The power–frequency curve obtained at the PV site can be incorporated in form of an empirical frequency droop function in characteristics curve of adjacent auxiliary power source(s). A prominent feature of this adaptive frequency droop is that it considers PV site loading levels during different hours, giving it leverage over common practice constant droop(s). A hardware-in-the-loop platform is presented allowing field derivation of adaptive frequency droop curves using hardware PMU time-series data analytics.

1 INTRODUCTION

Deterministic and probabilistic (or empirical) assessment and modelling techniques have been widely used in various fields including power systems. Deterministic methods are based on pre-defined system parameter values, neglecting parameter uncertainty’s inherent properties that can result in inaccurate models due to over/under-estimating the parameter uncertainty’s impact [1, 2]. In fact, power system operations with renewable energy sources (RES) exhibit a high level of inherently stochastic dependence and parameter uncertainty [3]. The grid frequency deviations is a multi-faceted function of load changes, synchronous generators operation as well as renewables and energy storage. Grid frequency also varies from primary and auxiliary frequency controllers operation such as governors and area generation controls (AGC) or demand response (DR). This frequency deviation from the equilibrium can be presented with (1) and is depicted for the components of a benchmark two area four machine power system (Figure 1).

$$\Delta f = \frac{\partial f}{\partial P_{L}} = \frac{\partial f}{\partial P_{G}} = \frac{\partial f}{\partial P_{ESS}}$$

(1)
The summation of frequency changes from inter- and intra-dependent operation of the various grid components during few minutes gives the total super short-term frequency deviation $\Delta f$ in the power system. However, solving this expression is cumbersome, taking into account the non-linear dynamics of each component and the inherently uncertain characteristics of RESs. Besides, levels of inter- and intra-dependence within the components of a power system vary with both variations in duration of frequency uncertainty as well as granularity of frequency data samples [3]. Considering the paramount importance of the issue and comparatively new frequency-related inherent uncertainties associated with utility-scale PV penetration increase, a systematic empirical approach is proposed in this paper, for assessing and characterizing the minutes-based timescale variations in system frequency originating from PV plant(s) inherent operation.

Empirical model development has been utilized for reliability, operation, and planning studies in power systems that deal with inherent parameter uncertainty [2]. For instance, from a power system reliability perspective, [4] have predominantly performed Monte Carlo (MC) simulation to build simplified empirical models being used in reliability evaluations. Authors in [5] developed a scenario-based techno-economic decision-making model to address optimal reactive power dispatch in the presence of wind power generation uncertainty and in the context of power system operations. Reference [6] developed an online decision-making and preventive control model using a control table strategy based on trajectory sensitivity analysis that reflects on state-variables’ variation sensitivity with respect to variations in some parameters. This addresses power system transient stability during cascading failures. Authors in [7] have addressed the importance of empirical studies to comprehend the effect of frequency-related load-damping on system frequency. It has shown how the misrepresentation of the load-frequency coefficient leads to the largest impact on frequency deviation. Authors in [2] presented a comprehensive review of the available deterministic and stochastic assessment methods that study the impact of rooftop PV systems penetration levels on the power quality indices. After evaluating the parameter uncertainty modelling approaches, the authors have come down to this conclusion that there is no single best approach and that opting for the proper modelling framework heavily depends on the nature of the study. However, among the plethora of methods that they have analyzed, empirical modelling based on MC simulation has been the most favourable computational method that results in satisfactory uncertainty representation in this realm, of course coming with computational costs. Eventually, the authors identify uncertainty modelling as an open challenge.
and ongoing areas of research, suggesting application of more advanced methods like probabilistic techniques, modeling correlation of the uncertain parameters. Thus, our empirical framework in this paper attempts to build toward these general lines of thought.

Before delving into presenting this research, further elaboration has been presented here in order to represent a valid hypothesis for this study. With the increasing penetration of utility-scale PV, the grid frequency will be adversely affected by minutes-based frequency fluctuations at PV plant’s point of grid interconnection (POI), that is, critical utility transformer HV-busbar having been impacted. Consider the power system of Figure 1a, in which each generator is equipped with a governor for primary frequency control and each control area is equipped with an AGC with its functionality described in [8] for secondary frequency control. A single (600MWp) PV plant in Area 2 is connected to Bus 10. The single-line diagram of the PV plant is depicted in Figure 1c with PMU-based measurements and monitoring at grid POI. The operation of the PV plant with a solar irradiance profile similar to Figure 1b infers that the larger the short-term (minutes-based) deviations in PV plant’s power from normal operating conditions (clear sky), the higher the frequency fluctuations will become at POI (Figure 2).

This type of measured seconds-based SIR fluctuations (Figure 1b) leading to minutes-based fluctuations at PV plant POI causes higher fluctuations in the grid frequency. Under specific circumstances, the MW-scale PV plant will need to be disconnected (islanded) from the host PV busbar according to distributed energy resources (DER) PV inverter interconnection standards such as the IEEE 1547a [9, 10]. This is to protect the PV plant from damages as well as to maintain grid frequency in compliance with grid regulatory standards. Figure 2 illustrates frequency excursions under higher PV penetrations in the test system. The plant is operating at a reference steady-state operating point e.g. standard testing conditions (STC).

Suddenly, PV generation as high as 300MW (more than half) is lost in Area 2 and as observed the frequency at POI drops more than 0.5 Hz in less than a minute. A common practice nowadays is to eliminate short-term load-generation equilibrium deviation from equality utilizing fast non-synchronous generation with frequency droop characteristics curve. However, the characteristics curves in past literature mostly incorporate a constant frequency droop at different stable equilibrium points. For instance, one main strategy for primary frequency regulation is the deloading droop control [11, 12]. It involves operating the PV generator at a voltage level lower than its maximum power point. Despite the effectiveness of this approach, the control strategy lacks incorporation of each PV-site specific meteorological weather conditions’ loading effect. In a recent study, NREL researchers have measured and shown the fast variations in frequency due to short-term changes in PV power through a real case study [13].

Analyzing the field study results reveals that the frequency droop curve is not constant under different steady-state operating conditions. In fact, from the virtue of PV plant location-and hour-dependent experimental measurements, the adaptiveness can be recognized. This has not been realized in their study as the authors have considered a constant frequency droop for frequency support. Thus, a variable frequency droop is yet to be characterized and modelled at each PV plant point of interconnection to the grid, with consideration of site-specific operating conditions imposed by PV-site steady-state loading levels during different hours of the day. The primary contributions of this paper are listed as following:

- Developing an empirical approach to characterizing/modelling minutes-based grid frequency variations caused by utility-scale PV plant(s) operation. As a result, statistical assessment is performed to verify the generic frequency droop deviations model for a wide range of operating conditions, that is, PV site loading $P_{M-req}$ levels.
- The characterization approach is illustrated for both single and spatially distributed utility PV plant(s), showing its leverage over common practice constant droop(s).

The result could be shown in the form of scatter plots or probabilistic representation (PDF and/or CDF). Figure 6 shows the scatter plot of trials as performed.

With spatially distributing the PV size across the control area, the benefits on system frequency and mitigation of frequency events due to extreme rise/fall in frequency have been observed. With an empirical approach, the controlled lab environment random experiments results can be shown in the form of scatter plots or probabilistic representation (PDF/CDF) [2]. Eventually, this empirical characterization of the POI frequency droop from PV variations, can bring the benefit of implementing decision-based adaptive controller design enhancements for power electronics interfaces (PEI) active in fast PV power fluctuations mitigation in the power grid. Thus, environmental datasets need to be available first to closely developing site-specific inherent models. The derived empirical model in this study is presented to ECC operators, to enable the consideration of each PV plant site-specific steady-state operating conditions. In the past, EV-VSIs have used a constant frequency droop in setting their active power reference set-point for vehicle-to-grid applications [14]. This has been the case with many EV models active in either primary or secondary frequency regulation [15], but the empirical model developed in our study can be incorporated into the characteristics curve of MW-scale energy storage systems (ESS) installed on the PV site, namely PV-SmartParks (PV-SP) [16] to realize its benefit in fast frequency support and site-specific adaptive PV power smoothing at the PV busbar. Furthermore, the entire system along with the PV power
plant(s) and their associated controllers are modelled using a real-time digital simulator (RTDS) platform. The advantage of incorporating RTDS is that it represents the detailed dynamics of the actual power system and its fast-switching power electronics devices, in such a way that any modelled component in RTDS can be replaced with practical hardware in any instance.

The remaining sections of this paper are as follows: Section 2 presents the approach to frequency characterization from PV operations at PV plant POI. In Section 3, the test power system is described, the POI SIL frequency droop characterization results is presented, and a HIL platform with hardware PMU has been set up for performing the aforementioned approach by a system operator. Eventually, the concluding remarks of this study are given in Section 4. The results and discussions presented pave the way for the implementation of enhanced PV power fluctuations mitigation/smoothing techniques in the smart grid.

## 2 Adaptive Frequency Droop Characterization

As earlier discussed in Section 1, SIR step/ramp events due to sudden cloud covers/removals can lead to frequency issues at POI affecting grid frequency, while ambient temperature has zero to minimal effect on the PV power output and POI frequency during sudden cloud covers removals. This is because cloud covers/removals happen in a matter of seconds to a few minutes in a given site. Thus, temperature can be neglected for frequency droop characterization. Solar step/ramp events have been categorized according to the type of research carried out by researchers, that is, SIR step/ramp events and solar power step/ramp events [17]. With facilities at the Real-Time Power and Intelligent Systems (RTPIS) Laboratory at Clemson University [18], high-time resolution (second-based) real-time/archived SIR data is accessible. Hawaii in the U.S. and Uppsala in Sweden have also reported measuring 1-sec resolution global horizontal irradiance at their corresponding weather stations [19]. Utilizing such data, probabilistic models have been developed in a spatial network. It is noteworthy that, the pyranometer measurement period must be short enough to capture the major dynamics of instantaneous irradiance. Often, these dynamics are averaged over a time period of one or more minutes [19]. In fact, the Surface Radiation Budget Network (SURFRAD) that is a network of observation stations across the U.S. logs high-quality \( i_{init} \) data with as high as 1-min resolution [20]. Further, [21] recommends 1-sec signal sampling SIR measurements in Baseline Surface Radiation Network (BSRN), so that 60 samples are averaged to form 1-min data. It allows downscale to seconds-based time-resolution in order to fit the desired data analysis requirements. Short-term solar irradiance variability is a key parameter to describing dynamic characteristics of irradiance that have significant transient effects in PV plant output power system performance. This is studied in the case of Chile and how temporal resolution smoothing has effect on irradiance timeseries [22]. Thus, seconds-based SIR step/ramp events are crucial for PV inverter control and real-time dispatch operations of PV plants. It will assist the balancing authority in the control area to better understand and deal with seconds-based SIR step/ramp events and the challenges it introduces in terms of short-term variability of PV power generation from its hour-based equilibrium (reference \( P_{\text{ref}} \)) at POI. In order to counteract the frequency deviations at POI from utility-scale PV plant operation during such inclement weather conditions, situational intelligence on these PV-generated frequency deviations seems to be a necessity to system operators at the energy control center (ECC) in the control area; that is to take proper measures in regulating the host PV busbar frequency in few seconds and in a cost-effective manner. Thus, characterization of the frequency droop deviations from utility-scale PV plant operation and identification of its power–frequency characteristics curve has been accomplished in multiple steps in this paper. The entire process is categorized in three steps and is presented in Figure 3.

### 2.1 Step 1: Replicating desired control area operating conditions

The first step to frequency droop deviations characterization from PV plant operation is to identify control areas in the interconnected power system and utility-scale PV plant(s) in each area. Then, define the control area (area \( \beta \)) that requires frequency droop deviations characterization from PV plant (\( j \)) operation in the area. Disconnect local ESSs and RESs (excluding PVs) in proximity of the area \( \beta \) PV busbar(s), while maintaining area frequency to nominal value, that is, 60 Hz at each \( \beta \).

#### \[ P_{\text{PV}}(k) \]

where \( P_{\text{PV}}(k) \) is the PV power output at time \( k \). Mean-frequency droop deviations characterization from PV plant operation is to identify control areas in the interconnected power system and utility-scale PV plant(s) in each area. Then, define the control area (area \( \beta \)) that requires frequency droop deviations characterization from PV plant (\( j \)) operation in the area. Disconnect local ESSs and RESs (excluding PVs) in proximity of the area \( \beta \) PV busbar(s), while maintaining area frequency to nominal value, that is, 60 Hz at each \( \beta \).

### 2.2 Step 2: Perturbations in PV plant power

Once Step 1 has been executed, measurements and real-time PMU data-streams stored in control area database \( DB \) and phasor data concentrator (\( PDC \)), Step 2 of the characterization process commences offline. This includes exposing the system to random ramp up/down perturbations in PV plant power, that is, \( \gamma \). Thus, seconds-based SIR step/ramp events are crucial for PV inverter control and real-time dispatch operations of PV plants. It will assist the

#### \[ P_{\text{PV}}(k) \cdot (100 \pm x(g))\% \]

where \( x(g) \) is a random number bounded to \( x_{\text{max}} \) for the duration \( t_{\text{duration}} \) at every \( \gamma \) given in (3). This measurement is repeated at every measurement time-step for
2.3 Step 3: Characterization of frequency droop deviations

In the third step, frequency droop deviations characterization is carried out by executing (2)–(6) as following:

\[
\begin{align*}
\Delta f_{PV_{\beta}}(t) &= f_{PV_{\beta}}(t) - f_{\text{ref}}^{*} [\text{Hz}] \\
\Delta P_{PV_{\beta}}(t) &= P_{PV_{\beta}}(t) - P_{\text{ref}}^{*} [\text{MW}] \\
\end{align*}
\]

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\[
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\Delta P_{PV_{\beta}}(t) &= P_{PV_{\beta}}(t) - P_{\text{ref}}^{*} [\text{MW}] \\
\end{align*}
\]
ARZANI AND VENAYAGAMOORTHY

TEST STUDIES, RESULTS, AND DISCUSSIONS

3.1 Real-time SIL simulation of a power system with utility-scale PV

Figure 1 has shown the single-line diagram of the power system. The entire system is modelled and simulated on a real-time digital simulator (RTDS) with utility-scale PV plants. The two-area multi-machine power system and its components are detailed in Section 2 of [8], while the PV plant inverter controllers’ structure is operating in the rotating synchronous dq-reference frame (SRF) [24] and with control block diagram similar to [25]. The PV plant is operating at unity power factor, with its governing equations presented in the Appendix of this paper. In this study, the common incremental conductance (InC) maximum power point tracking algorithm [26] has been implemented for the PV inverter in order to obtain the dc-link voltage reference set-point. This method has advantage over the perturb and observe (P&O) algorithm that can show poor MPP tracking under extreme perturbations in irradiance. Furthermore, P&O presents higher fluctuations around the operating point that may lead to skewed power measurements at POI, deeming it undesirable for data-driven modelling studies. All four generator buses and sending-receiving ends of the tie-lines are equipped with RTDS GTNETx2 card virtual PMUs, namely GTNET-PMU for GPS-synchronized frequency and voltage/current phasor estimation at a 30 Hz sampling rate and in compliance with the IEEE C37.118 standard. A GTNET-PMU is a software PMU in RSCAD, of which with the aid of a GTNET card, PMU firmware, and a GTSYNC timing card within RTDS, its processed real-time measurements become capable of emulating hardware PMU outputs [27]. OpenPDC as well as OpenECA [28] is used for collecting all GTNET-PMU data in each area, with main purpose of real-time monitoring and post-processing operations via the RSCAD-MATLAB interface. Hence, replicating an actual system for real-time control center operations and also providing better situational awareness to the system operator at both area ECCs. Under normal operating conditions, for tie-line power flow control purposes, Area 1 AGC uses PV plant’s PMU power calculation to decide the outputs of \( G_1, G_2 \) in Area 1. The PV plant is connected to the host transmission network, that is, Bus 10 through 0.48 kV/0.48 kV, 0.48 kV/13.8 kV, and 13.8 kV/230 kV low-frequency isolation and interconnection transformers, respectively. For safety considerations of grid-tied PV systems, a 1:1 isolation transformer becomes an integral component [25, 29], while interconnection transformer(s) may be a requirement by the host utility for interfacing the PV system with medium- and high-voltage power grid [25]. The most heavily loaded busbar, that is, Bus 9 is located in Area 2. The balancing authority in Area 2 is jointly operating the PV plant and the synchronous generators in the area and communicating with Area 1. In order to define and compare the performance and pattern of the proposed characterization approach and metric, the study is carried out on (a) control Area 2 with a single PV plant, (b) control Area 2 with distributed PV with same aggregate PV MW \( P_{PV} \) of (a). The SIL results are presented and discussed in the following subsections.

3.2 Single utility-scale PV

For the case of a 600MW \( P_{PV} \) single PV connected in the vicinity of a synchronous generator in control Area 2 of the two...
area four machine system, the results have been presented in Figures 4 and 5. \( P_{PRBS} \) signal has been applied to the PV system for 30 min runtime at every \( P_{\text{ref}} \) loading for case \( x_1 = 25 \), and repeated for cases \( x_2 = 50 \) and \( x_3 = 65 \) of (5). The results are shown in Figure 4b. The power–frequency variations seem to follow a similar rate change at each \( P_{\text{ref}} \) loading. A short-term increase in \( P_{\text{ref}} \) production leads to a minutes-based increase in \( P_{\text{ref}} \) POI and area frequency, while a minutes-based decrease in \( P_{\text{ref}} \) power generation leads to decrease in \( P_{\text{ref}} \) POI and area frequency.

Further, delving into \( \Delta P_{\text{ref}} - \Delta f_{\text{ref}} \) waveforms at every \( \Delta P_{\text{ref}} = 0.1 pu \) increments implies \( \Delta f_{\text{ref}} / \Delta P_{\text{ref}} \) moving lines at each \( P_{\text{ref}} \) are scattered along a linear curve. Curve slope corresponds to \( \Delta B_{P_{\text{POI}}} = (\partial \Delta f_{\text{ref}} / \partial \Delta P_{\text{ref}})(x,q) \) ratio that remains constant at each \( P_{\text{ref}}(k) \) to keep the \( P_{\text{ref}} \) POI minutes-based frequency variations due to \( P_{\text{ref}} \) power constant (zero), no matter how significant the minutes-based PRBS ramps in \( P_{\text{ref}} \) due to cloud covers/removals are at the corresponding \( P_{\text{ref}}(k) \). This is to decouple \( P_{\text{ref}} \) POI minutes-based rapid frequency variations from the half-an-hour slower frequency changes associated with the net injected power of \( P_{\text{ref}} \) bus at different \( P_{\text{ref}}(k) \). Note that frequency variations originating from the half-an-hour-based PV power changes due to \( P_{\text{ref}}(k) \) change have been taken care of using Area 2 generators as explained in step 1 of Section 2.1. Figure 5b shows the corresponding ratio at measured \( P_{\text{ref}}(k) \) that will contribute to devising a frequency droop deviations model, indicating the extra amount of power resource required at every \( P_{\text{ref}}(k) \) from an auxiliary source of generation/storage installed on-site of the \( P_{\text{ref}} \) plant, for example, a SmartPark to compensate for Bus \( j \) minutes-based frequency variations.

FIGURE 4 Steady-state PV plant POI power–frequency variations with respect to \( (P_{\text{ref}}(k), f_{\text{ref}}(k)) \), that is, under minutes-based PV power perturbations during 1800sec simulation run for all \( P_{\text{ref}}(k) = 0.1 : 1 pu \) (a) Pearson correlation heat-map for (b) and (c) results; (b) single \( P_{\text{ref}} = 600MW \) at \( G_4 \) (GTNET – PMU10); (c) spatially distributed \( P_{\text{ref}} = 300MW \) at \( G_4 \) (GTNET – PMU10), and \( P_{\text{ref}} = 300MW \) at \( G_3 \) (GTNET – PMU11).
due to PV$_{2j}$ power variations caused by sudden cloud covers/removals during each $t_{\text{runtime}}$.

In fact, to be more accurate in our representation, Figure 5b also depicts percentage variations in $\Delta B_{PV_{2j}}^{(\beta_j)}$ ratio with respect to $P_{PV_{2j}}^{(\beta_j)-\text{ref}}(k)$ change at $G_3$ location $\delta \Delta B_{PV_{2j}}^{(\beta_j)} / \delta P_{PV_{2j}}^{(\beta_j)-\text{ref}}(k)$. The results indicate a linear increase in $\Delta B_{PV_{2j}}^{(\beta_j)}$ ratio (%) as $P_{PV_{2j}}^{(\beta_j)-\text{ref}}(k)$ increases in increments of 0.1 pu.

The Pearson correlation method is further utilized as a quantitative estimate of linear correlation among the two parameters under aforementioned conditions. This established statistical method is explained in detail in [30] and is used in various fields including power and energy systems [3, 31, 32]; for example, authors in [33] have utilized it to assess dynamic frequency regulation reserve requirements. A correlation coefficient ($r$) between 0.1 - 0.3 shows small correlation, 0.3 - 0.5 moderate correlation, and larger than 0.5 indicates strong correlation [34].

In this paper, $r_{\text{threshold}}$ is set to 0.85, when proceeding through step 3 of Figure 3. Figure 4a partly shows the Pearson correlation coefficient heatmap for the single 600 MW$_p$ PV plant bus. To derive the heat-map for this plant, $r$ is calculated using the formulation presented in the Appendix and for $n$ pairs of processed PMU datapoints (at each $P_{PV_{2j}}^{(\beta_j)-\text{ref}}(k)$ case). It is observed that $r \geq 0.91$ for all $P_{PV_{2j}}^{(\beta_j)-\text{ref}}(k)$ cases, indicating a very strong linear correlation among $\Delta f_{PV_{2j}}$ and $\Delta P_{PV_{2j}}^{(\beta_j)}$. Thus, one can permissibly take advantage of this linearity by interpolating and devising a frequency droop deviations model for all $P_{PV_{2j}}^{(\beta_j)-\text{ref}}(k)$ with incremental increase from 0 - 1 pu. This represented PV$_{\beta_j}$ busbar frequency droop deviation characterization for a single utility-scale PV.

Figure 4b shows that as single PV plant MW$_p$ increases, there is possibility of grid-code non-compliant frequency rises/falls with sudden transients in $P_{PV_{2j}}$ due to sudden cloud covers/removals. To mitigate this phenomenon, the 600 MW$_p$ PV is distributed into two smaller in size 300 MW$_p$ PV and spatially distributed in Area 2. In the following subsection, the feasibility of frequency droop deviations characterization is investigated for distributed PV plants in a control area.

### 3.3 Distributed utility-scale PV

**Distributed PV site locations**: NREL SIR data in repository [35] is utilized for a period of near-normal sunny days (5 days) in two locations resembling locations of $G_3$ (reference site) and $G_4$ (25km apart from $G_3$) in the system under study. Average SIR variations between each site location at each instance is approximated with respect to the reference site ($PV_{21}$ site at $G_3$).

Frequency droop deviations characterization results for distributed PV, that is, $PV_{21}$ (300 MW$_p$ at $G_3$ location and
3.4 Realization of PV power fluctuations smoothing at POI

Fast-acting auxiliary generation/storage devices (aux) such as large-scale battery energy storage systems [36, 37] are presented with numerous control methods for PV power smoothing in the past literature [38], but majority with a constant frequency droop ($B_{aux}^{(cte)}$). Frequency characterization at POI (Figure 3) reveals that frequency droop is no longer constant and is a function of PV plant power loading at POI (Figure 5b). In fact, with a $P_{PV}−ref(k)$-dependent droop deviation from $B_{aux}^{(cte)}$, namely $ΔB_{PV}^{(k)}$, the adaptive frequency droop $B_{aux}^{(aw)}(k)$ can now be formulated in (7), with depicted characteristic curves of Figure 6.

$$B_{aux}^{(aw)}(k) = (B_{aux}^{(cte)} - ΔB_{PV}^{(k)})/%. \quad (7)$$

Now consider the aux plant as a MW-scale ESS, that is, SmartPark with a time-dependent $SOC(t)$ connected to PV plant POI. According to Figure 6, for a sudden frequency deviation at $POI_{PV}−ref$, the discharge/charge operation will occur at a higher power-rate for SP equipped with a controller adaptive to $P_{PV}−ref(k)$ in comparison to one with a constant droop. It is noteworthy that SP is not designed for operating day and night. It is deemed to smooth-out PV power short-term minutes-based rapid fluctuations due to cloud movements at the PV site, considering SmartPark’s SOC limitations. Furthermore, the aforementioned comparison can be carried out only under identical $POI_{PV}−SP$ conditions of: (a) $P_{PV}−ref(k)$, (b) frequency deviation magnitude and minutes-based duration, (c) SP $P_{max}$, (d) SP $SOC(t)$, and (e) $SOC_{min}(t) < SOC(t) < SOC_{max}(t)$. By incorporating adaptive frequency droop-based controller for an aux plant, benefits in fast frequency support and enhanced PV power smoothing can be realized for all $P_{PV}−ref(k)$ loadings at the PV site.

3.5 Characterization of frequency droop deviations using hardware PMU data analytics

Figure 7 presents the HIL setup for the $PV_{21}$: 600MW PV plant POI monitoring and data-archiving via synchrophasor measurements. The setup is prepared in order to provide a platform for PV plant operators to monitor and characterize frequency droop deviations through time-series analysis of hardware PMU data at the PV plant POI and in accordance with the generic approach presented in Figure 3. Three PC workstations are configured, one for local transmission substation, the other for an energy control center, and the third workstation is capable of executing the droop characterization procedures implemented in MATLAB and in synchronization with the modeled system in RTDS software, that is, RSCAD. The data transfer and communication among all devices is established through Ethernet TCP/IP communication protocol. The PV plant POI busbar GTNET-PMU is replaced with Schweitzer Engineering Laboratories SEL-487E transformer protection hardware relay installed for POI HV busbar protection and configured as a PMU. The three-phase measured voltage and current at POI are fed to the SEL487E-PMU through $±10V$ analog output ports of the RTDS GTAO card and after proper amplification. Then, the SEL487E-PMU...
4 CONCLUSIONS

In this study, an empirical approach to characterizing (modeling) variations in power system frequency originating from the effect of seconds-based cloud covers/removals on PV plant(s) operation is proposed. For this purpose, both single and spatially distributed utility-scale PV plants’ operation at different steady-state operating conditions and under stochastic meteorological conditions have been investigated on a real-time simulator. Statistical assessment of the characterization curves is performed and a very strong linear correlation among the two variables of interest is verified for a wide range of operating conditions, that is, \( p_{PV\_ref} - f_{PV\_ref} \) levels. It is further observed that with spatially distributing a single PV plant into smaller units across the same control area, stronger linear correlation can be achieved. In addition, the number of frequency events can be mitigated with this distribution. Furthermore, a hardware-in-the-loop platform has been presented that will allow field studies at PV plant facilities for monitoring and derivation of adaptive frequency droop curves using hardware PMU data analytics. The findings from this study pave the way for accommodating higher levels of PV penetration in the grid by development and implementation of decision-based adaptive frequency droop controllers for PV power smoothing. As a result, better frequency stability can be achieved, minimizing the concern for grid instabilities.

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**NOMENCLATURE**

**Abbreviations**

| Abbreviation | Description |
|---------------|-------------|
| AGC | area generation control |
| AVR | automatic voltage regulator |
| CTRL | controller |
| DB | database |
| DER | distributed energy resource |
| DR | demand response |
| ECC | energy control center |
| ESS | energy storage system |
| EV-VSI | EV voltage source inverter |
| G | synchronous generator |
| GOV | governor |
| HIL | hardware-in-the-loop |
| HV | high voltage |
| MC | monte carlo |
| MV | medium voltage |
| LD | load |
| PCC | point of common coupling |
| PDC | phasor data concentrator |
| PEE | power electronics interface |
| PMU | phasor measurement unit |
| POI | point of grid interconnection |
| PRBS | pseudo-random binary signal |
| PSS | power system stabilizer |
| PV | photovoltaic |
| PV-ESS | PV plant with bulk energy storage system |
| PV-SP | solar electrified vehicle parking lot |
| RES | renewable energy system |
| RTDS™ | real-time digital simulator |
| SIL | software-in-the-loop |
| SIR | solar irradiance |
| SIL | state of charge |
| SRF | synchronous reference frame |
| STC | standard test condition |

**Subscripts and Indices**

- \( d \) - direct & quadrature components of SRF
- \( f \) - filter
- \( ref \) - reference
- \( \beta_j \) - plant \( j \) located in Area \( \beta \)

**Parameters and Variables**

- \( \Delta f \) - super short-term total change in control area frequency
- \( \Delta f_{CTRL} \) - \( \Delta f \) from frequency controllers operation & DR
- \( \Delta f_G \) - \( \Delta f \) due to \( G \) power fluctuations
- \( \Delta f_{PV} \) - super short-term change in \( POI_{PV} \) frequency due to minutes-based PV power fluctuations
- \( P_{AGC} \) - active power from AGC operation
- \( P_{CTRL} \) - active power from CTRLs operation
- \( P_{DR} \) - active power from DR
- \( P_{ESS} \) - active power from ESS
- \( P_G \) - active power from \( G \)
- \( P_{GOV} \) - active power from governor operation
- \( P_{inertia} \) - active power from rotational components
- \( P_L \) - active power from load
- \( P_{zero-inertia} \) - active power from zero-inertia components
- \( g_{ij}, b_{ij} \) - conductance and susceptance of the \( ij \)-th line
- \( X_{ij} \) - admittance of the \( ij \)-th line
- \( V_{dc} \) - PV inverter dc-link voltage
- \( C_{dc} \) - PV inverter dc-link capacitance
- \( R_j, L_j, C_f \) - PV inverter output filter resistance, inductance, and capacitance
- \( i_{ncn}, i_{fabc}, i_{raf} \) - injected current at PCC in SRF
- \( v_{ref} \) - inverter terminal & PCC voltages in SRF
- \( i_{dabc}, m_{dabc} \) - injected active- and reactive-power at PCC
- \( t_{time} \) - \( k \)-th simulation duration in RSCAD
- \( t_{pert} \) - perturbation instance
- \( \omega_k \) - grid voltage angular frequency
- \( f_{switch} \) - switching frequency
- \( r \) - pearson correlation coefficient

**Equations**

\[
P_{PRBS} = \text{PRBS pseudo-random binary signal applied case numbers} \in 1, 2, ..., q
\]

\[
x(q) = \text{a random number bounded to } x_q \text{ for the duration } t_{time} \text{ at every } P_{PV_{\beta,j}}(k) \%\]

\[
P_{PV_{\beta,j}} = \text{j-th PV plant, situated in control area } \beta \text{ frequency at POI of } P_{PV_{\beta,j}} [Hz]
\]

\[
SIR_{PV_{\beta,j}(k)} = \text{seconds-based SIR of } P_{PV_{\beta,j}} \frac{W}{Hz}
\]

\[
SIR_{PV_{\beta,j}(k)} = \text{seconds-based SIR of } P_{PV_{\beta,j}} \frac{W}{Hz}
\]

\[
\Delta f_{PV_{\beta,j}}(t) = \Delta P_{PV_{\beta,j}}(t) \text{ data-point at } t \frac{[Hz]}{MW}
\]

\[
\Delta B_{PV_{\beta,j}(k)}(t) = \text{curve-fitted function obtained from a set of } \Delta B_{PV_{\beta,j}(k)}(t) \text{ data-points} \frac{[Hz]}{MW}
\]

\[
\Delta B_{PV_{\beta,j}(k)}(t) = \text{frequency droop deviation from } B_{PV_{\beta,j}}(k) \frac{[Hz]}{MW}
\]

\[
\Delta B_{PV_{\beta,j}(k)}(t) = \text{auxiliary static power supply adjacent to } P_{PV_{\beta,j}} \frac{MW}{Hz}
\]

\[
\omega_k = \text{grid voltage angular frequency}
\]

\[
f_{switch} = \text{switching frequency} [kHz]
\]

\[
pu = \text{per-unit}
\]

\[
r = \text{pearson correlation coefficient}
\]
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APPENDIX A

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The power-stage circuit diagram of a three-phase grid-tied inverter is depicted as Figure 3 of [24], used for its mathematical modelling. The following assumptions are considered:

(a) Converter conduction losses disregarded.

(b) Balanced three-phase system and impedance, thus no zero-sequence component injected from three-wire PV inverter, enabling dq—modelling.
Each current-fed inverter encompasses a cascade control structure similar to [24]. By regulating the dc-link voltage of the current-fed inverter, the PV inverter can be operated as a PV-VSI. Thus, the main governing equations in both abc- and dq-frames can be represented as following for the PV-VSI power-stage circuit.

### abc-frame Equations

\[
\begin{align*}
    v_{a} &= \sqrt{2}V_{f}\cos(\theta + \phi_{a}) \\
    v_{b} &= \sqrt{2}V_{f}\cos(\theta + \phi_{b} - \frac{2\pi}{3}) \\
    v_{c} &= \sqrt{2}V_{f}\cos(\theta + \phi_{c} + \frac{2\pi}{3}) \\
    i_{la} &= L_{f} \frac{dv_{a}}{dt} + R_{f}i_{la} + \tilde{v}_{ja} + \tilde{v}_{ag} \\
    i_{lb} &= L_{f} \frac{dv_{b}}{dt} + R_{f}i_{lb} + \tilde{v}_{ja} + \tilde{v}_{bg} \\
    i_{lc} &= L_{f} \frac{dv_{c}}{dt} + R_{f}i_{lc} + \tilde{v}_{ja} + \tilde{v}_{cg} \\
    \tilde{v}_{ag} &= \frac{1}{3} (\tilde{v}_{ja} + \tilde{v}_{jb} + \tilde{v}_{jc}) = 0
\end{align*}
\]  

### dc-side :

\[
\begin{align*}
    i_{dc} &= C_{dc} \frac{dv_{dc}}{dt} + i_{PV,\text{VSI}}^{PV} \\
    i_{PV,\text{VSI}}^{PV} &= i_{a}^{PV,\text{VSI}} + i_{b}^{PV,\text{VSI}} + i_{c}^{PV,\text{VSI}} \\
    \tilde{i}_{dc} &= \tilde{i}_{a} + \tilde{i}_{b} + \tilde{i}_{c}
\end{align*}
\]  

### dq-frame Equations

\[
\begin{align*}
    \forall \alpha_{qf} = 0 \quad \left\{ 
    \begin{array}{l}
    P &= \frac{3}{2} (v'_{d0}i'_{dq} + v'_{q0}i'_{dq}) = \frac{3}{2} \frac{v'_{d0}v'_{dq}}{2} \\
    Q &= \frac{3}{2} (v'_{d0}i'_{dq} - v'_{q0}i'_{dq}) = \frac{3}{2} \frac{v'_{d0}v'_{dq}}{2} \quad (A.5)
    \end{array} \right.
\end{align*}
\]

\[
\begin{align*}
    \begin{bmatrix}
    \frac{dv'_{dq}}{dt} \\
    \frac{dv'_{dq}}{dt} \\
    \frac{dv'_{dc}}{dt}
    \end{bmatrix} =
    \begin{bmatrix}
    -R_{f} & \frac{m_{d}L_{f}}{2} & 0 \\
    -\omega_{f} & -R_{f} & \frac{m_{q}L_{f}}{2} \\
    -m_{d} & -m_{q} & 0
    \end{bmatrix}
    \begin{bmatrix}
    v'_{dq} \\
    v'_{dq} \\
    V_{dc}
    \end{bmatrix} \\
    +
    \begin{bmatrix}
    -\frac{1}{L_{f}} & 0 & 0 \\
    0 & -\frac{1}{L_{f}} & 0 \\
    0 & 0 & \frac{1}{C_{dc}}
    \end{bmatrix}
    \begin{bmatrix}
    i'_{dc} \\
    i'_{dq} \\
    i'_{dq}
    \end{bmatrix} \\
    \quad (A.6)
\end{align*}
\]

To derive Figure 4a heat-map for a plant, its Pearson correlation coefficients are calculated for \( n \) pairs of processed PMU datapoints, i.e. \( \{\Delta P_{\text{VW},2}^{W_{2}}(k,x(g))\}, \Delta f_{\text{VW},2}^{W_{2}}(k,x(g))\} \) and according to:

\[
\begin{align*}
    r\left(\Delta P_{\text{VW},2}^{W_{2}}(k,x(g)), \Delta f_{\text{VW},2}^{W_{2}}(k,x(g))\right) &= \frac{\sum_{i=1}^{n} \left(\Delta P_{\text{VW},2}^{W_{2}}(k,x(g)) \Delta f_{\text{VW},2}^{W_{2}}(k,x(g))\right)}{\sqrt{\sum_{i=1}^{n} \left(\Delta P_{\text{VW},2}^{W_{2}}(k,x(g))\right)^{2}} \times \sqrt{\sum_{i=1}^{n} \left(\Delta f_{\text{VW},2}^{W_{2}}(k,x(g))\right)^{2}}} \\
\end{align*}
\]