CIGRÉ-US National Committee
2016 Next Generation Network Paper Competition

An Integrated Approach to Analyzing the Impact of Increasing Distributed PV Generation on Dynamic Stability in Oahu

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SUMMARY

The Hawaiian electric power industry is at a critical nexus. The State of Hawaii is leading the US in the adoption of distributed photovoltaic (DPV) solar energy generation with 343MW installed at the end of 2015 as the state strives towards 100% renewable generation by 2045. In addition to DPV, an additional 140MW of utility-scale solar PV projects has been approved on the 1200MW peak load power system. With considerable changes taking place on the system, robust engineering and economic planning studies are critical.

Because of the fundamental differences between synchronous machines and power electronic technologies, it is important to evaluate and understand the dynamic performance of the power system. As power electronic-based generation increases, synchronous machine-based generation is displaced, which raises the potential for the grid's dynamic performance to erode. The dynamic performance is assessed by the frequency response of the power system to contingency events like a loss of generation or a loss of load.

Current industry practice typically evaluates contingencies and frequency stability for one or two grid conditions, often the most severe conditions, which may not provide a comprehensive view of system operating conditions. While it is necessary to ensure grid stability and reliability at all times, it is important to understand the regularity and magnitude of critical operating periods. This understanding will ensure that mitigations to prevent or avoid grid stability challenges will be properly evaluated. For example, low-probability events may be best addressed using changes to operating practices or even under-frequency load shedding because the probability of occurrence is low, whereas high-probability events may be better addressed with new technologies and capital investments.

The authors, in conjunction with the Hawaii Natural Energy Institute, have taken a fresh approach to the dynamic stability study of the Oahu power system. Instead of running thousands of dynamic simulations for each hour of operation in a given study year to understand the full operating range and probability of each system condition, the team used a statistical method to combine an entire year of production cost simulations with detailed dynamic simulations of the grid. This was achieved by a careful examination of key variables

associated with grid frequency response, the development of a composite metric estimating system risk, and a close calibration of this composite metric to the outputs of dynamic simulations.

The results of the analysis are presented from both the in-depth view of the system showing dynamic frequency response seconds after a simulated contingency event and a broader perspective of system risk across an entire year of operation. Probability density functions are used to show the expected deviation in frequency for a given N-1 contingency event given a year of operation. With these views of the system, the reader is much better equipped to evaluate the impact of increasing levels of DPV generation, the efficacy of mitigations like over-frequency response from renewables, and others.

This combination provides a broad perspective of the impact of increasing power electronic devices while retaining the detailed dynamic results like frequency nadir and apex, enabling new insights for how to plan and operate the system as it evolves towards renewable resources.

Acknowledgement: This research was sponsored by the Hawaii Natural Energy Institute, with funding from the U.S. Department of Energy and Hawaii State Barrel Tax (SB359)

KEYWORDS

Hawaii, Oahu, grid stability, transient stability, dynamic stability, renewable integration, distributed generation, distributed energy resources, distributed photovoltaics, solar, wind, island power system

INTRODUCTION

For reliable power system operation, it is particularly important that the grid be properly positioned to respond to critical emergency events like a loss of generation across a wide range of operating conditions. If a generator trips offline, the power system loses generation immediately and system frequency declines rapidly. These changes occur within a few seconds and corrective actions must be taken within those few seconds to restore balance and avoid grid collapse. While large generator trips are not common, the grid operator must position the grid to recover from such events while considering economic and environmental objectives. As wind and solar generation increases, conventional methods of restoring system frequency after contingency events are eroding because conventional generation is being de-committed more often. The evolution of the grid is demanding new approaches for evaluating the security of the grid. In the past, contingency studies drew recommendations based on the simulated system response to a few operating conditions, which were often chosen to be severe conditions. However, examination of only a few severe conditions often led to overly conservative conclusions, which potentially limits further renewable generation development. A new methodology is proposed to evaluate system performance not just over a few selected conditions, but rather over a year of system conditions selected by economic dispatch in order to inform better decision-making for system planning and operations.

The proposed methodology outlined herein was tested and evaluated on the Oahu power grid, which is at the forefront of renewable energy adoption with 21% of load served by renewables[1]. By the end of 2015, one of every three single family homes on Oahu had rooftop solar panels installed[2]. As is the case with many island power grids, the Oahu grid is unique relative to large interconnected power systems. A relatively small fluctuation in either generation or load can lead to large, and potentially unstable, deviations in system frequency for several reasons:

1. **Large Single Contingency:** Oahu's largest generating unit, the AES coal plant, can account for up to 30% of the grid's total load and up to 50% of the grid's net load (load minus wind and solar output). As a result, a trip of the AES unit will lead to a substantial loss of generation and frequency excursion.
2. **Low number of synchronous generators**: Relative to large interconnected grids, Oahu has a low number of other synchronous generators online and available to provide primary frequency response. As renewable penetration increases, fewer synchronous generators are committed to serve load.
3. **No interconnections to neighboring systems:** The Oahu power grid is an isolated system. Large interconnected grids in North America can lean on neighbors during contingency events for support. Oahu does not have this luxury and must provide all frequency response locally.
4. **High Level of Distributed PV Penetration:** The Oahu grid has very high penetration of DPV. While many of the DPV inverters have been upgraded to include frequency ride-through capability, there are still some legacy PV systems online (about 70 MW) that do not have this feature available. As a result, if system frequency declines below 59.3 Hz, the legacy PV will trip offline as well, increasing the magnitude of the original contingency event and causing the system frequency to decline even further.

As a result, the Oahu grid operators rely on a combination of generator governor response and under frequency load shedding (UFLS) during contingency events. The current UFLS scheme has several set points to shed load in an effort to halt the decline in system frequency. As frequency declines, distribution feeders will be disconnected from the grid to quickly reduce system load and balance supply and demand. UFLS is very effective in arresting system frequency decline, making it a powerful tool for maintaining overall grid stability. However, it interrupts customers' electric service without notice and should therefore only be used rarely, as a measure of last resort. In addition, the increase in penetration of DPV on load feeders decreases the net load available to be shed during an emergency, thereby reducing the effectiveness of UFLS to protect grid stability. Thus, it is critical to understand the impact of increasing DPV on Oahu's system frequency

[1] State of Hawaii Public Utilities Commission, "Renewable Portfolio Standards (RPS) Annual Reports, 2015" http://puc.hawaii.gov/reports/energy-reports/renewable-portfolio-standards-rps-annual-reports/
[2] H. K. Trabish, "17% of Hawaiian Electric customers now have rooftop solar", UtilityDIVE, February 1, 2016. http://www.utilitydive.com/news/17-of-hawaiian-electric-customers-now-have-rooftop-solar/413014/

response and to better understand alternative tools and mitigations available to the utility to enhance grid stability.

A NEW METHODOLOGY

To analyze the impact of increasing DPV penetration on system frequency response, a variety of models and techniques were employed in this analysis to simulate both system operations and dynamic grid stability. While these models are not measuring real system conditions, they have been routinely benchmarked and validated against historical operations and are consistent with engineering practices utilized by the Hawaiian Electric Company (HECO) and other industry stakeholders. The methodology employed in this analysis included four steps as illustrated in Figure 1.

Figure 1: Analytical Process

Step 1 - Production Cost Simulations (GE MAPS): The first step in the analysis was to conduct detailed hourly production cost simulations. The GE-MAPS production cost model simulates the power system operation on an hourly, chronological basis over the course of the year. The model simulates the system operator's unit commitment (on or offline) and dispatch (MW output) decisions necessary to supply the electrical load in a least cost manner, while appropriately reflecting transmission flows across the grid and simultaneously preparing the system for unexpected contingency events and variability. The chronological modelling is crucial to understanding renewable integration because it simulates chronological changes to electrical load and the underlying variability and forecast uncertainty associated with wind and solar.

Step 2 – Selecting System Dispatch Conditions for Dynamic Simulations: The second step in the analysis included a detailed review of the production cost simulations. This process selected system dispatch conditions that were passed from the production cost results to the dynamic frequency response simulations. To do this, four key variables were analyzed for each hour of simulation and were then translated to a single contingency severity metric (CSM), which is described in detail later in this paper and is calculated for each hour and dispatch condition.

Step 3 – Dynamic Frequency Response Simulations (GE PSLF): Each of the hours selected in Step 2 were evaluated in greater detail through dynamic frequency response simulations using the GE PSLF model. Using the dispatch conditions provided by Step 2, including system load and unit generation, a positive-sequence time-domain simulation of a loss of generation contingency event was performed so that key performance indicators like the system frequency nadir could be captured.

Step 4 – Estimating Frequency Response for all Dispatch Conditions: In the final step of the analysis, the results calculated in Step 3 were statistically evaluated to examine the relationship between the calculated CSM and the system's frequency nadir. A quadratic regression was then estimated using frequency nadir as the dependent variable and the CSM as the independent variable. The resulting equation was then used to estimate the frequency deviation and UFLS for each hour and dispatch condition of the year, across both scenarios. This allows for a more complete picture of system risk that shows the frequency of occurrence of different risk levels over the course of the year.

PRODUCTION COST SIMULATIONS

To evaluate the impact of DPV on grid stability, two scenarios were evaluated in which the hourly economic dispatch over the course of an entire year was determined for each scenario from production cost simulations using GE MAPS. Scenario 1 included 400 MW of installed DPV capacity and Scenario 2 had 700 MW of DPV installed. Scenario 1 represents the likely installed DPV capacity online by 2017, assuming a continuation of recent trends and Scenario 2 represents potential near-term solar growth in Hawaii. The hourly chronological solar output profiles were scaled linearly between the two scenarios, and the spinning regulating reserve requirements were adjusted accordingly. All other inputs and assumptions were held constant across the scenarios, isolating any changes due to increased DPV penetration. Results of the production cost analysis highlight the expected changes in system operations (commitment and dispatch) with increased wind and solar penetration.

Table 1 provides an overview of the installed renewable capacity and available energy (prior to potential curtailment) for each of the scenarios evaluated. In the absence of curtailment, annual wind and solar energy penetration would be between 16% in Scenario 1 to 22% in Scenario 2.

Table 1: Installed Wind & Solar Capacity & Available Energy by Scenario

	Installed Capacity (MW)				Available Energy (GWh)			
	DPV	CPV	Wind	Thermal	DPV	CPV	Wind	Load
Scenario 1	400	149	123	1660	635	282	356	7960
Scenario 2	700	149	123	1660	1111	282	356	7960

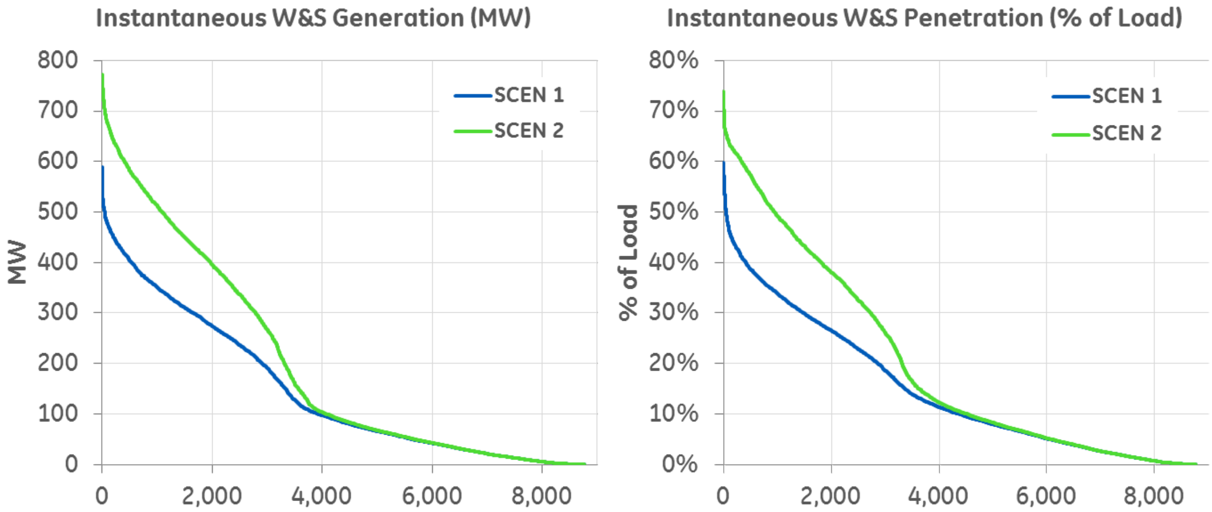

Figure 2: Hourly Duration Curves of Wind and Solar Penetration by Scenario

DEVELOPING THE CONTINGENCY SEVERITY METRIC

The second step in the analysis included a detailed review of the production cost simulations in an effort to select certain system dispatch conditions to pass from the production cost results to the dynamic frequency response simulations. To do this, each hour was quantified based on its expected risk of instability for a loss of generation event. A new contingency severity metric (CSM) was developed that incorporated four important factors to frequency response into a single quantifiable measure. On the Oahu grid, it was assumed that the following four variables would be the largest differentiators in frequency response:

1. **Largest generator contingency:** This variable represents the dispatch (MW) of the largest unit online in a given hour and is used as a measure of the severity of the stimulus to the system. Typically this is the output of AES because it is the largest and most economic unit on the system.
2. **Thermal unit commitment:** This variable was added as a proxy for system inertia and represents the amount of total capacity committed (MW) during every hour. Even if the unit is dispatched at P-min for a given hour, the unit's full rated capacity is counted as being online. A larger the thermal commitment implies higher system inertia and more grid support from online synchronous generators immediately following a loss of generation.
3. **Up-reserves online:** This variable represents the amount (MW) of frequency response available to the system. Also referred to as headroom, it is measured by taking the difference between each unit's maximum net capacity and the corresponding dispatch loading. Only thermal units with frequency

response enabled are included in this metric. The more up-reserves online, the more frequency response is available to support the grid during contingency events.

4. **Legacy DPV generation:** This variable represents the MW output of legacy DPV on the system. It is a proxy for the sympathetic DPV tripping that will occur given the inability of legacy DPV inverters (approximately 70 MW of capacity) to ride through frequency disturbances. As a result, with higher legacy DPV output, the system will experience more sympathetic tripping and thus exacerbate the loss of generation contingency event.

In order to combine the four variables listed above into a single metric, or CSM, a weighting factor was applied to each of the variables based on its expected influence on the magnitude and direction of system frequency in response to a generator trip event. Because the CSM is meant to define system risk, the sign of the weighting factor depends on each variable's contribution to a frequency deviation. Therefore, the largest generator contingency and legacy DPV generation variables are multiplied by a positive weighting factor because they are directly related to frequency deviation (the higher the variable the higher the expected frequency deviation). The thermal unit commitment and up-reserves online variables are multiplied by a negative weighting factor because they are inversely related to frequency deviation (the higher the variable the lower the expected frequency deviation).

The magnitude of the weighting factors was also related to the expected impact on system frequency and was developed to strengthen the relationship with the observed frequency response from the dynamic simulations and the calculated CSM. A variable that is likely to have a larger relative impact on frequency deviation received a larger weight. The standard deviation of each variable was also taken into account when creating the weighting factors to make the scaling consistent with the overall spread of the sample size selected for dynamic simulations. The equation below shows the mathematical formation of the metric.

$$CSM = \left(g_i * w_g\right) + \left(c_i * w_c\right) + \left(r_i * w_r\right) + \left(d_i * w_d\right)$$

where:

g is the size of the largest generator contingency.
c is the amount of committed thermal unit capacity.
r is the amount of up-reserves online.
d is the amount of legacy DPV generation.
i is the observation of each variable for the hour.
w is the weighting factor applied to each variable.

The following table provides an example of the metric calculation for one hour of the year in Scenario 1. This calculation illustrates how the variables are combined into a single CSM value. While the number itself does not have any absolute meaning, it provides a relative measure for system risk over the course of the year. A higher CSM indicates a larger expected frequency deviation during a generator trip event, and therefore higher system stability risk.

Table 2: CSM Calculation Example, Hour 2340, Scenario 1

Hour 2340	Largest Contingency (MW)	Thermal Unit Commitment (MW)	Up-Reserves Online (MW)	Legacy DPV Generation (MW)	CSM
Observation	180.0	817.1	320.8	53.7	
Weight	0.0558	-0.0115	-0.0112	0.0713	
Weighted Score	10.05	-9.43	-3.59	3.83	**0.86**

Using the 8,760 hourly results from a year of simulation completed in Step 1 and the CSM calculation discussed above, each hour of the year can be ranked from highest expected risk to lowest based on the system dispatch conditions for a given hour. The resulting duration curve is provided in Figure 3 and created by sorting each hour of the year from highest to lowest based on the calculated CSM. From the 8,760 dispatch conditions, a sample of 13 dispatch conditions in each scenario were selected for simulation and validation of the CSM's ability to estimate system frequency, and therefore, system risk. The hour selections were made to include the highest CSM hour, a large spread of the overall CSM, and to include a spread of the individual variables. The individual hour validation points are highlighted in Figure 3. The dispatch conditions for each validation point were passed from the production cost simulations to the dynamic simulations.

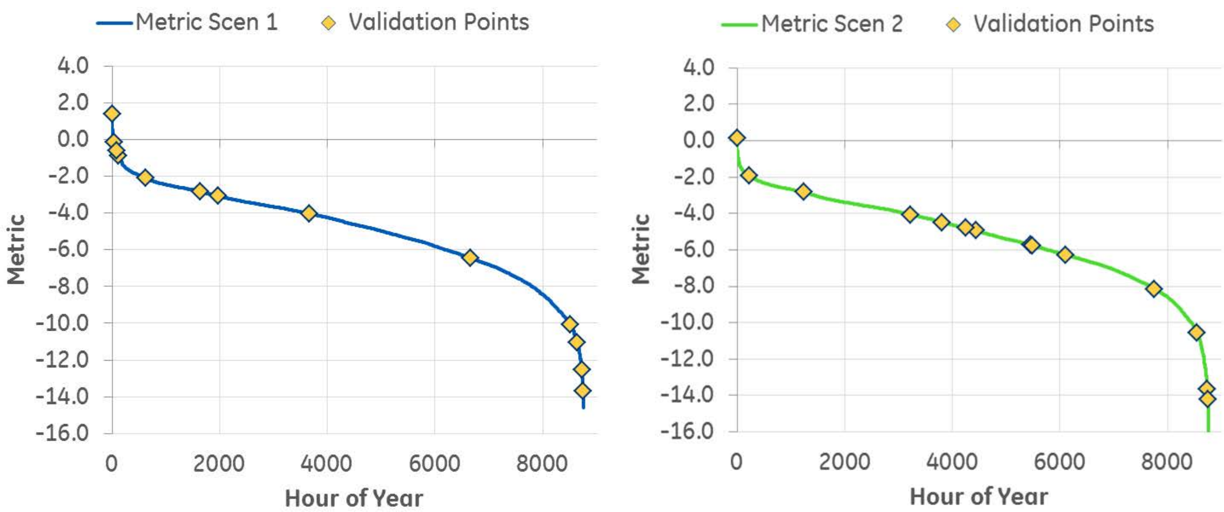

Figure 3: Hourly Metric Duration Curve with Selected Validation Points

DYNAMIC SIMULATION MODEL

The Oahu power system was modelled in PSLF and included the Oahu transmission network topology and major equipment details like generator dynamic models and transformer ratings. The network captures the lines and buses at the 46kV level and above, with lines and buses at lower voltages included for generation plants. A representation of the overall model is shown in Figure 4. Special consideration was given to modelling the DPV on the system and the interaction between the DPV and the under-frequency load shedding (UFLS) system, as these have a significant impact on the performance and recovery of the system following a system-wide event like a loss of generation.

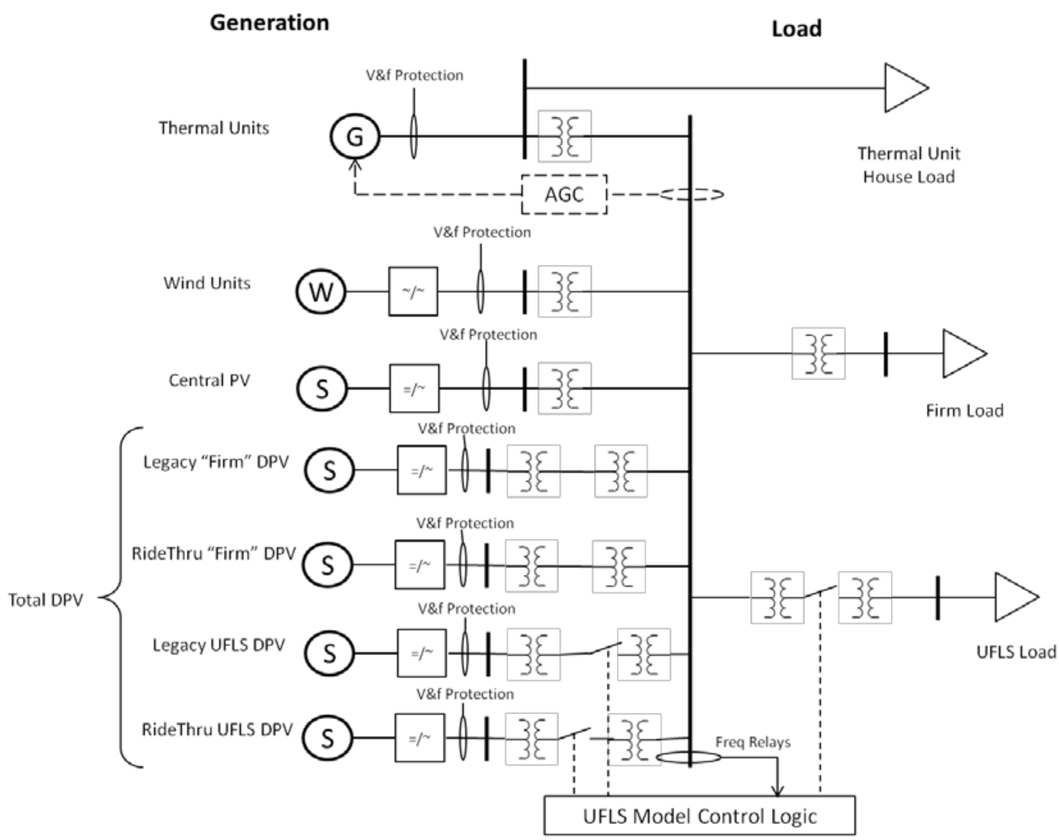

Figure 4: Overview of the Oahu Dynamic Simulation Model

The distributed PV generation was modelled as 31 aggregate PV plants interspersed throughout the model. Each of the DPV models connects to a 480V bus, where an aggregate transformer with an impedance assumed to be typical of two transformers in series connect the 480V PV bus to the 46kV transmission system bus. A dynamic model of typical of distributed PV systems was used.

There are two groups of DPV on the Oahu grid with significantly different frequency ride-through settings, and so they are treated separately in the model. The “Legacy DPV” group is set to trip at 59.3Hz and 60.5Hz, where it is assumed there was 70 MW of legacy DPV capacity installed on the system. The “Ride-Through DPV” group is set to trip at 57.0Hz and 63.0Hz, and this comprises the remainder of installed DPV. For a given DPV MW production, fraction of legacy DPV production to capacity was the same as the fraction of total DPV production to total DPV capacity.

The load associated with each block of load shedding is determined by calculating the total load participating in the UFLS scheme for a given hour. This participating load is then proportionally allocated among the 5 load shedding blocks in the same proportions used to allocate the DPV that falls behind the UFLS relays. It was assumed that 30% of the DPV capacity is installed behind one of the UFLS breakers, which assumes that the location of future DPV installations follows historical trends. It was further assumed that 30% of the DPV capacity that is installed behind one of the UFLS breakers is a legacy DPV unit. Because the legacy DPV will have tripped before the first UFLS block, this DPV is subtracted from the total DPV capacity in the UFLS scheme to result in a value for non-legacy DPV behind a UFLS breaker. This non-legacy DPV in the UFLS scheme is proportionally allocated among the 5 UFLS blocks.

To capture the interaction between the UFLS system and the DPV, the model included control logic that monitored system frequency and instructed the connection and disconnection of DPV and load to simulate the response of the UFLS scheme, in which a selectable amount of load is tripped for a specified system frequency threshold and delay time. In addition, a selectable amount of DPV is tripped simultaneously with load, representing the DPV that is lost on feeders tripped by UFLS.

DYNAMIC SIMULATION RESULTS

A time-domain dynamic simulation of the Oahu system was performed for many operating conditions chosen from each scenario, where the primary indicator for the severity of an event is the frequency nadir, or the minimum value of system frequency reached after the loss of generation event. Note that in the simulations, the generator is tripped at a time of 10 seconds and that after system recovery, system frequency settles to a new equilibrium that is lower than nominal frequency as secondary frequency response like automatic generation control (AGC) has not taken effect.

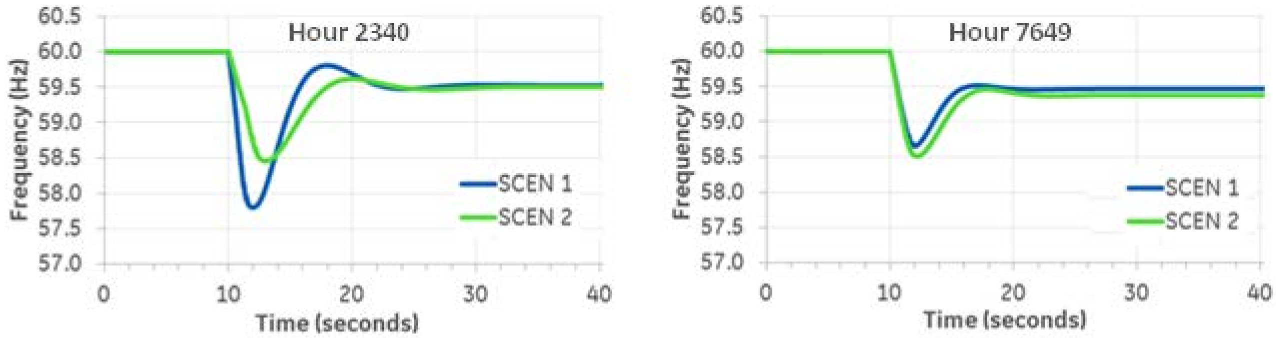

Figure 5: System Frequency Response, Scenario 1 vs Scenario 2 for Hour 2340 (a) and Hour 7649 (b)

The frequency response of the system is shown in Figure 5a for two hours in both Scenario 1 and Scenario 2. In the left chart, hour 2340, even with the reduced system inertia from some thermal units being cycled offline, the net frequency response of the system was improved. The frequency nadir was 58.5 Hz, 0.65 Hz higher than the nadir Scenario 1). In this example the system frequency response improved due to the re-dispatch (lower output) of the largest unit online.

However, this will not always be the case and there may be times when other thermal units are cycled offline to accommodate the increased DPV generation, but the largest unit is not yet turned back to lower loading levels. As a result, there are hours where system stability will erode with increased DPV generation (as shown in Figure 5b for hour 7649). This is caused by reduced UFLS capability, because of the additional DPV generation behind the UFLS breakers being tripped off-line during the contingency event, and fewer thermal units online to respond.

As a result, under some operating conditions frequency response will improve with increasing DPV and erode in others. Therefore it is important to look at multiple operating points over the course of a year and develop a holistic view of system stability. To ensure this, the dynamic simulations were repeated for each of the 13 dispatch conditions selected in Step 2 for each scenario.

ESTIMATING SYSTEM PERFORMANCE

Using the results from the 27 dynamic frequency response simulations (13 in Scenario 1 and 14 in Scenario 2), the final step of the analysis investigated the relationship between the metric developed in Step 2 with the observed frequency response metrics calculated in Step 3. As discussed earlier, the metric was designed to exhibit a direct relationship between the CSM and system stability; the higher the CSM, the higher the expected frequency deviation (lower frequency nadir) and system risk following a generator trip event. Figure 6 shows the relationship of system frequency deviation (dependent variable) as a function of the CSM (independent variable) for each of the 27 dynamic simulations conducted in Step 3. This was done for both Scenario 1 (blue markers) and Scenario 2 (green markers) to see the relationship between the frequency nadir and metric with increasing DPV penetration.

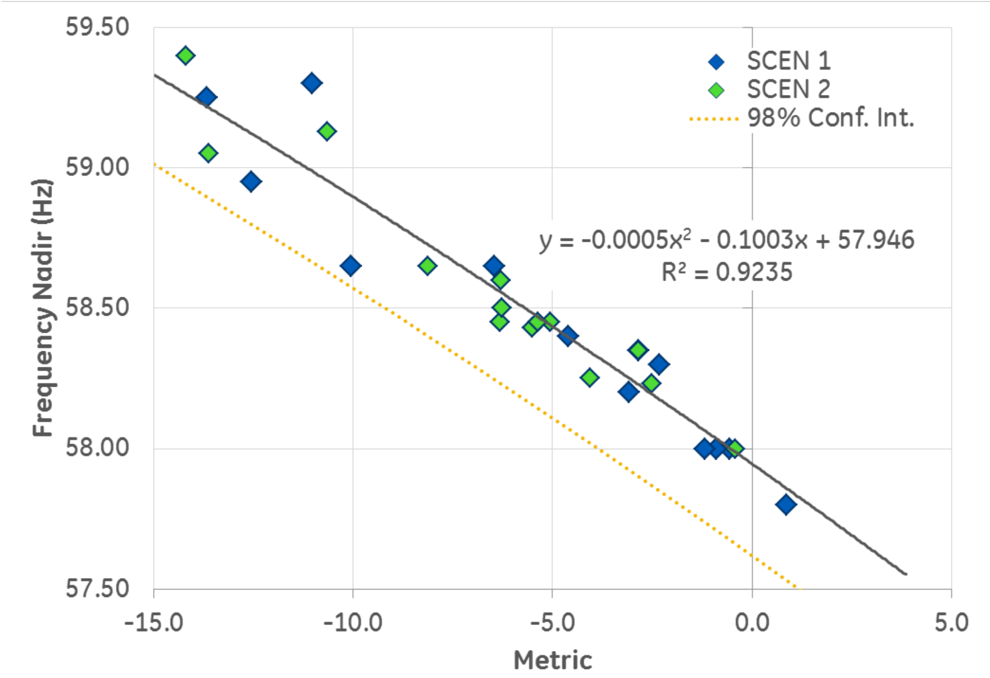

Figure 6: Regression of Frequency Nadir as a Function of the CSM

A quadratic best-fit trend line was then calculated for the 20 operating points as the following equation, where x is the CSM and y is the expected frequency nadir:

$$y = -0.0005x^2 - 0.1003x + 57.946$$

The resulting function represents the relationship between the CSM and the expected frequency nadir. The chart and best-fit line show a clear relationship between the CSM developed from the GE MAPS dispatch outputs and the resulting frequency nadir from the PSLF dynamic simulations. In addition, the relationship between the frequency nadir and CSM is consistent between Scenario 1 and Scenario 2 observations. While the estimated value is likely not a perfect measure of frequency response, the difference between the estimate and the observation (residual) for the 27 selections is small based on the high R-squared value (a statistical measure of how close the observed data is to the estimated regression line).

The quadratic best fit trend line can be used to estimate the frequency nadir, frequency deviation and UFLS for any CSM value (and thus system dispatch condition), without the need for additional dynamic frequency response simulations. This was done for all 8,760 hours in both Scenario 1 and Scenario 2. By doing this, the overall system risk can be estimated under each system dispatch condition and ultimately provide a better understanding of trends between scenarios and under different operating conditions. In addition, it allows the reader to draw conclusions about the probability or frequency of different operating conditions, as opposed to previous analysis that only evaluated the most extreme operating points that may only occur rarely throughout the year. This increased understanding is largely unavailable using conventional reliability methods that evaluate only a few, often conservative, operating points throughout the year.

Figure 7 and Figure 8 show the expected magnitude and probability of a frequency deviation for a generator trip event for each hour of the year based on an entire year’s worth of system operation. Also demarcated on the charts are lines representing points where the UFLS schemes take place. If the frequency deviation exceeds the threshold for a given block, a breaker will quickly open and reduce over system load in time to reduce the frequency deviation. From these charts it can be seen that while expected frequency deviation to a generator contingency event does not change dramatically, it is reduced when additional distributed PV is added to the system. More importantly, the larger frequency excursions are expected to be reduced, shown by the reduction in the top left portion of the duration curve in Figure 8 and the right hand portion of the histogram. This is an important observation - all other things equal, increased DPV penetration (with frequency ride-through enabled) will not erode grid stability to large N-1 generator trip events under the penetrations evaluated in this study.

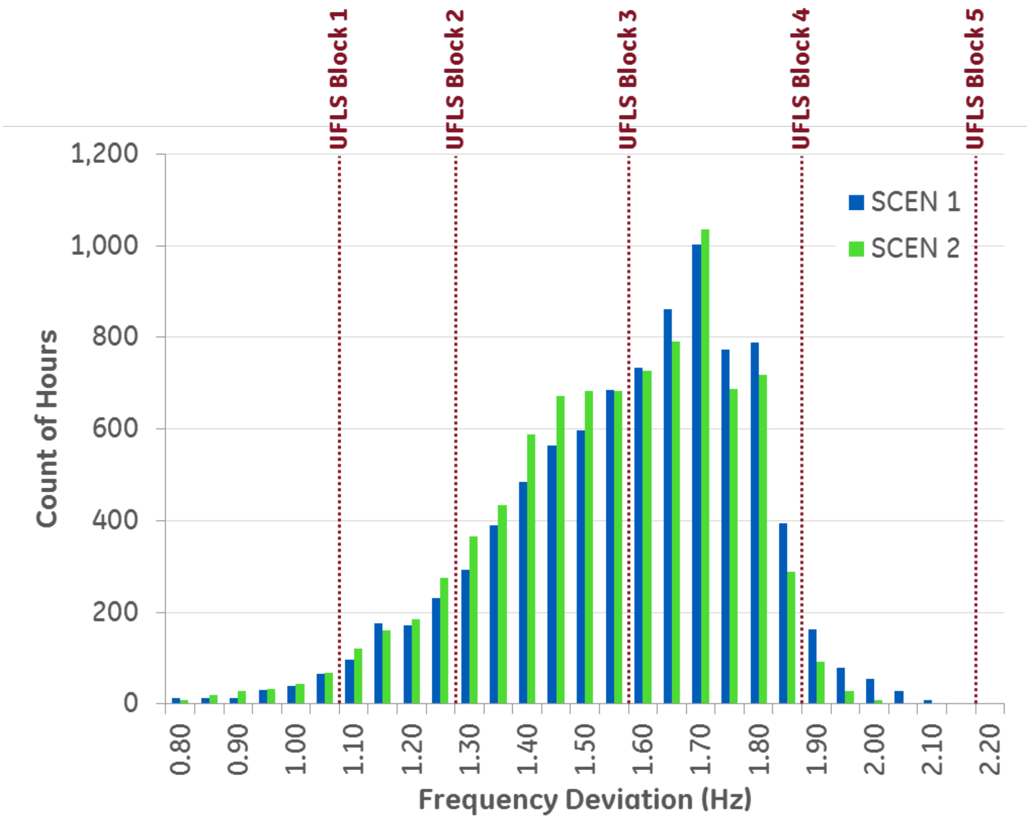

Figure 7: Histogram of Expected Frequency Deviations by Scenario

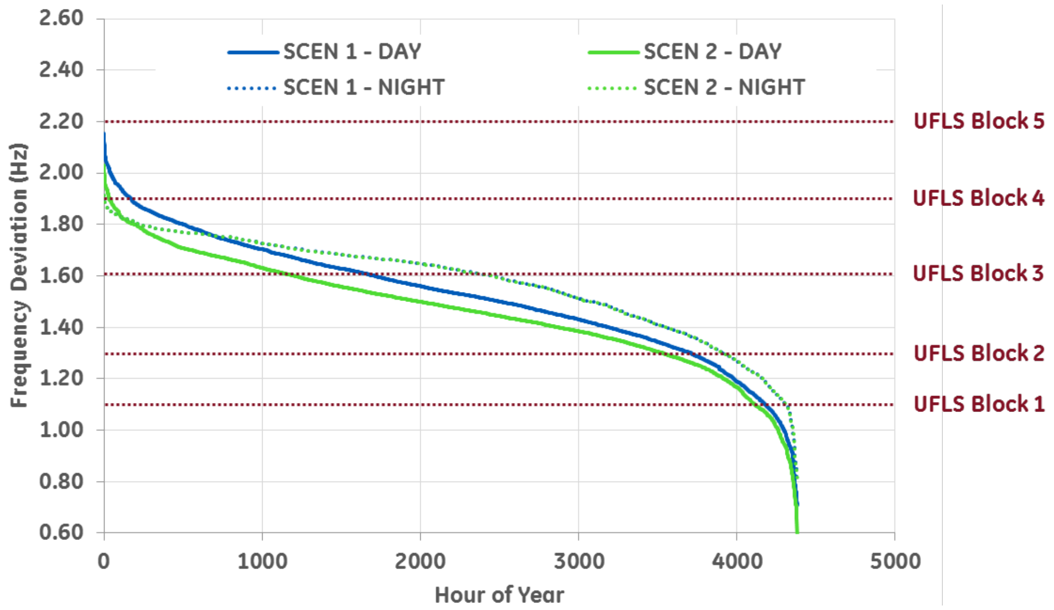

Figure 8: Duration Curve of Expected Frequency Deviation by Scenario

CONCLUSIONS

While the expected frequency response in some hours may have been reduced when adding 300 MW of DPV, the net result when evaluating the entire year of operations is a slight improvement in system frequency response to a generator contingency. This result is somewhat counter-intuitive and unique to the Oahu power system, but made apparent through the application of this method to quantify system performance for a broad range of system conditions spanning an entire year. Such conclusions would be difficult to draw from a traditional method in which only a few selected conditions are evaluated. This conclusion is bolstered by deeper examination of individual simulations which show that with increasing DPV, the system frequency response to a generator contingency event improves during peak solar, mid-day hours because the additional solar displacement reduces the largest generator contingency and increases the amount of up-reserve provision from the thermal units.

The turndown of large generators to lower loading levels during high solar output is a primary driver of the reduced system risk. It should be noted that this is an alignment of economic and stability objectives. However, if the largest unit online remains dispatched at full output then the severity of the contingency event is not reduced. In these circumstances curtailed wind and solar can provide the additional frequency response required to compensate for the larger contingency event.

Much of the dynamics work that was done in the past focused on a select few number of operating points, often evaluating only the very extremes of system operation. While it is necessary to ensure grid stability and reliability at all times, it is important to understand the regularity and magnitude of critical operating periods. This understanding will ensure that mitigations to prevent or avoid grid stability challenges will be properly evaluated. For example, low-probability events may be best addressed using changes to operating practices or even under-frequency load shedding because the probability of occurrence is low, whereas high-probability events may be better addressed with new technologies and capital investments.

The CSM methodology is an effective means of providing the perspective across a broad range of operating conditions for assessing the impact to the power system, as shown by the generation trip example for Oahu. However, this methodology is not specific to island power systems, nor to generation trip events. In an era of increasing complexity of the power system driven by the proliferation of renewables, the CSM methodology can provide valuable insights for load trip events, weak grid evaluations, and be used with sensitivity analysis to evaluate the efficacy of mitigations, equipment changes, and infrastructure upgrades.

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