Photovoltaic inverter-based quantification of snow conditions and power loss

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Abstract. Snow is a significant challenge for photovoltaic (PV) systems at northern latitudes, where the pace of deployment is rapid but snow-related power losses can exceed 30% of annual production. Accurate snow-related power loss estimation methods for utility-scale sites can support snow mitigation strategies, inform resource planning and validate predictive snow-loss models. This study builds on our previous work on inverter-based detection of snow, and its implications for utility-scale power production, by validating the accuracy of our snow-loss method across different PV sites and system designs and highlighting its value in bringing greater visibility to PV plant operations in winter. Our estimation method is both novel and scalable, requiring only standard monitoring data to correlate snow-related losses with meteorological data. As demonstrated here, our validation method involved three main steps: 1) estimation of performance losses for multiple systems by comparing measured inverter data to modeled data; 2) application of a detection framework to identify which performance losses are snow-related; and 3) comparison of snow-related losses among three utility-scale sites differing in tilt angle. Results show that utility-scale systems at higher tilt angles consistently shed snow more quickly or completely than their lower-tilt counterparts. Further, monthly and seasonal snow losses are inversely and non-linearly correlated with tilt angle when normalized for cumulative snowfall. These results are consistent with the findings of previous studies and support the broad applicability of this method to fixed-tilt utility-scale PV systems around the world that routinely experience snow-related performance losses.

Keywords: Snow / photovoltaic / utility / analytics

1 Introduction

Many studies have demonstrated that snow significantly compromises photovoltaic (PV) output during winter [1–3], often a period of high energy demand in snowy regions, with power losses documented to be as high as 90%–100% of monthly production - thus exceeding 30% of annual production - for some systems [1,4,5].

Large-scale PV systems are particularly vulnerable to snow losses, as the labor requirements of mechanical snow clearing increase with system scale beyond the point of financial feasibility. Despite these challenges, the solar industry continues to expand northward with installed utility-scale (defined as >1 MW) PV capacity above 40 latitude increasing by over 700% since 2015 to reach 18.8 GW in 2021 [6]. Based on this trend, effective snow mitigation techniques may not be required to motivate asset owners to further expand into snowy regions. However, as renewable penetration on the electric grid expands and non-renewables are phased out, the year-round reliability of PV systems will become increasingly important to the communities that they power. In this scenario, accurate estimates of snow-related losses will be critical for resource availability assessments and long term expansion planning. Predictive snow loss models will also become increasingly useful to real-time operations, and robust snow loss estimation methods will be necessary to validate these models. To support a zero carbon electricity supply, utilities require a more reliable supply of renewable energy, which will likely spur efforts to optimize PV system design for winter performance. Creating optimal winterized designs that facilitate passive snow shedding and minimize the need for mechanical clearing will require quantitative comparison of the individual and combined impacts of design components on utility-scale system performance [7]. Snow-related power loss will again be a key metric in such comparisons.

Snow losses can be estimated either through weather-based modeling (loss modeling) or by analyzing power generation data (loss quantification). A variety of loss modeling and loss quantification approaches have been...
published over the last 20 years [3,8–11], but they have generally been developed using small research-scale systems. Many modeling methods require panel or ground snow depth measurements [9,10], which are not typically installed as part of a standard utility-scale monitoring systems. Additionally, many established snow loss models have not been validated on utility-scale systems [4,9,10,12]. The introduction of the power electronics and electrical connections needed for utility-scale systems can significantly alter power production from that of a small system [13]. This effect is particularly pronounced in snowy conditions, where nonuniform cover can lead to mismatch losses. In a utility-scale system, snow can decrease the output of the modules it covers but it can also change the output of any uncovered modules it is connected to in series or in parallel. Such collateral mismatch losses are usually minimal within small systems, but they can significantly decrease the power output of a utility-scale system [14]. It is typical at utility-scale sites for hundreds of modules to be operated at a single maximum power point (MPP), which is determined by the inverter according to an algorithm to maximize the power output within its operating range. As the number of modules connected in series or the number of strings connected in parallel in a system increase, so does the magnitude of potential mismatch losses due to array-level non-uniformities in snow cover. Additionally, significant snow cover may lower a system’s operating voltage enough that it approaches its inverters’ minimum voltage threshold. This may induce unexpected behavior that varies from inverter to inverter, as some inverters will adjust the operating conditions away from the true MPP to maintain a voltage that is above the minimum threshold. The exclusion of these effects in model development and validation makes implementation using utility-scale data challenging. For example, Andrews et al. [8] applied a direct-loss model to utility-scale PV site data but cited mismatch losses and inverter behavior as a possible cause of poor fit of the model.

In addition to these limitations, approaches where power loss is calculated by estimating snow cover assume snow cover to be opaque [11,15] or opaque and uniform [9]. These models do not allow for power production by fully snow-covered PV systems, which our research has shown occurs frequently [16]. Past simulation-based studies [17] have attempted to characterize the electrical signature of opaque and transparent snow, but identification in utility-scale field data was not published until recently. Our work [16] identified five distinct operational modes corresponding to measured vs. modeled voltage and current ratios in utility-scale inverter data. The presence of snow conditions associated with these modes was validated on both research and utility-scale systems using time-series imagery.

In this article, we introduce and implement an approach for quantifying snow losses in utility-scale inverter data sets that builds our previous work on snow detection and operational mode classification in field data. Required data is limited to measurements collected by standard utility-scale monitoring equipment. Off-maximum power point behavior is eliminated or corrected by rigorous data filtering routines specific to inverters. Power losses are calculated for three utility-scale sites using a performance model, and data is classified into loss modes based on ratios of measured vs. modeled operating current and voltage. We compare losses and modal frequencies across sites, and find that increases in tilt angle enable systems to shed snow earlier and more quickly. We find that higher tilt systems experience significantly lower snow losses on both a monthly and seasonal scale even after cross-site differences in cumulative snowfall are accounted for. Both of these results are consistent with previous findings [3]; the results, in and of themselves, are not novel. However, the replication of previous findings serves as a demonstration of the validity of this method. Additionally, the identification of physical snow conditions presented in this paper serves as evidence of the untapped potential in analysis of standard monitoring data.

2 Methods

2.1 Data

Fifteen-minute resolution data sets for three monofacial fixed-tilt utility sites located within thirty miles of one another in the northeastern United States were provided by an electric utility, including 1247 days from March 2019 to June 2023. The sites are referred to as S10, S20, and S35 to indicate the system tilt angle in degrees. Data and metadata types collected from all sites are listed in Table 1. All data collected are readily available from typical utility-scale monitoring systems and are typically recorded by inverters. All three sites have panels oriented in portrait;
Further specifications for each site are listed in Table 4. All sites were leveled during construction. Monthly and seasonal snowfall data sourced from the archive of historical weather data maintained by the National Centers for Climate Information (NCEI) demonstrates that the sites experience similar snowfall patterns (Tabs. 2 and 3).

### Table 2. Monthly aggregated snowfall [in] and number of distinct snowfall events.

<table>
<thead>
<tr>
<th></th>
<th>S10</th>
<th></th>
<th>S20</th>
<th></th>
<th>S35</th>
<th></th>
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</thead>
<tbody>
<tr>
<td>November 2019</td>
<td>2.6</td>
<td>3</td>
<td>0.3</td>
<td>1</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>December 2019</td>
<td>26.4</td>
<td>6</td>
<td>22.8</td>
<td>5</td>
<td>23.2</td>
<td>4</td>
</tr>
<tr>
<td>January 2020</td>
<td>6.1</td>
<td>6</td>
<td>5.4</td>
<td>3</td>
<td>7.3</td>
<td>4</td>
</tr>
<tr>
<td>February 2020</td>
<td>6.1</td>
<td>7</td>
<td>3.6</td>
<td>3</td>
<td>6.9</td>
<td>5</td>
</tr>
<tr>
<td>March 2020</td>
<td>2.8</td>
<td>3</td>
<td>2.9</td>
<td>3</td>
<td>6.5</td>
<td>3</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>44.0</strong></td>
<td><strong>29</strong></td>
<td><strong>35.0</strong></td>
<td><strong>15</strong></td>
<td><strong>44.4</strong></td>
<td><strong>17</strong></td>
</tr>
</tbody>
</table>

### Table 3. Seasonally aggregated snowfall [in] and number of distinct snowfall events.

<table>
<thead>
<tr>
<th></th>
<th>S10</th>
<th></th>
<th>S20</th>
<th></th>
<th>S35</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2019 – 2020</td>
<td>44.0</td>
<td>29</td>
<td>35.0</td>
<td>15</td>
<td>44.4</td>
<td>17</td>
</tr>
<tr>
<td>2020 – 2021</td>
<td>47.5</td>
<td>20</td>
<td>26.5</td>
<td>15</td>
<td>39.5</td>
<td>13</td>
</tr>
<tr>
<td>2021 – 2022</td>
<td>39.7</td>
<td>20</td>
<td>24.7</td>
<td>13</td>
<td>25.6</td>
<td>11</td>
</tr>
<tr>
<td>2022 – 2023</td>
<td>56.4</td>
<td>18</td>
<td>30.2</td>
<td>15</td>
<td>36.0</td>
<td>16</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>187.6</strong></td>
<td><strong>82</strong></td>
<td><strong>116.4</strong></td>
<td><strong>58</strong></td>
<td><strong>145.5</strong></td>
<td><strong>57</strong></td>
</tr>
</tbody>
</table>

### Table 4. System and instrument specifications. Minimum DC voltage indicates the turn-on voltage of the system’s inverter and is expressed as a percentage of the array’s rated DC voltage when operating at its MPP under standard testing conditions (STC).

<table>
<thead>
<tr>
<th></th>
<th>S10</th>
<th></th>
<th>S20</th>
<th></th>
<th>S35</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Azimuth</td>
<td>180°</td>
<td></td>
<td>225°</td>
<td></td>
<td>180°</td>
<td></td>
</tr>
<tr>
<td>Panel</td>
<td>LG400NW-A5</td>
<td></td>
<td>REC345TP72</td>
<td></td>
<td>REC340TP72</td>
<td></td>
</tr>
<tr>
<td>Inverter</td>
<td>Yasakawa SGI 500 kW</td>
<td></td>
<td>Yasakawa PVI 60 kW</td>
<td></td>
<td>Yasakawa PVI 60 kW</td>
<td></td>
</tr>
<tr>
<td>ILR ratio</td>
<td>1.32</td>
<td></td>
<td>1.25</td>
<td></td>
<td>1.22</td>
<td></td>
</tr>
<tr>
<td>Minimum DC voltage</td>
<td>71%</td>
<td></td>
<td>76%</td>
<td></td>
<td>78%</td>
<td></td>
</tr>
</tbody>
</table>

To retain measurements impacted by snow conditions, it is first necessary to identify whether data is collected while the system is offline due to insufficient irradiance caused by snow. If the system omits data records of DC voltage or records null values for DC voltage, then these data must be altered to include missing time records and all DC voltages and currents should be set to zero rather than null so that power losses can be estimated. Missing timestamps should be imputed by assuming current and voltage to be zero.

General quality checks should be performed to verify that instrument performance is consistent over multi-year timescales. Assuming that all instruments were functioning correctly upon commissioning, periods of faulty or missing measurements can be identified by through multi-year plots. Environmental measurements made by pyranometers and thermocouples should be included in these quality checks.

2.2 Data filtering procedures

A key difference between the data quality routines employed in this paper and other published practices is the selective inclusion of outliers [18]. By definition, periods of snow cover appear in data as outliers. Estimating snow losses requires correcting and filtering data to isolate snow events from other periodic losses caused by clipping, shading, or inverter outages.
An important component of this data quality routine is identifying periods of time when operating conditions are outside of the inverter’s maximum power point tracking (MPPT) range. This step is necessary because one needs to make an assumption about the system’s operating point to quantitively snow losses. Losses are identified by comparing measured data to a single value of modeled system output. To calculate that value, a single diode model is used to generate an irradiance and temperature-dependent IV-curve. Without the inverter’s MPPT algorithm, it is not guaranteed that the system will operate at the curve’s MPP. When the operating conditions are within the inverter’s MPPT range, it can be assumed that the algorithm is active and the system is operating at the MPP of the IV-curve. This allows one to make a valid comparison between a measured MPP and a modeled MPP.

This is not to say that all periods when the system is operating outside of the MPPT range during daylight hours are excluded from analysis. Snow is a credible cause for such behavior, and is accounted for by setting inverter measurements to zero when the system is operating below the inverter’s turn-on voltage. This allows for estimates of what snow losses would look like if an inverter went offline once operating conditions deviate its MPPT range, which many inverters do.

Off-MPP behavior caused by mechanisms other than snow can be identified by enforcing physical operating limits defined in the inverter’s specification sheet. A key filtering step is to set both current and voltage to zero under open-circuit conditions. Open-circuit conditions are generally experienced during periods of extremely low irradiance (e.g., nighttime) outside of the systems’ MPPT range, and cannot be compared to a modeled MPP. Sanity checks should be performed by dividing measured current collected under conditions similar to standard test conditions (STC) by the number of strings connected in parallel to the combiner; the result should be similar to the module nameplate. A similar check should be done with measured voltage, the number of modules connected in series per string, and the module’s nameplate.

The most common cause of off-MPP behavior in this analysis was clipping, as sites had DC-AC ratios between 1.2 and 1.32 (see Tab. 4). Clipping was identified based on inverter nameplate limits on AC power and MPPT DC voltage range. DC voltage, current, and power values associated with timestamps where DC voltage was less than the lower bound on the inverter’s MPPT voltage range were set to zero. Timestamps where DC voltage was greater than the upper bound on the inverter’s MPPT voltage range were excluded from analysis, as it was assumed that snow losses and clipping losses did not occur at the same time. Periods where AC power was above 95% of the nameplate maximum were also excluded from loss analysis.

This approach of excluding off-MPP behavior does have several pitfalls. Setting inverter measurements to zero when the system is operating below the inverter’s turn-on voltage almost certainly inflates the rate of complete outages (mode 0, see Sect. 2.5) over partial outages (modes 1–3). Additionally, anecdotal evidence suggests that excluding periods of clipping may deflate the rate of partial outages caused by light-transmissive snow (mode 3). Mode 3, as is defined in Section 2.5, is identified as periods with high (relative to a performance model) operating voltage and low current. Under high irradiance, it is possible that a system under light-transmissive snow may still produce a voltage in excess of the MPPT range coupled with a low current. Anecdotal evidence for this phenomenon was found in systems’ AC power output, which was often <50% of their inverter’s rated capacity while excess voltage was being clipped. However, it is unclear how one can distinguish between clipping and the combination of clipping and light-transmissive snow conditions, as clipping invalidates the comparisons to MPPT performance models needed to contextualize low AC power measurements. Further exploration of how snow shading interacts with inverter turn-on and MPPT limits are needed in this area of research.

2.3 Shade detection

Two types of persistent shading - horizon and inter-row - are known to cause string-level current mismatches and lead to off-MPP behavior. Solar positions where onsite pyranometers measured irradiance that was significantly lower than modeled clearsky values over multiple years were identified as being subject to horizon shading. Onsite pyranometers were heated, and it is assumed that the irradiance measured by the devices was not subject to snow-related decreases. Clearsky irradiance values were modeled using the Ineichen clearsky model implemented in pvlib [19]. Ratios between measured and clearsky values are plotted as a function of solar position in Figure 1 using a diagramming method developed by [20].

Persistent self-shading between rows at the beginning and end of the day was accounted for using a time-varying derate factor. Using the procedure outlined in [21], a site-level self-shaded fraction was calculated for each system as a function of projected solar zenith angle (PSZA) (Fig. 2). Shaded fraction was assumed to be uniform across each system, as all systems’ series-connected strings span multiple rows. A derate factor based on the shaded fraction was calculated using the formula given in [22] and used to scale the power output by the performance model.
transmission, a dimensionless quantity, quantifies the effective transmission. Effective transmission based on measured voltage, effective transmission, and voltage PI modeled using effective transmission. Effective transmission is within one standard deviation of the mean for all systems. Perfect performance index (PI) at each system is within 4% of a power measurement. Periods where modeled DC voltage or DC current compromise the validity of results. As was done with measured data, periods where modeled DC voltage or DC current were outside of the inverter’s MPPT range were excluded or associated values were adjusted to reflect the inverter’s turn-on mechanism. Figures 3 and 4 validate the quality of the model fit. Figure 3 shows that the majority of power measurements are within 10% of model predictions for all systems studied. Figure 4 shows that the mean voltage performance index (PI) at each system is within 4% of a perfect fit. Additionally, more than 80% of voltage PIs are within one standard deviation of the mean for all systems.

2.4 Performance modeling

Module output was modeled using pvlib-python to solve the single diode model [19] with module nameplate parameters retrieved from the California Energy Commission (CEC) module database. Modeled voltage was scaled up by the number of modules per string; modeled current was scaled by the number of strings per combiner. Inter-row shading losses were accounted for by multiplying modeled power by a time-varying derate factor (see Sect. 2.3). This model of power production does not account for loss mechanisms such as wiring losses, resistive losses, and soiling losses. Given the frequency at which snow was detected on the systems, it is assumed that soiling does not build up over multiple years and therefore remains minimal. The approach assumes that the combined impact of wiring, resistive, and soiling losses on power production is on the order of 1%. Given that the goal of this study is to identify significant snow losses, these exclusions do not compromise the validity of results. As was done with measured data, periods where modeled DC voltage or DC power were outside of the inverter’s MPPT range were excluded or associated values were adjusted to reflect the inverter’s turn-on mechanism. Figures 3 and 4 validate the quality of the model fit. Figure 3 shows that the majority of power measurements are within 10% of model predictions for all systems studied. Figure 4 shows that the mean voltage performance index (PI) at each system is within 4% of a perfect fit. Additionally, more than 80% of voltage PIs are within one standard deviation of the mean for all systems.

2.5 Mode definition and categorization

Data was categorized into five distinct operational modes based on measured voltage, effective transmission, and voltage PI modeled using effective transmission. Effective transmission, a dimensionless quantity, quantifies the fraction of available POA irradiance that is converted to electrical current. This can be conceived as the effective transmission of light-blocking matter on the array, $T_{eff}$, which is independent of irradiance. The procedures to calculate $T_{eff}$ and voltage PI are described at length in [16], so we only briefly summarize them here. $T_{eff}$ is estimated using the Sandia Array Performance Model (SAPM) [23] with measured current [A], POA irradiance [$\frac{W}{m^2}$] and BOM temperature data [$°C$]:

$$I_{mp} = N_{strings} \times I_{mp0} \left( C_0 \frac{E_{POA}}{E_0} T_{eff} + C_1 \left( \frac{E_{POA}}{E_0} T_{eff} \right)^2 \right) \times \left( 1 + \alpha_{Imp}(T_{cell} - T_0) \right),$$

(1)

where $C$ is a vector of coefficients specific to the module type, $E_{POA}$ is POA irradiance, $E_0$ is a reference irradiance (1000 [$\frac{W}{m^2}$]), $T_{cell}$ is cell temperature, $T_0$ is a reference temperature (25 $°C$), $I_{mp0}$ is the nameplate $I_{mp}$ of the module, and $N_{strings}$ is the number of strings connected in parallel to the combiner measurement system. Inverter voltage [V] given $T_{eff}$ is modeled using the SAPM,

$$V_{mp} = N_{modules} \times \left[ V_{mp0} + C_2 N_s \delta \ln(E_t T_{eff}) \right. \left. + C_3 N_s \left( \delta \ln(E_t T_{eff}) \right)^2 + \beta_{Vmp}(T_{cell} - 25) \right],$$

(2)

using sensor data, where $N_s$ is the number of cells connected in series per module, $V_{mp0}$ is the nameplate $V_{mp}$ of the module, and $N_{modules}$ is the number of modules connected in parallel per string. $V_{ratio}$, which is equivalent to the average snow-free fraction of the array, is defined as the PI of measured voltage in relation to $V_{mp}$.

Figure 5 shows the mode-based framework developed by [16]. Modes differ from each other based on whether $V_{ratio}$ or $T_{eff}$ significantly deviate from typical values observed under snow-free conditions (defined as $C_{V}$ and $C_{T}$, see Tab. 5). Identifying relative frequencies of modes and cumulative power losses per mode provides insight on the physical mechanisms that contribute to snow-based power losses in each system. Mode 0 refers to outages caused by either full or extensive partial opaque snow coverage such that the system is unable to reach the minimum turn-on voltage (see Tab. 4). This scenario is easy to envision as heavy snowfall that clings to the array. Mode 1 corresponds to lower-than-predicted current and voltage, which we attribute to non-uniform snow conditions (i.e. coverage by both light-transmissive and opaque snow). Opaque snow cover activates substring bypass diodes and decreases the system voltage while active strings operate at a lower current under light-transmissive snow. Mode 1 is hypothesized to occur when partial coverage by opaque snow (lower-than-predicted voltage, as-predicted current). Mode 2 can...
occur when individual modules are partially covered, or when a system has both uncovered modules and covered modules. At the resolution of inverter data, determining the actual distribution of snow cover across specific modules is not feasible. However, system-to-system comparisons of frequencies of modes 1 and 2 can be the basis for a comparison of the systems’ shedding rate, as a faster shedding rate should lead to shorter periods of opaque cover. Mode 3 captures partial to full cover by light-transmissive snow (as-predicted voltage, lower-than-predicted current). One potential physical condition that generates mode 3 behavior is snowmelt, which is the dominant mechanism through which low-tilt panels lose their snow cover. Here, snow melt is defined as water that is close to 0 °C, and has a transmittance that is significantly closer to one than the equivalent volume of snow [24]. Anecdotal evidence also points to the presence of frost as a contributor to occurrences of mode 3. Mode 4 refers to business-as-usual operations, where there may be small losses due to inefficiencies in an inverter’s MPPT algorithm or model inaccuracy.

By defining thresholds $C_V$ and $C_T$ in relation to individual system behavior, the framework is translatable across sites. For each system, modes were bounded based on typical system behavior observed between the months of May and October of each year (hereafter referred to as summer), when the measured snowfall is zero (see Tabs. 2 and 3). $V_{\text{ratio}}$ and $T_{\text{eff}}$ values were randomly sampled $n_1 = 200$ times with size $n_2 = 5000$ from timestamps recorded during summer months. A cumulative distribution was calculated for each sample, and the $V_{\text{ratio}}$ and $T_{\text{eff}}$ values corresponding to the 95th percentile were recorded. Figure 6 illustrates the sampling process. Threshold values on $V_{\text{ratio}}$ and $T_{\text{eff}}$ for typical, snow-free behavior (mode 4) were calculated from averages of this set of 95th percentiles and became $C_V$ and $C_T$ (Tab. 5). Modes 1–4 were defined based on these values, while mode 0 was defined based on inverter turn-on voltage ($V_{\text{turn-on}}$).
3 Results

3.1 Power losses and modal frequencies

Monthly comparisons of energy loss for the winter of 2019-2020 (Fig. 7) revealed that while all sites experienced greater power losses during periods of snowfall (e.g., heavy snowfall in December 2019, recorded in Tab. 1), S20 and S10 experienced significantly higher rates of snow-related losses than S35. Seasonal energy losses for all four winters were normalized by seasonal snowfall (Fig. 8), and display a consistent negative correlation with tilt angle for the systems surveyed. Energy losses shown in Figures 7 and 8 excluded minor losses incurred while systems were operating in mode 4. All three systems received similar amounts of snow (Tab. 4) in the period plotted in Figure 7. Normalized power losses for a single site vary slightly between seasons, which may reflect time-varying differences in snow conditions beyond quantity, or otherwise unaccounted for losses.

Modal frequencies during winter months (November - March) showed that S10 and S20 had significantly higher rates of complete outages (mode 0 occurrences) than S35 (Fig. 9). Over the study period, S35 consistently was subject to similar, but slightly higher amounts of snowfall than S20. The frequency of distinct snowfall events at S20 and S35 was roughly equal over the course of the study period. In contrast, S10 received up to 60%-80% more annual snowfall than S20 and S35 and experienced almost double the number of distinct snowfall events. Given these differences in environmental conditions, modal frequencies at S20 and S35 are compared, but S10 is treated separately.

Given their demonstrably similar snow conditions, the higher rate of mode 0 occurrences observed at S20 suggests that the average duration of the outage associated with each snow event was longer at S20 than at S35. In turn, this suggests that it took longer for snow to shed or melt enough that power production could resume at S20 than at S35.

S20 also experienced higher frequencies of mode 1 than S35, though the margin of difference is slimmer than the differences in mode 0 frequencies. Given that mode 1 occurs when partially shed opaque snow is covered by a light-transmissive layer of snow, this suggests that S20 was slightly more likely to be partially covered at the time of snowfall than S35.

Frequencies of mode 2, which indicate the presence of partially shed opaque snow, were low across S20 and S35 and overlapped within the margin of error. This may be attributed to the systems’ turn-on voltage and portrait module orientation. The inverters installed at all three sites have high turn-on voltages relative to their systems’ rated STC voltages (Tab. 4), meaning that the systems will remain off until at least 71% – 78% of all strings are

Table 5. Average threshold values with standard deviations calculated by sampling.

<table>
<thead>
<tr>
<th></th>
<th>S10</th>
<th>S20</th>
<th>S35</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_V$</td>
<td>0.99 ± 0.001</td>
<td>0.91 ± 0.002</td>
<td>0.93 ± 0.000</td>
</tr>
<tr>
<td>$C_T$</td>
<td>0.67 ± 0.012</td>
<td>0.68 ± 0.013</td>
<td>0.60 ± 0.007</td>
</tr>
</tbody>
</table>

Fig. 7. Monthly aggregated energy losses from modes 0–3. See Table 2 for monthly snowfall data.

Fig. 6. Probability (blue) and cumulative (red) distribution functions for a $n_2=5000$ sample size. Threshold values based on the location of the 95th percentile are identified with the black dashed line.

Fig. 5. Mode-based framework for snow identification. Modes with low voltage correspond to conditions with partial coverage by opaque snow; modes with low current correspond to full or partial coverage by light-transmissive snow. Values for $C_V$ and $C_T$ were determined using a thresholding process.

Table 5. Average threshold values with standard deviations calculated by sampling.
operating. This limits the visibility of shedding behaviors. Additionally, a comparison of snow losses between portrait and landscape-orientation modules was previously performed using this detection framework [16] and found that standard three-substring portrait-orientation modules were less likely to experience mode 2 behavior than three-substring landscape-orientation modules.

It is notable that S10 experienced mode 2-like behavior at approximately the same rate as S20 and S35. Given that S10 experienced significantly more snowfall events than S20 and S35, one would expect that there would be more partial shedding events captured at S10. The paucity of mode 2 events at S10 may be due to the conventional three-substring interconnection design of its modules. If we conceive of snow as generally shedding downwards uniformly, all three of the substrings of one of the S10 modules would remain partially covered even after snow sheds off of the top half of the module. This is in contrast to a landscape-orientation module, which would reveal fully uncovered substrings sequentially. The portrait orientation modules used at S20 and S35 have a “shade-tolerant” half-cut cell and butterfly interconnection design, such that the module can produce power if at least half of it is free of snow. This is an improvement over the conventional interconnection design of S10’s modules, which decreases the likelihood that S10 turns on until shedding is nearly complete (light reaches all rows of cells).

Occurrences of mode 3 for S20 and S35 were within the margin of error; frequencies of mode 3 were slightly higher for S10. This is most likely a product of S10’s increased rate of snowfall.

4 Conclusions

Snowfall-normalized utility-scale PV system power losses were quantified over a 4 yr period for three systems with different modules, inverters, and tilts using standard monitoring data. For two systems that experienced similar amounts of snow, the higher-tilt system consistently reported lower energy losses on monthly and annual scales, which is consistent with previous findings for other unobstructed systems [3,5].

Comparisons between modal frequencies of S20 and S35 suggest that shedding takes less overall time at S35 than at S20. This is evidenced by the fact that it takes more time for S20 to transition out of mode 0 and the increased likelihood that shedding was incomplete for S20 before the next snowfall. However, it is unclear if snow shedding initiates earlier at S35 or if the entire shedding process at S35 is simply shorter.

High turn-on voltages limited visibility into mode 2 behavior across the systems, but differences in module interconnection design were evident in frequencies of mode 2 at S10 (conventional three-substring interconnection) and S20 (butterfly interconnection); despite S10 experiencing almost double the number of distinct snowfall events that S20 was subject to, rates of partial shedding behavior were roughly equal across the two sites. This suggests that the butterfly interconnection design at S20 and S35 allowed the systems to turn-on under partial shedding conditions more frequently or sooner than S10.

These results are an example of the type of nuanced information that can be gleaned from inverter data. Future studies should continue to seek performance insights using monitoring even when system instrumentation is as minimal as that of the systems surveyed in this study.

The methods described in this study are location-agnostic and can easily be adapted to different data resolutions and system configurations. Potential research applications of this work include validation for advanced snow shedding models and predictive snow loss models. There is also a substantial audience for whom this approach
and future improvements to it have immediate industry applications; as such, implementing this approach in an industry-friendly tool is of high priority. Asset owners may use snow losses to value sites, while developers may use snow losses for system design comparisons beyond tilt angle. Grid planners may use historic snow losses to increase the accuracy of resource adequacy assessments.

Future uses of these methods should include an analysis of the impact of bifaciality on modal frequencies and losses, as well as the behavior of diverse cell interconnections and non-silicon technologies under snow conditions.

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**Conflicts of interest**

All authors declare that they have no conflicts of interest.

**Data availability statement**

The entire data set and metadata characteristics used for this analysis is not publicly available. A demonstration analysis, along with a subset of data, will be made available through pv-snow-analysis, a Python repository hosted by @eccoope on Github.

**Author contribution statement**

This project was directed by Laurie Burnham. The analysis was conceived of and designed by all authors. Emma Cooper and Jennifer Braid were responsible for developing theory, contributing analytical tools, and interpreting results. Analysis was performed by Emma Cooper. Manuscript was written by Emma Cooper and Jennifer Braid, with oversight from Laurie Burnham.

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