Photovoltaic inverter data-based snow conditions and power loss quantification

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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 are needed for resource planning and to validate snow mitigation strategies. In this study, we demonstrate a snow loss estimation approach for time-series inverter data, building on a snow detection and classification framework. We use utility-scale inverter data with automated filtering and performance modeling to estimate snow losses and identify the contributing physical snow conditions. We implement this method to compare snow-related power losses and loss modal frequencies between three utility-scale sites differing in tilt angle. Results show that utility-scale systems at higher tilt angles shed snow earlier and more quickly/completely than their low-tilt counterparts. Further, monthly and seasonal snow losses are inversely and non-linearly correlated with tilt angle when normalized for cumulative snowfall.**

I. 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 PV power loss as high as 90% - 100% during winter months 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 past 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]. As renewable penetration on the electric grid increases, the winter performance of these utility-scale systems will become of increasing importance to the communities that they power. To contribute to year-round reliability, systems must be designed to facilitate passive snow shedding and minimize the use of mechanical clearing. This optimization requires quantitative comparison of the individual and combined impacts of design components on utility-scale system performance [7]. Snow-related power loss will be a key metric in such comparisons. Additionally, snow losses will be an increasingly important component of resource adequacy assessments as demand on the grid is increasingly met by weather-dependent generators.

The development of methods for estimating snow losses has, until this point, not been targeted for utility-scale application. A variety of snow loss identification/quantification approaches have been published over the last twenty years [3], [8]–[11]. While some have been employed in studies to reduce error in generation predictions during winter months [1], many either explicitly require panel or ground snow depth measurements [1], [10] or have been shown to significantly underpredict snow losses if they do not reference panel snow cover conditions [1], [4], [8], [9], [12]. Standard utility-scale monitoring systems are typically limited to inverter-level DC and AC-side monitoring, plane-of-array (POA) irradiance, and back-of-module (BOM) temperature. A reliance on high temporal resolution snow depth measurements or other site-specific snow condition measurements precludes the use of these models to determine snow losses for existing utility-scale systems. Beyond requiring specialized instruments that are not typically installed at utility-scale sites, many established snow loss models have only been validated on smaller test systems [4], [9], [12]. Andrews *et al.* [8] validated a direct-loss model on a utility-scale site, and cited inverter clipping behavior as a possible cause of the poor fit of the model to the measured data. In addition to these limitations, approaches where power loss is calculated by estimating snow cover assume snow cover to be opaque [11], [13] or opaque and uniform [9]. However these models do not allow for power production by fully snow-covered PV systems, which our research has recently shown occurs at significant frequencies [14]. Our recent work [14] identified four distinct snow-loss modes corresponding to decreases in voltage and/or current in utility-scale inverter data.

In this article, we introduce and demonstrate an approach to quantifying snow losses in utility-scale inverter data sets that builds our previous work on snow detection and power loss mode classification in field data. Power losses are calculated for three utility-scale sites using a performance model, and data is classified into snow-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.

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TABLE I

Data types	Metadata
DC voltage $[V]$ DC current $[A]$ AC power $[W]$ POA irradiance $[W/m^2]$ BOM temperature $[°C]$	Location Panel tilt [°] and azimuth [°] Panel make/model Inverter make/model (MPPT voltage range $[V]$, maximum AC power output $[W]$) Number of strings connected in parallel to each combiner, number of modules connected in series to each string

II. Methods

A. Data

Fifteen-minute resolution data sets for three monofacial fixed-tilt utility sites (>1 MW installed DC capacity) located within thirty miles of one another in the northeastern United States were provided by an electric utility. 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 I. All data collected is readily available from typical utility-scale monitoring systems and are recorded as standard by the inverters. Monthly and seasonal snowfall data sourced from the archive of historical weather data maintained by the National Centers for Climate Information (NCEI) demonstrated that the sites experience similar snowfall patterns.

B. Performance modeling

Module output was modeled using *pvlib_python* to solve the single diode model [15] and obtain with module nameplate parameters retrieved from the California Energy Commission (CEC) module database. Modeled voltage was scaled up to the measured resolution by the number of modules per string; modeled current was scaled by the number of strings per combiner. Periods where the system operated outside of its nameplate limits (i.e. clipping, shading) were excluded from analysis or corrected.

C. Mode definition and categorization

Data was categorized into five distinct snow-related modes based on measured voltage, effective transmission, and a voltage PI based on the effective transmission. The effective transmission of light-blocking matter on the array, T_{eff}, is estimated using the Sandia Array Performance Model (SAPM) [16] with measured current, irradiance, and BOM temperature data:

$$I_{mp} = N_{strings} \times I_{mp0}(C_0 E_e T_{eff} + C_1 (E_e T_{eff})^2) \times (1 + \alpha_{Imp}(T_{cell} - T_0)) \quad (1)$$

where C is a vector of coeffients specific to the module type, E_e is effective irradiance, T_{cell} is cell temperature, T_0 is 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 given T_{eff} is modeled using the SAPM,

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

using T_{eff} and 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}.

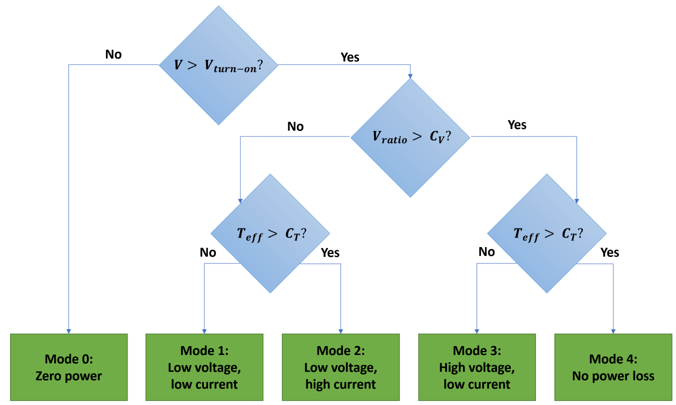

Fig. 1. Mode-based framework for snow identification. Modes with low voltage correspond to conditions with partial coverage by opaque snow; modes with low current correspond to full or partial coverage by light-transmissive snow.

Figure 1 shows the mode-based framework developed by [14]. 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. Mode 1 corresponds to lower-than-predicted current and voltage, which we attribute to non-uniform snow conditions with partial coverage by both opaque and transparent snow. Mode 1 is hypothesized to occur when partially shed or melted snow is covered by a second, newer layer of snow. Modes 2 and 3 correspond to physical conditions where there is partial coverage by opaque snow (lower-than-predicted voltage, as-predicted current) and partial to full coverage by transparent snow (as-predicted voltage, lower-than-predicted current), respectively. Mode 2 captures periods of shedding while mode 3 describes periods of snow melt or very light snow cover. 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.

III. Results

A. Power losses and modal frequencies

Seasonal comparisons of normalized energy loss $[\%/in]$ (Figure 2) revealed that while all sites experienced greater power losses during periods of snowfall, S20 and S10 consistently experienced significantly higher rates of snow-related losses than S35. Energy losses shown in Figure 2 excluded minor losses incurred while systems were operating in mode 4.

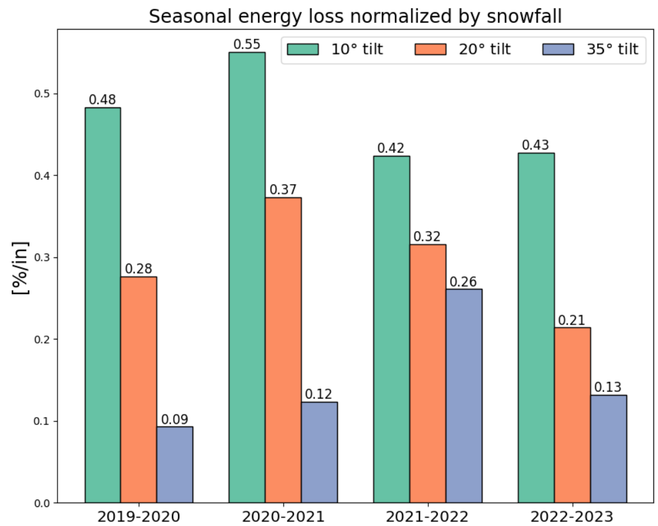

Fig. 2. Seasonally aggregated energy losses from modes 0 - 3 [%] normalized by seasonal snowfall [in]

Modal frequencies during winter months (November - March) showed that S10 and S20 had significantly higher rates of complete outages (mode 0 occurrences) than S35 (Figure 3), indicating a negative correlation between tilt angle and outage duration. Tilt angle was also negatively correlated with mode 1 occurrences, but the margin of difference in mode 1 occurrences between the sites was decidedly 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, the higher frequencies of mode 1 seen at lower tilt sites indicate that snow sheds slower from lower tilt angle systems.

Frequencies of mode 2, which indicate the presence of partially shed opaque snow, were low across sites and overlapped within the margin of error. The low frequencies can likely be attributed to the systems' portrait module orientation. As snow sheds downward, snow cover is roughly uniform across the bottom edge of a module. For a portrait-orientation module, this means that all three of its substrings remain partially covered as snow sheds off of the top half of a module, as opposed to a landscape-orientation module which would reveal substrings sequentially. If snow cover is opaque, this would translate into a decreased likelihood that the portrait-orientation system 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. Mode 3 behavior is caused by a melting snow cover or very light snow cover; frequency patterns suggest that residual patches of light-transmissive snow may tend to remain on panels at S10 slightly longer. This slower melting rate may be due to the higher angle-of-incidence (AOI) between the sun and a lower tilt system during the winter.

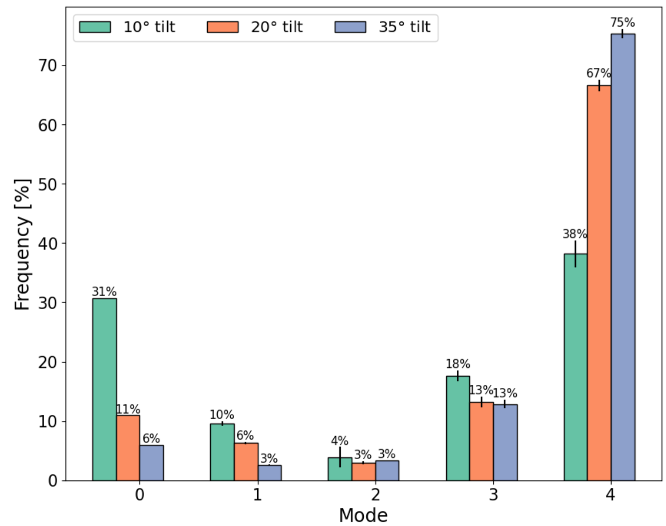

Fig. 3. Modal frequencies during the months of November, December, January, February, and March. Error bars were assigned using the spread in modal frequencies generated by varying modal threshold values by their calculated standard deviations (see Table **??**).

IV. Conclusions

Snowfall-normalized utility-scale losses are quantified over a four year period for three systems with different modules, inverters, and tilts using standard monitoring data. Seasonal comparisons of normalized energy loss reveal that, for the systems surveyed in this study, lower tilt systems tend to lose more energy than higher tilt systems under the same snowfall conditions. Normalized power losses for a single site vary slightly between seasons, which may reflect time-varying differences in snow conditions beyond quantity. Modal frequency analyses show that tilt angle enables both earlier shedding and shorter shedding durations. 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 is 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.

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