Snow Loss Modeling for Roof Mounted Photovoltaic Systems: Improving the Marion Snow Loss Model

Mari B. Øgaard, Iver Frimannslund, Heine N. Riise, and Josefine Selj

***Abstract*—Accurate PV energy yield assessments for cold climates necessitate understanding and estimation of snow loss. Estimation of snow loss for a specific system requires a snow loss model. Multiple models to estimate snow loss are suggested in the literature, but extensive validation is lacking. In this work, we describe the effect of snow on PV systems by analyzing signatures in monitoring data and we evaluate the accuracy of a modified adaption of the Marion snow loss model. Eight different systems with a total installed capacity of 1.6 MW$_P$, installed on both tilted and flat roofs, are analyzed. In the modified model we use different snow clearing rate coefficients for thin and thick snow covers to model the natural snow clearing process. The snow depth dependent coefficients yield lower error in the total modeled snow loss and capture climatic variations between locations more accurately compared to the standard constant coefficient. For most of the systems the total absolute snow loss is modeled with an error of less than 11 %, on average 23 percentage points lower than with the default implementation of the Marion model. Some of the systems have larger modeling errors, which can be related to effects not taken into account in the model, such as the effect of building heat leakage and shading on snow clearing.**

***Index Terms*—Photovoltaics (PV), PV performance, PV systems, Snow, Snow loss modeling, Soiling**

I. INTRODUCTION

As cost reductions have made photovoltaics (PV) a favorable choice for electricity generation also in colder climates, deployment rates in regions with snowfalls are rapidly increasing [1], [2]. Snow coverage on PV modules will lead to significant power loss. For certain locations snow can result in zero electricity production in the winter season and more than 30 % annual loss [3]. Consequently, it is an important parameter to consider in PV system models. In PV simulation software, snow loss is typically either not considered [4] or estimated by monthly constant soiling values [5], [6]. Snow loss is, however, expected to vary between different locations and system configurations, and to achieve accurate loss estimates a snow loss model considering the influential parameters is needed. It has been shown that both the uncertainty in energy yield assessments [7]–[9] and forecasting [10] can be reduced if snow loss models are included. Robust snow loss models could also be used in monitoring to estimate the probability of snow cover to separate snow loss from other loss mechanisms, and to build realistic synthetic datasets for use in e.g. system design optimization or testing of fault detection algorithms. Because the parameters influencing the snow cover and resulting PV system loss are manifold, accurate snow loss modeling is challenging. The parameters that affect the snow loss include weather/climate conditions, system mounting and configuration [2], module technology [11] and type of snow [3]. Multiple snow loss models for PV have been suggested [3], but extensive validation is typically lacking [8].

Many of the suggested PV snow loss models are based on empirical approaches, ranging from simple linear correlations [3] to machine learning [12], [13]. In our previous work [14], we show that the snow loss model suggested by Marion et al. [7], performs better than simpler empirical models where a model is built by directly relating snow power loss to system and weather data. In the Marion model snow cover and loss are estimated by using empirical correlations to predict 1) when natural snow clearing of the PV modules occur and 2) how fast the snow is cleared off the modules. Ryberg et al. [8] and van Noord et al. [15] achieve good estimates of the annual loss in PV data using the Marion snow loss model, and the model is implemented in the System Advisor Model (SAM) [8] and pvlib python [16]. The snow clearing rate used in the model is expected to vary between different system configurations. In our initial evaluation of the model, we estimate the snow clearing rate for a system where modules are installed with a low tilt and no additional elevation on a flat roof [14]. We also show that for thin snow covers, the natural snow clearing rate is faster compared to thicker covers. By including this effect in the Marion model, the error in the modeled snow loss is

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Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org reduced. With a machine learning model specifically trained for each PV system in their dataset, the authors of [13] achieve lower modeling errors than both the original and the modified Marion snow loss model. The models in [13] are, however, system specific, and will require historical data from the system you want to model.

For models with empirical coefficients estimated from one dataset, it is important to validate the model with the same coefficients for other systems with similar system configurations to assure model transferability. In this paper, we validate the results presented in [14] and evaluate the modified adaption of the Marion model where a snow depth dependent clearing rate coefficient is used on an extended dataset. PV installations in different regions of Norway, with different climatic conditions are evaluated. We assess two different system types: residential systems on tilted roofs and large-scale systems installed with low tilts on flat roofs. Parts of the methodology and results have previously been presented in an IEEE PVSC proceedings paper [17]. In this enhanced version, the dataset, analysis and literature review are extended, and the methodology for estimating loss from PV data is updated to strengthen the conclusions. A broad validation of snow loss modeling on multiple similar systems is necessary to demonstrate the generality of the model. This is, however, preliminary work, and further validation is needed to broaden the model's applicability and accuracy.

In Section II, a review of the literature relevant to describe snow cover on PV systems is presented. Section III describes A. the analyzed data, B. how snow loss is estimated from the PV data, and C. the snow loss modeling. In Section IV.A. the effect of snow on the production data is described, and the snow loss model performance is presented in Section IV.B. and discussed in Section IV.C-E. Section V concludes the article.

II. Snow Cover On PV Modules

To estimate the effect of snow on PV energy generation, we consider 1) what conditions results in snow cover on PV modules, and 2) how large loss do the snow covers induce in a PV system. Because snow covers can be partial or translucent, a snow cover does not necessarily lead to 100 % loss [14]. The coverage and transmittance can be non-uniform at both module and array level, and to estimate snow loss under partial or translucent snow cover, in-depth information about the snow cover and the array and module configuration is required. In this work, our main focus will be on estimating the presence of a snow cover on PV modules as this is a necessary first step in snow loss modeling. The presence of a snow cover is related to accumulation of snow, and when and how fast snow is cleared.

During snowfall, snow accumulation on a tilted surface has been shown to increase with decreasing tilt [18]. The properties of the snow are also influential, and for a tilted surface the accumulation of snow is higher for wet snow than for dry snow [18]. Compared to dry snow, wet snow is expected to have stronger adhesion [19] and cohesion [18], [20]. Very high liquid water content can, on the other hand, reduce the snow adhesion again, as seen for cable surfaces [21]. Frost on the module surface during snowfall is expected to give increased accumulation [22]. If snow is falling during windy conditions, or the wind conditions and snow properties enable horizontal redistribution of snow [20], [23], this can give uneven snow accumulation. Whether this impacts the snow cover on the PV modules, will depend on wind patterns, amount of snow, and the physical layout of the system and surrounding objects. Snow moved horizontally by wind will settle in areas with lower wind speeds [23]. This can give increased snow accumulation on the leeward side of a roof [24], obstructions, or elevated PV modules [25]–[27]. The snow cover on PV systems is normally described as a snow layer on the module surface, but for some occasions PV systems can be fully or partly submerged in snow, either because of large amounts of snow [17] or because of snowdrift development [27].

Snow cover on PV modules is mainly reduced or cleared by sliding or melting [3], [28], but also sublimation [24] or wind erosion [20], [23] can have an impact. Whether or not the snow slides, will depend on the tilt of the module, friction and adhesion between the snow cover and the PV module, and if there are elements obstructing snow sliding. Friction and adhesion will vary with snow properties and detailed quantification is therefore difficult. Snow properties are expected to continuously change, as they depend on morphology of snow crystals, liquid water content, snow temperatures, mechanical motion of snow, freezing/thawing cycles, weather exposure, etc. [19], [29]. Particularly fast changes are expected around 0 °C [29] and during rain or sleet. High friction/adhesion are expected for conditions with freezing between the snow cover and the module surface [28]–[30]. Water between the snow and module surface is expected to act as a lubricant and significantly reduce friction [22]. Snow melting can thus also influence snow clearing through increased sliding. Elements observed to obstruct snow sliding include the module frame [11], [31], and the ground or roof below the modules if there are no available space for the snow to slide [9], [25], [32], which again is related to the amount of snow. For tilted roof systems, interference can be caused by high roof friction [29] or snow guards [19]. Because the sliding is impacted by many parameters, it can develop in different ways. Snow can slide down the module, leaving the upper part of the module snow free [28], but it is also observed that the snow on the lower part of the module is shed first [31], [33].

The most important factors influencing snow melting are ambient temperature, irradiance, and the temperature of the system. The temperature of the system is influenced by system design, as some system aspects can impact the heat transfer/absorption of the system. Bifacial modules in ground mounted systems [34] and building heat leakage for roof mounted systems [20] are for example expected to give increased heat absorption and reduced snow load. With translucent or partial snow covers, increased heat absorption in the PV modules is also expected to give increased snow melting on and around the modules [25], [26], [35]. Depending on the snow shading pattern and activation of bypass diodes, this could either be uniform heat in the unshaded area (with ~20 %

reduction if the radiative energy is converted to current) [14], or hotspots in the shaded area.

Both the accumulation and the clearance of snow is thus related to both PV system configurations, weather conditions and snow properties. Snow properties are again related to the development of the weather with time. Modelling snow loss is consequently a complex task, which can explain why the suggested empirical snow loss models in the literature have large variations in input parameters [3]. To make a transferable and general model based on a direct empirical correlation, data from many different weather conditions and system configurations is needed. Even with such data available, it may be challenging to extract a general model, because of e.g. non-linear correlations and the impact of the evolution of parameters with time. For building a general model, we therefore find the approach used in the Marion model [7] promising, as it aims to estimate the presence of the snow cover by predicting 1) snow accumulation, 2) when the snow is melting, and 3) how fast the snow is cleared during melting. With increased knowledge about how different parameters influence these three processes, and which parameters has the greatest impact, the model can be improved.

III. Methods

A. PV Data

Eight PV installations located in Norway with crystalline silicon modules and a total installed capacity of 1.6 MW_p are evaluated. Five of the systems are residential installations on tilted roofs with modules installed in portrait orientation. Three systems are commercial large-scale systems on flat roofed buildings where the modules are installed in landscape orientation with 10° tilt, array height of one module, and east/west orientation. 10° tilt and east/west orientation are not optimal for total annual production in Norway but is commonly used on flat roofed buildings to increase the packing density and reduce the seasonality of the production profile. The tilted roof systems (dubbed R1-R5) have all modules connected in one string and installed in two or three rows on the roof. The flat roof systems (dubbed C1-C3) have multiple arrays of around 20 modules in series and three series in parallel. All systems have variations in exact azimuth, the tilted roof systems have variations in tilt, and the flat roof systems have variation in packing density. C1 has two subsystems, C1a and C1b, which are installed on two different roofs. R1-R3 have no obstructions on the roofs, but R4 and R5 have a dormer window next to the PV arrays. R4 has two subsystems, R4a and R4b, installed on each side of the dormer. Except for this, the design of the systems within the two categories are assumed to be similar.

Geographical position, module tilt, climate zone, and length of analysis period for each system is given in Table I. The analyzed installations are situated in three different Köppen-Geiger (KG) [36] climate zones: Humid continental climate (Dfb), subarctic climate (Dfc) and oceanic climate (Cfb). Average monthly snowfall and temperature during the analyzed time period is given in Fig. 1. Estimations of daily snow fall and snow depth on the ground are taken from snow maps based on the seNorge snow model [37], [38]. Hourly temperature and global horizontal irradiation (GHI) pyranometer data are collected from nearby weather stations from the network of the Norwegian Meteorological Institute [39]. For the flat roof systems, the effective in plane irradiance and cell temperature are measured by reference cells mounted on the upper frame of a PV module. None of the irradiance sensors are regularly cleaned, and the pyranometers are not heated. The tilted roof systems have no on-site sensors. The production data (current, voltage and power) are collected from the inverters. The inverters have a nominal power of 3 kW at the residential systems, and between 20 and 36 kW at the commercial systems. At the time of the analysis, the inverters are between 7 and 3 years old, and the output is stable, with only a few cases of downtime. Clipping or curtailment are not occurring in the winter season. Periods with inverter downtime or lacking sensor data are removed from the analysis, and nighttime irradiance values are set to zero.

This dataset is chosen because the system types are representative for most roof mounted systems, and because the systems of the same type are built with similar design. Because of the similar design, it should be expected that the snow loss is modeled the same way. Additionally, the data are from multiple years and different climate zones are represented. The lack of on-site sensors for the residential installations will reduce the accuracy of the validation, but as systems with this design is very common, it is included for proof of concept.

TABLE I
ANALYZED PV SYSTEMS

System	Position (°)	Tilt (°)	Climate zone	Analysis period
		Commercial, flat roof systems		
C1a	59.6, 10.7	10	Dfb	2015-01 – 2021-06
C1b	59.6, 10.7	10	Dfb	2017-01 – 2021-06
C2	60.9, 10.9	10	Dfb	2018-01 – 2021-06
C3	60.4, 5.5	10	Cfb	2018-01 – 2021-06
		Residential, tilted roof systems		
R1	60.8, 11.1	26	Dfb	2019-01 – 2021-06
R2	61.3, 10.2	24	Dfc	2018-01 – 2021-06
R3	60.9, 11.0	40	Dfb	2019-01 – 2021-06
R4a/b	61.1, 10.5	35	Dfb	2018-01 – 2020-12
R5	60.8, 10.6	38	Dfc	2019-01 – 2021-06

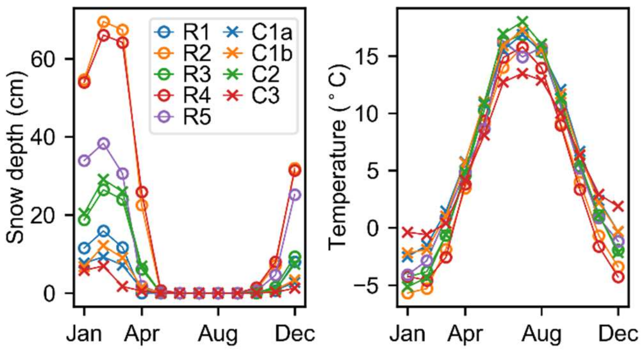

Fig. 1. Average monthly snowfall and temperature in the analysis period of the different systems.

B. Estimation of Snow Loss from PV Data

Estimation of snow loss from PV monitoring data requires an accurate model of the system to estimate the lost production from the difference between actual and expected output. The model needs to estimate all losses in the system not related to snow, including both constant system loss and seasonal loss caused by e.g. low irradiance and high angles of incidence, typical for high latitude locations in the wintertime [40]. It is also necessary to separate snow loss from system faults. This is achieved by evaluating the periods with substantial loss in the winter season, and it is ensured that the loss is related to snowfall and that the loss signatures are similar to expected snow signatures [14].

For estimations of snow loss from monitoring data, the procedure we describe in [41] is used. To model the system output, the expected module DC output is first modeled in pvlib python [16]. For the flat roof systems, the measured effective irradiance and cell temperature is used together with module datasheet values as input to a single diode model. For the tilted roof systems GHI and ambient temperature measurements are used to model effective irradiance and module temperature, and from this the module DC output is modeled. The pvlib models used are described in [17], [41]. The constant and seasonal losses in the systems are estimated from the daily losses in the historical production data for periods without snow. The ratio between the production data and the output from the PV module model is calculated and seasonal and trend decomposition using loess (STL) [42] is used to find the seasonal loss component. The periodicity is set to 365 and lowess [43] is used for seasonal smoothing. The implementation in version 0.11.0 of the statsmodels package in Python is used [44]. STL is designed to handle missing values in time series decomposition, which is essential in this case, as there are frequent and long periods of missing data in the winter season caused by the filtering of snow periods. Despite the missing data, the estimation of the seasonal trend seems to be sufficient, giving a correction that reduces the impact of systematic seasonal losses, and improves the PV modeling accuracy through the year. When the seasonal loss is corrected for, the constant loss is found. The constant and the seasonal loss are added to the modeled module DC output to estimate the system energy output, and the difference between this value and the production data in periods with snow are assumed to be snow loss.

The uncertainties in the estimation of the energy lost because of snow are thus governed by the uncertainty in the PV system model. The mean absolute error (MAE) in modeled energy generation for months without snow, varies from 2 to 5 kWh/kWp for the tilted roof systems, and is below 2 kWh/kWp for the flat roof systems. No systematic trend in the error of modeled monthly energy for the snow free months is observed. An additional effect increasing the uncertainty in snow loss estimation, is the possibility of snow on the irradiance sensor, leading to underestimation of the expected system output. To reduce this effect, the reference cell irradiance data was compared to and corrected by irradiance measurements from nearby pyranometers. Pyranometers are assumed to have lower risk for snow cover than reference cells, because of their hemispherical shape. To evaluate the risk of snow shading on the pyranometer, comparisons were made between the pyranometer measurements and satellite-based irradiance data. Pyranometer snow cover was not found to be prevalent in the dataset.

C. Modeling Snow Loss with the Modified Marion Model

In the Marion snow loss model [7] it is assumed that the modules will be fully covered after a snowfall. A snowfall giving accumulation of snow is in this work defined as a daily snowfall of above 1 cm. 1 cm is the default snowfall threshold used in SAM and pvlib to improve the robustness in the prediction of snow accumulation and is observed to fit well with the data analyzed in this work. Further it is assumed that when the snow starts to melt, it is cleared by sliding/melting off the modules. Snow melting is expected to happen during the following conditions:

$$T_{amb} > G_{POA}/m, \tag{1}$$

where T_{amb} is the ambient temperature, G_{POA} is the in plane irradiance and m is an empirically defined value of -80 W/(m^2 °C). How much the snow will slide (or melt) during the time period where the conditions described with Eq. 1. is true, measured in fractions of the total row height, is determined by the tilt of the modules and an empirical snow clearing coefficient (*sc*):

$$Snow\ slide\ amount = sc * \sin{(tilt)}. \tag{2}$$

For roof mounted systems Marion et al. found *sc* to be 0.20 [7], which is set to be the default *sc* in the implementation of the model in pvlib python [16] and the PV modeling software SAM [8]. This coefficient is, however, expected to depend on different system and module designs, because technical aspects can either promote or obstruct natural snow clearing and consequently impact the snow clearing rate. To our knowledge, *sc* values for other system designs than the ones initially evaluated by Marion et al. are not estimated. As previously mentioned, we have found that with a snow depth dependent snow clearing coefficient, differentiating between thin and thick snow covers, the modeling error can be reduced [14]. For the C1a system we found that a *sc* of 0.06 for estimated snow

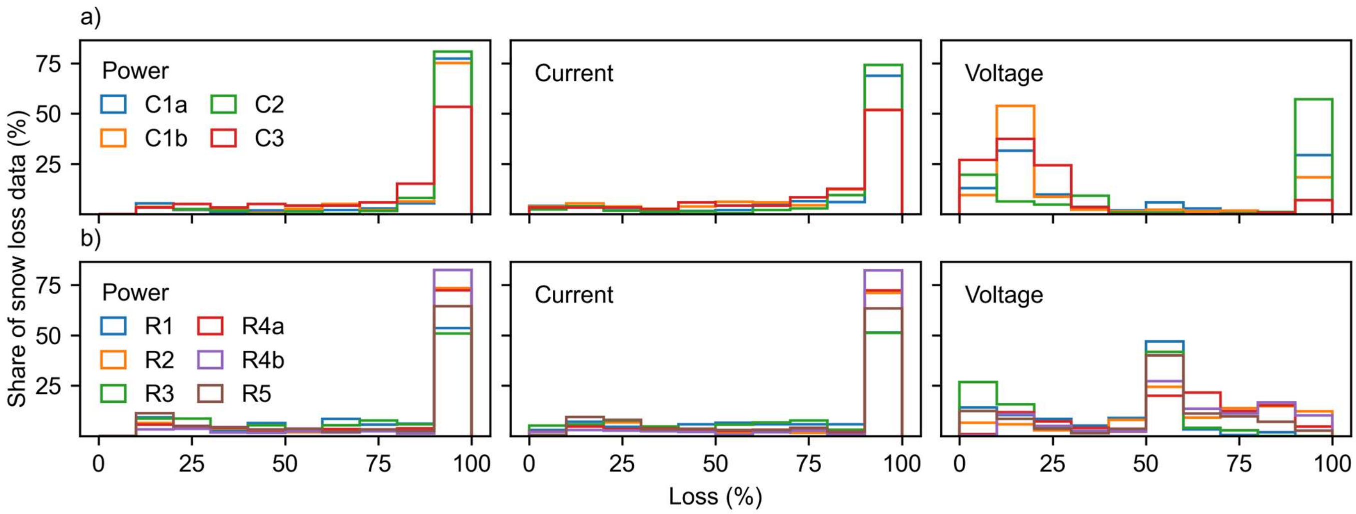

Fig. 2. Distribution of the size of the daily loss (power loss > 10 %) in power, voltage and current for time periods with snow for, a) the flat roof systems, b) the tilted roof systems.

depths larger than 3 cm, and 0.40 for snow depths less than 3 cm minimized modeling errors [14]. One possible explanation for this difference is high roof interference. With modules installed with no extra elevation above the roof, giving just a few centimeters between the roof and the lower module frame, the interference from the roof reduces the possibility for snow sliding during thick snow covers, slowing down the snow clearing. Snow depths above approximately 10 cm, would significantly reduce the possibility for full snow shedding. For C1 and C3, around 40 % of the days with snow have estimated snow depths on the ground above 10 cm. For C2, this number is 70 %. The coefficients found for C1a are compared to constant *sc* values for all the flat roof systems in this study, as they have the same system design and are expected to have the same snow loss under equal conditions. Additionally, when the estimated snow depth is surpassing the height of the upper frame of the modules, $sc = 0$. It is generally assumed that the snow load on roofs are lower than on the ground because of stronger winds giving less accumulation and higher erosion, in addition to heat leakage from the building [20], [26]. The snow depth on the ground is thus not expected to be an accurate measure of the thickness of the snow cover on the modules on the flat roof systems, but it is still used as an indicator of the thickness of the module snow cover.

Modeled snow loss using varying constant *sc* and a snow depth dependent *sc* is also evaluated for the tilted roof systems. Here, because of the higher tilt giving more sliding, snow depth on the ground was not found to be representative for the snow on the modules. Accumulated snowfall since last time the modules were snow free is instead used as an indicator of thin or thick snow cover. Based on evaluation of the snow loss modeling with varying constant *sc* values, the optimal values for thin and thick snow covers were found to be 0.3 and 0.05, respectively. This is quite similar to the identified values for the flat roof systems. Considering that the roof interference of the two system types is expected to be different, this was not anticipated. With no onsite sensors, the modeling is, however, less accurate for the residential systems, and optimization of the *sc* parameter is more uncertain.

From the assumption about full snow cover after snowfall and the calculated *snow slide amount* (Eq. 2.), the snow coverage on the modules is estimated. The snow loss is subsequently estimated from the calculated snow coverage by estimating how many of the module substrings that are covered by snow. If a module substring is partially covered by snow, the power output is assumed to be zero. The pvlib python implementation of the Marion model was used to model the relative snow loss. The implemented pvlib version (v0.8.0) does not set the snow coverage to zero when the snow depth on the ground is zero such as in the SAM implementation [8]. This assumption can be useful in certain applications to correct the modeled result and reduce the false positive snow cover estimations. In our work we aim to investigate how well the model predicts snow clearing, and this assumption is therefore not included. To estimate the absolute energy loss, the relative snow loss estimated from the modified Marion model was multiplied with the modeled energy output of the system.

The accuracy and time resolution of the temperature and snowfall data will have impact on the modeled result. Snow maps can be based on satellite data, weather models or local measurements [38], all impacted by uncertainties in different ways. If weather modeling is used, as in this case, misinterpretation of snow as rain (or vice versa) when the temperature is around zero gives rise to uncertainty in the estimation of snow cover. Relying on daily snowfall values makes it challenging to separate between situations where the snow falls before sunrise, during the day, or after sunset, yielding uncertainties relating to the onset of the production loss. Inaccurate temperature measurements can give false estimation of snow melting/no snow melting, giving high uncertainty in the estimation of melting when the temperature is close to zero.

IV. Results

A. The Effect of Snow in PV Data

Fig. 2. shows the distribution of the size of the daily loss in power, current and voltage for periods with assumed snow loss for all the systems. For both system types, the distribution is

similar for the loss in current and power. Most of the current and power loss events are in the range of 90-100 % loss. For the flat roof systems, the voltage loss is typically either 90-100 %, assumed to be related to full, opaque snow covers, or below 40 %. The low voltage losses could be related to array configuration: the parallel connection of the array limits the opportunity to bypass shaded modules because the voltage in all the strings in the array is the same. For the tilted roof systems all the modules are series connected, and we observe large variation in voltage loss. This indicates that modules are bypassed, but with no clear pattern in how many modules in the string that are bypassed. The modules are installed in two or three rows, and when the snow slides or melts, the shading can be different in different rows. High loss in current and lower loss in voltage indicates that the modules are producing under a semitransparent snow cover [14]. It is observed that for situations where the loss is not 100 %, there can be large variation in the loss of similar arrays in the flat roof systems, indicating nonuniformity of the snow cover.

Gradual loss recovery has been suggested as an identifier for snow loss [45]. Gradual recovery of power loss is often observed, but there are large variations in the rate of this recovery. Both longer periods with 100 % loss, gradual snow loss recovery over multiple days, and recovery the same day as the snowfall are observed in the data, depending on climatic conditions. The recovery of the voltage loss is not necessarily gradual. It is for example observed that voltage loss can vary from high to low and back to high again for the same snow cover, apparently related to the irradiance level: For high irradiance the transmitted light will be high enough for voltage generation, but that is not the case for low levels.

The snow signatures observed for the analyzed dataset fits with the snow signatures described in [14], and support the conclusion that system configuration, and the transmittance and nonuniformity of a snow cover impacts the total loss.

B. Snow Loss Modeling Performance

In Fig. 3. the mean absolute error (MAE) of modeled absolute annual snow loss for all the systems is compared for different constant *sc* values and the snow depth (*sd*) dependent *sc.* The MAE shows the difference between modeled loss and loss estimated from the data. As the absolute values of both the modeled and estimated loss is based on the PV system model, the error in the model is mainly related to the prediction of snow coverage. For the constant *sc*-values, there are variations in the *sc*-value giving minimum MAE. Most systems have their minimum at 0.05, R2 and C1b has minimum MAE at 0.10, and only C3 has minimum at 0.2, the value estimated in the original development of the Marion model and the default value in the implementations of the model. For C2, where the snow depth regularly is higher than the height of the system, the MAE is large for all the constant coefficients. The snow depth dependent *sc* does not give minimum MAE for each individual system, but it appears to be the best choice if one *sc* value was chosen to model all the systems of the same type. The benefit of using a snow depth dependent *sc* is, however, clearer for the flat roof systems than the tilted roof systems in this dataset. This, and how the MAE varies with the *sc* values for different systems, can be explained by certain variations in *system parameters* and *snow conditions*, further discussed in Section IV.C and IV.D.

Fig. 4. shows loss estimated from PV data for the two C1 subsystems together with modeled snow cover for one winter. We find that the modeled snow cover fits quite well with the losses estimated from the production data, as snow cover and loss are expected to be related, but not direct proportional [33]. Fig. 5. shows yearly, monthly and daily estimated snow loss for all the systems compared to modeled snow loss, using the snow depth dependent *sc*. For yearly and monthly loss, we find a linear relationship between modeled and estimated loss, with a few examples of large deviations. For daily loss we more often find that days with modeled snow loss correspond to days with no loss in the data, and opposite, giving a poorer linear relationship. The error in modeled total absolute loss is given in the legend, varying from 3 % to 46 %. The error is in average reduced with 23 percentage points compared to the default implementation of the Marion model.

C. Impact of System Parameters on Modeling Results

The flat roof systems could be expected to have similar snow loss under the same snow conditions, because they have the same module tilt, array configuration, and are all installed with no additional elevation above the roof. From Fig. 4. it is, however, observed that C1b often has lower loss than C1a, despite the fact that they are co-located. C1b also has higher error in the *sd* dependent *sc* (Fig. 3.) and total modeled loss (Fig. 5.). Based on information from the building owner on indoor temperatures and roof isolation for the two buildings, we believe that this is caused by differences in heat leakage through the roof giving faster snow melting for C1b. Heat leakage from buildings is commonly used in roof snow load estimations [20]. This suggests that also the melting threshold and the *m* value in the model can be impacted by system design.

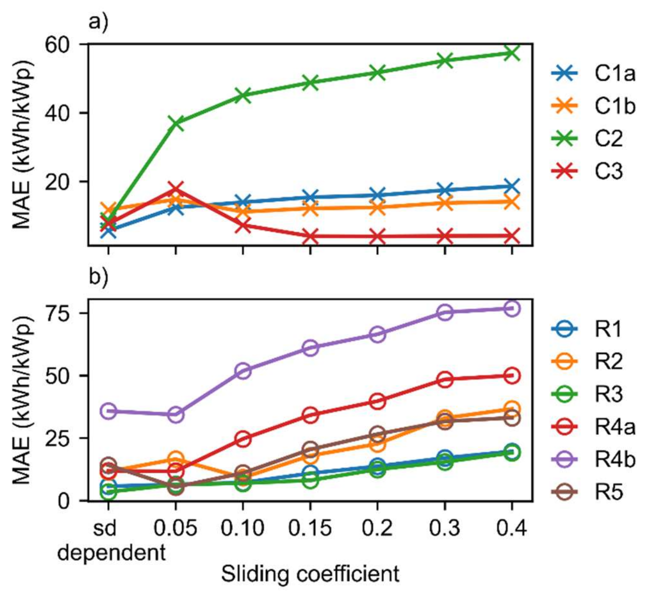

Fig. 3. Comparison of MAE values for modeled absolute annual snow loss using different snow clearing coefficients for the a) flat roof systems and b) the tilted roof systems.

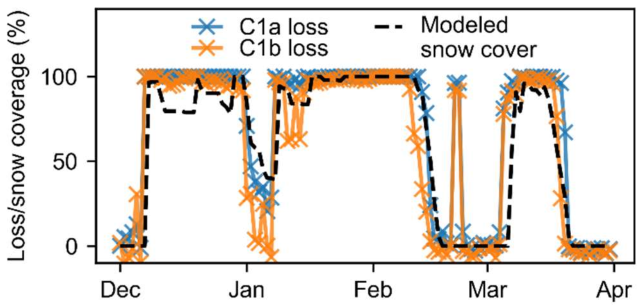

Fig. 4. Estimated daily loss from production data for C1a and C1b and modeled snow cover for one winter.

roof tiles below the modules typically have higher friction than the module surface [29]. Possible explanations can be that the roof interference is equally high for both types of systems, or that it takes equally long time to fully melt the interface layer between the snow and the module surface when we have thick snow covers.

D. Impact of Snow Conditions on Modeling Results

From Fig. 1. it can be seen that C2 is experiencing lower temperatures and larger amounts of snow than the other flat roof systems. Situations where the system is fully submerged in snow can occur, and sliding is not possible. Snow clearing by melting, sublimation and erosion is slow compared to sliding and gives high MAE for all the constant coefficients (Fig. 3.).

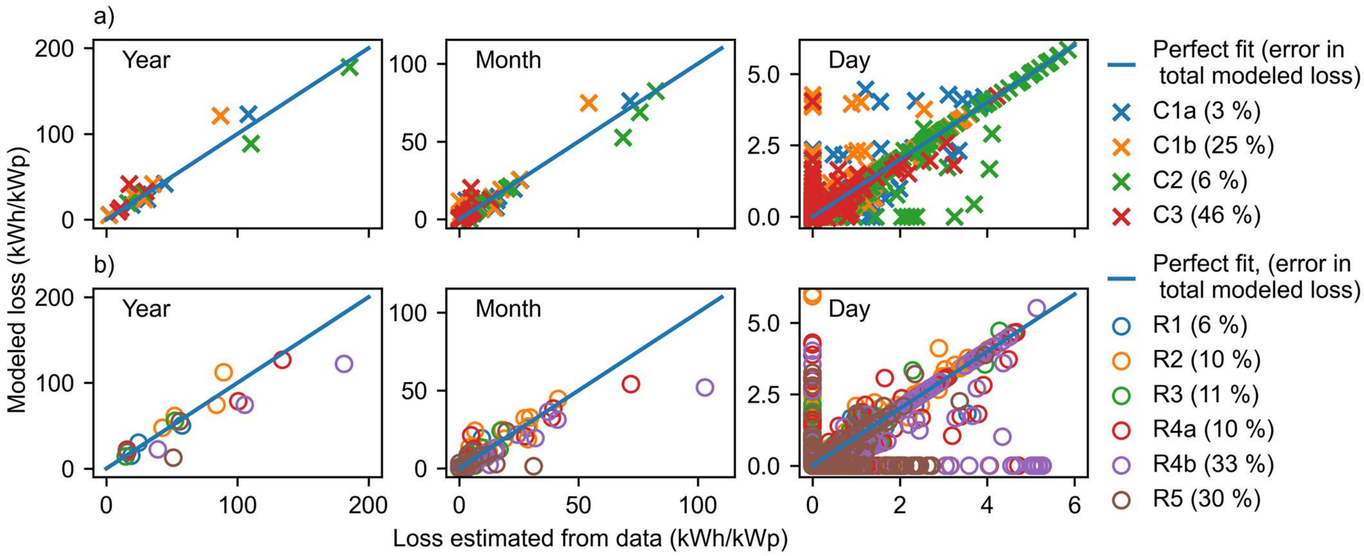

Fig. 5. Yearly, monthly and daily modeled loss versus loss estimated from production data for a) the flat roof systems and b) tilted roof systems. The loss is modeled with snow depth dependent snow clearing coefficients. Errors in modeled total absolute loss are given in the legends.

R4a and R4b are also co-located and have the same system design. Both the measured loss (as seen in Fig. 5.) and error in the modeled snow loss (Fig. 3.) are, however, larger for R4b. The systems are installed on each side of a dormer, which will shade parts of the R4b system. It is reasonable to believe that this will give slower snow melting for R4b, as the actual irradiance on the system will be lower than the estimated irradiance. Shading from a dormer is also expected to give slower snow clearance for R5, but to a lesser degree as the house is more south-oriented than R4. This can explain why the snow depth dependent *sc* gives higher MAE for R5 than a *sc* of 0.05. An additional effect for these systems, is that we can get increased snow accumulation on the modules close to the dormer if snow is falling during windy conditions or strong winds give redistribution of snow.

We also see that both the flat roof and the tilted roof systems can be modeled with a low *sc* of around 0.05 for thick snow covers. For the flat roof systems, we expect low *sc* because the snow has nowhere to slide away, i.e. high roof interference. Roof interference could also occur for the tilted roof systems as the PV modules are not installed at the edge of the roof, and the

With the assumption that no snow clearing will occur for the flat roof systems when the snow depth is larger than the system height, the *sd* dependent *sc* gives much lower MAE than the constant coefficients.

C3 is located in an oceanic climate. This gives higher temperatures and less snow compared to the other systems (Fig. 1.). For this system, a high snow clearing coefficient gives lower MAE than the lower coefficients (Fig. 3.). The *sd* dependent *sc* gives higher MAE than constant *sc* values larger than 0.05, indicating that the snow depth is not always enough to separate between situations with fast or slow snow clearing. Additionally, because of the higher temperature, we can expect increased uncertainty in the classification of the precipitation as snow. From Fig. 5. we see that the absolute errors in monthly and annual modeled loss are small, but because the total loss also is small, the relative modeling errors in total absolute loss are large in this case.

For the tilted roof systems without dormer (R1-R3) there are small differences between the MAE in modeled annual loss when a constant *sc* of 0.05 and a varying *sc* is used in the modeling. We do, however, observe from the data that the reduction in snow loss is best modeled with a high *sc* during thin snow covers. But as all the systems experience cold weather with large amounts of snow (Fig. 1.), this do not occur very often, and do not contribute much to the total energy loss.

E. Snow Loss Model Evaluation

The fact that allegedly identical arrays in the same system can have differences in snow loss (Section IV.A.), underlines that accumulation and clearing of snow is a complex process. Ambient temperature, irradiance, module tilt, empirical snow clearing coefficients, and the assumption that partially shaded module substrings will not generate energy, will consequently not give sufficiently detailed information to model snow cover and resulting loss accurately on high time resolution. The model does, however, appear to be useful for estimating the probability of snow cover and high loss in the system, and by accumulating over multiple days, the errors will be reduced, yielding satisfactory modeling results on monthly and annual data.

To transfer the model to new systems we should consider: 1) how close the snow accumulation and clearing process follow the assumptions in the Marion model, and 2) what the *sc* and *m* values of the new systems are. For the tilted roof systems without a dormer, the snow accumulation and snow clearing are expected to follow the assumptions in the Marion model closely: snow accumulate during snowfall, and the snow slides off the modules when it melts. For systems that are fully or partially submerged in snow because of snowdrift or large amounts of snow, the assumptions of the model may not be valid. The systems in this study within the same type, were assumed to have similar design. Because of variations in heat leakage and shading, it was, however, found that not all the systems were similar in the parameters that influence snow clearing. Parameters that can influence the *sc* value and melting threshold must be identified, and before transferring the empirical values from one system to another, it should be considered if they have the same technical design in the parameters that influence snow clearing.

V. Conclusion

In this paper we describe the effect of snow on a set of roof mounted PV systems by analyzing signatures in the monitoring data, and we evaluate a modified adaption of the Marion snow loss model. Low voltage loss, high current loss, and large variations between similar arrays during partial covers, support previous results suggesting that non-uniformity and transmittance of snow cover is important for explaining snow loss. Predicting the resulting loss from a specific snow cover is consequently a challenging task. From the literature, we find that the process of accumulation and clearing of snow on PV modules is complex, impacted by many different parameters. Still, in this work we show that it is possible to model total absolute snow loss with an error of less than 11 % for most of the systems in our dataset, using a model based on a limited set of parameters with high impact on PV system snow cover and a set of empirical snow clearing coefficients. The systems with larger modeling errors are found to either have small absolute loss or deviations compared to other systems in parameters that impact snow clearing, such as shading and heat leakage from building. Compared to the default implementation of the Marion model, the error in total absolute loss is reduced with 23 percentage points on average.

Multiple aspects should be further investigated to broaden the model's applicability and accuracy. To increase the generality in the model, effects that can give variations in the snow clearing rate and melting threshold should be identified. To use empirical values estimated on one system in the snow loss modeling of other systems, we need to ensure that the systems are similar in parameters impacting accumulation and clearing of snow. Ground mounted systems will e.g. not necessarily have the same parameters influencing snow accumulation and clearing as roof mounted systems, and further validation of the model for these types of systems is required. We also find that the model can be further enhanced by finding improved methods for considering the effect of different snow conditions. The next steps planned, are both further validation of the suggested model on ground mounted systems and thorough investigation of parameters influencing the presence of snow cover.

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