

Simple Approach to Estimating PV System Snow Losses Applied to Long-term PV Generation Datasets for Different Tilt Angles and Mounting Styles

Erik Janssen, David Nixon, Svend De Bruyn, Gil Amdurski and Leigh St. Hilaire
Sustainable Technologies Evaluation Program (STEP) of Toronto and
Region Conservation Authority (TRCA), Vaughan, ON, L4K 5R6, Canada

ABSTRACT

In a cold climate, it's important to evaluate the snow coverage of photovoltaic (PV) arrays. General snow loss models and values are available in the literature, but the actual snow losses are specific to local climate conditions. Thus, most generic models have not been validated for specific locations. This study presents measured power yield and estimated snow loss data spanning from 2011 to 2017 from PV arrays located in Ontario, Canada, mounted at several different tilt angles, also considering pole and roof-mounting styles. The data is itself useful for snow loss model validation, and the approach used to estimate snow losses is simple and easily applied to other installations. It only requires daily energy generation data that is commonly available to system owners, which is then used in conjunction with free software tools and environmental datasets available online. This proposed approach allows systems owners to estimate snow losses more directly based on their own system energy generation data. Empirical data on snow losses is useful to system owners for a variety of reasons. For example, it can quantify the lost revenue, inform decision-making around snow removal, help explain shortfalls and variations in energy yield, and provide useful information for buildings seeking net-zero energy. Also, the approach can be used to more accurately evaluate the techno-economic feasibility of a prospect PV project for a given snowy region, provided the model has been previously validated for such a region.

INTRODUCTION

Modelling tools for photovoltaic (PV) installations are capable of highly accurate results. However, in a cold climate, modules will sometimes be entire-

ly covered by snow and this is difficult to predict within a model. A recent report from the National Renewable Energy Laboratory (NREL) [1] summarized that there have been a range of different snow loss values reported in the literature and various efforts to generate snow loss models (as an example, see [2]). A significant issue is that models have not been widely validated and losses vary with local climates. In general, the modeling community is still in need of a widely validated solution. The researchers from [1] propose the model from [3], now integrated into NREL's System Advisor Model (SAM) modeling tool. They showed that the model generated better agreement with actual generation data for two installations. However, they note that the model is best at estimating annual losses and worse agreement is seen at shorter timescales, suggesting that there is still significant room for improvement.

In the literature, the different approaches to estimating PV system snow losses might be placed in two categories. The first category, used in [1], is to show that the application of a snow loss model generates better agreement with actual PV system energy generation. The actual losses due to snow could then be determined by modeling the system both with and without the snow loss component of the model. However, for a model to achieve good agreement at all, regardless of snow, all model parameters need to be accurately defined. This could be done through an iterative calibration process where certain model parameters are adjusted until good agreement is achieved. This may be an onerous process that is not feasible for many system owners that could benefit from snow loss estimates.

The second category is to devise an experimental set-up that more directly determines the losses without explicitly needing a model to estimate them. This can involve thermostatically-heated modules (that would never be covered in snow) compared to non-heated modules [4-5], direct removal of snow from one module in a matched pair [6], or additional on-site irradiance measurements [7]. The drawback of the first category is that it is not necessarily as robust as more direct experimental measurements, and the calibration of the model can be potentially onerous. The drawback of the second category is that the set-up used to experimentally determine losses can itself be onerous—requiring measurements or other equipment not typically available in general installations.

This article provides long-term snow loss data from a set of installation in Toronto, ON, Canada, and outlines a more straightforward approach to estimating snow losses that relies only the typically available data for most PV installations. As will be shown, the approach used in this study did incorporate PV system modeling but it was simple and only required a few input parameters. In fact, the only requirement on the PV system model was that it was

sufficient to catch outlier data, and then quantify the extent to which that data was an outlier. This meant that the model parameters could be much more loosely defined, and no significant model calibration process was required. It is therefore more accessible to a broader segment of PV system owners that can benefit from snow loss estimates for their installations.

STUDY SITE

In 2010, a number of PV arrays were installed at the Sustainable Technologies Evaluation Program (STEP) PV Test Lab located near Toronto, ON, Canada, to investigate snow losses. Different mounting styles were considered. Pairs of modules were ground-mounted on poles in portrait orientation at tilt angles of 0° , 10° , 20° , 30° , 40° , 70° and 90° (Figure 1). The module pair mounted at 40° was an exception—one module was mounted in portrait orientation and the other, in landscape. An array of eight modules was installed on a roof-section with a roof slope of 30° (Figure 2). Four were mounted in portrait orientation and four in landscape. An array of four modules mounted with ballast on a flat deck (Figure 3).

Pole-mounted modules were from Sanyo (HIP-190BA2) with a maximum power point of 190W. These modules were removed from a previous installation and were manufactured in 2003. As of 2019 there was notable delamination along the busbars of the PV cells—this would affect the specific yield but not the estimates of snow losses. Modules on the roof-section and on the flat deck were from Solgate (SG17524) with a max power point of 175 W. They were manufactured in 2010. As of 2019, no notable issues were apparent from visual inspections. The Inverters were M200 or M190 Series from Enphase. The azimuthal orientation of the modules was due South and there were no shading objects. Modules were not actively cleaned. Module-level daily energy data from 2011 to 2017 was obtained from the Enphase Enlighten monitoring portal. In this study, loss estimates hinged on a comparison of actual and modeled energy. SAM was used for modeling, and environmental data was obtained from NREL's National Solar Resource Database (NSRDB).

ANALYSIS

Modelled energy data was compared to actual energy data for each day of the study period from 2011 to 2017 and for each module. The modeling was used to identify days affected by snow coverage and estimate the energy that was lost. The approach used to estimate snow losses is summarized below.



Figure 1.

Several modules pairs were mounted on poles at different tilt angles



Figure 2. Eight modules were mounted on a roof-section.



Figure 3. Four modules were mounted with ballast on a flat deck.

- 1) *Compile daily actual energy generation data from the installation and download environmental data* for the site from the SRDB covering the same span of time as the actual data.
- 2) *Create a simple model of the system in SAM.* The model inputs are array tilt, azimuth, inverter and module models. Losses were set at 0%. Snow losses were not considered. An isotropic sky model was used.
- 3) *Calibrate the modeled energy data against the actual energy data.* A linear fit of uncalibrated modeled versus actual data was used to generate a calibration curve. The calibration curve transformed the uncalibrated data such that there will be a slope of 1 when the calibrated modeled generation data is plotted against the actual generation data. Only data that were not affected by snow were considered for the calibration curve. These data were identified as those days where the snow depth on the ground, and the snowfall, was zero. In Canada, snowfall and snow depth data is available from Environment Canada.
- 4) *Clean the actual energy generation data.* Actual energy data was sometimes missing. This data was flagged and replaced with calibrated model data. Where replacement was necessary, it was always done across all modules. Missing data is summarized in Table 1 both for the entire year and for days that would likely have been affected by snow losses. Missing data from 2016 and 2017 is significant. Between a quarter to a third of the data is missing when there was snow on the ground. These days could have had snow losses, but those losses could not be included in the calculation.
- 5) *Determine the baseline standard deviation (σ) of the modeling error in the absence of snow.* The modeling error is the calibrated modeled energy subtracted by the actual energy. Baseline data unaffected by snow was selected as in Step 3). Baseline data from one module pair is shown in Figure 4.
- 6) *Use σ to identify outlier data points.* See Figure 5 and 6. Any day where the modeled energy was $+3\sigma$ away from the calibration line was suspected of snow losses. About 0 kWh actual energy generation, $+2\sigma$ was used as the threshold. This was done based on the data visualization which suggested that the $+3\sigma$ filter was missing days affected by snow near 0 kWh actual energy generation.
- 7) *Total the modeling error* for all the points identified in Step 6. This is the estimated energy lost due to snow.

Table 1. Days with Missing Data

Year	Total Days Missing From Year	Total Days Missing When Snow Depth > 0 cm	Total Days with Snow Depth > 0 cm
2011	31	5	70
2012	0	0	30
2013	9	9	97
2014	0	0	95
2015	0	0	64
2016	32	22	68
2017	41	20	59

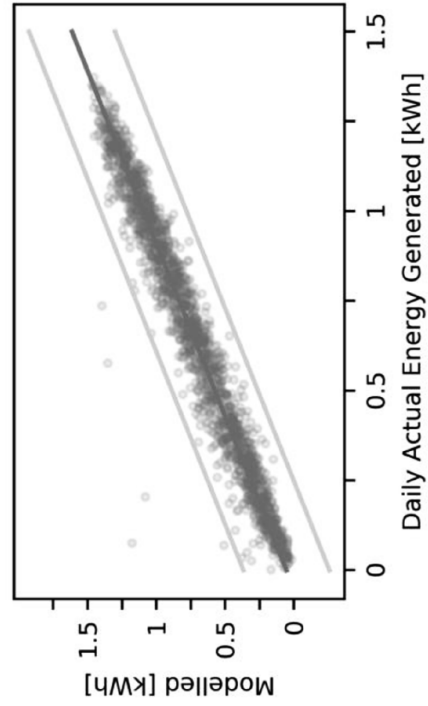


Figure 4. The baseline standard deviation of the modeling error is determined using data that is unaffected by snow—i.e. when there was no snow-fall or no snow on the ground. The data in this plot are for a 0° tilt. The light grey lines represent $\pm 3\sigma$.

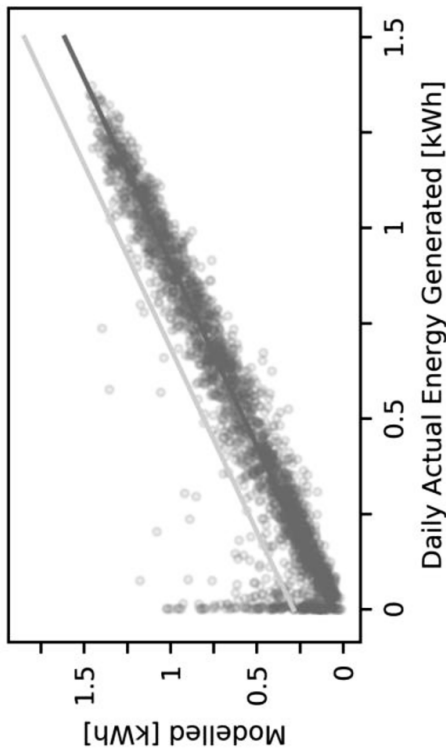


Figure 5. Days affected by snow have a modeled energy that is much greater than the actual energy. These days can be identified by the modeling error, which is greater than a threshold value determined from the baseline standard deviation (light grey line represents $+3\sigma$). The data in this plot is for a 0° tilt.

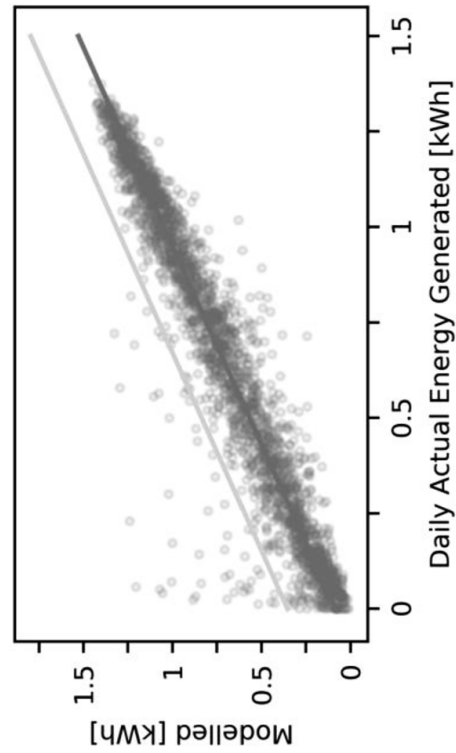


Figure 6. The data in this plot is for the 30° tilt. As expected, there are fewer outliers, and therefore lower snow losses, when compared to Figure 5. Note that the data points where the actual energy is notably greater than the modeled energy may be related to albedo, which was not considered in detail within the modeling.

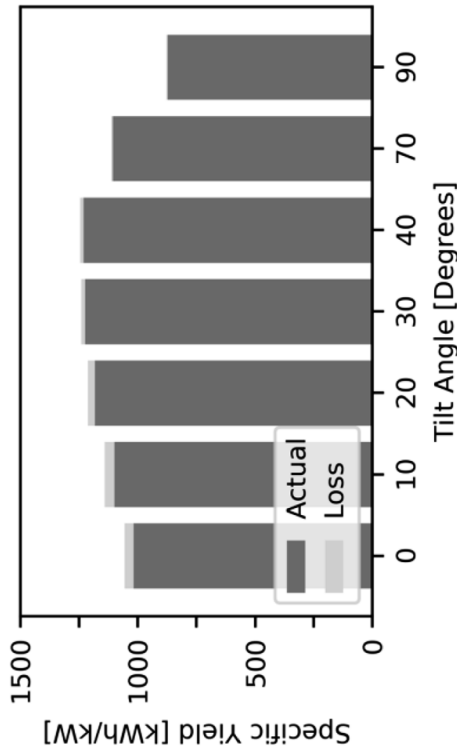


Figure 7. Mean annual yield and estimated losses from 2011 to 2017. Losses decrease with increases tilt.

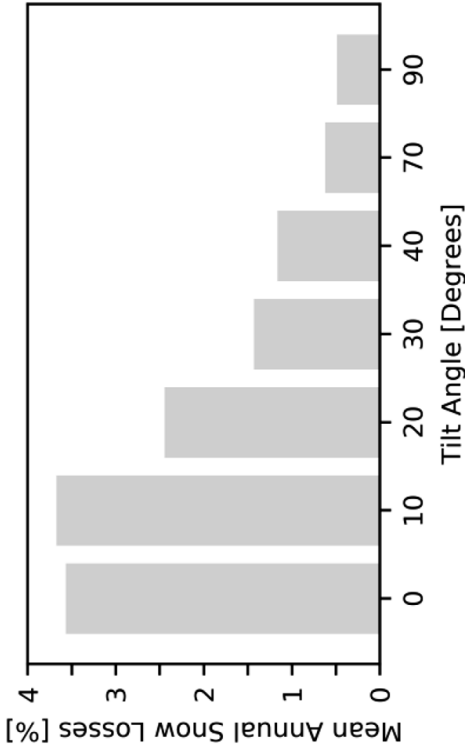


Figure 8. The mean annual estimated snow loss decreases with increasing tilt angle.

Table 2. Annual Summary of Measured Yield (kWh/kW) and Estimated Snow Losses (%) (Losses in Brackets)

Year	0°-Pole	10°-Pole	20°-Pole	30°-Pole	40°-Pole	70°-Pole	90°-Pole	Roof Port.	Roof Lan.	Ballasted
2011	992 (3)	1079 (4)	1143 (3)	1196 (2)	1190 (2)	1083 (2)	862 (1)	1164 (6)	1179 (6)	1175 (7)
2012	1095 (0)	1177 (0)	1225 (0)	1260 (0)	1246 (0)	1084 (0)	810 (0)	1305 (1)	1322 (1)	1321 (1)
2013	1030 (3)	1114 (3)	1185 (3)	1218 (3)	1229 (2)	1105 (1)	877 (0)	1191 (8)	1202 (8)	1267 (5)
2014	972 (6)	1043 (7)	1147 (4)	1198 (2)	1217 (1)	1117 (0)	903 (0)	1186 (8)	1196 (8)	1182 (10)
2015	1022 (9)	1117 (7)	1226 (4)	1284 (3)	1302 (2)	1184 (1)	951 (1)	1291 (9)	1295 (10)	1281 (10)
2016	1076 (2)	1137 (3)	1247 (1)	1278 (0)	1279 (0)	1135 (0)	887 (1)	1317 (3)	1359 (3)	1287 (4)
2017	931 (1)	1022 (2)	1103 (1)	1132 (1)	1146 (0)	1021 (0)	810 (0)	1179 (2)	1223 (2)	1163 (3)

There are two main benefits to this approach. Firstly, high accuracy is not required for the modeling component of the algorithm because it only needs to identify days affected by snow, and it is calibrated against actual data using a simple linear fit in Step 3). Secondly, there is confidence that the calculated energy lost is, in fact, largely due to snow and not some other modeling error since only those days with a very large error were considered. The main drawback is that there may be days with a small amount of energy loss due to snow that were not identified as outliers and not included in the loss calculation. Note that there were no shading objects at the STEP PV Test Lab. Installations with significant shading would need to take this into account within the modeling.

RESULTS

Pole-mounted modules

The mean specific yield (i.e. the ratio annual kWh energy yield over the kW rating of the array), and estimated losses, from each of the pole-mounted module pairs over the study period is shown in Figure 7 and Table 2. Losses are also presented in Figure 8. As expected, losses decrease with increasing tilt. Differences in the specific yield and snow losses between the 40° portrait and landscape modules were <1% and comparable to the other module pairs where both were mounted in portrait orientation.

The authors note that pole mounting of modules as has been done in this study is not a common configuration for ground-mounted installations. It was used in this case as an experimentally-expedient way of incorporating ground mounted modules at different tilt angles. A larger ground-mounted array on conventional racking with a tilt angle of 30° was adjacent to the other arrays. Power production data for this array was not available. However, image data suggests approximately comparable snow coverage between the pole-mounted and conventional rack-mounted modules (Figure 9).

The annual snow losses correlate approximately with the sum of daily snow depths for the year (Figure 10; snow data in Table 3 is from Environment Canada). This variable was identified in [1] and is defined in Equation 1, where D_{annual} is the annual sum of daily snow depths and D_i is the snow depth on any given day indexed by the subscript i . The variable incorporates snowfall amounts but also indirectly incorporates other important variables like temperature.

$$D_{annual} = \sum_{i=1}^{365} D_i \quad \text{Eq. 1}$$

Modules on Roof-Section and Flat Deck

The mean specific yield and estimated snow losses for the modules mounted on the roof section and flat deck are shown in Figure 11 and 12. Annual values are in Table 2. Annual losses vary from 0% to as much as 10%. The specific yields of the roof-mount and ballasted modules are higher than the corresponding pole-mounts. This is because the modules are newer and in a better state of repair. Losses are much greater than the corresponding pole-mounted modules.

The poorer snow-shedding of the roof-mounted arrays was also evident from image data. Figure 9 shows the 0°, 10°, and 20° pole-mounted modules

Figure 9. (Left) Pictures taken at noon over 4 consecutive days from Jan 16th to Jan 19th, 2014 (from top to bottom), of the 20°, 10° and 0° pole-mount arrays (from left to right), as well as the roof-mounted and ballasted array. It's clear that the 20° pole-mounted array (the left-most pole-mounted modules) is shedding snow much better than the roof modules which are at a lower tilt. The images also show a larger roof-mounted array that remained covered in snow. Records of this array are not available, but it is believed to have not been operating while these pictures were taken.



as well as the 30° roof section and 37° ballasted modules at noon over 4 consecutive days. The 20° pole-mounted module is fully free of snow much sooner than the 30° roof section modules and 37° ballasted modules. The issue is that snow accumulates at the bottom frame of these modules and does not shed easily. On the ballasted modules, there is a flat ledge upon which snow can accumulate and prevent melting snow from fully shedding (as would happen in an actual installation mounted on a flat roof). There were no significant differences between the portrait and landscape modules, similar to the 40° pole-mounted modules.



(Right) A larger ground-mounted array installed on more conventional racking at a 30° tilt is shown at the same time of day and covering the same time period. Data were not available for the modules on this array, but the image data suggest comparable (or better) snow-shedding behaviour to the 20° pole-mounted module.

Table 3. Snow Data.

<i>Year</i>	<i>Total Snow [cm]</i>	<i>Annual Sum of Daily Snow Depths [cm]</i>	<i>Max Snow Depth [cm]</i>
2011	155	922	35
2012	105	143	14
2013	180	1074	37
2014	176	1883	38
2015	90	855	28
2016	163	506	25
2017	109	356	20

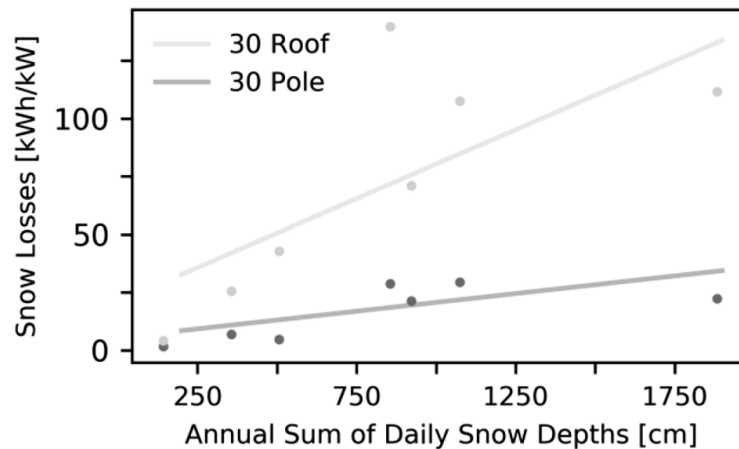


Figure 10. As an example, annual losses for the 30° pole- and roof-mounted modules correlate with the sum of daily snow depths (R^2 of 0.52 and 0.63, respectively).

Procedure Applied to Freely Available Datasets

Another important strength of this method for estimating snow losses is that it can be applied to freely available PV generation datasets, of which there are many. This can aid in overall efforts to validate snow loss models. For example, Enphase allows system owners the option of making a subset of their PV system performance data viewable to the public. The public sites also typically provide system information like module model, tilt, and azimuthal orientation. This is enough information for a system model that can be used to estimate snow losses. This section provides a concrete example of the calculation procedure applied to a freely available PV generation dataset.

A publicly viewable Enphase PV installation with system ID GSMz94049

was found via internet search. It is a residential system located in Calgary, Alberta, Canada, and was installed in July 2012. It consists of 1 array with 12 modules. The tilt is 18.4° and the azimuthal orientation is 180° (due South). Modules models were CS6P-215PE from Canadian Solar. A precise address was not provided, nor were any pictures of the installation. The presence of any shading objects was determined by investigating the shape of the daily generation curve for clear-sky days near the winter solstice and spring equinox—again, these data were freely available from the public view of the instal-

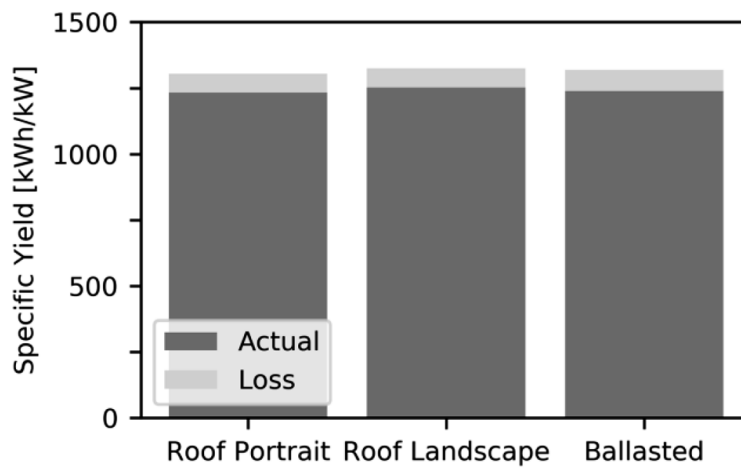


Figure 11. The mean annual snow losses are greater for the modules mounted on the roof section and ballasted on the flat deck, when compared to the pole-mounted modules (Figure 7).

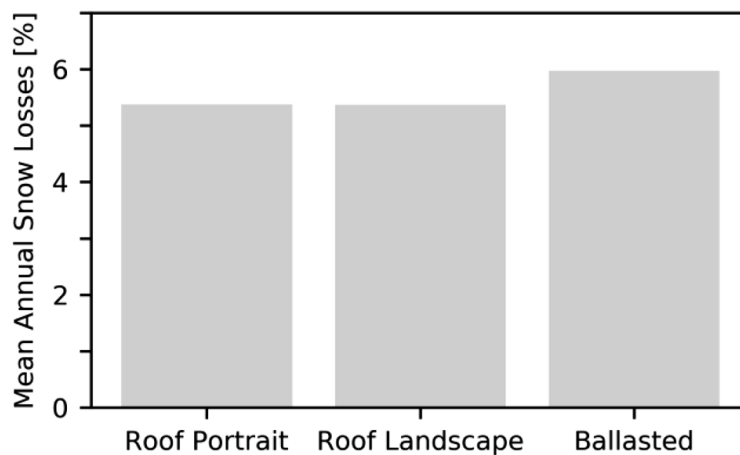


Figure 12. Mean annual snow losses are between 5 and 6% for the arrays mounted on the roof-section and ballasted on the flat deck. The landscape and portrait modules mounted on the roof section had comparable performance.

lation. The daily energy generation profile for different clear-sky days is shown in Figure 13. The symmetry and shape show that there is no significant shading—and it follows that any outlying data points in the modeling are not attributable to shading objects.

Daily energy generation for 2013 to 2017 was collected from the public view of the installation accessible online. A SAM model was created using the available system information and environmental data from NSRDB. A constant albedo was assumed. An isotropic sky model was used. All losses were set to 0%. The daily actual energy generation versus uncalibrated modeled data is shown in Figure 14. The figure also shows a linear calibration curve created by considering only those points from June, July and August. All modeled data were then adjusted by the calibration curve. The modeling error using data from June, July and August, was used to determine the baseline standard deviation of the modeling error in the absence of any snow. A maximum modeling error of $+3\sigma$ was used to identifying outlying data points.

The modeling error of points above the threshold was then aggregated to estimate the total energy lost due to snow. The annual actual generation and estimated losses is shown in Figure 15. The annual sum of daily snow depths for this installation had a relatively narrow range and was not well correlated with total annual energy loss due to snow.

DISCUSSION

This article has suggested a simple empirical approach to estimating snow losses based on daily energy generation data that is often available for PV systems. It requires no extra sensors and uses freely available tools (SAM) and environmental datasets (NSRDB). The modeling component is simple and only requires a few system parameters. The additional analysis is straightforward to perform in standard spreadsheet software package. It could therefore be performed by PV system owners with minimal modeling experience. Empirical data on snow losses is useful to system owners for a variety of reasons. For example, it can quantify the lost revenue, inform decision-making around snow removal, help explain shortfalls and variations in energy yield, and help inform energy consumption targets for buildings seeking net-zero energy.

The analysis of the various PV arrays at the STEP PV Test Lab demonstrates the effectiveness of the method. The analysis has shown very clearly that when the only days considered have no snow on the ground or no snowfall, the agreement between modeled and actual generation follows a very tight

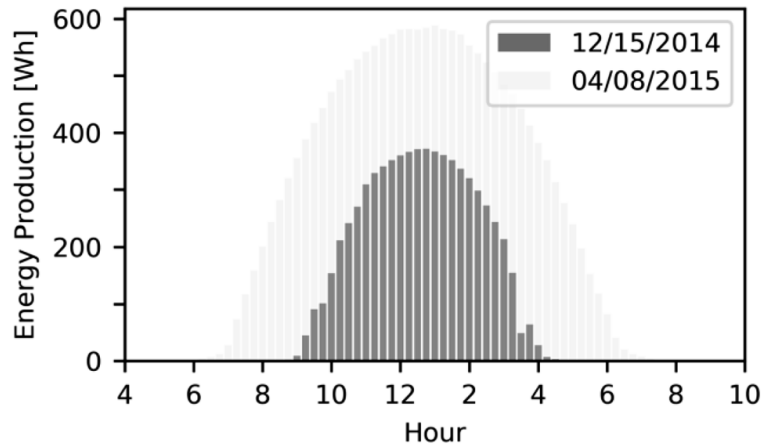


Figure 13. The symmetry of the generation curve for clear-sky days near the winter solstice and spring equinox shows that there is no significant shading for this installation. However, there does appear to be a small shading object in the western sky that has a small impact when the sun is at its lowest elevation.

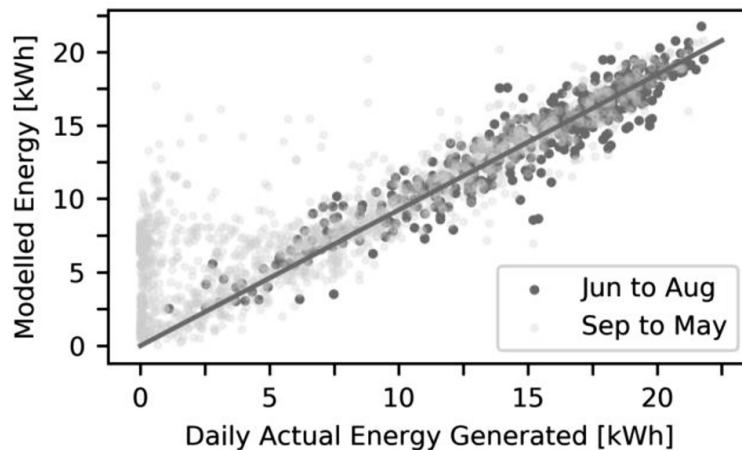


Figure 14. The uncalibrated modeled data are shown for 2013 to 2017 and have been separated into days occurring in June to August and days occurring in the rest of the year. It's clear that the statistical spread of the summer data, with no presence of snow, is lower than when compared to that for the rest of the year.

distribution (this was shown in Figure 4). When data that may have been affected by snow is included, obvious signatures (Figure 5) show up that can be isolated and quantified based on the baseline standard deviation of the modeling error. Furthermore, the expected trends occur when the method is applied to increasing tilt angles, with the losses being greatest for the lowest tilts. It was also shown that the losses estimated using this approach correlate with snow data. These observations all support the validity of the approach.

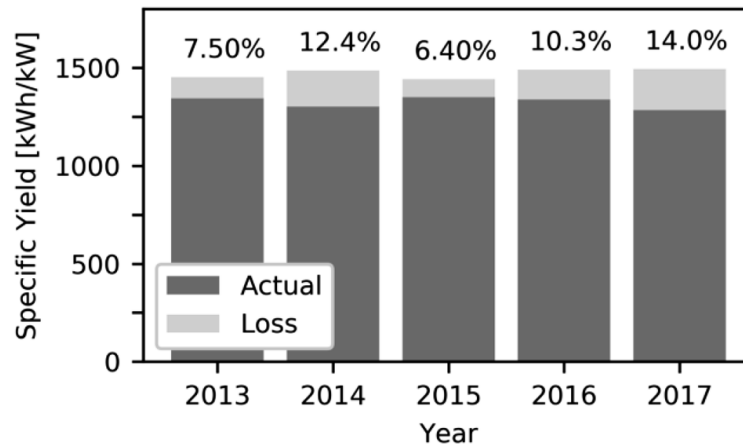


Figure 15. The actual energy generation and estimated losses from snow coverage are shown for each year that data was available. This plot demonstrates that it is possible to estimate snow losses using freely available datasets, relatively few parameters and a simple system model.

It's important to note that the research team had no affiliation with the publicly viewable Enphase site in Calgary. All the data and tools used to estimate snow losses were freely available online. Continuing to use Enphase as an example, this is only one of many sites and it is straightforward to see how this basic approach could be used to estimate snow losses of PV systems across the Northern U.S. and Canada by using actual system energy production data. A map of Enphase installations is available in [8]—it claims more than 895,000 installations. A small subset of these are publicly accessible. That data can be used to generate an experimental map of PV system snow losses across different geographical areas, years, and system types, based on the simple approach outlined in this article. It follows that the generation of snow loss estimates and validation of snow loss models using real-world data across a large number of sites covering different geographical regions should be feasible without significant effort obtaining experimental data.

CONCLUSION

This study presented measured yield and estimated snow loss data spanning from 2011 to 2017 from PV arrays mounted at several different tilt angles, also considering pole and roof-mounting styles. It found that the greatest snow losses in any particular year (10%) occurred for the roof-mounted modules and the modules mounted with ballast on the flat deck. The data is useful for

snow loss estimates in the immediate geographical area of the study. The range of tilt angle and mounting styles considered also makes the dataset useful for snow loss model validation efforts. This study also showed that the approach used to estimate snow losses could easily be applied to other installations using typically available system data and free software tools. This makes empirical estimates of snow losses more accessible to a broader number of PV system owners. Such estimates can be used to monetize the energy loss, inform decision-making around snow removal, help explain shortfalls and variations in energy yield, and help inform energy consumption targets for buildings seeking net-zero energy consumption.

Acknowledgements

Base funding for STEP low-carbon technology evaluations is provided by the Region of Peel, York Region and The City of Toronto. Financial support for STEP's PV Test Lab has been provided by Natural Resources Canada. Note that the contents of this article do not necessarily represent the policies of the supporting agencies. Although every reasonable effort has been made to ensure the integrity of the article, the supporting agencies do not make any warranty or representation, expressed or implied, with respect to the accuracy or completeness of the information contained herein. Mention of trade names or commercial products does not constitute endorsement or recommendation of those products.

References

- [1] D. S. Ryberg, and J. Freeman. "Integration, validation, and application of a PV snow coverage model in SAM," NREL Technical Report TP-6A20-68705, 2017.
- [2] R. Andrews and J. Pearce. "Prediction of energy effects on photovoltaic systems due to snowfall events," in 38th IEEE Photovoltaic Specialist Conference, pp. 3386-3391, 2012.
- [3] B. Marion, R. Schaefer, H. Caine, and G. Sanchez. "Measured and modeled photovoltaic system energy losses from snow for Colorado and Wisconsin locations," *Solar Energy*, vol. 97, pp. 112-121, 2013.
- [4] L. Powers, J. Newmiller, and T. Townsend. "Measuring and modeling the effect of snow on photovoltaic system performance," in 36th IEEE Photovoltaic Specialist Conference, pp. 973-978, 2010.
- [5] T. Townsend and L. Powers. "Photovoltaics and snow: An update from two winters of measurements in the SIERRA," in 37th IEEE Photovoltaic Specialist Conference, pp. 3231-3236, 2011.
- [6] Northern Alberta Institute of Technology Alternative Energy Program. "Solar photovoltaic reference array report." March 2016. Accessed online July 2019: solaralberta.ca/sites/default/files/NAIT%20Reference%20Array%20Report.pdf.
- [7] N. Heidari, J. Gwamuri, T. Townsend and J. Pearce. "Impact of snow and ground interference on photovoltaic electric system performance," *IEEE Journal of Photovoltaics*, vol. 5, issue 6, 1680-1685, 2015.
- [8] Enphase Installation Map. Accessed online May 2019: enphase.com/en-us/map.



ABOUT THE AUTHORS

Erik Janssen is an analyst with the Sustainable Technologies Evaluation Program (STEP) of the Toronto and Region Conservation Authority (TRCA). For several years he has been a scientific lead on STEP pilot projects evaluating emerging low-carbon energy technologies. He is a CMVP and holds an M.A.Sc. in Engineering Physics, a Swedish Magisterexamen in Solar Energy Engineering and a B.Sc.(Hon) in Physics. Email: erik.janssen@trca.ca

David Nixon is an advisor to STEP and his experience with renewable energy spans more than 20 years, including the installation of on- and off-grid wind and PV systems, residential and commercial solar hot water systems, the design and manufacturing solar electric equipment, and device-level research in a laboratory setting.

Svend De Bruyn is a Renewable Energy Specialist with more than 10 years at STEP. He has 25 years experience in the PV and wind industries regarding sales, service, and installation. He has been a consultant for the Canadian Wind Energy Association and an instructor at Durham College.

Gil Amdurski is Technical Coordinator with STEP, specializing in the instrumentation of renewable energy systems. He holds a Diploma in Electromechanical Engineering, a Post-Graduate Certificate in Renewable Energies, and is Certified Measurement and Verification Professional with the Association of Energy Engineers.

Leigh St. Hilaire is a Project Manager with STEP, where he has managed a diverse set of energy-related research projects. Prior to STEP, Leigh worked for Exova, where he was responsible for designing, procuring, certifying and deploying a PV testing laboratory. Leigh holds a B.A.Sc in Electrical Power System Engineering.