2018

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Publisher Citation

Bosman, L. & Darling, S. (2018). Performance Modeling and Valuation of Snow-Covered PV Systems: Examination of a Simplified Approach to Decrease Forecasting Error. Environmental Science and Pollution Research, 25(6), 15484-15491

Performance Modeling and Valuation of Snow-Covered PV Systems: Examination of a Simplified Approach to Decrease Forecasting Error

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Abstract—The advent of modern solar energy technologies can improve the costs of energy consumption on a global, national, and regional level, ultimately spanning stakeholders from governmental entities, to utility companies, corporations, and residential homeowners. For those stakeholders experiencing the four seasons, accurately accounting for snow-related energy losses is important for effectively predicting photovoltaic performance energy genreation and valuation. This paper provides an examination of a new, simplified approach to decrease snow-related forecasting error, in comparison to current solar energy performance models. A new method is proposed to allow model designers, and ultimately users, the opportunity to better understand the return on investment for solar energy systems located in snowy environments. The new method is validated using two different sets of solar energy systems located near Green Bay, WI, USA: a 3.0 kW micro-inverter system and a 13.2 kW central inverter system. Both systems were unobstructed, facing south, and set at a tilt of 26.56 degrees. Data were collected beginning in May 2014 (micro-inverter system) and October 2014 (central inverter system), through January 2018. In comparison to reference industry standard solar energy prediction applications (PVWatts and PVsyst), the new method results in lower Mean Absolute Percent Errors per kWh of 0.039% and 0.055%, respectively, for the micro-inverter system and central inverter system. The statistical analysis provides support for incorporating this new method into freely available, online, up-to-date prediction applications, such as PVWatts and PVsyst.

Keywords— solar, photovoltaic, debris, snow, loss, derate

1. INTRODUCTION

Increasing solar energy installations is a top priority in the U.S. and many other countries (U.S. Energy Information Administration 2015), and a central pillar of these efforts is the race to maximize efficiency of solar energy systems, which can potentially improve the costs of energy consumption on a global, national, and regional level (Raugei et al. 2012). Interest in solar and renewable energy sources spans from governmental entities, to utility companies, corporations, and residential homeowners; however, in each case the question of if and when the investor will recoup their initial investment is an important barrier to be considered. Lab-conducted accelerated environmental stress tests provide a wealth of knowledge about solar module performance expectations at standard test conditions. However, estimating factors and interactions of real-world performance can be complex and difficult. There are several freely available, online, up-to-date PV system prediction applications (Clean Energy Decision Support Centre 2004; Clean Energy Decision Support Centre 2005; Energy Matters LLC 2009; Klise and Stein 2009; Long et al. 2014; Marion 2008; National Renewable Energy Laboratory 2013; National Renewable Energy Laboratory 2014; Su et al. 2012; Thevenard and Pelland 2013), which make an attempt to better understand, or at least better account for, these uncertainties and real-world variables and provide an effective starting point for quantifying anticipated energy production and value. Unfortunately, many of these models have several limitations, especially with respect to the impact of snow on annual solar energy performance and valuation. While the models do sometimes include a discount to account for losses due to shade and soil, the discount factor is commonly assumed to be constant and devoid of seasonal or monthly changes, such as snow fall.

More recently, researchers have developed add-on models to account for snow loss (Andrews and Pearce 2012; Marion et al. 2013; Powers et al. 2010). However, in many cases, the community has yet to incorporate these add-on models into freely available, online, up-to-date PV system prediction applications. NREL's System Advisor Model (SAM) has updated its model to incorporate Marion et al.'s (Marion et al. 2013) snow coverage energy loss calculations to decrease the error associated with solar energy generation forecasting (Ryberg and Freeman 2015). This new approach to calculating losses from snow takes into consideration daily snow depth, hourly plane-of-array irradiance, hourly air temperature, and PV array tilt. This approach provides improvements in the estimation of losses related to the presence of snow, but the purpose of the current paper is to provide a more simplified approach using TMY2 data. The proposed method will allow model designers, and ultimately users, the opportunity to better understand the return on investment for solar energy systems located in snowy climates.

2. BACKGROUND

Solar energy system performance for fixed flat-plate panels can be calculated using Equation 1 (Dobos 2014), including the given variables.

$$\text{Eq. 1} \qquad P_{mod} = \frac{I_M}{I_0} * P_{DC} * [1 + \gamma * (T_M - T_0)] * \delta$$

- P_{mod} = module estimated AC power generation, W
- I_M = module plane-of-array irradiance, W/m^2
- I_0 = STC solar irradiance, W/m^2

- P_{DC} = module rated maximum DC power, W
- γ = module temperature coefficient, %/˚C
- T_M = module temperature, ˚C
- T_0 = STC temperature, ˚C
- δ = derate factor

Within this equation, the greatest uncertainty, resulting in the greatest solar energy estimation inaccuracies, is limited to three variables including I_M (module plane-of-array irradiance, W/m^2), T_M (module temperature, ˚C), and δ (derate factor).

The module plane-of-array irradiance (W/m^2) and ambient temperature, used to estimate module temperature (˚C), are commonly derived from TMY (Typical Metrological Year) data (Wilcox and Marion 2008). The stages of TMY data sets are shown in Table 1. TMY data sets are commonly used to design renewable energy performance models. However, the data sets are not interchangeable due to the variation in data structures and variables collected (Hong et al. 2013). The TMY data sets offer hourly values of solar irradiance and meteorological parameters for 1-year periods for locations within the United States and existing territories. Because of the "typical" nature of the data sets, they are not designed for worst-case conditions. The methodology applied to determine the individual months for each location is the Sandia method (Hall et al. 1978), which selects 12 typical months from different years based on five parameters: global horizontal radiation, direct normal radiation, dry bulb temperature, dew point temperature, and wind speed (Marion and Urban 1995; Wilcox and Marion 2008). For example, in the case of the TMY2 data sets, the method analyzes all 30 January months to determine the most average or typical January, and then a similar process is followed for each of the other months, with the end result being a conglomeration of the 12 most typical months to form an entire year (Marion and Urban 1995). The TMY2 data sets cover fewer locations than TMY3, however, they offer a greater spread of time consistently across all locations. Additionally, they offer insight into snow depth and snow fall, which is of particular importance for this study. An important consideration for future models is the fact that historic 30-year averages may be poor predictors of future environmental conditions in the context of a changing climate.

Table 1: Stages of TMY Data

Data Set	*Locations/Stations*	*Years*
TMY1	229	1948-1980
TMY2	239	1961-1990
TMY3	1020	1976-2005 (where available) 1991-2005 (all)

Module irradiance is the summation of three components: beam, ground, and diffuse. The beam and diffuse components require a calculation of the angle of incidence, which varies depending upon the type of PV tracking system: e.g. fixed, 1-axis, or 2-axis. The module of irradiance beam components is the most dependent upon tilt, and is the product of the direct normal irradiance and the cosine of the angle of incidence. The module irradiance ground component considers the albedo coefficient, as a portion of Global Horizontal Irradiance (GHI), reflected by the ground or surface in front of a tilted PV array (Andrews and Pearce 2013; Brennan et al. 2014). The module irradiance diffuse component describes the radiation that has been scattered by particles in the atmosphere, essentially, the illumination coming from the clouds and sky. There are many models available to estimate the diffuse component (Isotropic model, Hay and Davies model, Perez model, Muneer model, Klucher model, and Reindl model); however, the Perez model (Perez et al. 1990; Perez et al. 1987) has proven to be the most effective method for predicting the POA diffuse component (Loutzenhiser et al. 2007).

Module temperature can be estimated through a variety of standard models including Sandia (King et al. 2004), Garcia (Garcia and Balenzategui 2004), Faiman (Faiman 2008), NREL – 3 Parameter (TamizhMani et al. 2003), and NREL – 5 Parameter (TamizhMani et al. 2003). These models estimate module temperature based on a subset of several different factors, including ambient temperature, plane-of-array irradiance, wind speed, wind direction, and humidity.

The derate factor accounts for potential energy losses due to a variety of variables. For example, PVWatts (the industry standard for solar energy estimation) uses a default derate factor of 14.08%, which includes losses attributed to soiling (2%), shading (3%), snow (0%), module mismatch (2%) wiring (2%), connections (0.5%), light-induced degradation (1.5%), nameplate rating (1%), age (0%), and availability (3%).

For the purpose of this study, the research investigates the influence of derate factors, Snow and Module Mismatch, on two types of inverter systems, central and micro, applying the TMY2 data set for Green Bay, WI.

3. METHODS

3.1 Data Collection

Data were collected through four main data sources. First, the College of Menominee Nation's Solar Energy Research Institute, located in northern Wisconsin, provided access to actual data, using 2 different systems (3.0 kW micro-inverter system and 13.2 kW central inverter system). PVWatts, originating out of the National Renewable Energy Laboratory in the United States, and PVsyst, developed by a research team in Switzerland, were used to provide comparison to industry standard reference solar energy performance estimation models to prove the robustness of the proposed new approach. Finally, the TMY2 data set for Green Bay, WI, provided snow related data for the purpose of proposing a new method for solar energy estimation in snow-laden locations.

Table 2: Summary of Data Sources

Data Source	**Description**
College of Menominee Nation Solar Energy Research Institute	Actual data using 2 different systems
PVWatts	Reference model 1
PVsyst	Reference model 2
TMY2	Used to develop new, simplified approach to snow loss

The College of Menominee Nation’s Solar Energy Research Institute (SERI) was established in 2014 and consists of two main systems, a 3.0 kW micro inverter system and a 13.2 kW central inverter system, in addition to performance and weather data collection systems. The 3.0 kW micro inverter system was installed in mid-April 2014 and consists of twelve 250 W Solar World standard crystalline silicon panels each with its own Enphase micro inverter. The panels are positioned at a fixed tilt on a metal roof 6/12 pitch of 26.56 degrees at a south-facing orientation of 180 degrees. The 13.2 kW central inverter system was installed in mid-September 2014 and consists of two SMA central inverters and forty-eight 275 W Solar World standard crystalline silicon panels. The panels are positioned at a fixed tilt on a metal roof 6/12 pitch of 26.56 degrees at a south-facing orientation of 180 degrees. The performance related data collection includes individual solar energy panel generation and inverter output in 1-hour time increments. The weather related data collection is also available in 1-hour time increments and includes plane-of-array solar irradiance, module temperature, ambient temperature, wind direction, and wind speed.

PVWatts was developed in 1999 by the National Renewable Energy Laboratory, and is the standard industry tool used to estimate PV system energy production and resulting cost of energy (Darling et al. 2011). Upon identifying a location to get started, the user must enter System Info, including DC System Size, Module Type, Array Type, System Losses, Tilt, and Azimuth. NREL offers an API website to assist in the development of a software application for model analysis using larger data sets. The results provide a monthly and hourly breakdown of AC energy production and the associated AC energy value.

Figure 1: Snow Covered Solar Panels (CMN’s Solar Energy Research Institute)

In a snowy and cold climate, it is important to take into consideration two specific derate factors, including Snow and Module Mismatch. First, the Snow derate factor takes into consideration the presence of snow built up on the panels (e.g. Shading) that will prevent solar irradiation from entering the panels, resulting in limited solar energy generation. In four-season locations, such as Wisconsin, snow may only be present for a few months, but the existence of built-up snow can greatly impact solar energy generation for that particular month or period of time, as shown in Figure 1. Second, the Module Mismatch derate factor takes into consideration the potential losses due to manufacturing inconsistencies and shading when using a central inverter. For example, when using a central inverter system, a small leaf shading a portion of the one solar panel will influence the performance outcome of all panels. However, when using a micro inverter system, each panel has its own individual inverter, promoting maximum array performance. As such, when snow is present, micro inverters work more efficiently than central inverters because of their ability to focus on one single panel rather than performing to the least productive panel in a string of panels.

The derate factors applied to the PV solar energy estimation model are shown in Table 3 for the two different types of inverter systems. With respect to the Snow derate factor, for both the 3.0 kW Micro Inverter System and the 13.2 kW Central Inverter System, it was difficult to know what percentage value to apply. One approach considered was to apply 33%, because in Wisconsin there is typically potential for snow four months out of the 12 months of the year. However, logic would suggest that applying this type of derate to the year-round performance estimation would result in a discounted, unrealistic valuation. As such, the Snow derate factor was left at 0% in an effort to showcase the need to consider the influence of snow on a monthly basis. With respect to the Module Mismatch derate factor, the 13.2 kW Central Invert System was left at 2% to take into consideration the potential losses due to manufacturing inconsistencies, whereas the 3.0 kW Micro Inverter System applied a 0% Module Mismatch because there are no issues of module dependency.

Table 3: Derate Factors for Input in PVWatts Solar Energy Estimation Model

Derate Factors	PVWatts: 3.0 kW Micro	PVWatts: 13.2 kW Central
Soiling	2%	2%
Shading	3%	3%
Snow	0%	0%
Module Mismatch	0%	2%
Wiring	2%	2%
Connections	0.5%	0.5%
Light-Induced Degradation	1.5%	1.5%
Nameplate Rating	1%	1%
Availability	3%	3%

Table 4: Derate Factors for Input in PVsyst Solar Energy Estimation Model

Derate Factors	PVsyst: 3.0 kW Micro	PVsyst: 13.2 kW Central
Soiling	5%	5%
Module Mismatch	0%	2%
Wiring	2.5%	2%
Light-Induced Degradation	1.5%	1.5%
Module Quality	1%	1%
Unavailability	3%	3%

3.2 New Simplified Method – Snowfall Modified

This simplified method has two main steps. First, the hourly solar energy was calculated using Equation 1 and TMY2 data set. The TMY2 data set for Green Bay, WI, location ID 14898, was used because it was the closest location to the test facility in Keshena, WI. Additionally, it provides information on Snow Depth and Days Since Last Snowfall, which are not available through the TMY3 data sets. The TMY2 data set for Green Bay was used to investigate and analyze a new method for estimating the impacts of snow, called Snowfall Modified. This initial step resulted in 8760 (24 hours × 365 days) rows of data for each system (3.0 kW micro-inverter and 13.2 kW central inverter). Each row was for a given hour during the year and included the estimated energy production in watt-hours (Wh).

In the second step, three additional pieces of TMY2 data were considered including (1) Days Since Last Snowfall (unit = inches), (2) Snow Depth (unit = inches), and (3) Ambient Temperature (unit = degrees Celsius). Each piece of information takes a binary approach to decision making whether or not to disregard the estimated energy production.

- If Days Since Last Snowfall is greater than 0, this implies that it is not snowing that day. In this case, the assumption is made that the panels are not covered and can generate electricity. If Days Since Last Snowfall equals 0, this implies that is it currently snowing that day. In this case, the assumption is that the solar panels are covered and cannot generate electricity, and the estimated energy production is disregarded.

- If Snow Depth equals 0, this implies that snow has not accumulated. In this case, the assumption is made that the panels are not covered and can generate electricity. If Snow Depth is greater than 0, this implies that snow has accumulated. In this case, the assumption is that the solar panels are covered and cannot generate electricity, and the estimated energy production is disregarded.

- If Ambient Temperature is less than 0, this implies that there is limited capability for ice and snow to melt and slide off the panels. In this case, the assumption is that the solar panels are covered and cannot generate electricity, and the estimated energy production is disregarded. If Ambient Temperature is greater than 0, this implies that snow can melt and/or slide off panels. In this case, the assumption is made that the panels are not covered and can generate electricity.

In summary, the new method Snowfall Modified considers eight scenarios, as summarized in the decision matrix provided in Table 5. Only two scenarios are assumed to prevent the panels from generating electricity. First, it is assumed no electricity is generated when the ambient temperature is below zero AND snow depth is greater than 0 AND the days since last snowfall equals 0. Second, it is assumed no electricity is generated when the ambient temperature is below zero AND snow depth is greater than 0 AND the days since last snowfall is greater than 0.

Table 5: Snowfall Modified Decision Matrix to Disregard Estimated Energy Production

Scenario	Days Since Last Snowfall (DSLS)	Snow Depth (SD)	Ambient Temperature (T_A)	Disregard Estimated Energy Production?
1	DSLS = 0	SD = 0	$T_A < 0$	No
2	DSLS > 0	SD = 0	$T_A < 0$	No
3	DSLS = 0	SD > 0	$T_A < 0$	Yes
4	DSLS > 0	SD > 0	$T_A < 0$	Yes
5	DSLS = 0	SD = 0	$T_A > 0$	No
6	DSLS > 0	SD = 0	$T_A > 0$	No
7	DSLS = 0	SD > 0	$T_A > 0$	No
8	DSLS > 0	SD > 0	$T_A > 0$	No

4. RESULTS AND DISCUSSION

A comparison was conducted to show the actual versus predicted for both the 3.0 kW micro inverter system and the 13.2 kW central inverter system. Specifically, four cases are considered, as summarized in Table 6. First, the College of Menominee Nation's Solar Energy Research Institute, located in northern Wisconsin, provided access to actual data, using 2 different systems (3.0 kW micro-inverter system and 13.2 kW central inverter system). Two reference models were used for each of the systems, both installed at 26.56 degree tilt at a south-facing orientation. The reference model data for PVWatts were obtained using the derate factors specified in Table 3. The reference model data for PWsyst were obtained using the derate factors specified in Table 4. Finally, the Snowfall Modified technique demonstrates the new simplified method explained in section 3.2.

Table 6: Cases Considered to Validate New Method

Case	**Description**
College of Menominee Nation Solar Energy Research Institute	Actual data (3.0 kW micro inverter system and 13.2 kW central inverter system)
PVWatts	Reference model 1
PVsyst	Reference model 2
Snowfall Modified	New simplified approach to snow loss

4.1 System 1: 3.0kW Micro Inverter

The monthly results are shown in Figure 2. Data are provided for May 2014 through January 2018. As expected, the summer (non-snow) months yield similar results for both the reference models, PVWatts and PVsyst, in comparison to the new predictive approach, Snowfall Modified. Furthermore, all three models are comparable to the actual performance data. However, the new approach, Snowfall Modified, is considerably closer to the Actual data during the winter (snow) months.

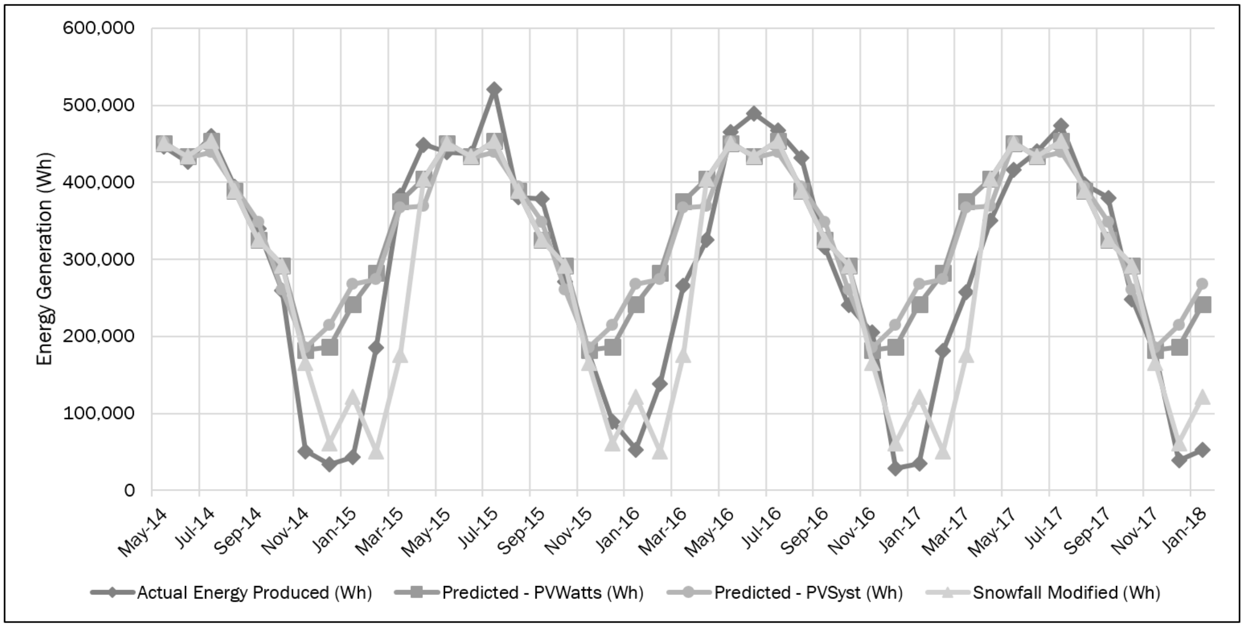

Figure 2: 3.0 kW Micro-Inverter Energy Generation - Actual vs. Predicted

Table 7 provides quantitative evidence supporting the accuracy of the new approach, Snowfall Modified, in comparison to the reference models, PVWatts and PVsyst, using (1) total difference, (2) paired differences t-Test and (3) mean absolute percent error. The Actual overall total energy generated over the 45-month period, May 2014 through January 2018, was 13,034,429 Wh. Both the reference models predicted energy generation inflated to almost two million Wh more than actual. In comparison, although the Snowfall Modified predicted a value slightly smaller than expected, it was considerably closer to the actual results. The paired differences t-Test was conducted using an alpha value of 0.05, comparing the Actual data to each of the three models. Both the reference models produced statistically significant p-values, resulting in a rejection of the null hypothesis, implying the data produced by the reference models are statistically different from the Actual data. In comparison, the new approach, Snowfall Modified, resulted in a failure to reject the null hypothesis, implying the data sets are statistical similar. Lastly, the mean absolute percent error (MAPE) value is considerably lower for the new approach, Snowfall Modified, suggesting an increased accuracy with this new approach.

Table 7: 3.0 kW Micro-Inverter Energy Generation – Statistical Analysis

	Total Difference from Actual (Over 45 Month Data Collection Period) in Wh	Paired Differences t-test (p-value)	Mean Absolute Percent Error per kWh
Reference Model: PVWatts	1,963,115	0.0005	0.090%
Reference Model: PVsyst	1,969,571	0.0015	0.100%
New Approach: Snowfall Modified	-377,420	0.3744	0.039%

4.2 System 2: 13.2 kW Central Inverter

The monthly results are shown in Figure 3. Data are provided for October 2014 through January 2018. As expected, the summer (non-snow) months yield similar results for both the reference models, PVWatts and PVsyst, in comparison to the new predictive approach, Snowfall Modified. Furthermore, all three models are comparable to the actual performance data. However, the new approach, Snowfall Modified, is considerably closer to the Actual data during the winter (snow) months.

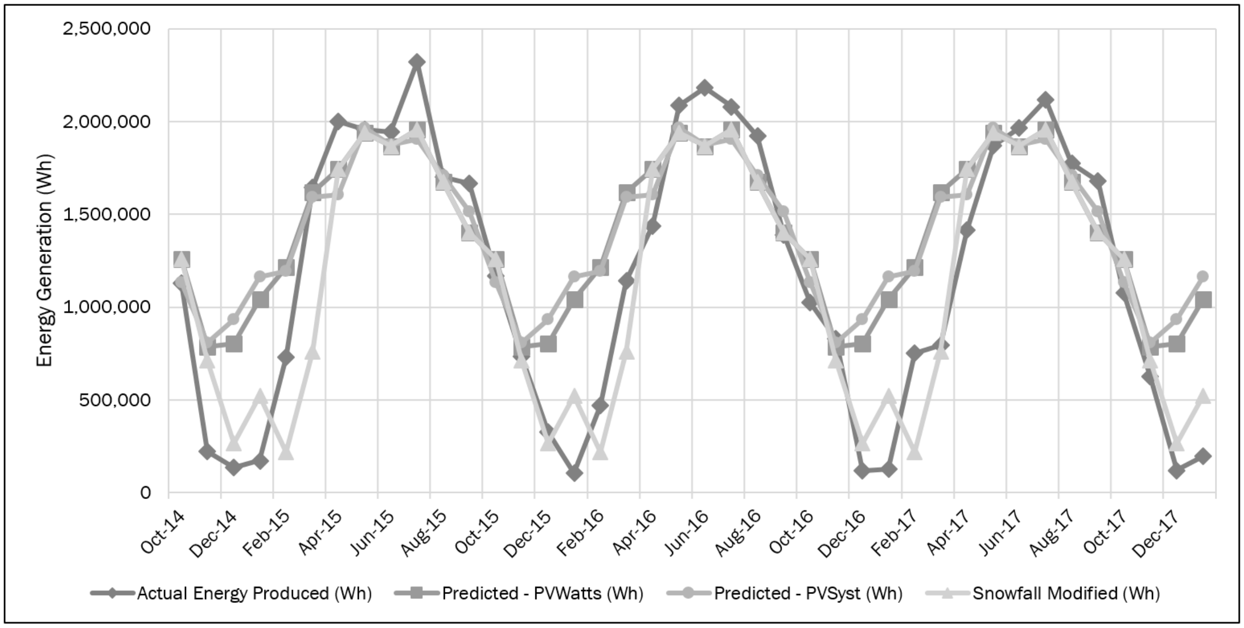

Figure 3: 13.2 kW Central Inverter Energy Generation - Actual vs. Predicted

Table 8 provides quantitative evidence supporting the accuracy of the new approach, Snowfall Modified, in comparison to the reference models, PVWatts and PVsyst, using (1) total difference, (2) paired differences t-Test and (3) mean absolute percent error. The Actual overall total energy generated over the 40-month period, October 2014 through January 2018, was 47,176,518 Wh. Both the reference models predicted energy generation inflated to almost two million Wh more than actual. In comparison, although the Snowfall Modified predicted a value slightly smaller than expected, it was considerably closer to the actual results. The paired differences t-Test was conducted using an alpha value of 0.05, comparing the Actual data to each of the three models. Both the reference models produced statistically significant p-values, resulting in a rejection of the null hypothesis, implying the data produce by the reference models are statistically different from the Actual data. In comparison, the new approach, Snowfall Modified, resulted in a failure to reject the null hypothesis, implying the data sets are statistical similar. Lastly, the mean absolute percent error (MAPE) value is considerably lower for the new approach, Snowfall Modified, suggesting an increased accuracy with this new approach.

Table 8: 13.2 kW Central Inverter Energy Generation – Statistical Analysis

	Total Difference from Actual (Over 45 Month Data Collection Period) in Wh	Paired Differences t-test (p-value)	Mean Absolute Percent Error per kWh
Reference Model: PVWatts	8,638,233	0.0013	0.132%
Reference Model: PVsyst	9,092,482	0.0019	0.148%
New Approach: Snowfall Modified	-1,453,719	0.4336	0.055%

5.0 CONCLUSIONS

In summary, based on testing from two different systems (Heidari et al. 2015), this study provides justification for the need to consider a new, simplified approach to more accurately forecast the performance and valuation of solar energy systems in environments where snowfall is common. This new and simplified method will allow model designers, and ultimately users, the opportunity to better understand the return on investment for solar energy systems located in snowy, cold climates. The TMY2 data sets offer a wealth of information related to snow fall, including accumulated depth and days since the last snow fall. It is recommended that solar energy performance models consider the incorporation of these data as a starting point to estimate the influence of snow on solar energy generation. Furthermore, it is important to consider that the TMY3 data set no longer includes information related to snow, and it is recommended that this information is included in future data sets.

As new PV technology continues to emerge (Darling and You 2013), there remains a wealth of uncertainties, growth opportunities, and future research. Some research has been published showcasing the impacts of snow and non-uniform shading on the performance and valuation of PV applications (Andrews et al. 2013; Azimoh et al. 2014; Bosman 2014; Powers et al. 2010; Rizzo and Scelba 2015). Future research should continue to consider the monthly, or seasonal factors, associated with solar energy generation. Specific to the United States, in addition to snow coverage in the Winter, future research should consider the potential for pollen build up in the Spring, tree shading during the Summer, and the soiling of leaves and debris in the Fall (Thevenard and Pelland 2013). For other dry-climate countries, future research should investigation better methods for forecasting dust and cloud coverage (Bonkaney et al. 2017). Furthermore, future research should focus on how to make the models more user friendly, specific to derate estimation, to enhance the benefit to additional stakeholders such as home appraisers, realtors, insurance underwriters, solar contractors, and utility companies.

6.0 ACKNOWLEDGEMENTS

This work was performed, in part, at the Center for Nanoscale Materials, a U.S. Department of Energy, Office of Science, Office of Basic Energy Sciences User Facility under Contract no. DE-AC02-06CH11357. This research has been supported, in part, by the National Aeronautics and Space Administration under Grant No. NNX14AG57A issued through the Education Opportunities in NASA STEM (EONS) program for NICE-T. This research has been supported, in part, by the National Science Foundation under Grant No. HRD-1417582 issued through the NSF Catalyzing Opportunities for Research and Education TCUP program. This research has been supported, in part, by the Environmental Protection Agency under Grant No. 83696601.

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