PERFORMANCE EVALUATION OF MONITORING ALGORITHMS FOR PHOTOVOLTAIC SYSTEMS

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ABSTRACT: Monitoring solutions for commercial photovoltaic (PV) systems are becoming increasingly widespread, but often performs poorly, especially in locations with varying weather conditions. In this work two standard performance metrics commonly used in PV system monitoring, temperature corrected performance ratio and specific yield, have been calculated and evaluated for real-world conditions. The data is collected from eight inverters of 13-18 kW_p each, installed at a commercial large-scale PV system in Norway. The results show that naïve use of the tested performance metrics give unreliable monitoring with high variation in the PV system performance estimation, often resulting in false alarms. Very low solar elevation and irradiance, snow and technical irregularities in the installation are the primary causes of false alarms in the monitoring. It is shown that for certain climates standard filtering approaches are not sufficient to solve these problems, and that site-specific filtering of data gives more stable monitoring output, entailing more data and less variation.
Keywords: PV systems, Monitoring, Performance, Rooftop

1 INTRODUCTION

With the recent year's increased focus on operation and maintenance of photovoltaic (PV) systems, an extensive number of algorithms and performance metrics have been proposed to improve the PV system monitoring solutions [1]. From very basic to more advanced – the aim of the algorithms is to detect when the PV system is deviating from normal operation and identify faults. The more advanced solutions are also targeting failure diagnosis. Despite that the demand for PV monitoring solutions is growing rapidly, the algorithms are still not sufficiently sophisticated to handle the noise and variations in real-world data in a satisfactory manner, resulting in noise also in the monitoring output. The noise originates from different issues that are difficult to capture in generalized algorithms, like certain weather conditions and differences in e.g. installation configurations, data quality and measurement availability. Consequently, analysis and estimations based on real-world data in commercial systems often conceal faults and degradation, and lead to frequent false alarms when used in monitoring. From an operational point of view, false alarms are just as problematic as undetected faults, as it reduces the trust in the monitoring system.

Common approaches to handle the noise in PV system performance estimates are filtering, such as clear sky filtering or irradiance value filtering [2–5], or lowering the time resolution. Although this can be useful for some applications, information which may be necessary to do advanced fault diagnosis (e.g. detecting faults impacting the low light performance of the PV modules [6]) or day to day monitoring in areas with challenging weather conditions may be lost. Lowering the time resolution by aggregating over longer periods of time introduce unknown uncertainties and increase the reaction time of the algorithm.

In this work, we evaluate two standard performance metrics commonly used in PV system monitoring: temperature corrected performance ratio (PR_{TC}) and specific yield (Y_f) inverter comparison. This is done by testing the methods on data from a commercial PV system located in Norway, where the PV modules are exposed to diverse types of challenging weather conditions (e.g. snow, high frequency of cloudy weather), and large variations in irradiation conditions throughout the year. The evaluation is conducted by calculating the metrics and assessing the periods where there are large deviations from the expected constant values. The effect of removing the main issues identified in the evaluation of the unstable periods is compared to standard filtering approaches. To efficiently remove the main issues, a new snow detection method was developed. As discussed in our previous work [7], there is a lack of methods for robust data-based snow detection in PV systems in periods with partial melting.

The aim of the described analysis is to improve the monitoring methods for commercial PV systems. This is done by providing an understanding of the current limitations, particularly with respect to noise and applicability in climates with large variations in weather. The evaluation allows for a further assessment of how these methods can be improved, and how they eventually should be modified for different types of PV installations in different climates to work more efficiently. This lays a foundation and identify a direction for the development of improved methods and efficient filtering strategies in performance analysis and fault detection for PV systems.

2 METHODS

2.1 Dataset

The data is collected from a 135 kW_p PV system, located in the South-Eastern part of Norway (59.9 °N / 10.8 °E). The PV modules are East oriented, with an azimuth of 112° and a tilt of around 10°, and they are installed on an approximate flat roof. The roof has a tilt of 1-2° in the North-South direction, meaning half of the PV modules has the same tilt North, and the other half has the same tilt South. The module type is IBC Solar PolySol 250 CS. The PV modules are connected to eight different inverters, and the PV capacity for each inverter varies from 13 to 18 kW_p. Plane of array (POA) irradiance is measured by a crystalline silicon reference cell. The temperature of the reference cell is measured, and it is used as an estimate of the PV module temperature.

Data from September 2014 to April 2018 is used, logged with 5 minutes averages. Night time values, i.e. logged values of 0 for current or irradiance, are not included in the analysis.

2.2 Performance metrics

Two basic performance metrics commonly used in monitoring are tested: Specific yield (Y_f) inverter comparison:

$$Y_{f\ comparison} = Y_{fDC\ inverter\ x} \,/\, Y_{fDC\ median\ all\ inverters}$$

and temperature corrected performance ratio (PR_{TC}):

$$PR_{TC} = \left(Y_{fDC} / (1 + \gamma(T_{mod} - T_{STC}))\right) / Y_r$$

Y_f is the specific yield – the energy generated in a given time interval, divided by the rated power of the system. Y_r is the POA insolation in the same time interval divided by the reference irradiance 1000 W/m^2 [8]. γ is the material dependent maximum power temperature coefficient. For the given technology this coefficient is -0.43%/ °C. T_{mod} is the estimated PV module temperature, and T_{STC} is the reference temperature 25°C. In the specific yield comparison, the inverter energy output is compared to the median inverter energy. In this way, weather conditions are inherently accounted for, and sensor data quality is not an issue. Using the median instead of the mean reduces the influence of faulty inverters in the comparison, should there be any.

2.3 Evaluation of performance metrics

The performance metrics are tested on the dataset by calculating the parameters on an hourly basis. Hourly averaged performance parameters are commonly used to provide a balance between resolution and stability. Here it is also used to enable separation between different effects influencing the behavior of the performance metrics. The assumption is that the metrics are stable under normal operation, while changes in the performance will lead to a decrease. However, this is not always a correct assumption: In some periods the metrics are unstable, giving very varying or unexpected results that are not caused by faults. These periods are qualitatively assessed to explain the large variations.

The standard deviation (σ) of the performance metrics can be used to quantify the variation in the metric under normal operation for a given system, as discussed in our previous work [9]. With lower variation in the metrics during normal operation conditions, the performance metric has a higher sensitivity for detecting abnormal situations. The standard deviation can hence be used to measure the stability and accuracy of the performance metrics.

To quantify the impact of the different effects causing periods with large variation in the hourly performance metrics, the standard deviation in the metrics is calculated before and after filtering out the effects. This is compared to the change in standard deviation after applying standard filtering to the metrics. The standard filtering approaches used is low irradiance and clear sky filter. The clear sky detection algorithm described in [10] as implemented in pvlib [11] is used for clear sky filtering. The python version of pvlib is also used in the estimation of the POA clear sky irradiance used in the clear sky detection algorithm, and for the estimation of solar elevation.

To evaluate if there are any differences in irradiance conditions between the inverter strings and between the inverter strings and the irradiance sensor due to e.g. slightly different installation angles or hard shadowing, the clear sky signal was estimated for the irradiance sensor and for each string using the statistical clear sky fitting algorithm proposed by [12]. Using this algorithm, the clear sky current and irradiance for each day through the year was estimated using the measured current and irradiance data. For the inverters, the current values were used instead of the power values to focus on the irradiance signal and exclude temperature effects.

3 RESULTS AND DISCUSSION

3.1 Performance evaluation using unprocessed data

The specific yield inverter comparison and the temperature corrected performance ratio for one inverter, using unfiltered hourly data, are presented in Figure 1. The trends are similar for all the inverters. The variation in the specific yield comparison and the temperature corrected performance ratio is large, both relatively (Figure 1) and absolutely (Figure 2). The average standard deviation of the Y_f inverter comparison of the 8 inverters is 0.38. For PR_{TC} it is 0.25. These large variations in the estimation of the normal state of the PV system challenge efficient use of these performance metrics for fault detection and performance evaluation. Fault detection is normally based on detecting when a system is operating outside normal conditions, such large variations will hence produce false alarms and result in low sensitivity [9].

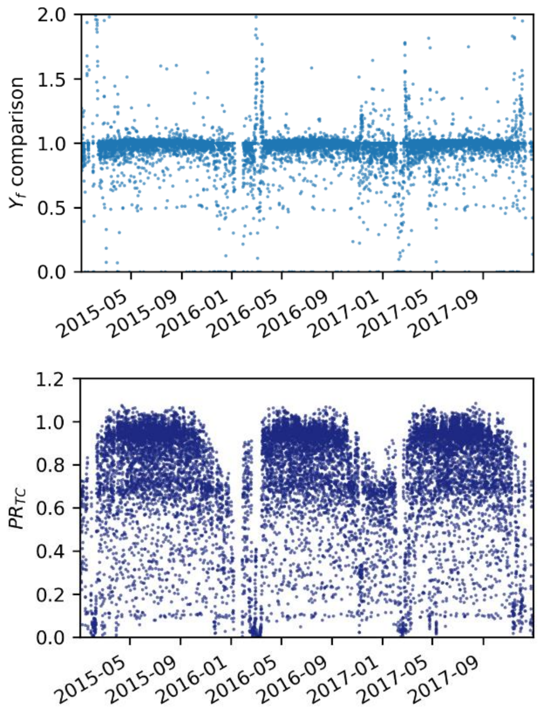

Figure 1: Variation during normal operation in Y_f comparison (top) and in PR_{TC} (bottom) using hourly data from one inverter.

3.2 Performance evaluation using standard filtering

To reduce the variation and increase the accuracy in PV performance analysis, it is common to filter out the low irradiance and/or applying a clear sky filter. In [2] a low irradiance threshold of 200 W/m^2 and a clear sky filter is proposed to remove time periods of poor or variable solar resource conditions to get a stable degradation estimate. The same irradiance threshold is also applied by [3] for fault detection, and also in this work it is observed that clear sky days have lower variation in the estimates of the current and power under normal conditions. The average standard deviation for all the inverters and the remaining data after applying the same irradiance threshold and a clear sky filter on the calculated Y_f comparison and the PR_{TC}, are given in Table I. The filtered results for the PR_{TC} are also visualized in Figure 3.

Filtering the data with the standard approach reduces the standard deviation of the data. However, the number of data points are also drastically reduced and not all large variations are removed. Adding the clear sky filter in addition to the low irradiance threshold increases the variation due to the large reduction in data points – also the ones that are stable. Hence, naïve filtering is not a global solution for all monitoring. Here the methods are both imprecise and too strict, leaving too little data to base the monitoring on.

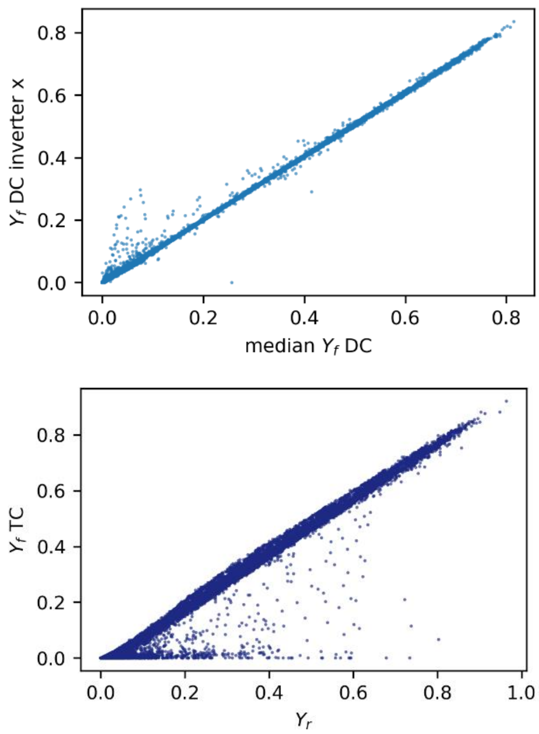

Figure 2: Absolute comparison between the inverter Y_f and the median Y_f (top) and between $Y_{f\,TC}$ and Y_r (bottom).

Table I: The average standard deviation (σ) of the two metrics for all inverters, without filters, and after consecutively removing low irradiance (< 200 W/m^2) and cloudy periods [11]. Remaining data after filtering is also given.

	Avg σ Y_f comparison	Avg σ PR_{TC}	Remaining data
Raw data	0.38	0.25	100 %
Low irradiance	0.16	0.17	38 %
Cloudy periods	0.21	0.21	6 %

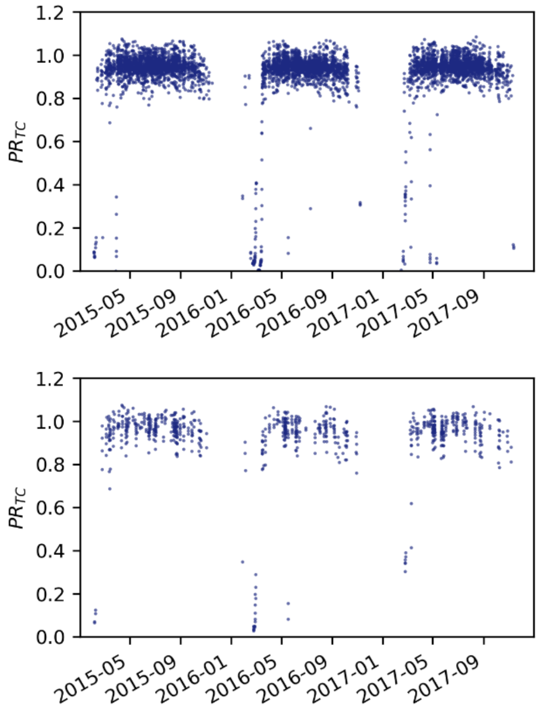

Figure 3: PR_{TC} using hourly data from one inverter, after consecutively removing (top) low irradiance (< 200 W/m^2) and (bottom) cloudy periods.

3.3 Evaluation of time periods with large variations

To better understand when the monitoring methods do not work, the time periods with large variations have been analyzed. The explanations for the largest variations can be divided into three major categories, discussed in the following subsections.

3.3.1 Snow

Snow is a well-known challenge in PV system monitoring in Northern climates. For the tested performance metrics, a full snow cover is unproblematic. With zero production, there are no variation between the inverters and consequently no variations in relative inverter performance. When the irradiance sensor is covered in snow, no low PR values will be calculated. The main challenge in PV system monitoring, is the melting period. When the snow is melting, the inverters and the irradiance sensor might receive different irradiance. Additionally, the inverters might have partial snow covers, giving signatures similar to faults.

To remove data from periods with snow covered PV modules, a new snow detection method was developed. Using local snow depth estimation from the Norwegian Water Resources and Energy Directorate [13], and power and irradiance data for the system, the variation in DC voltage for the system under normal conditions and for snow melting periods was found. In periods with partial snow cover, the DC voltage of each string has increased variation compared to normal operation, and there is larger variation between different inverters. A threshold for DC voltage variation was determined empirically. The periods with full snow cover and partial snow cover was accordingly removed based on a combination of snow depth data and the DC voltage variation limit for normal operating conditions.

3.3.2 Morning/evening effects

As expected, there were large relative variations in Y_f and PR_{TC} in the morning and evening. One of the main explanations for this is variations in low light behavior of the PV modules and inverters. Both the low irradiance and the increased share of diffuse light in the morning and evening will influence variation in PV module behavior. Additionally, small variations in PV module tilts, as discussed in depth in the next section, can lead to significant differences in the angle of incidence of the incoming light, and consequently a variation in reflected and received irradiance. By relating the Y_f and PR_{TC} to irradiance level and solar elevation, it was found that for this specific system, these effects were most prominent for irradiance values < 50 W/m^2 and solar elevation < 10°. A general algorithm for estimating the optimal filtering threshold of these values for different locations is proposed in [9].

3.3.3 Physical irregularities in the installation

Due to physical limitations in PV system installations such as variations in roof inclination, topography, objects shadowing the PV modules, different PV modules/inverter strings might receive different irradiance, resulting in different energy output. This can also affect the irradiance sensor. Also, other technical irregularities in the installation and variations in local climate can lead to variation for a PV system in e.g. temperature and soiling patterns. For this system, particularly two installation specific irregularities influence the monitoring output: the modules in one of the strings had a different tilt angle from the rest, and there was a difference in the tilt of the modules and the POA irradiance sensor. The effect of each of these aspects of the installation are explained in the following.

The variation in received irradiance on the different inverter strings are illustrated in Figure 4, using the DC current. As shown in this figure, inverter 6 has a current curve with a clearly different shape than the other inverters. This is due to the 1-2° tilt in the North and the South direction of the roof (while the PV modules are faced East). Where the rest of the inverters have PV modules that is both tilted slightly towards South and North, inverter 6 has only South tilted modules. This leads to significant variation in irradiance conditions, also on an hourly basis, between inverter 6 and the rest of the inverters and weakens the basis for comparison.

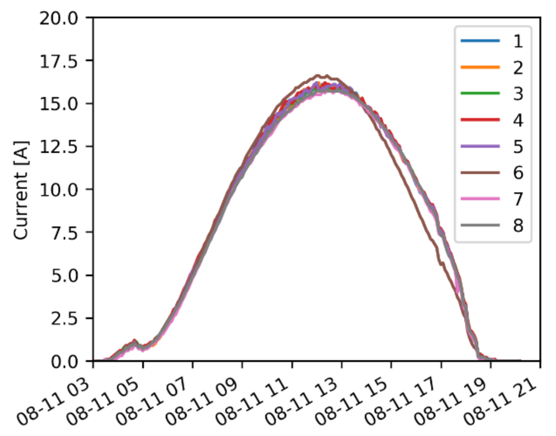

Figure 4: The DC current for each inverter during one clear day (5 minute averages), illustrating the variation in received irradiance for the inverter strings.

For the PR_{TC} values, it was observed especially high values in the morning, and very low values in the afternoon. This was found to be because of the tilt of the reference cell, which was 1-2° lower than the average tilt of PV-modules. Additionally, it had a 1-2° tilt towards South. Consequently, there are several hours the reference cell is not measuring a representative irradiance for the PV system. Difference in tilt between reference cell and the PV modules is an issue that will influence most irradiance based performance metrics.

These effects were filtered out based on deviations between the estimated clear sky behavior [12] for each inverter and between the inverters and the reference cell.

3.4 Effect of the identified issues on the performance metric variation

The effect of consecutively removing the issues identified and described in Section 3.3, are shown for each inverter in Figure 5, and for the average of all the inverters in Table II. The percentage of remaining data after removing the effects is also given in the table.

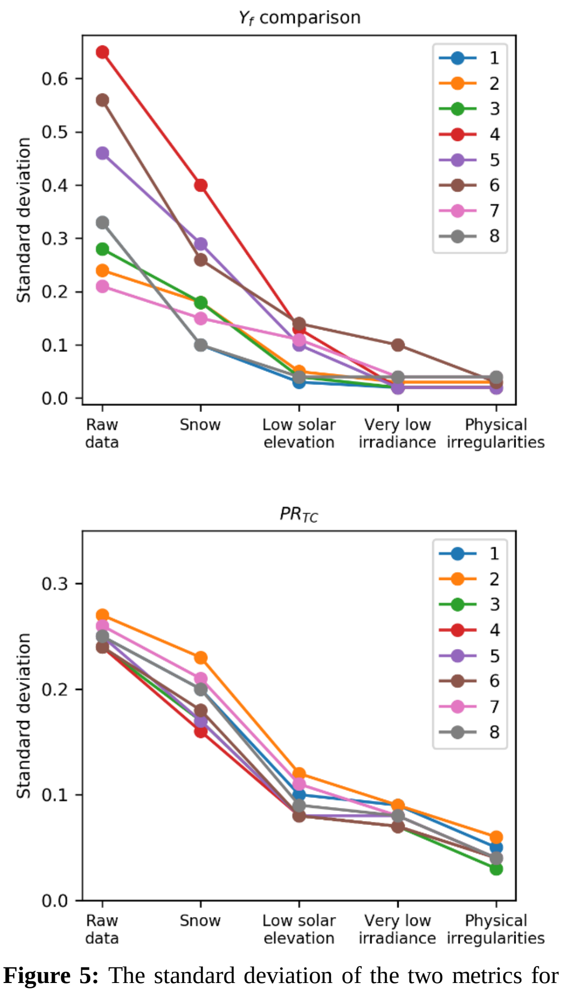

Figure 5: The standard deviation of the two metrics for each inverter, where the effects leading to unstable periods are consecutively removed.

Compared to the results of the standard filtering approach presented in Table I, the variation is significantly decreased and at the same time less data is removed. In the comparison of the specific yield, removing periods where there were large variations in incoming irradiance because of physical deviations was only relevant for inverter 6, as this is the only inverter that has significantly different installation configurations compared to the other inverters. For the PR_{TC}, removing this effect influence the variation for all the inverters because the irradiance sensor has different tilt angles than all the PV module strings.

Table II: The average standard deviation of the two metrics for all inverters, where the effects leading to unstable periods are consecutively removed. Remaining data after filtering is also given.

	Avg σ Y_f comparison	Avg σ PR_{TC}	Remaining data
Raw data	0.38	0.25	100 %
Snow	0.21	0.19	84 %
Low solar elevation	0.08	0.09	63 %
Very low irradiance	0.04	0.08	58 %
Physical irregularities	0.03	0.04	Inverter specific

4 CONCLUSIONS

The results show that naive use of standard performance metrics such as specific yield and temperature corrected performance ratio in a monitoring system for PV installations, give unreliable results with high variation in the PV system performance estimation. This will both reduce the sensitivity and the fault detection ability of the monitoring system and typically result in false alarms. Very low solar elevation and irradiance, snow and technical irregularities in the installation are the primary causes of the high variation in the monitoring output. It is shown that for certain climates standard filtering is not sufficient to solve these problems, and that site-specific filtering of data gives more stable monitoring output, entailing more data and less variation.

REFERENCES

[1] A. Triki-Lahiani, A.B.-B. Abdelghani, I. Slama-Belkhodja, Fault detection and monitoring systems for photovoltaic installations: A review, Renew. Sustain. Energy Rev. (2017). doi:https://doi.org/10.1016/j.rser.2017.09.101.
[2] D.C. Jordan, C. Deline, S.R. Kurtz, G.M. Kimball, M. Anderson, Robust PV Degradation Methodology and Application, IEEE J. Photovoltaics. (2017) 1–7. doi:10.1109/JPHOTOV.2017.2779779.
[3] S. Silvestre, L. Mora-López, S. Kichou, F. Sánchez-Pacheco, M. Dominguez-Pumar, Remote supervision and fault detection on OPC monitored PV systems, Sol. Energy. 137 (2016) 424–433. doi:10.1016/j.solener.2016.08.030.
[4] G. Belluardo, P. Ingenhoven, W. Sparber, J. Wagner, P. Weihs, D. Moser, Novel method for the improvement in the evaluation of outdoor performance loss rate in different PV technologies and comparison with two other methods, Sol. Energy. 117 (2015) 139–152. doi:10.1016/j.solener.2015.04.030.
[5] K. Kiefer, D. Dirnberger, B. Müller, W. Heydenreich, A. Kröger-Vodde, A Degradation Analysis of PV Power Plants, Proc. 25th Eur. Photovolt. Sol. Energy Conf. (2010) 5032–5037. doi:10.4229/25thEUPVSEC2010-5BV.4.26.
[6] D.C. Jordan, S.R. Kurtz, The dark horse of evaluating long-term field performance-Data filtering, IEEE J. Photovoltaics. 4 (2014) 317–323. doi:10.1109/JPHOTOV.2013.2282741.
[7] M.B. Øgaard, H. Haug, J. Selj, Methods for Quality Control of Monitoring Data from Commercial PV Systems, in: Eur. Photovolt. Sol. Energy Conf. Exhib. METHODS, 2018: pp. 2083–2088. doi:10.1093/annonc/mdy039/4835470.
[8] B. Marion, J. Adelstein, K. Boyle, H. Hayden, B. Hammond, T. Fletcher, D. Narang, A. Kimber, L. Mitchell, S. Richter, Performance parameters for grid-connected PV systems, Photovolt. Spec. Conf. 2005. Conf. Rec. Thirty-First IEEE. 31 (2005) 1601–1606. doi:10.1109/PVSC.2005.1488451.
[9] Å. Skomedal, M.B. Øgaard, J. Selj, H. Haug, E.S. Marstein, General, robust, and scalable methods for string level monitoring in utility scale PV systems, 36th Eur. Photovolt. Sol. Energy Conf. Exhib. (2019).
[10] M.J. Reno, C.W. Hansen, Identification of periods of clear sky irradiance in time series of GHI measurements, Renew. Energy. 90 (2016) 520–531. doi:10.1016/j.renene.2015.12.031.
[11] W. F. Holmgren, C. W. Hansen, M. A. Mikofski, pvlib python: a python package for modeling solar energy systems, J. Open Source Softw. (2018). doi:10.21105/joss.00884.
[12] B. Meyers, M. Tabone, E.C. Kara, Statistical Clear Sky Fitting Algorithm, Conf. Rec. IEEE Photovolt. Spec. Conf. (2018) 1–6. http://www.wcpec7.org/eWCPEC/manuscripts/MeWCPEC930_0521112519.pdf.
[13] NVE, seNorge, (n.d.). www.senorge.no (accessed September 1, 2019).