On the Construction of Energy Efficiency-based Degradation Indicator for Photovoltaic Solar Inverters

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Abstract

Photovoltaic systems are essential in the renewable energy sector, addressing global energy needs. Photovoltaic (PV) inverters, which convert direct current (DC) from solar panels to alternate current (AC) for grid use, are the most failure-prone components in these systems. This study aims to develop a degradation indicator based on energy efficiency for PV inverters to enhance their reliability and lifetime management. Through analysis of data from 35 PV plants in central Europe, involving eight inverter brands and fourteen models, this research identifies trends in inverter efficiency degradation. Despite literature suggesting minimal efficiency impact over time, our findings demonstrate measurable efficiency degradation, providing a new key performance indicator for proactive maintenance and replacement strategies.

1. Introduction

Photovoltaic (PV) systems have become a cornerstone in the renewable energy landscape, providing a sustainable solution to the increasing global energy demands. Central to the operation of these systems are PV inverters, which convert the direct current (DC) produced by solar panels into alternating current (AC) for grid use. Despite their critical role, PV inverters are the most failure-prone components in solar energy systems, significantly affecting overall system performance and reliability (Gunda et al., 2020; Lindig et al., 2022). Furthermore, their failure can lead to the shutdown of the entire system.

Unscheduled interruptions of the system operation will decrease production, increase operational costs and reduce the quality of service, and profitability. Predicting the lifetime of the devices allows better scheduling of maintenance interventions to avoid unexpected downtime. Reliability is a concept that is difficult to measure and quantify, current techniques to predict wear-out failures include model-based lifetime prediction methods or data-driven methods (Rahimpour et al., 2022). This is quite a challenging task; it requires an initial lifetime analysis, which consists of investigating the failure mechanisms of different components of the system along with identifying the failure data for the assessment (Abuelnaga, Narimani, & Bahman, 2021). It is followed with a lifetime prediction, evaluating failure rates at the component level. Then the provided failure rates are summed to generate the system-level lifetime estimation. This process requires the estimation of both the random failure behavior and the prediction of wear-out failures. The latter includes several steps, such as collecting data from the mission profile (any possible stressors to the components), test data, and field data. The next step is to translate the data to a thermal profile using an electro-thermal model. After a cycle counting process, a proper lifetime model should be chosen to provide the number of cycles to failure (Rahimpour et al., 2022).

Given the complexity and amount of required data of current methods to develop a lifetime prediction model, this article proposes to simplify the process of lifetime management via the measurement of the trend of efficiency of the inverters as a Key Performance Indicator (KPI). This work will present in which manners the different failures and performance of the inverter are related, and how using appropriate methods, the trend of efficiency of the inverter can be measured.

Inverter efficiency degradation is a topic that has not been much explored yet in the literature. Current literature suggests that the inverters do not degrade enough over time to impact the performance of the system significantly. However, that does not mean that the trend of efficiency can not be measured. In this paper, we propose an innovative method for measuring the trend of inverter efficiency. In that way, this paper presents some significant findings from over thirty-five PV plants located in central Europe, eight different inverter brands, and a total of fourteen different inverter models. Our investigation shows the degradation of the inverters' efficiency over time, which can then be used as a KPI for the lifetime management of the component.

The organization of this paper is as follows. Section 2 presents the main operating principles of an inverter, followed by an explication of the basic electrical losses found in the inverter. The relationship these losses have with temperature, failure modes, and performance and why they matter to develop a new health indicator are explored in this section. Section 3 presents the current position the literature has on the long-term degradation of the efficiency of inverters, followed by a new proposed methodology to measure the trend of efficiency on inverters. Section 4 presents the dataset employed for the development of this article and the results found regarding the measurement of the trend of degradation in inverters. Finally, the conclusions are presented in section 5.

2. OVERVIEW OF PHOTOVOLTAIC INVERTERS AND LIFETIME MANAGEMENT

Grid-connected PV systems are composed of PV modules, inverters, and transformers. The first of these generates DC power from the incoming irradiance. This DC power needs to be transformed into AC power to be fed into the grid, this is the job of the inverter, it converts the DC power into AC power among other responsibilities. Before entering the grid, the transformer raises the voltage of the AC power to minimize conduction losses.

The inverters' main goal is to convert DC power into AC by controlling the use of insulated gate bipolar transistors (IGBTs) or metal-oxide-semiconductor field-effect transistor (MOSFET) that act as switches. Power MOSFETs are used for low operating power and higher switching frequencies, whereas IGBTs are used for higher operating power and lower switching frequencies (Nagarajan, Thiagarajan, Repins, & Hacke, 2019). There operating principles remain the same, they are both voltage controlled devices. These switches control the direction of the current, and the time it passes through the load to simulate a sinusoidal wave typical of AC current. The whole process receives the name of pulse width modulation (PWM)

Inverters are a critical component of the PV system because a failure or malfunction means that the production of every module connected to it will be lost, impacting the profitability of the PV system. This is especially true for large inverters that have a large amount of modules connected to them. Furthermore, PV inverters are the most prone to failure components in the system (Lindig et al., 2022; Jordan, Marion, Deline, Barnes, & Bolinger, 2020; Filho, Zúñiga, Fernandes, Branco, & Pais, n.d.). Not surprisingly, given the key role of the inverter in the system, its failures account for very important energy losses, up to 36 % in (Golnas, 2013). The high frequency of inverter failures is attributed to the multiple subsystems (with little redundancy in power electronics) that support a multitude of functions in harsh environments (Gunda et al., 2020).

2.1. Losses and cycles to failure

The lifetime of an inverter can be studied through a physics of failure assessment (Nagarajan et al., 2019). A physics-of-failure assessment is understood through the fail mechanism of the components of power converters and external physical stressors, such as ambient temperature, solar irradiance, and relative humidity (Wang et al., 2014; Chung, Wang, Blaabjerg, & Pecht, 2015; Y. Yang, Sangwongwanich, & Blaabjerg, 2016). Possible and common failures that occur at the grid-connected inverter include IGBT failure, such as open circuit (OC) or short circuit (SC), or DC link capacitor failure (Kurukuru, Khan, & Malik, 2021; Kurukuru & Khan, 2022).

The failure modes of the power electronics are complicated and are affected by many factors, but thermal cycling is one of the most critical failure causes in power inverters (Nagarajan et al., 2019). The switching devices can suffer several types of losses, such as switching losses, conduction losses, or reverse conduction losses. This power losses lead to temperature fluctuations within devices, leading to different materials having mismatched coefficients of thermal expansion (CTE), causing disconnection in the contacting areas after certain cycles, and ending in the failure of the devices. Furthermore, the short lifetime of power electronic devices is mostly due to thermal stresses in their switching devices (such as the IGBT), and these wear-out failures affect the device's long-term performance (Rahimpour et al., 2022).

Conduction losses in a MOSFET or IGBT are an example of how temperature and losses are related to each other. Eq. (1) defines the power conduction losses, P_{cond}, in a MOSFET:

$$P_{cond} = I_D^2 \times R_{DSON} \tag{1}$$

where I_D corresponds to the drain current and $R_{DS(ON)}$ is the on-state resistance between the drain and the source. The $R_{DS(ON)}$ parameter is dependent on the junction temperature of the power MOSFET and is given in the specification sheet from the manufacturer. The variation of the on state resistance against junction temperature for a given MOSFET can be seen in Fig. 1. This means, an increase in temperature translates to an increase in conduction losses. The other main source of losses in a switch are the switching losses, which are also increased as the junction temperature increases. This can be seen in the data-sheet of any IGBT, an example is provided in Fig. 2.

Temperature cycling is also one of the main causes of failures in the inverter. A popular model used to predict failures caused by cracks or deformations due to thermomechanical stresses in electronic components is the Coffin-Manson model. It predicts the number of kilocycles to failure, N_f, as seen in Eq. (2):

$$N_f = a \times (\Delta T_j)^{-n} \times e^{\frac{kT_m}{E_a}} \quad (2)$$

where a is the experimental coefficient, ΔT_j are the different junction temperatures, n is the Coffin-Manson coefficient, E_a is the activation energy, k is the Boltzmann constant and T_m is the mean junction temperature. What this equation tells us is that the more temperature swings in the junction, the sooner the component will fail. Other models like the Norris-Landsberg or the Bayerer model expand the above equation, but in all cases, the number of cycles to failure is decreased with the increase in junction temperature fluctuations.

2.2. Failure modes & performance loss of PV inverters

IGBT failure can be classified in wear-out failures and catastrophic failures. The first are experienced due to long-time operation of the device and power cycling (Gao, Cecati, & Ding, 2015), the latter occur due to over-stress events such as a sudden rise in voltage, current or temperature. The failure of the power switching devices can also be divided into chip-related failure mechanism and package-related failure mechanism (S. Yang et al., 2010). Most of the chip-related failures are catastrophic failures since they may permanently damage the module . Chip-related failures occur due to excessive electrical, thermal or mechanical stress. Module packaging failures are more associated with wear-out failures that occur due to thermomechanical fatigue stress and do not necessarily mean the complete failure of the system but can impact performance.

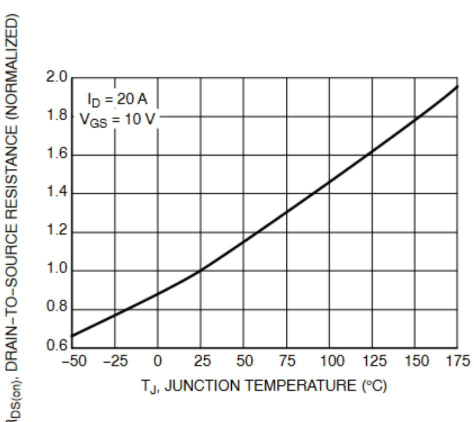


Figure 1. $R_{DS(ON)}$ variation with junction temperature, T_j for an NTB5860NL MOSFET

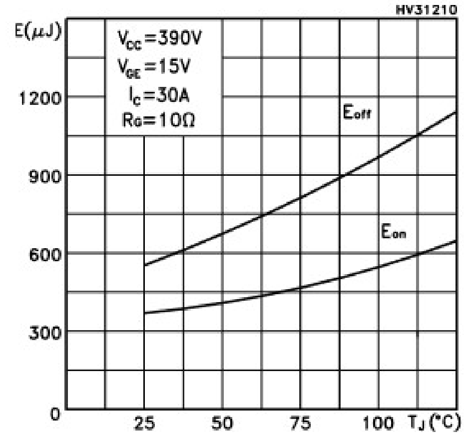


Figure 2. Switching losses vs temperature in IGBT STGW39NC60VD

The failure mechanism that are most frequently observed in power devices are due to thermomechanical fatigue stress experienced by the packaging materials (S. Yang et al., 2010). These failures occur mostly due to the mismatch in the CTE of the materials used for the chip and the packaging. Some examples of these failures are bond wire liftoff and solder fatigue.

(I) Bond Wire Liftoff: Bond failures are mainly caused by crack growth at the bond wire/chip interface due to temperature swings and the different CTE between Si and Al (Held, Jacob, Nicoletti, Scacco, & Poech, 1997; Kurukuru et al., 2021). The strain difference between the two materials causes stress, and that depends on the temperature.

(II) Solder Fatigue: solder fatigue is one of the major causes of wear-out failure in IGBT (Kurukuru et al., 2021). Solder fatigue generates a cracking between the module substrate and the base plate and/or the device chip and substrate (Ratchev, Vandevelde, & DeWolf, 2004). This failure arises because the silicon die and copper substrate have different CTE, resulting in stress in the solder layer and eventually cracks (voids) (S. Yang et al., 2010). These voids reduce the effective area for heat to escape by conduction from the die; therefore, extremely localized heating occurs in the die due to increased thermal resistance, and the process accelerates as the voids grow (Koziarz & Gilmour, 1995; Ciappa & Castellazzi, 2007). The severe localized heating due to increased thermal resistance can damage the chip (S. Yang et al., 2010).

These failures can have a significant impact on the reliability and performance of the inverter. Bond-wire liftoff is one of the main causes of failure mechanisms in power electronic devices. Solder fatigue is an example of how a wear-out failure can turn into a catastrophic failure.

Regarding the impact on performance, a study (Kaplar et al., 2011) tested the performance of IGBT devices under normal and extreme operating conditions. These devices were tested by supplying the maximum rated current for 45 minutes while controlling the temperature. Most inverters showed negligible degradation, however, a few devices degraded considerably even under rated conditions. Several defects appeared during these tests, such as an increase in leakage current and increased gate oxide leakage current. The first failure does likely not cause the failure of an inverter but can degrade performance. Gate oxide leakage current will mean the device will no longer be able to control the current. The inverter will not be able to operate correctly under this conditions.

The AC stress that the IGBTs are subject to were also tested to emulate the conditions found inside an inverter. Due to the PWM technique employed by the inverter the IGBT operates under current levels that exceed rated operating conditions (only for very short periods of time). Damage resulting from this scenario could potentially be cumulative, as the device will be subject to numerous on-off cycles.

In summary, electrical losses in the semiconductors can be translated to an increase in temperature, which leads to a reduced number of cycles to failure or a reduced remaining useful life (RUL) of the component. Not only that, the increase in temperature also increases the chance of wear-out failures occurring, which reduces the performance of the inverter. This is illustrated in Fig. 3. These relationships indicate the same mechanism impacting the efficiency of the inverter and its RUL. Therefore, it is sensible to believe that the RUL and the efficiency of an inverter are related.

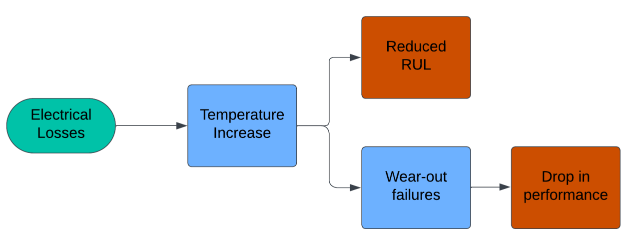


Figure 3. Relationship between electrical losses, temperature, remaining useful life and performance

3. ENERGY EFFICIENCY-BASED HEALTH INDICATOR

3.1. Inverter efficiency and degradation

The efficiency of the inverter (η_{inv}) is defined as the output AC power divided by the input DC power.

$$\eta_{inv} = \frac{P_{AC}}{P_{DC}} \tag{3}$$

The efficiency of the inverter is affected by several factors, and it is shown in (Boyson, Galbraith, King, & Gonzalez, 2007) that voltage and load level have the most impact on efficiency. Load level (α) is defined as the ratio between the output AC power and the nominal power of the inverter.

$$\alpha = \frac{P_{AC}}{P_{nom}} \tag{4}$$

Fig. 4 shows how, using these two parameters , manufacturers describe the efficiency curve of an inverter for different voltage and load level values. Manufacturers also provide a single numeric value to estimate the overall efficiency of the inverter, the euro-efficiency or Californian Energy Commission (CEC) efficiency of the inverter. The Euro-efficiency of an inverter is defined as:

$$\begin{aligned}\eta_{euro} = 0.03\eta_{5\%} + 0.06\eta_{10\%} + 0.13\eta_{20\%} + \\ 0.1\eta_{30\%} + 0.48\eta_{50\%} + 0.2\eta_{100\%}\end{aligned} \tag{5}$$

It is an estimation of what percentage of operating time will an inverter be functioning under certain load levels. Those estimations are for an inverter installed in central Europe, which is the case for the dataset handled in this article.

Most of the work regarding PV inverters has to do with failure modes or failure rates. There seems to be little work done in measuring the degradation of the efficiency, but there is some. Work done towards studying the PV fleet degradation (Jordan et al., 2022) suggests there is no inverter efficiency degradation. When both AC and DC data from one PV plant were available, performance loss ratios (PLRs) for both were computed and compared. AC and DC PLR are centered on zero, indicating that changes in inverter performance over time do not generally contribute to system PLR.

Further work comparing the efficiency of inverters installed

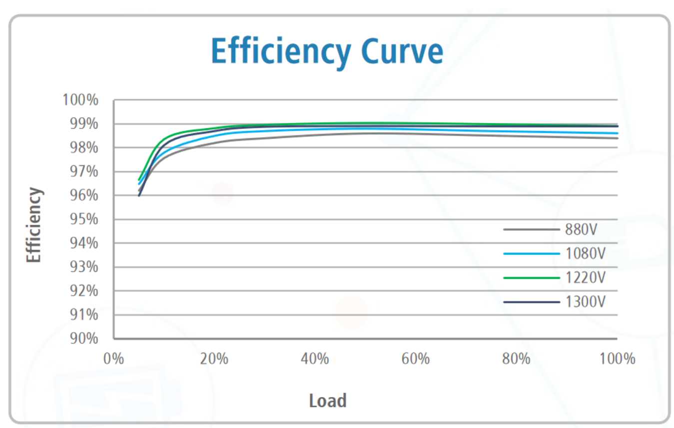


Figure 4. Efficiency curves of Huawei SUN2000-100KTL-H1

in 2014 and 2019 (Lightfoote, Wilson, & Voss, 2021) found them to perform almost exactly the same and arrived at the conclusion there is no inverter efficiency degradation. In a similar manner, work studying different performance metrics of a PV plant over 10 years found no significant degradation on the efficiency of the inverter, however, elevated ambient temperature left a negative impact on the inverter efficiency (Mishra, Rathore, Varma, & Yadav, 2024).

Another article studied the factors affecting the efficiency of the inverter in the lower northern region of Thailand (Ketjoy, Chamsa-ard, & Mensin, 2021). This work points to temperature as a factor affecting the efficiency of the inverter, and when the ambient temperature rises above 37ºC, the efficiency is decreased by 2.5%. However, by maintaining the installed inverters at a controlled temperature of 25ºC during the four-year study, the efficiency of the inverter did not decrease during the whole test period.

Work studying the efficiency of switching devices did not identify any trend in long-term efficiency degradation of the inverter. However, it states that high frequency of switching contributes to a decrease in efficiency, albeit minimum (0.2 %), and an increase in the temperature of the case of the switches (Anthon, Zhang, Andersen, & Franke, 2015).

Overall, the literature suggests the efficiency of inverters do not degrade, or not enough to impact the production significantly. There is also consensus that high temperatures impact the efficiency of the inverter. This is not surprising, by recalling section 2 it is clear that temperature and losses in the inverter are correlated. Additionally, an increase in mean junction temperature or temperature swings will decrease the lifetime of the inverter , and increase conduction and switching losses. For these reasons, it is sensible to believe that inverters that show a decrease in efficiency will also be more prone to failure than those that do not.

It is possible that the efficiency of the inverter does not degrade enough to significantly impact the production while there still could be a measurable (although not significant for the performance) degradation of the inverter. The next section will present a method to measure the efficiency of an inverter over time.

3.2. Construction of energy efficiency-based health indicator

The proposed method for the construction of inverter health indicators based on energy efficiency features is divided into three steps: (1)-data cleaning and pre-processing; (2)-efficiency curve construction, and (3)-degradation trend testing.

3.2.1. Data cleaning and pre-processing

Simple pre-processing techniques are employed to remove unwanted data and allow the necessary computations to be performed. In the first place, the nominal power from each inverter is assumed by using the data of the top power-producing moments. Data is then normalized between 0 and 1 using this value. The efficiency and load level are computed at every timestamp according to Eq. (3) and Eq. (4). Efficiency values over one are removed since they are physically impossible.

3.2.2. Efficiency curve construction

To measure the trend on inverter efficiency, the collected data for each inverter is divided by month, and the efficiency curve (as seen in Fig. 4) is generated from data. To compute the curve, every data point is floored and grouped to an integer value. The median value of that group is chosen to be the representative of the efficiency for that load level in that month. A visualization of this method can be seen in Fig. 5, where the blue data points represent the individual samples, and the red dot is the median value for that integer group of values.

Equation (5) is a good way to reduce the efficiency curve to a single number if the goal is to understand the impact it has on production (the weights associated with each load level represent the expected time the inverter will work under that operating condition), but the goal of this study is to measure any possible efficiency degradation whether it impacts or not the performance of the inverter. For that reason, the area under the curve (AUC) of the efficiency curve is decided as a measurement of the efficiency of the inverter. This ensures that every load level receives the same importance.

This method runs into problems when comparing the AUC of a winter month against a summer month. During the winter, the maximum irradiance values are lower than during the summer (sun does not shine as bright), hence, the inverters highest capacity is not reached.This means there is no data to draw a complete curve across all the load levels (neither

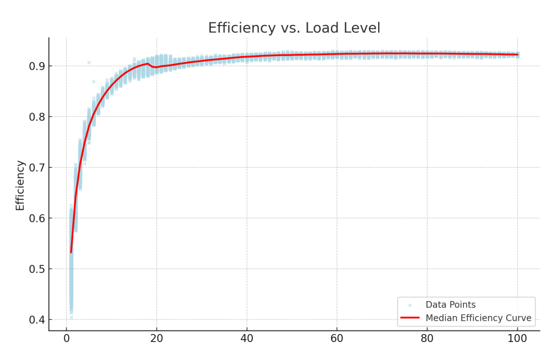


Figure 5. Visual representation of the computation of the efficiency curve

would there be data to complete Eq. (5)), as illustrated in Fig. 6.

The solution proposed to be able to follow the trend of efficiency is to divide the analysis by bins of load level range. Each bin is equal to 10 consecutive load levels (e.g.,1-10, 11-20). If every load level within the bin has an associated efficiency value, the AUC for that bin and month can be calculated. This ensures that the computation of the AUC is not affected by the lack of data at certain ranges of operation during winter.

This, however, means that for higher load levels, there will inevitably be missing data, as some months do not present data for those load levels. To measure the trend in the evolution of the efficiency for each bin, it is necessary to have/dispose a method that can handle missing data appropriately.

3.2.3. Degradation trend testing

The Mann-Kendall test is designed to statistically assess if there is an upward or downward monotonic trend. A monotonic trend means that the variable consistently increases or decreases over time, but the trend might not be linear. Consider a time series of data points $(x_1, x_2, \ldots, x_n)$. For each pair of observations (x_i, x_j) where $i < j$:

$$\text{sign}(x_j - x_i) = \begin{cases} +1 & \text{if } x_j - x_i > 0 \\ 0 & \text{if } x_j - x_i = 0 \\ -1 & \text{if } x_j - x_i < 0 \end{cases} \tag{6}$$

The statistic S is the sum of these signs:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}(x_j - x_i) \tag{7}$$

If S is a positive number, observations obtained later in time tend to be larger than observations made earlier. If S is a negative number, then observations made later in time tend to be smaller than observations made earlier. The variance $\text{Var}(S)$ under the null hypothesis (no trend) is given by:

$$\text{Var}(S) = \frac{n(n-1)(2n+5)}{18} \tag{8}$$

The standardized test statistic Z is calculated as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \tag{9}$$

A positive value of Z indicates that the data tends to increase with time. A negative value indicates data tends to decrease with time. To test the statistical significance of the results, the p-value is computed in the case of no ties with an algorithm provided in (Best & Gipps, 1974). In cases of missing data, the test will run as usual, simply comparing the available consecutive data points.

3.3. Software and tools used

To work in this article was developed in VScode, using Python 3.11.3. The libraries used were Pandas (2.2.1) and scikit-learn (1.4.1).

4. CASE STUDY

4.1. Description of the Dataset

The acquired dataset consists of inverter data production from over thirty-five different PV plants located in central Europe, eight different inverter brands and a total of fourteen different inverter models compose the dataset with a total of 646 inverters. The total capacity of the inverter ranges from 1 kW to up to 400 kW. Overall, the operational time of the PV plants ranges from 2 and a half years to almost 6 (71 months). We can assume the inverter's lifetime is equal to the PV plant since the data comes from PV plants that have been re-powered. The distribution of nominal power of the inverters and operational time of each PV plant can be seen in Fig. 7.

Being such a heterogeneous dataset, with different locations, inverter brands and models, plant size and even acquisition techniques, the data quality is also varied across different PV plants. We can identify two distinct cases: when the DC power reading comes directly from the inverter and when it does not. In the first scenario, the data quality is higher. This means that the cloud of data points across the efficiency against load level graph better resembles what we expect from an inverter. In the second scenario, the DC power must be computed from the readings of current and voltage per each MPPT that goes into the inverter, this creates noisy efficiency curves. This is due to several reasons:

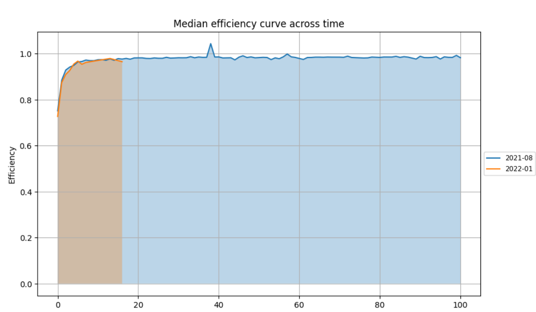
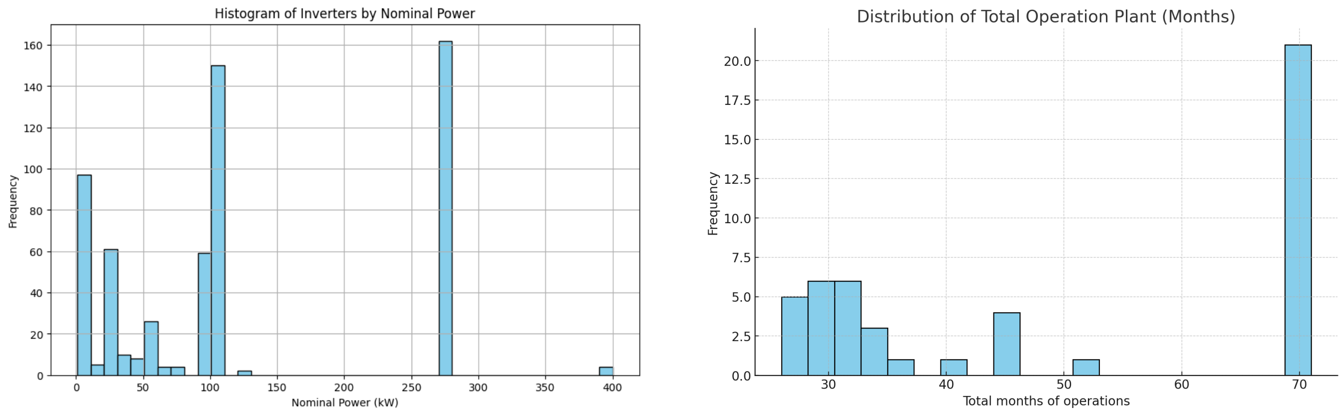


Figure 6. Comparison of the AUC for the efficiency curve of an inverter in August against January



(a) Distribution of nominal power of the inverters

(b) Distribution of operational time of the PV plants

Figure 7. Distribution of (a) Inverters by Nominal Power and (b) operational time of different PV plants

1. Sensors are all connected close to the inverter input, close to one another. This increases the risk of inference from one sensor to another.
2. The maintenance crew have observed how disconnected strings still have positive readings of currents flowing through them, this is due to residual currents.
3. DC data are more likely instantaneous data compared with the more commonly time-averaged AC data (Jordan et al., 2022).

This generates data points that are clearly erroneous, such as efficiency values over one, which is physically impossible for any system. These data points need to be handled appropriately.

4.2. Results and discussion

Visualizing the trend of efficiencies for each bin makes it apparent that the lowest load level bin (1 to 10) has a much higher variability. For this reason, this bin of load level is excluded from the analysis.

Following the process described in section 3.2.2, delivers one efficiency value for each load level range each month. Fig. 8 is an example of the trend of AUCs obtained for one inverter; each point is the efficiency of a given load level range at a certain month, and each color follows the trend for one load level range. This particular example follows the expected behavior of an inverter: lower load levels have a lower efficiency, and the efficiency then stabilizes slowly and reduces for the highest load level. This example also shows decreasing trends of efficiency for eight out of nine of the bins. The results of the Mann-Kendall tests can be seen in Table 1.

Fig. 9 and Table 2 shows the data points and the simplified test results for an inverter where the degradation is only identified for a few subsets of the bins. Utilizing this methodology, we are able to identify degradation patterns that are not as clear (unlike those in Fig. 8). By dividing the performance of the inverter into different bins of operating ranges, it is possible to identify degradation specific to these ranges, allowing to find characteristics that would otherwise been left unnoticed.

Running the methodology provided 509 successful tests. For each inverter, 9 curves are analyzed. This is a total of 4581 curves. The distribution of the results can be seen in Fig. 10.

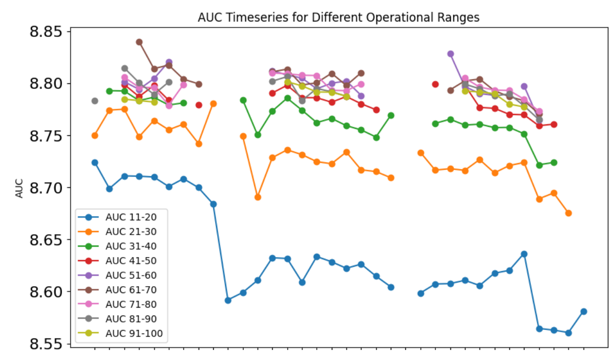


Figure 8. AUC trend of load level bins for inverter with 8 bins with descending trend

Table 1. Results of the Mann-Kendall test for different data segments.

L.L. Range	Trend	p-value	Z	S
11-20	decreasing	0.000002	-4.756785	-308.0
21-30	decreasing	0.000001	-4.996947	-295.0
31-40	decreasing	0.000002	-4.760975	-217.0
41-50	decreasing	0.000803	-3.351858	-112.0
51-60	decreasing	0.043546	-2.018439	-50.0
61-70	decreasing	0.000119	-3.848413	-111.0
71-80	decreasing	0.040816	-2.045396	-55.0
81-90	decreasing	0.043546	-2.018439	-50.0
91-100	no trend	0.299665	-1.037151	-18.0

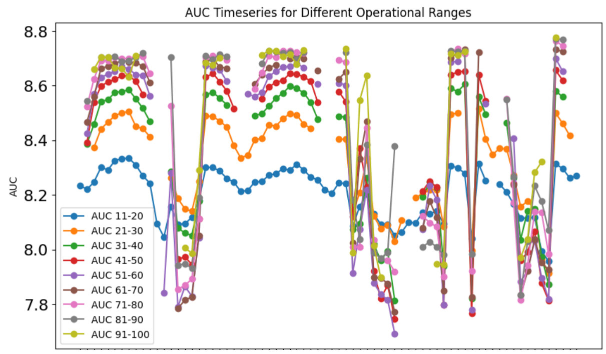


Figure 9. AUC trend for inverter with three bins degrading

Table 2. Trend classification for different data segments.

Load Level Range	Trend
11-20	decreasing
21-30	decreasing
31-40	decreasing
41-50	no trend
51-60	no trend
61-70	no trend
71-80	no trend
81-90	no trend
91-100	no trend

More than half the curves show no trend, and there are almost 4 times more decreasing trends than increasing. Further analysis revealed that only 17 out of the 509 inverters (3.34 %) presented both increasing and decreasing trends for different bins. This suggests that the results are not random.

Simplified results divided by load level can be seen in table 3. The amount of increasing trends across the different load levels is quite stable. In contrast, the number of decreasing trends increases as the load levels are higher. These ranges of load level present a more linear behavior (Fig. 4), and thus, small degradation trends should be more easily identifiable.

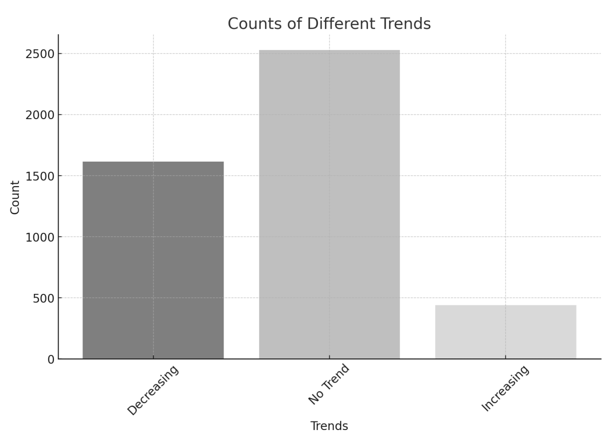


Figure 10. Distribution of trends of AUC for all inverters

Table 3. Trend counts for different data segments.

Load Level Range	Decreasing	No trend	Increasing
11-20	134	329	46
21-30	147	313	49
31-40	136	329	44
41-50	164	299	46
51-60	187	272	50
61-70	197	262	50
71-80	240	217	52
81-90	237	222	50
91-100	172	285	52

5. CONCLUSIONS

This study has shown how power losses relate to temperature changes in the switching devices, as well as compiling state of the art suggesting that temperature impacts the performance of the inverter. Additional relationships between the temperature changes and the probability of a wear-out failure have been presented. Given these relationships, the study of the degradation of efficiency in photovoltaic solar inverters provides critical insights into the long-term performance and reliability of PV systems. This research identifies key factors contributing to inverter efficiency loss, including thermal cycling, electrical overstress, and environmental conditions such as ambient temperature.

The findings indicate that while inverter efficiency degradation over time is generally not significant enough to impact the overall production of PV plants, it is nonetheless present and measurable. The proposed method for measuring efficiency degradation, utilizing the area under the curve (AUC) approach, dividing the efficiency curve by bins and using the Mann-Kendall test, proves effective in identifying trends in efficiency that would have otherwise gone unnoticed.

There are already existing methods for lifetime management of power electronic converters. However, these methods are complicated, require several steps and have big data requirements. Defining the health indicator by means of its efficiency is very simple, as it only requires to know the input DC power and output AC power of the inverter.

To study the relationship between this new KPI and the failure of the inverter remains work for the future. This includes identifying examples of inverter failures using the production data and the maintenance tickets, followed by studying how the KPI behaves before those instances. But still, another way to define the failure of the component is by performance loss, which can be achieved using this methodology.

In conclusion, while the degradation of inverter efficiency may not drastically reduce PV plant output, it remains a factor in the overall reliability and economic viability of solar energy systems. Ongoing monitoring, combined with strategies to mitigate the identified stressors, will be crucial in enhancing the durability and efficiency of future PV inverters. This research contributes valuable knowledge towards optimizing PV system maintenance and improving the resilience of solar power infrastructure by identifying the link between efficiency and RUL and showing new ways to measure small changes in efficiency in inverters that are not clearly identifiable by looking at the overall performance.

Future work includes the acquisition of a dataset that spawns over the lifetime of an inverter. These usually have life expectancy of over 10 years, however in the current dataset the longest recorded data is almost six years long. Examples of inverters that operate until death will provide additional information on the behavior of the inverter at the latest stages of life. Additional steps in that regard include setting thresholds for the inverter efficiency to estimate when the component has entered the wear-out phase and begin the estimation of the RUL.

REFERENCES

Abuelnaga, A., Narimani, M., & Bahman, A. S. (2021). A Review on IGBT Module Failure Modes and Lifetime Testing. *IEEE Access*, *9*, 9643–9663.

Anthon, A., Zhang, Z., Andersen, M. A. E., & Franke, T. (2015, March). Efficiency evaluation on a CoolMos switching and IGBT conducting multilevel inverter. In *2015 IEEE Applied Power Electronics Conference and Exposition (APEC)* (pp. 2251–2255). Charlotte, NC, USA: IEEE.

Best, D. J., & Gipps, P. G. (1974). Algorithm AS 71: The Upper Tail Probabilities of Kendall's Tau. *Applied Statistics*, *23*(1), 98.

Boyson, W., Galbraith, G., King, D., & Gonzalez, S. (2007, September). *Performance model for grid-connected photovoltaic inverters.* (Tech. Rep. Nos. SAND2007-5036, 920449).

Charalambous, A., Hadjidemetriou, L., & Polycarpou, M. M. (2024, May). Junction Temperature Control for Lifetime Extension of Multi-Functional Photovoltaic Inverters. *IEEE Transactions on Industry Applications*, *60*(3), 4125–4137.

Chung, H. S.-h., Wang, H., Blaabjerg, F., & Pecht, M. (Eds.). (2015). *Reliability of Power Electronic Converter Systems*. Institution of Engineering and Technology.

Ciappa, M., & Castellazzi, A. (2007, April). Reliability of High-Power IGBT Modules for Traction Applications. In *2007 IEEE International Reliability Physics Symposium Proceedings. 45th Annual* (pp. 480–485). Phoenix, AZ, USA: IEEE.

Filho, E. A. S., Zúñiga, A. A., Fernandes, J. F. P., Branco, P. J. C., & Pais, A. R. (n.d.). FAILURE RATES IN PHOTOVOLTAIC SYSTEMS: A CAREFUL SELECTION OF QUANTITATIVE DATA AVAILABLE IN THE LITERATURE.

Gao, Z., Cecati, C., & Ding, S. (2015). A Survey of Fault Diagnosis and Fault-Tolerant Techniques Part II: Fault Diagnosis with Knowledge-Based and Hybrid/Active Approaches. *IEEE Transactions on Industrial Electronics*, 1–1.

Golnas, A. (2013, January). PV System Reliability: An Operator's Perspective. *IEEE Journal of Photovoltaics*, *3*(1), 416–421.

Gunda, T., Hackett, S., Kraus, L., Downs, C., Jones, R., McNalley, C., ... Walker, A. (2020). A Machine Learning Evaluation of Maintenance Records for Common Failure Modes in PV Inverters. *IEEE Access*, *8*, 211610–211620. (Publisher: Institute of Electrical and Electronics Engineers Inc.) doi: 10.1109/ACCESS.2020.3039182

Held, M., Jacob, P., Nicoletti, G., Scacco, P., & Poech, M.-H. (1997). Fast power cycling test of IGBT modules in traction application. In *Proceedings of Second International Conference on Power Electronics and Drive Systems* (Vol. 1, pp. 425–430). Singapore: IEEE.

Jordan, D. C., Anderson, K., Perry, K., Muller, M., Deceglie, M., White, R., & Deline, C. (2022, October). Photovoltaic fleet degradation insights. *Progress in Photovoltaics: Research and Applications*, *30*(10), 1166–1175.

Jordan, D. C., Marion, B., Deline, C., Barnes, T., & Bolinger, M. (2020, August). PV field reliability status—Analysis of 100 000 solar systems. *Progress in Photovoltaics: Research and Applications*, *28*(8), 739–754.

Kaplar, R., Brock, R., DasGupta, S., Marinella, M., Starbuck, A., Fresquez, A., ... Atcitty, S. (2011, June). PV inverter performance and reliability: What is the role of the IGBT? In *2011 37th IEEE Photovoltaic Specialists Conference* (pp. 001842–001847). Seattle, WA, USA: IEEE.

Ketjoy, N., Chamsa-ard, W., & Mensin, P. (2021, November). Analysis of factors affecting efficiency of inverters: Case study grid-connected PV systems in lower northern region of Thailand. *Energy Reports*, *7*, 3857–3868.

Koziarz, W., & Gilmour, D. (1995). Anomalous thermal conductivity in regions of non-uniform die attach integrity [MCM. In *33rd IEEE International Reliability Physics Symposium* (pp. 107–111). Las Vegas, NV: IEEE.

Kurukuru, V. S. B., & Khan, I. (2022, December). Failure Mode Effect Analysis of Power Semiconductors in a Grid-Connected Converter. In A. Haque & S. Mekhilef (Eds.), *Fault Analysis and its Impact on Grid-connected Photovoltaic Systems Performance* (1st ed., pp. 149–184). Wiley.

Kurukuru, V. S. B., Khan, M. A., & Malik, A. (2021). *Failure mode classification for grid-connected photovoltaic converters* (Vol. 170; A. Haque, F. Blaabjerg, H. Wang, Y. Yang, & Z. Jaffery, Eds.). (Pages: 249)

Lightfoote, S., Wilson, S., & Voss, S. (2021, June). Investigation of More Than 100,000 Months of Inverter Power Conversion Efficiency Data Using the Power Factors Database. In *2021 IEEE 48th Photovoltaic Specialists Conference (PVSC)* (pp. 2360–2362). Fort Lauderdale, FL, USA: IEEE.

Lindig, S., Gallmetzer, S., Herz, M., Louwen, A., Koumpli, E., Sebastian Enriquez Paez, P., & Moser, D. (2022). Towards the development of an optimized Decision Support System for the PV industry: A comprehensive statistical and economical assessment of over 35,000 O&M tickets. *Progress in Photovoltaics: Research and Applications*. doi: 10.1002/pip.3637

Mishra, P. R., Rathore, S., Varma, K. V., & Yadav, S. K. (2024, April). Long-term performance and degradation analysis of a 5 MW solar PV plant in the Andaman & Nicobar Islands. *Energy for Sustainable Development*, *79*, 101413.

Nagarajan, A., Thiagarajan, R., Repins, I. L., & Hacke, P. L. (2019, October). *Photovoltaic Inverter Reliability Assessment* (Tech. Rep. Nos. NREL/TP-5D00-74462, 1573462).

Rahimpour, S., Tarzamni, H., Kurdkandi, N. V., Husev, O., Vinnikov, D., & Tahami, F. (2022). An Overview of Lifetime Management of Power Electronic Converters. *IEEE Access*, *10*, 109688–109711.

Ratchev, P., Vandevelde, B., & DeWolf, I. (2004, March). Reliability and Failure Analysis of Sn-Ag-Cu Solder Interconnections for PSGA Packages on Ni/Au Surface Finish. *IEEE Transactions on Device and Materials Reliability*, *4*(1), 5–10.

Wang, H., Liserre, M., Blaabjerg, F., De Place Rimmen, P., Jacobsen, J. B., Kvisgaard, T., & Landkildehus, J. (2014, March). Transitioning to Physics-of-Failure as a Reliability Driver in Power Electronics. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, *2*(1), 97–114.

Yang, S., Xiang, D., Bryant, A., Mawby, P., Ran, L., & Tavner, P. (2010, November). Condition Monitoring for Device Reliability in Power Electronic Converters: A Review. *IEEE Transactions on Power Electronics*, *25*(11), 2734–2752.

Yang, Y., Sangwongwanich, A., & Blaabjerg, F. (2016, December). Design for Reliability of Power Electronics for Grid-Connected Photovoltaic Systems. *CPSS Transactions on Power Electronics and Applications*, *1*(1), 92–103.