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Final report from 8 July 2024

ASSURED-PV

Assessing uncertainties and risks in photovoltaic plant performance and operation

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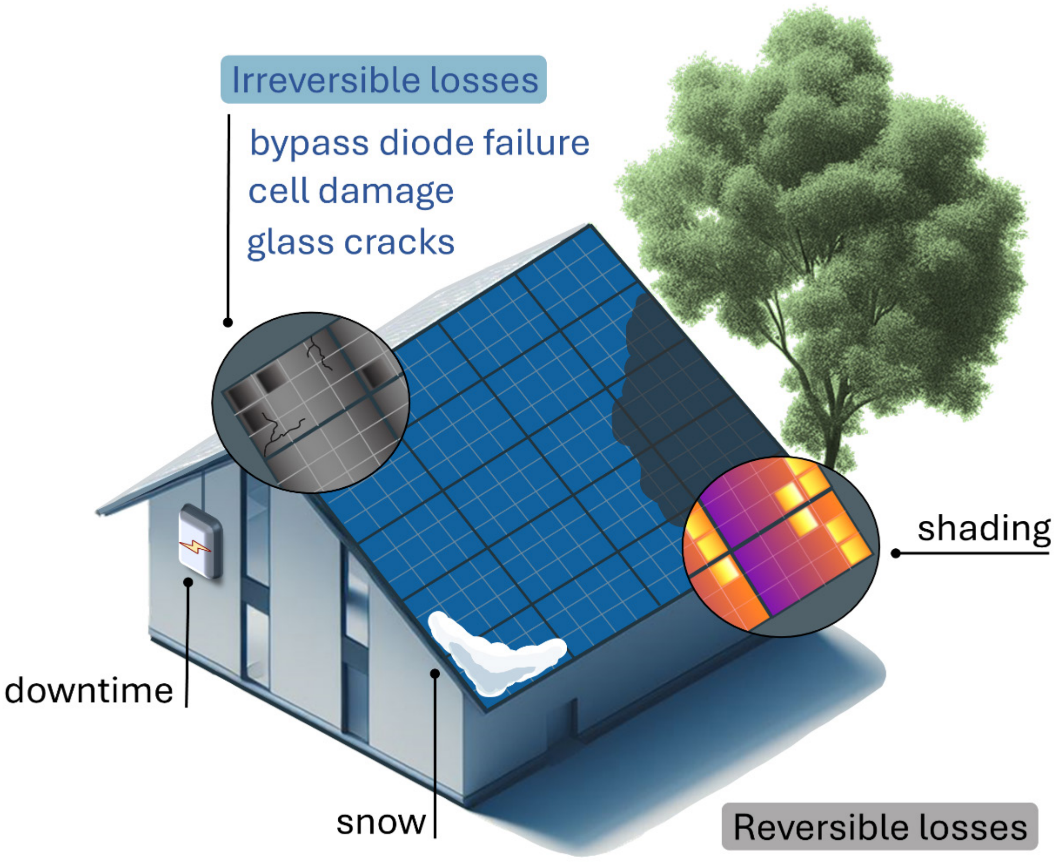

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Summary

Switzerland aims to install 30 to 40 GWp of photovoltaic capacity in the next 30 years to meet Energy Strategy 2050 targets. This goal is complicated by the prevalence of small- and medium-scale residential and commercial systems, which face higher risks of degradation and have limited data quality compared to larger utility-scale systems. This work aims to evaluate the performance of PV systems in the built environment in Switzerland through two lenses: (1) identifying reversible and non-reversible loss effects and their impact on system health, and (2) developing new data-based methodologies to determine PV system long-term performance with minimal uncertainty. This process aims to optimise PV system design, thereby increasing energy yield and helping to meet Switzerland's 2050 energy targets. A fault detection and diagnosis algorithm (FDDA) was developed and validated using the acquired datasets, successfully identify partial shading, snow and downtime losses. In parallel, an alternative to the most common performance loss rate statistical method (the year-on-year (YoY)) was developed, the multi-annual year-on-year (multi-YoY), which improves both accuracy and precision in long-term performance assessments.

Zusammenfassung

Die Schweiz will in den nächsten 30 Jahren 30 bis 40 GWp an Photovoltaikleistung installieren, um die Ziele der Energiestrategie 2050 zu erreichen. Dieses Ziel wird durch die Verbreitung kleiner und mittlerer Wohn- und Gewerbeanlagen erschwert, die im Vergleich zu größeren Energieversorgungsanlagen ein höheres Risiko der Degradation und eine begrenzte Datenqualität aufweisen. Diese Arbeit zielt darauf ab, die Leistung von PV-Anlagen in der gebauten Umwelt in der Schweiz aus zwei Blickwinkeln zu bewerten: (1) Identifizierung von reversiblen und nicht-reversiblen Verlusteffekten und deren Auswirkungen auf die Systemgesundheit und (2) Entwicklung neuer datenbasierter Methoden zur Bestimmung der langfristigen Leistung von PV-Anlagen mit minimaler Unsicherheit. Dieser Prozess zielt darauf ab, die Auslegung von PV-Anlagen zu optimieren und dadurch die Energieausbeute zu erhöhen und dazu beizutragen, die Energieziele der Schweiz für 2050 zu erreichen. Es wurde ein Algorithmus zur Fehlererkennung und -diagnose (FDDA) entwickelt und anhand der erfassten Datensätze validiert, der erfolgreich Teilabschattungen, Schnee und Ausfallverluste identifiziert. Parallel dazu wurde eine Alternative zur gebräuchlichsten statistischen Methode der Leistungsverluste (year-on-year (YoY)) entwickelt, nämlich die multi-annual year-on-year (multi-YoY), die sowohl die Genauigkeit als auch die Präzision bei langfristigen Leistungsbewertungen verbessert.

Résumé

La Suisse vise à installer 30 à 40 GWp de capacité photovoltaïque au cours des 30 prochaines années afin d'atteindre les objectifs de la stratégie énergétique 2050. Cet objectif est compliqué par la prévalence des systèmes résidentiels et commerciaux de petite et moyenne taille, qui sont confrontés à des risques de dégradation plus élevés et pour lesquels la qualité des données est limitée par rapport aux systèmes de plus grande taille utilisés par les services publics. Ce travail vise à évaluer la performance des systèmes photovoltaïques dans l'environnement bâti en Suisse sous deux angles : (1) l'identification des effets de perte réversibles et non réversibles et leur impact sur la santé du système, et (2) le

développement de nouvelles méthodologies basées sur des données pour déterminer la performance à long terme des systèmes photovoltaïques avec un minimum d'incertitude. Ce processus vise à optimiser la conception des systèmes photovoltaïques, augmentant ainsi le rendement énergétique et contribuant à atteindre les objectifs énergétiques de la Suisse pour 2050. Un algorithme de détection et de diagnostic des défauts (FDDA) a été développé et validé à l'aide des ensembles de données acquises, identifiant avec succès l'ombrage partiel, la neige et les pertes de temps d'arrêt. Parallèlement, une alternative à la méthode statistique de taux de perte de performance la plus courante (le year-on-year (YoY)) a été développée, le multi-annual year-on-year (multi-YoY), qui améliore à la fois l'exactitude et la précision des évaluations de performance à long terme.

Main findings («Take-Home Messages»)

- A large representative dataset of BAPV and BIPV systems in Switzerland was collected and analysed, focusing on improving our understanding and optimising PV system performance in the built environment. The project successfully identified key loss patterns and their effect on system reliability, highlighting the importance of planning and maintenance to reach the Swiss 2050 Energy Strategy targets.

- The combination of fault detection methods with long-term performance data analytics brings many interesting insights regarding the reliability of PV systems. The double approach enables the decoupling of intrinsic and extrinsic performance loss effects. The results highlight the importance of considering loss factors when analysing PV system data, as they can cause significant biases in the final PLR value.

- The multi-YoY approach, proposed as an alternative to the standard YoY method for evaluating PLRs, demonstrates enhanced accuracy and precision, particularly effective for linear performance loss trends. The primary benefit of the multi-YoY method lies in its ability to minimize uncertainty, achieving significantly narrower confidence intervals (reduced by one order of magnitude) compared to the traditional YoY method.

This work establishes the tools and methodology needed to streamline the analysis of long-term PV plant performance with increased accuracy and precision. These tools enhance the statistical significance of such analyses, as well as the general understanding of loss mechanisms in PV systems, creating a positive feedback loop that improves the design phase for the next generation of PV systems.

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List of abbreviations

SFOE	Swiss Federal Office of Energy
PV	Photovoltaic
BAPV	Building-Applied Photovoltaics
BIPV	Building-Integrated Photovoltaics
PR	Performance Ratio
PLR	Performance Loss Rate
i-PLR	Intrinsic Performance Loss Rate
FDD	Fault Detection and Diagnosis
FDDA	Fault Detection and Diagnosis Algorithm
O&M	Operations and Maintenance
KPI	Key Performance Indicator
Rd	Degradation Rate
BPD	Bypass Diode
LF	Loss Factor
DM	Degradation Mode
YoY	Year-on-Year
Multi-YoY	Multi-annual Year-on-Year

1 Introduction

1.1 Initial situation and background

In Switzerland between 30 and 40 GWp of photovoltaic (PV) capacity should be installed over the next 30 years to meet Energy Strategy 2050 targets. As of 2024, Switzerland's total installed PV capacity is approximately 6.2 GW, with an additional 1.5 GW of new solar capacity in 2023, reflecting a nearly 40% growth compared to the previous year. Beyond the sheer number of new systems that should be installed, the Swiss context poses another unique challenge in that most PV systems are small- (1-20 kWp) and medium-scale (20-1000 kWp) residential and commercial PV building applied or integrated (BAPV or BIPV). BAPV and BIPV systems are at greater risk of degradation and early failure because of the elevated operating temperatures and regular shading present in their operating environment. Additionally, data quality from small systems is usually more limited, for instance, requiring the use of satellite meteorological data to determine performance, in contrast to calibrated ground-based sensors used in large utility-scale systems.

1.2 Motivation of the project

In this context, ASSURed PV aims to assess the long-term performance of a statistically significant number of PV plants in Switzerland, with the main objective to understand poor practices in PV system design (i.e. excessive shading, poor selection of components, etc.), while highlighting good practices. Triggering this learning process – thus optimizing PV system design practices - should allow to increase the energy yield of the corresponding installed PV capacity, helping solar electricity to maximise its effectiveness in view of the 2050 energy targets.

1.3 Project objectives

The ASSURed PV project aims to answer two main research questions by increasing the accuracy of performance and degradation assessment for PV systems:

1. **Can operational faults be identified through daily production data and correlated to long-term performance?** Elevated operational stresses are present in BAPV and BIPV systems, so can faults related to these be identified in the daily production data and correlated to system lifetimes? System faults may present features or fingerprints in operational data, such as unexpected voltage or current changes. By identifying problematic systems early, proactive operations and maintenance (O&M) can be taken to mitigate long-term effects. Identification of these faults can also be used to improve the design of new PV modules and systems for improved fault resilience.

2. **How can statistical uncertainty be minimised in long-term performance assessment methodologies?** With less accurate meteorological data and varying stressors compared to utility-scale PV, BAPV and BIPV system would benefit from improved methods for PLR assessments. The goal is to develop new ways of dealing with PV performance data to lower statistical uncertainty in PLR results, combined with the aforementioned fault detection algorithm, thus contributing to a better understanding of systems in the built environment and their long-term health.

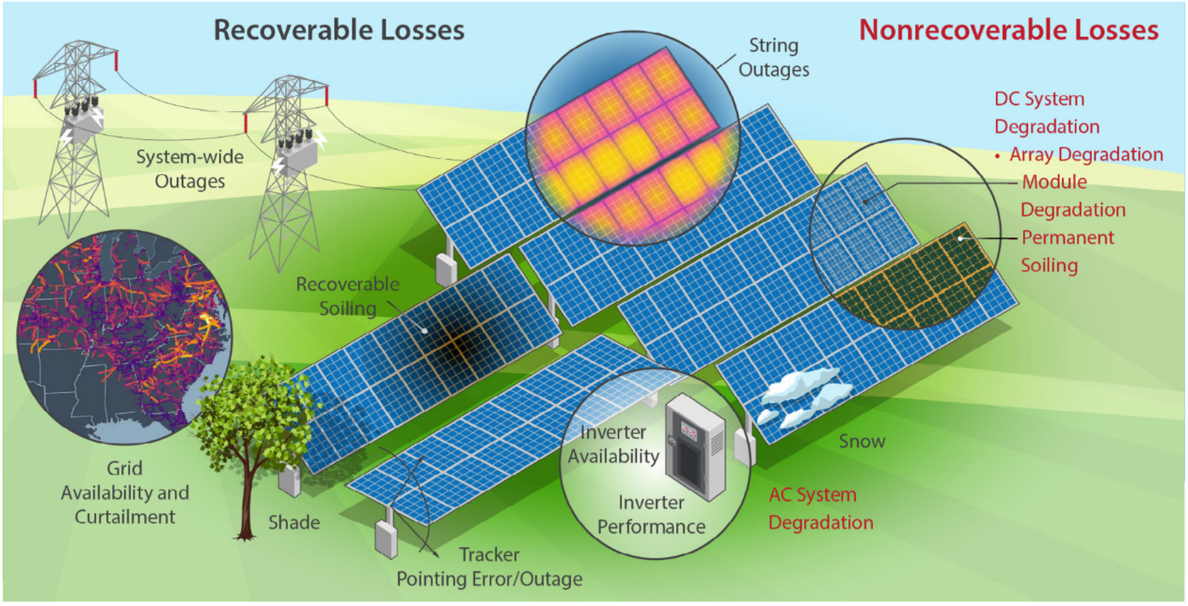

Figure 1: Recoverable (black text) and nonrecoverable (red text) losses. Recoverable losses can be mitigated in principle, although it is not always practical to mitigate them entirely in practice. Both recoverable and nonrecoverable losses contribute to PLR. Image taken from Deceglie et al. (2023) [1].

2 Approach and method

2.1 Performance loss rates – brief review

PV system performance is most commonly assessed with the performance loss rate (PLR) metric. While certain key performance indicators (KPI), e.g. the performance ratio (PR), are clearly defined in standards such as the IEC 61 724-1:2021, there is still no consensus for the definition of the PLR [1], [2], [3], [4]. The most common misconception observed in literature is the commutable use of the terms degradation rate (Rd) and PLR: in general, PLR refers to system-level performance losses, including both reversible (e.g. soiling, shading, snow, etc.) and irreversible effects, such as module-level degradation. In this work, the PLR is defined as the change in annualised performance ratio relative to the first year, following the definition of Deceglie et al. [3]. The degradation rate (Rd), defined as the rate at which a PV module efficiency decreases over time, is therefore a component of the PLR.

An additional layer of complexity in the PLR is the abundance of methods and variations of the PLR metric [2], [5], [6]. Although the general steps to compute the PLR are similar in all cases, the statistical model to extract the final reported value can vary significantly, leading to large differences in results as well as complex uncertainty assessments. Lindig et al. provide a succinct summary of the state of the art and best practises for PLR calculations [2]. Common PLR analysis pipelines include (i) input data quality evaluation, (ii) data filtering, (iii) performance metric selection, (iv) aggregation, (v) PLR calculation using statistical models. However, there are no uniform approaches – nor standards - to reliably calculate the PLR, as concluded by the International Energy Agency (IEA) Photovoltaic Power System Program (PVPS) Task 13 report [1]. Instead, an ensemble approach is deemed the most reliable calculation method, which consists in comparing multiple analysis pipelines (varying the filtering approaches and statistical models) and taking the mean inlier estimate. In this work, the Year-on-Year (YoY) methodology is used as the statistical model, as it is considered one of the most reliable regression analysis methods for long-term performance assessment of PV systems [7], [8], and is implemented directly in

PLR analysis pipelines such as *RdTools* [9]. Other statistical models include least-squares linear regression (LR) [10], seasonal trend decomposition using LOESS (locally estimated scatterplot smoothing) (STL) [11], [12], statistical clear-sky fitting (SCSF) [13], [14], and various non-linear models such as Facebook Prophet (FBP) [15], [16] and piece-wise regression [17], [18].

Lindig et al. also emphasise other challenges and opportunities for performance loss estimations, such as the potential actionable insights that can be gained through a component break-down analysis of the PLR. Detailed knowledge of individual performance losses could inform operations and maintenance (O&M) activities and reduce noise in the PLR value. More recently, Deceglie et al. further highlight the importance of distinguishing recoverable and non-recoverable losses [3], see Figure 1, which have implications in the O&M and module technology and operational environments, respectively. This work aims to answer this open question, providing a method to filter reversible and irreversible performance losses.

2.2 Loss factors and degradation modes

In this work, a fault is used as the general term for any effect causing module power loss or safety issues [19], [20], [21], [22], [23]. Within PV system faults, certain categorisations are useful to further distinguish between a permanent, irreversible effect, known as a degradation mode (DM) [24], or transient, reversible losses, hereby called a loss factor (LF) [25]. Importantly, as well as causing intermittent output losses, in the long run LFs may lead to DMs, causing irreversible damage. For example, a typical loss factor is recurring shading, which causes performance loss and may evolve into hot spots, potentially leading to long-term damage such as delamination, glass cracks, etc. [26], [27], [28], [29]. There is therefore a complex interplay between these LFs, which can act as stressors on multiple system components and levels, leading to further system faults [30]. Figure 2 (A) shows the decomposition of the PLR between DMs and LFs, with example fault types.

Typically, PV manufacturer warranties state that module performance should remain above 80 % of nominal power after 25 years, which translates to module degradation below 0.8 %/year, assuming a linear trend. Figure 2 (B) shows typical performance loss scenarios with the impacting degradation modes. To ensure modules last long and continue to perform above the warranty levels, it is vital to avoid early and midlife degradation which would cause severe, irreversible power loss. However, as discussed above, when considering data-based approaches to quantify module or system performance loss, loss factors and external faults are embedded in the PLR metric. This can cause unexplained high

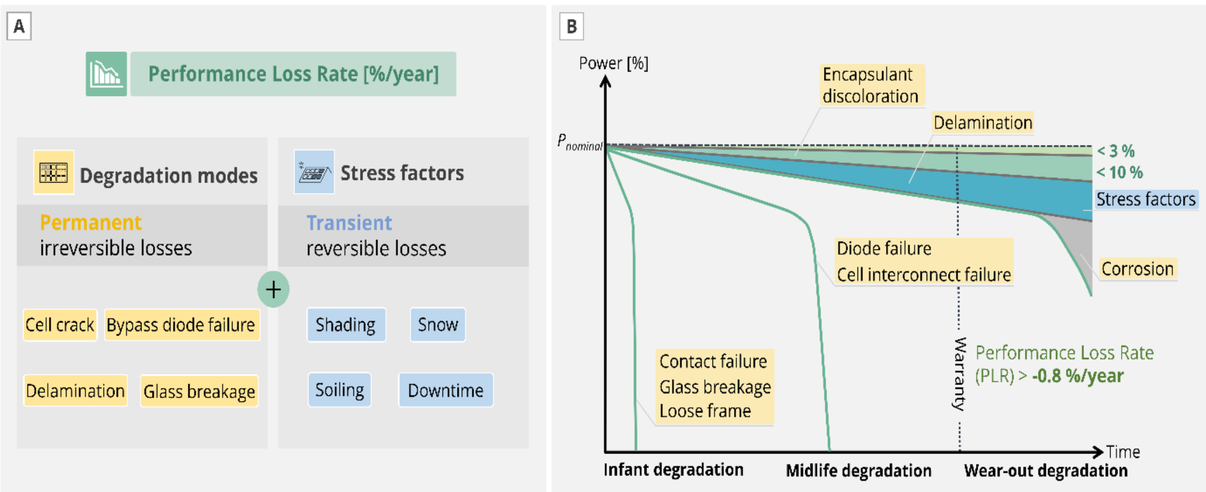

Figure 2: (A) Two components of the performance loss rate (PLR): degradation modes and loss factors. (B) Typical performance loss scenarios for PV modules, adapted from Kontges et al. (2014). A few typical degradation modes are highlighted in yellow, and loss factors in blue -- varying stressors over time can impact the performance trend. The goal of this work is to decouple these various hidden effects from the performance trend.

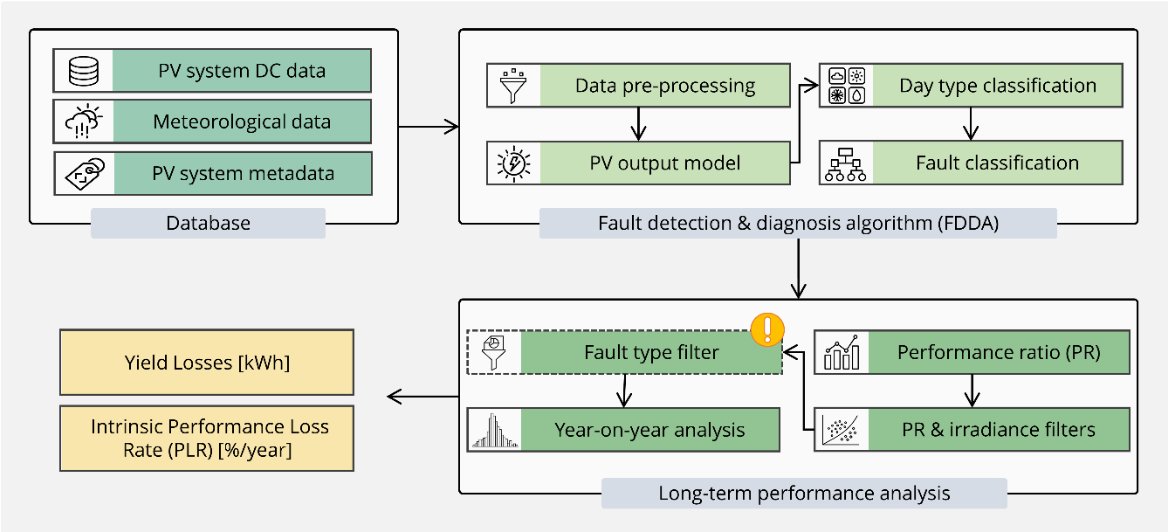

Figure 3: Simplified flowchart of the developed fault detection and diagnosis algorithm (FDDA) and long-term performance assessment. The outputs of the FDDA are used to filter the loss factors and compute corresponding yield losses, leading to the definition of the intrinsic PLR (i-PLR) reflecting system degradation.

values of performance loss, for example due to evolving and growing losses over time. In particular, PV systems in the built environment are often subjected to recurring shading events and high temperature working conditions [31], [32], [33], which can therefore have both direct effects on their long-term performance, or cause negative bias in the performance trend analyses. While high temperatures are relatively well understood and studied, with the IEC TS 63126 directly addressing solutions and modification in PV installations with high temperatures [34], [35], shade-induced degradation is not yet fully understood [26]. With routine shading events being prevalent in these types of systems, bypass diode (BPD) activation is expected to occur more frequently, which could lead to accelerated degradation due to the heat dissipation and potential damage to the BPD or nearby components [36], [37], [38].

2.3 Proposed integrated solution

This work proposes a novel method to evaluate the PLR of PV systems by applying a **fault detection and diagnosis (FDD)** procedure that allows the filtering of shading, snow, and downtime losses. Compared to standard filtering methods, which do not reflect the intrinsic system health due to the inherent inclusion of reversible losses in the data, the addition of FDD analysis within PLR pipelines offers a solution to avoid the influence of such reversible effects, enabling the determination of what we call the **intrinsic PLR** (i-PLR).

Moreover, this work proposes a new methodology to compute the PLR itself, aiming to minimise the statistical uncertainty of the metric. The goal is to improve both the precision and accuracy of PLR estimations. Despite the lack of industry-wide consensus and standardised methods for extracting PLR values from field data, the year-on-year (YoY) method is often considered the most robust regression analysis. However, achieving reproducible results with minimal uncertainty remains a challenge. This work therefore proposes the **multi-annual YoY (multi-YoY)** approach, which reduces the statistical uncertainty of the metric through increased usage of available data. The concept is straightforward: instead of comparing data points only to the following year, the multi-YoY method compares them to all subsequent years, increasing the number of available comparisons.

The detailed methodology for the FDD can be found in the published work by Quest et al. [39]. For the multi-YoY, the proceeding [40] details the method, and a paper has been submitted Progress in Photovoltaics in May 2024. The next section will outline some of the main results, although additional details can be found in the respective publications.

3 Work performed and results

3.1 Collected datasets

Table 1 and Figure 4 summarise the accessed datasets for the first project milestone (M1.1 – accessing at least 200 PV system datasets). Three different data providers were used: Baur AG, Solstis, and SIG. In total, more than 400 individual PV systems are available, equivalent to more 900+ inverters/strings. The data is collected at DC or AC level, depending on the system and data collection method. System capacities range from small BIPV/BAPV systems of 10 – 30 kWp, up to large utility scale systems of 500 – 4000 kWp. All systems are located in Switzerland.

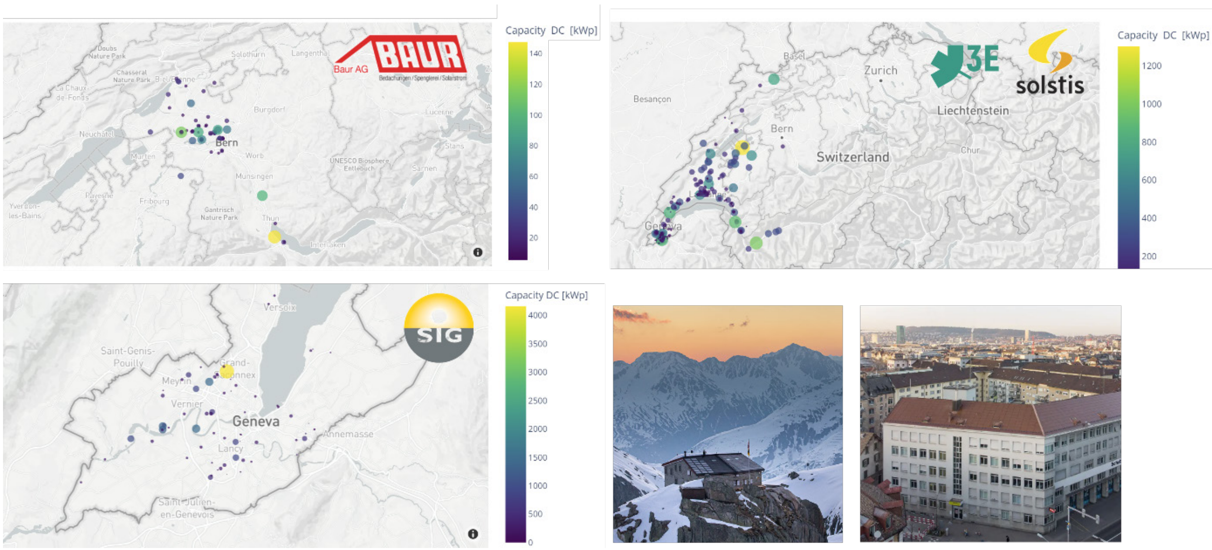

Figure 4: Collected datasets during the ASSURed-PV project: BAPV and BIPV systems from the installer Baur AG (see photos of typical BIPV systems using modules from 3S Swiss Solar Solutions AG), BAPV systems from the installer Solstis, and BAPV systems from SIG in Geneva.

Table 1. List of accessed data sources and PV system datasets.

Data provider	API access	# PV systems	# PV strings	DC Capacity range [kWp]
Baur AG	Solar-Log	200+	350+	10 - 150
Solstis	3E SynaptiQ	235	400+	2 - 1300
SIG	Meteocontrol	66	150+	27 - 4200

3.2 Multi-YoY validation

In order to validate the proposed multi-YoY method, a synthetic dataset with known PLR is generated. In this way, the main issue of not knowing the true PLR value of a system is overcome, and it is artificially set to a chosen value and the accuracy and precision of PLR assessments can be compared. Figure 5 summarises the validation steps and results. First, synthetic PV system DC power is simulated using satellite-based irradiance data from the CAMS solar radiation service [41] and the Python pvlib library [42]. An artificial -1 %/year PLR is added to the data, creating a known “true” value of relative performance loss trend. The second step consists of the computation of the performance ratio (PR), and multiple aggregation strategies are compared (daily, weekly, monthly and yearly mean values). From the PR trends, the standard YoY and multi-YoY methods are then applied to extract the PLR values, generating statistical distributions from which the median PLRs and their uncertainties are extracted using bootstrapping. The distributions of median PLRs are shown in Figure 5.3, and Figure 5.4 compares the final obtained PLR values and their 95 % CI for standard and multi-YoY methods. For each aggregation level, the top value represents the standard YoY results, while the bottom value represents the multi-YoY. The true PLR of -1 %/year is highlighted in green.

Overall, the standard YoY results in a wide distribution of PLR values, with significant variation depending on the level of aggregation, while the multi-YoY method shows tighter distributions and better agreement between all sampling levels. The main outcomes are as follows:

- The average relative error of the PLR estimation compared to the “true” PLR value of -1 %/year is 2 % for the standard YoY, and 1.7 % for the multi-YoY. This reflects the accuracy of the methods, and the multi-YoY therefore yields more accurate estimations of the PLR.
- For both methods, the 95 % confidence intervals contain the true value of the PLR within their bounds.
- Comparing the RME of both methods, which serves as a measure of precision, the multi-YoY yields an average RME of 0.02 for all aggregations, while the standard YoY has a mean RME of 0.23. This translates to an impressive reduction in uncertainty of over 90 % with the multi-YoY method, or an improvement of one order of magnitude.
- Regarding the data aggregation strategy, using shorter aggregation periods yield the lowest RME for both methods, although the difference is marginal for the multi-YoY.

Overall, the multi-YoY approach not only improves the accuracy of PLR estimations but also significantly enhances precision.

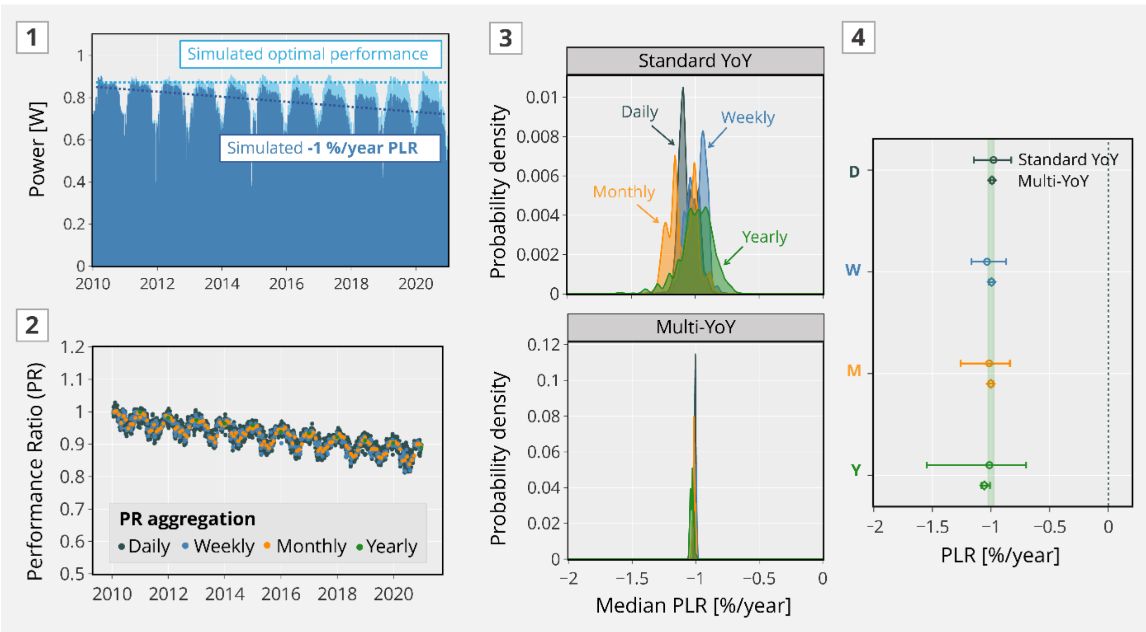

Figure 5: Validation of multi-YoY method with synthetic data. (1) Simulated PV production with artificial -1 %/year PLR. (2) Computed performance ratio (PR) at different aggregation levels - Daily (D), Weekly (W), Monthly (M), Yearly (Y). (3) Probability density function of the median PLRs for standard and multi-YoY methods. (4) Estimated median PLRs and uncertainties comparing standard and multi-YoY.

3.3 Fault Detection and Intrinsic PLR

Identified fault types and loss factors

Figure 6 shows example daily profiles of DC current I_{DC} [A] and voltage V_{DC} [V], with statistical thresholds based on simulated model outputs I_{sim} and V_{sim} shown as shaded areas. Heat maps below each fault type example show detected faults (at 15 min. time steps) as well as relative current loss [%], which is a quantification of the relative difference between the simulated and actual currents. These fault examples are extracted from different PV system string, hence the variations in current and voltage axis ranges. The following comments can be made for each fault type:

- F0 | Normal: Voltage and current are both within the defined thresholds. This example shows a typical clear-sky day for a good performing system, with the expected gradual voltage drop due to increasing irradiance and thus operating temperature during the day.
- F1 | Snow: Extremely low current and reduced voltage indicate partial coverage of modules with opaque snow, causing the limited module(s) to dictate current behaviour, and bypass diode activation causing the voltage drop.
- F2 | Cloudy: Typical cloudy or overcast days see a voltage curve which does not diminish in the middle of the day like in the example of F0, as the temperature is more stable. Here, a drop in voltage during short-term inhomogeneous irradiance conditions is observed in the morning, likely due to a mismatch between the satellite-based irradiance data and the actual observed irradiance.
- F3 | Shading (BPD activation): A 50 % drop in voltage is observed in the afternoon, indicating bypass diode activation due to some form of partial shading in the string.
- F4 | Shading (MPPT): In this case of irradiance mismatch, the maximum power point tracker (MPPT) adjusted the voltage and current to the local instead of global MPP, causing a limited current and high yield losses.
- F5 | Downtime: The system disconnected for around 30 minutes in the evening, causing a gap in the data.

Fleet analysis results – loss patterns and intrinsic PLR bias

A total of 250+ individual strings were analysed, from 60+ BIPV and BAPV systems in Switzerland. After data cleaning and processing, results are obtained for 54 systems, corresponding to 160 strings. The goal here is to determine the different types of biases caused by the reversible faults categorised through the Fault Detection and Diagnosis Algorithm (FDDA). The pipeline described in Figure 3 is applied to the system strings, extracting the fault patterns, loss quantifications, as well as PLR and i-PLR values. A detailed case study showing the impact of partial shading is shown in [39].

The results for the fleet of systems are used to distinguish the impact of loss factors on the PLR, with a focus on partial shading, which is especially relevant to PV systems in the built environment. To do so, the FDDA and PLR pipelines are applied to all 160 strings, and the i-PLR is compared to the PLR along with the evolution of estimated shading losses over time. The results of this analysis yielded four categories of losses, or four typical patterns of PLR bias due to the influence of evolving shading losses in time. Figure 6 shows the results for four representative BIPV strings, selected for each category. The standard and intrinsic PLR values are compared, with the corresponding PR trends, as well as the evolution of relative shading losses in time. The main loss and bias patterns are categorised as follows:

- Increasing shading: when shading losses increase over time, the standard PLR is negatively biased and shows higher values than the intrinsic PLR due to the down shift in PR. This results in an overestimation of the PV string performance degradation.

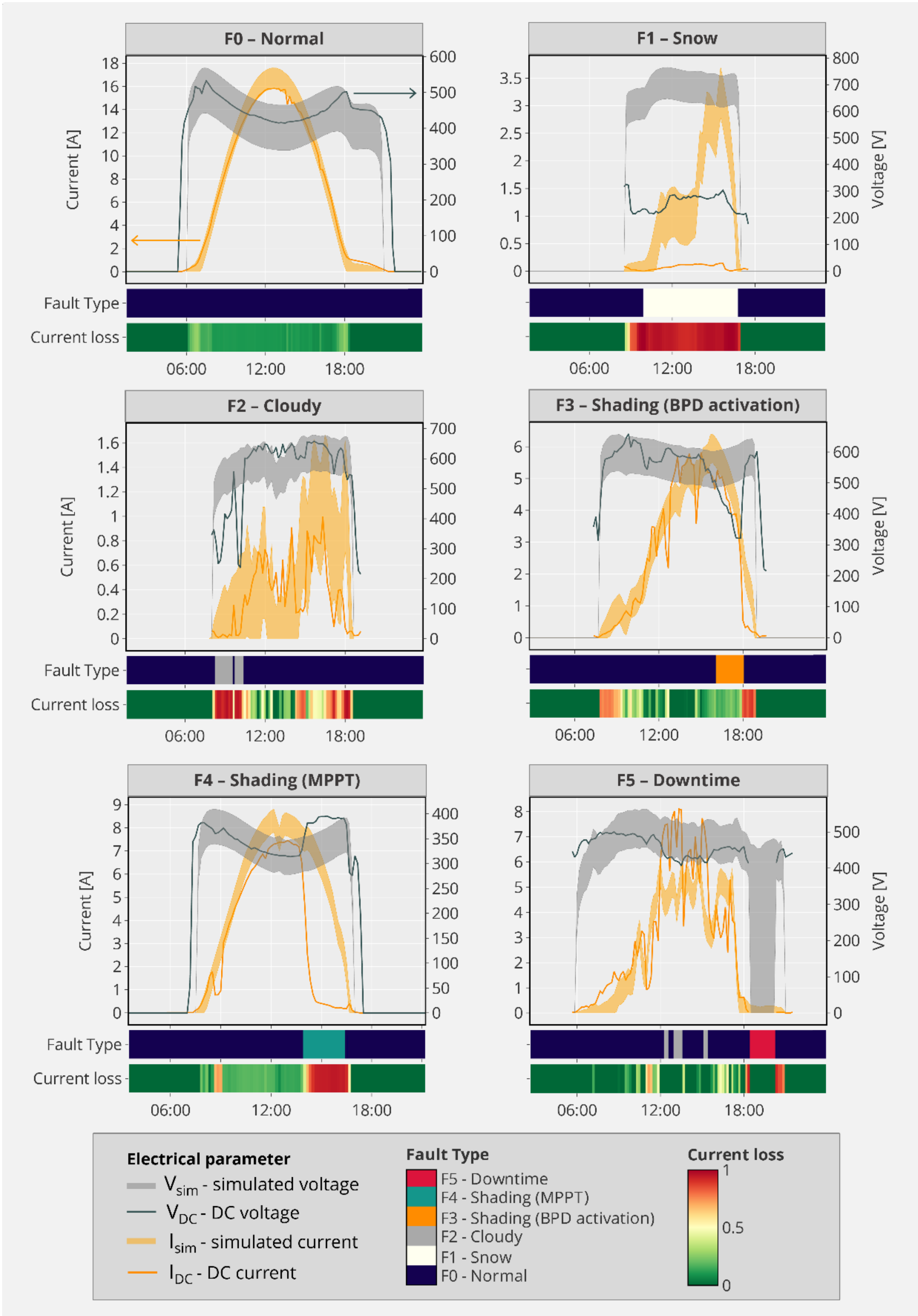

Figure 6: Comparison of daily PR trends for the intrinsic and standard PLRs for the four identified shading loss scenarios (exemplified with different BIPV systems), highlighting the potential shift in PR after filtering for loss factors and the impact on the PLR evaluation. Corresponding yearly relative shading loss evolution are also shown.

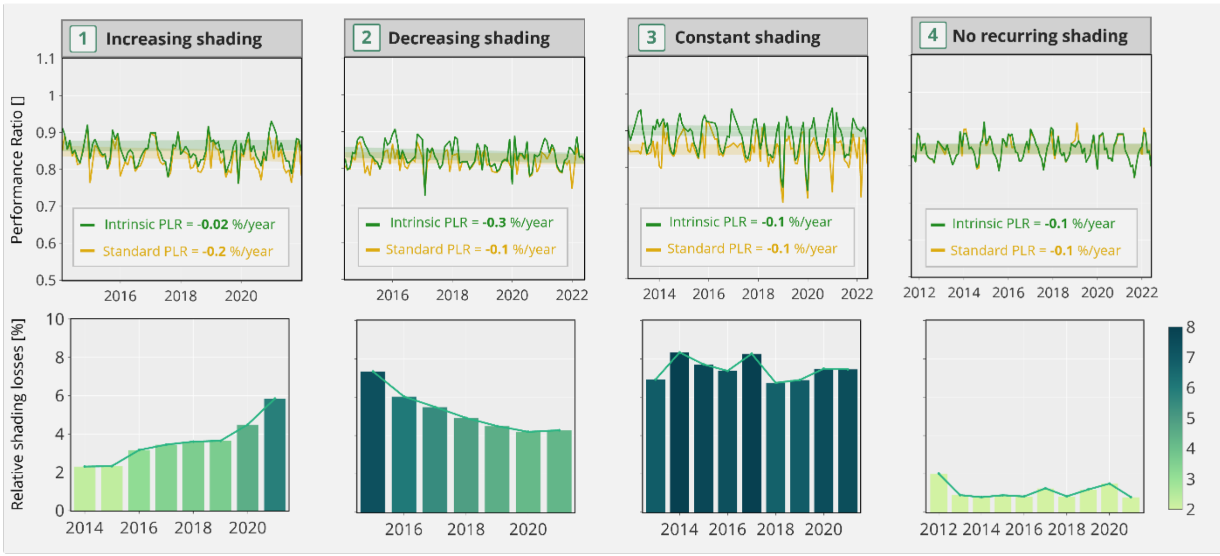

Figure 7: Comparison of daily PR trends for the intrinsic and standard PLRs for the four identified shading loss scenarios (exemplified with different BIPV systems), highlighting the potential shift in PR after filtering for loss factors and the impact on the PLR evaluation. Corresponding yearly relative shading loss evolution are also shown.

- Decreasing shading: when shading losses decrease over time, the standard PLR is positively biased and shows lower values than the intrinsic PLR due to the up shift in PR. This results in an underestimation of the PV string performance degradation.
- Constant shading: when shading losses do not vary over time, the standard and intrinsic PLR are the same, as there is a constant shift in PR trends.
- No recurring shading: when there are no or very low shading losses over time, the standard and intrinsic PLR are the same and there is no shift in PR trends.

4 Discussion and further steps

4.1 Multi-YoY approach

Method validation and robustness

The proposed multi-YoY alternative to the standard YoY approach for performance loss rate evaluations was validated for synthetic datasets with known PLR values, showing improvements in both accuracy and precision in the case of a linear performance loss trend. The main advantage of the multi-YoY method is the reduction in uncertainty, with a reduced confidence interval (one order of magnitude decrease) compared to YoY. The introduction of noise in the data further confirmed the robustness of the approach, with stable and accurate results for various aggregation levels. Overall, the multi-YoY shows low deviations between the daily, weekly, monthly or yearly resampling strategies, which is also an advantage over the standard YoY. For installers, project planners or general O&M of PV systems, having a PLR of -2 %/year or -0.5 %/year can change the LCOE and profitability of solar projects drastically [43], especially for large installations, which further highlights the importance of having precise estimations of the PLR. Based on warranty levels stating that modules should maintain 80 % of their initial power rating after 25 years, the maximum acceptable PLR would be -0.8 % per year, and having uncertainties around this value could lead to warranty claim issues. With regards to non-linearity in the performance ratio, the standard or multi-YoY can be used to automatically identify non-linearity through the

YoY instance distribution, where multiple peaks indicate segments of the time series with varying loss trends. Change point detection algorithms can then automatically segment the PR time series, and individual PLR values can be computed for each section.

Limitations and future work

The PLR plays an important part in system maintenance as well as project planning – uncertainties and inaccurate estimations can have financial consequences or lead to module warranty issues [26], [44], [45], [46]. Although the multi-YoY shows promising results and large improvements in the uncertainty assessment of the PLR, therefore potentially reducing financial risks and aiding in system O&M activities, there remain limitations and questions that should be addressed in future work:

- Harmonisation of PLR pipelines: the multi-YoY addresses only one step of the PLR calculation process, and reduces only the statistical uncertainty. The prior steps, including the choice of performance metric, the various filtering approaches and selection of thresholds, or the initial data sources, all have an impact on the PLR estimation. Although this work shows that the multi-YoY result does not depend on the aggregation or resampling strategy, other filters could have an impact and further work should evaluate and quantify these effects.
- Non-linearity: ideally, non-linear performance ratio trends should be segmented? with the PLR calculated for each section. An alternative proposed by Theristis et al. [47] is to use the mean PLR instead of the median, which could be more representative in non-linear cases. Nevertheless, automatic segmentation offers the best results, showing the evolution of a PV system's performance over time, which often does not follow linear trends over its whole lifetime (e.g. early degradation patterns, catastrophic failures during service lifetime, accelerating degradation mechanisms over time, etc.).
- Statistical soundness: increasing the number of YoY comparisons is shown to effectively decrease the statistical uncertainty. However, this also introduces a certain form of data redundancy. It is not clear through the current results that this negatively affects the PLR estimation, but future work could extend or rework the multi-YoY to minimise this data overlap. For example, comparing similar days around the same dates for each year, with varying weights, in order to avoid repetition in the computed gradients.
- Statistical robustness: the multi-YoY method is tested against noisy data and non-linearity, however there are other data biases that could be tested. For instance, the impact of weather data sources (ground-based or satellite-derived irradiance), various outliers, or the presence of reversible loss effects such as partial shading, soiling or snow. Regarding the comparison of ground-based and satellite irradiance data, Özkalay et al. showed that satellite data can be used in an ensemble method taking the mean PLR [48], however further work should confirm and generalise the applicability to the multi-YoY strategy. There also exist methods that do not rely on weather measurements which could be tested, as they could provide a solution to avoid irradiance-related uncertainties [13], [49]. Regarding climate- and technology-dependence of the YoY method, recently discussed by Theristis et al. [47], the multi-YoY could provide a solution to minimise the different behaviours observed, however this should be further tested and confirmed in future work.

4.2 Intrinsic PLR

The definition of the intrinsic PLR and the developed methodology combining FDD and PLR assessments into one analysis pipeline was shown to successfully decouple the reversible losses, which are also quantified, from the PV system degradation. The following discussion will go through the scientific innovations of the proposed method, as well as the caveats and limitations.

Scientific impact and innovations

- The combination of fault detection methods with long-term performance data analytics brings many interesting insights regarding the reliability of PV systems. The double approach enables the decoupling of intrinsic and extrinsic performance loss effects, which has been highlighted in recent works as an important research area for PV system reliability [2], [3]. The results highlight the importance of taking into account loss factors when analysing PV system data, as they can cause significant biases in the final PLR value.

- The defined intrinsic PLR metric is therefore a reflection of module degradation, although it still accounts for other system components degradation. Consequently, it serves as valuable information for installers and O&M companies in relation to contractual guarantees and module warranties. The FDD outputs may hold significant relevance for optimising O&M procedures, facilitating the transition from reactive/preventative maintenance to a predictive maintenance approach. With strong potential savings in O&M costs, this solution can help increase the reliability and profitability of PV projects [43].
- This work also highlights the importance of a correct definition of performance metrics in the PV reliability field. The standard PLR is still a useful and informative metric; however, its scope is often misrepresented in literature and in industry applications. The intrinsic PLR defined here can be considered a step closer to the quantification of system degradation, although this value should still not be confused with module-level degradation.
- The results presented in this work have a unique focus on small-scale PV systems in the built environment. Various studies have already reported utility-scale systems performance [4], [50], but such findings may not be readily applied to small systems [26], where the definition of the intrinsic PLR is particularly relevant given the prevalence of shading faults, which are seen to have a high impact on the PLR.
- Focusing on small-scale PV systems also allows for higher granularity in the treatment of data – the developed algorithms and analysis methods can be applied on a string-level (e.g. 20 modules connected in series), as opposed to the typical system-level approach most common in literature. This adds valuable insights in the observed mismatches in performance and allows for more detailed and effective classification of defects. In large-scale PV installations, the use of central inverters typically reduces data granularity, leading to the overlapping of loss factors and degradation modes.

Limitations and future work

- The current work is only applied to BIPV and BAPV systems, although the methodology is not limited to any system configuration. The input requirements are simply the DC system outputs and satellite or ground-based weather data. In general, small-scale systems will benefit from higher data granularity, but lack on-site meteorological data monitoring, while utility scale systems are often equipped with pyranometers or weather stations but tend to have low spatial granularity in terms of inverter data. There is therefore a trade-off between the precision of FDD and uncertainty of performance trend: results of the FDD analysis will typically be more detailed for small-scale systems, as there can be superposition of degradation modes for larger installations. However, uncertainty linked to solar resource inputs may be lower for larger systems, which can impact the assessment of the PLR.
- The identified loss factors do not cover all potential reversible loss effects. Extensions could include soiling, which is a reversible fault causing bias in the PV system data [50]. The main limitation in the case of soiling is that the losses do not manifest in a finite time step with specific DC output fingerprints; the losses are progressive, affecting mainly the current, and are often too low to be able to quantify accurately without soiling sensors. A potential way around the soiling impact in system performance is to filter for clear-sky days that occur after precipitation events, which would minimise the impact of soiling accumulation.
- There are many sources of uncertainty in the analysis pipeline, which compound and transfer to the final PLR value: measurement uncertainties related to the inverters and meteorological data sources (high for satellite-based), uncertainties in the fault detection and statistical thresholds, errors in the performance metric (PR), and statistical uncertainty in the PLR calculation (here the YoY method). Minimising these uncertainties will be the focus of future work.

- Climate and technology have also been shown to impact the accuracy and uncertainty of PLR assessments [47]. The proposed method in this work, namely the inclusion of fault detection steps in the PLR analysis pipeline, is in theory climate- and technology-independent. Specifically, the concept of filtering reversible losses from PV system data should be independent of the system location or module type. Nevertheless, given that the YoY statistical method is used to compute the PLR, and that this method has been shown to be biased in certain climates, future work should examine the sensitivity of the intrinsic PLR in various conditions (e.g., using synthetic data with induced faults and PLR for various technologies and climates).
- Although the intrinsic PLR is a better reflection of the degradation modes affecting the PV system, and therefore arguably serves as a better representation of system reliability linked to the manufacturer's warranty, it is still not to be confused with module-level degradation and includes all system and electrical losses.

5 Conclusions

Improving long-term performance assessments

The PLR is a key metric in PV system planning, O&M and reliability. The incorrect assessment of a system's PLR can have high financial consequences, and a robust estimation is therefore critical. This work proposes a simple solution to improve the statistical confidence interval of the YoY PLR, which we call the multi-YoY approach. By utilising all available comparison points instead of just those separated by one year, the multi-YoY method aims to reduce bootstrap uncertainty through improved data representativeness and robustness. The method is validated using synthetic PV performance data with a known PLR value and is further tested using high-quality IEA PVPS Task 13 publicly available datasets. Results with the multi-YoY show a factor of 10 decrease in RME compared to the standard YoY. Furthermore, results indicate that the sampling level (or aggregation strategy) of the performance metric (in this case the PR) does not impact the PLR estimation in the multi-YoY, effectively reducing one level of variability in the PLR pipeline. The methods' robustness to noisy datasets and non-linearity in the PR trend are also tested, showing improvements over the YoY in both precision and accuracy. In the case of non-linear trends, automatic segmentation is preferred in order to capture the evolving PLR. Several limitations and unanswered questions remain for future work. These include the lack of harmonisation in pre-processing steps within PLR pipelines, which can impact results, and the need for further robustness tests comparing weather data sources and examining the effects of reversible losses or outliers.

Fault Detection and Diagnosis Algorithm

This work is a first attempt to bridge the gap between the fields of FDD and PLRs in PV systems. Reversible loss factors, which impact short-term PV system performance, are shown to impact and bias the PLR evaluation of PV systems. The developed fault detection method is shown to successfully identify partial shading, snow and downtime losses in a case study with on-site validation, where evolving yield losses over time led to a shift in performance ratio trend. This approach may be extended to further identify, classify and filter other LFs (e.g. soiling). Furthermore, a fleet analysis of PV systems in the built environment enabled the identification of four distinct PLR bias patterns associated with changes in yield losses over time. While the presented results are specific to building-integrated and building-applied PV systems, the combined FDD and PLR pipeline is applicable to all PV system configurations, and future work will examine larger PV system fleets with varying configurations and capacities. Overall, the introduction of the newly defined intrinsic PLR, with the additional filtering of reversible losses, provides a more accurate reflection of PV system health and reliability compared to the standard PLR. Future work in the field should therefore consider integrating such filtering steps to improve accuracy in performance assessments and avoid erroneous interpretations of the PLR. Additionally, further research should address the limitations of the presented work, such as improving the coverage of identified loss factors and minimising the sources of uncertainty in the analysis pipeline.

6 Outlook and future implementation

The developed multi-YoY methodology is shared via a public repository: https://zenodo.org/records/11562418. The method can therefore be implemented easily into existing analysis pipelines. The function was developed following the guidelines of the *RdTools* library [9], widely used for the standard YoY method, which simplifies the adoption of this new method.

Future work will aim to address some of the remaining open questions of the project, possibly in an extension or second phase of the ASSURed-PV project**.** Some of the potential topics addressed are the following:

- Extending the loss factors of the FDDA, e.g. with soiling loss quantification.
- Focusing on non-reversible degradation modes and their impact of system reliability. This can be done for systems with confirmed degradation modes with access to long-term data.
- Detailed analysis of datasets which were not yet fully covered in the ASSURed-PV project, such as the SIG datasets of BAPV systems in Geneva.
- Performance assessment of datasets shared by the BFH with more than 30 years of operation and similar module technologies. These datasets will give insights into the impact of system configuration (roof, open-rack, façade) and climate (temperature and high altitude).
- Analysing utility-scale PV systems with the developed frameworks. So far, the system capacity has been limited as the focus was PV in the built environment. However, the methodologies can also be applied to larger scale PV systems and could bring interesting insights into their O&M, moving towards predictive maintenance.
- The large collection of Swiss PV system data could also be used to review the performance evolution of the Swiss PV installation in the past decade. A follow-up project could provide insights in the general performance statistics of PV systems in Switzerland. This would provide useful information for the 2050 Swiss Energy Strategy.

7 National and international cooperation

The ASSURed-PV project benefitted from collaboration with multiple national and international institutions and groups:

- International Energy Agency (IEA) Photovoltaic Power Systems Programme (PVPS) Task 13: exchanges with experts in the field of PV reliability and usage of shared data sources for the development of the multi-YoY methodology.

- National Renewable Energy Laboratory (NREL): exchanges and discussions with experts in the field of PV reliability.

- University of Applied Sciences and Arts of Southern Switzerland (SUPSI) PVLab: discussions and common projects, shared data, measurements campaigns, and planned publications with the PVLab team.

- Berner Fachhochschule (BFH) Laboratory for Photovoltaic Systems: common projects and data sharing.

- Österreichisches Forschungsinstitut (OFI): discussions, measurements campaigns, and planned publications.

8 Publications

8.1 Conference participations and proceedings

- **Poster**: “Intrinsic performance loss rate: decoupling shading losses from photovoltaic system data for reliable degradation estimations”, 21st Swiss National Photovoltaic Conference (Nationale Photovoltaik-Tagung), March 2023, DOI: 10.13140/RG.2.2.12033.12644
- **Poster**: “Towards a Robust Performance Loss Rate Estimate: Minimising the Uncertainty in the Analysis of Photovoltaic System Degradation”, 40th European Photovoltaic Solar Energy Conference (EU PVSEC), September 2023, DOI: 10.13140/RG.2.2.32771.89126
- **Proceeding**: “Towards a Robust Performance Loss Rate Estimate: Minimising the Uncertainty in the Analysis of Photovoltaic System Degradation”, 40th European Photovoltaic Solar Energy Conference (EU PVSEC), September 2023, DOI: 10.4229/EUPVSEC2023/4CV.1.14
- **Poster:** “30+ years of operation - a comprehensive review of the long-term performance of the Mont-Soleil PV power plant”, 22nd Swiss Photovoltaic Conference (Schweizer Photovoltaik-Tagung), March 2024, DOI: 10.13140/RG.2.2.32003.72487 (poster award)

8.2 Peer reviewed articles

- Quest H, Ballif C, Virtuani A. Intrinsic performance loss rate: Decoupling reversible and irreversible losses for an improved assessment of photovoltaic system performance. *Prog Photovolt Res Appl*. 2024; 1-16. doi:10.1002/pip.3829
- Submitted to Progress In Photovoltaics (May 2024): Quest H, Ballif C, Virtuani A. Multi-annual Year-on-Year: Minimising the Uncertainty in Photovoltaic System Performance Loss Rates.

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