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Grid-Tied Photovoltaic Performance Analysis Under Mediterranean Operating Conditions: A Residual Performance Diagnostic Framework

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Abstract

Conventional photovoltaic performance indicators provide useful benchmarking but do not determine whether production deficits arise from expected weather and module effects or from unresolved plant-side behaviour. This study develops a residual performance diagnostic framework for data-limited grid-connected photovoltaic plants and applies it to two adjacent fixed-tilt crystalline-silicon systems, each rated at 99.36 kW_p, in South Corfu, Greece, over 2016–2023. An expected-energy baseline was constructed using hourly irradiance and meteorological data from the Photovoltaic Geographical Information System after explicit correction for incidence-angle effects, irradiance-level response, module temperature, and first-order air-mass and spectral effects. Measured alternating-current energy delivered to the grid, obtained from the Hellenic Electricity Distribution Network Operator, was then compared with the corrected expected energy through a weather-adjusted system-efficiency indicator and its complementary residual-loss coefficient. The explicit module and weather loss envelope remained close to 9.01%, with temperature as the largest modelled component. Residual losses increased from 10.76% to 14.53% in Plant 1 and from 10.51% to 16.26% in Plant 2. The fitted apparent annual declines were 0.453 percentage points per year for Plant 1 and 0.609 percentage points per year for Plant 2. A generation-hour uncertainty analysis based on independent observations from the Hellenic National Meteorological Service gave expanded uncertainties of $\pm 5.80\%$ for expected energy and $\pm 5.89\%$ for the system-efficiency indicator. The framework is therefore presented as an uncertainty-bounded screening method for prioritizing inspection and maintenance, not as a root-cause diagnostic or a formal performance-loss-rate assessment.

Keywords: grid-connected photovoltaic systems; PV performance assessment; PVGIS-SARAH3; residual loss; system-efficiency index; Mediterranean climate; uncertainty propagation



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1. Introduction

Grid-connected photovoltaic (PV) plant performance is commonly evaluated through delivered alternating-current energy, final or specific yield, reference yield, capacity factor, and performance ratio (PR), as formalized in IEC 61724-1 monitoring practice [1]. These indicators enable standardized comparison across systems of different capacities and resource levels, but their diagnostic value depends on the system configuration, application,

and available evidence [2]. A decline in energy yield or PR therefore identifies underperformance relative to a reference, but it does not determine whether the deficit is meteorological, optical, thermal, electrical, operational, or progressive. This creates a practical research gap for small- to medium-sized PV plants that possess long-term energy records but lack high-resolution supervisory control, soiling, inverter, and string-level measurements.

The problem is particularly relevant under Mediterranean operating conditions, where high solar resource and high operating temperature occur simultaneously during the most productive months. Jayawardene et al. compared identical monocrystalline silicon modules in Oslo, Sevilla, and Tozeur and found substantially higher energy production at the sunnier sites, together with lower summer PR as temperature increased [3]. Tahir et al. likewise showed, across four climatic zones and five module technologies, that high temperature reduced conversion efficiency while wind cooling partly offset the thermal penalty, especially in coastal and high-altitude environments [4]. Mediterranean performance assessment must therefore distinguish the production benefit of high irradiance from the concurrent temperature penalty and from other seasonal effects such as dust, humidity, and sea-salt exposure.

The Photovoltaic Geographical Information System utilizing the SARA3 database offers hourly data on irradiance, meteorological conditions, geometric parameters, and reference production, suitable for establishing an external expected-energy baseline [5]. The utility and limitations of such comparisons are documented in various field studies. Krawczak observed that estimates derived from the Photovoltaic Geographical Information System accurately reproduced the annual scale of four rooftop systems, although the level of agreement varied according to season and orientation [6]. Boulmrharj et al. reported minimal daily simulation errors but significantly larger annual discrepancies when long-term calculations depend on generated rather than measured weather data [7]. Truong et al. demonstrated that operational events, including maintenance activities, could result in considerable monthly deviations between measured and modelled energy production [8]. Therefore, the concordance between two model-derived energy series indicates the consistency of the reference calculation, rather than the elimination of plant-side losses.

A residual assessment is meaningful only after the principal module and weather mechanisms have been represented explicitly. The Huld formulation describes the irradiance- and temperature-dependent relative efficiency of crystalline-silicon modules and shows increased sensitivity at low irradiance [9]. The Faïman model relates module temperature to irradiance, ambient temperature, and wind cooling [10]. Front-surface transmission is treated through the Martín–Ruiz incidence-angle modifier [11]. Atmospheric optical path is represented separately through the Kasten–Young air-mass expression and established solar-geometry relations [12,13]. Keeping these terms distinct prevents optical, thermal, irradiance-level, and first-order spectral effects from being absorbed indiscriminately into a single empirical residual.

The remaining measured–expected deficit, however, is not an exclusive physical failure mode. The review conducted by Alhmoud and the case study of large plants demonstrate that factors such as incidence angle, soiling, temperature, mismatch, cabling, inverter, transformer, degradation, and transmission effects can occur concurrently [14]. It is important to note that soiling is not a constant derate; extended periods without cleaning have led to significant power reductions in temperate installations [15], and seasonal dust losses have shown considerable variation between Australian and Indonesian climates [16]. Further field studies have identified cracks, browning, discoloration, corrosion, and persistent deposits as potential indicators of degradation [17]. Practices related to design, installation, operation, and maintenance may also contribute to additional losses [18], as can the behaviour of converters and inverters [19]. Conditions related to reactive-power operation and grid interface can influence the energy delivered [20,21], while environmental factors

such as humidity, rainfall, atmospheric deposits, wind, shading, and fluctuations in irradiance interact as environmental stressors [22]. Without associated diagnostic measurements, these mechanisms can only be regarded as plausible contributors to an unresolved residual.

Long-term trends necessitate a consistent interpretive approach. Lindig et al. differentiate the system-level performance loss rate—encompassing both reversible and irreversible effects—from module degradation, which pertains specifically to irreversible ageing [23]. Their multistep methodology also illustrates that reliance on a single linear fit may obscure distinct segments of performance loss [24]. Multi-annual year-on-year analytical methods diminish trend uncertainty when conditions are appropriate [25], and their efficacy has been further evaluated for incomplete and noisy field datasets [26]. Reported rates are influenced by climate and location: Frick et al. observed more rapid deterioration of multicrystalline silicon in Nicosia compared to Stuttgart [27], whereas Li et al. demonstrated that the transferability of degradation models significantly improves when regionalization based on climate is implemented [28]. Tonita et al. additionally documented the long-term behaviour of systems within cold and snowy climates [29]. Consequently, a slope derived solely from delivered energy should be characterized as an apparent weather-adjusted system-performance trend, rather than a formal performance loss rate or module degradation.

Paired field evidence provides an additional constraint, but not automatic causal identification. Zdyb and Gulkowski showed that four module technologies exposed at the same Polish site did not share the same loss structure [30]. Zdyb and Sobczynski likewise reported substantial seasonal variation in module efficiency under changing external conditions [31]. Gulkowski et al. later found markedly different long-term PR and year-on-year loss rates among technologies operating at the same location and tilt [32]. These findings show that common exposure reduces meteorological confounding but does not guarantee identical trajectories when module response, balance-of-system behaviour, maintenance, or local exposure differ.

The primary aim of this study is to develop and assess an uncertainty-bounded residual performance framework for data-limited grid-connected photovoltaic (PV) systems. The approach involves constructing a plant-parameterized expected-energy denominator, following explicit adjustments for incidence angle, irradiance levels, module temperature, and first-order air-mass effects. The energy measured and delivered to the grid is then compared to this denominator to derive a weather-adjusted system-efficiency index and its associated residual-loss coefficient. These indicators are intentionally designed to be simple measurements relative to expected values; the scientific contribution resides in the physically structured denominator, the explicit treatment of uncertainty, and the paired-plant interpretation, rather than in algebraic innovation.

The framework is applied to two adjacent fixed-tilt crystalline-silicon plants in South Corfu, Greece, each with a licenced capacity of 99.36 kW_p and evaluated over a period from 2016 to 2023 utilizing energy records from the Hellenic Electricity Distribution Network Operator. Their shared site, capacity, tilt, azimuth, meteorological-input chain, and analytical model facilitate establishing common forcing, thereby enabling differentiation from persistent plant-specific divergence. This design does not eliminate variations such as differential soiling, unequal cleaning, local shading, drainage, vegetation, row-level exposure, inverter behaviour, wiring mismatch, availability, curtailment, or maintenance history. Consequently, the paired difference is interpreted as a screening signal for further investigation rather than as definitive proof of a specific root cause.

The contribution pertains to the framework level and comprises four interconnected components. First, a physically structured expected-energy baseline is established utilizing hourly SARA3 inputs. Second, the explicit module and weather envelope are delineated from the remaining measured–expected residual. Third, the two adjacent plants

are analyzed within a common model chain to identify shared as well as plant-specific behaviours. Fourth, uncertainty is propagated employing a Greece-specific wind-height formulation [33] and independent three-hourly observations from the Hellenic National Meteorological Service [34]. The resulting diagnostic layer complements power resolution, temperature-corrected power resolution, and formal performance-loss-rate analysis; it is designed for inspection and maintenance prioritization when detailed supervisory and component-level data are not available.

The remainder of the paper is organized as follows. Section 2 describes the plants, data sources, expected-energy model, residual indicators, paired-plant metric, and uncertainty methodology. Section 3 presents the conventional indicators, annual and seasonal module/weather losses, residual trends, paired divergence, year-month diagnostics, and propagated uncertainty. Section 4 discusses the interpretation relative to established performance metrics, the limitations on causal attribution, and the operational implications. Section 5 summarizes the principal conclusions.

2. Materials and Methods

2.1. Study Plants, Data Sources, and Analysis Period

The analysis was conducted for two adjacent fixed-tilt grid-connected photovoltaic installations situated in South Corfu, Greece (39.403° , 20.046°). The site elevation is approximately 40 m. Both plants are connected to the low-voltage grid. The study encompasses eight full operational years (2016–2023). PV arrays are installed at a tilt angle of 25° and an azimuth of 0.45° . Each plant uses crystalline-silicon modules rated at 235 Wp under standard test conditions. The installed module-nameplate capacity is 99.405 kW_p, while the licenced nominal capacity is 99.36 kW_p. The latter value was used as the reference capacity, P₀, for normalization, PVGIS configuration, expected energy, specific yield, and capacity-factor calculations. The PV panel power temperature coefficient was taken as $-0.45\% \text{ }^\circ\text{C}^{-1}$, equivalent to $\gamma = -0.0045 \text{ }^\circ\text{C}^{-1}$.

Hourly irradiance and meteorological data were obtained from PVGIS using the SARA3 radiation database [5]. The extracted variables included tilted-plane irradiance components, ambient temperature at 2 m, solar-position variables, air-mass-related variables, and wind speed at 10 m. Measured production was obtained from official HEDNO hourly records and was treated as settlement-grade delivered/exported AC energy at the grid-connection level. Three-hourly dry-bulb temperature at 2 m and wind speed at 10 m from the HNMS Corfu station (station code 16641) were used only for uncertainty evaluation [34]. HNMS wind speed was supplied in knots and converted to m s^{-1} . A separate PVGIS-SARA3 series was retrieved at the HNMS station coordinates (39.605° N, 19.910° E) so that temperature and wind were compared at the same location and nominal heights. These data did not replace or bias-correct the PVGIS-SARA3 input chain used in the expected-energy calculation.

The terminology and performance index logic follow IEC 61724-1, where applicable [1]. Relative-efficiency and module-temperature calculations use the Huld and Faïman formulations [9,10]. Incidence-angle correction follows the Martín-Ruiz model [11], while optical air mass and solar geometry follow the Kasten–Young and solar-engineering formulations [12,13]. An adjustment for wind speed at different heights was required because PVGIS provides wind speed at 10 m, whereas the module-temperature model requires wind speed representative of the module heat-exchange environment. This adjustment was conducted using a power-law formulation with a regional exponent derived from spatially resolved wind-profile analysis [33].

2.2. Data Hierarchy and Reporting Scale

The framework employs two primary calculation layers and one independent uncertainty-check layer. The first calculation layer is the hourly PVGIS-SARAH3 model chain, which is used to compute plane-of-array irradiance, effective irradiance, module temperature, relative conversion efficiency, first-order air-mass/spectral correction, and expected energy. The second calculation layer is derived from measured HEDNO delivered/exported AC energy records. The independent HNMS layer is used only to quantify generation-hour uncertainty in ambient temperature and wind speed at matching nominal heights. It is not used to replace or bias-correct the PVGIS-SARAH3 input series.

Hourly expected power, $P(t)$, is converted into energy, $E_{\Delta T}$, over a reporting interval, ΔT , using Equation (1):

$$E_{\Delta T} = \sum_{t \in \Delta T} P(t) \Delta t \quad (1)$$

where Δt is the hourly time step. The same aggregation principle was applied to annual and monthly reporting intervals. Annual values were used to evaluate long-term behaviour, while monthly values were used to examine seasonal structure and residual deviations that may be obscured in annual averages.

2.3. Plane-of-Array Irradiance and Loss-Free Baseline

The incident irradiance on the module plane was defined as the sum of the direct, diffuse, and ground-reflected components. These inclined-plane components were obtained from the PVGIS-SARAH3 output corresponding to the specified tilt and azimuth. The total plane-of-array irradiance, G_{POA} , is calculated using Equation (2):

$$G_{\text{POA}}(t) = G_{b,\text{POA}}(t) + G_{d,\text{POA}}(t) + G_{r,\text{POA}}(t) \quad (2)$$

where $G_{b,\text{POA}}$, $G_{d,\text{POA}}$, and $G_{r,\text{POA}}$ are the direct, diffuse, and ground-reflected plane-of-array components, respectively.

The loss-free POA-scaled power, P_{POA} , is then obtained from Equation (3):

$$P_{\text{POA}}(t) = P_0 \frac{G_{\text{POA}}(t)}{G_{\text{ref}}} \quad (3)$$

where $P_0 = 99.36 \text{ kW}_p$ and $G_{\text{ref}} = 1000 \text{ W m}^{-2}$. The corresponding loss-free energy over ΔT , $E_{\text{POA},\Delta T}$, follows from Equation (4):

$$E_{\text{POA},\Delta T} = \sum_{t \in \Delta T} P_{\text{POA}}(t) \Delta t \quad (4)$$

Equations (3) and (4) define a reference state before optical, irradiance-level, temperature, and wavelength-related corrections. This reference state is not interpreted as physically deliverable AC energy.

2.4. Incidence-Angle Correction and Effective Irradiance

The angle-of-incidence correction was applied before the relative-efficiency calculation because AOI affects the fraction of incident irradiance transmitted through the module cover. The beam component was corrected using the Martín-Ruiz incidence-angle modifier [11]. The beam modifier, IAM_b , is calculated from Equation (5):

$$IAM_b(\theta) = \frac{1 - \exp(-\cos\theta/a_r)}{1 - \exp\left(-\frac{1}{a_r}\right)} \quad (5)$$

where θ is the beam incidence angle and a_r is the Martín–Ruiz angular-loss coefficient. When the sun was behind the module plane, the beam contribution was set to zero.

The effective irradiance after front-surface angular correction, G_{eff} , is calculated by Equation (6):

$$G_{\text{eff}}(t) = IAM_b(\theta)G_{b,\text{POA}}(t) + IAM_d G_{d,\text{POA}}(t) + IAM_r G_{r,\text{POA}}(t) \quad (6)$$

where IAM_b , IAM_d , and IAM_r are the effective incidence-angle modifiers for the beam, diffuse, and ground-reflected irradiance components, respectively. The AOI-corrected power, P_{AOI} , is then obtained from Equation (7):

$$P_{\text{AOI}}(t) = P_0 \frac{G_{\text{eff}}(t)}{G_{\text{ref}}} \quad (7)$$

The AOI loss over the reporting interval, $L_{\text{AOI},\Delta T}$, is calculated from Equation (8):

$$L_{\text{AOI},\Delta T} = 1 - \frac{\sum_{t \in \Delta T} P_{\text{AOI}}(t) \Delta t}{\sum_{t \in \Delta T} P_{\text{POA}}(t) \Delta t} \quad (8)$$

2.5. Module Temperature

Module temperature was estimated with the Faiman formulation [10]. Before applying the thermal model, the PVGIS 10 m wind speed was adjusted to 2 m using Equation (9):

$$WS_{2\text{m}}(t) = WS_{10\text{m}}(t) \left(\frac{2}{10} \right)^\alpha \quad (9)$$

where $WS_{10\text{m}}$ is the PVGIS wind speed at 10 m, $WS_{2\text{m}}$ is the adjusted wind speed near module height, and α is the wind-profile exponent. The selected exponent $\alpha = 0.172$ is consistent with the mapped mean exponent for Greece reported by Jung and Schindler [33]. Thus, $WS_{2\text{m}}$ was used as the module-height wind speed, WS_{mod} , in Equation (10). Because HNMS and PVGIS wind speeds were both available at 10 m, their empirical discrepancy was evaluated directly before any height adjustment. The exponent α therefore affects only the subsequent 10 m-to-2 m conversion in the Faiman model. Sensitivity cases $\alpha = 0.14$, $1/7$, 0.172 , and 0.21 changed the annual temperature-loss proxy by 0.286 percentage points across the complete range; the $1/7$ case differed from $\alpha = 0.172$ by 0.120 percentage points. The literature-based value $\alpha = 0.172$ was retained as the baseline.

The module temperature, T_{mod} , is calculated using Equation (10):

$$T_{\text{mod}}(t) = T_{\text{amb}}(t) + \frac{G_{\text{eff}}(t)}{U_0 + U_1 WS_{\text{mod}}(t)} \quad (10)$$

where T_{amb} is ambient air temperature, G_{eff} is AOI-corrected irradiance, and U_0 and U_1 are empirical heat-loss coefficients. The values used were $U_0 = 25 \text{ W m}^{-2} \text{ K}^{-1}$ and $U_1 = 6.84 \text{ W m}^{-3} \text{ s K}^{-1}$. The coefficients U_0 and U_1 are empirical heat-loss coefficients, not velocities. The effective heat-loss term $U_0 + U_1 WS_{\text{mod}}$ varies hourly because the PVGIS wind speed series varies hourly.

2.6. Irradiance- and Temperature-Dependent Relative Efficiency

The crystalline-silicon relative-efficiency correction followed the empirical Huld/PVGIS formulation [9]. The normalized effective irradiance, G' , and the module-temperature deviation from standard test conditions, T' , are defined by Equations (11) and (12):

$$G'(t) = \frac{G_{\text{eff}}(t)}{G_{\text{ref}}} \quad (11)$$

$$T'(t) = T_{\text{mod}}(t) - 25 \quad (12)$$

For $G'(t) > 0$, relative efficiency, η_{rel} , was calculated from Equation (13):

$$\eta_{\text{rel},k} = 1 + k_1 \ln(G'_k) + k_2 [\ln(G'_k)]^2 + k_3 T'_k + k_4 T'_k \ln(G'_k) + k_5 T'_k [\ln(G'_k)]^2 + k_6 (T'_k)^2 \quad (13)$$

For crystalline-silicon modules, the coefficients were $k_1 = -0.017237$, $k_2 = -0.040465$, $k_3 = -0.004702$, $k_4 = 0.000149$, $k_5 = 0.000170$, and $k_6 = 0.000005$.

The expected module-side power before wavelength-related correction, P_{rel} , was then calculated using Equation (14):

$$P_{\text{rel}}(t) = P_0 \frac{G_{\text{eff}}(t)}{G_{\text{ref}}} \eta_{\text{rel}}(t) \quad (14)$$

Equation (14) includes AOI correction, irradiance-level response, and temperature response. It does not include inverter conversion, transformer loss, wiring loss, mismatch, curtailment, availability, unmodelled soiling, or grid-interface effects.

2.7. Separation of Irradiance-Level and Temperature Losses

Irradiance-level loss was isolated by evaluating the relative-efficiency model at the standard module temperature. Under this condition, $T'(t) = 0$, and the irradiance-only relative efficiency, η_G , is calculated from Equation (15):

$$\eta_G(t) = 1 + k_1 \ln G'(t) + k_2 [\ln G'(t)]^2 \quad (15)$$

The irradiance-corrected power, P_G , is then defined by Equation (16):

$$P_G(t) = P_0 \frac{G_{\text{eff}}(t)}{G_{\text{ref}}} \eta_G(t) \quad (16)$$

The irradiance-level loss, $L_{G,\Delta T}$, is calculated from Equation (17):

$$L_{G,\Delta T} = 1 - \frac{\sum_{t \in \Delta T} P_G(t) \Delta t}{\sum_{t \in \Delta T} P_{\text{AOI}}(t) \Delta t} \quad (17)$$

The temperature loss, $L_{T,\Delta T}$, was calculated sequentially relative to the irradiance-only corrected power using Equation (18):

$$L_{T,\Delta T} = 1 - \frac{\sum_{t \in \Delta T} P_{\text{rel}}(t) \Delta t}{\sum_{t \in \Delta T} P_G(t) \Delta t} \quad (18)$$

This ordering prevents double-counting between irradiance and temperature responses. Temperature is a significant factor at South Corfu because the highest-resource months coincide with elevated module temperatures.

2.8. First-Order Air-Mass Correction

A first-order air-mass term was used to represent the wavelength-related part of the module/weather envelope. The relative optical air mass, AM_r , was calculated with the Kasten–Young expression [12], given in Equation (19):

$$AM_r(t) = \frac{1}{\cos \theta_z(t) + 0.50572 [96.07995 - \theta_z(t)]^{-1.6364}} \quad (19)$$

where θ_z is the solar zenith angle in degrees. The pressure-corrected air mass, AM , was then calculated from Equation (20):

$$AM(t) = AM_r(t) \frac{p}{p_0} \quad (20)$$

where $p_0 = 101,325$ Pa. Because measured site pressure was unavailable, pressure at the 40 m site elevation was estimated using a standard-atmosphere approximation.

The first-order correction factor, f_{AM} , was calculated using Equation (21):

$$f_{AM}(t) = 1 + s[AM(t) - 1.5] \quad (21)$$

where s is the first-order wavelength-sensitivity coefficient and 1.5 is the $AM1.5$ reference condition. The final expected power after explicit module/weather correction, P_{exp} , is calculated from Equation (22):

$$P_{exp}(t) = P_{rel}(t) f_{AM}(t) \quad (22)$$

The wavelength-related loss term, $L_{spec,\Delta T}$, is calculated from Equation (23):

$$L_{spec,\Delta T} = 1 - \frac{\sum_{t \in \Delta T} P_{exp}(t) \Delta t}{\sum_{t \in \Delta T} P_{rel}(t) \Delta t} \quad (23)$$

The term L_{spec} is retained as the manuscript notation, but it is interpreted as a first-order air-mass/spectral correction rather than as a directly measured spectral-response loss. The coefficient $s = 0.11$ was adopted as a first-order modelling assumption and was not calibrated against site-specific spectral measurements. Accordingly, the correction may be positive or negative relative to the $AM:1.5$ reference condition. Positive winter values represent a modelled correction gain under high-air-mass conditions, not a physically measured negative loss. A $\pm 10\%$ sensitivity test of s changed the mean annual correction by approximately ± 0.021 percentage points, confirming its minor influence on E_{exp} . Measured spectral irradiance and module-specific spectral-response data were unavailable.

2.9. Expected Energy and Explicit Module/Weather Loss

Expected energy after explicit module/weather correction, $E_{exp,\Delta T}$, was calculated from Equation (24):

$$E_{exp,\Delta T} = \sum_{t \in \Delta T} P_{exp}(t) \Delta t \quad (24)$$

$L_{mod,\Delta T}$, the combined explicitly modelled module/weather loss, was calculated relative to the loss-free POA-scaled baseline using Equation (25):

$$L_{mod,\Delta T} = 1 - \frac{E_{exp,\Delta T}}{E_{POA,\Delta T}} \quad (25)$$

For reporting, the same loss envelope was also expressed through its sequential components using Equation (26):

$$1 - L_{mod} = (1 - L_{AOI})(1 - L_G)(1 - L_T)(1 - L_{spec}) \quad (26)$$

All terms in Equations (25) and (26) are calculated as energy ratios.

The expected energy E_{exp} , is the energy predicted after explicit module/weather correction. It is not a full AC production model. Inverter conversion, transformer losses, wiring losses, mismatch, curtailment, availability, unmodelled soiling, grid-interface effects, metering uncertainty, and modelling uncertainty remain outside the explicit module/weather envelope.

2.10. Residual System-Loss Coefficient and Weather-Adjusted System-Efficiency Index

The residual system-loss coefficient, SL_{res} , was calculated from measured HEDNO delivered/exported AC energy and the expected energy after module/weather correction using Equation (27):

$$SL_{\text{res},i,\Delta T} = 1 - \frac{E_{\text{meas},i,\Delta T}}{E_{\text{exp},\Delta T}} \quad (27)$$

where i denotes Plant 1 or Plant 2. The corresponding weather-adjusted system-efficiency index, SEI , was defined by Equation (28):

$$SEI_{i,\Delta T} = \frac{E_{\text{meas},i,\Delta T}}{E_{\text{exp},\Delta T}} \quad (28)$$

From Equations (27) and (28), SEI and SL_{res} are related by Equation (29):

$$SEI_{i,\Delta T} = 1 - SL_{\text{res},i,\Delta T} \quad (29)$$

SL_{res} The two quantities are derived residual indicators. They are not IEC standardized metrics, formal PLR values, inverter efficiencies, soiling ratios, or degradation rates. Since inverter behaviour, transformer loss, wiring, mismatch, availability, curtailment, unmodelled soiling, grid-interface limitations, metering uncertainty, and model uncertainty are not parameterized separately, their combined effect remains embedded in SL_{res} .

2.11. Total-Loss Partition and Apparent Annual Decline

The strict total loss relative to the loss-free POA-scaled baseline, L_{tot} , was calculated from Equation (30):

$$L_{\text{tot},i,\Delta T} = 1 - \frac{E_{\text{meas},i,\Delta T}}{E_{\text{POA},\Delta T}} \quad (30)$$

For diagnostic reporting, the total loss was also written as the percentage-point partition shown in Equation (31):

$$L_{\text{tot},i} \approx L_{\text{mod}} + SL_{\text{res},i} \quad (31)$$

Equation (31) is used only for interpreting the loss budget in figures and tables. The strict energy-ratio definition in Equation (30) remains the primary definition.

The annual SEI trend was fitted with the linear model in Equation (32):

$$SEI_i(y) = a_i + b_i y + \varepsilon_i(y) \quad (32)$$

where y is the year, a_i is the intercept, b_i is the annual slope, and ε_i is the annual residual. When SEI is expressed in percent, b_i has units of percentage points per year.

The relative apparent annual decline, D_i , was calculated using Equation (33):

$$D_i = -\frac{b_i}{S\bar{E}I_i} \quad (33)$$

where $S\bar{E}I_i$ is the mean annual SEI of the plant i . This quantity is reported as the apparent weather-adjusted AC system-performance decline. It is not reported as a formal PLR or module degradation because the analysis does not include a full PLR workflow with high-frequency filtering, normalization, statistical extraction, uncertainty propagation, or independent evidence of degradation [23–29].

2.12. Paired-Plant Residual Divergence

Because both PV plants have the same licenced capacity, location, tilt, azimuth, PVGIS-SARAH3 input data, and analytical model, their residual difference provides an additional diagnostic constraint. The paired-plant residual divergence, ΔSL_{res} , was defined by Equation (34):

$$\Delta SL_{\text{res},\Delta T} = SL_{\text{res},2,\Delta T} - SL_{\text{res},1,\Delta T} \quad (34)$$

ΔSL_{res} , positive values of Equation (34), indicate a higher unresolved residual loss in Plant 2. Since the two systems share the same explicit module/weather envelope, persistent non-zero values of ΔSL_{res} are less likely to be driven solely by regional meteorological forcing. They remain diagnostic signals, not root-cause proof.

The divergence was assessed on an annual basis, segmented by calendar month over an eight-year period, and analyzed within each year-month cell. This methodology facilitated the exploration of three primary inquiries: whether residual loss exhibited an increasing trend over time, whether it demonstrated seasonal concentration, and whether it was characteristic of both plants or specific to individual plants.

2.13. Scope and Limitations

The PVGIS-RPD framework is intended for performance screening when long-term delivered-energy records are available, but component-level diagnostics are limited. It uses PVGIS-SARAH3 irradiance and meteorological data, installation parameters, and HEDNO delivered/exported AC energy records to separate the explicit module/weather envelope from the remaining measured-expected residual.

The method does not replace SCADA-based fault diagnosis, formal PLR analysis, soiling measurements, cleaning records, inverter logs, string-level measurements, I-V curve tracing, thermography, or power-quality assessment. Following the uncertainty analysis in Section 2.14, SEI , SL_{res} , and ΔSL_{res} are interpreted as uncertainty-bounded screening indicators rather than deterministic root-cause measurements. Same-site operation reduces common meteorological confounding but does not exclude differential soiling, unequal cleaning, local shading, inverter behaviour, wiring mismatch, curtailment, grid-interface effects, or undocumented maintenance history.

2.14. Uncertainty Analysis and Sensitivity Treatment

Meteorological-input uncertainty was evaluated using three-hourly HNMS observations from the Corfu station [35]. Complete calendar years 2016–2022 were used, providing 20,407 observations from the expected 20,456 three-hour records. HNMS temperature and wind were measured at 2 m and 10 m, respectively, matching the nominal heights of PVGIS $T_{2\text{m}}$ and $WS_{10\text{m}}$. A PVGIS-SARAH3 series at the HNMS station coordinates was matched to the observations. Only PV-generation hours with modelled PVGIS power greater than zero were retained, and the comparison was weighted by plane-of-array irradiance so that the hours contributing most energy had the greatest influence. The nominal UTC alignment produced 9473 valid matched generation observations after quality control.

The HNMS observations were not treated as uncertainty-free reference values. The empirical PVGIS–HNMS discrepancy reflects contributions from both datasets, including sensor and reporting uncertainties, local exposure, temporal representativeness, and gridded model uncertainty [36]. Using a separate PVGIS series at the station coordinates and comparing variables at the same nominal heights reduced spatial and height-related mismatch. The full uncorrected, generation-weighted RMSE was nevertheless propagated as a conservative combined standard discrepancy. A separate HNMS instrument term was not added because no instrument-specific calibration certificates were available and doing so would partly double-count uncertainty already embedded in the empirical discrepancy.

For each matched generation-hour observation t , the PVGIS–HNMS discrepancy was defined as Equation (35).

$$e_{x,t} = x_{PVGIS,t} - x_{HNMS,t} \quad (35)$$

The GPOA-weighted mean bias and RMSE were calculated using Equations (36) and (37).

$$b_x = \frac{\sum_{t=1}^n w_t e_{x,t}}{\sum_{t=1}^n w_t} \quad (36)$$

$$RMSE_x = \sqrt{\frac{\sum_{t=1}^n w_t e_{x,t}^2}{\sum_{t=1}^n w_t}} \quad (37)$$

The RMSE was used as the standard uncertainty input $u(x)$, because the PVGIS-RPD calculation was not bias-corrected. The weights were defined as $w_t = GPOA_t$, so that the uncertainty estimate reflected PV-generation relevance rather than nighttime agreement. Expanded uncertainty was calculated with coverage factor $k = 2$, following the conventional uncertainty-propagation approach [35].

$$U_x = ku(x), k = 2 \quad (38)$$

Under the nominal UTC alignment, the GPOA-weighted PVGIS-minus-HNMS bias and RMSE were -2.733 °C and 3.172 °C for ambient temperature, and -0.637 m s^{−1} and 1.712 m s^{−1} for wind speed at 10 m. After applying $\alpha = 0.172$, the standard uncertainty of WS_{mod} at 2 m was 1.298 m s^{−1}. The timestamps in both input files were labelled UTC; therefore, no fixed 2 h timezone correction was applied. A +1 h alignment minimized the joint generation-weighted discrepancy, while +2 h minimized wind RMSE and nearly removed wind bias. Both were retained as temporal-alignment sensitivity cases. Irradiance uncertainty remained a PVGIS Type-B component with relative standard uncertainty $\pm 1.186\%$.

Uncertainty was propagated through the Faïman module-temperature model using the local sensitivity coefficients in Equations (39)–(41).

$$\frac{\partial T_{mod}}{\partial T_{amb}} = 1 \quad (39)$$

$$\frac{\partial T_{mod}}{\partial G_{eff}} = \frac{1}{U_0 + U_1 WS_{mod}} \quad (40)$$

$$\frac{\partial T_{mod}}{\partial WS_{mod}} = -\frac{G_{eff} U_1}{(U_0 + U_1 WS_{mod})^2} \quad (41)$$

The propagated module-temperature uncertainty was calculated from ambient temperature, irradiance, and wind speed contributions using Equation (42).

$$u(T_{mod})^2 = u(T_{amb})^2 + \left(\frac{\partial T_{mod}}{\partial G_{eff}} u(G_{eff}) \right)^2 + \left(\frac{\partial T_{mod}}{\partial WS_{mod}} u(WS_{mod}) \right)^2 \quad (42)$$

The relative uncertainty of expected energy was then calculated by combining the irradiance, temperature, and wind speed contributions in quadrature, as shown in Equation (43).

$$u_r(E_{exp}) = \sqrt{u_r(E_H)^2 + u_r(E_T)^2 + u_r(E_{WS})^2} \quad (43)$$

The uncertainty of SEI was calculated from the uncertainties of the measured and expected energy, as shown in Equation (44). The central standard uncertainty of the measured HEDNO delivered energy was taken as 0.5%.

$$u_r(SEI) = \sqrt{u_r(E_{meas})^2 + u_r(E_{exp})^2} \quad (44)$$

Since $SL_{res} = 1 - SEI$, the same absolute uncertainty applies to SL_{res} .

$$u(SL_{res}) = u(SEI) \quad (45)$$

Sensitivity treatment was concentrated on input assumptions that directly influence the expected-energy denominator and were substantiated by available data. Temporal alignment was examined at 0 h, +1 h, and +2 h. The wind-height exponent α was assessed independently through the 10 m-to-2 m model conversion, using $\alpha = 0.172$ as the baseline and considering alternatives of 0.14, 1/7, and 0.21 [33]. Uncertainty in irradiance was addressed as a PVGIS Type-B component [5], while measurement uncertainty in energy was appraised through metering-uncertainty scenarios. Additionally, $\pm 10\%$ perturbations were applied to G_{POA} , WS_{mod} , γ , U_0 , U_1 , and the first-order air-mass/spectral coefficient s . The normalized sensitivity coefficient and finite output change were evaluated utilizing Equations (46) and (47). The fitted annual SEI slopes were reported with 95% confidence intervals, separately from the expanded uncertainty of SEI and SL_{res} , since regression confidence and measurement/model uncertainty pertain to different quantities [35].

$$S_{y,x_i} = \frac{\frac{\Delta y}{y}}{\frac{\Delta x_i}{x_i}} \quad (46)$$

$$\Delta y_i = y(x_i + \Delta x_i) - y(x_i) \quad (47)$$

3. Results

3.1. Expected-Energy Consistency and Conventional Performance Indicators

The PVGIS-RPD workflow summarized in Figure 1 outlines the diagnostic sequence: PVGIS-SARAH3 provides hourly irradiance and meteorological inputs; producer and installation data are used to parameterize the expected energy chain; and HEDNO records offer measured data on delivered and exported AC energy. This sequence is important because the default PVGIS output is not a substitute for measured performance but a benchmark for residual analysis based on plant-parameterized expected energy, E_{exp} .

Figure 2 compares the annual plant-parameterized expected energy with PVGIS projections from 2016 to 2023. The two series closely match, with cumulative expected energy at 1426 MWh per plant and PVGIS at 1419 MWh. The difference was 6.701 MWh, an average deviation of +0.47%. This shows that the plant-parameterized expected energy aligns with PVGIS, serving as the denominator for weather-adjusted SEI and SL_{res} .

The agreement in Figure 2 does not validate the measured plant output. Both the analytical expected-energy series and PVGIS output are model-based. Their close match shows consistency between the two energy estimates, not the absence of inefficiencies or losses. This agrees with previous studies where annual agreement was affected by seasonality, orientation, weather-input accuracy, and operational events [6–8].

Recorded data from HEDNO show that between 2016 and 2023, Plant 1 delivered 1250 MWh and Plant 2 delivered 1241 MWh. Their mean annual energies were 156.20 and 155.06 MWh, respectively. Normalized to 99.36 kW_p, the mean annual specific yields were 1572.09 kWh/kW_p for Plant 1 and 1560.59 kWh/kW_p for Plant 2.

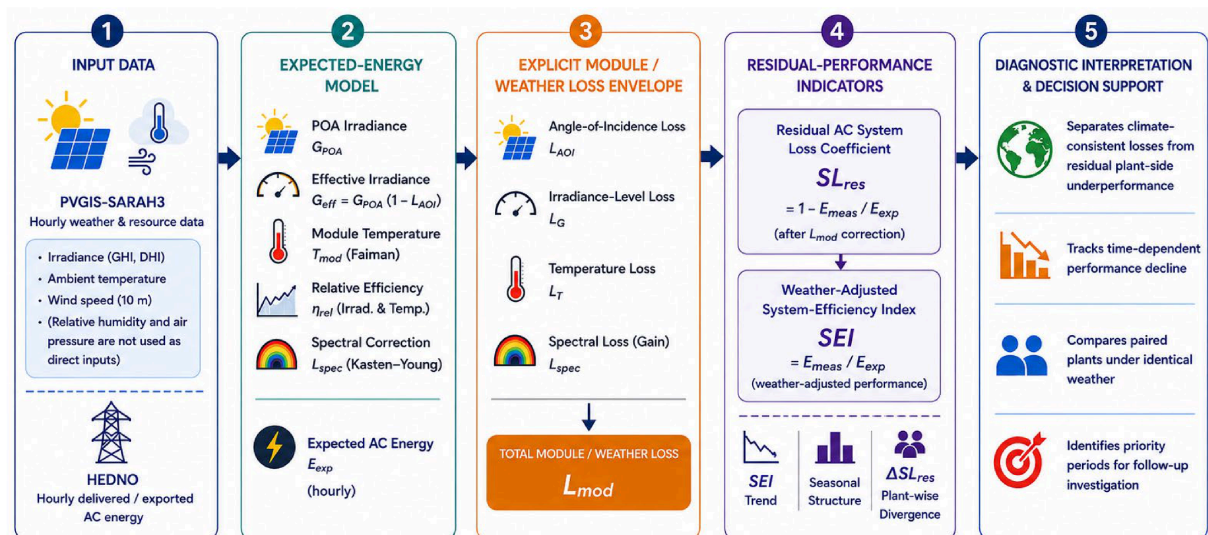


Figure 1. PVGIS-informed residual performance diagnostic (PVGIS-RPD) framework.

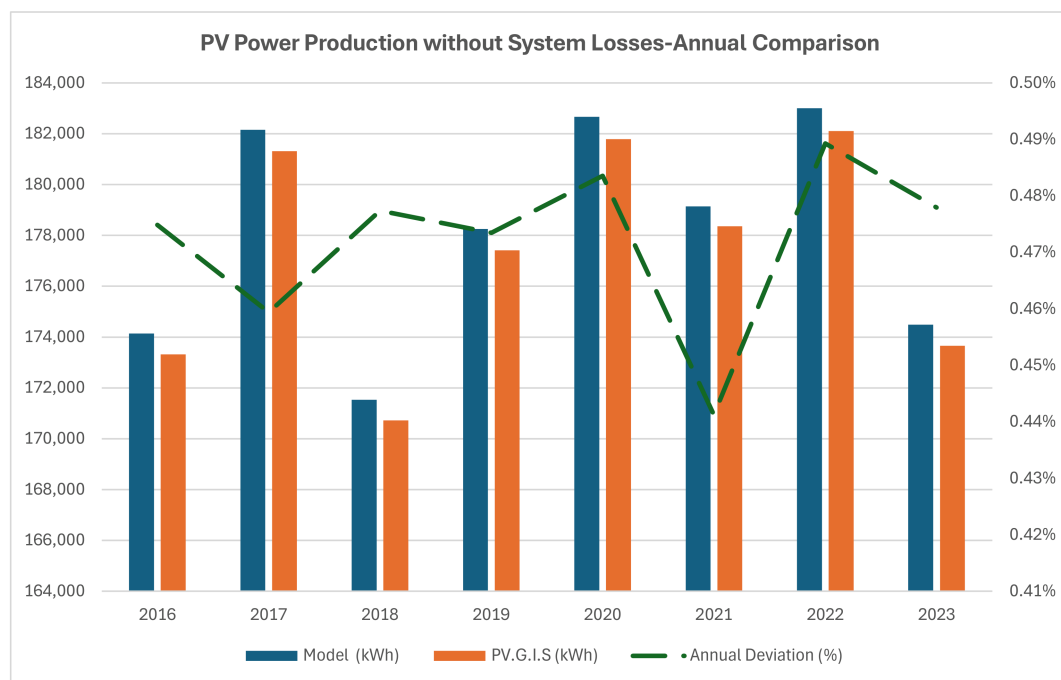


Figure 2. Analytical expected energy and PVGIS expected energy, 2016–2023.

These indicators show similar production between the two systems. The total plant-to-plant difference was 9.14 MWh over eight years, about 0.73% of Plant 1's output. However, energy and yield alone do not clarify whether deviations arise from module/weather effects or unresolved plant-side losses. Field studies confirm that yield and PR reflect combined effects like irradiance, module technology, temperature, inverter, and system losses, rather than specific causes [30–32].

Table 1 compares the roles and fitted trends of PR, temperature-corrected PR (PRT), and SEI, and positions them conceptually relative to formal PLR. PR, PRT, and SEI identify a common declining trajectory but use different denominators and therefore have different diagnostic meanings. Formal PLR was not estimated because the study does not implement the filtering, normalization, and multistep extraction required for formal PLR analysis [23,24], or the multi-annual year-on-year procedures used to reduce trend uncertainty [25,26].

Table 1. Comparison of established PV performance metrics and the proposed residual indicators.

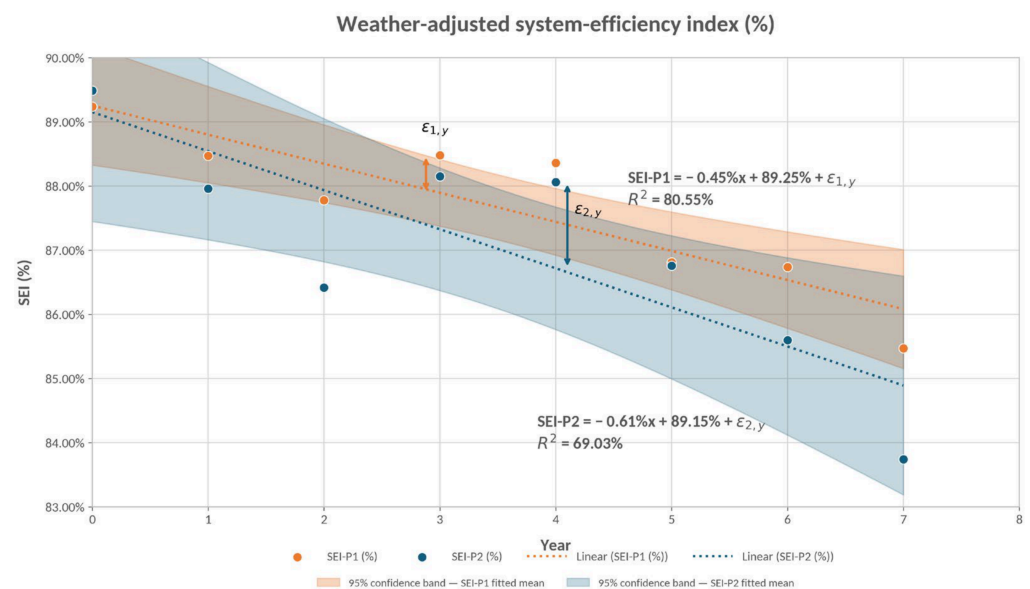
Metric	Plant 1 Slope (pp y ^{−1})	Plant 1 R ²	Plant 2 Slope (pp y ^{−1})	Plant 2 R ²
PR	−0.437	0.773	−0.580	0.651
PRT	−0.422	0.762	−0.572	0.658
SEI	−0.453	0.805	−0.609	0.690

3.2. Weather-Adjusted System-Efficiency Index and Apparent Annual Performance Decline

Table 2 shows the annual weather-adjusted system-efficiency index (SEI) for both plants, and Figure 3 illustrates the fitted trends. SEI compares measured HEDNO delivered/exported AC energy with expected energy after explicit module/weather correction. It is a residual screening indicator and is not interpreted as module efficiency, inverter efficiency, PLR, or degradation rate.

Table 2. Annual weather-adjusted system-efficiency index, 2016–2023.

Year	Plant 1 SEI (%)	Plant 2 SEI (%)
2016	89.24	89.49
2017	88.47	87.96
2018	87.78	86.42
2019	88.48	88.15
2020	88.36	88.06
2021	86.81	86.76
2022	86.74	85.60
2023	85.47	83.74
Linear slope	−0.45% year ^{−1}	−0.61% year ^{−1}
Relative annual decline	≈0.52% year ^{−1}	≈0.70% year ^{−1}

**Figure 3.** Annual SEI values and fitted linear trends, 2016–2023. Shaded bands denote the 95% confidence intervals of the fitted mean trends and depict regression uncertainty.

Both plants exhibited a negative fitted SEI trend over 2016–2023. Plant 1 decreased from 89.24% in 2016 to 85.47% in 2023, with a fitted slope of −0.453 percentage points per year, $R^2 = 0.805$, RMSE = 0.510 percentage points, and $p = 0.0025$. Plant 2 decreased from 89.49% to 83.74%, with a fitted slope of −0.609 percentage points per year, $R^2 = 0.690$, RMSE = 0.934 percentage points, and $p = 0.0106$. The 95% confidence intervals of the fitted slopes were

$[-0.675, -0.230]$ percentage points per year for Plant 1 and $[-1.016, -0.201]$ percentage points per year for Plant 2. These results indicate statistically negative apparent weather-adjusted performance trends, with stronger dispersion and a steeper decline in Plant 2.

After normalization by the mean annual SEI, the apparent weather-adjusted system-performance declines are approximately 0.52% per year for Plant 1 and 0.70% per year for Plant 2. These values should not be reported as formal PLR or module degradation, because formal PLR is due to issues explained earlier.

3.3. Annual Mediterranean Module/Weather Loss Envelope

Table 3 shows the annual module and weather loss components: L_{aoi} , L_G , L_t , L_{spec} , and L_{mod} . Figure 4 illustrates how these losses changed over the years. L_{mod} is the modelled loss from angle-of-incidence effects, irradiance-level response, module temperature, and the main air-mass/wavelength correction. It does not include inverter conversion, transformer loss, wiring loss, mismatch, curtailment, availability, unmodelled soiling, or grid-interface effects. The annual values in Table 3 show that L_{mod} stayed steady over the eight years, ranging from 8.75% to 9.43%, with an average of 9.01%. Temperature loss was the largest part, averaging 5.23% each year. Loss from the angle of incidence (L_{AOI}) averaged 2.68%, and irradiance-level loss averaged 1.47%. The air-mass and wavelength term was small and slightly negative, averaging -0.21% .

Table 3. Annual module/weather loss components.

Year	L_{AOI} (%)	L_G (%)	L_T (%)	L_{spec} (%)	L_{mod} (%)
2016	2.73	1.56	4.84	−0.23	8.75
2017	2.65	1.41	5.12	−0.20	8.82
2018	2.72	1.59	5.50	−0.21	9.43
2019	2.69	1.46	5.29	−0.21	9.07
2020	2.67	1.41	5.25	−0.22	8.95
2021	2.66	1.46	5.03	−0.19	8.80
2022	2.64	1.37	5.47	−0.22	9.11
2023	2.69	1.53	5.33	−0.21	9.18
Mean	2.68	1.47	5.23	−0.21	9.01

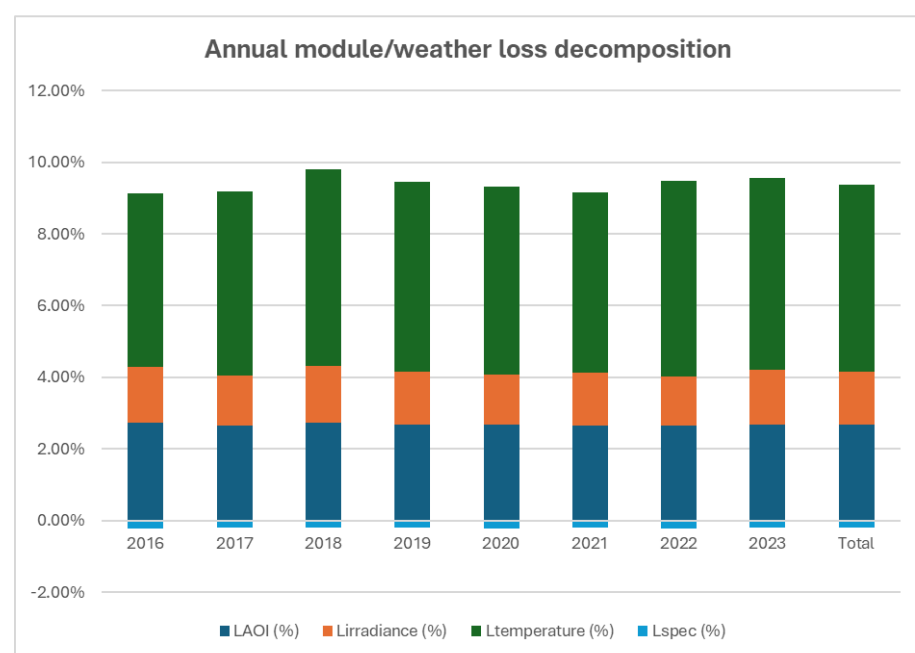


Figure 4. Annual module/weather loss decomposition, 2016–2023.

Figure 4 shows a non-steady increase of the module and weather losses from 2016 to 2023. This finding is important for diagnosis. In contrast, Mediterranean module and weather penalty repeats and stays fairly stable, but the residual loss, as will be discussed later, grows over time. So, the long-term drop in SEI is not due to a steady rise in the modelled AOI, irradiance level, temperature, or air-mass/wavelength terms. The order of the loss components matches the physical features of Mediterranean crystalline-silicon systems. Temperature loss is the main factor because the months with the most irradiance also have higher ambient and module temperatures. The Huld/PVGIS relative-efficiency model, Faiman module-temperature formula, Martín–Ruiz AOI correction, and Kasten–Young air-mass expression each show a different part of this module and weather loss envelope [11–13]. In this analysis, these terms set a baseline for expected losses, not a full AC-side loss model.

3.4. Seasonal Structure of Module/Weather Loss Components

This analysis shows how the Mediterranean module and weather loss envelope change over the year. Table 4 lists the monthly averages and standard deviations for L_{AOI} , L_G , L_t , L_{spec} , and L_{mod} from 2016 to 2023. Figure 5 illustrates these results. For each month, values from 2016 to 2023 were grouped together, so all monthly data were combined and statistically processed. This method avoids reducing the data to a single yearly average and helps reveal how losses shift between optical, irradiance, temperature, and air-mass factors throughout the seasons.

Table 4. Month-controlled statistics of explicit module/weather loss components, 2016–2023.

Month	L_{AOI} Avg $\pm$ SD (%)	L_G Avg $\pm$ SD (%)	L_t Avg $\pm$ SD (%)	L_{spec} Avg $\pm$ SD (%)	L_{mod} Avg $\pm$ SD (%)
January	2.74 $\pm$ 0.14	2.56 $\pm$ 0.63	0.84 $\pm$ 0.60	0.87 $\pm$ 0.02	4.20 $\pm$ 0.83
February	2.72 $\pm$ 0.14	2.09 $\pm$ 0.76	0.98 $\pm$ 0.48	0.54 $\pm$ 0.03	5.13 $\pm$ 0.59
March	2.74 $\pm$ 0.21	1.68 $\pm$ 0.53	2.15 $\pm$ 0.83	0.23 $\pm$ 0.02	6.24 $\pm$ 0.36
April	2.81 $\pm$ 0.09	1.35 $\pm$ 0.22	3.60 $\pm$ 0.80	0.04 $\pm$ 0.01	7.58 $\pm$ 0.63
May	2.82 $\pm$ 0.11	1.47 $\pm$ 0.36	5.26 $\pm$ 0.89	−0.03 $\pm$ 0.01	9.39 $\pm$ 0.78
June	2.72 $\pm$ 0.11	1.15 $\pm$ 0.16	7.30 $\pm$ 0.70	−0.07 $\pm$ 0.00	11.00 $\pm$ 0.61
July	2.61 $\pm$ 0.04	0.98 $\pm$ 0.05	8.41 $\pm$ 0.45	−0.05 $\pm$ 0.00	11.80 $\pm$ 0.41
August	2.55 $\pm$ 0.06	0.95 $\pm$ 0.08	8.98 $\pm$ 0.37	0.01 $\pm$ 0.00	12.22 $\pm$ 0.38
September	2.59 $\pm$ 0.06	1.20 $\pm$ 0.14	7.49 $\pm$ 0.48	0.15 $\pm$ 0.01	10.92 $\pm$ 0.44
October	2.51 $\pm$ 0.10	1.45 $\pm$ 0.36	5.65 $\pm$ 0.94	0.40 $\pm$ 0.02	9.07 $\pm$ 0.63
November	2.76 $\pm$ 0.12	2.62 $\pm$ 0.46	2.47 $\pm$ 0.84	0.74 $\pm$ 0.03	7.02 $\pm$ 0.54
December	2.80 $\pm$ 0.15	2.79 $\pm$ 0.77	0.74 $\pm$ 0.95	0.97 $\pm$ 0.01	4.43 $\pm$ 1.58

Table 4 shows that in winter and in months with less irradiance, temperature losses are low, but losses from irradiance and air mass are higher. For example, in December, L_t was just 0.74%, while L_G was 2.79% and L_{spec} was 0.97%. These results are consistent, as a lower sun position in the sky results in reduced irradiance, a longer atmospheric path for irradiance, and minimal influence on module temperatures by primary loss factors. The elevated L_G during winter aligns with the dependence of crystalline-silicon efficiency on irradiance, as modelled by the Huld/PVGIS framework, which exhibits increased sensitivity under low-light conditions. The positive winter L_{spec} [9] results from the manner in which the air mass is managed, given that larger zenith angles correspond to a longer atmospheric path. This is shown by the Kasten–Young air-mass model and the solar geometry framework, which help separate the effects of solar position, tilt, and atmospheric path [12,13].

In summer, the pattern is different. Table 4 shows that L_t rises from under 1% in January and February to 7.30% in June, 8.41% in July, and 8.98% in August. The highest monthly average for L_{mod} also appears in August, at 12.22%. Figure 5 shows that summer losses are mainly due to heat, not optical or low-irradiance effects. This is because fixed-

tilt crystalline-silicon modules in Mediterranean climates get more irradiance in summer, which increases power but also raises module temperatures and lowers efficiency. This explanation matches the Faiman module-temperature model, which links T_{mod} to irradiance, air temperature, and wind speed. Field data also show that module output depends on temperature, wind cooling, mounting, and climate [4,10].

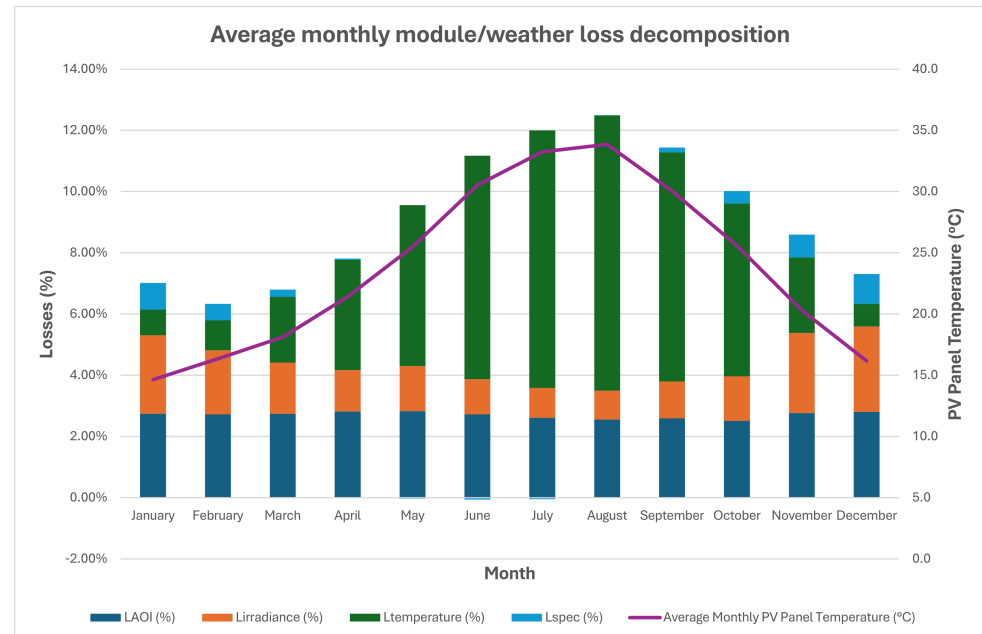


Figure 5. Monthly mean module/weather loss components, 2016–2023.

Spring and autumn are transitional periods rather than definitive loss categories. During these seasons, L_t fluctuates with the thermal cycle, whereas L_G and L_{spec} exhibit opposite trends, indicative of low irradiance and high air mass. Table 4 illustrates that April and May transition from winter optical and irradiance effects to summer thermal effects, while September and October revert accordingly. This phenomenon is anticipated due to the fixed module configuration encountering varying solar angles, irradiance levels, temperatures, and wind cooling throughout the year.

AOI loss behaves differently from the other loss types. Table 4 shows that L_{AOI} stays fairly steady, ranging from about 2.51% to 2.82% each month. This means AOI acts as a steady front-surface optical correction, not a main cause of seasonal changes. This matches the Martín–Ruiz angular-loss model, where angular losses depend on the angle of irradiance, tilt, latitude, and the condition of the cover glass, including dust effects [11]. In these plants, the seasonal change in L_{AOI} is much smaller than in L_t , so the yearly thermal cycle, not AOI, mainly drives seasonal loss patterns in the Mediterranean.

Breaking down the data by season, as shown in Table 4 and Figure 5, is key to understanding the other loss terms discussed later. High total losses in July or August do not necessarily indicate that the plant is underperforming, since a large thermal penalty is expected in Mediterranean summers. On the other hand, high losses in months with low or moderate L_{mod} are more likely due to other factors and should be checked alongside SL_{res} , weather-adjusted SEI, and comparisons with similar plants. Looking at each month separately helps avoid misreading the annual average L_{mod} of 9.01% as a constant loss. In winter, losses mainly come from low irradiance and air mass, while in summer, module temperature is the main factor.

Figures 4 and 5 show that the annual module and weather loss envelope are stable, but their internal composition exhibits strong seasonality. This means annual averages

hide a significant physical structure: winter losses are driven by low-irradiance, spectral, and optical factors, while summer losses are mainly due to module temperature. This distinction is vital for interpreting residual system losses. High summer losses should not be interpreted as plant underperformance, because a thermal penalty is expected under Mediterranean conditions. Conversely, higher losses during low- or moderate- L_{mod} periods are likely residual effects and should be analyzed using SL_{res} .

3.5. Unresolved Residual Loss and Residual-Driven Underperformance

Following removal of the explicit module/weather envelope, the remaining measured–expected deficit was expressed through the residual system-loss coefficient, SL_{res} , using Equation (27). Table 5 presents the annual diagnostic partition between the explicitly modelled module/weather loss, L_{mod} , and SL_{res} for both plants. Figure 6 shows the corresponding year-to-year behaviour of the two diagnostic layers.

Table 5. Annual loss partitioning into module/weather and residual system components.

Year	L_{mod} (%)	Plant 1 SL_{res} (%)	Plant 1, $L_{\text{tot,diag}}$ (%)	Plant 2 SL_{res} (%)	Plant 2, $L_{\text{tot,diag}}$ (%)
2016	8.75	10.76	19.51	10.51	19.26
2017	8.82	11.53	20.35	12.04	20.87
2018	9.43	12.22	21.65	13.58	23.01
2019	9.07	11.52	20.59	11.85	20.92
2020	8.95	11.64	20.59	11.94	20.89
2021	8.80	13.19	21.99	13.24	22.04
2022	9.11	13.26	22.37	14.40	23.51
2023	9.18	14.53	23.71	16.26	25.44

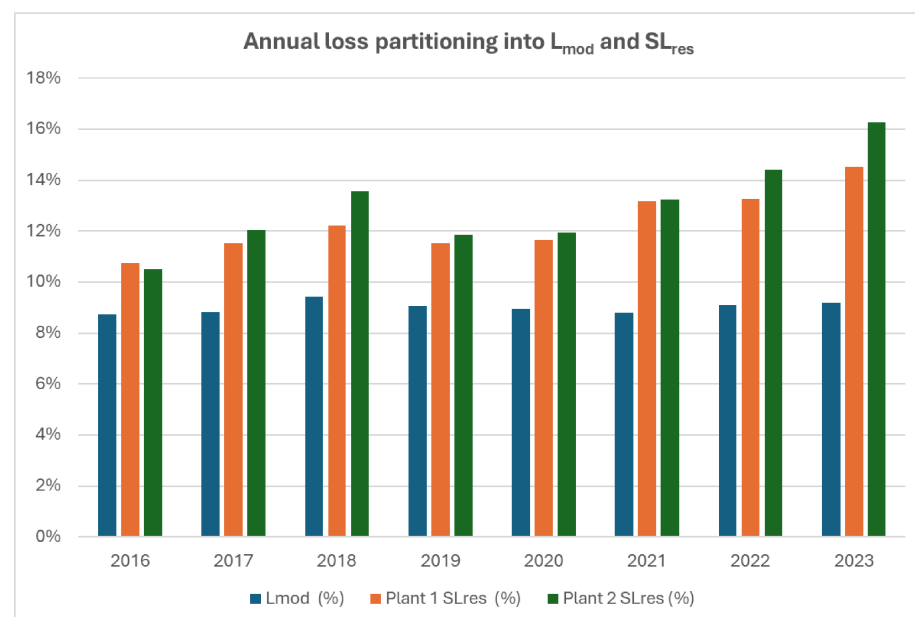


Figure 6. Diagnostic annual percentage-point partition into L_{mod} and SL_{res} .

The annual values presented in Table 5 demonstrate that the explicit module/weather loss remained relatively stable throughout the period. In contrast, the residual component increased for both facilities. Specifically, Plant 1 recorded residual losses of 10.76% in 2016 and 14.53% in 2023, representing an increase of 3.77 percentage points. Similarly, Plant 2’s residual loss increased from 10.51% to 16.26%, a 5.75 percentage-point increase. During the period from 2016 to 2023, the average annual residual loss was 12.33% for Plant 1 and 12.98% for Plant 2.

Figure 6 provides the principal evidence that the long-term decline is concentrated in the residual layer. Annual L_{mod} remains close to 9% and shows no comparable upward trend, whereas SL_{res} increases over time, particularly in Plant 2. Accordingly, the observed SEI decline is not explained by a progressive increase in the explicitly modelled AOI, irradiance level, temperature, or air-mass/spectral terms. It is associated with the unresolved residual remaining after those effects have been represented; this residual includes omitted mechanisms and model and measurement uncertainty and is not a directly measured plant-side loss.

It is important to note that the residual layer is not a measured physical mechanism. It may include soiling and seasonal dust accumulation [15,16], visible material deterioration such as cracks, discoloration, browning, corrosion, or persistent dust deposition [17], design and installation effects, shading, maintenance practices, and cleaning access [18], converter and inverter operating losses [19], reactive-power and grid-interface effects [20,21], and interacting environmental stressors such as humidity, rainfall, atmospheric deposits, wind, shading, and irradiance variability [22]. These mechanisms are plausible contributors to SL_{res} , but they are not individually resolved by the present dataset.

The available HEDNO records comprise settlement-grade delivered/exported energy; however, they do not include soiling measurements, cleaning records, inverter event logs, string-level measurements, I–V traces, thermography, or power-quality data. Consequently, the residual increase depicted in Table 5 and Figure 6 should be interpreted as unresolved measured–expected underperformance rather than as a directly measured plant-side loss.

3.6. Month-Controlled Residual-Loss Matrix and Plant-to-Plant Divergence

Table 6 shows the residual-loss and total-loss stats by month, focusing on the average difference between Plant 2 and Plant 1. Figure 7 presents monthly averages of weather and system losses. This subsection extends the annual residual analysis to examine whether underperformance is seasonal and whether it is shared equally across plants or concentrated in one plant.

Table 6. Month-controlled residual-loss and total-loss statistics, 2016–2023.

Month	L_{mod} Avg $\pm$ SD (%)	Plant 1 SL_{res} Avg $\pm$ SD (%)	Plant 2 SL_{res} Avg $\pm$ SD (%)	Plant 1 L_{tot}^{Σ} Avg $\pm$ SD (%)	Plant 2 L_{tot}^{Σ} Avg $\pm$ SD (%)	Mean ΔSL_{res} P2 – P1 (%)
January	4.20 $\pm$ 0.83	16.24 $\pm$ 2.87	14.70 $\pm$ 3.45	20.43 $\pm$ 3.04	18.90 $\pm$ 3.65	−1.54
February	5.13 $\pm$ 0.59	12.42 $\pm$ 2.75	12.41 $\pm$ 2.53	17.54 $\pm$ 2.67	17.53 $\pm$ 2.39	−0.01
March	6.24 $\pm$ 0.36	8.88 $\pm$ 4.47	9.72 $\pm$ 4.48	15.12 $\pm$ 4.47	15.97 $\pm$ 4.45	0.84
April	7.58 $\pm$ 0.63	11.17 $\pm$ 3.51	13.23 $\pm$ 4.28	18.75 $\pm$ 3.34	20.82 $\pm$ 4.40	2.07
May	9.39 $\pm$ 0.78	11.65 $\pm$ 2.25	12.43 $\pm$ 2.29	21.05 $\pm$ 2.53	21.82 $\pm$ 2.59	0.77
June	11.00 $\pm$ 0.61	12.32 $\pm$ 1.48	13.92 $\pm$ 2.81	23.32 $\pm$ 1.62	24.92 $\pm$ 3.01	1.60
July	11.80 $\pm$ 0.41	12.97 $\pm$ 2.23	13.91 $\pm$ 2.08	24.76 $\pm$ 2.38	25.71 $\pm$ 2.26	0.94
August	12.22 $\pm$ 0.38	13.05 $\pm$ 2.49	14.14 $\pm$ 2.46	25.27 $\pm$ 2.39	26.36 $\pm$ 2.36	1.08
September	10.92 $\pm$ 0.44	11.86 $\pm$ 5.09	13.16 $\pm$ 4.98	22.78 $\pm$ 5.39	24.08 $\pm$ 5.25	1.30
October	9.07 $\pm$ 0.63	11.43 $\pm$ 2.41	11.43 $\pm$ 3.26	20.50 $\pm$ 2.81	20.50 $\pm$ 3.70	0.00
November	7.02 $\pm$ 0.54	11.99 $\pm$ 2.63	11.20 $\pm$ 2.14	19.02 $\pm$ 2.38	18.23 $\pm$ 1.82	−0.79
December	4.43 $\pm$ 1.58	16.29 $\pm$ 2.95	13.90 $\pm$ 4.59	20.71 $\pm$ 3.69	18.33 $\pm$ 5.37	−2.38

Table 6 shows Plant 2’s surplus residual underperformance mainly occurred during high-productivity months. The largest positive mean residual differences (Plant 2 minus Plant 1) were in April (+2.07 percentage points), June (+1.60), September (+1.30), and August (+1.08). Residual losses in spring and summer have a greater impact on energy performance than similar differences in winter.

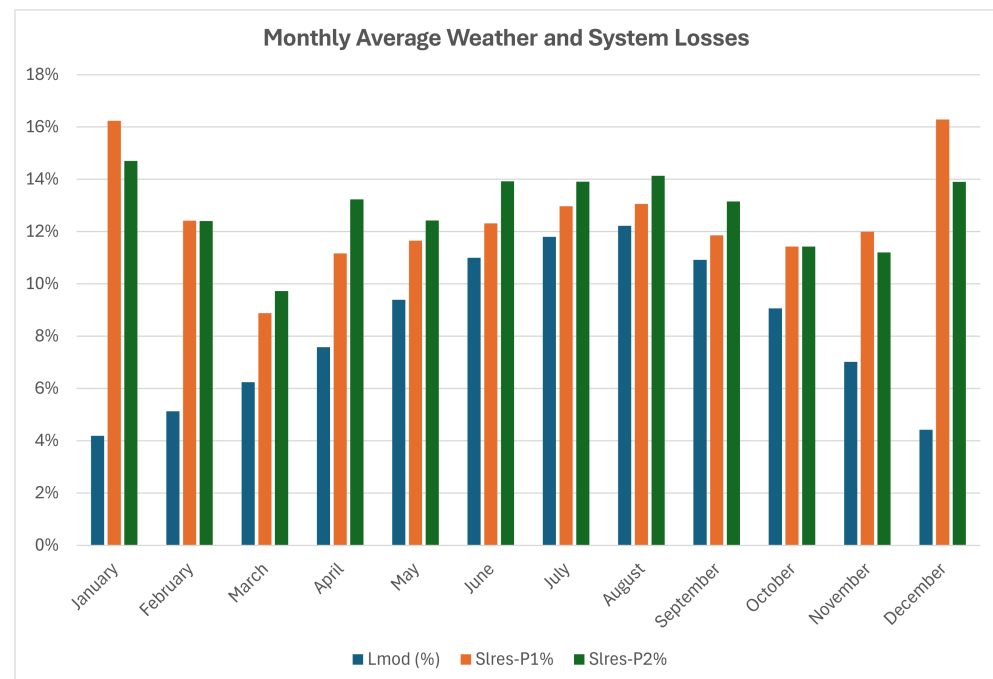


Figure 7. Monthly average weather and system losses.

Figure 7 shows that the monthly residual layer is less smooth than the module/weather envelope, with significant variability in September and March. September's residual system loss was $11.86 \pm 5.09\%$ for Plant 1 and $13.16 \pm 4.98\%$ for Plant 2, indicating year-specific residual excursions rather than seasonal patterns.

The paired-plant setup improves the diagnostic value of Table 6 and Figure 7. Both plants share the same location, capacity, tilt, azimuth, PVGIS-SARAH3 data, and models. This makes it unlikely that regional weather alone causes differences in SL_{res} . Although the cause cannot be identified from the available data, part of the residual underperformance appears plant-specific, particularly for Plant 2.

3.7. Interannual Monthly Residual-Loss Extremes and Heat-Map Diagnostics

Figure 8 shows diagnostics of interannual monthly residual losses, highlighting key year-month events and three quantities: maximum expected weather-related loss, maximum unresolved residual loss, and paired-plant residual divergence.

The most significant explicitly modelled module/weather loss was recorded in August 2018, when L_{mod} attained 13.01%. This occurrence aligns with the summer thermal regime and constitutes the most severe anticipated module/weather penalty within the dataset. It does not, in isolation, indicate abnormal plant behaviour.

In September 2023, the maximum unresolved residual loss occurred in both plants: 23.83% for Plant 1 and 24.94% for Plant 2. The corresponding diagnostic total-loss values were 35.42% and 36.53%. This event combined an elevated residual with the prevailing module/weather penalty and therefore warrants follow-up inspection; it does not identify a specific failure mechanism.

Figure 8 highlights key plant-specific residual differences. In April 2018, Plant 2 exceeded Plant 1's residual system loss by 8.48 percentage points; by June 2023, the gap was 8.47 points. Since both plants face similar weather and module corrections, these periods warrant further investigation at the plant level. The available data cannot distinguish among causes such as differential soiling, inverter derating, grid-interface effects, curtailment, shading, or degradation.

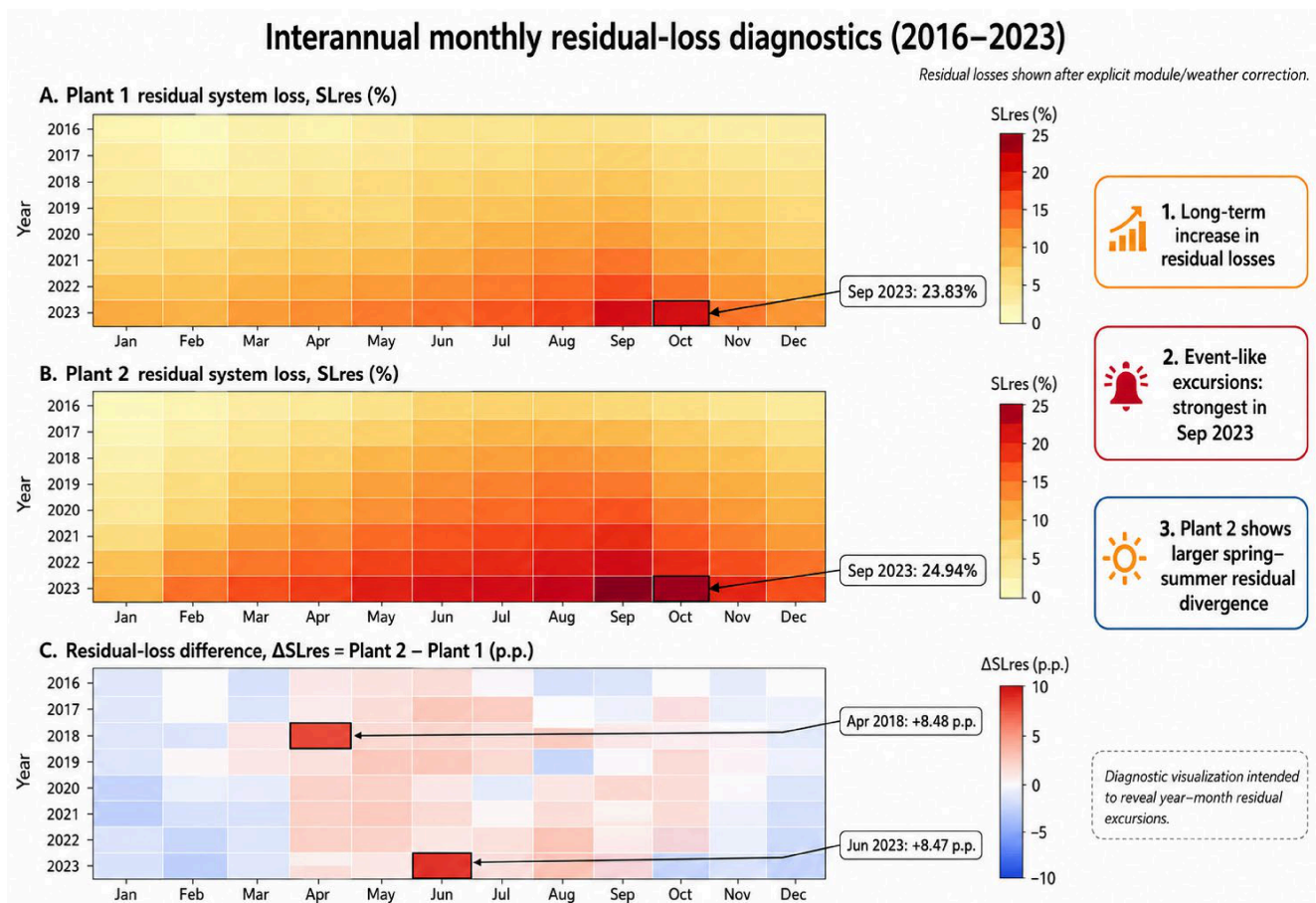


Figure 8. Interannual monthly residual-loss diagnostics. Red tones indicate higher residual loss or positive Plant 2 minus Plant 1 divergence; blue tones indicate negative paired divergence. Highlighted cells identify the largest residual excursions.

3.8. Input-Data Uncertainty and Sensitivity Analysis

The HNMS–PVGIS comparison, summarized in Tables 7 and 8, retained 9473 valid generation-hour observations under nominal UTC alignment. Errors were defined as PVGIS minus HNMS and weighted by G_{POA} . The weighted temperature bias was $-2.733\text{ }^{\circ}\text{C}$ and the weighted RMSE was $3.172\text{ }^{\circ}\text{C}$. For wind at 10 m, the corresponding bias and RMSE were -0.637 m s^{-1} and 1.712 m s^{-1} . The comparison used the same nominal heights and PVGIS coordinates as the HNMS station. During quality control, 481 PVGIS $WS_{10\text{m}}$ values equal to 37.79 m s^{-1} in December 2017 were identified as invalid/fill values and excluded rather than interpreted as physical wind observations. Because α does not enter the 10 m validation, its effect was reported independently as a Faiman model-conversion sensitivity.

Table 7. Generation-weighted HNMS–PVGIS discrepancy statistics used for uncertainty propagation, 2016–2022.

Variable	GPOA-Weighted Bias	Standard Uncertainty (RMSE)	Expanded Discrepancy, $k = 2$
Ambient temperature, 2 m	$-2.733\text{ }^{\circ}\text{C}$	$3.172\text{ }^{\circ}\text{C}$	$6.343\text{ }^{\circ}\text{C}$
Wind speed, 10 m	-0.637 m s^{-1}	1.712 m s^{-1}	3.423 m s^{-1}
Module-height wind uncertainty, 2 m	—	1.298 m s^{-1}	2.595 m s^{-1}
Alternative +1 h/+2 h sensitivity	T: -1.651 to $-0.370\text{ }^{\circ}\text{C}$; W: -0.324 to $+0.048\text{ m s}^{-1}$	T: 2.587 – $2.947\text{ }^{\circ}\text{C}$; W: 1.618 – 1.648 m s^{-1}	Reported in Table 8

Table 8. Propagated uncertainty under nominal and alternative temporal alignments.

Quantity	Value
Temperature uncertainty input	$\pm 3.172\text{ }^{\circ}\text{C}$
Wind uncertainty input at 10 m	$\pm 1.712\text{ m s}^{-1}$
Irradiance relative standard uncertainty	$\pm 1.186\%$
Expanded uncertainty of E_{exp} , $k = 2$	$\pm 5.80\%$
Expanded uncertainty of SEI, $k = 2$	$\pm 5.89\%$
Expanded uncertainty of L_{mod} , $k = 2$	± 4.77 percentage points

The standard relative contributions to E_{exp} were 1.565% from temperature, 2.176% from wind, and 1.108% from irradiance. Their quadrature combination gave an expanded E_{exp} uncertainty of 5.80%. Including the 0.5% standard metering term gave an expanded SEI uncertainty of 5.89%.

The HNMS-based analysis materially affects the interpretation of L_{mod} . The standard contributions to the temperature-loss term were 1.460 percentage points from ambient temperature and 2.030 percentage points from wind, while the irradiance-mediated contribution was 0.099 percentage points. The combined standard uncertainty of L_{mod} was 2.386 percentage points, and the expanded uncertainty was 4.772 percentage points. Monthly expanded values ranged from approximately 4.18 to 5.04 percentage points. Thus, L_{mod} remains a physically structured module/weather envelope with a robust seasonal pattern, but its absolute monthly magnitude is uncertainty-sensitive and should not be treated as an exact deterministic loss.

The $\pm 10\%$ parameter tests in Table 9 show that irradiance scaling has the largest direct effect on expected energy, while U_0 , U_1 , WS_{mod} , and γ affect the temperature-dependent correction. The annual SEI trends remained statistically negative when the magnitude of γ was varied by $\pm 10\%$: the Plant 1 slope ranged from -0.458 to -0.448 percentage points per year and the Plant 2 slope from -0.612 to -0.605 percentage points per year; both 95% confidence intervals remained below zero. The air-mass/spectral coefficient had a negligible annual effect because L_{spec} is small.

Table 9. Sensitivity of the module-temperature and expected-energy calculations to selected input perturbations.

Input	Perturbation	$\Delta T_{\text{mod}}\text{ (}^{\circ}\text{C)}$	Approximate ΔE_{exp}
G_{POA}	$\pm 10\%$	± 1.688	$+9.12\%/ -9.28\%$
T_{amb}	$\pm 2\%$	± 2.000	$\pm 0.95\%/ +0.95\%$
WS_{mod}	$\pm 10\%$	$-0.576/+0.625$	$+0.27\%/ -0.30\%$
U_0	$\pm 10\%$	$-1.021/+1.168$	$+0.49\%/ -0.56\%$
U_1	$\pm 10\%$	$-0.576/+0.625$	$+0.27\%/ -0.30\%$
$ \gamma $	$\pm 10\%$	—	$-0.56\%/ +0.56\%$
s	$\pm 10\%$	—	$<0.03\%$
HEDNO metre	0.2%/0.5%/1.0%	—	Propagated to SEI

4. Discussion

4.1. Expected-Energy Reference and KPI Interpretation

The annual match between the plant-parameterized expected energy and the default PVGIS production scale shows that the reference calculation is consistent. However, this does not confirm actual plant operation, since both values come from models. Measured HEDNO data should be compared to the weather-corrected expected energy, not just to the PVGIS annual total. As shown in Section 3.1, the two plants have similar delivered energy and specific yield, but these indicators do not reveal whether any measured deficit is due

to module or weather effects, or to issues on the AC side. That is why SEI and SL_{res} are used as diagnostic tools, instead of relying only on annual yield, capacity factor, or PR to evaluate or interpret performance.

4.2. Mediterranean Module/Weather Envelope

The module/weather envelope provides physical separation for Mediterranean operation. Annually, L_{mod} remains near 9% and does not increase in parallel with the residual. Temperature is the dominant component, followed by angle-of-incidence and irradiance-level effects, while the first-order air-mass/spectral term remains small. The uncertainty analysis shows that the exact magnitude of L_{mod} is sensitive mainly to wind-driven module-temperature estimation; nevertheless, the winter-to-summer hierarchy remains physically robust. Accordingly, high summer L_{mod} values are expected thermal penalties, not by themselves evidence of plant malfunction.

4.3. Residual Loss and Paired-Plant Evidence

Following the removal of the common module and weather envelope, the remaining measured–expected deficit is concentrated in SL_{res} . This residual layer increases over time in both plants, with a more pronounced effect in Plant 2. Because the two systems are located at the same site and share the same capacity, tilt, azimuth, PVGIS-SARAH3 inputs, and analytical model, persistent residual divergence is less likely to be attributable solely to regional meteorological influences. The paired configuration therefore provides diagnostic information that a single-plant analysis cannot offer. It helps separate common residual behaviour from plant-specific underperformance and identifies year–month cells requiring further inspection. These signals remain diagnostic and do not constitute causal evidence.

4.4. Position Relative to PLR, Degradation, and Root-Cause Diagnosis

The SEI trend should not be interpreted as formal PLR or module degradation. Formal PLR extraction requires filtering, normalization, outlier treatment, and separation of reversible and irreversible effects [23,24]; multi-annual year-on-year methods address a different trend-uncertainty problem [25,26]. The present framework instead reports an apparent weather-adjusted system-performance decline based on delivered energy. The residual may include soiling and cleaning effects [15,16], material deterioration and maintenance-related effects [17,18], converter and grid-interface losses [19–21], and interacting environmental stressors [22]. Because these mechanisms are not resolved separately, SL_{res} represents unresolved measured–expected underperformance rather than a specific physical loss.

The relative SEI declines of approximately 0.52% and 0.70% per year are of the same order as system-level performance-loss rates reported in the broader literature, but direct numerical equivalence is not justified because the normalization and extraction methods differ [23,25,26]. Climate-dependent studies also show that multicrystalline-silicon loss rates can differ between Mediterranean and cooler locations [27]. The steeper Plant 2 trajectory under the common modelling chain therefore supports prioritization of plant-specific investigation, but it does not distinguish module ageing from differential soiling, inverter behaviour, wiring, shading, or maintenance history.

Possible temporal changes in Greek low-voltage-grid voltage quality or reactive-power requirements could not be reconstructed from the delivered-energy records. These effects therefore remain unresolved grid-interface mechanisms rather than demonstrated causes of the observed residual trends [20,21].

4.5. Practical Use and Limitations

The practical value of the PVGIS-RPD framework is prioritization. It localizes unresolved measured–expected deficits in time, separates expected Mediterranean mod-

ule/weather penalties from residual losses, and distinguishes shared from plant-specific behaviour under limited-data conditions. After uncertainty propagation, SEI, SL_{res} , and ΔSL_{res} should not be interpreted as deterministic root-cause measurements. They are uncertainty-bounded screening indicators. They identify when and where further inspection is justified; they do not identify the physical root cause without additional evidence from SCADA, inverter logs, soiling measurements, cleaning records, string-level measurements, I–V tracing, thermography, or power-quality monitoring.

5. Conclusions

This research developed and applied a residual performance diagnostic approach, informed by PVGIS, for two adjacent fixed-tilt crystalline-silicon photovoltaic (PV) facilities in South Corfu, Greece. The methodology was specifically adapted for practical scenarios where extensive long-term data on delivered or exported alternating-current (AC) energy is available, yet detailed SCADA data, as well as information concerning soiling, cleaning, inverter operations, string-level diagnostics, thermographic images, or power-quality assessments, are not accessible. PVGIS-SARAH3 was utilized as the source for hourly irradiance and meteorological data, while the expected-energy chain was recalculated based on the plant's geometry and module parameters as specified by the manufacturer. The standard PVGIS production output was employed solely as an external benchmark to ensure consistency.

The plant-parameterized expected-energy series aligned with the default PVGIS production scale. From 2016 to 2023, the cumulative analytical expected energy totalled 1426 MWh per plant, compared with 1419 MWh reported by PVGIS, resulting in an average annual deviation of approximately +0.47%. This concordance reinforces the internal consistency of the expected energy baseline; however, it does not rule out plant-side losses, since both figures are model-derived.

The recorded data from HEDNO indicated high production levels for both systems. Plant 1 contributed 1249.62 MWh and Plant 2 contributed 1240.48 MWh over the eight-year period, with average annual specific yields of 1572.09 and 1560.59 kWh per kW_p and year, respectively. Thus, conventional performance indicators categorize both plants within the same general performance class. Nevertheless, these indicators did not elucidate the origin of the observed deficit relative to E_{exp} .

The explicit Mediterranean module and weather loss envelope remained stable. The annual L_{mod} fluctuated between 8.75% and 9.43%, with an average of 9.01%. The predominant component was temperature loss, with a mean annual L_t of 5.23%, followed by the angle of incidence (AOI) loss at 2.68%, irradiance-level loss at 1.47%, and a minor mean air-mass/wavelength-related component of −0.21%. The monthly analysis indicated that winter losses were primarily influenced by low-irradiance and air-mass-related effects, while summer losses were mainly driven by module temperature. August exhibited the highest mean monthly L_{mod} , at 12.22%, primarily because L_t reached 8.98%.

The prolonged deterioration was not attributable to a progressive increase in the explicit module/weather envelope. Rather, it was associated with the residual layer. Plant 1 residual loss, denoted as SL_{res} , increased from 10.76% in 2016 to 14.53% in 2023. Similarly, Plant 2 increased from 10.51% to 16.26%. The corresponding SEI slopes were −0.453 percentage points per year for Plant 1 and −0.609 percentage points per year for Plant 2, equivalent to apparent weather-adjusted system-performance declines of 0.52% and 0.70% per year, respectively. These figures are not formal PLR or module degradation metrics.

The comparison of paired plants introduced a diagnostic constraint that would not be available through a single-plant measured or modelled analysis. Since both plants are situated on the same site, with the same nominal capacity, tilt, azimuth, PVGIS-SARAH3

input data, and analytical model, persistent differences in SL_{res} are less likely to be solely attributable to regional meteorological variability. Plant 2 demonstrated more pronounced residual underperformance, particularly during the productive months. The most significant mean monthly differences, calculated as Plant 2 minus Plant 1, were observed in April, June, September, and August, with differences of +2.07, +1.60, +1.30, and +1.08 percentage points, respectively.

The year–month residual diagnostics distinguished climate-consistent module/weather stress from abnormal residual excursions. The highest modelled module/weather loss occurred in August 2018, with L_{mod} reaching 13.01%. Conversely, the maximum unresolved residual loss was recorded in September 2023, with SL_{res} values of 23.83% for Plant 1 and 24.94% for Plant 2. The most pronounced paired-plant residual divergences were observed in April 2018 and June 2023, with Plant 2 exceeding Plant 1 by approximately 8.5 percentage points. These months should be prioritized for follow-up inspection.

Consequently, the proposed PVGIS-RPD methodology provides an intermediate diagnostic layer between conventional yield benchmarking and data-intensive fault diagnosis. The HNMS-based generation-hour analysis narrows the interpretation of SEI, SL_{res} , ΔSL_{res} , and L_{mod} : they are uncertainty-bounded screening quantities, not deterministic root-cause measurements. The expanded uncertainties were 5.80% for E_{exp} , 5.89% for SEI, and 4.77 percentage points for L_{mod} ; the +1 h and +2 h sensitivity cases gave similar SEI bounds of 5.50% and 5.62%. The negative SEI trends remained statistically significant under $\pm 10\%$ variation in the module-temperature coefficient. Because both adjacent plants use the same PVGIS-SARAH3 input chain and analytical model, paired comparison remains useful for identifying persistent plant-specific divergence. Absolute residual values and individual months should nevertheless be interpreted cautiously and followed by targeted SCADA, inverter, soiling, cleaning, string-level, I–V, thermographic, or power-quality investigation.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation/Symbol	Definition
AC	Alternating current
AOI	Angle of incidence
BOS	Balance of system
CF	Capacity factor
DC	Direct current

E_{exp}	Expected energy after explicit module/weather loss modelling
E_{meas}	Measured delivered AC energy
E_{POA}	Loss-free POA-scaled energy
$G_{b,\text{POA}}$	Direct component of plane-of-array irradiance
$G_{d,\text{POA}}$	Diffuse component of plane-of-array irradiance
$G_{r,\text{POA}}$	Ground-reflected component of plane-of-array irradiance
G_{POA}	Plane-of-array irradiance
G_{ref}	Reference irradiance under standard test conditions
HEDNO	Hellenic Electricity Distribution Network Operator
HNMS	Hellenic National Meteorological Service
I_{AM}	Incidence-angle modifier
I_{AM_b}	Beam incidence-angle modifier
I_{AM_d}	Diffuse incidence-angle modifier
I_{AM_r}	Ground-reflected incidence-angle modifier
L_{AOI}	Angle-of-incidence loss
L_{G}	Irradiance-level loss
L_{T}	Temperature loss
L_{tot}	Strict energy-ratio total loss
$L_{\text{tot,diag}}$	Diagnostic percentage-point total loss
O&M	Operations and maintenance
P_0	Nominal installed DC power
PLR	Performance loss rate
POA	Plane of array
PR	Performance ratio
PRT	Temperature-corrected performance ratio
PV	Photovoltaic
PVGIS	Photovoltaic Geographical Information System
PVGIS-RPD	PVGIS-informed residual performance diagnostic framework
R^2	Coefficient of determination
RMSE	Root mean square error
SCADA	Supervisory control and data acquisition
SEI	Weather-adjusted system-efficiency index
SL_{res}	Residual system-loss coefficient
STC	Standard test conditions
T_{amb}	Ambient-air temperature
T_{mod}	Module temperature
$U(x)$	Expanded uncertainty of x
$u(x)$	Standard uncertainty of x
U_0	Faiman constant heat-loss coefficient
U_1	Faiman wind-dependent heat-loss coefficient
$ur(x)$	Relative standard uncertainty of x
WS	Wind speed
$WS_{10\text{m}}$	Wind speed at 10 m
$WS_{2\text{m}}$	Wind speed adjusted to 2 m
WS_{mod}	Wind speed used in the module-temperature model
Y_{sp}	Specific yield
Greek symbol	Definition
α	Wind-profile exponent
γ	PV module relative power temperature coefficient
ΔSL_{res}	Paired-plant residual divergence
Δt	Time-step duration
η_{rel}	Relative PV operating efficiency

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