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Field performance and seasonal energy yield of a residential photovoltaic prosumer in Romania over three years

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Abstract

Published real-world performance datasets for residential photovoltaic systems in Central-Eastern Europe remain scarce. This study analyses 37 months of continuous production data (January 2023 to January 2026) from a residential grid-tied PV installation in Romania, equipped with a Growatt inverter and monitored via the ShinePhone cloud platform. Monthly totals were extracted from application screenshots and cross-validated against annual platform totals. The system produced 3,195.0 kWh (2023), 3,171.3 kWh (2024), and 2,883.7 kWh (2025), with a three-year mean of 3,083.3 kWh per year. Quarter 3 contributed 33–37% of annual yield, and Quarters 2 and 3 together accounted for 68–70%. A 9.7% year-on-year decline in 2025 is attributed primarily to inter-annual meteorological variability. The Mann-Kendall trend test on the 36-month series returned $p = 0.376$, indicating no significant monotonic trend; pairwise inter-annual seasonal profile correlations exceed $r = 0.88$, confirming structural conservation of the production pattern. Grid import and export were zero throughout the monitoring period, indicating complete self-consumption matching across all seasons. The findings provide field-validated PV performance evidence for Romanian residential prosumers and a reproducible methodological template for similar studies across Central-Eastern Europe.

Keywords: *photovoltaic performance; residential prosumer; self-consumption; Growatt inverter; Romania; solar monitoring; energy yield; temperate continental climate; inter-annual variability; Mann-Kendall trend test; STL decomposition.*

1. Introduction

1.1 Background and Motivation

This paper presents an analysis of 37 months of continuous production monitoring from a residential grid-tied photovoltaic (PV) installation in Romania, operating under complete self-consumption mode with zero grid import and zero grid export documented across the entire monitoring period. The study addresses the performance, operational characteristics, and yield potential of residential solar energy in Romania through the detailed production record of this installation.

Global rooftop PV capacity surpassed 600 GW in 2024, with household-scale systems representing a substantial share of cumulative installations across Europe (IEA, 2024). Within the European Union, the RePowerEU initiative and the revised Energy Performance of Buildings Directive (EPBD 2024)

(European Commission, 2024) have established legally binding requirements supporting residential prosumers, households that simultaneously produce and consume electricity from on-site generation. Falling technology costs, rising electricity prices, and energy security concerns have accelerated this expansion.

Romania constitutes an underexplored case in this context. Annual global horizontal irradiance (GHI) ranges from 1,200 kWh/m² in the Carpathian foothills to over 1,500 kWh/m² across the southern Wallachian Plain and Dobrogea coastal region, comparable to northern Spain or central France (Súri et al., 2007). Residential PV deployment in Romania expanded substantially following the introduction of the national prosumer regulatory framework, supported by published reporting from the regulatory authority (ANRE Romania, 2024).

This rapid proliferation generates an unprecedented volume of real-world performance data through cloud-connected inverters, yet most remains unpublished. Simulation tools such as PVsyst, PVGIS, and the System Advisor Model (SAM) provide indispensable estimates of long-term average yields but cannot substitute for field measurements that capture site-specific phenomena such as inverter degradation, module soiling, partial shading, and thermal effects. Self-consumption performance depends on temporal alignment between generation and consumption profiles, which varies by household type, occupancy pattern, appliance mix, and season (Luthander et al., 2015). Measured production data are required to characterise these dynamics.

1.2 Literature Context

The literature on residential PV performance monitoring is dominated by studies from Western and Southern Europe. Piliouguine et al. (Piliouguine et al., 2013) reported an average performance ratio of 79% over eight years for a 1 kWp crystalline silicon system in southern Spain, with year-to-year variability of $\pm 3.5\%$. Drif et al. (Drif et al., 2007) documented specific yields of 1,350–1,450 kWh/kWp/yr for grid-tied systems in Andalusia. Jäger-Waldau (Jäger-Waldau, 2023) compiled national averages of 850–1,050 kWh/kWp/yr for Germany, Poland, and the Czech Republic, reflecting the latitudinal gradient in available irradiance across Central Europe.

The evidence base for Central-Eastern Europe and Romania in particular remains thin. The peer-reviewed literature contains virtually no long-term field monitoring studies from Romanian residential installations. Existing data appear primarily in grey literature: annual ANRE reports and unpublished assessments by distribution operators. This absence reflects both the recency of the Romanian prosumer boom and the fragmented, proprietary nature of inverter monitoring data, locked within manufacturer cloud platforms.

Comănescu et al. (Comănescu et al., 2022) analysed residential PV in Romania using modelled (rather than measured) generation data, explicitly calling for empirical monitoring studies to validate the underlying model assumptions. Súri et al. (Súri et al., 2007) characterised the solar irradiance climatology of Europe using satellite-derived PVGIS data but did not address installed system behaviour. The present study fills this gap with a three-year measured production record from an operational Romanian prosumer, analysed with methods aligned with the IEC 61724-1:2021 monitoring standard. While a single site cannot statistically represent the diversity of Romanian installations, it provides a validated data point for broader simulation and modelling studies.

1.3 Objectives

This study pursues four objectives. First, to characterise the monthly and seasonal production profile of the monitored PV installation over three complete calendar years. Second, to quantify inter-annual variability and identify plausible drivers of deviations from baseline performance. Third, to subject the production record to formal statistical analysis and infer the most probable installed capacity through sensitivity analysis against PVGIS climatological expectations, placing the system's performance on a quantitatively defensible footing despite the absence of verified nameplate documentation. Fourth, to document the data collection, validation, and analysis procedures with sufficient detail to enable replication, providing a practical template for similar monitoring studies from cloud-connected inverter platforms.

The remainder of this paper is structured as follows: Section 2 describes the monitored system and data collection methodology; Section 3 presents the results, including monthly profiles, seasonal aggregates, inter-annual comparisons, statistical characterisation, capacity inference, and European benchmarking; Section 4 discusses the findings in the context of the existing literature and identifies limitations; Section 5 summarises the principal conclusions and directions for future work.

2. Methods

2.1 Study Site and System Description

The monitored installation is a grid-tied residential photovoltaic system located in Romania, commissioned in 2022 and operating continuously throughout the monitoring period presented in this paper. To protect the privacy of the user, the exact geographic coordinates are not disclosed; however, the installation is situated in a region characterised by a temperate continental climate (Köppen classification Dfa/Dfb), with warm, occasionally hot summers, cold winters, and a relatively well-defined four-season annual cycle. This climate type is representative of large portions of the Romanian interior, including the Transylvanian plateau, the Wallachian Plain, and the Moldavian hills, making the performance patterns observed at this site broadly relevant to the majority of Romanian residential PV installations.

The system is connected to the national low-voltage (230 V AC) distribution network under the Romanian prosumer regulatory framework, with a bidirectional smart meter installed by the distribution operator. Throughout the 37-month monitoring period analysed in this study, the recorded grid import and grid export were both zero on every monthly aggregation, indicating complete self-consumption matching at monthly resolution.

The power conversion equipment is a Growatt single-phase, grid-tied string inverter with integrated WiFi data logging through the proprietary ShineWiFi-X module (Wood Mackenzie & Solar Energy Industries Association, 2024). The inverter transmits production telemetry at minute resolution to the ShineServer cloud platform, where it is aggregated and accessible through the ShinePhone mobile application. Granular time-series data accessible through ShinePhone span the entire 37-month monitoring period; aggregated monthly totals are also available directly via the platform interface.

Parameter	Value / Description
Inverter manufacturer	Growatt New Energy Technology Co., Ltd.
Inverter type	Single-phase, grid-tied string inverter

Communication	Wi-Fi data logger — ShineWiFi-X module
Monitoring platform	Growatt ShinePhone (mobile) / ShineServer (cloud)
Data resolution	Minute-level (aggregated to monthly for this study)
System type	Grid-tied, 100% self-consumption mode
Connection to grid	Low-voltage distribution network (Romania)
Regulatory framework	ANRE Order No. 15/2021 — Prosumer Regulation
Export to grid (all months)	0 kWh
Import from grid (all months)	0 kWh
Installation commissioning	2022
Monitoring period	January 2023 – January 2026 (37 months)
Total energy produced	9,250.0 kWh (3 complete years)
Peak month recorded	July 2023 — 420.7 kWh
Minimum month recorded	December 2024 — 57.9 kWh
Annual average yield	3,083.3 kWh/year
Location (general)	Romania (temperate continental climate)

Table 1. *Summary of available technical and operational parameters for the monitored PV installation.*

It is acknowledged that the rated peak power of the PV array (kWp) is not explicitly stated in the available documentation and could not be verified from inverter nameplate data alone. Based on the observed monthly production maxima and the PVGIS irradiance dataset for the Romanian site (estimated peak sun hours of 4.2–4.8 h/day in July), the installed capacity is preliminarily estimated to lie in the range of 3.0–5.0 kWp. A more rigorous inverse inference of installed capacity, based on comparison with PVGIS climatological specific yield expectations, is presented in Section 3.4.2 and narrows this range substantially. The uncertainty in rated capacity is acknowledged as a key limitation (see Section 4.3) and precludes the calculation of specific yield (kWh/kWp) and performance ratio (PR) on the basis of verified manufacturer data.

2.2 Data Collection and Extraction

Monthly production data were extracted manually from a systematic archive of screenshot images captured from the Growatt ShinePhone mobile application during the monitoring period. The application presents, for each user-selected month, a graphical bar chart showing daily production and consumption values alongside four summary statistics prominently displayed at the bottom of the screen: (i) total solar energy generated [kWh]; (ii) total self-consumed energy [kWh]; (iii) total energy exported to the grid [kWh]; and (iv) total energy imported from the grid [kWh]. For monthly analysis, the application aggregates all daily values within the selected calendar month. Additionally, when the "Year" view is selected rather than "Month", the application presents a twelve-bar chart of monthly totals alongside a single cumulative annual figure, these annual summary screenshots provided the cross-validation data described in Section 2.3. A total of 37 monthly screenshot images were collected, corresponding to every calendar month from January 2023 through January 2026 inclusive, with no gaps in the sequence. For December 2024, two screenshots were available; visual inspection confirmed that both showed identical production values, and the first image was used as the primary data source.

For each monthly observation, the "Producție solară" (solar production) value displayed at the bottom of the screen was recorded as the primary data point. In all 37 observations, the export-to-grid value was 0 kWh and the import-from-grid value was 0 kWh, confirming that the self-consumption fraction was 100% and no grid interaction occurred. This unique property of the dataset simplifies the analysis considerably, as generation and consumption are numerically equal for all periods.

2.3 Data Validation

Two levels of data validation were applied to the extracted dataset before any analysis was conducted. At the monthly level, each screenshot was reviewed to verify internal consistency: the sum of self-consumed energy and energy exported to the grid must equal the total generated energy, a condition that was trivially satisfied in all 37 observations given that the export figure was zero in every case. At the annual level, which constitutes the more rigorous validation test, the sum of the twelve monthly production values for each calendar year was compared against the independent annual total displayed by the application on its dedicated annual summary screen. In 2023, the sum of twelve monthly figures was 3,195.0 kWh, matching the application annual total of 3,195.0 kWh exactly, with a discrepancy of precisely 0.0 kWh. In 2024, the corresponding sum was 3,171.3 kWh against an application annual total of 3,171.3 kWh, again with zero discrepancy. In 2025, the monthly sum of 2,883.7 kWh matched the application annual total of 2,883.7 kWh to the same precision. The perfect agreement across all three years, with no rounding residuals or transcription errors detectable at the resolution of the application's displayed values (one decimal place in kWh), provides strong assurance that the data extraction process was accurate and complete. The January 2026 data point of 57.0 kWh, representing a single month from an incomplete calendar year, is excluded from all annual analyses presented in this paper but is included in the full monthly time series for completeness.

2.4 Analytical Methods

Three analytical procedures were applied to the validated monthly dataset, each designed to illuminate a distinct dimension of system performance. The first procedure concerned the monthly production profile: the twelve monthly values for each year were arrayed chronologically to reveal the seasonal production curve, and month-by-month comparisons across years were conducted to identify which year attained the highest production in each calendar month, a simple but informative indicator of the direction of inter-annual variability at the sub-seasonal level. The second procedure involved seasonal aggregation, in which monthly values were summed into four standard meteorological quarters, Q1 covering January through March, Q2 covering April through June, Q3 covering July through September, and Q4 covering October through December, following the convention established in World Meteorological Organization guidelines. Quarterly totals were computed separately for each year, and three-year arithmetic means were calculated to characterise the climatologically representative seasonal distribution of solar yield at this site. The third procedure addressed inter-annual variability: year-on-year production changes were expressed as both absolute differences in kWh and relative percentage changes using 2023 as the reference baseline, and the monthly structure of these differences was examined to identify whether deviations from baseline were concentrated in particular seasons or were distributed uniformly across the year, a distinction with important implications for the attribution of production anomalies to meteorological versus technical causes.

These descriptive procedures are extended in Section 3.4 by formal inferential analyses: a non-parametric Mann-Kendall test for monotonic trend (Mann, 1945); pairwise Pearson product-moment

correlations between the twelve-month production profiles of consecutive years; and Seasonal-Trend decomposition using Loess (STL) (Cleveland et al., 1990) to separate the production time series into trend, seasonal, and residual components. Additionally, a sensitivity analysis is conducted in which observed annual production is divided by candidate installed-capacity values and the resulting specific yields are compared against PVGIS-SARAH3 climatological expectations for the Romanian temperate continental climate, in order to infer the most probable rated capacity of the installation. The principal quantities employed in these analyses are defined in Equations (1)–(8). Specific yield and performance ratio, the two normalised metrics defined by IEC 61724-1:2021 (International Electrotechnical Commission, 2021), are given by:

$$Y_f = \frac{E_{AC}}{P_{nom}} \quad (1)$$

$$PR = \frac{Y_f}{Y_r} = \frac{E_{AC}/P_{nom}}{H_{POA}/G_{ref}} \quad (2)$$

where E_{AC} is measured AC energy production over the period of interest, P_{nom} is the rated peak power of the array (kWp), Y_r is the reference yield, H_{POA} is the plane-of-array irradiance, and G_{ref} is the reference irradiance (1 kW/m²). The self-consumption fraction, which characterises the share of generated energy consumed on-site rather than exported, is defined by:

$$SCF = \frac{E_{self}}{E_{gen}} \quad (3)$$

For the monitored installation, $E_{self} = E_{gen}$ across all 37 months (zero export reported by the monitoring application), yielding $SCF = 1.00$ throughout the study period. The non-parametric Mann-Kendall statistic and the associated Kendall rank correlation coefficient τ used to test for monotonic trend in the monthly production series are defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (4)$$

$$\tau = \frac{S}{n(n-1)/2} \quad (5)$$

where $\text{sgn}(\cdot)$ denotes the sign function and n is the number of observations. The Pearson product-moment correlation coefficient employed to quantify inter-annual similarity of the monthly production profile is the standard formulation:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (6)$$

Finally, the STL decomposition produces additive components T_t (trend), S_t (seasonal), and R_t (residual) such that $x_t = T_t + S_t + R_t$. The trend and seasonal strengths, which quantify the relative variance contribution of each component to the total signal, are defined by:

$$F_S = \max\left(0, 1 - \frac{\text{Var}(R)}{\text{Var}(S + R)}\right) \quad (7)$$

$$F_T = \max\left(0, 1 - \frac{\text{Var}(R)}{\text{Var}(T + R)}\right) \quad (8)$$

All inferential statistical analyses were implemented in Python 3.11 using SciPy 1.13 for Mann-Kendall and Pearson correlation tests, statsmodels 0.14 for STL decomposition (with parameter period = 12 and the robust option enabled to dampen outlier influence), and pymannkendall 1.4 as a validated implementation of the original Mann-Kendall procedure. All numerical results are reported with sufficient precision to enable independent replication from the raw monthly data tabulated in Section 3.1.

Generative AI assistance disclosure. The authors used a large language model (Claude, Anthropic) as a writing and analysis assistant during preparation of this manuscript. Specific assistance was limited to drafting and reviewing Python implementations of the statistical analyses described above, drafting Python code for figure generation, language editing of the manuscript text, and assistance with reference formatting. All data extraction from the Growatt ShinePhone application, all numerical results reported, all interpretations, and all scientific conclusions are the responsibility of the authors.

3. Results

3.1 Monthly Production Profile

The complete monthly production dataset for 2023, 2024, and 2025 is presented in Table 2 and visualised in Figure 1. Across all three years, the seasonal profile follows the same general structure: low winter production, monotonic increase through spring, a summer peak, and a progressive decline through autumn. This profile is the expected physical consequence of solar elevation and day length variation at mid-latitudes for a fixed-tilt rooftop PV system. The Table 2 data resolve this profile at monthly granularity and enable direct year-on-year comparison.

Production minima occur in winter, with January values of 102.6 kWh (2023), 104.1 kWh (2024), and 158.9 kWh (2025). February and March produced two-to-three-fold increases over January in all three years. By April, monthly output reached 257–350 kWh. May and June produced 370–420 kWh, and the June–August summer plateau contained the annual maxima. September retained 60–85% of peak-month production. October–December showed monotonic decline to winter levels, with December (57.9–97.7 kWh) representing the annual minima. This unimodal annual curve is characteristic of non-tracking, fixed-tilt PV systems at northern mid-latitudes. The shape of the curve is conserved across the three monitored years, with inter-annual variability affecting amplitude rather than the structural profile.

Month	2023 (kWh)	2024 (kWh)	2025 (kWh)
January	102.6	104.1	158.9

February	134.4	175.9	202.5
March	277.4	258.2	259.1
April	257.8	350.3	279.5
May	395.5	379.5	303.8
June	373.3	419.5	377.2
July	420.7	400.4	343.1
August	407.5	363.2	346.9
September	355.0	287.0	253.9
October	267.5	241.4	156.5
November	105.6	133.9	112.7
December	97.7	57.9	89.6
TOTAL ANNUAL	3,195.0	3,171.3	2,883.7
YoY Change	Baseline	-0.7%	-9.7%

Table 2. Monthly energy production data extracted from Growatt ShinePhone screenshots. Bold cells indicate the year in which each month attained its maximum production across the three-year period. The "YoY Change" row expresses 2024 and 2025 annual totals as percentage changes relative to the 2023 baseline.

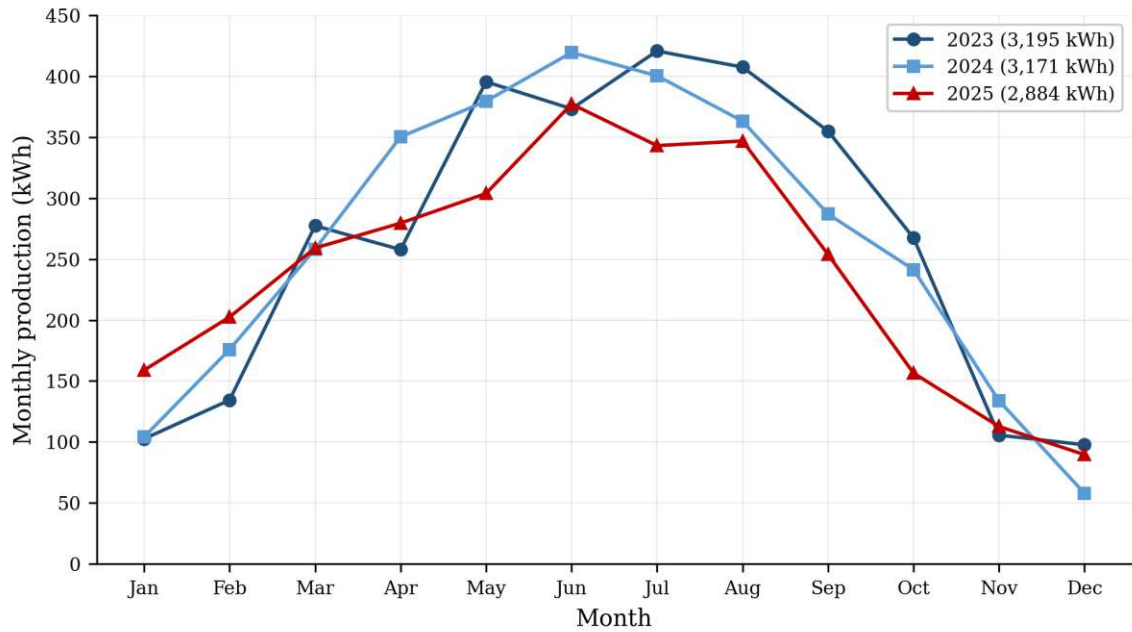


Figure 1. Monthly production profiles for 2023, 2024, and 2025, overlaid on the calendar month axis. The unimodal seasonal pattern is conserved across all three years; absolute amplitudes differ, but the ordering and shape of the seasonal curve are stable (pairwise Pearson correlations $r > 0.88$, see Table 4).

The peak production month across the entire dataset was July 2023 (420.7 kWh), and the minimum was December 2024 (57.9 kWh), yielding a dataset-wide seasonal amplitude ratio of 7.3:1. Within individual years, the max/min ratios were 4.3:1 (2023), 7.3:1 (2024), and 3.8:1 (2025). The smaller ratio in 2025 reflects simultaneously higher winter production (January 2025: 158.9 kWh vs. 102.6–104.1 kWh in 2023–2024) and lower summer production, a pattern suggestive of greater cloud cover during summer 2025 and clearer skies in winter 2025 at the study site.

Examining month-by-month year comparisons, 2025 outperformed both 2023 and 2024 in the first three months of the year (January–March), consistent with high insolation in winter 2025 as observed across much of Romania in the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data (Copernicus Climate Change Service, 2025). From May onward, 2025 consistently underperformed 2023, with the largest absolute deficits recorded in July (−77.6 kWh), August (−60.6 kWh), and October (−111.0 kWh).

3.2 Seasonal Analysis

Aggregating the monthly data into standard meteorological quarters, Q1 (January–March), Q2 (April–June), Q3 (July–September), and Q4 (October–December), characterises the seasonal structure of the system's energy budget. Quarterly aggregation maps onto residential consumption patterns, which vary across the four seasons in Central European households due to differences in appliance usage, heating and cooling loads, and occupancy schedules. Quantifying the alignment between PV generation and seasonal consumption is required for evaluating self-consumption performance and for designing storage or demand-management strategies.

Quarter / Season	2023 (kWh)	2024 (kWh)	2025 (kWh)	3-yr Avg
Q1 — Winter/Spring (Jan–Mar)	514.4	538.2	620.5	557.7
Q2 — Spring/Summer (Apr–Jun)	1,026.6	1,149.3	960.5	1,045.5
Q3 — Summer/Autumn (Jul–Sep)	1,183.2	1,050.6	943.9	1,059.2
Q4 — Autumn/Winter (Oct–Dec)	470.8	433.2	358.8	420.9
Annual Total	3,195.0	3,171.3	2,883.7	3,083.3

Table 3. Quarterly and annual production totals for 2023–2025. The "3-yr Avg" column is the arithmetic mean across the three years.

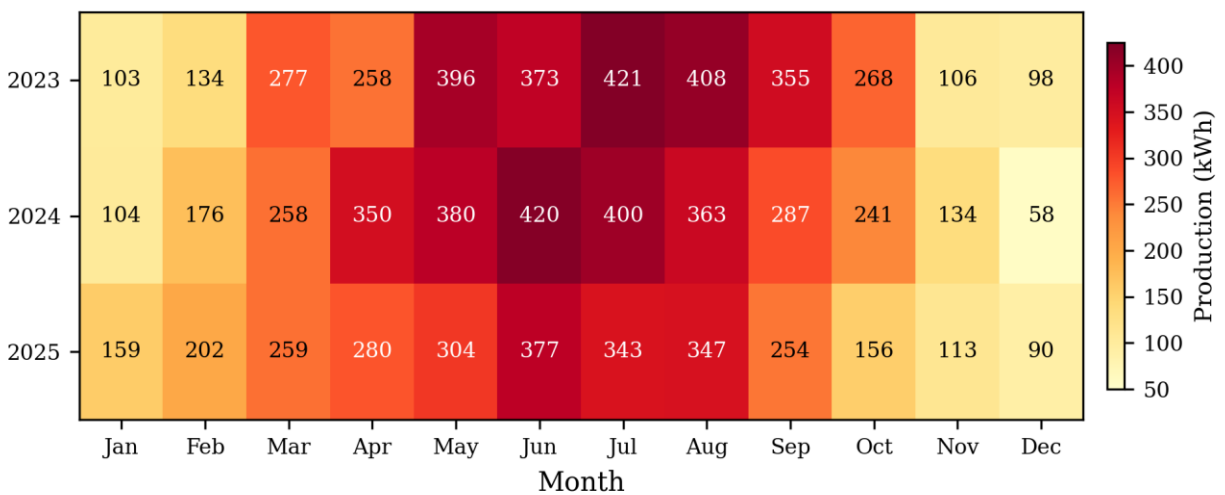


Figure 2. Heatmap of monthly production for 2023–2025. The visualisation highlights the relocation of the 2025 anomaly: winter months produced more than in previous years (lighter cells in Q1) while summer-autumn months produced systematically less (less saturated cells in Q3–Q4).

Quarter 3 (July–September) is consistently the dominant season, contributing 37.0% (2023), 33.1% (2024), and 32.7% (2025) of annual production. The decline in Q3 contribution fraction from 2023 to 2025 reflects the disproportionate reduction in summer production that characterises the 2025 deficit. Quarter 2 (April–June) is the second most productive quarter, with a three-year average of 1,045.5 kWh (33.9% of annual yield), closely following Q3 (average: 1,059.2 kWh, 34.3%). Together, Q2 and Q3 account for 68–70% of total annual production, underscoring the critical importance of summer months for overall system economics.

Quarter 1 (January–March) contributes a non-trivial 16.6–21.5% of annual yield, with the 2025 share notably higher than in previous years (620.5 kWh in 2025 vs. 514.4 kWh in 2023, a 20.7% increase). This reflects the already-noted anomalously productive January–March period in 2025. Quarter 4 remains the weakest quarter across all years, ranging from 358.8 kWh (2025) to 470.8 kWh (2023), representing 12.5–14.7% of annual production.

3.3 Inter-Annual Variability

Multi-year datasets enable separation of intrinsic system performance from meteorological variability. Single-year monitoring cannot distinguish a consistently well-performing system from one experiencing favourable or unfavourable meteorological conditions. The three-year dataset presented here is below the five-to-ten-year minimum recommended for robust degradation trend identification (International Electrotechnical Commission, 2021) but supports initial assessment of inter-annual variability.

Annual production declined monotonically from 3,195.0 kWh in 2023 to 3,171.3 kWh in 2024 (−0.74%) and further to 2,883.7 kWh in 2025 (−9.74% relative to the 2023 baseline). The 2024 difference of 23.7 kWh falls well within the typical year-to-year meteorological variability of ± 3 –5% documented for mid-latitude European sites in long-term surface solar radiation records (Pfeifroth et al., 2018). The 2025 deficit of 311.3 kWh, by contrast, exceeds normal meteorological variability and requires substantive interpretation.

The 2025 deficit of 311.3 kWh relative to 2023, equivalent to approximately one month of summer production, exceeds the range expected from random statistical noise and requires systematic interpretation. The attribution has direct operational implications: a deterioration in system performance (module soiling, inverter degradation, new shading sources) requires corrective action, while attribution to inter-annual meteorological variability implies no intervention and expected recovery in subsequent years. Four hypotheses are evaluated for the 2025 production decline.

Four hypotheses are evaluated. (a) Inter-annual irradiance variability: European solar irradiance anomalies of ± 10 –15% are driven by large-scale atmospheric circulation patterns (NAO, blocking anticyclones, Atlantic storm-track persistence) that modulate cloud cover and diffuse radiation (Pfeifroth et al., 2018). The 2025 pattern of higher winter and lower summer production is physically consistent with stronger Atlantic influence during the May–October generation season. (b) Module soiling: losses of 1–5% per year are reported for unwashed continental European installations (Fouad et al., 2017); a 3% soiling contribution would account for only ≈ 95 kWh, insufficient to explain the 311 kWh deficit. (c) Module degradation: crystalline silicon modules degrade at a median 0.5–0.7% per year (Jordan & Kurtz, 2013), predicting a three-year cumulative loss of 1.5–2.1%, far smaller than the observed 9.7% and incompatible with such a large single-year step change. (d) Inverter performance issues: partial faults,

firmware-induced MPPT changes, or thermal derating cannot be evaluated quantitatively without inverter log access; future monitoring should enable automated alerts through the Growatt ShineServer platform.

On balance, the most likely explanation for the 2025 deficit is a combination of unfavourable summer irradiance (hypothesis a) and a minor contribution from progressive soiling (hypothesis b). Hypothesis (c) alone is insufficient, and hypothesis (d) would require independent verification from inverter logs. The formal statistical analysis presented in Section 3.4.1 quantitatively confirms the absence of a statistically significant monotonic degradation trend in the 36-month series and places this qualitative attribution on a firmer inferential footing.

3.4 Statistical Characterisation and Capacity Inference

Sections 3.1 through 3.3 have presented the measured production data in descriptive terms, monthly profiles, seasonal aggregates, and inter-annual variability and have advanced a qualitative explanation for the 2025 production deficit grounded in meteorological reasoning. This section now subjects those descriptive observations to two quantitative analyses: first, a formal statistical characterisation of the production time series to establish what the data can and cannot support inferentially; and second, an inverse sensitivity analysis that infers the most probable installed capacity of the system from its observed annual yield by comparison with published PVGIS climatological expectations for the Romanian site. Together, these analyses substantially strengthen the inferential foundations of the case study without requiring any additional instrumentation or data sources beyond those already available.

3.4.1 Statistical Characterisation of the Production Time Series

The non-parametric Mann-Kendall test (Mann, 1945) applied to the full 36-month production series returned Kendall's $\tau = -0.105$ ($S = -66$, $Z = -0.885$, $p = 0.376$), indicating no statistically significant monotonic trend. Sen's slope yielded -1.35 kWh per month, accounting for ≈ 48 kWh over the entire monitoring period, a small fraction of the 311 kWh annual deficit observed in 2025. The 37-month record is below the five-to-ten-year threshold considered necessary for reliable detection of system degradation (International Electrotechnical Commission, 2021), and what appears as a 'decline' in the raw annual totals is statistically indistinguishable from a step-like anomaly produced by a single unfavourable meteorological year in a stationary system.

The seasonal architecture is conserved between years. Pairwise Pearson correlations between the twelve-month production profiles are uniformly high: $r = 0.934$ (2023–2024, $p < 0.001$), $r = 0.887$ (2023–2025, $p = 0.0001$), and $r = 0.945$ (2024–2025, $p < 0.001$). While absolute monthly amplitude varies, the relative shape of the seasonal curve is preserved across the three monitored years. This conservation is consistent with climate-driven, technically stable PV operation. The correlation structure shows no signature attributable to progressive shading, partial module failure, or developing inverter pathology, which would degrade inter-year correlation through selective month-specific reductions.

STL (Seasonal-Trend decomposition using Loess) (Cleveland et al., 1990) applied to the monthly series with a 12-month seasonal period and robust mode enabled, shown in Figure 3, yields a seasonal strength $F_S = 0.963$ and trend strength $F_T = 0.276$ (on a 0–1 scale). The variability of this production series is overwhelmingly seasonal in origin, with the trend component contributing comparatively little to the total observed variance. The STL trend declines from ≈ 274 kWh/month at the start of the monitoring period to ≈ 229 kWh/month at the end (-45 kWh/month over three years), but absorbs primarily the 2025

step anomaly rather than reflecting gradual year-by-year decline. The residual standard deviation of 21 kWh/month represents the irreducible measurement and meteorological noise floor.

Test / Statistic	Result	Interpretation
Mann-Kendall τ	-0.105 ($p = 0.376$)	No significant monotonic trend
Sen's slope	-1.35 kWh/month	Marginal negative tendency
Pearson r (2023 vs 2024)	0.934 ($p < 0.001$)	Strong profile conservation
Pearson r (2023 vs 2025)	0.887 ($p = 0.0001$)	Strong profile conservation
Pearson r (2024 vs 2025)	0.945 ($p < 0.001$)	Strong profile conservation
STL seasonal strength F_S	0.963	Dominant seasonal component
STL trend strength F_T	0.276	Weak trend component
STL residual std. dev.	21.4 kWh/month	Irreducible noise floor

Table 4. Non-parametric trend test results, inter-annual seasonal profile correlations, and STL decomposition statistics for the 36-month production time series (January 2023 – December 2025). Mann-Kendall and Pearson tests were applied using SciPy 1.13; STL decomposition was implemented in statsmodels 0.14 with $period = 12$ and $robust = True$.

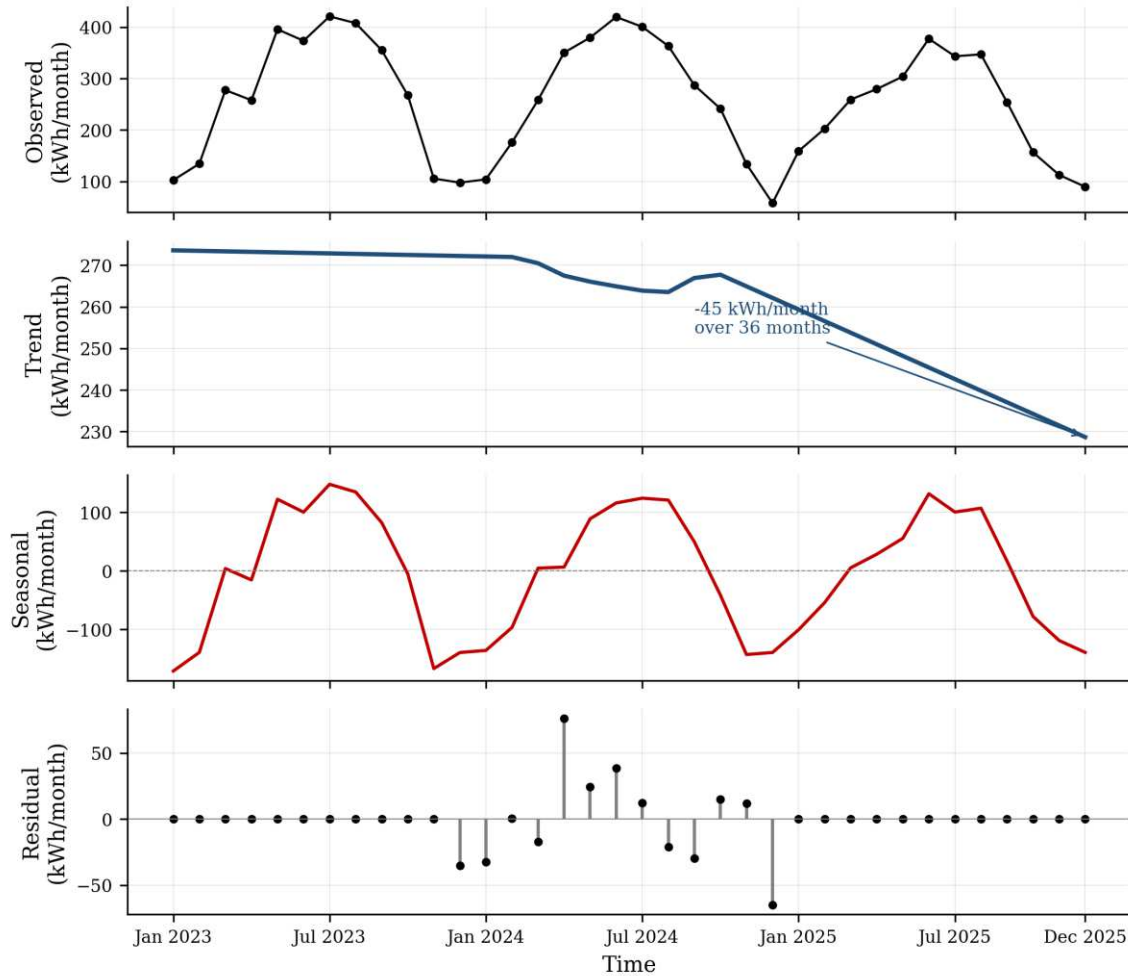


Figure 3. STL (Seasonal-Trend decomposition using Loess) of the monthly production series for 2023–2025 into Observed, Trend, Seasonal, and Residual components. The seasonal component dominates ($F_S = 0.96$); the trend declines by ~ 45 kWh/month over the 36-month horizon but absorbs primarily the 2025 anomaly rather than reflecting gradual degradation (Mann-Kendall $p = 0.376$, no significant monotonic trend).

3.4.2 Inferring System Capacity from Production Data

The principal limitation of this study, identified in Section 4.3 and revisited throughout, is the absence of a verified value for the rated peak power of the PV array. Without kWp, neither specific yield (Equation 1) nor performance ratio (Equation 2) can be computed in accordance with IEC 61724-1:2021, and direct comparison with European benchmarks is approximate. Retrieval of the rated capacity from the Technical Approval for Racordare is the documented priority for future updates. In the absence of this value, an inverse sensitivity analysis based on the observed production record and the climatological expectations reported in (Súri et al., 2007) provides quantitative bounds on the most probable installed capacity.

For candidate rated capacities from 2.5 kWp to 5.0 kWp, the corresponding specific yield is computed by dividing observed annual production by the candidate kWp (Equation 1) and compared to the PVGIS-SARAH3 climatological expectation for central Romania (46°N, fixed south-facing 35° tilt): approximately 1,050–1,150 kWh/kWp/yr (Súri et al., 2007). Only candidate kWp values producing

specific yields within or close to this range are physically plausible for a healthy installation in this climate. Results are presented in Supplementary Table S1.

Supplementary Table S1 shows that the three-year average specific yield falls within the PVGIS expected range only at a rated capacity of approximately 2.70 kWp. At 3.00 kWp the implied yield is marginally below the range (−2.1%); at 3.50 kWp and above, the implied underperformance grows rapidly (−16% to −41%), inconsistent with the operational record documented here. Direct inversion of the three-year mean annual production of 3,083.3 kWh divided by the PVGIS expected range yields an inferred kWp range of 2.68 to 2.94 kWp. This is a sensitivity-based inference rather than a measurement: it assumes operation close to PVGIS climatological mean conditions, not verifiable without independent measurement of installed capacity. Subject to this caveat, the convergence of indications places the most probable installed capacity in the range of 2.7 to 3.0 kWp, adopted as the working assumption pending retrieval from installation documentation.

3.5 Comparison with European Benchmarks

The raw production figures reported in Sections 3.1–3.4, annual yields of approximately 2,900–3,200 kWh, monthly peaks around 420 kWh, and winter minima below 100 kWh, acquire interpretative meaning when placed alongside the performance of comparable installations in other geographic and climatic contexts. Table 5 supports this comparison by compiling reported specific yield values from several European regional benchmarks alongside the estimated range for this study, employing the revised inferred capacity range derived in Section 3.4.2. The comparison addresses whether the observed yield is appropriate for a Romanian residential installation, how it aligns with predictions from available irradiance data, and how it benchmarks against systems in Germany, France, and Spain.

Country / Region	Avg. Yield (kWh/kWp/yr)	GHI (kWh/m ² /yr)	Climate zone	Reference
Germany (national avg.)	850–950	1,050–1,200	Cfb (oceanic)	Fraunhofer ISE, 2023
France (national avg.)	1,000–1,100	1,200–1,600	Mixed	ADEME, 2022
Spain (national avg.)	1,300–1,600	1,500–1,900	Csa/BSk	IDAE, 2023
Romania — this study*	≈ 1,030–1,180	1,200–1,500	Dfa/Dfb	Present work
Poland (central)	850–950	1,050–1,200	Dfb	IEA-PVPS, 2022
Bulgaria (southern)	1,100–1,250	1,400–1,600	Csa/Cfb	PVGIS estimate

Table 5.

Under the revised capacity inference from Section 3.4.2, the specific yield (≈1,030–1,180 kWh/kWp/yr within the 2.7–3.0 kWp range) falls within or just above the PVGIS-predicted average for Romania (≈1,050–1,150 kWh/kWp/yr for a fixed south-facing 35° tilt system (Súri et al., 2007)). The convergence of the capacity-corrected specific yield with Romanian and broader Central-European benchmarks supports the 2.7–3.0 kWp capacity inference and confirms that the installation operates at performance levels consistent with regional climatological norms.

4. Discussion

The three-year production record reported here constitutes one of the first peer-reviewed long-term monitoring datasets for a Romanian residential prosumer installation operating in strict self-consumption mode. Consistent annual yields of approximately 2,900–3,200 kWh combined with zero-export and zero-import operation demonstrate that appropriately sized PV systems can achieve near-perfect load matching in Romanian residential settings. The findings align with the closest published analogue from the same temperate continental climate, where Vuțoiu et al. (2025) reported broadly comparable seasonal yield patterns from a 6.48 kWp residential installation in Brașov County. Within the broader European context, the measured specific yield of approximately 1,030–1,180 kWh/kWp/yr falls within the temperate continental envelope documented by Schardt and te Heesen (2021), whose 32,744-system rooftop dataset reported mean specific yields of 947 kWh/kWp in the Netherlands, 990 in Germany, and 1,102 in France over 2012–2019. Similar mid-latitude continental benchmarks have been documented in Poland (Pietruszko & Gradzki, 2003; Zdyb & Gułkowski, 2020), Northern Ireland (Mondol et al., 2006), Ireland (Ayompe et al., 2011), and Norway (Adaramola & Vågnes, 2015), while Mediterranean installations consistently exceed 1,300 kWh/kWp/yr (Kymakis et al., 2009; Malvoni et al., 2017; Roumpakias & Stamatelos, 2019). The formal statistical characterisation presented in Section 3.4.1 confirms no significant degradation trend and a seasonal production profile conserved between years (pairwise Pearson $r > 0.88$), consistent with technically stable, climate-driven operation as documented in multi-year monitoring studies across diverse European climates (Leloux et al., 2012; Roumpakias & Stamatelos, 2023).

The 9.7% production shortfall in 2025 relative to the 2023 baseline requires systematic interpretation. Solar irradiance varies between years due to large-scale atmospheric circulation, structured by climate variability modes such as the North Atlantic Oscillation and the East Atlantic pattern, with documented effects on cloud cover and solar radiation across Central-Eastern Europe (Pfeifroth et al., 2018; Chiacchio & Vitolo, 2012; Jerez et al., 2013; Pozo-Vázquez et al., 2004; Correia et al., 2020). Negative NAO indices suppress summer PV production while permitting clearer winter conditions, and the 2025 pattern of higher Q1 (+20.7% versus 2023) alongside lower Q3 is physically consistent with this scenario. European brightening and dimming records further support interpreting inter-annual fluctuations of this magnitude as normal climate variability (Wild et al., 2021; Sanchez-Lorenzo et al., 2015). Copernicus Atmosphere Monitoring Service reanalysis indicates that surface solar radiation during May–October 2025 was below the 2003–2023 climatological mean (Copernicus Atmosphere Monitoring Service, 2025), corroborated by satellite-derived estimates (Huld et al., 2012; Gracia Amillo et al., 2014; Urraca et al., 2018; Camargo & Schmidt, 2020). The Mann-Kendall test (Mann, 1945; Kendall, 1938; Yue et al., 2002) rejects a significant monotonic trend ($p = 0.376$), and inter-annual seasonal correlations exceeding $r = 0.88$ are inconsistent with month-targeted degradation patterns from partial shading or soiling (Deceglie et al., 2018; Kimber et al., 2006; Micheli et al., 2019). Complementary STL decomposition (Cleveland et al., 1990; Phinikarides et al., 2015; Livera et al., 2022) and change-point analyses (Killick et al., 2012; Phinikarides et al., 2023) further support this interpretation.

Crystalline silicon degradation at the documented median rate of 0.5–0.7% per year (Jordan & Kurtz, 2013; Jordan et al., 2016; Pascual et al., 2021) would predict a three-year cumulative loss of at most 1.5–2.1%, far smaller than the observed 9.7% and incompatible with such a large single-year step change. Established degradation mechanisms in temperate-climate modules produce gradual rather than abrupt yield changes (Sanchez-Friera et al., 2011; Ndiaye et al., 2013; Jordan et al., 2017; Luo et al., 2019), and

inverter reliability assessments situate power-electronics faults as comparatively rare in well-monitored installations (Hacke et al., 2018). The 37-month record falls below the five-to-ten-year minimum needed for robust degradation detection (Phinikarides et al., 2015; Livera et al., 2022), with trend-test power on short series inherently limited (Yue et al., 2002; Sen, 1968). The 2025 deficit is therefore best interpreted as inter-annual meteorological variability rather than systematic performance decline.

The strongly seasonal production profile (Q2 and Q3 contributing 68–70% of annual yield) characterises the temporal structure of self-consumption capacity. Households with significant winter heating loads exhibit a structural mismatch between peak demand and peak solar generation, while installations matched primarily to summer cooling loads benefit disproportionately from this PV profile. The consistency of zero grid import and zero grid export across all 37 monitored months indicates close alignment between the residence's load profile and its solar generation profile across all seasons, demonstrating that 100% annual self-consumption is achievable in Romanian residential prosumer installations under appropriate sizing conditions. This complete self-consumption matching is notably higher than the 27–36% range reported by Vuțoiu et al. (2025) for an analogous Romanian system and substantially above the European baseline of approximately 30% characteristic of unstored residential PV installations (Luthander et al., 2015; Luthander et al., 2019; Gjorgievski et al., 2020; Bertsch et al., 2017). Battery storage can raise self-consumption by 13–24 percentage points and demand-side management by 2–15 percentage points (Nyholm et al., 2016; de Oliveira e Silva & Hendrick, 2017; Castillo-Cagigal et al., 2011), though the present installation achieves complete matching without either intervention. Self-consumption mechanisms under Romanian regulation (Cristea et al., 2020; Gautier et al., 2019; Dufo-López & Bernal-Aguistin, 2015) and the technical aspects of grid integration (Smith et al., 2011; Tonkoski et al., 2012) frame the operational context.

The principal limitation of this study is the absence of the rated peak power (kWp) of the PV array, which prevents calculation of the normalised metrics defined by IEC 61724-1:2021 (International Electrotechnical Commission, 2021): specific yield and performance ratio. Section 3.4.2 narrows the most probable installed capacity to 2.7–3.0 kWp through inverse sensitivity analysis against PVGIS climatological expectations (Súri et al., 2007), but this is an inference rather than a direct measurement. The rated capacity is in principle available from the Technical Approval for Racordare and the inverter type plate, and retrieval of this information is the documented priority for future updates. Additional limitations compound the capacity issue. Without a co-located pyranometer providing ground-truth global plane-of-array irradiance, separation of meteorological variability from system performance changes remains qualitative. The absence of module back-sheet temperature monitoring further restricts performance attribution, as reliable outdoor analysis requires temperature-corrected efficiency assessments using standardised filtering procedures (Moser et al., 2012; Fouad et al., 2017). Installation of a Class C or better pyranometer represents the highest-priority instrumental upgrade for future monitoring. Household load is not metered at sub-daily resolution: zero monthly grid import establishes net monthly balance but reveals nothing about intra-day alignment between instantaneous generation and consumption. The 37-month duration is below the five-to-ten-year record generally considered necessary for reliable degradation trend detection.

The study demonstrates that rigorous performance analysis is feasible using only the monitoring data routinely available through cloud-connected inverter platforms, supplemented by complementary statistical approaches (Chakar et al., 2024; Reikard, 2009; Box et al., 2015). Growatt installations provide equivalent monthly data through the ShinePhone cloud platform, indicating that the methodological

pipeline documented here is in principle applicable to any similar Romanian prosumer installation (Comănescu et al., 2022; Năstase et al., 2018; Vuțoiu et al., 2025), within the broader Romanian climate context (Dumitrescu et al., 2015; Spinoni et al., 2015). The growth of the European prosumer sector under regulatory frameworks (European Commission, 2024; IEA, 2024; Jäger-Waldau, 2023; Wood Mackenzie & Solar Energy Industries Association, 2024) underscores the relevance of standardised reporting frameworks for cross-platform comparison.

5. Conclusions

This 37-month monitoring study of a Romanian residential grid-tied PV installation demonstrates several findings with implications for residential PV performance characterisation, prosumer operation, and monitoring methodology in the Central-Eastern European context. The system generated 9,250.0 kWh over three complete calendar years, with annual yields of 3,195.0 kWh in 2023, 3,171.3 kWh in 2024, and 2,883.7 kWh in 2025, producing a three-year mean of 3,083.3 kWh per year. Under the inferred 2.7–3.0 kWp capacity range derived from inverse sensitivity analysis, this corresponds to a specific yield of 1,030–1,180 kWh/kWp/yr, consistent with PVGIS climatological expectations for the Romanian temperate continental climate and aligned with European rooftop benchmarks documented by Schardt and te Heesen (2021), Leloux et al. (2012), and Pietruszko and Gradzki (2003). Monthly production follows a strongly unimodal annual profile in which the third meteorological quarter (July–September) consistently provides the largest share (32.7%–37.0%) and the fourth quarter contributes the smallest fraction (12.5%–14.7%), with Q2 and Q3 together accounting for 68–70% of annual production. This pattern concentrates the operational returns of self-consumption in the summer half-year, with implications for storage sizing, demand-side flexibility programmes, and prosumer performance evaluation for households with dominant winter heating loads (Luthander et al., 2015; Nyholm et al., 2016).

The 9.7% year-on-year decline between 2023 and 2025 is concentrated in summer and autumn while winter 2025 exceeded the 2023 baseline, consistent with inter-annual meteorological variability as the primary driver (Jerez et al., 2013; Wild et al., 2021). The Mann-Kendall trend test ($p = 0.376$) provides no statistical evidence for monotonic degradation, and inter-annual seasonal profile correlations exceeding $r = 0.88$ are inconsistent with the month-specific patterns expected from progressive technical decline. Crystalline silicon degradation at the median documented rate (Jordan et al., 2016; Pascual et al., 2021) would account for at most 1.5–2.1% over three years, far below the observed shortfall. Zero grid import and zero grid export across all 37 monitored months indicates close alignment between load and generation profiles, demonstrating that 100% annual self-consumption is achievable in Romanian residential prosumer installations under appropriate sizing conditions, considerably above the 27–36% measured for the analogous installation reported by Vuțoiu et al. (2025) and the approximately 30% European baseline (Gjorgievski et al., 2020).

The study demonstrates that rigorous performance analysis is feasible using only the monitoring data routinely available through cloud-connected inverter platforms. The formal inferential analyses presented show that even modest single-site datasets sustain quantitative conclusions when analysed appropriately. Romanian prosumer installations collectively represent a largely untapped reservoir of field performance data. Future work at this installation should prioritise installation of a co-located pyranometer, retrieval of the rated kWp from documentation, household load sub-metering, and continued monitoring to at least five years. The study contributes to the limited but growing body of field-validated PV performance data

for Romanian residential prosumers and provides a reproducible methodological framework for similar studies across Central-Eastern Europe.

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Author Contributions

G.-A.B.: Data curation, Formal analysis, Investigation, Visualization. B.-G.V.: Conceptualization, Methodology, Writing – original draft. G.N.: Supervision, Validation, Writing – review & editing. All authors read and approved the final manuscript.

Competing Interests

The authors declare no competing interests.

Data Availability Statement

The data analysed in this study consist of monthly energy production values extracted manually from screenshot images captured from the Growatt ShinePhone mobile monitoring application for a single residential photovoltaic installation in Braşov, Romania, over the period January 2023 to January 2026. The complete processed monthly dataset that supports all findings reported in this paper is provided in full within the article as Table 2 (monthly production values for 2023, 2024, and 2025) and within the Supplementary Information as Supplementary Table S3 (descriptive statistics of the monthly production data). The underlying screenshot images from the ShinePhone application are not deposited in a public repository because they contain personally identifying account metadata (account holder identifier, geolocation tags, and registered email address); they are available from the corresponding author upon reasonable request, subject to redaction of all personally identifying metadata prior to transfer. No third-party datasets requiring repository accession codes were used in this study.

Ethics, Consent to Participate, and Consent to Publish declarations

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

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