Diagnostics and Forecasting of Photovoltaic Module Degradation: Analysis of Problems and Research Directions

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Abstract. The purpose of this paper is to systematize the current state of research on photovoltaic (PV) module degradation, analyse existing methods for its diagnosis and forecasting, and identify unresolved problems relevant to information-measurement and intelligent monitoring systems. These objectives were achieved through a structured review of publications from 2023 to 2026 covering degradation mechanisms, instrumental and data-driven diagnostic techniques, and physical, data-driven, and hybrid forecasting approaches, complemented by a comparative analysis of the methods presented in two summary tables and four generalizing diagrams. The most important results are as follows: a systematized classification of degradation mechanisms, including electrochemical corrosion, potential-induced degradation, delamination, microcracks, and technology-specific mechanisms in PERC, HJT, and perovskite tandem cells; a comparative characterization of diagnostic methods, showing that instrumental techniques (I–V tracing, infrared thermography, electroluminescence, and UAV-based inspection) provide high spatial accuracy but limited scalability, whereas data-driven methods (year-on-year analysis, performance loss rate estimation, and machine-learning-based trend models) can be scaled to large arrays but remain sensitive to data quality; and the identification of four unresolved scientific problems: separation of reversible and irreversible performance losses, automatic correction of erroneous retrospective data, quantitative real-time assessment of the degree of degradation, and forecasting of the remaining useful life (RUL) of PV modules. The significance of the obtained results lies in demonstrating that a hybrid prognostic model combined with training-sequence decimation, the k-FC method, and a reflexive learning approach, previously developed by the authors for PV power-plant monitoring, provides a coherent methodological basis for addressing all four problems without requiring additional diagnostic hardware.
Keywords: photovoltaic module degradation; diagnostics; forecasting; performance loss rate; remaining useful life; machine learning; k-FC method.

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Diagnosticarea și prognozarea degradării modulelor fotovoltaice: analiză a problemelor și a direcțiilor de cercetare

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Rezumat. Scopul lucrării este de a sistematiza stadiul actual al cercetărilor privind degradarea modulelor fotovoltaice (PV), de a analiza metodele existente de diagnosticare și de prognozare a acestui fenomen și de a identifica problemele științifice nerezolvate relevante pentru sistemele de măsurare și achiziție a datelor, precum și pentru monitorizarea inteligentă. Obiectivele propuse au fost realizate printr-o analiză structurată a publicațiilor apărute în perioada 2023–2026, care abordează mecanismele de degradare, tehnicile de diagnosticare bazate pe instrumentație și pe analiza datelor, precum și metodele de prognozare bazate pe modele fizice, pe date și pe abordări hibride. Analiza a fost completată prin compararea metodelor examinate, rezultatele fiind sintetizate în două tabele comparative și patru diagrame de sinteză. Principalele rezultate obținute sunt următoarele: sistematizarea mecanismelor de degradare, incluzând coroziunea electrochimică, degradarea indusă de potențial (PID), delaminarea, microfisurile și mecanismele specifice tehnologiilor PERC și HJT, precum și celulelor tandem pe bază de perovskit; caracterizarea comparativă a metodelor de diagnosticare, care evidențiază faptul că tehnicile instrumentale — trasarea curbei curent–tensiune (I–V), termografia în infraroșu, electroluminescența și inspecția cu drone (vehicule aeriene fără pilot — UAV) — oferă o rezoluție spațială ridicată, dar prezintă limitări în ceea ce privește scalabilitatea, în timp ce metodele bazate pe date — analiza evoluției anuale, estimarea ratei de pierdere a performanței și modelele de analiză a tendințelor bazate pe învățarea automată — pot fi aplicate la scară largă în parcurile fotovoltaice, dar rămân sensibile la calitatea datelor; identificarea a patru probleme științifice nerezolvate: diferențierea pierderilor de performanță reversibile de cele ireversibile, corectarea automată a datelor retrospective

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eronate, evaluarea cantitativă în timp real a gradului de degradare și prognozarea duratei de viață utilă rămase (RUL) a modulelor fotovoltaice.
Cuvinte-cheie: degradarea modulelor fotovoltaice; diagnosticare; prognoză; rata de scădere a performanței; durata de viață utilă rămasă; învățare automată; metoda k-FC.

Диагностика и прогнозирование деградации фотоэлектрических модулей: анализ задач и направлений исследований

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Аннотация. Целью статьи является систематизация современного состояния исследований в области деградации фотовольтаических (ФВ) модулей, анализ известных методов её диагностики и прогнозирования, а также выявление нерешённых задач, актуальных для информационно-измерительных и интеллектуальных систем мониторинга. Поставленные задачи решены путём структурированного обзора публикаций 2023–2026 гг., охватывающего механизмы деградации, инструментальные и данных-ориентированные методы диагностики, а также физические, данных-ориентированные и гибридные методы прогнозирования; сравнительный анализ методов представлен в двух сводных таблицах и четырёх обобщающих схемах. Важнейшие результаты: систематизированная классификация механизмов деградации (электрохимическая коррозия, потенциал-индуцированная деградация, деламинация, микротрещины, а также механизмы, специфические для элементов PERC, HJT и перовскитных тандемов); сравнительная характеристика методов диагностики, показывающая, что инструментальные методы (снятие вольт-амперной характеристики, инфракрасная термография, электролюминесценция, обследование с помощью БПЛА) обеспечивают высокую пространственную точность, но плохо масштабируются, тогда как данных-ориентированные методы (анализ Year-on-Year, оценка показателя скорости потери производительности, трендовые модели машинного обучения) масштабируются на большие массивы, но остаются чувствительными к качеству данных; выявление четырёх нерешённых научных задач – разграничение обратимых и необратимых потерь производительности, автоматическая коррекция ошибочных ретроспективных данных, количественная оценка степени деградации в реальном времени и прогнозирование остаточного ресурса (RUL) ФВ-модулей. Значимость полученных результатов состоит в обосновании того, что гибридная прогностическая модель в сочетании с децимацией обучающей последовательности, методом k-FC и рефлексивным подходом обучения, разработанными ранее авторами для мониторинга ФВ-станций, образует согласованную методологическую основу для решения всех четырёх задач без дополнительного диагностического оборудования, что открывает возможность количественной оценки деградации на уровне отдельного модуля и дифференцированного планирования обслуживания крупных ФВ-массивов. Сформулированы четыре задачи дальнейших исследований.
Ключевые слова: деградация фотовольтаических модулей; диагностика; прогнозирование; показатель скорости потери производительности; остаточный ресурс; машинное обучение; метод k-FC.

I. INTRODUCTION

Photovoltaic (PV) energy is one of the most dynamic sectors of the global power industry. According to the International Energy Agency Photovoltaic Power Systems Programme (IEA PVPS), the cumulative installed PV capacity worldwide exceeded 2,260 GW by the end of 2024, corresponding to a 29% increase over the previous year [1]. In 2025 the IEA recorded a new record of 605 GW of newly installed PV generation capacity [2]; in the same year the world added approximately four gigawatts of new solar capacity for every gigawatt of new wind capacity, which illustrates the dominant position of photovoltaics within newly commissioned renewable generation [3].

This rapid capacity growth is shifting the focus of industry research: ensuring the reliable and efficient long-term operation of commissioned assets is coming to the fore. A key factor governing long-term operation is the degradation of photovoltaic modules – the progressive decline of their conversion efficiency under the influence of external and internal factors. Throughout this paper degradation is understood in its irreversible sense: unlike reversible losses such as soiling, snow cover or partial shading, which are recovered by cleaning or by a change in operating conditions, degradation reflects a permanent change in the materials and interfaces of the module. The separation of these two components is itself one of the open problems addressed below.

The importance of the problem stems from several interrelated aspects. First, annual power losses (typically 0.5–1.0% per year) accumulate

over a 25–30-year service life and materially affect the levelized cost of electricity (LCOE). Second, the nonlinear and stochastic nature of degradation processes complicates long-term capacity-balance planning. Third, existing generation-forecasting models for PV plants generally do not account for the gradual change in photoelectric-conversion parameters, which leads to a systematic deviation of the forecast from actual output [4, 5, 6].

A review of the literature reveals a persistent gap between the maturity of degradation-mechanism research, which is by now extensive, and the maturity of tools that can turn continuous monitoring data into an actionable, module-level, real-time indicator of degradation severity and remaining useful life. Instrumental diagnostic techniques provide high accuracy but do not scale to routine monitoring of large arrays, whereas purely data-driven approaches scale well but are limited by the quality of retrospective data and by the absence of a validated method for separating reversible losses from true, irreversible degradation. It is this gap in the literature that motivates the present review.

The purpose of this paper is to systematize the current state of research on PV-panel degradation, to analyze known methods of its diagnostics and forecasting, and to identify unsolved problems relevant to the application of information-measurement and intelligent monitoring systems.

II. MECHANISMS OF PHOTOVOLTAIC PANEL DEGRADATION

A. Classification of degradation mechanisms.

Degradation of PV modules results from the interaction of multiple physical, chemical and mechanical processes. The principal contributing factors include temperature and its cyclical variation, humidity, dust soiling, discoloration of encapsulation materials, formation of microcracks, and delamination of module layers [7].

Electrochemical corrosion. Corrosion processes cover electrochemical mechanisms that attack metallic contacts, solder joints and conductive coatings. A recent comprehensive review of solar-panel corrosion identifies humidity, temperature fluctuations, ultraviolet radiation and saline environments as the four principal accelerating factors, and specifically implicates the encapsulant, solder interconnections and conductive coatings as the sites where corrosion initiates [8]. Frames, mounting hardware and electrical connections made of unprotected steel or aluminum are particularly susceptible; corroded joints raise series resistance and reduce both the power output and the service life of the affected string [8].

Potential-induced degradation (PID). PID is caused by leakage (stray) currents that arise from the voltage potential between the solar cells and the grounded frame or mounting structure, especially in modules with a negative voltage to ground; it is accelerated by high system voltage, high temperature and high humidity [9]. The effect can reduce module efficiency by up to 30% and is not captured by the standard qualification tests of the IEC 61215 series, which makes it particularly important for early field diagnostics [9]; a dedicated test procedure is specified separately in IEC TS 62804-1, whose current revision combines potential and light stress within a single test sequence. PID is commonly detected with electroluminescence imaging, which reveals characteristic shunted-cell patterns, and can be partially reversed by grounding the positive pole of the array or by elevated-temperature treatment, although the latter is generally unsuitable as a routine remedy because it additionally stresses the module materials [9].

Mechanical defects: cell cracks and ultraviolet degradation. According to the DuraMAT consortium (NREL, USA), cell cracking and UV-induced degradation of encapsulants and backsheets have been identified as key degradation mechanisms for new module designs, alongside light- and elevated-temperature-induced degradation (LeTID), which is now tracked as a distinct field-relevant mechanism in long-term module-lifetime studies [10].

Delamination. Delamination is the loss of adhesion between the encapsulant and the glass, the cell or the backsheet. It is driven by moisture ingress, thermal cycling and ultraviolet ageing of the encapsulant, and it acts in two ways: directly, through the optical losses caused by the air gap that forms at the delaminated interface, and indirectly, by opening a diffusion path for moisture that accelerates the corrosion mechanisms described above [7, 8].

B. Quantitative characteristics of degradation.

The degradation rate of crystalline-silicon modules is fundamentally nonlinear rather than strictly linear over the module lifetime. Reported values lie predominantly within the 0.5–1.0% per year band quoted in Section I; as an illustration, a monitoring campaign at an NREL test facility

analysed with the Suns-Vmp method yielded a mean rate of about 0.7% per year, attributed to encapsulant discoloration and weakened solder bonds [11]. This value should be read as a site- and technology-specific result rather than as a universal norm, and it is not directly comparable with the nominal −0.5% per year adopted as a planning convention in Section IV-A. For newer high-efficiency cell concepts – passivated emitter and rear cell (PERC), passivated emitter with rear locally diffused cell (PERL/PERT) and silicon heterojunction (SHJ/HJT), which by 2020 already accounted for roughly 80% of market share, displacing the previously dominant aluminum back-surface-field (Al-BSF) design – degradation is dominated by a decline in open-circuit voltage (Voc), in contrast to the short-circuit current (Isc) or fill-factor degradation typical of older Al-BSF modules [12]. Because long-term field data for these newer technologies remain scarce, published early-life degradation rates still show considerable spread across manufacturers, climates and measurement protocols [12].

C. New and unresolved degradation mechanisms

For emerging tandem solar cells based on metal-halide perovskites (MHP), specific unresolved degradation mechanisms have been identified: limited thermal stability and high ionic mobility give rise to degradation pathways – including moisture-triggered phase transitions of the perovskite layer that are strongly accelerated by the simultaneous presence of oxygen and light – that are not reproduced by standard qualification tests [13]. This creates a methodological gap: existing IEC-based accelerated test protocols, developed for crystalline-silicon technology, cannot yet be assumed to be predictive for perovskite and perovskite-silicon tandem modules.

Table 1 below summarizes the principal degradation mechanisms discussed above together with their dominant physical driver and the module technologies to which they are most relevant.

Table 1

Principal degradation mechanisms of PV modules

Mechanism	Dominant driver(s)	Most affected technologies	Typical effect
Electrochemical corrosion	Humidity, UV, saline environment	Metal contacts, solder joints, frames (all technologies)	Rising series resistance, gradual power loss
Potential-induced degradation (PID)	High system voltage, heat, humidity, negative voltage to ground	Crystalline-Si modules, high-voltage strings	Up to 30% efficiency loss; partly reversible
Cell cracking	Mechanical/thermal stress, transport, snow/wind load	All crystalline-Si; thin high-efficiency wafers	Localized power loss, hotspot risk
UV / LeTID degradation	UV exposure; elevated temperature under illumination	Encapsulants, backsheets; PERC cells	Discoloration, gradual power loss
Delamination	Moisture ingress, thermal cycling, UV ageing of the encapsulant	Encapsulant/glass and encapsulant/backsheet interfaces (all technologies)	Optical losses; moisture path accelerating corrosion
Voc-dominated early-life loss	Technology-specific defect passivation	PERC, HJT (high-efficiency cells)	Early-life Voc decline (vs. Isc/FF in Al-BSF)
Perovskite phase degradation	Moisture, oxygen + light, limited thermal stability	Metal-halide perovskite tandem cells	Rapid, non-standardized degradation

III. METHODS OF DEGRADATION DIAGNOSTICS AND DETECTION

Figure 1 shows a generalized scheme of information extraction and processing in the

principal methods used to diagnose PV-panel degradation.

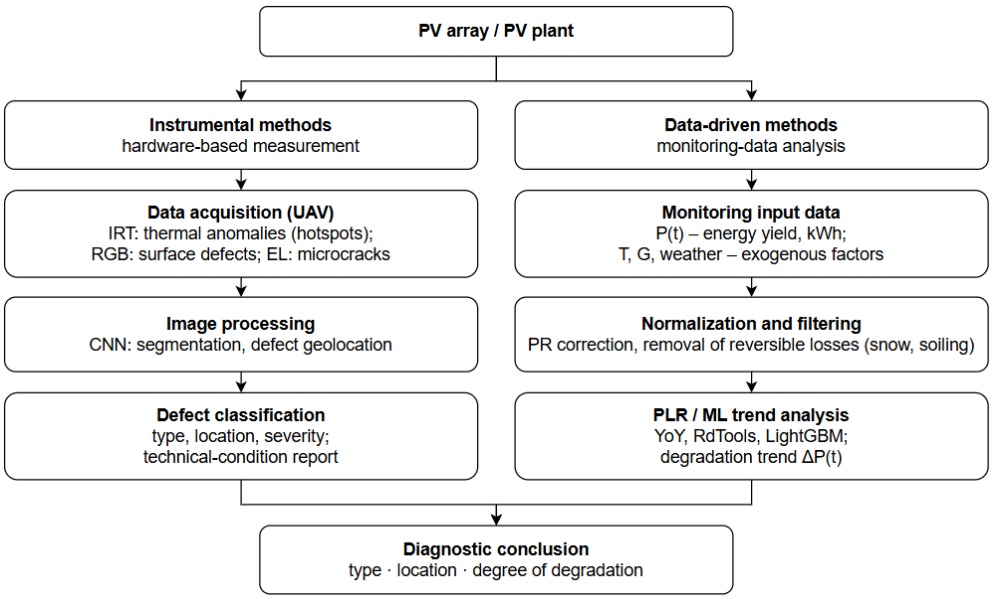


Fig. 1. Information extraction and processing scheme in PV-panel degradation diagnostic methods.

A. Instrumental diagnostic methods

The most common inspection methods for PV installations include measurement of the current-voltage characteristic (I-V), thermographic imaging, and luminescence imaging – electroluminescence (EL) and photoluminescence (PL) [14].

Infrared thermography (IRT). IRT is a powerful non-contact diagnostic tool. Traditional methods – I-V tracing, EL and PL – are, as a rule, suitable only for laboratory conditions or require the system to be taken offline [15]. Combining IRT with convolutional neural networks (CNN) allows automatic classification of detected faults, reducing the dependence of inspection quality on operator expertise [16].

UAV-based aerial inspection. UAV systems equipped with a suite of different sensors enable scalable inspection of large PV arrays. A thermal infrared camera detects temperature anomalies – "hotspots" – together with bypass-diode failures and string faults, because a defective cell dissipates energy as heat [17]. An RGB camera captures surface visual indicators: soiling, delamination, encapsulant discoloration, and mechanical damage [17]. EL imaging in the short-wave infrared range (SWIR) makes it possible to detect microcracks and interconnection damage that are invisible to RGB and IR cameras [18]. Challenges of geolocation accuracy and of quantifying the impact of detected defects on production remain unresolved [18].

B. Data-driven methods for degradation determination

Performance Loss Rate (PLR). PLR captures both reversible and irreversible losses combined. The absence of a single, consensus definition of PLR complicates the comparison of results between different studies [19]. Even after normalization, monitoring signals contain fluctuations that affect the accuracy of the PLR estimate, and the impact of data quality and local climate on that accuracy has been shown to be substantial [20].

Year-on-Year (YoY) method. The standard evaluation process consists of three steps: normalization, filtering and statistical analysis. The open-source RdTools library provides a standardized implementation of this process [21]. A multi-annual variant of the method (multi-YoY) has been shown to substantially reduce the statistical uncertainty of the PLR estimate compared with a single-year YoY calculation, but most PV systems worldwide are still relatively new and have not yet accumulated the three-plus years of data that the method requires for a stable estimate [22].

Prognostic baseline models. A LightGBM model used as a baseline: a growing deviation between the forecast and measured production values effectively signals degradation trends and has been proposed as a general framework for PLR estimation [23].

V–P curve derivative analysis. A method based on the first derivative of the voltage–power curve (2025) allows the degree of degradation to be assessed; an LSTM network is used for classification of the resulting degradation signatures [24].

C. Comparative analysis and unresolved problems in diagnostics

First, the problem of separating reversible and irreversible losses: analytical and statistical uncertainty in performance-ratio (PR) measurements remains significant, and no generally accepted method exists for decoupling the two components of PLR [19]. Second, the problem of retrospective data quality: meteorological and production archives contain erroneous records that distort the training of data-driven models, and the sensitivity of PLR estimates to data quality has been shown to be substantial [5, 20]. Third, the problem of scalability: instrumental methods are practically inapplicable for the regular, routine monitoring of large PV arrays, since they require either equipment mobilization (UAV, portable I-V tracers) or a temporary shutdown of the inspected string.

IV. METHODS OF PHOTOVOLTAIC PANEL DEGRADATION FORECASTING

Figure 2 shows the classification of degradation-forecasting methods proposed in this paper, covering three fundamentally distinct approaches.

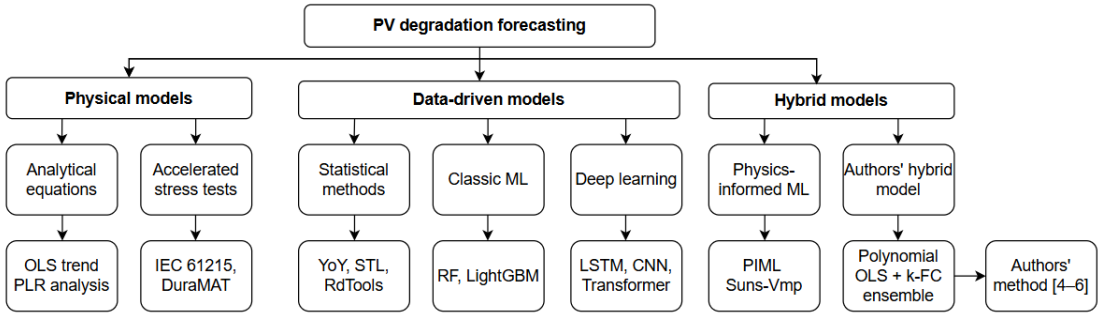


Fig. 2. Classification of PV-panel degradation forecasting methods.

Figure 3 shows a generalized information-processing pipeline common to the forecasting methods discussed in this section.

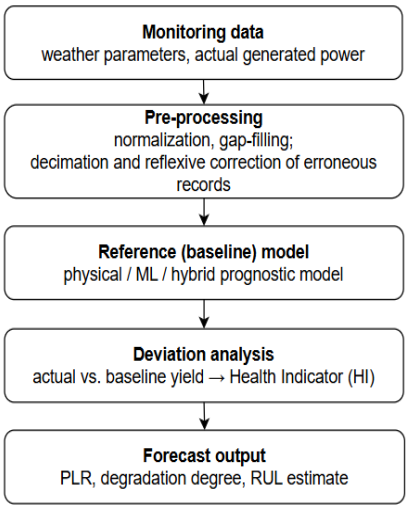


Fig. 3. Information-processing pipeline in PV-panel degradation forecasting methods.

A. Physical (model-based) forecasting methods

For long-term profitability assessments of PV systems, a nominal value of PLR = −0.5% per year is typically assumed as a planning convention rather than as a measured quantity; however, real PLR trends depend substantially on climate, module technology and other parameters, and can deviate from this nominal value by a factor of two or more depending on site conditions [25]. Accelerated stress tests under IEC 61215 and DuraMAT methodologies require correlation with real operating data before their results can be used for field-relevant lifetime prediction.

B. Data-driven forecasting methods

The multi-YoY method substantially reduces the statistical uncertainty of the PLR estimate; the main practical limitation, as noted above, is that most PV systems are new and have not accumulated a three-year data record [22]. Random Forest and LightGBM algorithms are particularly well suited to representing nonlinear relationships between environmental parameters and degradation patterns, and have been proposed as part of AI-based predictive-maintenance frameworks for PV systems [26]. Long-term neural-network modeling is able to reveal the underlying degradation trend without overfitting to short-term effects such as soiling cycles or

seasonal irradiance variation [27]. Where sufficient historical records exist, purely statistical forecasting methods, benchmarked for example in [28], can also provide a useful, low-complexity baseline for comparison with more complex ML models.

C. Hybrid approaches

Hybrid methods are classified into three categories: physics-informed machine-learning models (PIML), optimized physical models, and physics-guided models [29]. In this classification, PIML models embed physical relationships directly into the learning architecture or loss function; optimized physical models use ML to tune the parameters of an otherwise physics-based model; and physics-guided models use physical outputs as additional input features to a data-driven model. Physical regularities in all three categories help prevent physically inconsistent forecasts and reduce the risk of overfitting compared with purely data-driven models [29]. For remaining-useful-life estimation specifically, graph neural networks have recently been surveyed as a promising hybrid architecture capable of representing spatial dependencies between cells or strings within a PV array, in addition to their established use in the RUL prediction of other engineering systems [30, 31].

D. Unresolved problems in degradation forecasting

The nonlinear behavior of degradation substantially increases statistical uncertainty when approximated by linear models [20]. No accepted separation exists between the PLR and Rd, the rate of irreversible material degradation of the module; filtering of reversible losses remains a methodologically unresolved task [19]. Most systems have not accumulated the required volume of data [22]. For forecasting the remaining useful life (RUL), no reliable "health indicator" exists that would correctly reflect irreversible material degradation while being robust to short-term reversible fluctuations [31].

Table 2

Comparative characterization of PV degradation diagnostic and forecasting method families

Method family	Scalability to large arrays	Extra hardware	Typical resolution	Key limitation
Instrumental (I-V, IRT, EL/PL)	Low – manual/periodic	Yes (cameras, tracers)	Module/cell level	Requires shutdown or mobilization
UAV-based inspection	Medium	Yes (UAV + sensors)	High spatial resolution	Weather-dependent; geolocation accuracy
Statistical (YoY, RdTools)	High	No	Plant/string level	Needs ≥1–3 years of clean data
ML trend models (RF, LightGBM, LSTM)	High	No	Plant/string level	Sensitive to data quality; limited interpretability
Hybrid / PIML	High	No	Plant/string level	Requires an accurate physical sub-model
Authors' hybrid + decimation/k-FC/reflexive (proposed; not yet validated)	High (expected)	No	Module level (expected)	Requires validation on field data (Task D)

V. STATEMENT OF THE RESEARCH PROBLEM

A. Generalized analysis of unresolved problems

Based on the literature review conducted in Sections II – IV, four open scientific problems are formulated: (1) separation of irreversible degradation (Rd) from reversible losses within the meaning of PLR; (2) erroneous records in

retrospective databases; (3) the absence of a method for the quantitative, real-time assessment of the degradation degree of a specific module; (4) forecasting of the RUL of PV panels, which remains only a partially solved problem.

B. Conceptual link to the authors' methodology

The PV-station monitoring system with prognostic models developed by the authors [4, 5, 6] contains a scientific foundation that can be applied to the solution of Problems 1–4.

The underlying idea is as follows: a prognostic model forms a calculated (reference) value of energy production.

If the actual value systematically deviates from the reference value, and this deviation cannot be explained by reversible factors, then the deviation itself is a direct measure of degradation.

Because these methods are referred to repeatedly below, they are summarised here for readers not familiar with [5, 6].

The training procedure of the prognostic model rests on three distinct methods proposed by the authors and applied jointly within a single training loop: decimation of the training sequence, reflexive learning, and the method of k friends-classmates (k-FC).

Decimation operates on the training residuals: the forecast produced at the training stage is compared with the metered output, the deviations are ordered, and the hours with the largest deviations are excluded from the training sequence as those carrying the largest errors of the meteorological data, after which the model is re-fitted.

Reflexive learning exploits the fact that the output of a PV plant depends on cloudiness far more strongly than on any other factor, so that the metered output of a given hour is itself an almost unambiguous indicator of the actual mean cloudiness of that hour.

The polynomial influence function of cloudiness obtained from the initial fit is therefore inverted, and the resulting estimate of actual cloudiness replaces the forecast value in the next training round.

In other words, the PV array itself is used as the feedback sensor that corrects the meteorological component of the training sequence.

The k-FC method is a modification of the well-known k-nearest-neighbours rule: in evaluating the proximity between the retrospective records and the data that characterise the moment being forecast; an additional term is included in the Euclidean norm which characterises the quality of the retrospective data themselves. Neighbors are therefore selected not only by their position in the space of exogenous factors but also by how trustworthy they are, by analogy with the advice to choose classmates who are both congenial and successful, from which the name derives.

Although minor in mathematical terms, in systemic terms the modification changes both the forecasting process and its results: the k-FC forecast is blended with the forecast of the cumulative ensemble with a mixing coefficient chosen to minimise the deviation from the metered output on a subset of the training sequence, while transferring the results along a feedback loop from the output of the model back to its input makes the procedure iterative.

Combined with the selection for training of precisely those records that correspond to the most accurate forecasts, this yields generation forecasts that are the least distorted by errors of the meteorological forecast – which is exactly the property that Problem 2 requires of the reference value of production.

This reference-deviation principle is methodologically attractive for three reasons. First, it is purely data-driven and requires no additional diagnostic hardware beyond the monitoring infrastructure already present at most PV plants (irradiance and temperature sensors, inverter production logs), in contrast to the instrumental methods discussed in Section III-A.

Second, because the reference model is built from the plant's own historical operating data, the deviation signal is naturally normalized to the specific site's climate, orientation and shading conditions, which addresses part of the PLR-comparability problem discussed in Section III-C.

Third, the same reference-deviation framework can, in principle, be evaluated at the level of an individual module or string rather than only at the level of the whole plant, which is a prerequisite for the differentiated, module-level maintenance strategy discussed in Section V-D.

The correspondence between the four unresolved problems and the elements of the authors' methodology is shown in Figure 4.

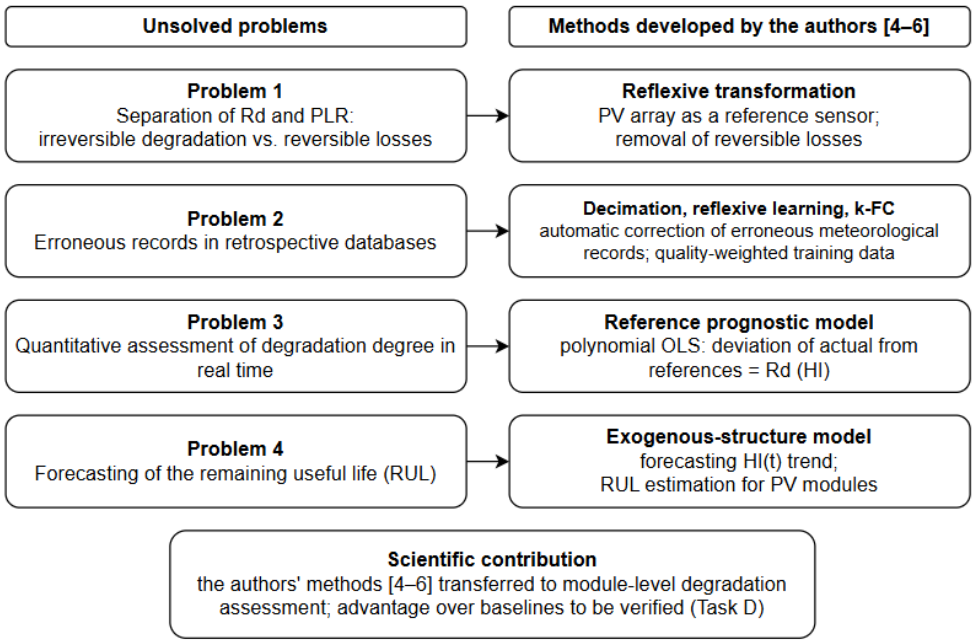


Fig. 4. Correspondence between the unsolved degradation problems and the methods developed earlier by the authors [4–6].

C. Formulation of scientific tasks for further research

Task A – development of a method for determining the degree of PV-panel degradation based on the analysis of the deviation of actual production from the reference value of a hybrid prognostic model (analytical block + polynomial OLS regression), as well as on irreversible changes in the polynomial functions describing the influence of exogenous factors [4, 6]. The deviation forms a module Health Indicator (HI).

Task B – adaptation of the training-sequence decimation, the k-FC method and the reflexive learning approach [5, 6] for the automatic correction of retrospective data used in degradation assessment.

Task C – development of a method for forecasting degradation and estimating RUL by modeling the trend of the HI over time, based on the exogenous structure of the prognostic model [4, 6].

Task D – verification of the developed methods on data from operating PV plants and a comparative analysis against known approaches (RdTools, YoY, LightGBM baseline).

D. Scientific novelty and practical value

The proposed approach differs from existing methods in three key aspects. First, it is entirely data-driven and requires no additional equipment. Second, it addresses the problem of retrospective data quality systemically, through the ensemble of decimation, k-FC and reflexive learning, rather than through ad hoc filtering rules. Third, it provides a quantitative assessment of the degree of degradation, rather than only its rate, which opens the possibility of differentiated maintenance of individual modules within a large PV array – for example, prioritizing cleaning, re-torquing of connections, or replacement for the specific modules whose HI indicates the fastest approach to an unacceptable performance threshold, instead of applying a uniform maintenance schedule to the entire array.

It should be stated explicitly that the reference-deviation idea as such is not new. A gradient-boosting baseline whose growing forecast error signals degradation has already been proposed as a general framework for PLR estimation [23], and a neural-network plant model that takes the time elapsed since commissioning as an input has been used to extract the long-term degradation trend without metadata assumptions [27]. The contribution claimed here lies elsewhere, in three points. First, in those works the reference model is fitted to the same archive whose anomalies it is expected to reveal, so that erroneous retrospective records propagate into the baseline itself; the decimation and k-FC steps address this inside the method rather than as external pre-processing. Second, the exogenous structure of the hybrid model is retained in explicit polynomial form, so that irreversible changes in the polynomial coefficients themselves – and not only the residual of the forecast – can be interpreted as a degradation signature. Third, the unit of evaluation is the individual module or string,

whereas [23] and [27] operate at plant or inverter level. Whether these distinctions translate into a measurable advantage in accuracy is precisely the subject of Task D.

VI. CONCLUSIONS

1. Degradation of PV panels is a multifactorial, nonlinear process accompanied by electrochemical corrosion, PID, delamination and microcracks. For newer cell technologies (HJT, PERC, perovskite tandems), the dominant mechanisms differ from those of conventional Al-BSF modules and remain insufficiently studied [7–10, 12, 13].

2. Existing diagnostic methods fall into two families: instrumental (IRT, EL, I-V, UAV) and data-driven (PLR analysis, YoY, ML). Instrumental methods provide high accuracy but are unsuited to continuous monitoring of large arrays, whereas data-driven methods scale well but remain sensitive to the quality of retrospective data [14–24].

3. Forecasting methods are classified as physical, data-driven and hybrid. Hybrid methods are the most promising. The key unresolved problems are: automatic correction of erroneous data, quantitative assessment of degradation, and RUL forecasting [19, 20, 22, 25–31].

4. It has been established that the hybrid prognostic model, the k-FC method, the reflexive learning approach, and erroneous-data decimation, developed earlier by the authors [4–6], form a scientific foundation for solving the four identified problems.

5. Four tasks for further research (A–D) have been formulated. They define two lines of subsequent work: the quantitative determination of the degree of degradation of an individual module, and the forecasting of degradation together with the estimation of the RUL of PV panels.

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