

Development of Digital Models and Algorithms for Assessing the Technical Condition, Early Fault Detection, And Efficiency Optimization of Photovoltaic Modules

 Maxammadiev Farrukh Mirazimovich

Head of The Laboratory "Electrical Technologies and Operation of Power Equipment" Of the Institute of Energy Problems of The Academy of Sciences of The Republic of Uzbekistan, Senior Researcher, Doctor of Technical Sciences, Uzbekistan

 Baratov Laziz Suyun o'g'li

Independent Researcher at The Institute of Energy Problems of The Academy of Sciences of The Republic of Uzbekistan. Assistant at The Department of Energy and Electrical Engineering of The Jizzakh Polytechnic Institute, Uzbekistan

 Matkarimova Tumaris Bisenbayevna

Electrical Technologies and Use of Energy Equipment, Institute of Energy Problems of The Academy of Sciences of The Republic of Uzbekistan, Technician, Uzbekistan

Received: 23 August 2026; **Accepted:** 19 September 2026; **Published:** 13 October 2026

Abstract: This paper proposes a digital-model-based approach for near-real-time assessment of the technical condition of photovoltaic (PV) modules, considering the influence of external operational and climatic factors and enabling early-stage fault detection. Solar irradiance, module temperature, ambient temperature, relative humidity, and soiling level are considered as input variables, while current, voltage, and power are treated as the key observable electrical outputs. The proposed method estimates the expected current, voltage, and power of a normally operating PV module by means of a physics-based digital model and compares these values with measured data. Normalized residuals are then used to construct an adaptive diagnostic threshold and a composite anomaly score. In addition, an integral Health Index (HI) is introduced for interpretable assessment of module condition. The approach is intended to distinguish natural power fluctuations caused by weather from genuine technical degradation and faults such as soiling, partial shading, hot spots, connection resistance growth, string faults, and long-term degradation. A hybrid architecture combining a physics-based model, digital twin principles, residual analysis, adaptive thresholds, and machine-learning classification is proposed as the basis for predictive maintenance of photovoltaic power plants.

Keywords: Photovoltaic module, solar power plant, digital model, digital twin, degradation, fault diagnosis, solar irradiance, module temperature, soiling, residual analysis, Health Index, machine learning, predictive maintenance.

1. Introduction:

The energy yield of a photovoltaic power plant depends not only on its installed nominal capacity, but also on solar irradiance, ambient and module

temperature, relative humidity, wind conditions, soiling, partial shading, and the actual technical condition of the PV modules and balance-of-system

equipment. Consequently, a reduction in generated power cannot automatically be interpreted as a fault. For example, a decrease in irradiance from 900 W/m² to 500 W/m² naturally reduces the output current and power, while an increase in module temperature mainly decreases the operating voltage.

For this reason, a scientifically justified diagnostic system should first determine how much current, voltage, and power a healthy module is expected to produce under the current environmental conditions. Only after this expected state has been estimated can the measured state be compared with the digital reference. This principle forms the basis of model-based condition monitoring and provides a more reliable foundation for early fault detection than fixed limits applied to raw power alone.

Modern PV monitoring practice requires synchronized measurement of electrical and meteorological variables, while current research trends increasingly combine physics-based models, thermal and visual inspection, artificial intelligence, and digital-twin concepts. The objective of the present work is to integrate these ideas into a compact diagnostic architecture suitable for operational assessment, early detection of abnormalities, and optimization of maintenance resources.

2. Research Objective and Problem Formulation

The main objective of the study is to develop digital

models and algorithms that estimate the normal electrical state of a PV module under varying operational and climatic conditions and detect abnormal deviations before they evolve into severe failures. The functional relation is expressed as:

$$[I, V, P] = f(G, T_m, T_a, RH, S, t)$$

where I is module current (A), V is module voltage (V), P is module power (W), G is plane-of-array solar irradiance (W/m²), T_m is module temperature (°C), T_a is ambient temperature (°C), RH is relative humidity (%), S is a soiling indicator, and t denotes operating time.

3. Digital Model of the Photovoltaic Module

A simplified model of expected PV power may be written as a product of irradiance scaling, temperature correction, and correction factors associated with soiling, humidity, and degradation:

$$\hat{P} = PSTC \cdot (G / GSTC) \cdot [1 + \gamma P(T_m - TSTC)] \cdot K_s \cdot KRH \cdot K_d$$

Here, $PSTC$ is the nominal module power under standard test conditions, $G_{STC} = 1000$ W/m², $T_{STC} = 25$ °C, γP is the power temperature coefficient, K_s is the soiling coefficient, K_{RH} represents the humidity-related correction, and K_d accounts for long-term degradation. The coefficients K_s , K_{RH} , and K_d should not be treated as universal constants; they should be identified or calibrated using data from the specific module technology and operating location.

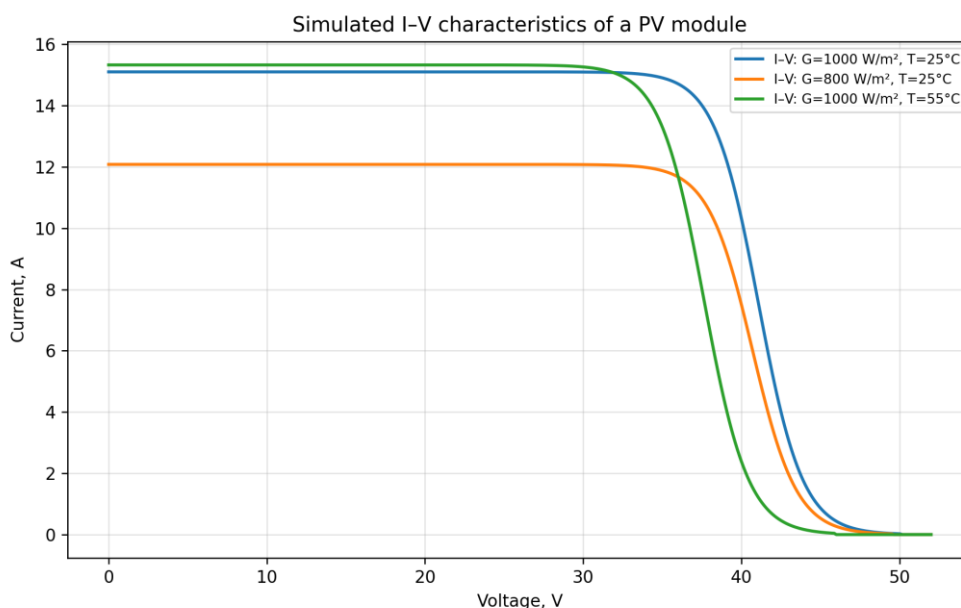


Figure 1. Simulated I–V characteristics under different irradiance and module-temperature conditions.

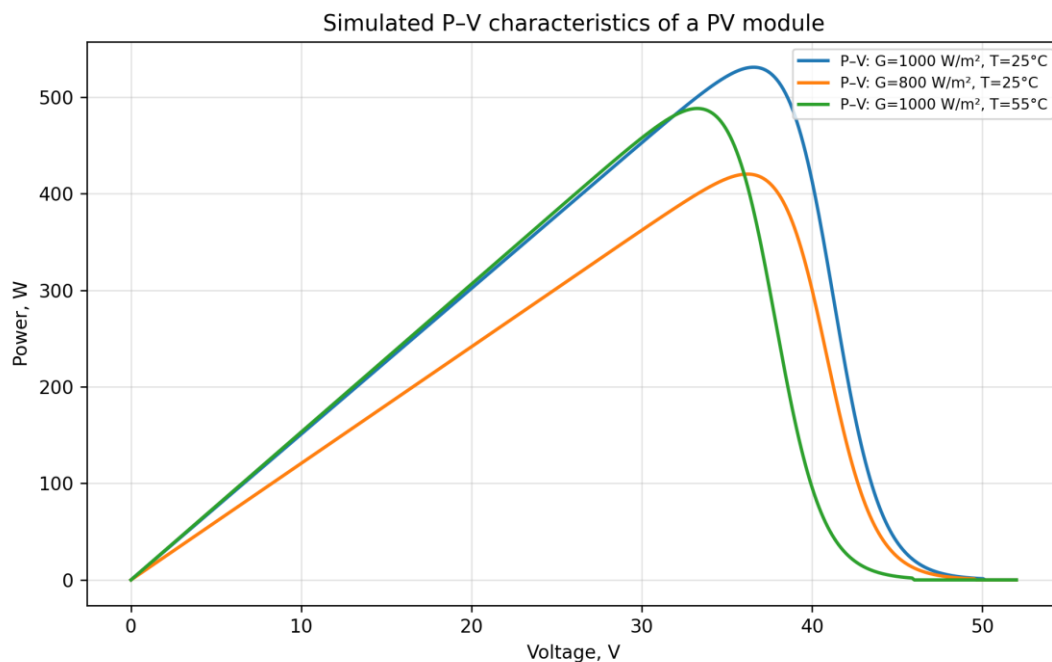


Figure 2. Simulated P–V characteristics under different irradiance and module-temperature conditions.

4. Effect of Irradiance and Module Temperature

For crystalline-silicon PV modules, increasing irradiance primarily increases current, whereas rising cell or module temperature generally decreases open-circuit voltage and maximum power. A first-order approximation of the temperature dependence can be written as:

$$P(T) = P_{25} \cdot [1 + \gamma_P(T_m - 25)]$$

For an illustrative power-temperature coefficient $\gamma_P = -0.0035 / ^\circ\text{C}$, the expected maximum power decreases as module temperature rises above 25°C . If temperature is ignored in the diagnostic model, normal thermal losses may be incorrectly classified as technical faults.

Digital model: irradiance–temperature–power surface

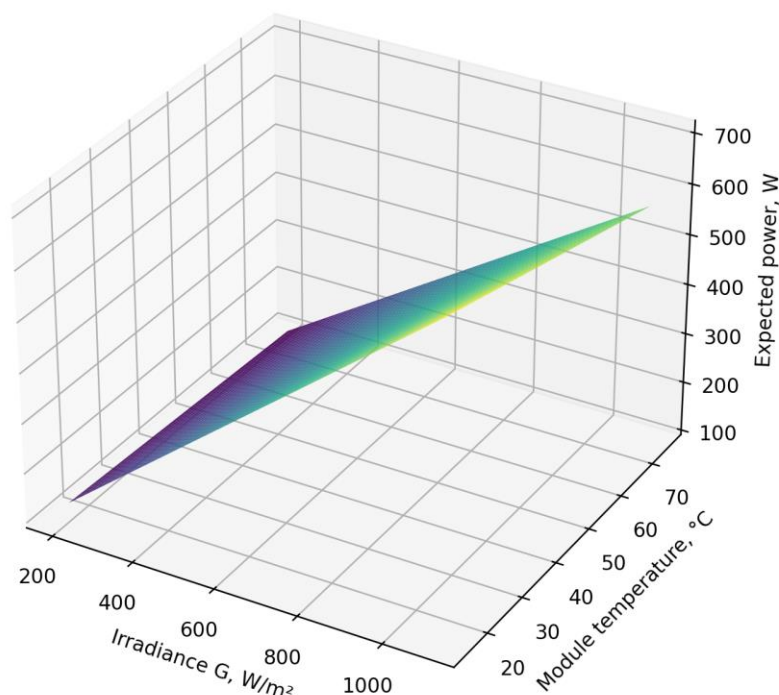


Figure 3. Simulated irradiance–temperature–power surface used as a digital reference model.

5. Modeling the Influence of Soiling

In dry and dusty environments, surface contamination can be one of the major operational causes of PV energy loss. A basic soiling coefficient can be defined as:

$$K_s = P_{soiled} / P_{clean}, \quad 0 < K_s \leq 1$$

In the proposed model, soiling is not represented by a single fixed percentage loss. Instead, its influence

may be expressed as a function of the contamination state, irradiance, humidity, and time elapsed since the previous cleaning event:

$$K_s = f(D, G, RH, \tau)$$

where D is a relative surface-contamination indicator and τ is the time since cleaning. The exact function must be identified experimentally for the local environmental conditions.

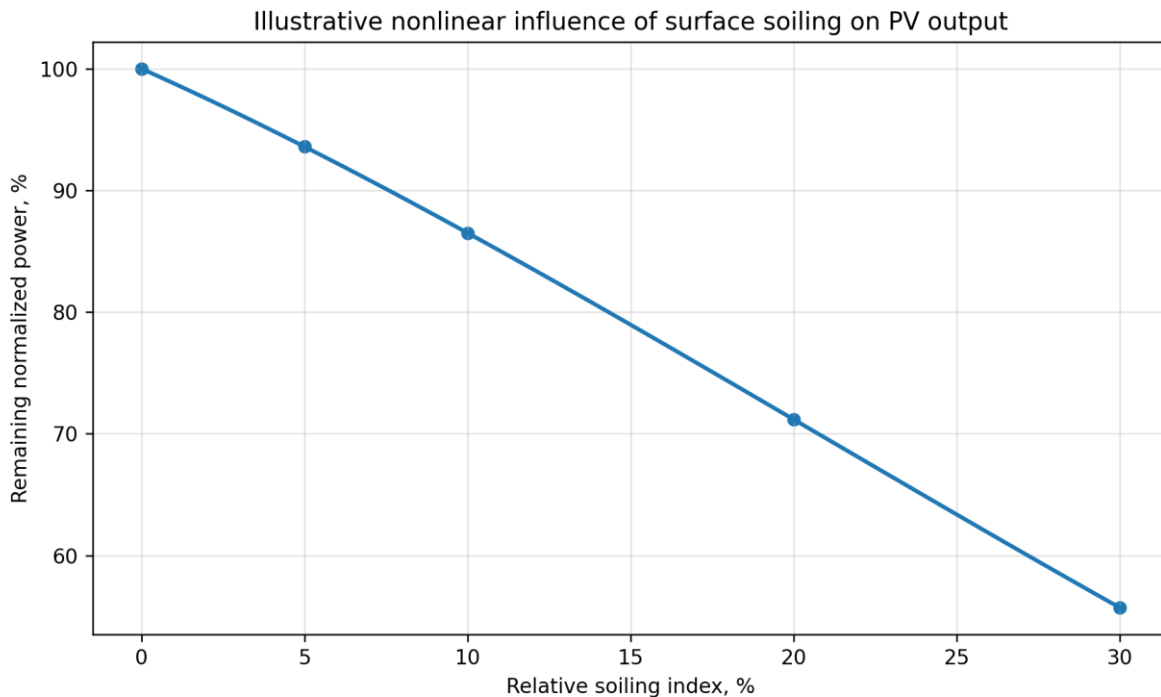


Figure 4. Illustrative nonlinear relation between relative soiling and normalized PV power. The curve is a simulation example and not a field measurement.

6. Proposed Early Fault Detection Method

The central idea of the proposed method is to compare the measured module state with the state predicted by a digital reference model rather than applying fixed alarm limits directly to raw measurements. The expected current, voltage, and power are described as:

$$\hat{I} = f_I(G, T_m, T_a, RH, S)$$

$$\hat{V} = f_V(G, T_m, T_a, RH, S)$$

$$\hat{P} = f_P(G, T_m, T_a, RH, S)$$

Normalized residuals are then calculated as:

$$r_I = (I - \hat{I}) / (\hat{I} + \epsilon)$$

$$r_V = (V - \hat{V}) / (\hat{V} + \epsilon)$$

$$r_P = (P - \hat{P}) / (\hat{P} + \epsilon)$$

The small positive value ϵ prevents division by zero. Residual analysis reduces the direct influence of weather variability and makes persistent deviations

from the expected healthy behavior easier to identify.

7. Composite Anomaly Score and Adaptive Diagnostic Threshold

The electrical and environmental deviations can be integrated into a composite anomaly indicator:

$$A(t) = w_P |r_P| + w_I |r_I| + w_V |r_V| + w_T r_T + w_S r_S$$

$$w_P + w_I + w_V + w_T + w_S = 1$$

Instead of a constant alarm threshold, an adaptive threshold is proposed so that the diagnostic sensitivity changes with the statistical behavior of recent healthy data. A robust implementation can be expressed using the median and median absolute deviation (MAD):

$$\vartheta(t) = \text{Median}[A(t-N:t)] + k \cdot \text{MAD}[A(t-N:t)]$$

An anomaly is registered when $A(t)$ exceeds $\vartheta(t)$ for a predefined persistence interval. Such persistence logic is important because single transient deviations

may be caused by moving clouds, sensor noise, or rapid operating-point changes.

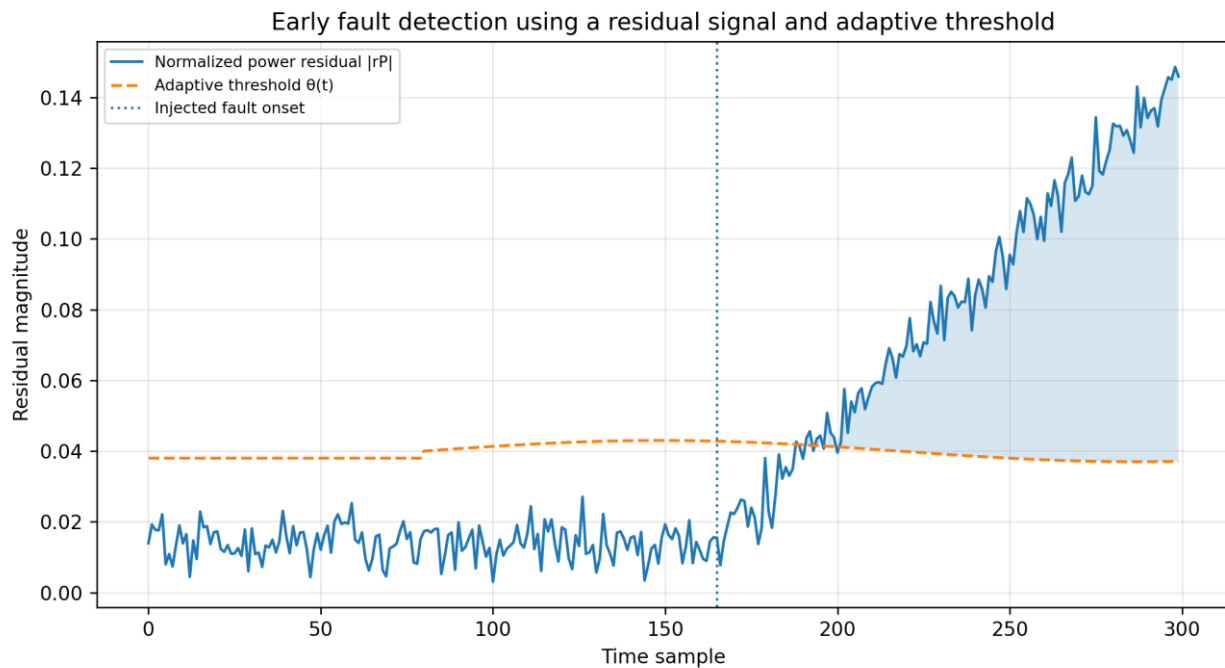


Figure 5. Simulated early-fault detection using a normalized residual and an adaptive threshold.

8. Proposed Health Index

To present the technical state in an interpretable form, a scalar Health Index is proposed. One possible mapping between anomaly score and health condition is:

$$HI = 100 \cdot e^{(-\lambda A)}$$

where λ is a calibration coefficient. The index can be divided into condition bands after validation on field data. For example, values close to 100% indicate normal operation, whereas a persistent decrease suggests that inspection, cleaning, or maintenance should be prioritized.

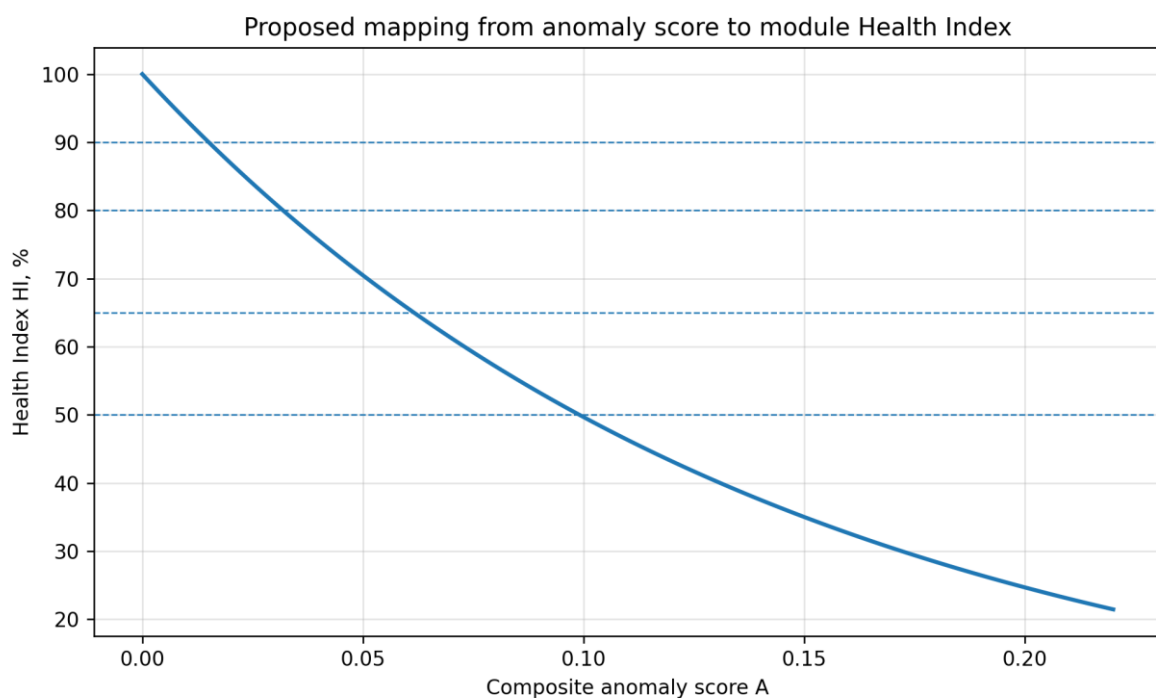


Figure 6. Proposed relationship between anomaly score and PV-module Health Index.

Illustrative HI range	Condition interpretation
90–100%	Good condition
80–90%	Acceptable; continue observation
65–80%	Diagnostic inspection recommended
50–65%	Maintenance or cleaning required
<50%	Critical condition / urgent inspection

9. Digital-Twin Diagnostic Architecture

The proposed digital twin is not merely a static mathematical model. It is a synchronized virtual representation of the operating PV system that continuously receives measurements and updates the expected healthy state. The digital twin may contain the state vector:

$$DT(t) = \{G, T_a, T_m, RH, S, I, V, P, \hat{I}, \hat{V}, \hat{P}, HI\}$$

The deviation between the real and digital states is used as a diagnostic signal. In a plant-scale implementation, the architecture can be connected to the PV array, DC combiner, inverter, AC bus, transformer, grid meter, and environmental sensors.

PV plant monitoring and digital-twin diagnostic architecture

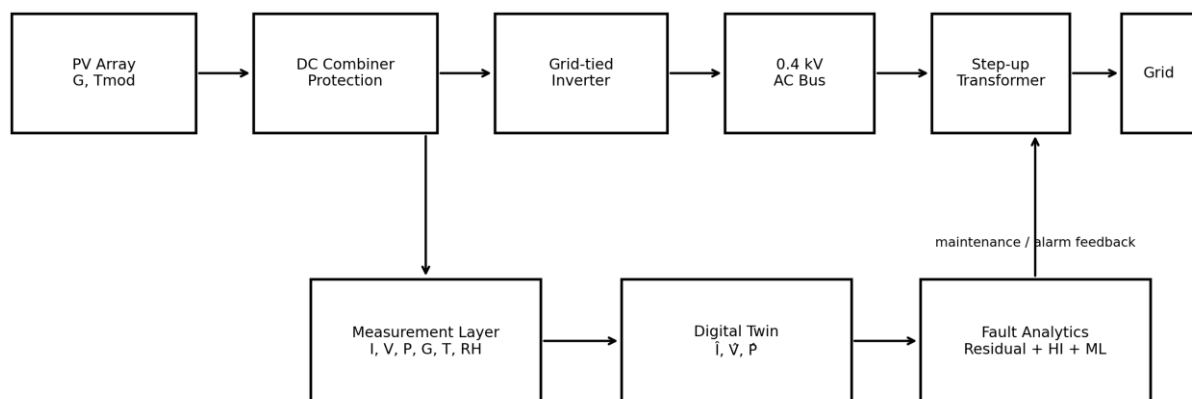


Figure 7. DigSILENT-style conceptual architecture of the PV plant and digital-twin diagnostic layer.

10. Fault Classification Logic

Different faults produce different combinations of electrical and thermal symptoms. Therefore, classification should use several features simultaneously rather than a single power threshold.

10.1 Partial shading

Partial shading typically reduces current and maximum power, while the voltage response depends on the shaded sub-string configuration and bypass-diode activation. A high measured irradiance combined with an unexpectedly low current is therefore a useful residual signature.

10.2 Soiling

Soiling generally develops gradually. A persistent reduction in normalized current and power, comparatively stable voltage behavior, and recovery after cleaning are characteristic indicators.

10.3 Hot spots

Localized heating may indicate cell damage, mismatch, partial shading, or bypass-diode malfunction. A thermal indicator can be expressed as $\Delta T = T_{\text{cell,max}} - T_{\text{module,avg}}$. Thermal imaging is particularly valuable when the residual-based system has already identified a suspicious module or string.

10.4 Connection and cable resistance

Increased contact or cable resistance can produce additional voltage drop, local heating, and power loss. Such faults can be differentiated by combining electrical residuals with thermal measurements and comparison among parallel strings.

10.5 Long-term degradation

Degradation is better detected from long-term trends of weather-normalized power than from raw power. The parameter $P_{norm}(t)$ should therefore be tracked after irradiance and temperature correction before a long-term decline is interpreted as module degradation.

11. Machine-Learning Enhancement

The digital model can be extended by a machine-learning classifier trained on features derived from both measured variables and model residuals:

$$X = [G, T_m, T_a, RH, I, V, P, r_l, r_v, r_P, dP/dt, dT/dt, HI] \\ F(X) \rightarrow C$$

where C may contain the classes Normal, Soiling, Shading, Hotspot, Degradation, and StringFault. Random Forest, gradient boosting, XGBoost, support-vector machines, or neural networks can be used, depending on data volume and deployment constraints. However, the recommended approach is not to rely exclusively on a black-box model. A physics-informed or hybrid system is preferable because the expected electrical behavior is constrained by known PV characteristics.

12. Proposed Scientific Novelty

1. A multi-factor digital model is proposed in which irradiance, module temperature, ambient temperature, humidity, soiling, and long-term degradation are considered jointly when estimating the expected electrical state.
2. Normalized residual variables r_l , r_v , and r_P are used instead of absolute power alone, allowing environmental effects to be separated more effectively from genuine technical deviations.
3. A robust adaptive anomaly threshold based on recent operating statistics is introduced instead of a single constant threshold.
4. An integral Health Index is proposed to convert several diagnostic indicators into a single interpretable technical-condition metric.

5. A hybrid diagnostic concept combines a physics-based model, digital-twin synchronization, residual analysis, adaptive thresholds, and machine-learning fault classification in one workflow.
6. The maintenance decision is linked to condition indicators and expected energy loss, creating a transition from time-based maintenance to condition-based and predictive maintenance.

13. Illustrative Operating Example

Assume that the measured operating conditions are $G = 950 \text{ W/m}^2$ and $T_m = 52^\circ\text{C}$. If the calibrated digital model predicts $\hat{P} = 540 \text{ W}$ while the measured power is $P = 515 \text{ W}$, then:

$$r_P = (515 - 540) / 540 = -0.0463 = -4.63\%$$

A deviation of this magnitude should not automatically generate a fault alarm if it occurs only briefly. If, however, the residual remains below approximately -4% for a sufficiently long persistence interval and is accompanied by a negative current residual, the algorithm can initiate a second-stage diagnostic check for soiling, shading, or degradation. If a significant localized temperature rise is also observed, the probability of a hot-spot-related fault increases.

14. Maintenance and Resource Efficiency Optimization

Fault detection should be connected to maintenance prioritization. For a soiling-related loss, the recoverable energy loss can be estimated from the difference between expected and measured power:

$$E_{loss} \propto P_{expected} - P_{actual}$$

Cleaning is economically justified when the expected monetary value of recovered energy exceeds the cost of cleaning and associated downtime. A generalized maintenance objective may be formulated as:

$$J = C_{loss} + C_{maintenance} + C_{failure} \rightarrow \min$$

This formulation changes maintenance from a fixed-calendar approach to a condition-based decision process. With sufficient historical data, the same framework can be extended toward predictive maintenance by estimating the probability and time-to-failure of critical components.

15. Proposed Operational Algorithm

The complete workflow consists of data acquisition,

validation, digital-state estimation, residual classification, health-index calculation, and calculation, adaptive anomaly detection, fault maintenance prioritization.

Proposed operational condition assessment and early-fault algorithm

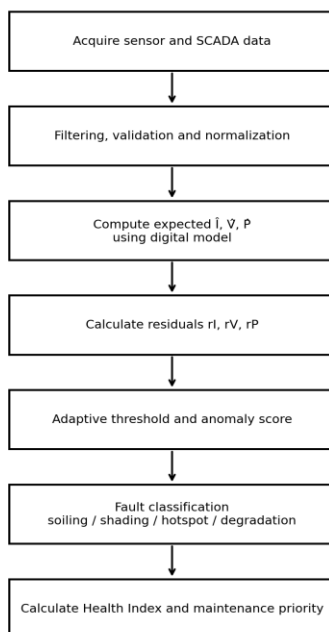


Figure 8. Proposed operational algorithm for PV condition assessment and early fault detection.

16. DISCUSSION

Electrical monitoring, I–V analysis, infrared thermography, electroluminescence imaging, UAV inspection, and data-driven artificial intelligence each provide different diagnostic strengths. Continuous thermography or electroluminescence inspection of every module is not always economically practical for large plants. Therefore, a two-stage diagnostic strategy is recommended. In the first stage, low-cost continuous monitoring and the digital twin identify suspicious strings or modules. In the second stage, targeted thermal, visual, or electroluminescence inspection is applied only where the model indicates abnormal behavior.

The simulation figures presented in this paper are intended to demonstrate the structure and behavior of the proposed algorithm. They are not claimed as field-measured experimental results. For publication as a fully validated experimental study, the model should be calibrated with real SCADA and sensor data and its performance should be reported using quantitative metrics such as MAE, RMSE, R^2 , precision, recall, F1-score, false-alarm rate, and detection delay.

17. CONCLUSION

A digital-model-based methodology for assessment of PV-module technical condition, early fault detection, and efficiency optimization has been developed. The method estimates expected current, voltage, and power from environmental and operating variables and compares these values with measurements through normalized residuals. Adaptive statistical thresholds are proposed to distinguish sustained abnormal behavior from normal variability caused by weather and measurement noise.

The introduced Health Index provides an interpretable summary of module condition, while the hybrid digital-twin and machine-learning architecture supports classification of faults such as soiling, shading, hot spots, connection problems, string faults, and degradation. The approach also creates a basis for condition-based maintenance and optimization of cleaning and inspection resources. The next research stage should include calibration and experimental verification using real PV-plant data in MATLAB/Simulink and/or DigSILENT PowerFactory-oriented simulation workflows.

REFERENCES

1. IEC 61724-1:2021. Photovoltaic system performance – Part 1: Monitoring. International Electrotechnical Commission, Geneva, 2021.
2. IEC 61215-1:2021. Terrestrial photovoltaic (PV) modules – Design qualification and type approval – Part 1: Test requirements. International Electrotechnical Commission, Geneva, 2021.
3. Integration of Renewable Energy Sources and Modeling the Transition to Sustainable Energy Supply in Central Asia T., Zhanbolot, Tursunbaev, B., Laziz, Baratov, M. F., Xomidova, M. F., ... S., Iskandarov, Shahzod, S., Murodjon, Shodiyev
4. Maxamadiyev F., Baratov L. O Analysis of the Status and Installed Capacity of Solar Photovoltaic Power Plants in the Republic of Uzbekistan // ENGINEERING AND ECONOMICS. – 2026. – Vol. 4. – No. 2.
5. Suyarov A. O., Baratov L. S. Simulation-Based Assessment of Power Losses and Stability in Distribution Networks with Highly Integrated Solar Photovoltaic Systems // Oscar Journal of Applied Science and Technology. – 2026. – Vol. 6. – No. 04. – pp. 37-41.
6. Makhamadiyev F. M., Baratov L. S. Study of Methods for Evaluating the Efficiency of Photoelectric Modules and Devices // PROBLEMS OF ENERGY AND SOURCES SAVING. – 2026. – No. 2. – P. 180-186.
7. Baratov L. Current issues of energy // Экономика и социум. – 2024. – No. 2-1 (117). – P. 191-195.
8. Baratov L. S. DISPATCH ENGINEERING SYSTEMS IN THE ENERGY SECTOR // Экономика и социум. – 2025. – No. 4-1 (131). – P. 132-134.
9. Baratov L. S., Tulakov J. T. THE SIGNIFICANCE OF SOLAR PHOTOELECTRIC CONVERTERS // Экономика и социум. – 2025. – No. 1-2 (128). – pp. 82-88.
10. DigSILENT GmbH. PowerFactory Knowledge Base: modelling and simulation of photovoltaic systems (Quasi-Dynamic, RMS and EMT approaches). www.digsilent.de, accessed: 09/23/2026.
11. Friedman D., Hacke P., Al-Jassim M., Ovatt S., Shoemaker S. 2024 Photovoltaic Inverter Reliability Workshop Summary Report & Proceedings. NREL, 2024. DOI: 10.2172/2447815.
12. Baratov L. S. THE SIGNIFICANCE OF SOLAR PHOTOVOLTAIC POWER PLANTS // Экономика и социум. – 2025. – No. 4-1 (131). – pp. 139-141.
13. Baratov L. S. ENERGY BASED ON ALTERNATIVE ENERGY SOURCES // Экономика и социум. – 2025. – No. 4-1 (131). – pp. 142-145.
14. Baratov L. S. ELECTROMAGNETIC PARAMETERS OF ELECTRIC POWER // Economics and Society. – 2024. – No. 5-1 (120). – P. 1123-1127.
15. Baratov L. S., Tulakov J. T. THE SIGNIFICANCE OF SOLAR PHOTOELECTRIC CONVERTERS // Экономика и социум. – 2025. – No. 1-2 (128). – pp. 82-88.
16. Baratov L. S., Tulakov J. T. AUTOMATED ENERGY SYSTEMS // Экономика и социум. – 2025. – No. 1-2 (128). – Pp. 89-91.
17. Baratov L. Current issues of energy // Экономика и социум. – 2024. – No. 2-1 (117). – P. 191-195.
18. Baratov L. S., Tulakov J. T., Otamurodov S. B. ENERGY BASED ON NON-TRADITIONAL RENEWABLE ENERGY SOURCES // Экономика и социум. – 2024. – No. 5-1 (120). – P. 128-131.