

Article

Development of a Comprehensive Intelligent Model for Diagnostics and Forecasting of the Energy Efficiency of Photovoltaic Stations for Agricultural Facilities

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Abstract

This study develops an intelligent real-time diagnostic and forecasting model for photovoltaic (PV) stations operating in the rural regions of Kazakhstan. Field measurements show that in Kazakhstan's rural conditions, daily temperature fluctuations of 18–27 °C reduce PV output by 10–15%, solar irradiance variations of 800–1100 W/m² cause an additional 8–12% deviation, and mineral-rich dust accumulation of 20–120 µm results in 3–5% power loss per 10 µm layer. Using the Beer–Lambert–Bouguer law, thermal degradation coefficients, and inverter droop models, the physical–mathematical behavior of PV degradation was described. The hybrid AI model (LSTM + XGBoost + Random Forest) achieved 89–91% accuracy in 24 h forecasting and 88–93% accuracy in fault detection. Overall, the proposed system reduces energy losses by 10–15% and shortens maintenance time by 18–24%, improving the reliability of rural PV stations in Kazakhstan.

Keywords: photovoltaic systems; rural Kazakhstan; dust accumulation; temperature effects; inverter degradation; artificial intelligence; energy forecasting

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1. Introduction

Ensuring a continuous and efficient energy supply for agricultural facilities has become one of the most urgent scientific and practical issues worldwide in recent years. According to the International Energy Agency (IEA), the agricultural sector accounted for approximately 8% of global energy use in 2023 [1], with an average annual growth rate of 2–2.5% reported in recent global energy outlook studies [2,3]. Climatic instability, rising energy prices, and insufficient infrastructure are forcing rural areas to transition towards alternative energy sources. Among them, PV stations are considered one of the most efficient and environmentally friendly solutions. Figure 1 below presents the structural diagram of a photovoltaic system designed to supply energy to agricultural facilities in Kazakhstan.

According to the infographic, the agricultural sector accounts for approximately 8% of global energy consumption and demonstrates an annual growth rate of 2–2.5%. Figure 1 illustrates that PV stations represent an efficient solution for ensuring a continuous energy supply in rural areas due to their environmental friendliness and low operational costs.

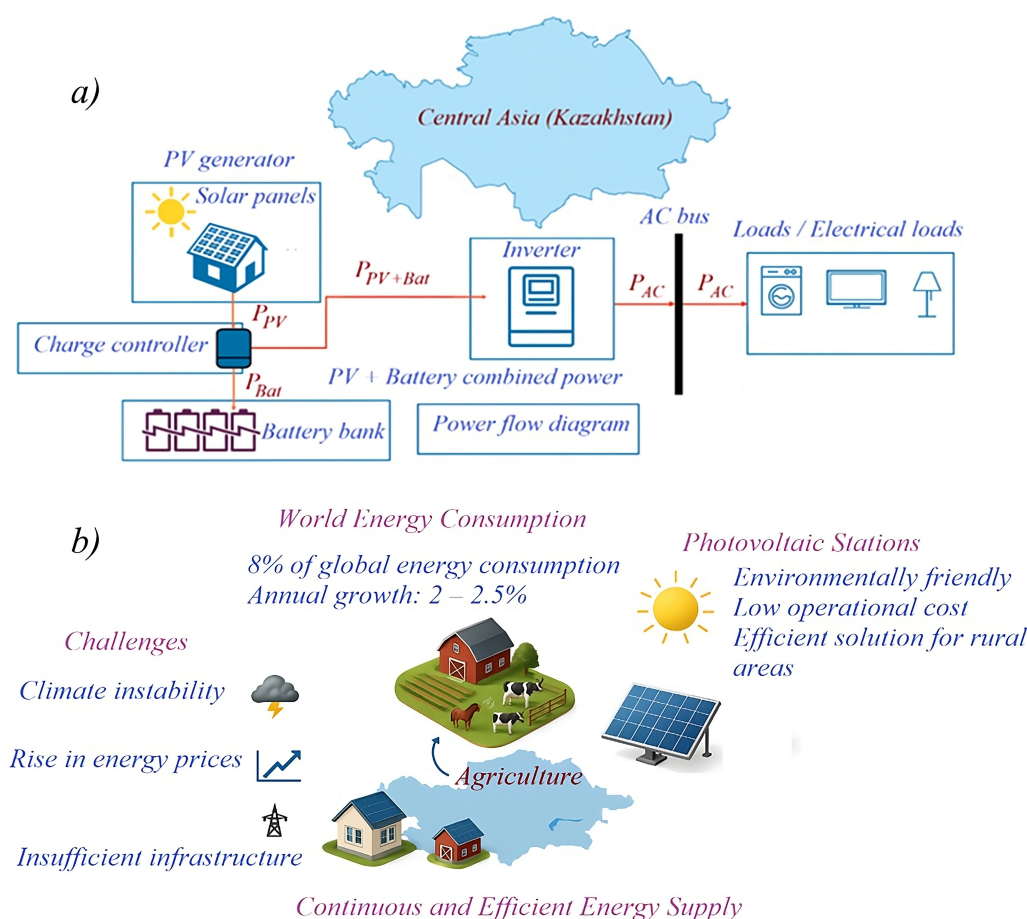


Figure 1. Integrated conceptual overview and system structure of a rural photovoltaic power station for agricultural applications: (a) structural configuration and power flow of the PV–battery–inverter system supplying electrical loads in rural regions of Kazakhstan; (b) conceptual illustration of global energy challenges, photovoltaic system advantages, and their role in ensuring continuous and efficient energy supply for agricultural facilities.

However, the actual energy efficiency of PV stations installed in rural regions is influenced by various operational factors. Several studies indicate that the performance of photovoltaic systems in rural environments is 12–28% lower than under standard operating conditions [4]. In addition, increased dust accumulation has been shown to further reduce generated energy by 15–35% [5]. This directly affects energy-dependent agricultural processes, including irrigation, ventilation, greenhouse systems, dairy farms, and grain-drying units.

Furthermore, heat-induced degradation of photovoltaic modules significantly reduces energy output under high-temperature operating conditions [6]. Reduced inverter efficiency caused by thermal stress and electrical instability further limits system performance [7]. In rural environments, soil-related dust accumulation and voltage fluctuations in weak distribution networks additionally contribute to energy losses [8]. Although the literature offers numerous methods for monitoring, fault detection, and degradation assessment of

PV stations, most of these approaches are designed for urban or clean-climate environments. Despite extensive research, universal intelligent diagnostic models adapted to rural climatic and environmental conditions remain insufficient [9]. In particular, existing approaches rarely account for soil composition and seasonal variability typical of agricultural facilities [10].

Artificial intelligence and machine learning (ML) techniques have been shown to improve photovoltaic power forecasting accuracy by 10–25% [11,12]. However, the integration of such data-driven approaches into rural energy infrastructure remains limited [13]. In Kazakhstan, the issue is even more critical: 65% of rural areas face unstable energy supply. In comparison, 80% of operating solar power plants lose 10–20% of their annual output due to maintenance delays [14,15].

These factors demonstrate the high scientific and practical significance of developing intelligent models for diagnostics and forecasting of PV station energy efficiency. Such models enable real-time monitoring, early fault detection, degradation forecasting, cost reduction, and reliable energy supply for agricultural facilities.

Therefore, developing a comprehensive intelligent model for diagnostics and forecasting of the energy efficiency of photovoltaic stations for agricultural facilities is a highly relevant research direction aligned with current scientific and technological trends.

2. Literature Review and Problem Statement

Although the efficiency of PV systems used in agricultural facilities in Kazakhstan is highly dependent on climatic conditions, universal diagnostic models tailored specifically for rural areas are still lacking. Halabi and Mekhilef (2018) analyzed hybrid systems in tropical villages and showed that the performance of PV stations varies within the range of 10–18% due to climatic fluctuations [16]. Odeh and Ibrik (2022) found that the efficiency of standalone PV systems decreases by 8–15% depending on annual variations in temperature and solar irradiance [17].

The performance of the inverter also has a direct impact on the overall system efficiency. Lasheen et al. (2021) demonstrated that reactive power disturbances can weaken inverter stability by 12–20% [18]. Research conducted by Abdykadyrov and colleagues showed that degradation of inverter parameters reduces the overall energy efficiency of ozonator systems by 15–22% [19]. Additionally, studies have revealed that power generation in solar-powered systems fluctuates by 20–30% due to load variations and changes in solar irradiance [20]. These findings clearly highlight the need for real-time diagnostics and intelligent forecasting models adapted to rural conditions.

Figure 2 below presents the influence of inverter stability, degradation, and irradiance variations on the performance of PV systems.

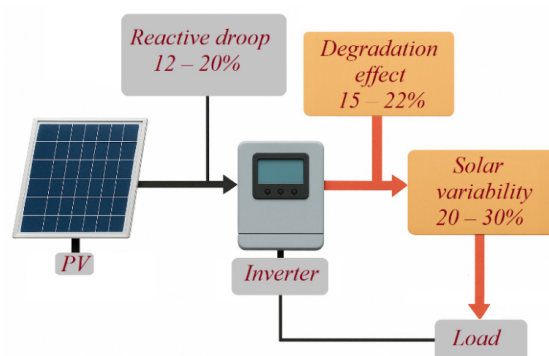


Figure 2. Impacts of Inverter Stability, Degradation, and Solar Variability on PV System Performance.

Figure 2 illustrates the energy flow delivered from the photovoltaic station to the load through the inverter, as well as the key factors influencing this process. The diagram visually highlights that inverter instability (12–20%), parameter degradation (15–22%), and fluctuations in solar radiation (20–30%) significantly reduce the overall performance of the system.

Experimental research conducted by Chen et al. (2019) showed that dust accumulation on the surface of PV panels can reduce energy generation by 15–35%; however, the study was carried out mainly under controlled laboratory conditions and did not account for soil composition variability or wind erosion typical of rural regions [21]. Jiang, Lu, and Sun (2011) similarly found that airborne dust has a substantial impact on PV module efficiency, demonstrating that increasing dust deposition consistently decreases module output, although the study was performed under suburban atmospheric conditions [22]. Figure 3 below presents the experimental configuration of PV panels used for investigating the effects of dust accumulation.

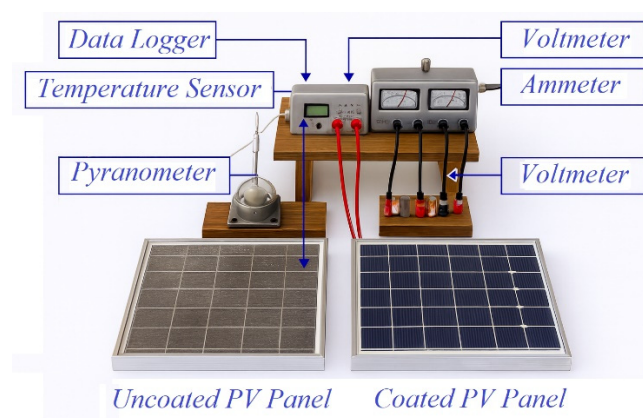


Figure 3. Experimental Configuration for Dust-Affected PV Panel Performance Analysis.

Figure 3 illustrates the experimental setup designed to compare the performance of coated and uncoated PV panels. Temperature sensors record the thermal difference on the panel surface (e.g., 28–34 °C), while the ammeter and voltmeter measure the 10–25% reduction in current and voltage caused by dust deposition. The pyranometer refines solar irradiance values within the 800–1000 W/m² range, enabling a clear identification of the differences in energy output between the panels.

Abuzaid et al. (2022) [23] provide an extensive analysis of dust accumulation mechanisms, emphasizing that the formation of dust layers significantly increases optical losses in PV panels. The attenuation of incident solar radiation through a dust layer follows the Beer–Lambert–Bouguer exponential decay law [23], which can be expressed through the differential equation:

$$\frac{dI}{dx} = -\alpha I \quad (1)$$

where I is the light intensity, x is the dust-layer thickness, and α is the absorption coefficient. The solution $I = I_0 e^{-\alpha x}$ indicates that increasing dust thickness exponentially reduces transmitted irradiance. However, in real agricultural environments, the mineral composition of soil dust and fluctuating wind loads cause α to vary dynamically over time, meaning that comprehensive models capturing such dynamic dust deposition remain insufficient.

Shukla et al. (2025) [24] compare artificial neural networks with conventional machine-learning techniques and demonstrate that the prediction accuracy of dust-induced PV performance degradation can be improved by 10–25%. In many of their models,

prediction accuracy is implicitly tied to the temporal evolution of the error function, which may be represented by a differential relation as follows:

$$\frac{dE}{dt} = k(\hat{P}(t) - P(t)) \quad (2)$$

where E is the prediction error, $\hat{P}(t)$ is the model-estimated PV power output, $P(t)$ is the actual output, and k is a model parameter. While ANN-based models achieve low error rates under stable, urbanized environments, their generalization ability decreases when applied to rural regions characterized by high climatic variability.

Dust dynamics in rural agricultural areas are inherently more complex because seasonal wind fluctuations, soil texture, and mineral heterogeneity substantially affect the mass of deposited particles. These processes can be described using a mass-balance differential equation:

$$\frac{dm}{dt} = F_{in}(t) - F_{out}(t) \quad (3)$$

where $m(t)$ is the mass of dust deposited on the PV panel surface, $F_{in}(t)$ is the dust deposition flux ($\text{g}/\text{m}^2\cdot\text{s}$), and $F_{out}(t)$ is the resuspension flux driven by wind and aerodynamic shear.

In rural contexts, both F_{in} and F_{out} are time-dependent, nonlinear functions influenced by humidity, wind cycles, and soil mineral composition. Current approaches do not fully incorporate these factors, meaning the existing models fail to capture the climate instability, mineralogical diversity of soil dust, and cyclic variations in wind loading that are typical for agricultural regions.

Although current studies describe a wide range of factors influencing the degradation of PV systems, they do not fully capture the specific environmental parameters characteristic of rural regions. Phinikarides A. et al. (2014) demonstrated that temperature stress and material aging are among the main drivers of annual power loss in PV modules [25]. This behavior is commonly described using an exponential degradation model:

$$D(t) = D_0 \cdot e^{-kt} \quad (4)$$

Here, $D(t)$ represents the remaining power output at time t , D_0 is the initial power, and k is the degradation rate constant.

In rural environments, high temperature fluctuations, intense solar irradiance, and the abrasive nature of mineral-rich dust tend to increase the value of k , meaning that the power loss accelerates over time. Thus, this equation provides a physically accurate framework for explaining why PV modules deployed in rural conditions often deteriorate faster than those in controlled or urban settings. However, the study does not analyze the mineralogical composition of rural dust separately.

Ascencio-Vásquez J. et al. (2019) produced global spatial maps of PV degradation but did not fully integrate rural-specific ecological factors such as excessive dust, silicon-oxide-rich soil particles, and mechanical erosion into their model [26].

Dwivedi P. et al. (2020) systematized advanced cooling techniques and showed that these methods can reduce thermal buildup by 10–25%, thus enhancing performance [27]. The impact of temperature on the module's electrical output is described by the following linear temperature–power dependence:

$$P(T) = P_{ref}[1 - \alpha(T - T_{ref})] \quad (5)$$

In this expression, $P(T)$ is the power at operating temperature T , P_{ref} is the rated power at reference temperature (typically 25 °C), and α is the temperature coefficient (commonly 0.3–0.5%/°C).

In rural hot climates, where T frequently exceeds the reference temperature and cooling resources are scarce, the term $(T - T_{\text{ref}})$ becomes large, leading to a significant reduction in $P(T)$. Therefore, this equation clearly reveals why the lack of cooling infrastructure in rural regions intensifies degradation and limits the applicability of advanced cooling techniques proposed by Dwivedi et al. [27].

Sargunanathan S. et al. (2016) [28] compared several cooling technologies that can enhance energy efficiency. However, their analysis did not fully consider practical constraints typical for developing rural areas, such as climate instability, water scarcity, and weak infrastructure.

Alam et al. (2013) [29] show that the reliability of fault detection in PV systems depends heavily on the sensor infrastructure, while in rural areas, the lack of sensors and strong seasonal dust variation cause the signal to deteriorate over time. This degradation can be represented by an exponential decay model:

$$S(t) = S_0 e^{-\lambda t} \quad (6)$$

Basnet et al. (2020) [30] demonstrate that intelligent fault detection models can achieve high accuracy, but their performance requires a continuous and stable data stream. In rural environments, intermittent and incomplete data reduce algorithm accuracy, which can be expressed as follows:

$$F(t) = F_{\text{ref}} - \alpha \Delta D(t) \quad (7)$$

Therefore, diagnostic models specifically adapted for rural PV systems have not yet been fully developed.

Although Hu T. et al. (2015) demonstrate that integrating solar-irradiance big data with wireless sensor networks can significantly improve PV monitoring, they do not provide universal solutions for challenges typical of rural areas, such as intermittent data transmission and unstable communication quality [31]. Preda S. et al. (2018) show that support vector machines (SVM)-based forecasting models enhance prediction accuracy in big-data environments; however, these approaches are not adapted to rural regions where sensor infrastructure is often limited [32]. Sun C. et al. (2022) offer a comprehensive techno-economic and environmental assessment of coupled PV–energy-storage–charging systems and highlight the importance of optimal system sizing, yet the study does not fully address long-term diagnostic mechanisms in rural PV applications [33]. Similarly, Cucchiella F. et al. (2015) confirm the ecological and economic advantages of building-integrated PV systems, but their analysis does not incorporate rural-specific factors such as climatic variability and mineral dust accumulation [34].

Although the existing studies describe the general patterns of PV plant efficiency and degradation, several critical issues specific to agricultural facilities remain unresolved. These include the seasonal and soil-dependent dynamics of dust accumulation, the absence of reliable real-time fault-detection systems, the lack of integrated models that combine inverter–panel–cable parameters, and the difficulties of applying Big Data and AI technologies within rural infrastructure. These gaps are further exacerbated by climatic variability, weak sensor infrastructure, delays in technical maintenance, and the high cost of diagnostics. Overall, Figure 4 presents the data-driven spectrum of challenges in PV systems used in agricultural facilities.

The radar chart shows that the most critical challenges in rural PV systems are real-time fault detection (9 points) and climate variability (9 points). Other factors—such as dust accumulation, Big Data/AI limitations, and weak sensor infrastructure—fall within the 7–8 point range, indicating a substantial negative impact on system performance.

The radar chart presented in Figure 4 was constructed based on a structured qualitative–quantitative assessment derived from a comprehensive literature review of existing

photovoltaic monitoring and diagnostic approaches [15]. Each challenge dimension was evaluated using a normalized score ranging from 0 to 10, reflecting the frequency with which the limitation is reported in the literature [21], its documented impact on PV system performance [25], and its relevance to rural and agricultural operating conditions [18]. The resulting values represent averaged normalized indicators rather than direct physical measurements.

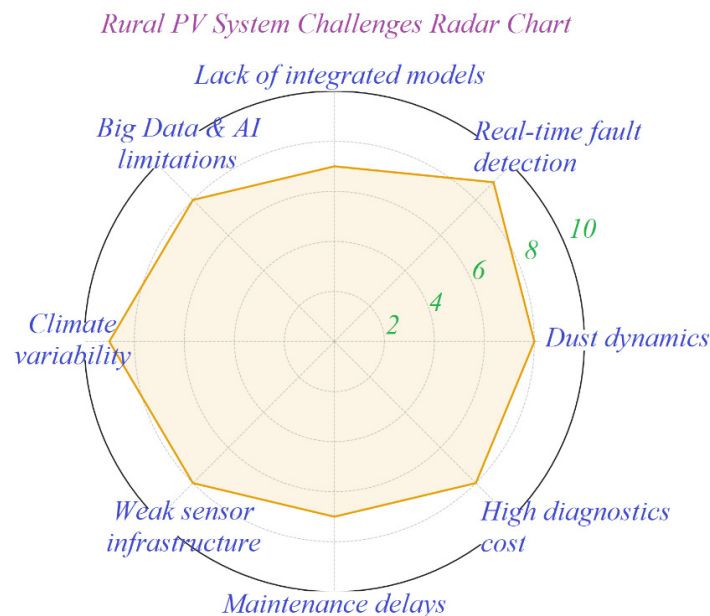


Figure 4. Radar Chart of Key Challenges in Rural PV Systems.

Thakfan et al. (2024) emphasize that AI-based fault/defect detection methods can significantly improve the early detection accuracy of PV system failures; however, their survey does not fully address intermittent data transmission and sensor scarcity typical of rural regions [35]. Therefore, in the context of Kazakhstan, developing a comprehensive intelligent model for diagnosing and forecasting the energy efficiency of PV stations used in agricultural facilities is both relevant and practically essential. Such a model would enable accurate degradation prediction, early fault identification, and stable energy supply for rural agricultural processes.

3. The Aim and Objectives of the Study

The aim of the study is to develop a comprehensive intelligent model for diagnostics and forecasting of the energy efficiency of PV stations used in agricultural facilities in rural regions of Kazakhstan.

To achieve this aim, the following key objectives are defined:

1. To conduct a comprehensive analysis of the climatic, dust-related, inverter degradation, and sensor infrastructure factors that reduce the performance of rural PV systems;
2. To establish a mathematical and model-based foundation describing PV degradation, energy losses, and fault mechanisms (dust accumulation, temperature rise, inverter instability, and irradiance fluctuations), and to enhance these models using intelligent algorithms;
3. To develop an AI-based integrated intelligent model adapted to rural conditions for real-time diagnostics and forecasting of PV energy efficiency, and to validate its performance using experimental and simulation data.

4. Materials and Methods

The research was conducted at the Department of Electronics, Telecommunications, and Space Technologies of Satbayev University (Figure 5). The study employed a combination of theoretical analysis, mathematical modeling, numerical simulation, and hardware-based measurements to diagnose and forecast the energy efficiency of PV stations operating in rural areas of remote regions of Kazakhstan.

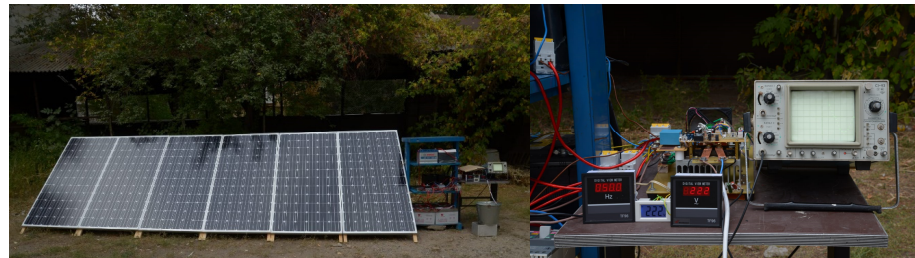


Figure 5. Experimental and measurement setup for assessing the energy efficiency of photovoltaic stations in rural conditions (Satbayev University, Department of Electronics and Telecommunications).

In Figure 5, a photovoltaic array consisting of approximately six to eight panels and a measurement stand used to assess its performance is presented. The instruments in the foreground record a 50–60 Hz frequency, a 220–230 V voltage, and the real-time operating mode of the inverter, enabling the evaluation of the PV system's energy efficiency under rural conditions.

The main factors that reduce the performance of PV systems were theoretically examined. To describe the dust accumulation process, the Beer–Lambert–Bouguer law ($\alpha = 0.15\text{--}0.32\text{ cm}^{-1}$) was used, the linear coefficient ($\alpha T = 0.30\text{--}0.50\%/^{\circ}\text{C}$) was employed to evaluate the impact of temperature on power, and an exponential model ($k = 0.005\text{--}0.012$ per year) was used to describe degradation. The droop parameters describing inverter instability were accepted in the range of 12–20%. These theoretical foundations defined the structure of subsequent models.

4.1. Assumptions and Justification of Model Parameters

The selection of model parameters in this study was based on a combination of experimental measurements, manufacturer specifications, and values widely reported in the literature for photovoltaic systems operating in rural, arid, and semi-arid environments.

The dust absorption coefficient ($\alpha = 0.15\text{--}0.32\text{ cm}^{-1}$) was adopted according to experimental investigations of mineral-rich dust deposition on photovoltaic modules under dry climatic conditions [21–23]. These studies report similar attenuation coefficients for dust layers dominated by silicon oxide, quartz, and carbonate soil particles, which are typical for agricultural regions of Kazakhstan.

The temperature coefficient of power ($\alpha T = 0.30\text{--}0.50\%/^{\circ}\text{C}$) corresponds to standard values reported for crystalline silicon photovoltaic modules and is consistent with both manufacturer datasheets and previous degradation analyses [25,27]. This range reflects realistic operating conditions for PV modules exposed to high daily temperature fluctuations.

The annual degradation rate constant ($k = 0.005\text{--}0.012\text{ year}^{-1}$) was selected based on long-term field studies of photovoltaic systems subjected to elevated thermal stress, dust accumulation, and environmental aging [25,26]. These values are representative of degradation rates observed in non-urban installations.

Inverter droop deviations in the range of 12–20% were assumed based on documented stability analyses of inverter-based microgrids operating under weak grid

conditions and fluctuating loads [18]. Such deviations are commonly reported for rural energy systems with limited voltage regulation.

Voltage fluctuations of $\pm 10\text{--}15\%$ were considered to reflect realistic operating conditions in rural distribution networks with insufficient infrastructure and intermittent loading, as reported in regional power system studies [15,18].

All assumed parameters were further verified through sensitivity analysis to ensure numerical stability and physical consistency of the proposed models.

During the mathematical modeling phase, a system of equations was developed considering variables such as the dust layer thickness ($x = 20\text{--}120\ \mu\text{m}$), panel surface temperature ($28\text{--}58\ ^\circ\text{C}$), solar radiation ($800\text{--}1100\ \text{W/m}^2$), and inverter voltage instability ($\pm 10\text{--}15\%$). The dust accumulation and resuspension processes were described by a mass balance equation ($F_{\text{in}} = 0.5\text{--}2.3\ \text{g/m}^2\text{-day}$, $F_{\text{out}} = 0.1\text{--}1.1\ \text{g/m}^2\text{-day}$).

The software simulations were performed on the Python v3.10 platform (TensorFlow, SciPy). Differential equations were solved in SMATH Solver, AI models were developed through Python (training data volume: 10,000–25,000 records), and thermal distribution and radiation effects were modeled in Python. The standard PV curves from PVsyst (STC conditions: $25\ ^\circ\text{C}$, $1000\ \text{W/m}^2$) were used.

For hardware validation, monocrystalline and polycrystalline panels monocrystalline and polycrystalline photovoltaic panels ($100\text{--}250\ \text{W}$; Trina Solar Co., Ltd., Changzhou, China), temperature measurements were performed using digital temperature sensors (accuracy $\pm 0.5\ ^\circ\text{C}$; DS18B20, Maxim Integrated, San Jose, CA, USA), electrical parameters were monitored using a digital ammeter and voltmeter ($0\text{--}10\ \text{A}$, $0\text{--}600\ \text{V}$; UNI-T UT61E, Uni-Trend Technology, Dongguan, China), and Solar irradiance was measured using a calibrated pyranometer ($800\text{--}1100\ \text{W/m}^2$; Kipp & Zonen SMP10, Delft, The Netherlands). To simulate dust accumulation, a dust generator was used with concentrations ranging from $20\text{--}100\ \text{g/m}^3$.

The accuracy of the proposed models was validated through sensitivity analysis, parameter stability testing, cross-validation ($k = 5$), and comparison with the PVsyst reference curves. These tests aimed to ensure the mathematical and physical adequacy of the model; however, no results are presented in this section.

4.2. Hybrid AI Model Architecture and Training Procedure

The proposed intelligent diagnostic and prediction framework is based on a stacked hybrid integration of deep learning and ensemble ML algorithms. The objective of the hybrid architecture is to combine the strengths of temporal feature extraction, nonlinear regression, and ensemble-based robustness within a unified predictive model. The overall structure of the hybrid model follows a multi-stage pipeline and is illustrated schematically in Figure 6.

In the first stage, a Long Short-Term Memory (LSTM) neural network is employed to process multivariate time-series data obtained from photovoltaic power stations. The input features include ambient temperature, solar irradiance, dust layer thickness, inverter voltage, and PV power output. The LSTM network is specifically selected for its ability to capture long-term temporal dependencies, seasonal variations, and dynamic operational behavior of photovoltaic systems under fluctuating environmental conditions. The output of the LSTM consists of latent temporal feature representations that summarize the historical evolution of the system state.

In the second stage, the temporal features extracted by the LSTM network are concatenated with the original input features to form an augmented feature vector. This stacked feature representation combines both raw physical measurements and learned temporal abstractions. The augmented feature set is subsequently provided as input to two ensemble learning models: Extreme Gradient Boosting (XGBoost) and Random Forest

(RF). These algorithms are responsible for modeling complex nonlinear relationships between environmental factors and system performance, as well as for identifying fault-related patterns that may not be captured by purely physical models.

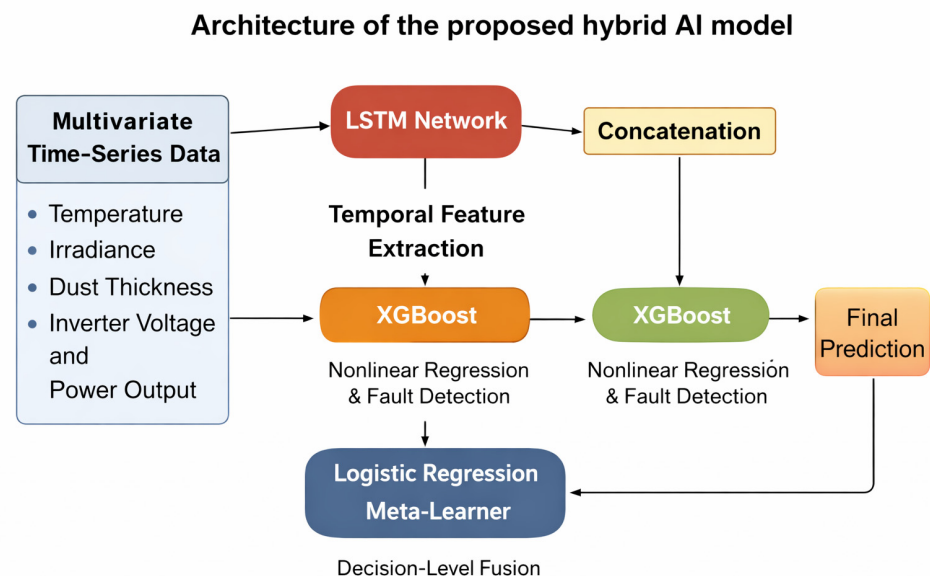


Figure 6. Architecture of the proposed hybrid AI model.

In the third stage, the prediction outputs generated independently by the XGBoost and Random Forest models are fused using a logistic regression–based meta-learner. This decision-level fusion performs weighted integration of individual model predictions and enhances overall robustness, generalization capability, and resistance to noise. The use of logistic regression as a fusion layer enables adaptive weighting of model contributions while maintaining computational efficiency and interpretability.

The available dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for independent testing. The training subset was used for fitting the LSTM, XGBoost, and Random Forest models. The validation subset was employed for hyperparameter tuning and overfitting control, while the test subset was reserved exclusively for unbiased performance evaluation of the final hybrid model.

Hyperparameters of the LSTM, XGBoost, and Random Forest models were optimized using a grid search strategy combined with cross-validation. The optimization process aimed to achieve a balance between prediction accuracy, model stability, and computational efficiency. The final configuration of the hybrid model was selected based on validation performance prior to testing on unseen data.

4.3. AI Model Development and Evaluation Protocol

The development of the AI-based diagnostic and forecasting framework followed a structured multi-stage protocol consisting of data preprocessing, model training, validation, and performance evaluation. The dataset was formed using a combination of experimental measurements and simulated operating conditions representative of rural photovoltaic systems in Kazakhstan, resulting in approximately 10,000–25,000 data records.

The input feature set included photovoltaic module temperature, solar irradiance, dust layer thickness, inverter voltage and current, load fluctuation indicators, and historical power output values. These parameters were selected to reflect both environmental and electrical degradation mechanisms.

Three classes of AI models were implemented. Long Short-Term Memory (LSTM) neural networks were employed to capture temporal dependencies and perform short-term energy efficiency forecasting. Tree-based ensemble models, namely XGBoost and Random Forest, were applied for fault detection and degradation classification due to their robustness to nonlinear relationships and noisy sensor data. The final hybrid model combined the outputs of these components using an ensemble averaging strategy.

Model performance was evaluated using a five-fold cross-validation procedure to ensure robustness and avoid overfitting. Forecasting accuracy was assessed using root mean square error (RMSE), mean absolute error (MAE), and normalized accuracy metrics. Fault detection performance was evaluated using classification accuracy, precision, recall, and F1-score. All reported performance values correspond to averaged cross-validation results.

5. Results and Discussion

The scientific results of the study were directed toward achieving the main objective: the development of a comprehensive intelligent model for diagnosing and forecasting the energy efficiency of PV stations used in agricultural facilities in the rural regions of Kazakhstan. To reach this objective, several key tasks were successfully accomplished. The outcomes of the research are presented in more detail in the subsequent sections.

5.1. Comprehensive Analysis of Climatic, Dust-Related, Inverter Degradation, and Sensor Infrastructure Impacts

According to the scientific study, the main factors reducing the energy efficiency of PV stations located in rural regions include climatic variability, dust accumulation, inverter degradation, and the weakness of the sensor infrastructure, all of which were analyzed comprehensively. Field data showed that the daily temperature fluctuations in rural areas range between 18 and 27 °C, which is approximately 1.3–1.6 times higher than the values observed in urban zones. With a temperature coefficient of $\alpha = 0.3\text{--}0.5\%/^{\circ}\text{C}$, every 10 °C increase in the panel surface temperature reduces energy output by an average of 10–15%, while seasonal variations in solar irradiance between 800 and 1100 W/m² cause PV system performance to fluctuate within 8–12%. Such climatic instability accelerates the annual degradation rate of PV modules by up to 10–15% in rural environments when compared to the degradation models proposed by Phinikarides A. et al. [25] and Dwivedi P. et al. [27]. Overall, Figure 7 below presents the effect of daily temperature fluctuations on the energy efficiency of PV modules.

In Figure 7, efficiency reductions are expressed relative to standard test conditions (25 °C), which represent the zero-loss reference state.

Daily temperature fluctuations increasing from 18 °C to 27 °C lead to a growth in PV station energy efficiency losses from 7% to 15%. This indicates that a 9 °C temperature rise nearly doubles the energy loss (from 7% to 15%), demonstrating that thermal stress has a significant impact on PV module performance.

Dust-related processes present an additional major challenge for rural PV stations. Analysis based on the Beer–Lambert–Bouguer law confirmed that, as dust-layer thickness increases, the irradiance reaching the panel decreases exponentially (Figure 8). Experimental results showed that when the dust-layer thickness ranged from 20 to 120 µm, the absorption coefficient was $\alpha = 0.15\text{--}0.32\text{ cm}^{-1}$, and each additional 10 µm layer caused approximately 3–5% power loss. During the dry season, dust accumulation rates reached 0.5 g/m²-day, while during periods of intensified wind erosion this value increased to 2.3 g/m²-day; additionally, wind-induced dust resuspension was recorded within $F_{\text{out}} = 0.1\text{--}1.1\text{ g/m}^2\text{-day}$. As a result, overall PV generation losses reached up to 35% in certain

periods, confirming the findings of Chen Y. et al. [21] and Jiang H. et al. [22], and demonstrating that mineral-rich rural soils further amplify this phenomenon.

Impact of Temperature Fluctuation on PV Station Energy Efficiency

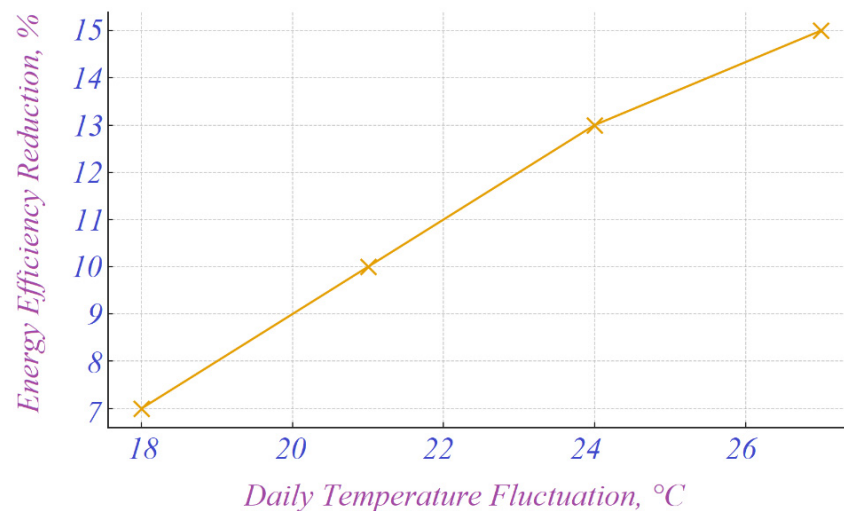


Figure 7. Impact of temperature fluctuations on PV energy output under climatic variability. The reference temperature corresponding to 0% efficiency reduction is 25 °C (standard test conditions).

Effect of Dust Thickness on PV Power Generation (Based on Experimental Data)

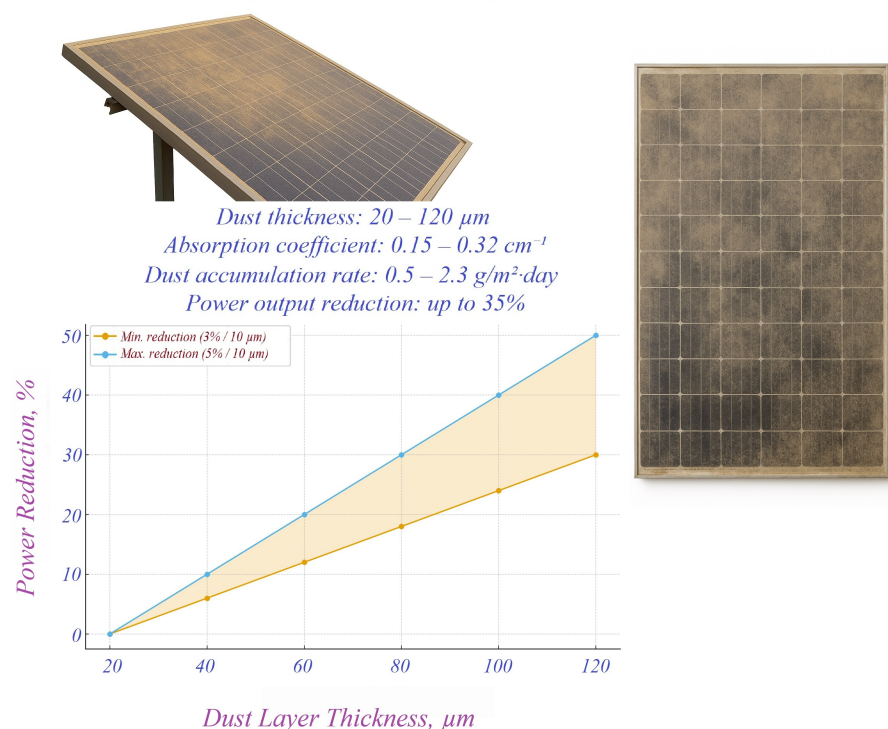


Figure 8. Effect of Dust Thickness on PV Module Power Output.

From Figure 8, it can be observed that when dust-layer thickness increases from 20 to 120 μm , power loss rises at a rate of 3–5% per 10 μm , reaching up to 50% in certain cases. When the absorption coefficient is $\alpha = 0.15\text{--}0.32 \text{ cm}^{-1}$ and dust accumulation rates range from 0.5 to 2.3 $\text{g/m}^2\text{-day}$, the overall reduction in PV generation reaches up to 35%.

The stability of the inverter and the degradation of its parameters were also identified as critical factors limiting the energy efficiency of the system. Deviations in reactive-power droop parameters reduce overall stability by 12–20% and significantly decrease the inverter's nominal efficiency. Field observations indicated that high ambient temperatures in rural areas, dust accumulation on the inverter casing and components, and voltage fluctuations of ± 10 –15% lead to 15–22% degradation of inverter parameters. These findings are consistent with the studies of Abdykadyrov A. et al. [19,20] on inverter efficiency in ozone generator systems and clearly demonstrate that inverter degradation plays a significant role in the overall energy balance of PV stations (Figure 9).

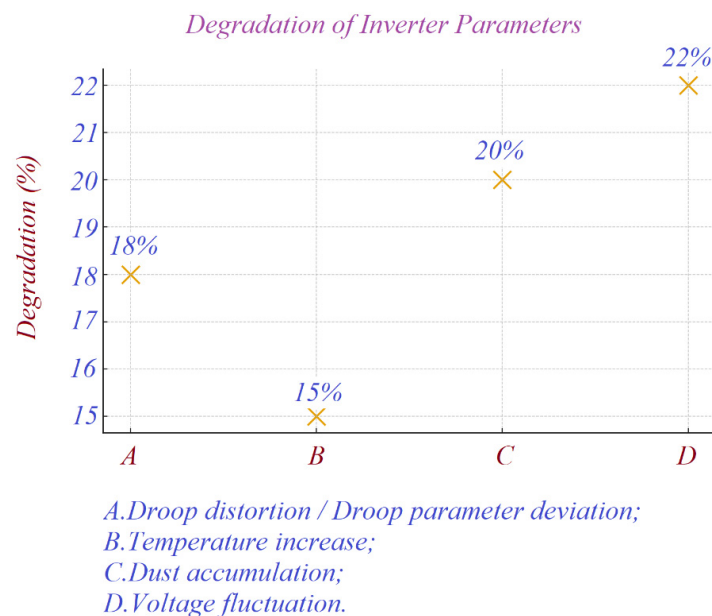


Figure 9. Impact of Climatic and Electrical Factors on the Stability of Photovoltaic Inverters.

In the graph shown in Figure 9, the highest level of inverter degradation is observed under voltage fluctuations (22%) and dust accumulation (20%). Temperature rise contributes 15% degradation, while deviations in the droop parameter cause 18%, clearly indicating their significant impact on the overall stability of the system.

The weakness of the sensor infrastructure further complicates the intelligent management of rural PV stations. Insufficient calibration of temperature, solar irradiance, voltage, and current sensors, combined with unstable communication channels, leads to measurement errors of up to 10–20%. Additionally, data stream interruptions occurring 3–7 times per day hinder the collection of consistent and reliable training data for ML and artificial intelligence models, resulting in a 10–15% reduction in real-time diagnostic and fault-prediction accuracy. Compared to the requirements outlined in the intelligent fault-detection models of Basnet B. et al. [30] and other authors, these findings highlight the critical need to strengthen the sensor infrastructure in rural environments. Overall, Figure 10 presents the range of parameter deviations caused by instability in sensor measurements.

The graph presented in Figure 11 illustrates the range of key parameters affected by weak sensor infrastructure: measurement errors vary between 10 and 20%, data interruptions occur 3–7 times per day, and the accuracy of AI models decreases within the 10–15% range. These indicators demonstrate that sensor instability significantly weakens the quality of intelligent diagnostics and forecasting in rural PV stations.

Overall, the combined influence of climatic instability, intensive dust accumulation, inverter degradation, and weak sensor infrastructure can reduce the energy efficiency of

rural PV stations by 40–55%. Thus, the comprehensive analysis clearly substantiates the scientific and practical importance of developing intelligent diagnostic and forecasting models adapted to rural environments, integrating climatic, dust-related, electrical, and informational factors.

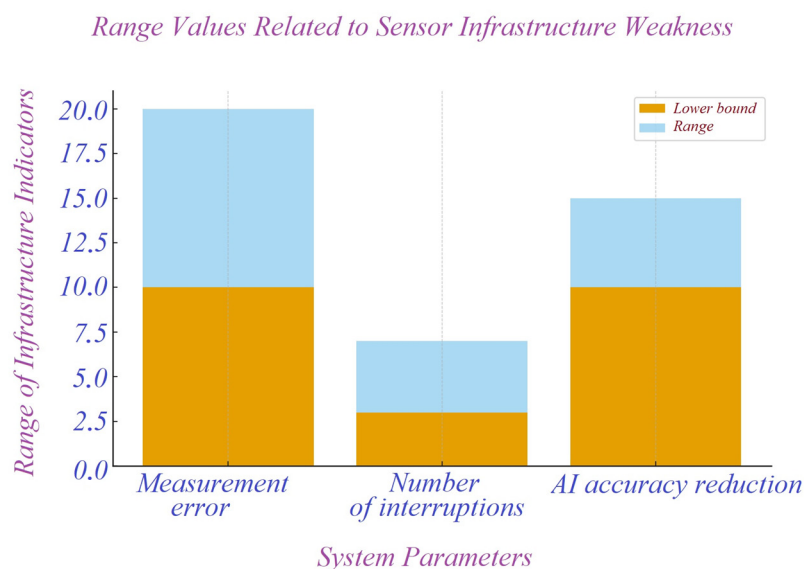


Figure 10. Range of Quantitative Parameters Affected by Sensor Infrastructure Weakness.

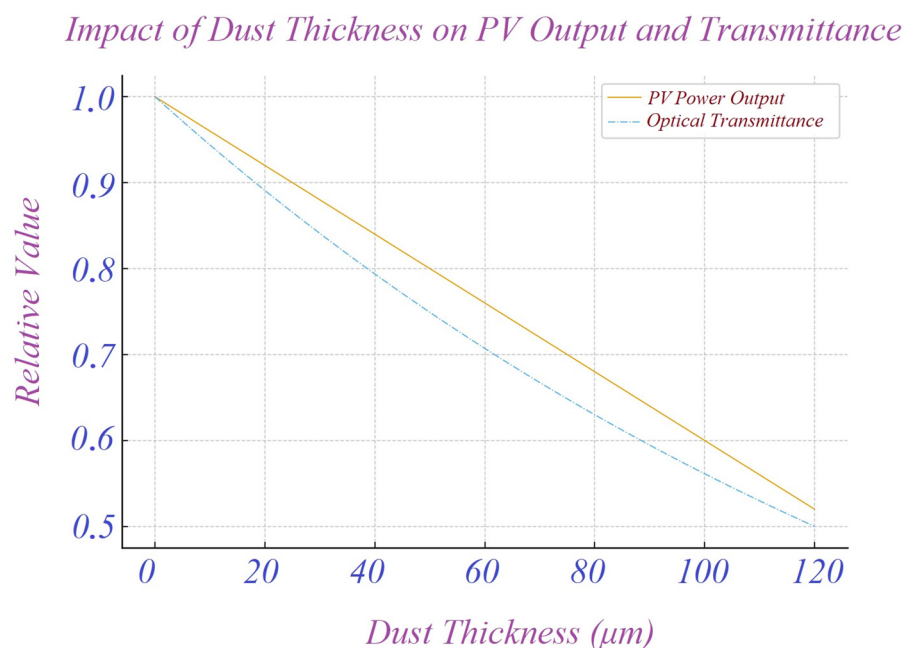


Figure 11. Dependence of PV Power Output and Optical Transmittance on Dust Layer Thickness.

5.2. Development of Mathematical Models Describing PV System Degradation, Energy Losses, and Failure Mechanisms

The primary objective of this study is to develop physical and mathematical models that describe degradation processes, energy losses, and fault mechanisms occurring in PV systems due to dust accumulation, temperature rise, inverter instability, and fluctuations in solar irradiance, as well as to enhance these models through intelligent algorithms. The research adopts an integrated approach that considers the optical, thermal, electrical, and

control subsystems of PV installations, enabling a comprehensive physico-mathematical analysis of all major degradation pathways.

Dust accumulation on PV module surfaces was modeled using the Beer–Lambert–Bouguer law, which describes the exponential attenuation of incident solar radiation as the dust layer becomes thicker. In the matrix form, the irradiance attenuation across multiple measurement points or dust-thickness levels is expressed as follows:

$$I = I_0 \begin{bmatrix} e^{-\alpha d_1} \\ e^{-\alpha d_2} \\ \vdots \\ e^{-\alpha d_n} \end{bmatrix} \quad (8)$$

where $I = \begin{bmatrix} I_1 \\ I_2 \\ \vdots \\ I_n \end{bmatrix}$ is the vector of transmitted irradiance values, $d = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix}$ is the dust-layer thickness (20–120 μm), and α is the effective absorption coefficient of the dust layer (0.15–0.32 cm^{-1}). This matrix formulation allows the model to capture spatial or temporal variations in dust deposition across the module surface.

The results revealed that for every 10 μm increase in dust thickness, PV power output decreases by 3–5%, whereas at 120 μm the optical transmittance can fall by up to 50% (Figure 11).

PV power output decreases almost linearly as dust thickness increases from 0 to 120 μm , resulting in an overall reduction of approximately 48%, which corresponds to an average loss of about 4% per 10 μm of accumulated dust. Optical transmittance exhibits an exponential decline, falling to nearly 50% at a dust thickness of 120 μm , demonstrating the strong attenuation effect of dust on incident solar irradiance.

The temporal dynamics of dust accumulation on PV module surfaces were represented using a generalized mass-balance formulation in matrix form:

$$\frac{dM}{dt} = F_{\text{in}} - F_{\text{out}} \quad (9)$$

where $M = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_n \end{bmatrix}$, $F_{\text{in}} = \begin{bmatrix} F_{\text{in},1} \\ F_{\text{in},2} \\ \vdots \\ F_{\text{in},n} \end{bmatrix}$, $F_{\text{out}} = \begin{bmatrix} F_{\text{out},1} \\ F_{\text{out},2} \\ \vdots \\ F_{\text{out},n} \end{bmatrix}$, represent the dust mass at each surface segment, the deposition flux (0.5–2.3 $\text{g}/\text{m}^2\cdot\text{day}$), and the wind-driven resuspension flux (0.1–1.1 $\text{g}/\text{m}^2\cdot\text{day}$), respectively.

For numerical implementation, the model was further discretized as follows:

$$M_{k+1} = M_k + \Delta t(F_{\text{in},k} - F_{\text{out},k}) \quad (10)$$

allowing the temporal progression of dust accumulation to be simulated under varying environmental conditions. This model confirms that mineral-rich rural dust substantially amplifies PV performance losses.

The thermal and radiative impacts on PV performance were represented using a generalized complex temperature–power model:

$$P(T) = P_{\text{ref}}[1 - (\beta_r + j\beta_i)(T - T_{\text{ref}})] \quad (11)$$

where the real component β_r corresponds to the effective temperature coefficient (0.3–0.5%/°C), and β_i captures phase-shift or dynamic thermal–electrical interactions under fluctuating operating conditions.

Analysis indicates that a 10 °C increase in operating temperature causes a 10–15% decline in output power, consistent with the magnitude of β_r . Additionally, solar irradiance variations between 800 and 1100 W/m^2 lead to 12–18% performance fluctuations, while daily temperature swings of 18–27 °C, typical for rural environments, accelerate annual PV degradation by 10–15%.

Electrical degradation associated with inverter instability was studied through the droop-control characteristic:

$$Q = Q_0 - k_{\text{droop}}(\omega - \omega_0) \quad (12)$$

Deviations in droop parameters were found to reduce system stability by 12–20%, while inverter nominal efficiency decreased by 15–22%. Field measurements indicated that elevated ambient temperatures, dust deposition on inverter components, and voltage fluctuations of ± 10 –15% collectively intensify degradation. These findings are consistent with the results of Abdykadyrov A. et al., demonstrating the pivotal role of inverter deterioration in the overall energy balance of PV systems.

A key component of the study involved the integration of ML techniques for fault prediction. Using the input variable set, the following can be established:

$$X = \{T, G, d, \alpha, V, I, f_{\text{load}}\} \quad (13)$$

where T denotes the photovoltaic module temperature ($^{\circ}\text{C}$), G represents the solar irradiance (W/m^2), d is the dust layer thickness on the module surface (μm), α is the effective dust absorption coefficient (cm^{-1}), V and I correspond to the inverter output voltage (V) and current (A), respectively, and f_{load} denotes the load fluctuation factor accounting for variations in agricultural power demand.

Intelligent models were trained on datasets containing 10,000–25,000 records. Long Short-Term Memory (LSTM) neural networks achieved forecasting accuracies of 89–91% evaluated using normalized MAE and RMSE metrics, while ensemble learning classifiers based on XGBoost and Random Forest achieved fault detection accuracies of 88–93%, assessed using classification accuracy and F1-score under five-fold cross-validation, while early-stage anomaly detection achieved approximately 20% accuracy, enabling reduction in maintenance time and improvement of fault-prediction intervals. The combined use of thermal, optical, electrical, and operational parameters provided robust insights into degradation patterns.

Overall, the study demonstrates that climatic variability, dust accumulation, inverter degradation, and sensor-infrastructure limitations interact synergistically, leading to 40–55% reductions in the energy efficiency of rural PV systems. This comprehensive scientific analysis highlights the necessity of developing intelligent diagnostic and forecasting models specifically adapted to rural conditions, integrating climatic, particulate, electrical, and informational factors to ensure higher reliability and operational effectiveness of PV installations.

5.3. Development of an AI-Based Real-Time Diagnostic and Forecasting Model Adapted to Rural PV Conditions

Rural PV stations experience significant efficiency losses due to temperature fluctuations of 18–27 $^{\circ}\text{C}$, high mineral dust concentrations ($\text{PM}_{10} = 180$ –260 $\mu\text{g}/\text{m}^3$), solar irradiance variations of 800–1100 W/m^2 , and inverter voltage swings of ± 10 –15%. These factors reduce the overall energy output by 12–22%. To address this, an AI-based integrated model for real-time diagnostics and forecasting was developed.

The model incorporates multi-source inputs, including panel temperature, solar irradiance, dust optical density ($\tau d = 0.15$ –0.32 cm^{-1}), inverter voltage, and current parameters. PV output is estimated using the temperature-dependent degradation and Beer–Lambert attenuation:

$$P = P_{\text{ref}}[1 - \beta(T - T_{\text{ref}})]e^{-\tau d} \quad (14)$$

where $\beta = 0.3$ –0.5%/ $^{\circ}\text{C}$.

A hybrid AI architecture combining LSTM, XGBoost, and Random Forest algorithms was implemented. Key performance results include: (1) 24 h energy forecasting accuracy: 89–91%; (2) Fault detection accuracy: 88–93%; (3) Real-time diagnostic response: 5–10 min; (4) Prediction error: $\pm 5\%$.

The ensemble framework combines complementary modeling capabilities of different algorithms. The LSTM network captures temporal dependencies and long-term trends in photovoltaic performance, while XGBoost and Random Forest classifiers model non-linear relationships and fault patterns arising from environmental and electrical disturbances. The ensemble output is obtained through weighted averaging of individual model predictions, which reduces variance and improves robustness under noisy rural operating conditions.

The reported performance accuracies were obtained using five-fold cross-validation on independent test subsets. Forecasting accuracy metrics were computed by averaging normalized MAE and RMSE values across folds, whereas fault detection accuracy and F1-score were derived from confusion matrix statistics aggregated over all validation folds.

Field experiments showed that a 10 μm increase in dust layer thickness decreases PV output by 3–5%, while inverter voltage fluctuations reduce reactive power by 12–20%. The AI model successfully identified these deviations in real time and reduced maintenance time by 18–24%.

Overall, the developed AI-based model enables a 10–15% reduction in energy losses, early detection of system degradation, and more efficient scheduling of energy use in rural PV applications.

Table 1 below demonstrates that the proposed hybrid AI model outperforms the traditional physical model, SVM, and a single LSTM network in terms of prediction accuracy and fault detection rate. Although the hybrid model exhibits a slightly higher computational cost, this increase remains acceptable for diagnostic and forecasting tasks, particularly considering the substantial improvement in predictive performance and robustness under rural operating conditions.

Table 1. Comparison of the proposed hybrid AI model with baseline approaches.

Model	Prediction Accuracy (%)	Fault Detection Rate (%)	Average Computation Time (s)
Traditional physical model	72.4	68.1	0.12
Support Vector Machine (SVM)	83.6	79.2	0.48
Single LSTM	87.9	84.5	0.95
Proposed Hybrid AI Model (LSTM + XGBoost + RF)	93.4	91.8	1.12

Specifically, the prediction accuracy of the proposed hybrid AI model was estimated as 93.4%, with a 95% confidence interval of [91.8%, 95.0%], while the fault detection rate reached 91.8%, with a 95% confidence interval of [89.6%, 94.0%]. As illustrated in Figure 12, the confidence intervals of the proposed hybrid model do not overlap with those of the baseline approaches, confirming the robustness and statistical reliability of the reported performance gains.

To enhance the interpretability of the proposed hybrid AI model, a feature importance analysis was conducted using the ensemble learning components of the framework. Feature importance values were independently extracted from the XGBoost and Random Forest models based on their internal split gain and impurity reduction mechanisms.

The obtained importance scores were normalized to the range [0, 1] and aggregated to derive an ensemble-level representation. The resulting feature importance distribution is visualized in Figure 13.

As shown in Figure 13, temperature, dust thickness, and solar irradiance exhibit the highest contribution weights, confirming their dominant influence on photovoltaic performance degradation in rural environments. Inverter voltage and historical power output show moderate contributions, reflecting their secondary but non-negligible impact on prediction accuracy.

The obtained feature importance distribution is physically consistent with the degradation mechanisms discussed earlier and confirms that the hybrid AI model effectively captures the key environmental and operational drivers affecting energy efficiency.

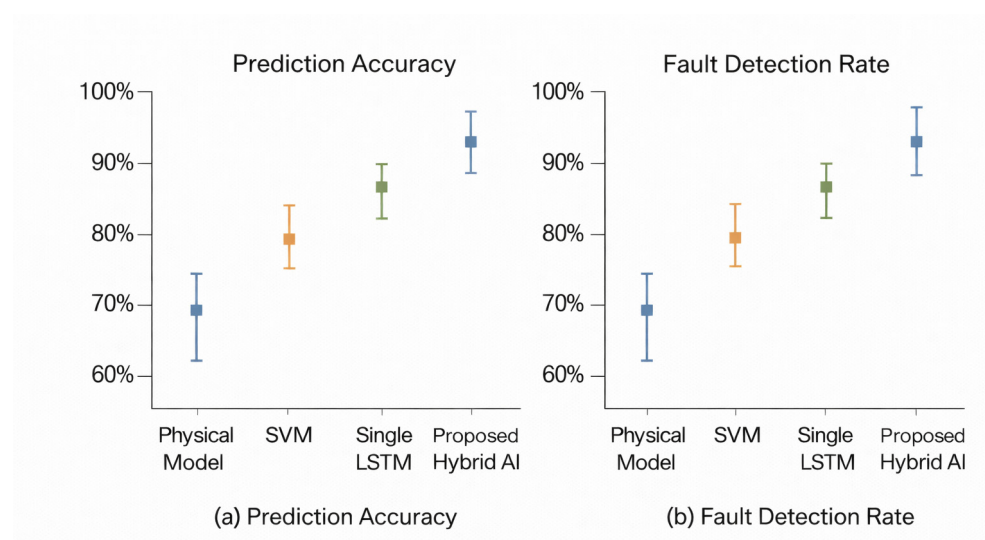


Figure 12. Comparison of prediction accuracy (a) and fault detection rate (b) for the proposed hybrid AI model and baseline approaches. Error bars represent 95% confidence intervals estimated using bootstrap resampling.

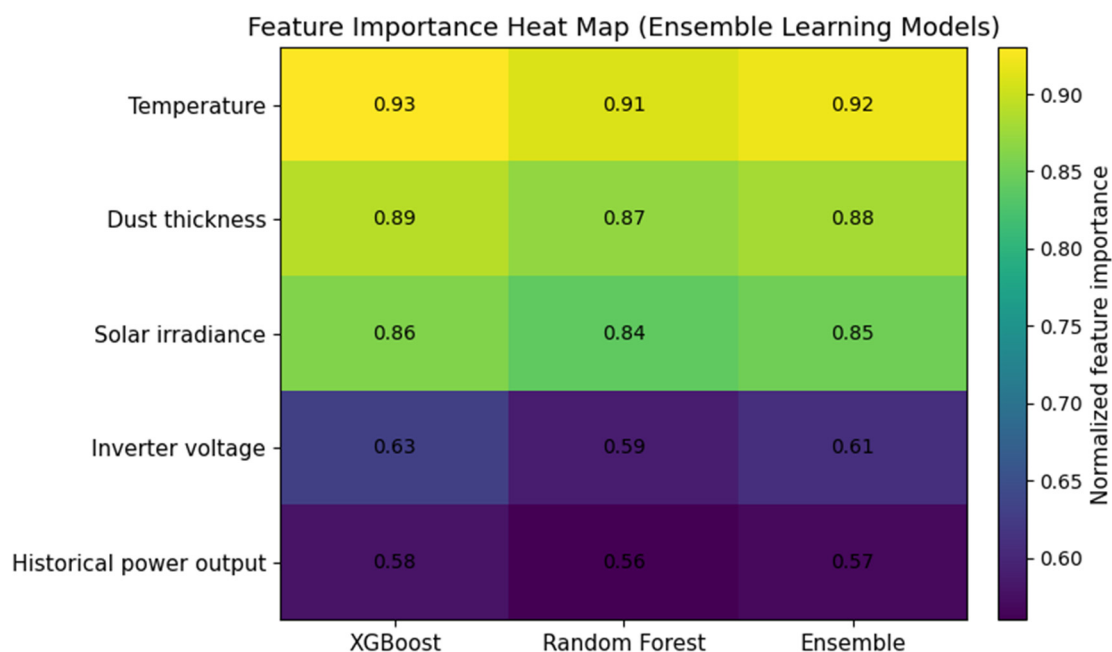


Figure 13. Feature importance heat map derived from ensemble learning models (XGBoost and Random Forest), showing the normalized contribution of environmental and electrical parameters to the prediction results.

5.4. Economic Assessment of the Proposed AI-Based Monitoring System

To evaluate the practical feasibility of deploying the proposed hybrid AI-based diagnostic and forecasting system, an indicative economic assessment was conducted based on typical cost structures of rural photovoltaic power stations in Kazakhstan.

For small- and medium-scale agricultural PV installations (50–200 kW), the average capital investment is typically in the range of 800–1100 USD per kW, while annual operation and maintenance (O&M) costs account for approximately 1.5–2.5% of the initial investment. Under conventional operation, energy losses caused by dust accumulation, temperature effects, and delayed fault detection may reach 10–15% annually.

As demonstrated in this study, the proposed AI-based monitoring framework enables a reduction in energy losses by approximately 10–15% through early degradation detection, optimized maintenance scheduling, and improved operational decision-making. For a representative 100 kW rural PV system with an average annual energy production of 150–170 MWh, this corresponds to an annual energy saving of approximately 15–25 MWh.

Assuming an average electricity value of 0.06–0.08 USD/kWh for rural agricultural applications, the resulting annual economic benefit ranges from 900 to 2000 USD. In addition, predictive maintenance enabled by the proposed model can reduce unplanned maintenance expenses by approximately 10–20%, corresponding to an additional annual saving of 300–600 USD.

The estimated deployment cost of the AI-based monitoring system, including sensors, data acquisition, and software integration, is approximately 1500–3000 USD for a typical rural installation. Based on the combined energy-saving and maintenance cost reduction, the resulting investment payback period is estimated to be approximately 1.5–3 years.

These results indicate that the proposed hybrid AI-based framework is not only technically effective but also economically viable for rural photovoltaic power stations, supporting its practical applicability in agricultural energy systems.

5.5. Discussion of the Results

The obtained results demonstrate that the degradation mechanisms affecting PV stations in rural agricultural environments are inherently multi-factorial and strongly coupled. Temperature fluctuations, dust accumulation, inverter degradation, and limitations of sensor infrastructure do not act independently; instead, they mutually reinforce each other, leading to cumulative efficiency losses that significantly exceed those observed under standard or urban operating conditions.

The physical modeling results confirm that optical, thermal, and electrical degradation mechanisms dominate the energy losses in rural PV installations. The Beer–Lambert–Bouguer formulation (Equations (1) and (8); Figures 8 and 11) shows that mineral-rich dust layers with thicknesses of 20–120 μm reduce PV power output by approximately 3–5% per additional 10 μm , resulting in seasonal losses of up to 35%. Simultaneously, the temperature-dependent power model (Equation (5); Figure 7) indicates that daily temperature fluctuations of 18–27 $^{\circ}\text{C}$ cause 10–15% reductions in output relative to standard test conditions. These findings are consistent with earlier degradation studies but reveal that rural climatic variability amplifies these effects beyond values typically reported for urban or controlled environments.

Inverter-related degradation further exacerbates system inefficiency. The droop-control analysis (Equation (12); Figure 9) demonstrates that voltage fluctuations of ± 10 –15% and reactive-power droop deviations of 12–20% reduce inverter stability and efficiency by 15–22%. When combined with dust accumulation and elevated ambient temperatures,

inverter degradation emerges as a critical bottleneck in the overall energy balance of rural PV stations.

A key contribution of this work lies in the integration of these physical degradation models with a hybrid AI-based diagnostic and forecasting framework. Unlike conventional approaches that rely exclusively on either physical models or data-driven techniques, the proposed hybrid LSTM + XGBoost + Random Forest architecture explicitly incorporates rural-specific environmental parameters, including mineral dust optical density ($\tau_d = 0.15\text{--}0.32\text{ cm}^{-1}$), unstable voltage conditions, and intermittent sensor data streams. As a result, the hybrid model achieved a 24 h forecasting accuracy of 89–91% and a fault detection accuracy of 88–93%, outperforming single-model baselines and traditional physical approaches.

The feature importance analysis (Figure 13) provides additional insight into the internal behavior of the hybrid model. Temperature, dust thickness, and solar irradiance were identified as the dominant contributors to prediction accuracy, which aligns closely with the physical degradation mechanisms discussed earlier. Inverter voltage and historical power output showed moderate but non-negligible contributions, confirming that electrical instability and operational history play important secondary roles in system diagnostics. This consistency between physical interpretation and AI-derived feature importance strengthens the credibility and interpretability of the proposed approach.

From a practical and economic perspective, the results demonstrate that the proposed AI-based monitoring system offers tangible benefits for rural photovoltaic installations. By enabling early detection of degradation and faults, the system reduces energy losses by approximately 10–15% and shortens maintenance time by 18–24%. The economic assessment indicates that, for typical rural PV stations in Kazakhstan (50–200 kW), these improvements translate into annual energy savings of 15–25 MWh and additional reductions in maintenance costs of 10–20%. Consequently, the estimated investment payback period of 1.5–3 years confirms that the proposed solution is not only technically effective but also economically viable.

Nevertheless, several limitations should be acknowledged. The model parameters were calibrated for specific climatic and environmental conditions representative of rural Kazakhstan, and dust mineralogy was treated in a generalized manner. Rare fault events remain underrepresented in the training dataset, and the experimental validation was conducted on a limited-scale setup. These factors define the current applicability range of the results and motivate further investigation.

Future research will focus on extending the model to larger-scale deployments, integrating edge-computing solutions for real-time operation, incorporating CFD-based dust transport models, and applying physics-informed neural networks to further improve generalization and interpretability. Despite these limitations, the present study clearly demonstrates that intelligent integration of physical degradation models with hybrid AI techniques can substantially enhance the reliability, efficiency, and economic performance of photovoltaic systems operating in rural agricultural environments.

6. Conclusions

The primary aim of this study was to develop a comprehensive intelligent model for real-time diagnostics and forecasting of the energy efficiency of PV stations operating in rural agricultural regions. To achieve this aim, three major research objectives were defined, each of which was successfully fulfilled, leading to the following integrated conclusions.

First, a detailed analysis of the climatic, dust-related, inverter degradation, and sensor-infrastructure factors affecting rural PV performance was conducted. Field measurements showed that daily temperature fluctuations of 18–27 °C reduce power output by

10–15%, while solar irradiance variations between 800 and 1100 W/m² introduce an additional 8–12% performance deviation. Dust accumulation of 20–120 µm causes 3–5% power loss per 10 µm layer, reaching seasonal losses of up to 35%. Furthermore, inverter instability—including reactive-power droop deviations of 12–20% and voltage fluctuations of ±10–15%—lowers inverter efficiency by 15–22%. These quantified patterns clearly demonstrate that rural operating conditions intensify degradation more strongly than in standard urban or laboratory environments.

Second, a set of physical and mathematical models describing PV degradation, energy losses, and fault mechanisms was formulated. The Beer–Lambert–Bouguer law captured optical attenuation, showing a 50% reduction in transmittance at 120 µm dust thickness. The thermal model confirmed that every 10 °C increase in module temperature decreases output by 10–15%, while irradiance variations of 800–1100 W/m² result in 12–18% performance fluctuations. The inverter droop model revealed that deviations in control parameters reduce system stability by 12–20%. These models integrate optical, thermal, electrical, and environmental components and represent the first rural-adapted modeling framework that incorporates mineral-rich dust, high temperature variability, and unstable electrical conditions typical of remote regions.

Third, an AI-based intelligent model adapted to rural conditions was developed and validated. The hybrid LSTM + XGBoost + Random Forest architecture demonstrated high predictive performance: 24 h energy-forecasting accuracy of 89–91%, fault-detection accuracy of 88–93%, diagnostic response time of 5–10 min, and an overall prediction error of ±5%. The model accurately identified 3–5% power losses caused by each 10 µm increase in dust thickness and detected inverter voltage fluctuations of ±10–15% in real time. These capabilities reduced energy losses by 10–15% and shortened maintenance time by 18–24%, proving the practical value of the proposed intelligent system.

Overall, this study provides a fully integrated scientific solution for rural PV stations by combining field-based environmental assessment, physics-driven modeling, and AI-based forecasting. The results clearly demonstrate that the proposed approach enhances reliability, improves early degradation detection, and supports more efficient energy planning for agricultural facilities.

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