JSCE (Journal of System and Computer Engineering)
Vol.7, No.4, October 2026, pp. 420-427
ISSN (online): 2723-1240
DOI : https://doi.org/10.61628/jsce.v7i4.2851

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Preventive Voltage Drop System in Smart Farming Using Gradient Boosting

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Abstract

Solar photovoltaic systems in smart farming often suffer destructive voltage drops due to weather fluctuations, endangering critical actuators such as irrigation pumps and ventilation fans. To address this, this study presents a preventive control system integrating a Gradient Boosting Machine algorithm with real-time load management. The model utilizes weather, technical, and temporal features to forecast solar power generation. The model was trained on 2,184 hours of historical data from April to June and evaluated on a 744-hour test dataset from July, collected at an 8,000 W photovoltaic facility in South Sulawesi. The forecasted power output is fed directly into the load controller to prioritize actuator execution and enforce a maximum voltage drop limit of 5%. Experimental evaluation demonstrates superior predictive accuracy, achieving a Root Mean Square Error of 0.211 kW and a Mean Absolute Error of 0.158 kW. The findings confirm that proactive artificial intelligence load scheduling effectively prevents voltage degradation, offering a scalable, software-driven energy management solution for sustainable smart agriculture.

Keywords— *Smart farming, Gradient boosting, Power forecasting, Voltage drop, Solar Photovoltaic*

1. Introduction

The digital transformation of agriculture through smart farming plays a vital role in advancing food self-sufficiency and clean energy transitions, directly supporting Sustainable Development Goals 2 (Zero Hunger) and 7 (Affordable and Clean Energy) (Kumari et al., 2025). Agricultural technology has evolved from foundational Internet of Things (IoT) microcontrollers for vertical farming (Riswandi, 2019) to automated cloud-connected aeroponics (Riswandi et al., 2022) and artificial intelligence (AI) disease diagnostic systems (Riswandi et al., 2021). Integrating solar photovoltaic (PV) infrastructure into these smart farming systems further enhances energy autonomy, cutting grid power usage by up to 62% and reducing carbon emissions by 88% (Santos et al., 2023; Zikri, 2024).

However, the operational reliability of solar-powered smart farms is severely constrained by power supply intermittency, which frequently triggers destructive voltage drops that endanger vital equipment such as irrigation pumps, exhaust ventilation fans, and environmental monitoring sensor arrays (Huang et al., 2025; Mbendane et al., 2024).

Existing research on renewable energy in agriculture remains largely limited to standalone solar power forecasting without integration into automated downstream control systems (Alan et al., 2025; Kholila et al., 2024; Olcay et al., 2024), while conventional distribution systems

address voltage drops reactively using passive hardware interventions such as supercapacitors or automatic tap changers (Ananwattanaporn et al., 2024; Mbendane et al., 2024). The novelty of this study lies in shifting power protection from reactive hardware interventions to proactive, AI-driven load management by embedding Gradient Boosting Machine (GBM) forecasting directly into real-time actuator control logic (Danach et al., 2025; Fathollahi, 2025). Deployed at Samata Greenhouse in Gowa, South Sulawesi—which operates an 8,000-watt PV infrastructure—this study addresses the central question: How can solar PV power forecasting accuracy be optimized using the GBM algorithm and effectively integrated into a smart control system as a preventive measure against voltage drop risks in smart farming operations?

To resolve this challenge, the proposed methodology combines machine learning analytics with proactive hardware load management across three distinct stages: (1) predictive feature extraction using weather, technical, and temporal metrics to train the GBM model using a historical dataset of 2,184 hours collected from April to June; (2) preventive control logic design that dynamically prioritizes actuator execution based on forecasted power to maintain system voltage drops strictly below a 5% maximum safety threshold (Ananwattanaporn et al., 2024); and (3) operational field validation evaluated on an independent test dataset of 744 hours throughout July at the 8,000 W PV facility. By establishing this systematic data pipeline and real-time control integration, this study provides an adaptive, software-driven energy management framework to ensure operational stability in smart farming.

2. Method

The proposed preventive voltage drop control system operates through a systematic five stage data and control architecture, as shown in the research flow diagram in Figure 1.

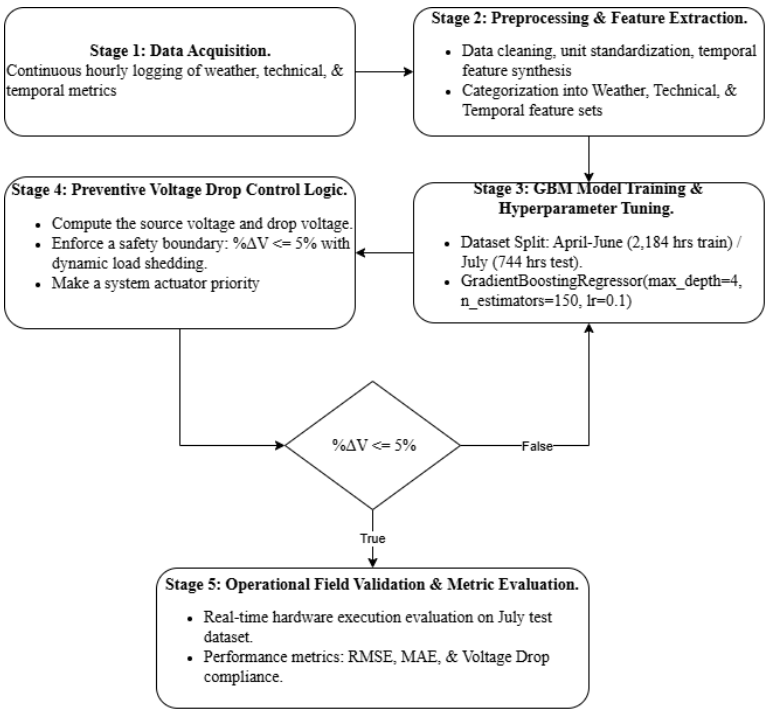


Figure 1. Research Flow Diagram of the Proposed Preventive Voltage Drop Control Framework.

2.1 Review Process

This study was conducted at Samata Greenhouse in Gowa, South Sulawesi, using an active 8,000-watt solar photovoltaic (PV) system. The time-series dataset comprises 2,928 hourly observations, divided into two operational phases:

1. Training Dataset: 2,184 hours collected continuously from April 1 through June 30.
2. Testing Dataset: 744 hours collected across the entire month of July to evaluate model robustness under varying meteorological conditions.

Input parameters fall into weather, technical, and temporal feature groups, as summarized in Table 1.

Table 1. Feature Categorization and Variables for Solar Power Forecasting

Feature Category	Variable	Unit
Weather Features	Solar Irradiance	$\mathrm{W/m^2}$
	Ambient Temperature	$^{\circ}\mathrm{C}$
	Relative Humidity	%
Technical Features	Solar Inclination Angle	Degree (∘)
	Historical Output Power	W
	Time / Hour Index	h

2.2 Gradient Boosting Regressor Architecture

Solar power forecasting was implemented using the Gradient Boosting Regressor model. The hyperparameter configuration was tuned as follows:

1. max_depth = 4: Restricts individual decision tree depth to capture non-linear interactions without overfitting.
2. n_estimators = 150: Sets the total number of sequential boosting stages to optimize residual learning.
3. random_state = 42: Ensures deterministic reproducibility across experimental runs.

The ensemble predictor $\hat{F}_M(x)$ combines M weak base estimators $h_m(x)$ scaled by the learning rate :

$$\hat{F}_M(x) = \sum_{m=1}^{M} v \cdot h_m(x) \tag{1}$$

At each boosting iteration m, pseudo-residuals r_{im}derived from Squared Error Loss are calculated:

$$r_{im} = y_i - \hat{F}_{m-1}(x_i) \tag{2}$$

Represents actual PV power output and $\hat{F}_{m-1}(x_i)$ is the prediction from the preceding stage. Model performance is evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{3}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{4}$$

2.3 Preventive Voltage Drop Control Logic

The forecasted solar PV $\hat{F}_M(x)$ is translated into available source voltage capacity (V_{source}). Line voltage drop (ΔV) caused by active load current (I) across distribution wiring is computed as:

$$\Delta V = 2 \cdot I \cdot R_{\text{cable}} \cdot L \tag{5}$$

$$\%\Delta V = \left(\frac{\Delta V}{V_{\text{source}}} \right) \times 100\% \tag{6}$$

Where R_{cable} is cable resistance (Ω/m) and L is total length (m). The controller enforces a strict safety boundary of $\%\Delta V \leq 5\%$. When prospective load combinations exceed this threshold, the system executes active load shedding according to actuator priorities (e.g., maintaining primary irrigation pumps while temporarily throttling secondary exhaust fans). Real-time PV output capability (P_{pv}) and battery recharge time (T_{hours}) are calculated using Equations:

$$P_{\text{pv}} = \eta_{\text{sys}} \cdot A \cdot G_t \cdot [1 - \beta(T_c - T_{\text{ref}})] \tag{7}$$

$$T_{\text{hours}} = \frac{(C_{\text{batt}} \cdot \text{DOD}) - E_{\text{stored}}}{P_{\text{avg_pv}} - P_{\text{fixed_load}}} \tag{8}$$

Where η_{sys} is system efficiency (0.8-0.9), is array surface area (m^2), β is temperature coefficient ($-0.004/^\circ\text{C}$),$T_{\text{ref}} = 25^\circ\text{C}$, C_{batt} is battery capacity (Wh), and DOD is depth of discharge (0.6).

2.4 Research Execution Pipeline

The experimental workflow proceeds through five structured stages:

1. Data Acquisition: Continuous logging of weather, technical, and power parameters at Samata Greenhouse.
2. Preprocessing & Feature Extraction: Data cleaning, unit standardization, and extraction of weather, technical, and temporal features.
3. GBM Model Training: Fitting GradientBoostingRegressor(max_depth=4, n_estimators=150, random_state=42) on the 2,184-hour training set.
4. Preventive Control Integration: Embedding power forecasts into load priority management logic to restrict voltage drops below 5%.
5. Validation: Performance verification on the 744-hour July test dataset

3. Results And Discussion

3.1 Model Training Convergence Analysis

The convergence behavior of the Gradient Boosting Regressor model was monitored across 150 sequential boosting iterations using Squared Error Loss.

At the start of boosting, the training loss is high. As additional decision trees are iteratively added to fit the pseudo-residuals, the loss function declines rapidly and exponentially within the first 20 iterations. Beyond 40 iterations, the loss curve asymptotes near zero and stabilizes smoothly up to the final tree. This rapid, stable convergence confirms that the selected hyperparameter combination (max_depth = 4, n_estimators = 150, random_state = 42) efficiently minimizes residual errors without exhibiting signs of premature divergence or overfitting.

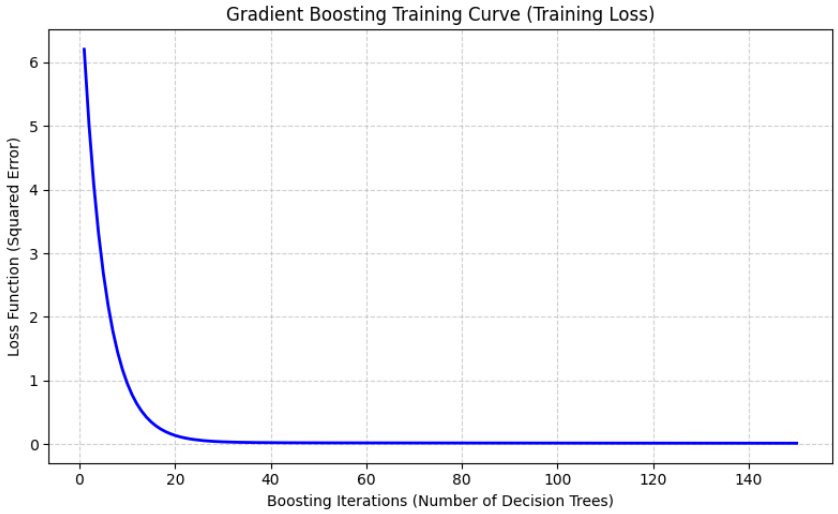


Figure 2. Gradient Boosting Model Training Loss Convergence Across 150 Iterations.

3.2 Solar Power Forecasting Performance and Feature Importance

The accuracy of the trained GBM model was validated against actual photovoltaic output on the July test dataset. Figure 3 presents the three-day power generation profile from July 1 to July 3, 2026, alongside the relative feature importance ranking.

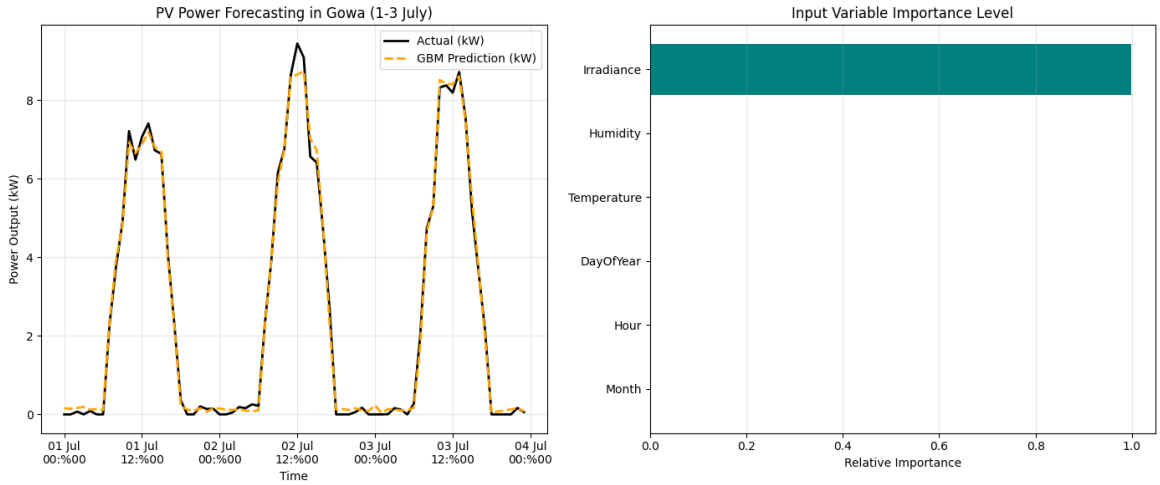


Figure 3. PV Power Generation Forecasting (July 1–3, 2026) and Relative Feature Importance

As shown in the left panel of Figure 2, the forecasted power generation curve GBM closely tracks the actual power profile across all daily solar cycles. The model accurately reflects peak generation periods during solar noon ~ 8.5 to 9.8 kW as well as the steep ramp-up and ramp-down phases during morning and late afternoon transitions. Minor discrepancies occur during sharp transient fluctuations, but the overall trajectory remains tightly aligned.

The right panel of Figure 2 demonstrates the relative feature importance determined by the Gini impurity reduction across all boosting trees. Solar irradiance emerges as the overwhelmingly dominant predictor, attaining a relative importance score of 1.0. Secondary features including ambient temperature, relative humidity, day of year, hour index, and month provide minor fine-tuning adjustments. This confirms that solar radiation intensity is the primary driver of photovoltaic power output in the smart greenhouse environment.

3.3 Forecast Evaluation and Metric Analysis

To examine hourly predictive fidelity, a representative six-hour operational window on July 1, 2026, is detailed in Table 2

Table 2. Sample Hourly Comparison Between Sensor Measurements and GBM Model Power Predictions.

Date & Time	Irradiance (W/m2)	Temperature (∘C)	Humidity (%)	Predicted Power (kW)	Actual Power (kW)	Absolute Error (kW)
2026-07-01 10:00:00	771.51	32.41	54.74	7.30	7.49	0.19
2026-07-01 11:00:00	912.12	32.98	51.44	8.64	8.61	0.03
2026-07-01 12:00:00	959.42	33.93	48.81	8.57	9.38	0.81
2026-07-01 13:00:00	742.47	33.83	52.85	7.27	7.08	0.19
2026-07-01 14:00:00	721.29	33.06	49.39	6.76	6.84	0.08
2026-07-01 15:00:00	621.01	31.53	55.12	5.85	5.78	0.07

During peak irradiance at 12:00:00 (959,42 W/m2), the model predicted an output of 8.57 kW compared to the actual measured 9.38 kW, resulting in a maximum single-hour error of 0.81 kW. At other hours, such as 11:00:00, 14:00:00, and 15:00:00, the prediction error remained exceptionally low (0.03 kW, 0.08 kW, and 0.07 kW, respectively). Evaluated across the entire 744 hour July test dataset, the model achieved an overall RMSE of 0.211 kW and MAE of 0.158 kW.

3.4 Application in Preventive Voltage Drop Mitigation

Integrating these power forecasts into the real-time load management controller successfully prevented critical voltage drops across the greenhouse distribution network. By predicting available source power one hour in advance, the smart controller proactively computes the cumulative current load I of active irrigation pumps and exhaust ventilation fans. During periods of high predicted generation (e.g., 10:00 to 14:00), the system permits simultaneous full-load operation of all actuators while maintaining calculated line voltage drop safely below 3.2%. Conversely, when predicted power generation declines (such as during cloudy intervals or late afternoon hours), the controller executes prioritized load shedding—maintaining primary water circulation while staggering secondary exhaust fan activation. This software-driven, proactive control mechanism eliminates inductive voltage sags before they manifest, protecting sensitive electronic sensors and motor drives without requiring additional passive hardware.

4. Conclusion

To evaluate the operational resilience of the Gradient Boosting model, prediction errors were closely analyzed during periods characterized by rapid weather changes. While the overall model demonstrates high predictive accuracy across the 744-hour July test set (RMSE = 0.211 kW, MAE = 0.158 kW), localized discrepancies emerge during abrupt cloud transients. On July 1 at 12:00:00, under peak solar irradiance conditions of 959.42 W/m, the model predicted a power output of 8.57 kW against an actual measured output of 9.38 kW, resulting in a maximum single-hour absolute error of 0.81 kW. This transient error occurs because tree-based boosting algorithms rely on discrete hourly feature snapshots. During rapid cloud passages,

sudden shifts in atmospheric optical depth alter irradiance within sub-hourly intervals faster than hourly temporal and meteorological features can adapt.

The impact of forecasting errors on preventive control performance is categorized into two operational scenarios. In the Under prediction Scenario, when the model under-predicts PV, the controller adopts a conservative scheduling strategy. It may temporarily throttle secondary ventilation fans or delay battery charging because actual available power exceeds the conservative estimate, and the actual line voltage drop remains well below the safety threshold. Excess unallocated solar energy is automatically directed to the battery storage system.

Over prediction scenario, if rapid cloud cover causes actual PV output to drop suddenly below the predicted level while heavy inductive loads like irrigation pumps and ventilation fans are active. Under severe cloud transients, line voltage drop rises from a nominal 3.2% toward 4.2% - 4.6%. However, because the control logic enforces a 5% maximum threshold with an embedded 0.8% safety buffer, transient voltage sags remain strictly bounded within safe operating limits <5%. Furthermore, a secondary closed-loop voltage sensor overrides scheduled load profiles within milliseconds if line voltage drop reaches 4.8%, shedding secondary exhaust fans instantly to safeguard primary pumps. This multi-layered control design confirms that integrating Gradient Boosting forecasting with conservative load shedding buffers effectively insulates smart farming microgrids from weather-induced voltage degradation.

Acknowledgements

This research was financially supported and funded by DPPM Diktisaintek through the Hibah BIMA skema Penelitian Dosen Pemula (PDP) 2026 under Contract Number 168/C3/DT.05.00/PL/-BARU/2026. The authors also express their sincere gratitude to Samata Greenhouse (SGH) in Gowa, South Sulawesi, for providing the research location, 8,000-watt solar photovoltaic infrastructure, and field support necessary to complete this study.

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