



AI-Enabled Predictive Load Management and Priority-Based Load Shedding for a Campus Solar Microgrid Using Edge LSTM Forecasting and Cloud IoT Monitoring

Ankur R. Ramteke¹, Aarambh D. Deshmukh², Hrunali I. Dhobale³, Sagar G. Tarone⁴, and Shreya G. Padalwar⁵, Prof. M. R. Shelke⁶

⁶ Under the guidance of

Department of Electrical Engineering

Priyadarshini College of Engineering, Nagpur, India

DOI : <https://doi.org/10.55248/gengpi.07.1026.3274>

ABSTRACT—

This paper presents an AI-enabled predictive load management scheme for a campus-scale solar microgrid. The prototype integrates a 30 W solar photovoltaic (PV) source, a 4 Ah lithium-ion battery and an Internet of Things (IoT) monitoring layer. Voltage, current, temperature, light and humidity sensors are sampled by an ESP32-S3 edge-computing unit, which exchanges data with an AI/ML engine. A Long Short-Term Memory (LSTM) network deployed with TensorFlow Lite Micro forecasts solar generation and load demand 24 hours ahead, using weather data from the OpenWeatherMap API. Based on the forecast, a smart relay module keeps critical loads (security lighting) energized and sheds non-critical loads (decorative lighting, fans) when an energy deficit is predicted, protecting the battery from over-discharge. Measurements are published over MQTT to a ThingsBoard CE cloud SCADA dashboard for remote monitoring. The work demonstrates a complete sensing–edge AI–cloud–control pipeline and is expected to reduce energy waste through intelligent load shedding.

Index Terms—Solar microgrid, load forecasting, LSTM, edge AI, TensorFlow Lite Micro, load shedding, IoT, MQTT, SCADA, ESP32-S3.

I. INTRODUCTION

Energy consumption in educational institutions has risen significantly because of increasing electrification. Conventional grid-dependent campuses face rising tariffs, power outages and the environmental burden of fossil-fuel generation. Solar microgrids provide a decentralized renewable alternative; however, most conventional microgrids rely on fixed scheduling that does not adapt to changing generation and demand patterns, which leads to wasted energy and deep battery discharge.

This work integrates artificial intelligence with a renewable microgrid. The proposed system forecasts solar generation and load demand from weather information and historical data, and then autonomously prioritizes loads to use the available energy efficiently. The main contributions of this work are:

- LSTM-based predictive analytics executed on an edge device;
- a real-time IoT sensor network for electrical and environmental parameters;
- an MQTT-based cloud SCADA dashboard for remote monitoring; and
- intelligent relay-based load shedding driven by the forecast.

The project is aligned with India's National Solar Mission and Smart Grid Vision.

II. LITERATURE REVIEW

Biswal et al. proposed an IoT-based hybrid XGBoost–LSTM load forecasting model combined with a priority-based demand-side management (DSM) framework on a Raspberry Pi for a greenhouse, reporting a MAPE of 5.3% and a 17.3% reduction in electricity cost [1]. Babu et al. evaluated several machine-learning regressors (MLR, Ridge, Lasso, SVR, Random Forest and Gradient Boosting) with feature engineering for solar energy forecasting; Gradient Boosting performed best with an R^2 of 0.827 [2].

Sammar et al. reviewed AI-based solar irradiance prediction models, including CNN, LSTM, GRU, GAN and hybrid approaches, and identified open research challenges [3]. Sakib et al. surveyed prediction-interval estimation methods such as quantile regression, LUBE, Bayesian neural networks and ensembles for quantifying uncertainty in solar, wind, tidal and hydro forecasting [4].

Research gap: existing solutions concentrate either on hardware (solar plus storage) or on software (forecasting alone). This work combines both layers in one end-to-end pipeline—sensing, edge AI, cloud visualization and autonomous control.

III. OBJECTIVES

- To design a campus-scale microgrid prototype (30 W solar, 4 Ah battery) supplying critical and non-critical DC loads.
- To display real-time electrical and environmental parameters using IoT sensors.
- To demonstrate Industry 4.0 compliance through IoT, edge AI and cloud analytics.
- To reduce energy waste through intelligent load shedding.

IV. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall Architecture

The architecture in Fig. 1 is organized into four layers: power flow, sensors, processing and communication. In the power-flow layer, the solar PV array charges the battery through a charge controller, and the battery supplies the load, which comprises both critical and non-critical loads. The sensor layer comprises voltage, current, temperature, light and humidity sensors together with a weather API that supplies forecast inputs. The processing layer consists of an ESP32-S3 edge-computing unit that collects the sensor data and exchanges it with an AI/ML engine in both directions; the engine's decisions are executed by a smart relay module that switches the load. In the communication layer, the edge unit publishes data to an MQTT broker, which feeds the monitoring dashboard.

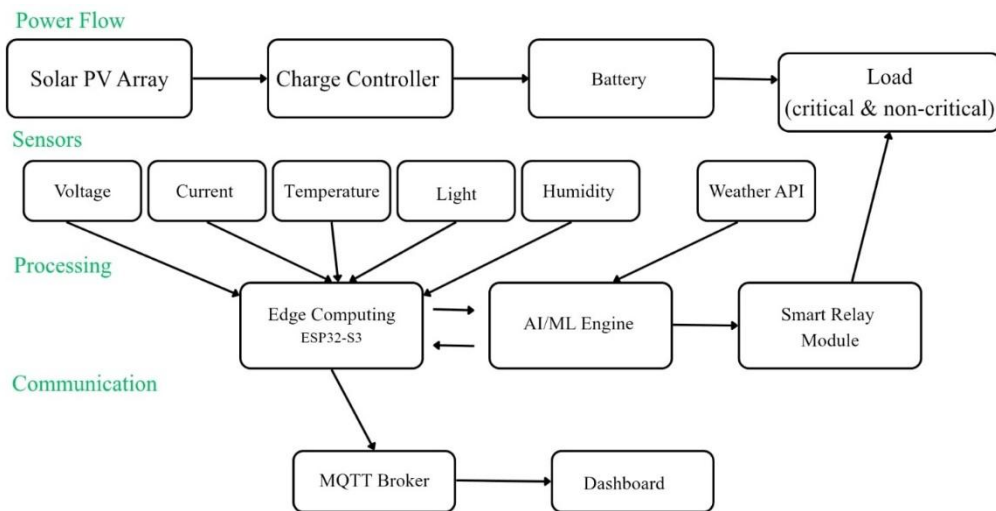


Fig. 1. System architecture of the AI-enabled solar microgrid showing the power-flow, sensor, processing and communication layers.

B. Hardware and Sensing

The prototype uses a 30 W solar panel and a 4 Ah lithium-ion battery. Voltage, current, temperature, light and humidity sensors are read through the ESP32-S3 ADC. Table I summarizes the main prototype parameters.

TABLE I. PROTOTYPE SPECIFICATIONS

Parameter	Value / Device
Solar PV capacity	30 W
Energy storage	Li-ion, 4 Ah
Controller	ESP32-S3
Sensors	Voltage, current, temperature, light, humidity
Forecast input	OpenWeatherMap API
Edge AI runtime	TensorFlow Lite Micro
Communication	MQTT
Dashboard	ThingsBoard CE

C. Load Classification

Loads are divided into two priority classes so that the controller can decide which loads to curtail (Table II).

TABLE II. LOAD CLASSIFICATION

Class	Examples	Policy
Critical	Security lights	Always on
Non-critical	Decorative lighting, fans	Shed on predicted deficit

D. LSTM-Based Forecasting

An LSTM network is trained on historical generation and load data together with weather inputs retrieved from the OpenWeatherMap API [6]. The trained model is converted for TensorFlow Lite Micro [5] and executed on the ESP32-S3 to predict solar generation and load demand 24 hours ahead. LSTM networks are well suited to this task because they capture temporal dependencies in irradiance and consumption series.

E. Predictive Load-Shedding Logic

The controller compares predicted generation, predicted demand and the present battery state. When the forecast indicates that stored plus generated energy will not cover the demand, the smart relay module disconnects non-critical loads in priority order while critical loads remain supplied. Non-critical loads are restored when the forecast indicates sufficient surplus. This avoids the over-discharge that occurs under fixed-schedule operation.

F. Cloud Monitoring

Measured and predicted values are published over MQTT to a ThingsBoard CE SCADA dashboard, enabling real-time remote monitoring and analytics.

V. IMPLEMENTATION STATUS

A web-based monitoring interface titled “AI Driven Microgrid” has been developed. Its secure login page, with username/e-mail and password fields, introduces the system as a smart energy solution that uses AI and real-time sensor data to improve efficiency; after authentication, the user accesses the microgrid dashboard to monitor and manage the system. Following review feedback, the loads were classified into critical and non-critical groups, the battery specifications and ratings were documented, and the web-page title was changed from “AI Solar Microgrid” to “AI Driven Microgrid.” Remaining work comprises fabrication of the hardware model, integration and testing, and final evaluation, scheduled through November 2026.

VI. EXPECTED RESULTS AND DISCUSSION

The system is expected to (i) keep security loads powered at all times, (ii) lower battery stress by curtailing non-critical loads ahead of predicted shortfalls, and (iii) reduce wasted energy compared with fixed-schedule control. Forecast quality will be assessed using standard metrics such as MAPE and R^2 , as in [1] and [2], and load-shedding performance by comparing battery depth of discharge and energy utilization with and without prediction. Quantitative results will be reported after testing is complete.

VII. CONCLUSION AND FUTURE WORK

This paper has presented an AI-enabled predictive load management scheme for a campus solar microgrid that combines IoT sensing, edge-deployed LSTM forecasting, MQTT cloud monitoring and relay-based load shedding in one pipeline. The architecture addresses the gap between hardware-only and forecast-only solutions. Future work includes completing hardware validation, reporting forecast accuracy and energy savings, and adding prediction-interval estimation [4] to account for forecast uncertainty.

ACKNOWLEDGMENT

The authors thank Prof. M. R. Shelke for guidance and the Department of Electrical Engineering, Priyadarshini College of Engineering, Nagpur, for support.

REFERENCES

- [1] S. R. Biswal et al., “An improved IoT based hybrid predictive load forecasting model for a greenhouse integrated with demand side management,” *IEEE Access*, vol. 13, pp. 108446–108460, 2025.
- [2] A. R. V. Babu et al., “Solar energy forecasting using machine learning techniques for enhanced grid stability,” *IEEE Access*, vol. 13, pp. 93735–93753, 2025.
- [3] M. J. Sammar et al., “Illuminating the future: A comprehensive review of AI-based solar irradiance prediction models,” *IEEE Access*, vol. 12, pp. 114394–114412, 2024.
- [4] N. Sakib et al., “Prediction interval in renewable energy forecasting: A comprehensive review of uncertainty quantification methods,” *IEEE Access*, vol. 13, pp. 185466–185486, 2025.
- [5] TensorFlow Lite Micro Documentation, Google Developers, Jun. 2025. [Online]. Available: <https://www.tensorflow.org/lite/micro>
- [6] OpenWeatherMap API Documentation, Jun. 2025. [Online]. Available: <https://openweathermap.org/api>