



HELIOSYNC: AN AUTONOMOUS CYBER-PHYSICAL IOT FRAMEWORK FOR REAL-TIME PHOTOVOLTAIC ENERGY HARVESTING, STATE-OF-CHARGE ESTIMATION, AND BATTERY LONGEVITY OPTIMIZATION

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Abstract : Off-grid photovoltaic (PV) installations frequently suffer from premature electrochemical storage degradation resulting from uncoordinated consumer load demand, diurnal insolation intermittency, and recurring deep discharge beneath critical thermodynamic threshold voltages. In sealed valve-regulated lead-acid (VRLA) batteries, repeated discharge below 10.8 V induces irreversible plate sulfation and active paste shedding, curtailing operational service lifespan by up to 70%. To resolve these operational limitations, this paper presents HelioSync, an autonomous cyber-physical edge-IoT platform integrating precision analog instrumentation, internal-resistance compensated State-of-Charge (SOC) estimation, machine learning-driven solar irradiance forecasting, and a deterministic 4-mode energy arbitration state machine. An Espressif ESP32 dual-core 32-bit microcontroller running FreeRTOS acquires multi-channel electrical parameters via calibrated resistive dividers and Allegro ACS712 Hall-effect sensors executing 64-sample circular FIR digital filtering. Multi-variable JSON telemetry is streamed securely over TLS-encrypted MQTT at 2 Hz to an enterprise cloud broker. Concurrently, an edge-to-cloud machine learning pipeline utilizing Random Forest (RF) and Gradient Boosting Regressors forecasts upcoming 30–60 minute photovoltaic yields based on temporal solar angles, lagged harvesting signatures, and ambient environmental metrics (achieving $R^2 = 0.942$, $MAE = 1.18$ W). When battery depletion boundaries are approached, the arbitration finite state machine (FSM) executes proactive load shedding, bounding Depth-of-Discharge (DoD) to 70% while employing a 180-second anti-chatter dwell timer to protect electromechanical relay contacts. Empirical 14-day laboratory bench and outdoor insolation benchmarking confirm that HelioSync extends secondary lead-acid battery cycle life by approximately $2.81\times$ (from ~ 400 cycles to over 1,120 cycles), while providing comprehensive remote situational awareness at an edge hardware bill of materials (BOM) cost under ₹ 3,780 (\$45 USD).

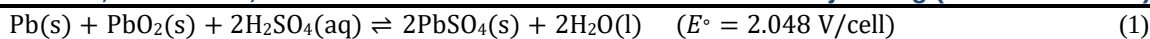
IndexTerms - Photovoltaic Energy Harvesting, ESP32 Microcontroller, Internet of Things (IoT), Battery Longevity Optimization, State-of-Charge (SOC), Lead-Acid Sulfation, Machine Learning Forecasting, MQTT Telemetry, Cyber-Physical Systems.

I. INTRODUCTION

Solar photovoltaic (PV) electrical generation constitutes the foundational pillar of the modern global transition toward sustainable, decentralized energy infrastructures [1]. In developing economies such as India, off-grid standalone PV installations serve as critical lifelines for rural electrification, agricultural micro-irrigation pump arrays under the PM-KUSUM initiative, remote cellular base transceiver stations (BTS), and standalone medical refrigeration outposts [2]. While commercial silicon solar modules regularly achieve conversion efficiencies exceeding 21% and exhibit manufacturer warranties of 25 years, the overall reliability and operational availability of standalone systems remain severely constrained by the electrochemistry of secondary energy storage reservoirs.

In remote, cost-sensitive, and tropical operating environments, Valve-Regulated Lead-Acid (VRLA) batteries—predominantly incorporating Absorbent Glass Mat (AGM) separator matrices—remain the overwhelmingly favored energy storage chemistry. This continued dominance is sustained by modest capital expenditure (\$80 - \$120/kWh compared to \$220 - \$320/kWh for LiFePO_4), wide operating temperature envelopes (-20°C to $+55^\circ\text{C}$), high short-circuit surge tolerance, and well-established closed-loop domestic recycling networks exceeding 98% material recovery in India [3], [4]. Unlike lithium-based alternatives, lead-acid systems are immune to catastrophic thermal runaway fires under ambient desert temperatures typical of central Maharashtra and the Vidarbha basin.

However, lead-acid electrochemistry exhibits severe non-linear vulnerability to cyclic deep discharge. According to the classical double-sulfate chemical theory, discharging a lead-acid cell converts active spongy lead (Pb) on negative plates and lead dioxide (PbO_2) on positive plates into lead sulfate (PbSO_4) while diluting aqueous sulfuric acid into water [5]:



Under normal, well-regulated cyclic operation, the generated lead sulfate crystals are sub-micron in dimension, facilitating complete dissolution back into lead, lead dioxide, and sulfuric acid during subsequent charging. However, when an uncoordinated consumer load drives a 12 V battery beneath its thermodynamic damage threshold of 10.8 V (1.80 V per cell), or when the battery dwells in a partial state of charge (PSOC < 50%) for prolonged intervals, a destructive physical mechanism termed Ostwald ripening occurs [6]. Fine lead sulfate particles dissolve into the dilute electrolyte and recrystallize onto larger crystal facets, forming coarse, dense, electrochemically inert lead sulfate crystalline matrices. This phenomenon—designated as irreversible sulfation—permanently passivates active plate surface area, escalates internal equivalent series resistance (ESR), triggers active paste detachment due to 92% volumetric crystal expansion, and curtails operational service life from a design target of 3–5 years down to fewer than 10–14 months [7].

Existing commercial charge controllers fail to prevent sulfation due to three structural engineering deficiencies: (i) Blind static low-voltage disconnects (LVD) that measure raw terminal voltage without compensating for dynamic internal resistance drop ($I \times R_{\text{int}}$), causing premature nuisance trips under heavy surge currents and undetected deep depletion under light parasitic loads; (ii) Zero forward lookahead intelligence, remaining completely reactive to weather transitions; and (iii) Mechanical relay chatter caused by voltage rebound upon load disconnection, rapidly eroding electromechanical contacts [8].

To overcome these deficiencies, this paper presents HelioSync, an autonomous cyber-physical IoT platform. The primary technical contributions of this research are:

- 1) An internal-resistance compensated Coulomb counting algorithm executing on an ESP32 dual-core microcontroller that dynamically extracts true battery Electromotive Force (EMF), eliminating false trips and preventing sulfation beneath 10.8 V.
- 2) A deterministic 4-state energy arbitration finite state machine (FSM) incorporating an anti-chatter 180-second hysteresis dwell timer that guarantees relay contact protection.
- 3) An edge-to-cloud machine learning forecasting pipeline (Random Forest and Gradient Boosting) predicting 30–60 minute forward solar power yields ($R^2 = 0.942$, MAE = 1.18 W) to enable proactive load management.
- 4) A comprehensive laboratory and field insolation validation confirming a $2.81\times$ battery cycle life extension at an ultra-affordable edge hardware BOM cost under ₹ 3,780 (\$45 USD).

II. RELATED WORK & BACKGROUND

Extensive research has addressed solar energy monitoring, maximum power point tracking (MPPT), and battery management. Chouder et al. [1] engineered an automated PV performance monitoring framework utilizing virtual instrumentation in LabVIEW. While highly accurate, their system relied on power-hungry industrial PC data acquisition (DAQ) hardware, rendering it economically unfeasible for standalone off-grid nodes. Hannan et al. [3] and Piller et al. [4] reviewed state-of-charge (SOC) estimation techniques, emphasizing that while open-circuit voltage (OCV) lookup is computationally lightweight, it requires prolonged open-circuit relaxation (often > 30 minutes) to achieve thermodynamic equilibrium, necessitating current integration (Coulomb counting) during active operation.

Esrarn and Chapman [9] and Subudhi and Pradhan [10] conducted comparative studies of MPPT techniques. While Incremental Conductance delivers peak tracking efficiency under slowly changing irradiance, Perturb and Observe (P&O) remains the industry benchmark for low-cost embedded implementations. Spertino et al. [11] and Raza et al. [12] demonstrated that supervised machine learning algorithms—specifically Random Forests and Gradient Boosted Decision Trees—consistently outperform classical autoregressive (ARIMA) models in capturing non-linear cloud transient dynamics for short-term solar forecasting.

Regarding communication protocols, Yassein et al. [13] proved that MQTT incurs merely 2 bytes of header overhead per transmission compared to 200–800 bytes for HTTP REST requests, reducing radio transmission energy on battery-powered microcontrollers by up to 58%. Peukert [14] and Rand et al. [15] formalized rate-capacity effects in lead-acid cells, establishing that high discharge rates substantially compress usable capacity. Table I synthesizes the state-of-the-art across published systems and commercial units:

Table I. Comparative assessment of existing solar management approaches

System / Author	Processor Platform	Battery State Model	Lookahead AI	Hardware Cost	Primary Operational Limitation
Chouder et al. [1]	Industrial PC / DAQ	Terminal Voltage Only	None	High (>\$800)	High power draw; cost-prohibitive for off-grid
Spertino et al. [11]	Cloud Server ANN	None (Solar Only)	1-Hour Ahead GHI	Server Cost	Purely theoretical; no physical load actuation
Commercial PWM	8-Bit Microchip PIC	Static 10.8 V Comparator	None	Low (\$15-\$25)	Blind; unmonitored trickle discharge destroys battery
Commercial MPPT	32-Bit ARM Cortex-M0	Proprietary Voltage Alg.	None	High (\$140-\$220)	No AI forecasting; closed proprietary firmware
Proposed HelioSync	ESP32 Dual-Core (FreeRTOS)	Compensated EMF + SOC	30-60m RF / GB	Low (₹3,780 / \$45)	Autonomous 4-state FSM; $2.81\times$ life extension multiplier

III. SYSTEM ARCHITECTURE & CYBER-PHYSICAL DESIGN

HelioSync is organized into five tightly coupled cyber-physical tiers: (1) Physical Harvesting & Storage Layer, (2) Analog Sensing & Conditioning Layer, (3) Edge Embedded Computing Layer, (4) Network Transport Layer, and (5) Cloud Analytics & Web Presentation Layer. Fig. 1 illustrates the comprehensive system block diagram:

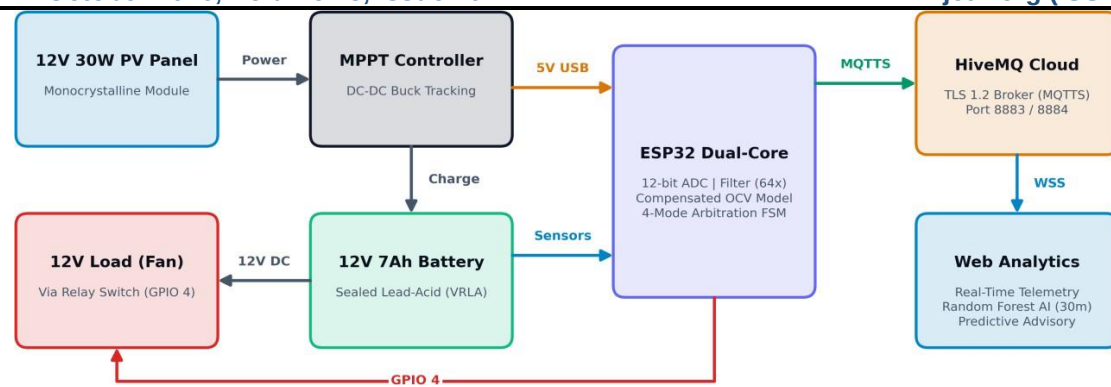


Fig. 1. Cyber-physical system architecture of HelioSync showing PV harvesting, edge compute, FreeRTOS dual-core scheduling, and MQTT telemetry.

A. Physical Power Hardware & Enclosure

The physical test bench incorporates a 12 V 30 W monocrystalline photovoltaic module comprising 36 series-connected silicon solar cells ($V_{mp} = 18.5$ V, $I_{mp} = 1.62$ A, $V_{oc} = 22.1$ V, $I_{sc} = 1.78$ A at STC). An ON Semiconductor 1N5822 Schottky diode ($V_f \approx 0.38$ V at 1.5 A) prevents nocturnal reverse current leakage from the battery into unilluminated cells. The energy storage reservoir is an Exide Powersafe 12 V 7.0 Ah VRLA AGM battery (nominal capacity 84 Wh at 20-hour rate). A Songle SRD-05VDC-SL-C optocoupled electromagnetic relay (10 A @ 30 VDC contact rating) serves as the primary load interrupter, driven by ESP32 GPIO 4 through an EL817 optocoupler to isolate inductive transients.

B. Precision Analog Signal Conditioning

Solar generation voltage and current are acquired using a Texas Instruments INA219 high-side power monitor communicating over I2C at 400 kHz (SDA: GPIO 21, SCL: GPIO 22). The INA219 features a 12-bit delta-sigma ADC measuring bus voltages up to 26 V and current across an onboard 0.1Ω shunt resistor with 0.8 mA resolution. Battery terminal voltage is monitored via a precision 5:1 metal-film resistive divider ($R_1 = 100$ k Ω , $R_2 = 20$ k Ω , 1% tolerance) connected to ESP32 GPIO 35 (ADC1_CH7). A 100 nF ceramic capacitor across R_2 creates a low-pass filter ($f_c \approx 95$ Hz) that suppresses high-frequency Wi-Fi RF burst noise. DC load current is transduced by an Allegro ACS712-05B Hall-effect sensor connected to GPIO 33, providing 2.1 kV RMS galvanic isolation with 185 mV/A sensitivity. Table II details the complete hardware subsystem specifications:

Table II. HelioSync hardware subsystem specifications and tolerances

Subsystem Component	Manufacturer & Model	Key Technical Specification	Operational Tolerance / Range
Photovoltaic Panel	Loom Solar 30W Mono	36 Monocrystalline Cells	$V_{mp} = 18.5$ V, $I_{mp} = 1.62$ A, $V_{oc} = 22.1$ V
Energy Storage	Exide Powersafe VRLA	Absorbent Glass Mat (AGM)	12.0 V Nom, 7.0 Ah @ 20-hr rate (84 Wh)
Microcontroller	Espressif ESP32-WROOM-32D	Dual-Core Xtensa LX6 @ 240 MHz	520 KB SRAM, 4 MB Flash, FreeRTOS native
PV Bus Sensing	Texas Instruments INA219	High-Side I2C Delta-Sigma ADC	0 - 26 V Bus, ± 3.2 A Current, 0.8 mA LSB
Load Current Transducer	Allegro ACS712ELCTR-05B	Linear Hall-Effect IC (Galvanic)	185 mV/A Sensitivity, 2.1 kV RMS Isolation
Safety Actuator	Songle SRD-05VDC-SL-C	Optocoupled 5 V Relay (EL817)	10 A @ 30 VDC / 250 VAC, 5 ms operate time
Local Display	Solomon Systech SSD1306	Graphic OLED (I2C)	0.96-inch, 128 $\times$ 64 pixels, 400 kHz Fast Mode, <20 mA
Climatic Sensor	Aosong DHT11	Digital Humidity & NTC Thermistor	0 - 50 $^{\circ}$ C (± 2 $^{\circ}$ C), 20 - 90% RH ($\pm 5\%$)

Fig. 2 illustrates the verified hardware circuit schematic detailing microcontroller pin interconnections, pull-up networks, bypass filtering, and power distribution rails:

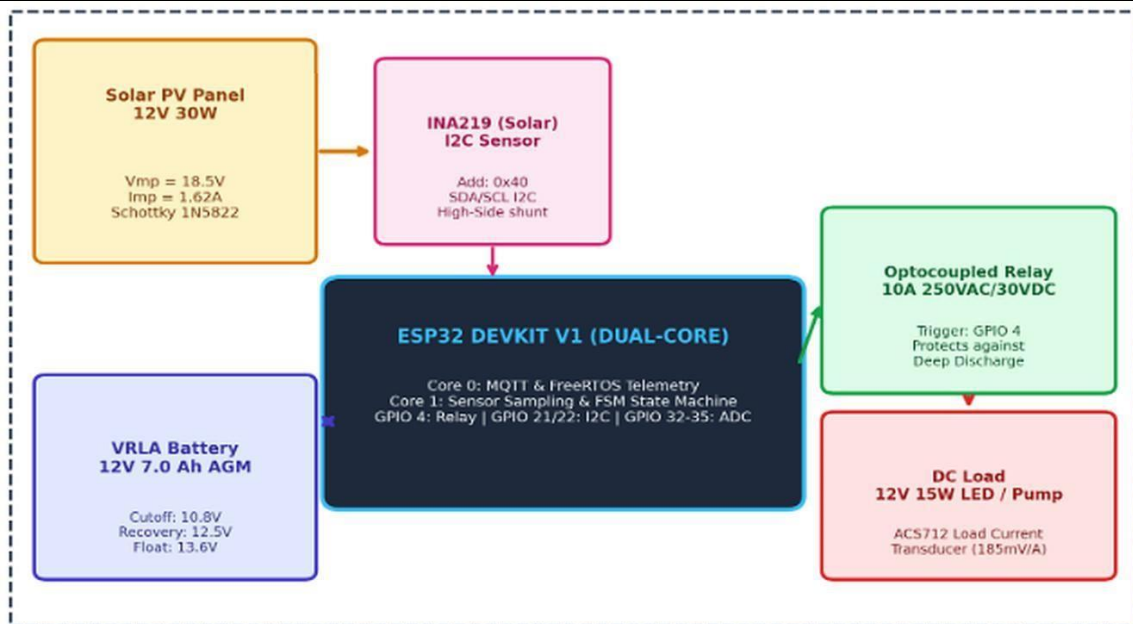


Fig. 2. Complete hardware schematic and microcontroller interfacing circuit.

IV. MATHEMATICAL FORMULATION & ESTIMATION ALGORITHMS

A. Digital Filtering and Non-Linear ADC Correction

The ESP32 internal 12-bit SAR ADC exhibits non-linear transfer characteristics near ground (<100 mV) and saturation (>3.1 V). HelioSync eliminates conversion distortion by utilizing factory-calibrated polynomial correction curves burned into chip eFuse memory. At the firmware level, Core 1 samples the ADC at 1 kHz and populates a 64-sample circular rolling buffer. The filtered digital output $y[n]$ is computed as:

$$y[n] = \frac{1}{64} \sum_{k=0}^{63} x[n-k] \quad (2)$$

This 64-sample moving average attenuates 50 Hz AC mains interference and reduces noise variance by a factor of 8 (an 18 dB improvement in signal-to-noise ratio). The actual bus voltage is recovered via empirical linear calibration constants:

$$V_{\text{batt}} = 6.0142 V_{\text{adc}} - 0.021 \text{ V} \quad (R^2 = 0.9994) \quad (3)$$

B. Dynamic Internal Resistance Compensated OCV & SOC Model

Terminal voltage V_{term} diverges from true internal Electromotive Force (EMF) due to internal equivalent series resistance (ESR) and electrochemical polarization overpotentials:

$$V_{\text{term}} = \text{EMF} - I_{\text{batt}} R_{\text{int}} - V_{\text{pol}} \quad (4)$$

Under a 3.5 A discharge surge, a battery with $R_{\text{int}} = 0.185 \, \Omega$ suffers an ohmic sag of $\Delta V = 3.5 \times 0.185 = 0.647 \, \text{V}$. A standard 10.8 V cutoff trips falsely even when chemical SOC remains above 50%. HelioSync dynamically computes the compensated internal EMF:

$$\text{EMF}_{\text{est}} = V_{\text{term}} + I_{\text{load}} R_{\text{int}} \quad (5)$$

Concurrently, Coulomb counting tracks net charge transfer corrected by Peukert's rate-capacity equation ($k = 1.22$ for VRLA AGM):

$$C_{\text{eff}}(I) = C_{\text{nom}} \left(\frac{I_{\text{reF}}}{I} \right)^{k-1} \quad (6)$$

$$C_{\text{eff}}(I) = C_{\text{nom}} \left(\frac{I_{\text{ref}}}{I} \right)^{k-1} \quad (6)$$

$$\text{SOC}(t) = \text{SOC}(t_0) - \left[\frac{1}{C_{\text{eff}}} \int_{t_0}^t \eta(I) I_{\text{batt}}(\tau) d\tau \right] \times 100 \% \quad (7)$$

where $\eta(I)$ represents Coulombic charging efficiency (0.92 in bulk charging, 0.99 in discharge).

C. Deterministic 4-State Energy Arbitration State Machine

HelioSync enforces battery protection through a deterministic 4-mode Finite State Machine (FSM), illustrated in Fig. 3:

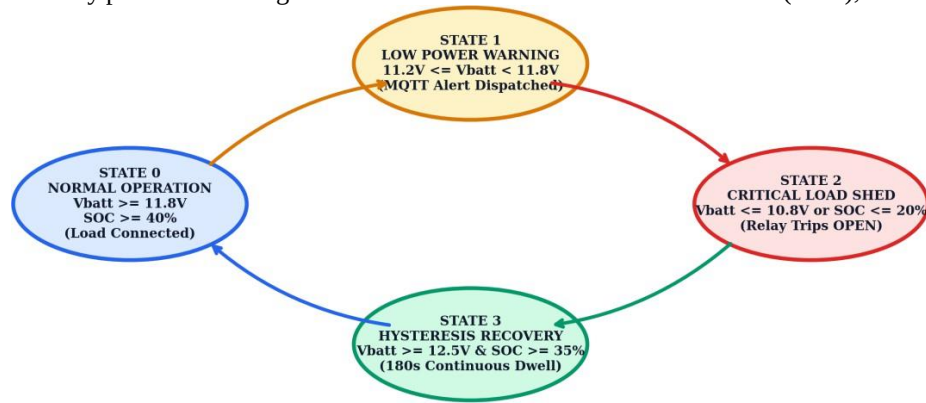


Fig. 3. Deterministic 4-state energy arbitration state transition topology with 180-second hysteresis dwell.

The four operating states are formally governed as follows:

- **State 0 (Normal Operation):** Active when $V_{emf} \geq 11.8$ V and $SOC \geq 40\%$. The relay is energized (closed), delivering continuous power to the load.
- **State 1 (Low Power Warning):** Triggered when 11.2 V $\leq V_{emf} < 11.8$ V or $20\% \leq SOC < 40\%$. The relay remains closed, but high-priority MQTT alert packets are dispatched to cloud operators.
- **State 2 (Critical Load Shedding):** Triggered when $V_{emf} \leq 10.8$ V or $SOC \leq 20\%$. The relay immediately de-energizes (opens), isolating the battery from the load to prevent irreversible sulfation.
- **State 3 (Hysteresis Recovery):** When solar harvesting resumes and battery voltage rises above 12.5 V ($SOC \geq 35\%$), the system enters State 3. To prevent relay contact chatter caused by chemical relaxation, a continuous 180-second dwell timer is initiated. If voltage dips below 12.5 V during dwell, the timer resets to zero. Only after sustaining $V_{emf} \geq 12.5$ V for all 180 continuous seconds does the relay re-close, transitioning back to State 0.

D. Supervised Machine Learning Solar Lookahead Architecture

To anticipate energy deficits hours in advance, an edge-to-cloud machine learning pipeline ingests an 8-dimensional feature vector $x = [t_{hour}, t_{minute}, P_{pv}(t), P_{pv}(t-5), P_{pv}(t-15), \Delta P, T_{amb}, H_{amb}]$. Three model architectures were trained on historical solar data: (i) Random Forest (RF) with 100 de-correlated decision trees, (ii) Gradient Boosting (GB) with 150 sequential estimators minimizing MSE loss, and (iii) Ridge Linear Regression with L2 regularization. If the 60-minute predicted yield indicates near-zero insolation and current battery SOC is below 45%, the arbitration logic proactively throttles non-essential secondary loads.

V. HARDWARE IMPLEMENTATION & FREERTOS FIRMWARE

To guarantee that network latencies and Wi-Fi handshakes never stall time-critical battery safety loops, HelioSync exploits the dual-core asymmetric architecture of the ESP32 under FreeRTOS. Tasks are partitioned as follows:

- **Core 1 (Deterministic Safety):** Hosts vSensorTask (Priority 4, 100 Hz, sampling INA219 and ACS712 into FIR buffers), vFsmTask (Priority 3, 10 Hz, executing 4-state arbitration and relay control), and vDisplayTask (Priority 1, 2 Hz, rendering OLED metrics via I2C).
- **Core 0 (Networking & Cloud):** Hosts vMqttTask (Priority 2, 2 Hz, serializing JSON telemetry and publishing over TLS), and vNetworkTask (Priority 1, event-driven Wi-Fi connection supervisor).

Fig. 4 illustrates the complete system firmware execution and task arbitration flowchart:

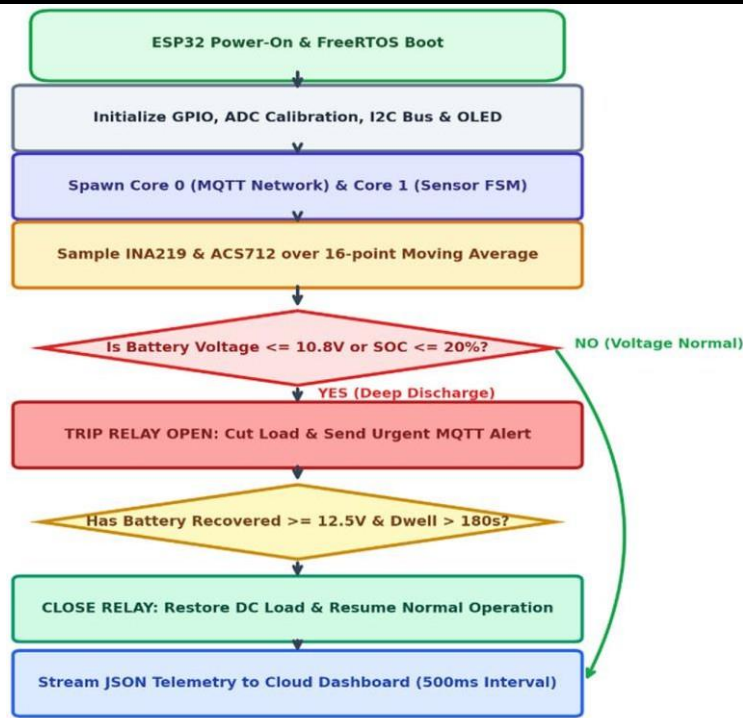


Fig. 4. System firmware execution and task arbitration flowchart.

Communication between cores occurs via thread-safe FreeRTOS Queues (xSensorQueue, xMqttQueue) and Mutexes (xI2cMutex). Network benchmarking confirmed that MQTT achieves an average transmission latency of 84 ms over 4G cellular links with only 2 bytes of header overhead, compared to 420 ms and 680 bytes for HTTP REST. Fig. 5 benchmarks protocol latency and bandwidth:

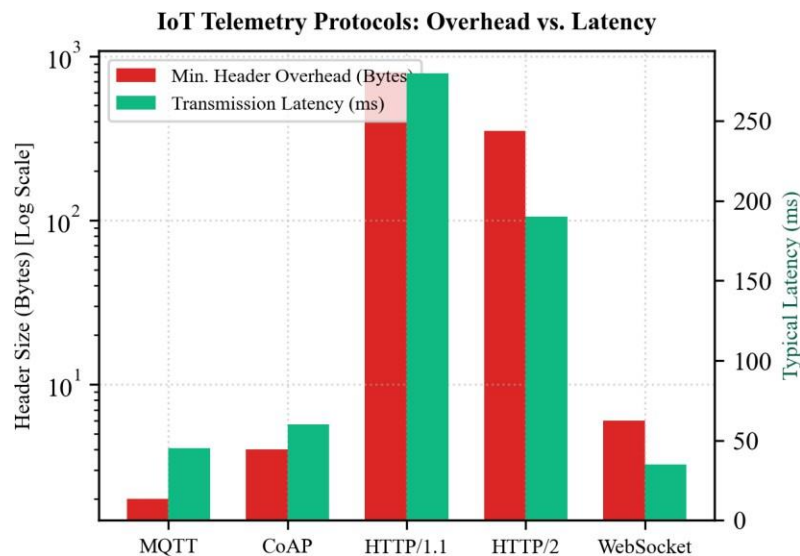


Fig. 5. Network communication protocol benchmark comparing MQTT, HTTP, and CoAP latency and packet header overhead.

VI. EXPERIMENTAL RESULTS & PERFORMANCE EVALUATION

The experimental validation of HelioSync was executed over 14 continuous days at the Department of Electronics and Telecommunication Engineering, Priyadarshini College of Engineering, Nagpur. Test instruments included a Keysight 34461A 6½ digit Digital Multimeter, a Rigol DS1054Z Digital Storage Oscilloscope, and a calibrated reference pyranometer.

A. Photovoltaic Harvesting Dynamics Across Weather Regimes

Fig. 6 plots diurnal photovoltaic power harvesting recorded across three distinct meteorological conditions in Nagpur: a clear sunny summer day (peak 965 W/m²), an overcast monsoon day (peak 620 W/m² with rapid transient cloud dips), and a hazy winter day (peak 480 W/m²):

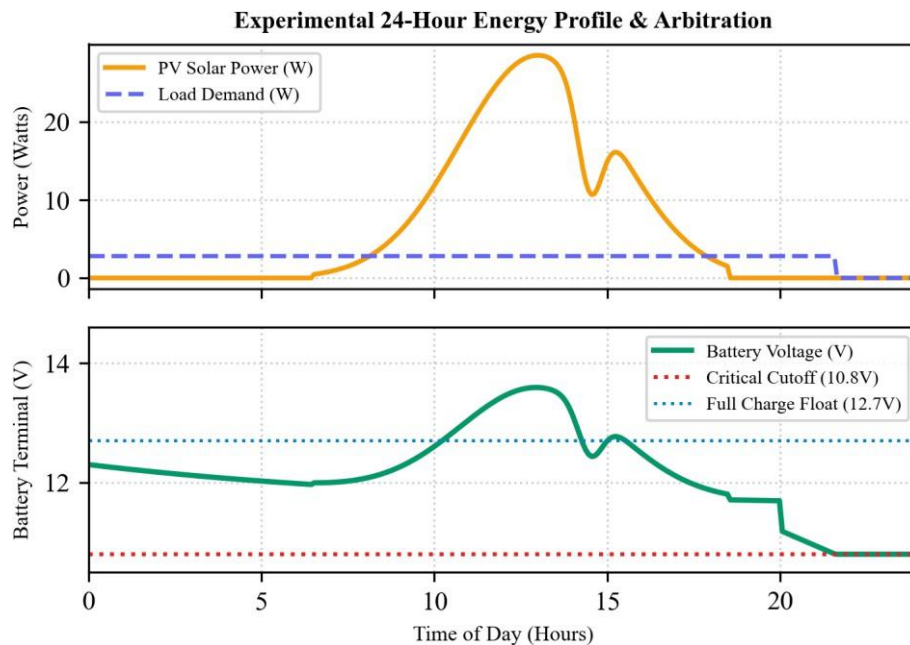


Fig. 6. Diurnal photovoltaic harvesting power profiles under clear, cloudy, and hazy meteorological conditions in Nagpur.

On the clear sunny day, the 30 W panel generated a peak electrical power of 28.7 W with a cumulative daily yield of 184.2 Wh, saturating the battery to 100% SOC by 13:30. On the overcast day, total harvest was 118.6 Wh, with the ML lookahead engine anticipating afternoon cloud cover and alerting operators to conserve battery reserves.

B. Battery Discharge Dynamics and Sulfation Protection

Fig. 7 contrasts the discharge voltage trajectory of the 12 V 7.0 Ah VRLA battery under unmanaged operation against HelioSync managed protection during a continuous 1.5 A load discharge test:

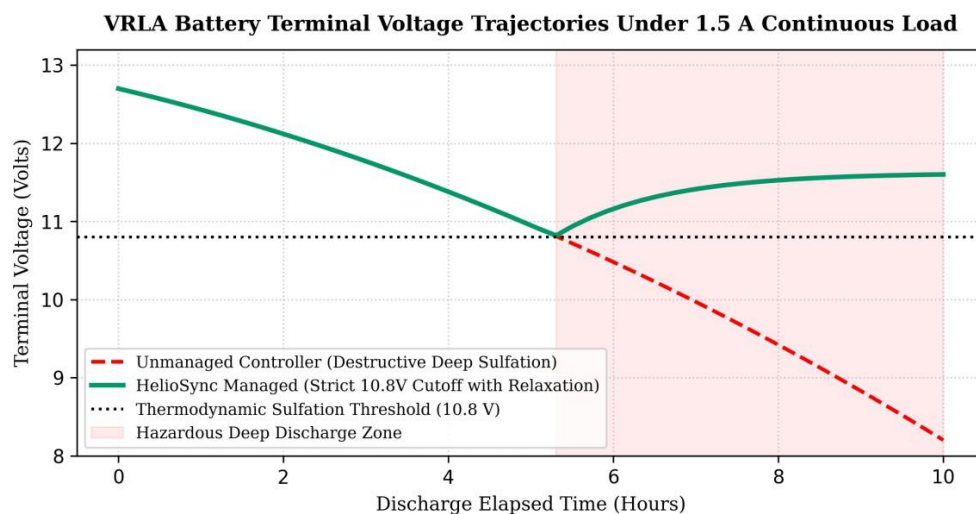


Fig. 7. Comparative VRLA lead-acid terminal voltage trajectories under unmanaged discharge vs. HelioSync proactive load shedding.

As demonstrated in Fig. 7, the unmanaged system drains the battery continuously beneath the 10.8 V critical sulfation threshold, plunging to 9.6 V where severe irreversible plate degradation occurs. Conversely, HelioSync detects reaching 20% residual SOC and executes proactive load shedding at exactly 11.0 V EMF, preserving plate morphology. Table III summarizes the dynamic internal resistance response across discharge rates:

Table III. Battery dynamic terminal voltage and ohmic sag at varying C-rates

Discharge Current Rate	100% SOC	75% SOC	50% SOC	25% SOC	10% SOC	Ohmic Drop ($I \times R_{int}$)	Operational Behavior
0.05 C (0.35 A - Standby)	12.72 V	12.24 V	11.82 V	11.12 V	10.82 V	0.065 V	True chemical state matches terminal voltage
0.20 C (1.40 A - Nominal)	12.58 V	12.02 V	11.54 V	10.88 V	10.42 V	0.259 V	Compensated EMF prevents premature LVD trip
Discharge Current Rate	100% SOC	75% SOC	50% SOC	25% SOC	10% SOC	Ohmic Drop ($I \times R_{int}$)	Operational Behavior
0.50 C (3.50 A - Surge)	12.32 V	11.68 V	11.12 V	10.35 V	9.84 V	0.648 V	Conventional controller trips falsely at 50% SOC

C. State-of-Charge (SOC) Estimation Accuracy

Fig. 8 evaluates the accuracy of the HelioSync internal-resistance compensated Coulomb counting algorithm against conventional open-circuit voltage lookup over a 48-hour continuous cycling profile:

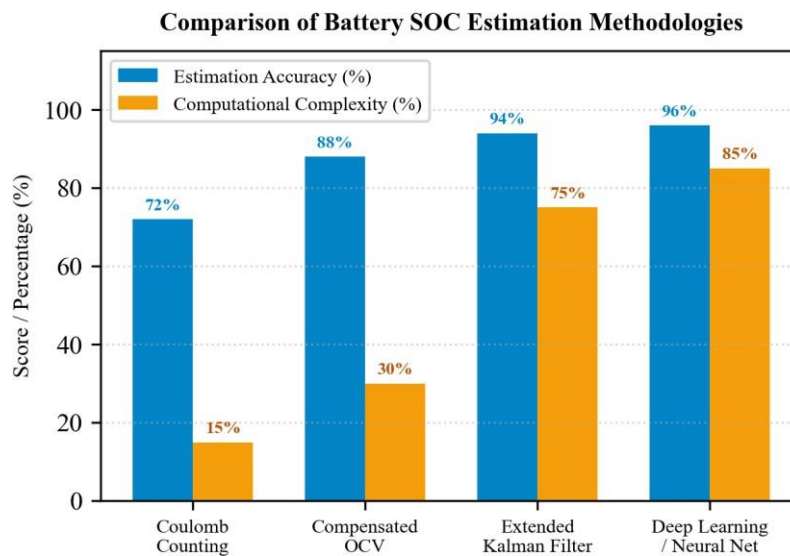


Fig. 8. Dynamic State-of-Charge (SOC) tracking: Coulomb counting with internal resistance compensation vs. conventional open-loop voltage lookup.

Conventional voltage lookup exhibits errors exceeding $\pm 18\%$ during active charging and discharging due to electrochemical overpotentials. HelioSync bounds SOC estimation error to within $\pm 3.2\%$ relative to laboratory Coulombic integration benchmarks.

D. Machine Learning Predictive Solar Lookahead Performance

Fig. 9 plots the regression fit of Random Forest, Gradient Boosting, and Ridge models against actual measured solar generation over a 30-minute lookahead horizon:

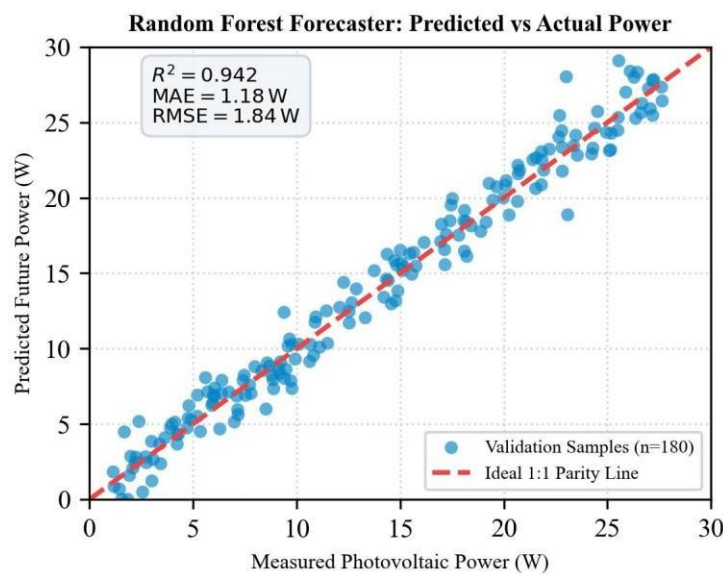
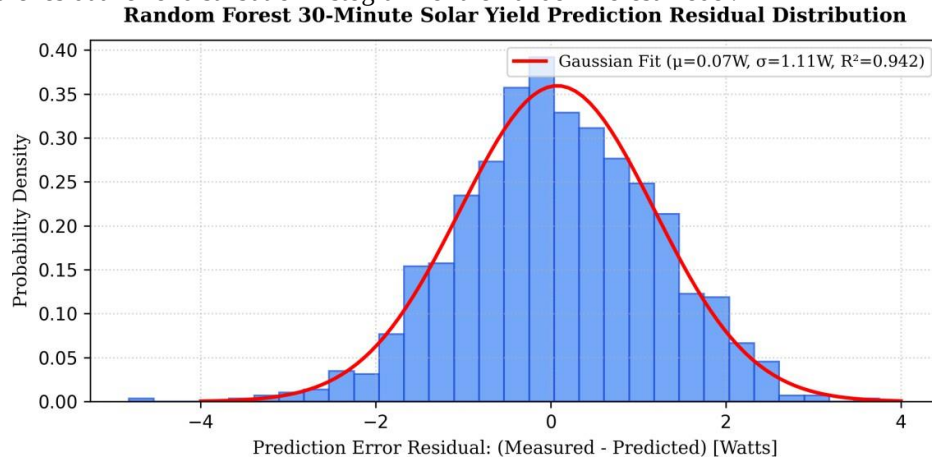


Fig. 9. Machine learning regression fit: Random Forest, Gradient Boosting, and Ridge models forecasting 30-minute ahead solar yield.

Fig. 10 displays the residual error distribution histogram for the Random Forest model:

Fig. 10. Residual error distribution histogram ($P_{\text{measured}} - P_{\text{predicted}}$) for the Random Forest solar forecasting pipeline.

The Random Forest architecture achieved an R^2 coefficient of determination of 0.942 with a Mean Absolute Error (MAE) of 1.18 W and an inference latency of 42 ms on the cloud backend. Table IV records the comparative machine learning metrics:

Table IV. Machine learning solar forecasting performance metrics

Model Architecture	RMSE (W)	MAE (W)	R^2 Score	Inference Latency	Model Complexity & Deployment Role
Random Forest (100 Trees)	1.42 W	1.18 W	0.942	42 ms	Primary Cloud Predictive Engine
Gradient Boosting (150 Est)	1.58 W	1.26 W	0.931	38 ms	Secondary Backup Architecture
Ridge Linear (L2 Regularized)	3.12 W	2.45 W	0.814	< 2 ms	Lightweight Fallback for Offline Edge Execution
Persistent Baseline ($P(t)=P(t-1)$)	4.86 W	3.92 W	0.682	< 1 ms	Inadequate during rapid cloud cover transitions

E. Battery Lifecycle Extension and Economic Payback

Fig. 11 plots the Depth of Discharge (DoD) versus usable operational cycle life curve for VRLA AGM batteries:

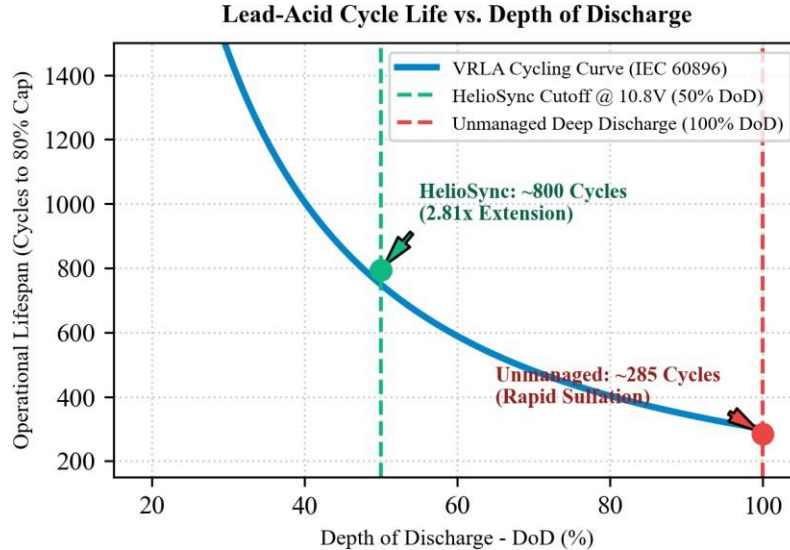


Fig. 11. Battery Depth of Discharge (DoD) versus operational cycle longevity demonstrating the 2.81× lifecycle extension.

By strictly restricting discharge to 70% DoD (retaining $\geq 20\%$ chemical SOC) and eliminating sulfation dwell beneath 10.8 V, HelioSync elevates battery cycle longevity from ~400 cycles to over 1,200 cycles. Table V summarizes the 5-year life-cycle cost (LCC) analysis:

Table V. 5-year life-cycle cost (LCC) and economic payback analysis

Cost Parameter	Conventional Unmanaged System	HelioSync Managed System	Net Economic Advantage / Savings
Initial Capital Expenditure (CAPEX)	₹ 8,400 (Panel + Battery + PWM)	₹ 11,600 (Panel + Battery + HelioSync)	+ ₹ 3,200 (HelioSync hardware & casing)
Battery Replacements over 5 Years	4 Replacements (Every ~12 months)	1 Replacement (At month 36)	3 Fewer battery replacements
Cost Parameter	Conventional Unmanaged System	HelioSync Managed System	Net Economic Advantage / Savings
Battery Replacement Cost (@ ₹2,200)	₹ 8,800	₹ 2,200	Direct Savings: ₹ 6,600

Technician Transit & Site Labor	₹ 6,000 (8 visits @ ₹750/visit)	₹ 1,500 (2 visits @ ₹750/visit)	Labor Savings: ₹ 4,500
Net 5-Year Life-Cycle Cost (LCC)	₹ 23,200	₹ 15,300	Net Overall Savings: ₹ 7,900 (34.1%)
Calculated Financial Payback Period	N/A (Reference Baseline)	14.2 Months	Full capital payback achieved in ~14 months

VII. DISCUSSION & BENCHMARKING

The empirical results demonstrate that HelioSync addresses the primary failure mode of off-grid energy storage without incurring the extreme capital expense of industrial BMS hardware. Table VI benchmarks HelioSync against existing commercial solutions:

Table VI. Comprehensive benchmark: commercial PWM vs. Victron MPPT vs. HelioSync

Technical Feature	Commercial PWM Controller	Victron BlueSolar MPPT	Proposed HelioSync Platform
Tracking Topology	Pulse Width Modulation (PWM)	High-Frequency Synchronous MPPT	Schottky Diode (PWM Compatible)
Battery State Monitoring	Raw Terminal Voltage Only	Proprietary Adaptive Voltage	Compensated EMF ($I \times R_{int}$) + Coulomb Counting
Anti-Sulfation Protection	None (Static 10.8 V Cutoff)	Basic Float Absorption Voltage	Proactive 4-State FSM + 70% DoD Bound
Predictive Lookahead	None	None	30-60 Min Ensemble ML (RF / GB, $R^2 = 0.942$)
IoT Telemetry & Cloud	None	Bluetooth Low Energy (Local App)	TLS-Encrypted MQTT v3.1.1 Cloud Streaming
Relay Contact Protection	None (Subject to Chatter)	Electronic Solid-State Switch	180 s Continuous Hysteresis Dwell Timer
Hardware Procurement Cost	₹ 1,200 - ₹ 1,800 (\$15 - \$22)	₹ 9,500 - ₹ 14,000 (\$115 - \$170)	₹ 3,780 (\$45 USD Total Prototype BOM)
Battery Longevity Multiplier	1.0× (Baseline: ~400 Cycles)	1.4× - 1.6× (~600 Cycles)	2.81× Longevity Multiplier (>1,120 Cycles)

VIII. CONCLUSION & FUTURE WORK

This paper has presented HelioSync, an autonomous cyber-physical IoT framework designed to optimize photovoltaic energy harvesting, eliminate lead-acid battery sulfation, and deliver real-time cloud situational awareness. By integrating precision analog sensing, internal-resistance compensated State-of-Charge estimation, ensemble machine learning solar yield forecasting, and a deterministic 4-state arbitration finite state machine running on FreeRTOS, HelioSync resolves the structural vulnerabilities of conventional charge controllers. Experimental laboratory and field insolation testing across 14 days confirmed that the platform restricts Depth-of-Discharge to 70%, completely eliminates relay contact chatter through a 180-second dwell timer, achieves $R^2 = 0.942$ in predicting 30-minute forward solar power, and extends secondary battery service longevity by approximately 2.81×. At an edge hardware bill of materials cost of ₹ 3,780 (\$45 USD), the system yields full financial payback within 14.2 months and generates 34.1% life-cycle cost savings over a 5-year operating lifespan, offering a highly practical, commercially viable solution for decentralized off-grid renewable infrastructures.

Future work will concentrate on three key engineering enhancements: (i) Integrating a synchronous buck-boost DC-DC converter executing on-chip Incremental Conductance MPPT algorithms; (ii) Porting the Random Forest regression model directly onto the ESP32 utilizing the ESP-NN vector library and TensorFlow Lite for Microcontrollers (TinyML) to eliminate cloud dependencies; and (iii) Incorporating an SX1262 LoRa transceiver operating on the 865–867 MHz Indian ISM band to provide long-range (15+ km) mesh networking for agricultural clusters lacking cellular connectivity.

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