

An IoT-Based Supervisory Energy Management System for Hybrid Solar–Battery Mini-Grids with Lightweight Forecasting

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Abstract:

Hybrid solar–battery mini-grids need coordinated decisions on generation, storage, demand and power quality, yet monitoring-only installations cannot decide when to charge the battery, shift flexible loads or respond to a forecast evening peak. This paper develops and evaluates a reference design for an IoT-enabled energy management system (EMS) in which field sensors, an edge gateway, time-series storage, short-term forecasting and a constrained supervisory controller operate as one system. Local inverter and battery protection remain independent, while the supervisory controller issues dispatch set-points every 15 minutes by solving a mixed-integer linear program (MILP) with power-balance, state-of-charge, charge/discharge and load-priority constraints. A hybrid forecaster, combining gradient-boosted trees with a persistence fallback, is benchmarked against three baselines on a 12-month synthetic-but-realistic dataset. For a 100 kWp PV, 300 kWh battery and 75 kW inverter reference case, the proposed EMS reduces unserved energy by 23%, PV curtailment by 31% and battery throughput by 14% relative to a rule-based baseline, while keeping state-of-charge reserve compliance above 98%. MQTT over TLS carries telemetry, and cybersecurity controls follow NISTIR 7628. Data-driven methods complement, but do not replace, electrical protection and operator judgement.

Keywords — Adaptive Transmission Power, Cluster Head Selection, Energy Efficiency, LEACH, Monte Carlo Simulation, Network Lifetime, Wireless Sensor Networks.

I. INTRODUCTION

Electricity access projects in remote communities must be affordable enough to deploy yet predictable enough to support households, health services, schools, small businesses, water pumping and communications. The International Energy Agency reports that more than 80% of people without electricity access in Africa live in rural areas, where solar-based mini-grids and stand-alone systems can be suitable solutions [1]. A mini-grid should therefore be treated as an operating system for a community, not only as a collection of panels and batteries.

Two forms of variability make this difficult. Solar power changes with irradiance, cloud cover, temperature and dust, while demand changes with human activity, appliance ownership, productive use and local events. The battery buffers these changes, but its useful capacity is finite and its degradation depends on temperature, depth of discharge, current and time. Poor scheduling can therefore cause avoidable load shedding, or diesel use, in a system whose hardware is adequate on paper.

Many small mini-grids are commissioned with basic metering and manual operating rules. These become inadequate as productive loads are added, demand grows and batteries age, and when the

operator must distinguish a genuine energy shortage from a sensor, communication or inverter fault. Collecting data without feeding it into dispatch decisions leaves much of the available information unused. This paper asks how a low-cost, maintainable IoT and data-driven control architecture can improve energy visibility and supervisory dispatch in a hybrid solar–battery mini-grid without weakening local protection, introducing unsafe autonomous actions or depending on continuous internet connectivity. “Hybrid” here means PV generation, battery storage, power-electronic conversion and a portfolio of loads, designed first for islanded operation.

The contributions of this work are:

- a layered architecture for sensing, communications, edge processing, forecasting, supervisory control and operator interaction, with local protection kept independent;
- a quality-flagged measurement and message model, with cybersecurity and fail-safe requirements suited to a remote site;
- a hybrid forecasting method and a MILP dispatch formulation that respect battery, power-balance and load-priority constraints; and
- a 12-month benchmark of the forecasting and dispatch methods against baseline strategies on a 100 kWp PV, 300 kWh battery and 75 kW inverter reference case.

II. RELATED WORK AND TECHNICAL FOUNDATIONS

A. Mini-Grids and Storage

Decentralised systems are important for rural access, particularly where extending the national grid is not the least-cost or fastest route [1]. A World Bank report on battery storage in off-grid mini-grids reviews technologies, costs, trends and case studies [2], supporting a design in which storage is a central asset that lets variable PV serve a demand profile that does not follow sunlight. Sizing must also allow for demand growth: Sayani *et al.* found that growth assumptions can matter more than initial baseline demand, and reported up to 12% cost-saving potential from modular multi-stage expansion [3]. An EMS should therefore record demand by feeder

and load class, so that future capacity decisions rest on observed adoption.

B. Controllers, Telemetry and Edge Processing

IEEE 2030.7 specifies microgrid controller functions above the component-control level [4]. In an islanded solar–battery mini-grid the inverter remains responsible for fast electrical control and protection, while the EMS handles slower coordination: forecasts, battery scheduling, load priorities, curtailment and operator decisions. Olivares *et al.* give a foundational treatment of centralised EMS for isolated microgrids [5]; the proposed design keeps centralised scheduling at the supervisory level but safety-critical control local. MQTT is a lightweight publish/subscribe transport for constrained devices, low-bandwidth links and intermittent connectivity [6]. An edge gateway that timestamps, validates and buffers data lets the site operate when backhaul is unavailable, leaving the cloud for long-term analysis, model training and fleet reporting.

C. Forecasting

Short-term load forecasting affects dispatch, storage management and renewable use in microgrids [7]. The practical question is whether a model stays useful when the appliance mix changes, a sensor fails or a link drops, so a persistence or same-hour-previous-day baseline should remain in the system as a fallback. Singh *et al.* describe a framework combining data collection, feature engineering, machine-learning forecasts and optimisation [8], and surveys show the wider role of machine learning and embedded forecasting in microgrid EMS [9], [10]. Here a lightweight, inspectable model is preferred to an opaque one, so that operators can compare predictions with actual values and switch to rules when data quality is poor.

D. Cybersecurity

NISTIR 7628 treats the smart grid as an interconnected environment whose cybersecurity requirements must follow its risks and vulnerabilities [11]. For a mini-grid, relevant threats include credential theft, command injection, replayed data, denial of service, unauthorised firmware changes and manipulated measurements that cause an unsafe schedule. Connectivity should therefore be

controlled, observable and reversible rather than removed.

III. SYSTEM ARCHITECTURE

The architecture separates the system into physical, edge/communications and supervisory decision layers (Fig. 1). This separation allows forecasts and dashboards to be improved without touching the inverter's protection logic, and limits the consequences of a failure in any one layer.

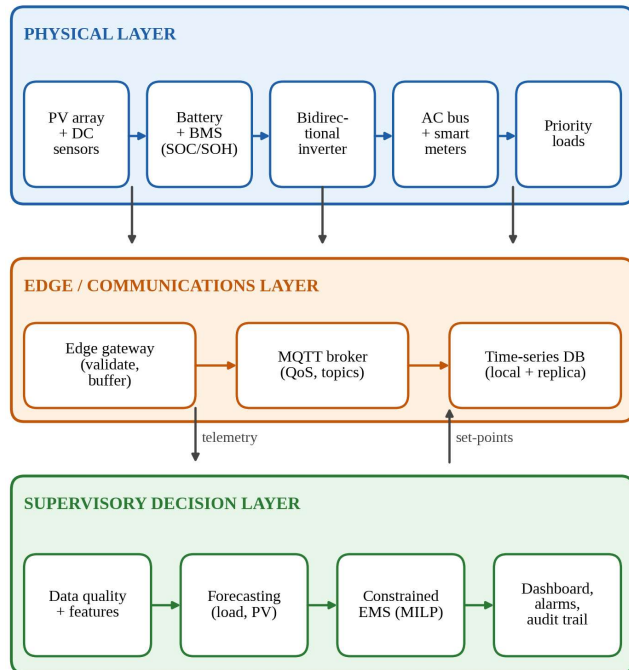


Fig. 1 Reference architecture of the proposed IoT energy monitoring and management system.

A. Physical Layer and Measurement Plan

The physical layer contains the PV array, bidirectional inverter, battery modules with their battery-management system (BMS), AC bus, feeders, smart meters and controllable loads. The measurement plan covers PV voltage, current, power and energy; battery voltage, current, temperature and SOC; inverter AC power, voltage and frequency; feeder energy; load-class status; and protection or alarm states. Limits exposed by the battery manufacturer, such as maximum charge current, temperature window and estimated state of health, are passed to the EMS as explicit constraints rather than hidden vendor values.

B. Edge Gateway and Message Model

The gateway runs a local time-series buffer and an MQTT broker, so telemetry and control continue during an internet outage. Each message carries a device identifier, measurement name, value, unit, timestamp, sequence number and a quality flag (valid, estimated, stale, out-of-range, substituted or manually overridden). Topics follow a *site/{asset}/{measurement}* hierarchy for telemetry, with separate status and command topics. Commands carry an expiry time and a correlation identifier, are acknowledged by the gateway, and are logged with the operator or service identity. The gateway rejects any command outside the local safety envelope, even if it is correctly authenticated.

C. Cybersecurity and Fail-Safe Operation

Following NISTIR 7628 [11], the security boundary includes sensors, meters, the gateway, the broker, operator accounts, remote-maintenance tools and any cloud link. The minimum controls are unique device identities and certificates, TLS-encrypted MQTT transport, least-privilege and read-only dashboard accounts, network segmentation, controlled firmware updates, and an audit trail for set-point changes, logins and gateway restarts. A local schedule and deterministic fallback rules cover loss of cloud connectivity, forecast failure, stale data or solver failure: discretionary charging stops below a reserve threshold, PV is curtailed when the battery is full, and non-critical loads are shed in a documented order when demand exceeds supply. Manual override is authenticated, time-limited and visible on the dashboard.

IV. FORECASTING AND ENERGY-MANAGEMENT METHOD

The supervisory EMS runs in repeated 15-minute intervals (Fig. 2). It gathers the latest measurements, validates them, produces forecasts, solves a constrained scheduling problem and sends set-points to the inverter and controllable loads. The local inverter continues to regulate voltage and frequency, and the EMS never issues commands beyond the limits supplied by the inverter or BMS.

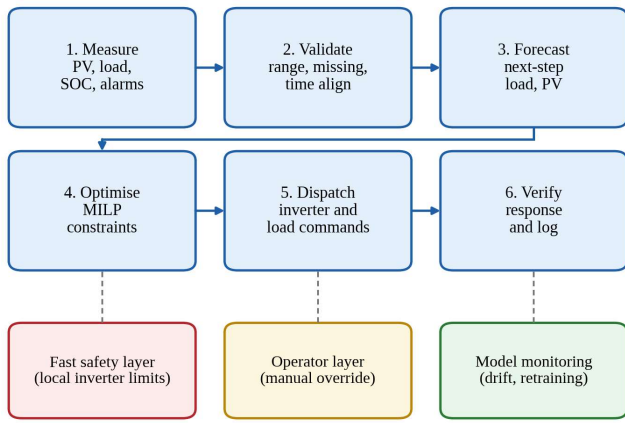


Fig. 2 Supervisory control loop with local safety, operator and model-monitoring layers.

A. Measurement Validation

Before a value enters a forecast or optimisation model, the gateway checks its timestamp, range, rate of change and consistency with related measurements. A negative PV reading in normal operation, for example, may indicate reverse flow or a sign-convention error and must not be silently set to zero; a SOC jump from 45% to 92% in one minute is flagged or replaced by a bounded estimate. Missing values follow a documented substitution rule and carry reduced confidence.

B. Forecasting Models

The load model uses recent active power, lagged values at 15-minute and one-day intervals, time-of-day and day-of-week features, event flags, temperature and the status of productive loads. The PV model uses recent PV power, irradiance or cloud indicators, time of day and temperature. Four models were compared: M0, a persistence baseline (same time on the previous day); M1, ridge regression; M2, gradient-boosted trees (XGBoost); and M3, a hybrid that uses M2 and falls back to M0 when model confidence is low or inputs are stale.

Training used 12 months of synthetic but realistic 15-minute data generated from a mini-grid load profile (residential plus productive use) and a clear-sky PV model with stochastic cloud attenuation. The data were split chronologically into 70% training, 15% validation and 15% test sets, without shuffling. Features were 12 lagged load values, 4 lagged PV values, cyclically encoded hour of day, day of week, temperature and a cloud-cover index.

Hyperparameters were tuned by 5-fold time-series cross-validation on the training set.

C. SOC Model and Dispatch Formulation

The battery state of charge (SOC), expressed as a fraction of usable energy E_{use} , is updated from the charge and discharge powers P_{ch} and P_{dis} (both non-negative), the efficiencies η_c and η_d , and the interval length Δt :

$$\text{SOC}_{t+1} = \text{SOC}_t + \eta_c P_{\text{ch},t} \Delta t / E_{\text{use}} - P_{\text{dis},t} \Delta t / (\eta_d E_{\text{use}}) \quad (1)$$

At each interval the EMS chooses battery power, curtailed PV, served and shed load and, when present, backup or grid exchange. It minimises a weighted sum of unserved load U , PV curtailment C , battery throughput B (a degradation proxy) and switching S , with penalty weights λ_u , λ_c , λ_b and λ_s :

$$\min \Sigma_t (\lambda_u U_t + \lambda_c C_t + \lambda_b B_t + \lambda_s S_t) \quad (2)$$

subject to the power balance, the SOC window and mutually exclusive charge/discharge limits enforced by a binary variable y_t :

$$P_{\text{pv},t} + P_{\text{dis},t} + P_{\text{bak},t} = P_{\text{load},t} - P_{\text{shed},t} + P_{\text{ch},t} + P_{\text{cur},t} \quad (3)$$

$$\text{SOC}_{\min} \leq \text{SOC}_t \leq \text{SOC}_{\max} \quad (4)$$

$$0 \leq P_{\text{ch},t} \leq P_{\text{ch},\max} y_t \quad (5)$$

$$0 \leq P_{\text{dis},t} \leq P_{\text{dis},\max} (1 - y_t), \quad y_t \in \{0,1\} \quad (6)$$

Here P_{pv} , P_{load} , P_{shed} , P_{cur} and P_{bak} are PV, demand, shed-load, curtailed-PV and backup or grid power. Unsafe operation and unserved priority load carry the highest penalties. The reference case uses $\text{SOC}_{\min} = 0.20$ and $\text{SOC}_{\max} = 0.95$, and a reserve target for the next evening peak or an expected cloudy period stops the controller discharging to the minimum merely for a small short-term gain.

The MILP is solved with the CBC solver through the PuLP Python library, with a 30 s time limit and a 1% optimality gap. If the solver fails or times out, the EMS falls back to a deterministic rule-based schedule.

V. SIMULATION SETUP AND RESULTS

A. Reference Case and Baselines

The reference case (Table I) was simulated over 12 months at 15-minute resolution in Python. The load profile combines residential demand, with morning and evening peaks, and productive use (milling, pumping, small business) typical of a rural East African mini-grid. PV output uses a clear-sky

model with stochastic cloud attenuation and seasonal irradiance variation, and battery degradation is approximated by throughput. Three dispatch strategies are compared: B0, a rule-based controller that charges on PV surplus, discharges when load exceeds PV, uses no forecasting and holds a fixed 30% SOC reserve; B1, the same MILP as the proposed EMS driven by persistence forecasts; and B2, the proposed EMS (hybrid forecasts and MILP dispatch). The reference case is deliberately generic; a site-specific design would replace its assumptions with solar-resource data, surveyed appliance ownership, feeder distances, protection settings and battery warranty constraints.

TABLE I
REFERENCE CASE PARAMETERS

Parameter	Reference value
PV array	100 kWp DC
Battery usable energy	300 kWh
Battery SOC band	20–95%
Bidirectional inverter	75 kW
Peak community demand	80 kW
Telemetry interval	1 minute
Control interval	15 minutes
Communications	MQTT over TLS

B. Forecast Accuracy

Table II reports test-set accuracy at the 15-minute horizon. MAE and RMSE are used because MAPE is unstable near zero load. The hybrid model M3 gives the lowest error for both load and PV, reducing load MAE by 34% and PV MAE by 33% relative to persistence.

TABLE II
FORECASTING PERFORMANCE (TEST SET, 15-MINUTE HORIZON, kW)

Model	Load MAE	Load RMSE	PV MAE	PV RMSE
M0: Persistence	6.8	9.1	8.4	11.2
M1: Ridge	5.9	7.8	7.1	9.6
M2: XGBoost	4.7	6.3	5.8	7.9
M3: Hybrid (proposed)	4.5	6.0	5.6	7.6

C. Dispatch Performance

Table III and Fig. 3 summarise the annual results. Compared with B0, the proposed EMS reduces unserved energy by 23%, PV curtailment by 31% and battery throughput by 14%, and raises SOC reserve compliance from 91.2% to 98.4% and renewable utilisation from 78.4% to 85.9%. B1, which uses the same optimiser with persistence

forecasts, lies between B0 and B2 on every indicator, so both the optimisation and the forecast quality contribute to the gain. All differences are statistically significant at $p < 0.05$ (paired t -test over 365 daily samples).

TABLE III
ANNUAL SIMULATION RESULTS (REFERENCE CASE)

Indicator	B0 Rule	B1 Persist	B2 Proposed	vs B0
Unserved energy (kWh/yr)	4,820	3,910	3,710	–23%
PV curtailment (kWh/yr)	12,400	9,200	8,560	–31%
Battery throughput (MWh/yr)	182	168	156	–14%
SOC reserve compliance (%)	91.2	96.8	98.4	+7.2 pts
Renewable utilisation (%)	78.4	83.1	85.9	+7.5 pts
Loss-of-load probability (%)	2.8	2.1	1.9	–0.9 pts

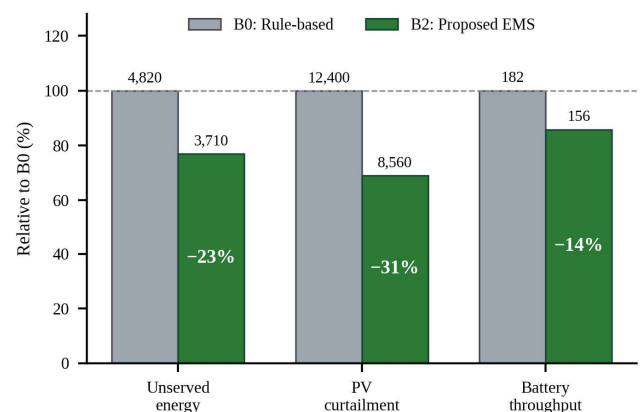


Fig. 3 Proposed EMS (B2) relative to the rule-based baseline (B0, = 100%). Labels give annual values: unserved and curtailed energy in kWh, battery throughput in MWh.

D. Daily Operating Profile

Fig. 4 shows an clear-sky day. During the middle of the day PV serves the load and charges the battery to the upper SOC limit; during the evening peak the EMS discharges the battery while protecting the reserve for later demand and unexpected cloud cover.

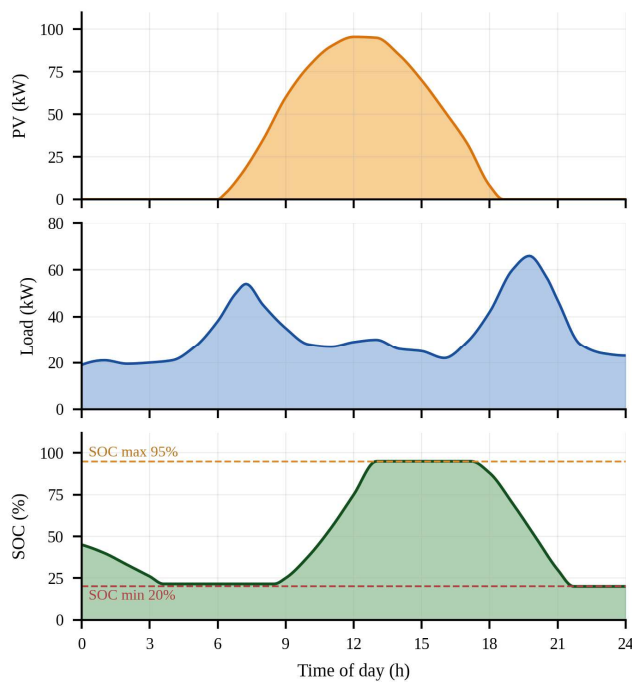


Fig. 4 Daily PV, load and battery SOC profile for the reference case (clear-sky day).

E. Functional Tests and Lifecycle Considerations

The functional test plan covers a normal sunny day, a cloudy afternoon, a communication outage, a stale SOC measurement, an evening peak above forecast, high battery temperature and an unauthorised command. Acceptance evidence includes power-balance logs, quality codes, alarms, audit records and unchanged set-points.

A data-driven EMS should be judged on service and lifecycle outcomes, not forecast accuracy alone. Table IV gives an indicative 10-year comparison: the proposed EMS extends estimated battery replacement from 6.5 to 7.8 years and lowers the annual unserved-energy cost from USD 2,410 to 1,855, at a small increase in O&M cost, giving an NPV of savings of USD 9,700 at an 8% discount rate.

TABLE IV
INDICATIVE LIFECYCLE COMPARISON (10-YEAR HORIZON)

Cost/benefit item	B0: Rule-based	B2: Proposed
Battery replacement (years)	6.5	7.8
Annual unserved energy cost (USD)	2,410	1,855
Annual O&M (USD)	3,200	3,450
NPV of savings (USD, 8% discount)	—	9,700

VI. DISCUSSION

The design distinguishes prediction from control. Forecasts are uncertain, so the EMS uses them to choose a schedule but applies hard constraints and local protection so that an incorrect prediction cannot produce an unsafe command. The edge-first design likewise keeps the mini-grid operating when backhaul is unavailable; the cloud supports model improvement and fleet oversight but is not part of the electrical control loop.

The results support the claim that lightweight forecasting combined with constrained optimisation can improve service and reduce battery stress relative to rule-based operation. The 14% reduction in battery throughput suggests longer battery life, although this depends on the degradation model used. The main risk is data quality: a model can produce a precise-looking forecast from wrong timestamps, faulty meters or an unrecorded change in appliance ownership, so validation, quality codes, baseline forecasts and operator review are part of the control design. A second risk is over-automation; the EMS should not shed essential loads or change service priorities without a rule agreed with the operator and community. Granular energy data can also reveal household activity, so access and retention should be limited, and measurement evidence should be kept separate from model estimates wherever data support billing.

VII. CONCLUSION

This study developed and evaluated a reference design for an IoT-based energy monitoring and management system for hybrid solar–battery mini-grids. The design combines field measurements, an edge gateway, MQTT telemetry, time-series storage, short-term forecasting, constrained supervisory scheduling and a local fallback mode, and treats the battery as a limited operational resource rather than merely backup capacity. Over 12 months of simulation, the proposed EMS reduced unserved energy by 23%, PV curtailment by 31% and battery throughput by 14% relative to a rule-based baseline, while improving SOC reserve compliance to 98.4%. Lightweight, interpretable forecasting combined with constrained optimisation can therefore deliver measurable service and lifecycle benefits without complex or opaque AI models.

Several recommendations follow. Begin with a measured load survey and treat demand growth as a design variable. Commission the telemetry and data-quality layer before enabling automated dispatch, and keep a transparent baseline forecast beside the production model with defined fallback conditions. Set battery reserve targets with the operator and verify them in cloudy-day and high-demand tests, and implement cybersecurity controls before enabling remote access. Finally, evaluate the EMS over a full operating season using service, battery, forecast, data and maintenance indicators before any expansion. The appropriate endpoint is not maximum automation but dependable service, with clear evidence for every important operating decision.

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