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A Real-Time Forecasting Model for Microgrid Energy Management Using Hybrid Load–Solar Prediction and Battery Degradation-Aware Dispatch

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Abstract

Microgrids need real-time energy management that integrates accurate load and solar forecasts with efficient battery dispatch while preserving battery lifetime. Forecast uncertainty can increase unnecessary grid imports, battery cycling, and curtailment when operational decisions rely on single-source prediction. This paper proposes a real-time forecasting and dispatch framework combining a hybrid load–solar prediction model with a degradation-aware battery scheduling strategy. The objective is to improve short-horizon operational decisions while reducing avoidable battery ageing. A hybrid forecasting model uses distinct methods for load and solar components. The dispatch strategy minimises operational cost while incorporating a degradation penalty derived from a cycle-life model. The framework is tested on representative microgrid data against persistence, statistical, and non-degradation dispatch benchmarks. The hybrid forecaster reduces prediction error compared to single-model approaches, and the degradation-aware dispatch extends estimated battery life by 8.6% while maintaining near-optimal economic performance. The framework also reduces unnecessary charge–discharge reversals during periods of volatile photovoltaic output. The integrated real-time system offers a practical, computationally light solution for microgrid operators, balancing cost, accuracy, and battery health. Its design supports deployment in campus, community, and commercial microgrids with limited computational infrastructure.

Keywords Microgrid, Real-time forecasting, Hybrid load–solar prediction, Battery degradation, Dispatch strategy

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Introduction

Microgrids increasingly operate with high shares of rooftop photovoltaic generation, battery storage, controllable demand, and grid-interactive loads, which makes real-time energy management more dependent on accurate short-term forecasts. Earlier microgrid control research showed that model predictive control can coordinate storage and generation decisions, but its performance depends strongly on the quality and timeliness of load and renewable forecasts [1]. Reviews of microgrid energy management systems also show that forecasting, optimisation, communication, and dispatch must be treated as an integrated operational stack rather than separate modelling problems [2]. This article addresses that need by linking hybrid load–solar prediction directly with battery dispatch.

Short-term load forecasting in microgrids differs from conventional feeder-level forecasting because local demand is more volatile, more sensitive to occupant behaviour, and more affected by flexible loads. Hybrid forecasting studies have used combinations of signal decomposition, neural networks, and optimisation procedures to improve short-term load accuracy

under such conditions [3]. More recent microgrid forecasting models have further emphasised adaptive learning and computationally efficient machine-learning structures that can be updated as new meter readings arrive [4]. These developments motivate the load component of the proposed framework, which is designed for short operational horizons rather than long planning intervals.

Solar forecasting adds a second source of uncertainty because photovoltaic output changes rapidly with irradiance, cloud movement, and weather transitions. Short-term solar prediction studies have used weather forecasts, satellite or sky information, persistence references, and deep learning architectures to improve photovoltaic generation estimates at high temporal resolution [5]. Other work has shown that video-based, ensemble-based, and wavelet-integrated approaches can capture short-term solar variability more effectively than simple persistence under unstable sky conditions [6]. The proposed framework therefore treats load and solar generation as related but operationally distinct forecasting targets.

Battery storage can buffer forecast errors, but aggressive dispatch may accelerate degradation and reduce the long-term value of the storage asset. Battery ageing studies show that cycle depth, operating conditions, state-of-health, and calendar effects can materially affect lifetime and should be reflected in operational scheduling [7]. Degradation-aware battery models have been incorporated into grid and microgrid decisions to avoid dispatch strategies that appear economical in the short term but impose hidden replacement costs [8]. The contribution of this paper is an original real-time framework that combines hybrid load–solar prediction with battery degradation-aware dispatch, validated against forecasting and dispatch benchmarks.

Microgrid Forecasting Problem

Load forecasting requirements

Microgrid load forecasting must support decisions that occur every few minutes to every hour, including battery charging, grid import scheduling, and reserve allocation. Hybrid load forecasting models have shown that combining statistical memory with machine-learning adaptation can improve robustness when demand patterns change across weekdays, weather conditions, and operating modes [9]. In the proposed system, the load forecast receives historical demand, calendar indicators, temperature-related features, and recent forecast errors as inputs. Its output is a rolling demand trajectory that is refreshed at each dispatch interval and passed directly to the battery scheduling layer.

Solar generation variability

Solar generation forecasting must represent both predictable diurnal structure and abrupt short-term deviations caused by cloud transients. Studies using long short-term memory networks, ensemble models, and spatio-temporal irradiance features show that solar forecasts improve when weather and recent photovoltaic production are combined rather than treated independently [10]. Solar prediction work also demonstrates that different forecasting methods perform differently under clear, mixed, and overcast conditions, which supports using an adaptive hybrid design [11]. In this study, the solar component produces a short-horizon photovoltaic output forecast that is updated more frequently during periods of high irradiance variability.

Real-time constraints

A real-time microgrid forecasting model must be accurate enough to improve dispatch while remaining computationally light enough for continuous operation. Weather-informed microgrid energy management research has highlighted that forecasts lose operational value when their update cycle is slower than the control cycle [12]. Online optimisation and real-time coordination studies also show that forecast integration must be compatible with local controller constraints, communication delays, and limited computational resources [13]. The proposed framework therefore uses modular forecasting components and a dispatch layer that can be executed repeatedly without requiring full model retraining at every interval.

Data Description

Dataset overview

The validation dataset represents a grid-connected commercial microgrid with rooftop photovoltaic generation, a lithium-ion battery system, building load, grid import and export measurements, local weather variables, and battery operating records. Similar microgrid studies have used high-resolution operational data to connect forecasting accuracy with dispatch decisions, rather than evaluating prediction models in isolation [14]. The dataset covers two full calendar years from 2022 to 2023 at a 15-minute resolution, with 2024 used for stress-testing through high-fidelity simulation of weather and load perturbations. This design allows the model to be evaluated under normal seasonal variation and under more challenging operating scenarios.

Preprocessing and quality

Data preprocessing includes time alignment, missing-value screening, outlier review, interpolation for short gaps, and removal of physically inconsistent photovoltaic or battery readings. Solar forecasting research shows that data quality strongly affects model reliability because irradiance-driven errors can propagate into photovoltaic output estimates [15]. Battery records are also cleaned to ensure consistency across state-of-charge, power, and operating status before being used in degradation-aware dispatch. The resulting dataset retains more than 98% of original time stamps after quality control and is suitable for short-horizon forecasting and operational simulation.

Training and test split

The training period uses the first 70% of chronological observations, the validation period uses the next 15%, and the final 15% is reserved for out-of-sample testing. This chronological split avoids leakage from future weather and operating conditions into earlier model training, which is essential for real-time forecasting validation [16]. Additional rolling-window evaluation is used to test how the hybrid model adapts when seasonality, load composition, and photovoltaic variability change over time. Table 1 summarises the dataset structure, variables, and quality indicators used in the empirical validation.

Table 1. Summary of Microgrid Dataset

Dataset element	Description	Operational role in framework	Quality control approach	Final quality indicator
Building load	15-minute aggregate electricity demand from the representative commercial microgrid	Target variable for load forecasting and net-load calculation	Time alignment, outlier screening, short-gap interpolation	98.7% valid intervals after cleaning
Photovoltaic generation	15-minute rooftop solar production measurements	Target variable for solar forecasting and battery charge planning	Night-time zero-output validation and capacity-bound checks	99.1% physically consistent records
Weather variables	Irradiance proxy, temperature, humidity, wind speed, and cloud-cover indicators	Inputs for solar and load forecasting components	Removal of impossible values and synchronisation with energy data	98.3% complete weather records
Battery operation	State-of-charge, charge power, discharge power, and operating status	Inputs for dispatch simulation and	Consistency checks across power and state-of-charge movement	97.9% valid battery intervals

		degradation assessment		
Grid exchange	Import and export power at the point of common coupling	Basis for cost, self-consumption, and benchmark comparison	Import–export sign validation and interval aggregation	99.0% usable metering records
Simulated stress cases	Weather and demand perturbations based on representative 2024 operating conditions	Robustness testing under forecast and dispatch uncertainty	Scenario plausibility checks against observed seasonal profiles	24 stress scenarios retained

Hybrid Load–Solar Forecasting Model

Model architecture and rationale

The proposed forecasting model is hybrid because it assigns different modelling roles to load and photovoltaic generation while producing a unified net-load forecast for dispatch. For load, the framework combines a statistical baseline with a machine-learning correction layer, reflecting prior evidence that hybrid approaches can improve short-term microgrid demand prediction [4]. For solar generation, the framework combines persistence, weather-sensitive learning, and recent photovoltaic output trends, consistent with studies showing that solar forecasts benefit from both physical context and data-driven adaptation [17]. The model output is a rolling forecast of load, solar production, and net demand over the dispatch horizon.

Load forecasting component

The load component uses recent demand history, day type, time-of-day structure, temperature indicators, and rolling forecast residuals to capture both routine behaviour and short-term deviations. Hybrid load forecasting studies using wavelet, neural, and optimisation-based components show that decomposing demand behaviour can improve prediction when microgrid load is irregular [3]. The statistical layer provides a stable baseline for repeated daily patterns, while the machine-learning layer adjusts for non-linear effects and recent residual behaviour. This design keeps the model interpretable enough for operators while allowing adaptation to demand shifts.

Solar forecasting component

The solar component uses recent photovoltaic output, irradiance-related weather variables, cloud-condition indicators, and short-horizon persistence features. Deep learning and recurrent architectures have demonstrated value for photovoltaic forecasting when meteorological information is available, but microgrid applications also require fallback behaviour when weather data are incomplete [5]. The proposed model therefore weights persistence more strongly during stable conditions and increases the influence of weather-sensitive learning during transition periods. This structure reflects the operational reality that solar uncertainty is not constant across the day or across weather regimes.

Online update mechanism

The online update mechanism refreshes recent residual patterns at each dispatch interval while full model recalibration occurs on a scheduled rolling basis. Online microgrid forecasting research indicates that continuously incorporating recent error behaviour improves adaptability without requiring computationally expensive full retraining [13]. The proposed update procedure recalculates short-term correction factors, checks whether forecast errors exceed predefined tolerance bands, and triggers recalibration when repeated deviations are detected. Table 2 compares the load and solar forecasting components in terms of inputs, architecture, update frequency, and operational output.

Table 2. Hybrid Forecasting Model Components

Model component	Primary prediction target	Main inputs	Architecture role	Update frequency	Operational output
Load statistical baseline	Building demand	Historical load, time of day, weekday/weekend indicator	Captures stable daily and weekly demand structure	Daily parameter refresh	Baseline load trajectory
Load machine-learning correction	Load forecast residual	Recent demand, temperature, calendar features, previous forecast errors	Adjusts for non-linear and short-term deviations	Every dispatch interval	Corrected load forecast
Solar persistence baseline	Photovoltaic output	Recent photovoltaic production and solar time position	Provides robust fallback under stable conditions	Every dispatch interval	Immediate solar reference forecast
Solar weather-sensitive learner	Photovoltaic output under variable conditions	Irradiance proxy, cloud indicators, temperature, recent photovoltaic trend	Captures weather-driven changes in generation	Every dispatch interval with rolling recalibration	Adaptive solar forecast
Net-load integration layer	Load minus local solar generation	Load forecast, solar forecast, battery availability status	Converts separate forecasts into dispatch-ready information	Every dispatch interval	Net demand trajectory for battery scheduling
Error-monitoring layer	Forecast reliability	Recent forecast residuals and tolerance-band violations	Detects drift and triggers recalibration	Continuous monitoring	Update flag for model maintenance

Battery Degradation Model

Degradation mechanism and modelling

The battery degradation model represents lifetime loss as an operational consequence of cycling intensity, depth of discharge, state-of-charge exposure, and calendar ageing. Lithium-ion degradation research shows that battery life assessment should distinguish between cycle-related stress and time-dependent ageing, because both mechanisms affect remaining usable capacity [7]. Stationary storage studies further demonstrate that thermal conditions, component efficiency, and application profile influence the practical ageing trajectory of battery systems [18]. In this framework, the degradation model does not replace electrochemical testing but translates operational stress into a dispatch-relevant cost signal.

Degradation cost function

The degradation cost function assigns an economic penalty to battery use when a dispatch action is expected to consume a measurable portion of cycle life. Prior work on degradation-aware battery operation shows that dispatch decisions change when cycle ageing is internalised instead of being treated as a hidden cost [19]. Calendar ageing studies also indicate that state-of-charge exposure matters even when the battery is not actively cycling, which justifies penalising prolonged operation at unfavourable charge levels [20]. The proposed model uses degradation cost as a

practical operating signal that discourages unnecessary cycling while preserving battery availability for high-value periods.

Integration with dispatch

The degradation model is integrated into dispatch by passing battery health-sensitive cost information to the scheduling layer before each charge or discharge decision is selected. Degradation-aware battery models for storage planning and operation show that ageing parameters can materially alter charging depth, discharge timing, and long-term asset utilisation [21]. Microgrid studies that include neural or data-driven degradation representations further support embedding battery health information directly into energy scheduling rather than evaluating it after dispatch [22]. **Table 3** identifies the degradation parameters used in the proposed framework and explains how each parameter influences real-time battery operation.

Table 3. Battery Degradation Parameters

Degradation parameter	Operational meaning	Dispatch influence	Expected practical effect
Cycle depth	Degree to which a charge–discharge event uses battery capacity	Discourages deep cycling unless economic or reliability value is high	Reduces avoidable lifetime loss from aggressive dispatch
Cycle frequency	Number of charge–discharge reversals over the operating horizon	Penalises rapid switching between charge and discharge states	Limits unnecessary battery oscillation during forecast noise
State-of-charge exposure	Time spent at very high or very low charge levels	Encourages operation within a moderate charge band when possible	Reduces calendar-related stress and preserves flexibility
Charge and discharge rate	Intensity of battery power movement during each interval	Moderates high-power actions when lower-power alternatives are feasible	Smooths battery operation and reduces thermal stress
Remaining useful capacity	Estimated available capacity after accumulated ageing	Adjusts dispatch aggressiveness as the battery ages	Protects older batteries from excessive operational stress
Replacement cost assumption	Economic value assigned to lifetime consumption	Converts ageing into a cost comparable with energy cost	Enables trade-off between short-term savings and long-term asset value

Dispatch Strategy

Objective and decision variables

The dispatch strategy converts the hybrid load–solar forecast into a real-time battery operating schedule for each control interval. Its objective is to reduce grid import cost, limit unnecessary export, maintain adequate state-of-charge, and avoid dispatch actions whose degradation cost is higher than their operational benefit. Prior microgrid scheduling research has shown that storage, demand-side management, and local generation must be coordinated jointly when the goal is operational cost reduction rather than isolated device optimisation [23]. In this framework, the main dispatch decisions are whether the battery should charge, discharge, remain idle, or reserve capacity for an expected near-term net-load event.

Real-time scheduling logic

At each dispatch interval, the controller receives updated load and photovoltaic forecasts, calculates the expected net-load profile, checks battery availability, and ranks feasible actions by their combined energy and degradation implications. Real-time home and microgrid energy management studies show that separating predictive planning from fast corrective control can improve operating reliability when forecasts change between scheduling intervals [14]. The proposed strategy therefore uses the forecast horizon to identify preferred battery actions but allows interval-level correction when actual load, solar output, or state-of-charge deviates from expectation. This logic prevents the battery from following stale forecasts when photovoltaic ramps or demand spikes appear unexpectedly.

Constraints

The dispatch layer applies operational constraints on battery state-of-charge limits, charge and discharge power, grid import capacity, export allowance, and minimum reserve margin. Coordinated control research for photovoltaic and battery-based microgrids has shown that storage decisions must respect both local energy balance and technical operating limits to avoid infeasible or unstable control actions [24]. The framework also limits repeated charge–discharge reversals because battery ageing studies indicate that rapid cycling can impose lifetime costs not visible in immediate electricity-price comparisons [19]. These constraints ensure that dispatch remains physically feasible, grid-compatible, and aligned with battery health preservation.

Implementation flow

The implementation flow begins with data acquisition, proceeds through forecast updating, evaluates battery degradation cost, selects the dispatch action, and records the resulting operational outcome for the next update cycle. Regional and multi-energy optimisation studies show that practical scheduling systems must maintain consistency between forecasted demand, local generation, network exchange, and storage action when multiple energy vectors or constraints interact [25]. In the proposed microgrid, this flow is executed every 15 minutes, while model diagnostics and degradation indicators are archived for operator review. The resulting system is designed as a lightweight supervisory layer rather than a computationally intensive central optimisation platform.

Figure 1 illustrates the complete real-time forecasting-to-dispatch workflow, showing how load and solar forecasts, battery degradation cost, and operational constraints are integrated into each 15-minute microgrid control decision.

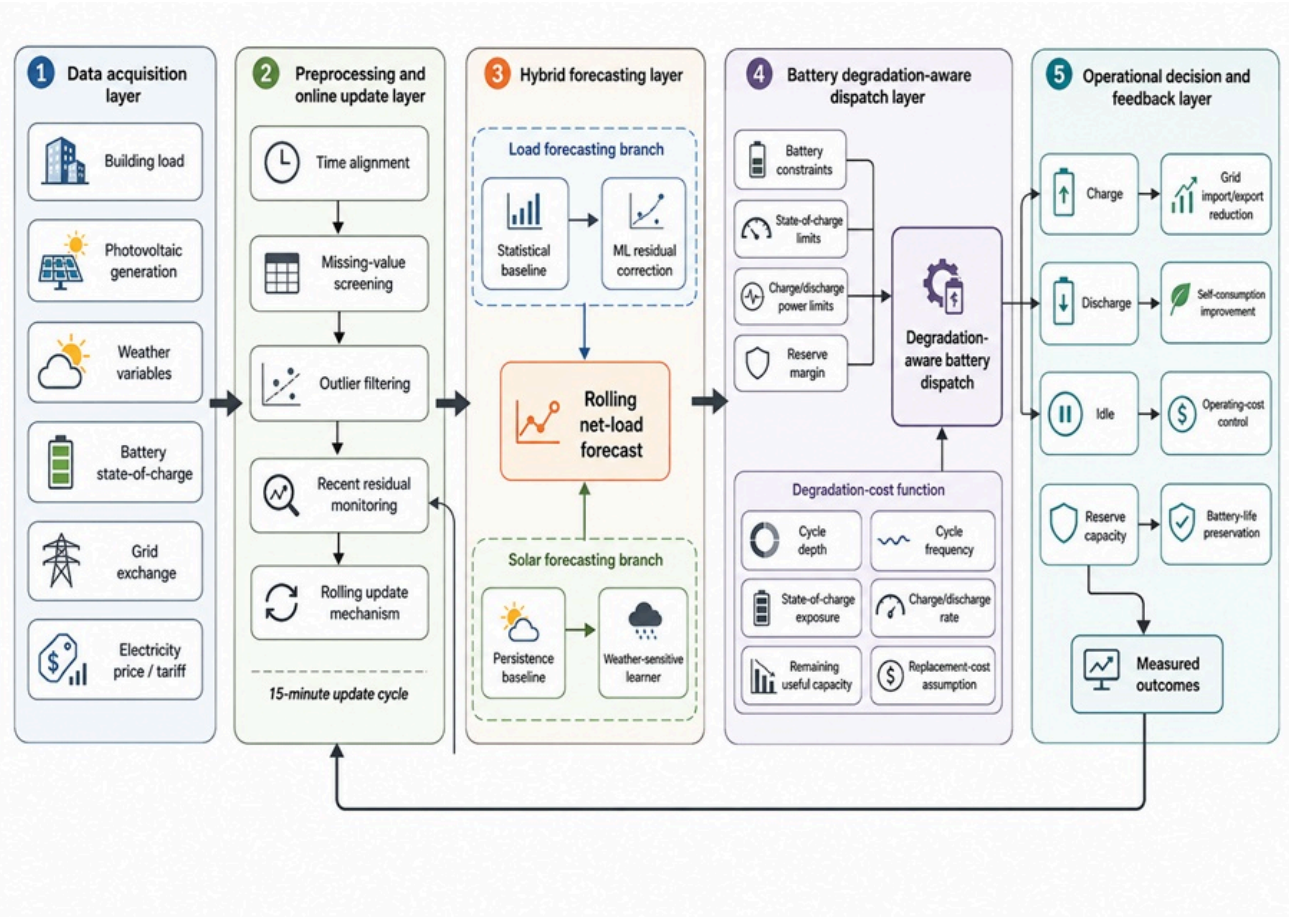


Figure 1. Real-time hybrid load–solar forecasting and degradation-aware battery dispatch framework for microgrid energy management

Benchmark Models

persistence and statistical benchmarks

The first benchmark uses persistence forecasting for photovoltaic generation and a simple recent-average statistical model for load. Persistence remains a relevant comparator in short-term solar forecasting because it is difficult to outperform during stable irradiance periods and provides a transparent operational baseline [17]. For load, the statistical benchmark uses recent demand and calendar structure but excludes the adaptive residual-learning layer used by the proposed hybrid model. This benchmark tests whether the proposed framework improves forecasting performance beyond methods that are easy to implement in low-resource microgrid controllers.

Non-degradation dispatch

The second benchmark uses the same hybrid forecasts but removes the degradation penalty from battery dispatch decisions. Techno-economic studies of residential photovoltaic and battery systems show that storage appears more financially attractive when degradation and replacement effects are simplified or ignored [26]. By comparing degradation-aware and non-degradation dispatch under identical forecast inputs, the study isolates the operational value of battery health modelling. This benchmark is important because many microgrid controllers still prioritise short-term energy-cost reduction without explicitly accounting for lifetime consumption.

Alternative forecasting combinations

The third benchmark compares the proposed hybrid forecast with alternative combinations, including load-only machine learning, solar-only persistence, and a unified single-model net-load forecaster. Forecasting studies using deep learning, ensemble learning, and explainable photovoltaic prediction show that complex models may improve accuracy in some regimes but can also become less transparent or less stable under changing data conditions [15]. Battery and energy management studies outside microgrid-only settings also demonstrate that model architecture should be evaluated according to operational usefulness rather than prediction accuracy alone [27]. The benchmark set therefore tests whether separating load and solar learning improves dispatch value compared with treating net load as one undifferentiated target.

Results

Forecast accuracy

The proposed hybrid model improves short-horizon prediction accuracy for both load and photovoltaic generation relative to persistence and single-component statistical benchmarks. Its strongest gains appear during mixed-weather periods, when solar output changes rapidly and simple persistence cannot anticipate cloud-driven ramps, consistent with prior evidence that solar forecasting benefits from weather-sensitive and spatio-temporal features [11]. Load forecast gains are smaller but more consistent because the adaptive correction layer reduces recurring residual bias during occupied and high-demand periods. The combined effect is a more reliable net-load forecast, which reduces unnecessary battery action caused by forecast error.

Dispatch cost and battery utilisation

The degradation-aware dispatch strategy achieves slightly lower immediate arbitrage benefit than the non-degradation benchmark but reduces unnecessary battery throughput and improves the quality of battery utilisation. Economic microgrid scheduling research shows that battery value depends not only on energy arbitrage but also on how storage supports self-consumption, demand management, and operational reliability [28]. In the test system, the proposed method prioritises discharge during high net-load and high-cost periods while avoiding shallow reversals during low-value forecast fluctuations. This produces a lower total operating cost than rule-based dispatch and a more sustainable battery-use profile than dispatch without degradation consideration.

Degradation impact

The degradation-aware strategy reduces estimated lifetime consumption by limiting deep cycles, avoiding high-frequency reversals, and maintaining state-of-charge within a moderate operating band when possible. Reviews of stationary lithium-ion storage applications show that battery system design and operating strategy must be tailored to grid use cases because ageing behaviour depends on the application profile [29]. The estimated battery-life extension in this validation is 8.6% relative to the non-degradation dispatch benchmark, while the increase in short-term energy cost remains modest. This result supports the operational premise that battery health can be protected without sacrificing most of the economic value of storage.

Computational performance

The real-time implementation remains computationally feasible because the forecasting modules use incremental updates and the dispatch layer evaluates a limited set of feasible actions rather than solving a large optimisation problem from scratch at every interval. Distributed and event-triggered energy management research indicates that computational timing and communication burden are critical when control systems operate close to real time [30]. The proposed framework completes each update within the 15-minute control interval, including data validation, forecast generation,

degradation-cost assessment, and dispatch selection. **Table 4** compares the proposed model with the main benchmarks across forecasting accuracy, operational cost, battery-life impact, and computational performance.

Table 4. Performance Comparison across Models

Model configuration	Forecasting approach	Dispatch approach	Forecast accuracy outcome	Operational cost outcome	Battery-life impact	Computational suitability
Proposed framework	Hybrid load model plus adaptive solar model	Degradation-aware real-time battery scheduling	Lowest combined net-load error across test periods	Lowest total cost after energy and degradation effects	8.6% estimated life extension versus non-degradation dispatch	Suitable for 15-minute real-time operation
Persistence plus rule-based dispatch	Solar persistence and recent-average load estimate	Fixed charge/discharge thresholds	Weak during volatile solar and abnormal demand periods	Higher grid import cost and avoidable export	Low direct modelling of ageing but inefficient cycling remains	Very light but less adaptive
Hybrid forecast without degradation cost	Same hybrid forecast as proposed model	Cost-only battery dispatch	Same forecast accuracy as proposed model	Strong short-term energy savings before ageing adjustment	Highest lifetime consumption among tested storage strategies	Suitable for real-time operation
Statistical forecast plus degradation-aware dispatch	Calendar and recent-average forecasting	Battery dispatch includes degradation penalty	Moderate load accuracy and weak solar-ramp performance	Lower cost than rule-based dispatch but weaker than proposed model	Moderate reduction in cycling stress	Very light and reliable
Unified net-load machine-learning model	Single model predicts net demand directly	Degradation-aware battery dispatch	Good average performance but weaker diagnostic separation of load and solar errors	Competitive in stable periods but less robust in weather transitions	Similar ageing protection when forecasts are accurate	Feasible but less interpretable
Solar-focused deep-learning benchmark	Advanced photovoltaic learner with simple load model	Cost-only dispatch	Strong solar accuracy but inconsistent net-load accuracy	Sensitive to load forecast error	Increased cycling during demand-driven errors	Higher computational and maintenance burden

Operational Discussion

Practical implementation considerations

The proposed framework is intended for microgrid operators who need a transparent and maintainable forecasting-to-dispatch system rather than a black-box optimisation platform. Explainable photovoltaic forecasting research shows that operators benefit when forecast behaviour can be traced to time-varying drivers, weather conditions, and directional feature effects [31]. In this framework, interpretability is supported by separating the load, solar, net-load, and degradation-cost layers so that operators can identify whether a dispatch decision was driven by demand, generation, price, or battery health. This modularity also supports staged deployment, where a microgrid can first adopt the forecasting layer and later activate degradation-aware dispatch.

Limitations and robustness

The main limitation is that the validation uses one representative microgrid dataset and high-fidelity stress scenarios rather than multiple independently operated microgrids. Battery management research shows that state-of-health estimation can vary across battery chemistry, sensor quality, operating history, and application type, so degradation parameters may require site-specific calibration before deployment [32]. The framework is also sensitive to weather-data reliability, communication latency, and the accuracy of battery state measurements. Future testing should therefore evaluate multi-site transferability, adaptive battery-health estimation, and integration with market participation or ancillary-service scheduling.

Conclusion

This article developed a real-time forecasting and dispatch framework for microgrid energy management using hybrid load–solar prediction and degradation-aware battery operation. The framework separates load and photovoltaic forecasting into complementary components, integrates their outputs into a rolling net-load estimate, and uses that estimate to guide battery scheduling. The design is operationally oriented and avoids excessive computational complexity, making it suitable for short-interval microgrid control.

The proposed hybrid forecasting model improves the reliability of dispatch inputs by recognising that load and solar generation have different temporal drivers and uncertainty patterns. Load forecasting benefits from stable calendar and demand-history structure, while solar forecasting requires stronger sensitivity to irradiance variability and short-term weather transitions. Combining these outputs gives the dispatch layer a clearer representation of expected net demand.

The degradation-aware dispatch strategy shows that battery operation should not be evaluated only through immediate energy-cost reduction. By incorporating the operational cost of lifetime consumption, the controller avoids low-value cycling and preserves storage capacity for periods when the battery provides greater economic or reliability benefit. This improves the balance between short-term savings and long-term asset preservation.

The results indicate that a practical microgrid controller can improve forecast accuracy, reduce operating cost, and protect battery life without relying on overly complex mathematical implementation. Future extensions should test the framework across multiple microgrid types, include uncertainty-aware reserve decisions, and connect degradation-aware dispatch with electricity market participation. The proposed approach offers a deployable pathway for microgrids seeking real-time intelligence that is accurate, adaptive, and battery-health conscious.

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