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AI-Driven Energy Management for a Solar-Integrated Smart Building: Forecast-Informed Battery Scheduling under Time-of-Use and Demand Charges

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ABSTRACT

Commercial buildings with rooftop photovoltaic (PV) generation and battery storage face a scheduling problem: solar output and building demand are both uncertain, while electricity prices vary by hour and by the monthly peak. This paper develops and evaluates an AI-driven energy management framework in which gradient-boosting models forecast day-ahead building load and PV output, and a linear-programming optimiser converts those forecasts into a battery schedule that minimises energy cost, demand charges and degradation cost. The framework is tested on a simulated 5,000 m² office building with a 200 kWp rooftop array and a 300 kWh / 100 kW battery in a hot semi-arid climate, using a synthetic three-year hourly data set (two years for training, one for testing). On the held-out year, the gradient-boosting load forecaster reached an RMSE of 5.1 kW (R^2 = 0.989), against 15.0 kW for a persistence benchmark. The forecast-driven schedule cut annual electricity cost by 10.0% relative to PV-only operation and by 6.6% relative to a rule-based battery controller, and reduced evening peak-tariff imports by 82%. It did not reduce the monthly maximum demand, which a perfect-foresight benchmark could cut by almost half; this gap quantifies the cost of forecast error. A sensitivity analysis over battery size and peak tariff shows that the value of storage depends strongly on the tariff spread, with simple payback ranging from about six to more than forty years under assumed capital costs. Building load, tariffs, costs and roof-structure parameters are simulated or assumed, so the results show relative performance of control strategies rather than predictions for a specific site.

Keywords: Smart Building; Energy Management System; Photovoltaic; Battery Storage; Load Forecasting; Gradient Boosting; Linear Programming; Time-Of-Use Tariff; Demand Charge

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Introduction

Buildings account for roughly a third of global final energy use and a comparable share of energy-related emissions, and the electricity share of that demand continues to grow [1]. Rooftop photovoltaic generation is now one of the cheapest ways to supply that electricity locally, and it turns building owners from passive consumers into prosumers who both draw from and feed the grid [2]. However, solar output peaks at midday while many commercial tariffs concentrate their highest prices in the evening, so a PV array alone does not guarantee low cost. The mismatch is typically addressed by adding battery storage and a control system that decides when to charge and discharge [3], [4].

A building energy management system (BEMS) is the software layer that makes these decisions. Conventional BEMS rely on fixed rules or schedules; they are simple and robust but cannot anticipate tomorrow's weather or occupancy [5]. Advances in machine learning have made it practical to forecast building load and PV output from weather and calendar data with high accuracy [7], [10], and optimisation-based controllers can use such forecasts to plan storage operation over a horizon [19], [20]. The combination is often described as "AI-driven" energy management, although the term covers a wide range of designs, from supervised forecasting feeding a classical optimiser to end-to-end reinforcement learning [22], [23].

Despite the volume of work, practical decisions remain difficult. A building owner needs to know how much of the benefit of an intelligent controller comes from better forecasts, how much from the optimiser, how sensitive the benefit is to tariff structure, and what happens to demand charges when forecasts are imperfect. Studies often report a single savings figure against a weak baseline, which makes it hard to separate these effects [5], [35]. In addition, rooftop PV is limited by structural spare capacity and wind uplift, constraints that are rarely examined alongside the control problem [32].

This paper addresses these questions with a transparent, reproducible simulation study. The contributions are: (i) a forecast-informed scheduling framework that couples gradient-boosting forecasts with a day-ahead linear program including time-of-use energy charges, a monthly demand charge and battery degradation cost; (ii) a controlled comparison of five operating strategies, including a persistence-forecast ablation and a perfect-foresight upper bound; (iii) a sensitivity analysis over battery size and tariff spread with simple payback estimates; and (iv) a preliminary rooftop capacity and wind-uplift screening to check that the assumed array is plausible. The remainder of the paper is organised as follows. Section 2 reviews related work, Section 3 states the research gap and objectives, Section 4 describes the methodology, Section 5 reports results, Section 6 discusses them, Section 7 lists limitations and Section 8 concludes.

Literature Review

Building energy management and model predictive control

Reviews of building energy management strategies identify model predictive control (MPC), demand-side management, optimisation and fault detection as the main families of approaches [5]. MPC repeatedly solves a finite-horizon optimisation using a model and forecasts of disturbances, and applies only the first actions before re-

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planning [18], [20]. Oldewurtel *et al.* demonstrated that weather forecasts materially improve the performance of predictive building climate control [19], and later surveys show MPC has become the dominant model-based paradigm for buildings [20]. The main practical obstacle is the effort needed to build and maintain accurate models [34], together with uncertainty in occupant behaviour [33]. Building simulation tools such as EnergyPlus provide high-fidelity physics but are too slow and cumbersome for direct use inside controllers [6], which motivates simplified or data-driven surrogates.

Forecasting building load and PV generation

Data-driven prediction of building energy use has been reviewed extensively, with artificial neural networks, support vector regression, and tree-based ensembles among the most used methods [7], [8]. Probabilistic forecasting adds uncertainty information that is valuable for operation under risk [9], [31]. For solar generation, reviews separate physical, statistical and machine-learning approaches and stress the role of cloud information and numerical weather prediction as inputs [10], [11], [12]. Gradient boosting [13] and its efficient implementations [14], [15] consistently perform well on tabular forecasting problems with calendar and weather features, while recurrent networks such as the long short-term memory (LSTM) architecture [16] are preferred when long sequences matter. Open-source libraries make these methods easy to reproduce [17].

Reinforcement learning and AI-based control

Reinforcement learning (RL) learns a control policy by interacting with an environment [25]; deep variants have shown human-level performance in games [26] and have been applied to building energy optimisation [21] and HVAC control [24]. Reviews note that RL promises model-free adaptation but faces challenges in sample efficiency, safety during learning, and the lack of standard benchmarks [22], [23]. Systematic reviews of artificial intelligence for demand response find that most published work is simulation-based and that comparisons between learning-based and optimisation-based controllers remain limited [23], [35]. Barriers to deployment also include market and tariff design [36].

Solar–storage integration and economics

Self-consumption of on-site PV can be increased through storage, demand shifting, or both, and the literature highlights that the optimal strategy depends on load shape, tariff and system sizing [4]. Microgrid reviews emphasise the coordination of generation, storage and loads as a key enabler [3]. Economic assessments of storage depend heavily on capital and lifecycle cost assumptions [27], [28], and optimisation models such as mixed-integer linear programs have long been used to size and operate distributed energy systems [37]. Linear programs are attractive for dispatch because they solve reliably in milliseconds with modern solvers [29].

Summary of the literature

Table 1 summarises representative studies and the aspects that remain open. The review shows a rich body of work on each component, but a smaller number of

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studies that isolate the contribution of forecast quality to the economic value of storage under combined time-of-use and demand-charge tariffs.

TABLE 1. Representative studies and open issues.

Reference	Focus	Approach	Open issue relevant here
[5]	BEMS strategies	Review of MPC, DSM, optimisation, FDD	Few quantitative comparisons across strategies
[19]	Weather-forecast MPC	MPC with forecasts, building climate	Focus on thermal comfort, not PV–storage tariffs
[20]	MPC for buildings	Tutorial and review	Model-development cost; limited demand-charge cases
[7], [8]	Load prediction	Review of data-driven methods	Forecast accuracy rarely linked to control value
[10], [12]	PV forecasting	Review of physical/statistical/ML	Evaluated by error metrics, not dispatch cost
[21]	Building energy optimisation	Deep RL on-line control	Benchmarked against few optimisation baselines
[22], [23]	RL for buildings and DR	Reviews	Safety, sample efficiency, benchmark gaps
[4]	PV self-consumption	Review of storage and DSM	Limited treatment of demand charges with AI forecasts

Research Gap and Objectives

Research gap

Three gaps emerge from the literature. First, forecasting studies [7], [10] are typically judged by statistical accuracy, while control studies [19], [21] often assume forecasts or learn policies end-to-end; the translation of forecast error into dollars saved or lost is seldom quantified. Second, many comparisons use a no-battery or fixed-schedule baseline, which exaggerates the apparent benefit of intelligent control [5], [23]; a fair comparison needs a rule-based battery controller, a naive-forecast optimiser, and a perfect-foresight bound. Third, demand charges, which are common in commercial tariffs, interact poorly with forecast error because they depend on a single worst interval, yet this interaction receives little attention in the AI-for-buildings literature [4], [35]. Finally, rooftop PV studies rarely verify that the array assumed in the energy analysis is compatible with structural spare capacity and wind uplift [32].

Objectives

The aim of this study is to quantify how forecast-informed battery scheduling performs against simple and idealised alternatives for a solar-integrated commercial

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building. The specific objectives are (i) to develop day-ahead load and PV forecasting models and benchmark them against persistence and linear baselines [9], [13]; (ii) to formulate a linear-programming battery scheduler that includes time-of-use energy charges, a monthly demand charge and degradation cost [29], [37]; (iii) to compare five operating strategies on cost, peak-period imports, PV self-consumption and monthly maximum demand; (iv) to assess the sensitivity of savings and payback to battery size and peak tariff [27], [28]; and (v) to screen the rooftop for wind uplift and spare capacity to check that the assumed array is plausible [32].

Methodology

Framework overview

Fig. 1 shows the framework. Meter and weather-forecast data feed a forecasting module that predicts hourly building load and PV output for the next 24 hours. The optimiser uses these forecasts together with the measured battery state of charge (SOC) and the running monthly peak to produce hourly charge and discharge set-points, which are applied to the battery during the day. At the start of the next day the measured SOC and demand re-initialise the plan. This day-ahead structure follows the receding-horizon logic of MPC [18], [20] but re-plans once per day, as is common in practice when forecasts are issued daily.

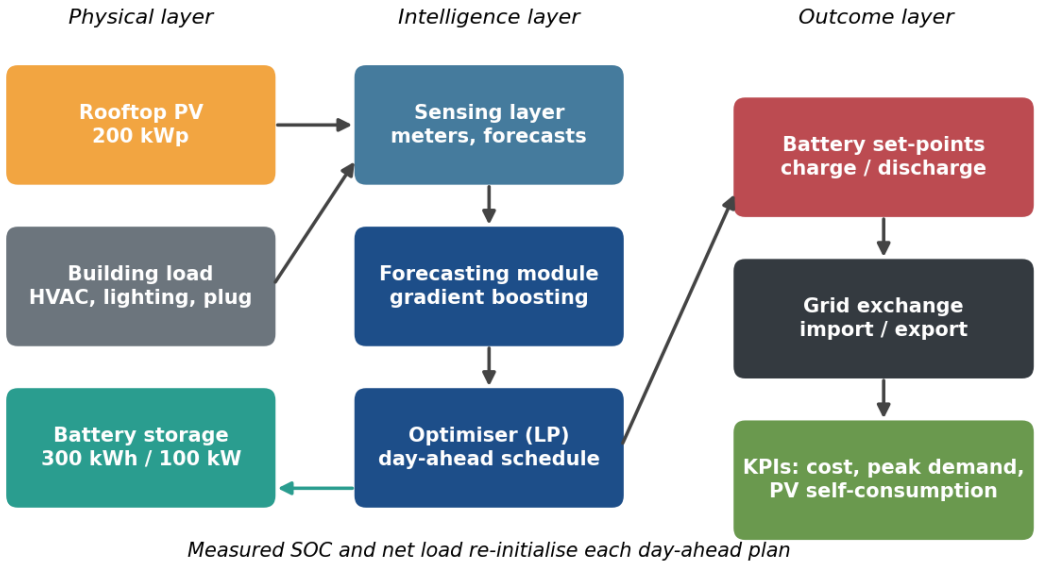


Fig. 1. Architecture of the AI-driven energy management framework. Forecasts of load and PV feed a linear-programming scheduler whose battery set-points are applied to the building; measured state is fed back each day.

Case building and synthetic data

The case is a four-storey, 5,000 m² office building in a hot semi-arid subtropical climate at about 30° N. No metered data were available, so load and weather were generated synthetically to support a controlled comparison. Hourly clear-sky irradiance is computed from solar geometry and scaled by a stochastic clearness index with seasonal reductions for the monsoon and winter fog periods; ambient

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temperature combines a seasonal cycle, a diurnal cycle and day-to-day autocorrelated variation. Building load is the sum of lighting and plug loads driven by an occupancy profile, a cooling component proportional to cooling degree-hours and solar gain divided by an assumed chiller coefficient of performance, a smaller heating component, and fan power, with 4% multiplicative noise and nine random weekday holidays [6], [34]. Three independent years were generated; the first two (17,520 h) were used for training and the third (8,760 h) for testing. The test year has an annual demand of 619 MWh, a mean load of 71 kW and a peak of 212 kW.

PV array and rooftop screening

A 200 kWp array is assumed, with output computed from plane irradiance, a temperature coefficient of −0.4 %/°C and a system performance factor of 0.84. The array yields 315 MWh in the test year, a specific yield of 1,576 kWh/kWp. A roof of about 1,250 m² accommodates roughly 1,000 m² of modules at this rating. To check plausibility, a screening calculation follows the velocity-pressure approach of Eurocode 1 [32]. An assumed basic wind speed of 35 m/s and air density of 1.25 kg/m³ give a reference dynamic pressure of 0.77 kPa; an assumed exposure factor of 1.9 for 18 m height raises the peak pressure to about 1.45 kPa. With assumed net pressure coefficients of −0.7 for interior zones and −1.2 for edge and corner zones on 15° tilted modules, the uplift is about 1.0 kPa and 1.7 kPa respectively. Assuming a system dead load of 0.15 kN/m² and a spare roof capacity of 1.0 kN/m², a ballast-only mounting needs about 0.9 kN/m² in interior zones, which fits within the spare capacity with limited margin, whereas edge zones need about 1.6 kN/m² and therefore require mechanical anchoring. This is a screening check only and not a structural design; all inputs are assumptions.

Forecasting models

Two forecasting tasks are defined: hourly load and hourly PV power for the next day, each issued at the start of the day. Features for load are hour, day of week, day of year, holiday flag, forecast temperature, forecast clearness index, clear-sky irradiance, and load at the same hour on the previous day and previous week. Features for PV are hour, day of year, forecast temperature, forecast clearness index, clear-sky irradiance, their product, and PV at the same hour on the previous day. Weather forecasts are simulated as the true daily clearness and temperature plus noise (standard deviations of 0.07 and 1.4 °C), so they know the day's general cloudiness but not intra-day variability [10], [12]. Three models are compared: (a) persistence (same hour one week earlier for load, one day earlier for PV), (b) ridge regression with one-hot hour and weekday encoding, and (c) histogram-based gradient boosting [13], [14], implemented in scikit-learn [17] with 400 iterations, a learning rate of 0.06 and 24 leaf nodes. Accuracy is reported as RMSE, MAE and R^2 on the test year. Probabilistic forecasts [9], [31] and recurrent networks [16] are left for future work.

Battery scheduling optimisation

For each day the scheduler solves a linear program over 24 hourly steps. Decision variables are battery charge c_t and discharge d_t, grid import g_t, export e_t, battery energy s_t, a daily peak variable P, and an exceedance variable Q above the running

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monthly peak P_0. The objective is

$$\text{minimise } \Sigma_t [\, \tau_t g_t - \varphi e_t + \delta (c_t + d_t) \,] + (\lambda/30) P + \lambda Q$$

where τ_t is the time-of-use price, φ the export credit, δ a degradation cost per kWh of throughput and λ the monthly demand charge. Constraints are the power balance $L_t + c_t + e_t = V_t + d_t + g_t$ (with L the forecast load and V the forecast PV), the energy balance $s_t = s_{t-1} + \eta\, c_t - d_t/\eta$, the bounds $10\% \le s_t \le 95\%$ of capacity, power limits, $g_t \le P$, $Q \ge P - P_0$, and a terminal SOC of at least 40% so that each day leaves usable energy for the next. The small daily weight $\lambda/30$ on P discourages the optimiser from setting a high monthly peak early and then treating it as free. The program is solved with the HiGHS solver [29] through SciPy [30]. Applying the schedule to actual rather than forecast load and PV produces the realised grid import, so forecast error enters the results exactly as it would in operation.

Strategies compared and performance indicators

Five strategies are compared. In the PV-only case there is no battery and surplus PV is exported. In the rule-based case the battery charges from any PV surplus and discharges whenever load exceeds PV, a common default in commercial inverters [4]. The persistence-forecast case uses the scheduler of Section 4.5 driven by naive forecasts, which isolates the value of better forecasting. The proposed case uses the same scheduler driven by gradient-boosting forecasts. Finally, a perfect-foresight case gives the scheduler the true load and PV, which provides an upper bound on what any forecast-based method can achieve with day-ahead planning [20].

Indicators are annual net electricity cost (energy charge − export credit + demand charge + degradation cost), imports during the 18:00–22:00 peak tariff window, PV self-consumption (share of PV not exported), and the sum over months of the maximum hourly grid import.

Forecast metrics and evaluation protocol

Forecast accuracy is reported with the root-mean-square error, $\text{RMSE} = \sqrt{(\text{mean}\ (\hat{y}_t - y_t)^2)}$, the mean absolute error, $\text{MAE} = \text{mean}\ |\hat{y}_t - y_t|$, the normalised RMSE (RMSE divided by the maximum observed value, in per cent) and the coefficient of determination, $R^2 = 1 - \Sigma(\hat{y}_t - y_t)^2 / \Sigma(y_t - \bar{y})^2$ [9], [31]. All models are trained only on the first two simulated years and evaluated once on the third, so no test information leaks into training and the chronological order of the data is preserved, as recommended for time-series forecasting [7], [8]. Economic indicators are computed from realised grid flows, not from forecasts. Because the forecasting and scheduling steps are deterministic once the random seeds are fixed, every number in this paper can be regenerated exactly from the scripts described in the data statement.

Assumptions

Table 2 lists the principal parameters. Tariffs, export credit, demand charge, battery cost and structural values are assumed and are not taken from a specific utility or site; capital-cost figures are of the order reported in storage cost studies [27], [28].

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TABLE 2. Principal parameters and assumptions.

Parameter	Value	Status
Building floor area / roof area	5,000 m² / 1,250 m²	Assumed case
PV capacity; performance factor	200 kWp; 0.84	Assumed
Battery capacity / power; round-trip efficiency	300 kWh / 100 kW; 0.90 (0.95 each way)	Assumed
SOC window; terminal SOC	10–95%; ≥ 40%	Assumed
Off-peak / peak energy price (18:00–22:00)	0.10 / 0.20 USD/kWh	Assumed
Export credit; demand charge	0.06 USD/kWh; 6 USD/kW-month	Assumed
Degradation cost	0.01 USD/kWh throughput	Assumed
Battery capital cost (payback analysis)	250 USD/kWh	Assumed [28]
Basic wind speed; exposure factor	35 m/s; 1.9	Assumed [32]
Net pressure coeff. (interior / edge)	−0.7 / −1.2	Assumed [32]
Dead load; spare roof capacity	0.15; 1.0 kN/m²	Assumed
Building load and weather	Three synthetic years, hourly	Simulated, not metered

Results

Load and PV profiles

Fig. 2 shows the simulated hour-by-day structure of load and PV in the test year. Building demand has the expected weekday and weekend banding and rises in the hot months because of cooling, while PV output follows the seasonal daylight pattern with cloudy periods visible as vertical streaks. Fig. 3 summarises monthly energy: PV supplies between about 35% of demand in January and about 65% in April, falling again in the summer when cooling demand is highest and the monsoon reduces irradiance. Over the year PV supplies 51% of demand in energy terms, but only part of that is coincident with load, which is why storage matters [4].

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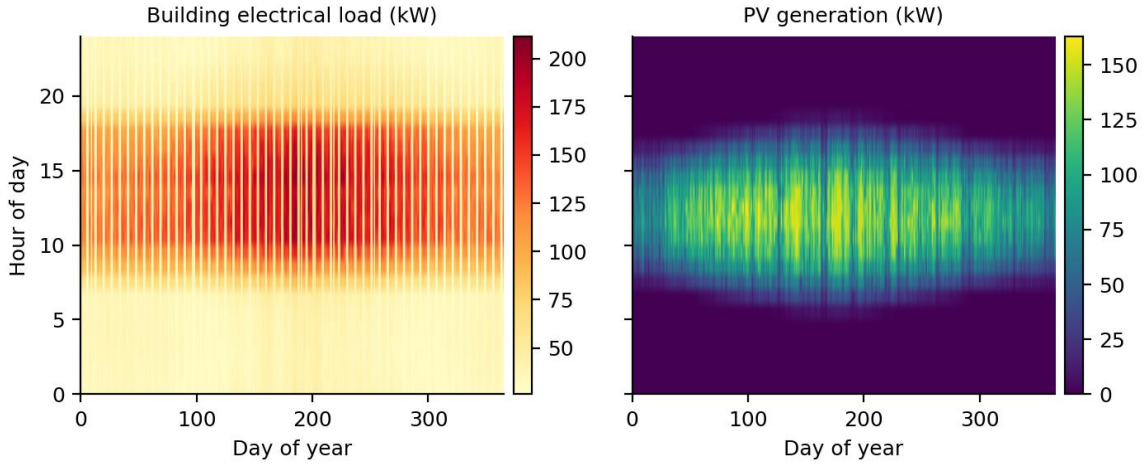


Fig. 2. Hour-by-day heat maps of simulated building load (left) and PV generation (right) for the test year.

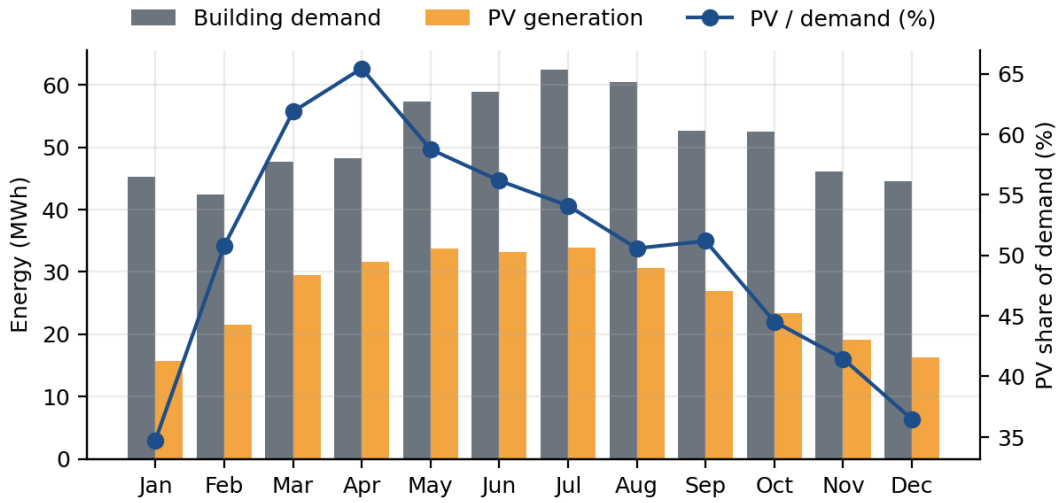


Fig. 3. Monthly building demand, PV generation and PV share of demand in the test year.

Forecast accuracy

Table 3 and Fig. 5 report test-year accuracy. For load, gradient boosting reduces RMSE from 15.0 kW (persistence) and 12.9 kW (ridge) to 5.1 kW, a 66.4% reduction over persistence, with R^2 of 0.989. The gain over ridge regression reflects non-linear interaction between temperature, occupancy and hour of day [7], [13]. For PV, ridge and gradient boosting perform almost identically (RMSE 7.5 and 7.6 kW), and both improve on persistence (11.6 kW); gradient boosting has a lower MAE, while ridge has a marginally lower RMSE. Fig. 4 shows a representative week. The residual PV error is dominated by intra-day cloud variability that the daily weather forecast cannot resolve, which is consistent with the solar forecasting literature [10], [12]. These numbers describe synthetic data generated with known structure and should not be read as expected accuracy on a real building.

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TABLE 3. Forecast accuracy on the test year (8,760 h).

Model	Target	RMSE (kW)	MAE (kW)	nRMSE (% of max)	R^2
Persistence	Load	15.0	6.5	7.1	0.899
Ridge regression	Load	12.9	7.1	6.1	0.925
Gradient boosting	Load	5.1	3.2	2.4	0.989
Persistence	PV	11.6	5.9	7.1	0.938
Ridge regression	PV	7.5	4.1	4.6	0.974
Gradient boosting	PV	7.6	3.9	4.7	0.974

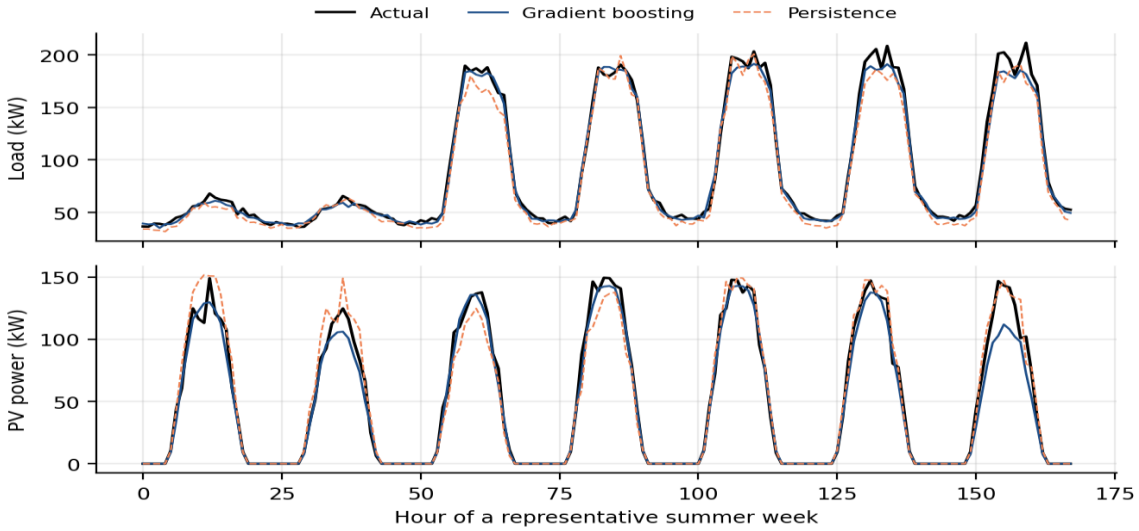


Fig. 4. Actual and forecast load (top) and PV power (bottom) over a representative summer week.

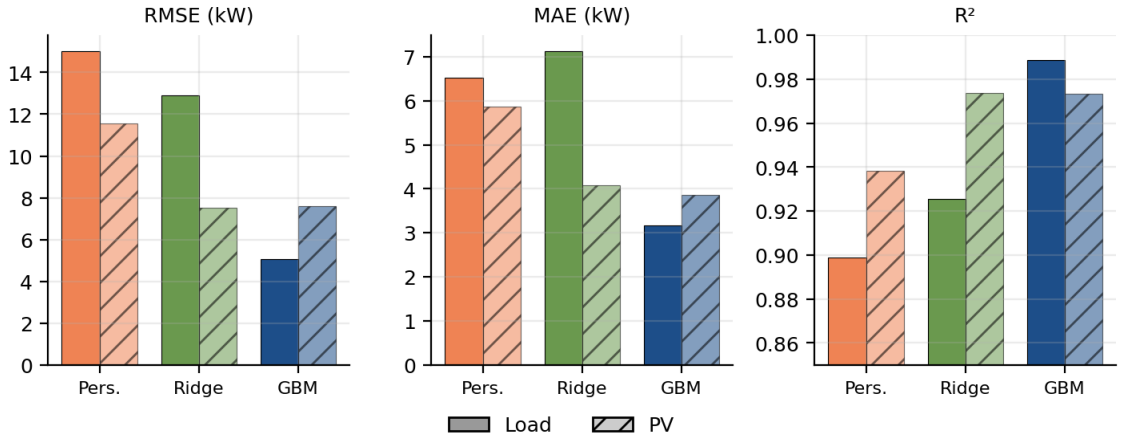


Fig. 5. Forecast error metrics by model for load (solid) and PV (hatched) on the test year.

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Dispatch behaviour

Fig. 6 compares operation on a summer weekday on which load exceeds PV in every hour. PV-only operation draws the full evening load from the grid at the peak price. The rule-based controller never charges on such a day, because there is no PV surplus, so its battery stays at the minimum SOC and gives no benefit; this illustrates why reactive rules underperform on days without surplus. The forecast-driven schedule instead charges from the grid at the off-peak price from late morning to mid-afternoon, which raises daytime import by up to about 40 kW, and then discharges through the 18:00–22:00 window, cutting peak-window import to a few kilowatts until the battery reaches its minimum SOC at about 20:00. It recharges from 21:00 to meet the terminal SOC requirement. The perfect-foresight schedule charges earlier, in the morning, showing a timing difference that forecast error and the demand-charge trade-off produce. This anticipatory behaviour is the practical benefit of combining forecasts with optimisation [18], [20].

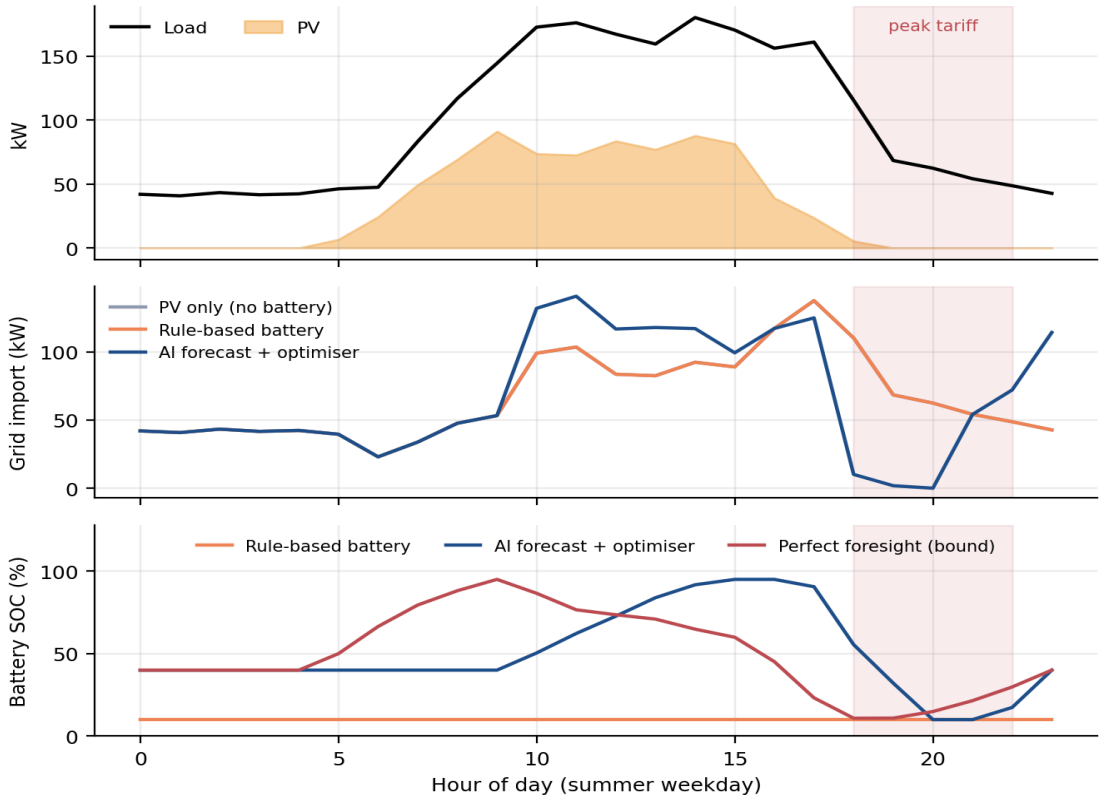


Fig. 6. Operation on a summer weekday: load and PV (top), grid import for three strategies (middle) and battery SOC for three strategies (bottom). The shaded band is the peak-tariff window.

Economic and technical performance

Table 4 and Figs. 7 and 8 give the annual outcomes. PV-only operation costs 49,046 USD per year. The rule-based battery lowers this by 3.7%, mainly by raising PV self-consumption from 86% to 95%. The proposed AI forecast + optimiser reaches 44,128 USD, a 10.0% saving over PV-only and 6.6% over the rule-based controller, and cuts

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peak-window imports from 77.2 MWh to 13.7 MWh. The persistence-forecast version achieves 8.9%, so better forecasts are worth about 563 USD per year, roughly a tenth of the total benefit of storage in this case. The perfect-foresight bound reaches 13.6%, leaving 1,749 USD per year that forecast error prevents the day-ahead scheme from capturing.

The decomposition of that gap is informative. Perfect foresight lowers the sum of monthly maximum imports from 144 kW to 78 kW, which cuts the demand charge from 9,254 to 4,459 USD. The forecast-driven schedules do not: the monthly maximum under AI scheduling is 150 kW, and under persistence 163 kW, compared with 144 kW for PV-only operation. A demand charge depends on one hour in the month, and a day-ahead forecast error of a few kilowatts in that hour, or a battery that has been used earlier in the day, is enough to miss the target. This is the clearest limitation of the day-ahead scheme and indicates that intra-day re-planning, probabilistic forecasts [9], [31] or a reserve of battery energy for peak shaving are worth investigating.

TABLE 4. Annual performance of the five strategies on the test year.

Strategy	Annual cost (USD)	Saving vs PV-only (%)	Peak-window import (MWh)	PV self-use (%)	Max. demand sum (kW)†
PV only	49,046	0.0	77.2	86.2	144
Rule-based battery	47,245	3.7	62.4	95.0	144
Persistence + optimiser	44,691	8.9	13.1	92.7	163
AI forecast + optimiser	44,128	10.0	13.7	93.6	150
Perfect foresight (bound)	42,379	13.6	45.3	95.0	78

† Largest hourly grid import in any month of the year.

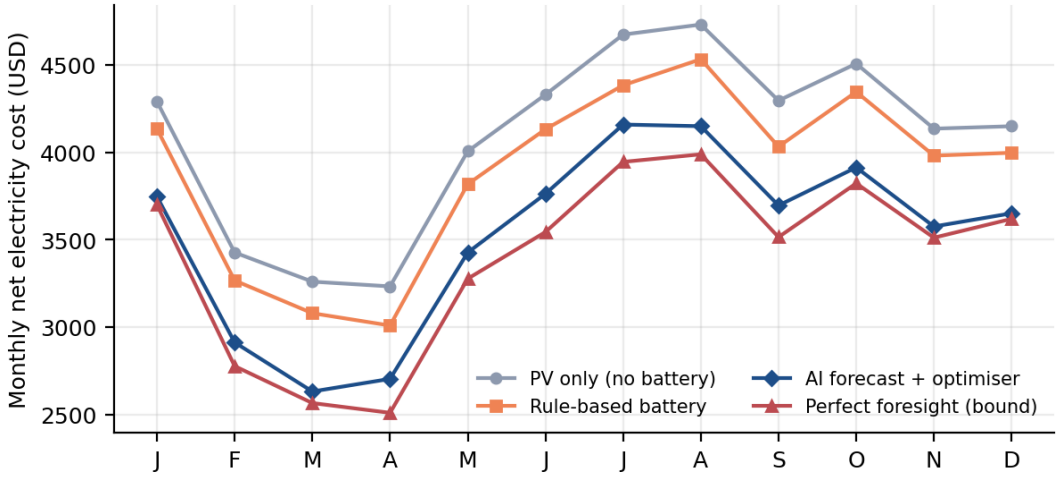


Fig. 7. Monthly net electricity cost (energy, demand and degradation less export

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credit) for four strategies.

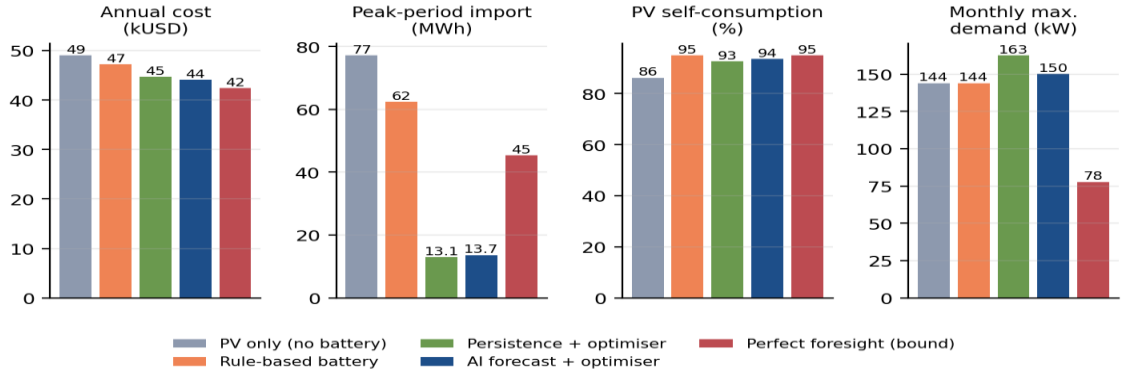


Fig. 8. Annual cost, peak-window import, PV self-consumption and maximum demand for the five strategies.

Sensitivity to battery size and tariff spread

Fig. 9 shows annual savings of the AI scheduler relative to PV-only operation as battery capacity (with power fixed at one third of capacity) and the peak-window tariff vary. Savings rise with both, but with diminishing returns in capacity once the battery can cover the whole evening window: at the base tariff of 0.20 USD/kWh, going from 300 to 600 kWh raises the saving from 4.9 to 6.7 kUSD per year, while at 0.12 USD/kWh a battery above 300 kWh adds almost nothing. With the assumed capital cost of 250 USD/kWh, the 300 kWh battery has a simple payback of 15.3 years at the base tariff, 6.0 years at a peak price of 0.32 USD/kWh, and 40 years at 0.12 USD/kWh. Whether storage is attractive therefore hinges on the tariff structure and installed cost rather than on the control algorithm alone [27], [28]. The simple payback ignores discounting, battery lifetime and replacement, incentives, and revenue from other services.

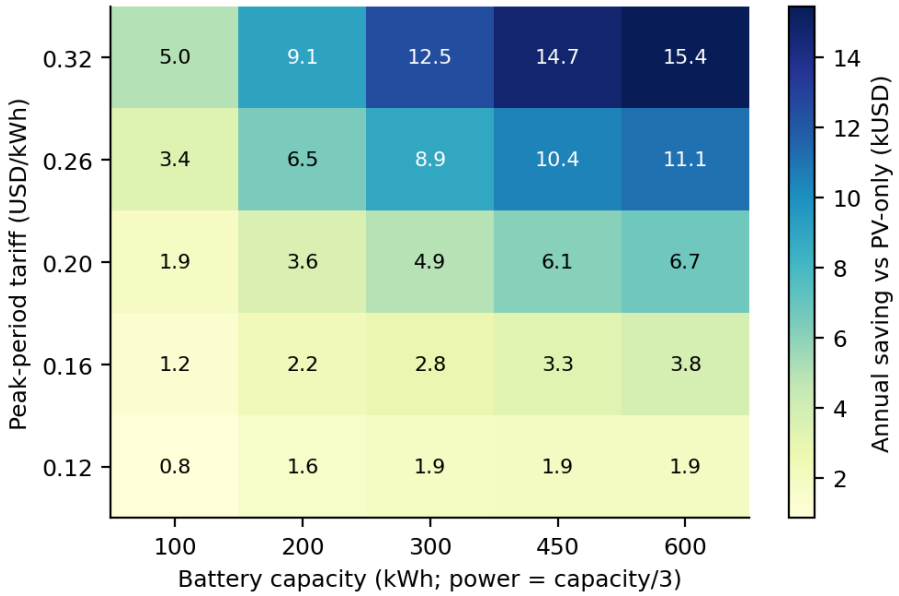


Fig. 9. Annual saving (kUSD) of the AI scheduler relative to PV-only operation as a

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function of battery capacity and peak-window tariff.

Discussion

In summary, gradient boosting reduced load RMSE to 5.1 kW from 15.0 kW for persistence [9], [13]. The forecast-driven scheduler saved 10.0% of annual cost against PV-only operation and 6.6% against the rule-based battery, while the perfect-foresight bound saved 13.6% [20]. Imports in the 18:00–22:00 window fell by 82% [4], but the monthly maximum demand was not reduced (150 kW against 144 kW), unlike the perfect-foresight case (78 kW). Simple payback of the 300 kWh battery ranged from about 6 to more than 40 years across the tariff range tested [27], [28].

Three points follow from these results. First, most of the economic benefit comes from operating storage with awareness of the tariff: a naive-forecast optimiser already saves about 8.9%, compared with 3.7% for the rule-based controller. This supports the view that the choice of control paradigm matters more than the forecast model within a given paradigm [5], [20]. Second, better forecasting adds a measurable further saving at little cost, since gradient boosting trains in seconds on ordinary hardware [14], [17]. Third, forecast error reduces the value of demand-charge management far more than it reduces energy-cost savings, which matters for tariffs with a demand component [4].

The results are consistent with the qualitative message of the MPC and reinforcement-learning literature that anticipatory control outperforms reactive control [19], [22], [23]. They also reinforce a caution from the RL reviews: a more complex learner is not obviously required when the problem has a well-understood structure that can be solved by a linear program with reliable forecasts [23], [35]. Reinforcement learning may still be preferable where the dynamics are hard to model, for example when HVAC thermal flexibility is included [24], [21]. Hybrid designs in which forecasts and learned policies complement an optimiser are a natural direction [38].

For practitioners, the sensitivity analysis suggests a sequence of decisions: confirm the tariff spread and demand-charge structure first, then size storage to the evening window, and only then invest in forecasting and optimisation software. The rooftop screening is a reminder that the array and any ballast must be checked against the structure before energy modelling is trusted [32]; in the assumed case the interior roof zones could be ballasted within the assumed spare capacity, but edge zones would need anchoring.

Implementation considerations

Deploying the framework in a real building requires more than the algorithms studied here. A data pipeline must collect interval meter readings, inverter and battery telemetry, and a day-ahead weather forecast, with quality checks for missing values and sensor faults [5], [36]. Forecast models should be retrained periodically, because occupancy patterns, equipment and tenancy change; tree-based models retrain in seconds, so a weekly or monthly schedule is practical [14], [17]. The optimiser should be wrapped in a supervisory layer that enforces manufacturer limits on the battery and falls back to a rule-based mode if forecasts or communication fail, since a rule-based controller was shown here to retain part of the benefit [4]. Interoperability with existing building automation, cybersecurity of connected assets, and clear

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performance verification against a measured baseline are further practical requirements that the literature identifies as barriers to uptake [5], [36].

Implications for tariff design

The sensitivity results link control value to tariff structure. A large peak-to-off-peak spread rewards storage that shifts energy, while a demand charge rewards storage that shaves the single highest interval, and the two reward different control capabilities [4], [27]. Where utilities wish to encourage flexible buildings, tariffs that expose a clear time-of-use signal, and net-metering rules that remain stable over the life of an installation, reduce the risk faced by investors [2], [36]. Conversely, a demand charge computed on a single interval penalises forecast-based control more than a charge computed on an average of the highest several intervals; designers and regulators may wish to consider this when specifying demand components. These remarks follow from the simulated tariffs used here and should be tested against actual tariff schedules.

Limitations

The building load is simulated, not metered, and the weather is synthetic, so forecast accuracy on a real building will differ and is likely to be worse because of occupant behaviour and equipment events [7], [33]. Tariffs, export credit, demand charge, degradation cost and capital cost are assumed, and the payback figures change with them, as Fig. 9 shows [27], [28]. The wind pressure coefficients and the spare roof capacity are also assumed values, and the rooftop check is a screening calculation rather than a structural design [32].

The study covers a single building, a single climate and one test year, so no uncertainty intervals across years or buildings are given. Only electrical dispatch is optimised; HVAC thermal flexibility, comfort constraints, battery ageing beyond a throughput cost, and grid export limits are not modelled [18], [34]. Schedules are planned a day ahead and applied without intra-day correction, which explains the missed demand-charge reduction, and closed-loop MPC would probably perform better [20]. Deep learning and reinforcement learning were not implemented, so statements about them rely on the published literature [22], [26].

Conclusions and Future Work

This study developed a forecast-informed battery scheduling framework for a solar-integrated smart building and evaluated it against a no-battery case, a rule-based controller, a naive-forecast optimiser and a perfect-foresight bound. On a simulated office building, gradient-boosting forecasts reduced load RMSE by about 66.4% relative to persistence; the resulting schedule lowered annual electricity cost by 10.0% over PV-only operation and 6.6% over a rule-based battery controller, and nearly eliminated peak-window imports. It did not reduce monthly maximum demand, which a perfect-foresight schedule could halve, showing that forecast error matters most for demand charges. The value of storage depends strongly on the tariff spread and on capital cost, with simple payback ranging from about six years to several decades in the assumed range [27], [28].

Future work should (i) validate the framework on metered data from a real building,

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(ii) replace day-ahead planning by closed-loop MPC with probabilistic forecasts [9], [20], [31], (iii) include HVAC thermal flexibility and comfort constraints [18], [34], (iv) compare against reinforcement-learning controllers on the same benchmark [22], [23], and (v) couple the energy model with a full structural assessment of the roof [32].

Data and Code Availability

The building load, weather and forecasts used here are synthetic and were generated by the Python scripts used to produce all figures and tables (NumPy, pandas, scikit-learn [17], SciPy [30]). The scripts and generated data are available from the authors on request.

Declarations

The authors declare no competing interests.

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