algorithms

MDPI

Article

Optimal Demand Response-Based Energy Management for Campus Buildings with Battery Energy Storage Systems: A Case Study of the ELB Building

Ali Beidoun, Quang Manh Hoang, Guilherme Vieira Hollweg and Van-Hai Bui*

Department of Electrical and Computer Engineering, University of Michigan-Dearborn, Dearborn, MI 48128, USA; alibeido@umich.edu (A.B.); manhhq@umich.edu (Q.M.H.); hollweg@umich.edu (G.V.H.)
* Correspondence: vhbui@umich.edu

Abstract

Buildings account for a significant portion of global electricity consumption, highlighting the need for cost-effective energy management strategies. This paper presents a measurement-driven energy management and decision-support framework integrating demand response (DR) and battery energy storage systems (BESSs) for campus buildings. Using measured electricity demand and rooftop photovoltaic generation data from the Engineering Laboratory Building (ELB) at the University of Michigan–Dearborn, a mixed-integer linear programming (MILP) model evaluates four operating scenarios under a utility tariff-based cost structure. A graphical user interface (GUI) is also developed to facilitate practical application of the framework and support campus operators in evaluating energy management and system upgrade alternatives. Results for May 2026 demonstrate electricity cost reductions of 19.6% with DR alone and 32.5% with coordinated DR–BESS operation, while the corresponding savings over six months are 14.3% and 26.9%. However, the estimated battery payback period of 14.5–16.6 years highlights the importance of economic feasibility in investment decisions. The findings provide actionable recommendations for campus operators, prioritizing DR implementation and identifying BESSs as a potential subsequent upgrade based on economic benefits and building load characteristics.

Keywords: building energy management system; demand response; battery energy storage system; optimal scheduling; campus buildings; electricity cost minimization

Academic Editors: Carolina Del-Valle-Soto and Bo Yang

Received: 14 October 2026
Revised: 17 November 2026
Accepted: 19 November 2026
Published: 21 November 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Buildings constitute a significant portion of global energy consumption, making improvements in building energy efficiency, operational control, and demand-side flexibility increasingly important for reducing operating costs and supporting more sustainable power systems [1–5]. Large commercial and institutional buildings are particularly relevant because their electricity demand varies with HVAC operation, lighting, occupancy, laboratory activities, and other time-dependent loads. At the same time, building energy management must balance energy consumption, peak demand, and operational requirements, including occupant comfort where applicable [3,4].

Demand response (DR) provides a mechanism for making part of this building demand controllable. DR enables consumers to modify the timing or magnitude of

electricity consumption in response to electricity prices, utility signals, or system conditions [6–8]. Optimization-based DR has been used to schedule flexible appliances and loads, reduce electricity payments, and reshape load profiles [7–9]. The controllability of electrical loads has also been studied from a broader power-system perspective, while specific load models have been developed to represent the response of HVAC and other controllable loads [10–13]. These studies establish the basic principle of using load flexibility as an energy-management resource rather than treating the building load as completely fixed.

The flexibility available from DR alone, however, is limited by the operating requirements of the loads. HVAC and lighting systems, for example, cannot be reduced or shifted without limits, and the available flexibility depends on equipment characteristics, operating schedules, and acceptable service conditions [10,11]. Once these limits are reached, additional load flexibility cannot be obtained simply by increasing the DR signal. Battery energy storage systems (BESSs) therefore provide a complementary source of flexibility. A BESS can charge during periods of low-cost electricity or available photovoltaic generation and discharge during high-cost or high-demand periods, providing energy shifting and peak-demand reduction [13–15].

The coordinated operation of flexible demand and energy storage has consequently become an established energy-management problem. Atzeni et al. [16] considered demand-side management together with distributed generation and storage, while Wang et al. [9] developed a coordinated price-based DR and BESS framework that explicitly considered battery state-of-charge management and uncertainty. Other building and microgrid studies have similarly combined renewable generation, storage, controllable loads, and grid transactions to reduce operating cost [17–20]. These studies demonstrate that DR and storage can provide complementary flexibility, but they also show that the resulting economic benefit depends on the building load profile, resource configuration, and electricity-market or tariff structure.

For commercial and institutional buildings, the electricity tariff is particularly important because the electricity bill may contain both volumetric energy charges and demand charges. A tariff with a demand component assigns a monetary cost to the customer's maximum demand over a specified billing period. Consequently, a short-duration reduction in the building's peak grid demand can have a much larger effect on the monthly bill than a comparable reduction in total energy consumption. Previous work has explicitly incorporated demand charges into BESS scheduling and building energy-management problems [20,21]. For example, Gao et al. formulated BESS scheduling as an MILP that includes energy costs, demand charges, and battery wear costs and evaluated the approach using measured campus-microgrid data [20].

The importance of the tariff structure has also been examined directly in commercial-building optimization. Hasan et al. developed a framework for optimizing commercial-building loads with renewable generation and BESSs under different utility rate structures and showed that the tariff type can strongly influence the economic value of storage [22]. More recent work has extended this idea to multiple tariff categories and analyzed how changes in energy and demand-charge components affect optimization results [22,23]. These studies make clear that the value of DR and BESSs cannot be separated from the billing mechanism under which a facility operates. However, tariff-oriented studies generally consider generalized tariff classes or collections of commercial-building profiles, whereas a facility-specific evaluation using the actual utility tariff and measured operating data provides a different practical perspective.

This issue is especially relevant for university campuses, where buildings combine laboratories, classrooms, offices, HVAC systems, lighting, and other loads with different degrees of flexibility. Existing campus studies have investigated price-based DR,

photovoltaic generation, storage, and energy-management systems using optimization-based approaches [18,19,24]. Previous research has also evaluated rooftop PV performance using metrics such as performance ratio, capacity factor, energy losses, and degradation rate, highlighting the importance of PV generation characteristics in building energy studies [25]. Real-building studies have also demonstrated the value of measured smart-meter data for building energy-management optimization [19]. In addition, commercial-building studies have shown that peak demand and load-profile characteristics can strongly affect the economic value of BESS deployment [15,20,21]. These results motivate a case-specific assessment in which the optimization is tied directly to the measured load of an institutional building and the tariff actually applied to that facility.

Motivated by this practical need, this paper develops an optimal energy-management framework for the Engineering Laboratory Building (ELB) at the University of Michigan-Dearborn. The building is supplied by the utility grid and an existing rooftop photovoltaic system, while a BESS is modeled as a proposed additional resource. The energy-management problem is formulated as a mixed-integer linear programming (MILP) model that jointly schedules flexible building demand and BESS charging/discharging subject to demand-response, battery, PV, grid-capacity, and power-balance constraints. The optimization is performed over the monthly billing period so that the demand-charge component can be represented directly. The electricity cost is calculated using the DTE Energy Primary Educational Institution Rate D6.2, including its energy, demand, and fixed service charges [26]. By integrating rooftop PV generation with coordinated DR and BESS scheduling, the proposed framework aligns with Sustainable Development Goal 7 (SDG-7), particularly its emphasis on affordable and clean energy.

The framework is evaluated using measured ELB electricity-demand data and measured rooftop-PV generation data. Four operating cases are compared under the same billing-period data and tariff: baseline operation, DR only, BESS only, and coordinated DR and BESS. This design isolates the contribution of demand flexibility, the contribution of storage, and the additional benefit obtained when the two resources are operated together. For the May 2026 case, DR alone reduces the monthly electricity bill by 19.6%, while coordinated DR and BESS operation reduces the bill by 32.5%. Additional BESS-capacity cases and a December 2025 case are used to examine how the observed savings vary with storage capacity and load-profile characteristics, and the analysis is extended to all six months with measured PV data, together with a payback estimate for the battery.

The main contributions of this study are:

1. Measurement-driven evaluation: An evaluation using measured campus building electricity demand, rooftop PV generation, and actual utility tariff data.
2. Economic assessment: A comparative economic analysis of DR and BESS alternatives to support cost-effective energy management and infrastructure upgrade decisions.
3. Operator-oriented GUI: Development of a graphical user interface (GUI) to facilitate the visualization of energy management results and support decision-making by campus building operators.
4. Practical recommendations: Actionable recommendations for campus operators regarding DR prioritization, BESS sizing, and future energy management improvements.

2. System Configuration and Operation Strategy

Figure 1 illustrates the system configuration and operation strategy. The framework is split into two layers: the optimization layer and the physical layer. The upper layer contains the data and optimization components: measured building loads recorded at 15 min intervals and used directly at that resolution, measured hourly rooftop PV generation, and the DTE D6.2 tariff. These inputs feed a mixed-integer linear program implemented

in Python 3.13, which determines the 15 min operating schedule for the billing period. The lower layer represents the physical building energy system. The ELB is supplied from the utility grid and from the existing rooftop solar array, both of which connect to the building bus. The battery energy storage system is modeled as a proposed addition rather than existing equipment and supplies power to the bus.

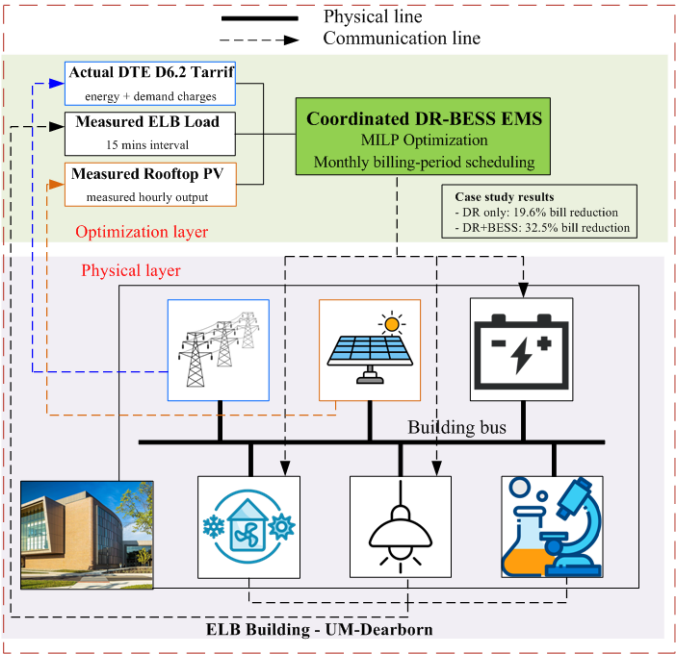

Figure 1. Building system configuration.

Figure 2 shows the overall data preparation and optimization procedure. The process is organized into two stages. In the first stage, we input measured load, solar generation, and utility tariff data for the ELB for each interval t of the billing month. At each interval, the building load is separated into a fixed component and a flexible component, where the flexible component consists of the HVAC and lighting loads available for demand response. Demand response limits, BESS parameters, and other operational constraints are then defined. This process repeats for every interval until $t = N$, after which the fully prepared dataset is passed to the optimization stage.

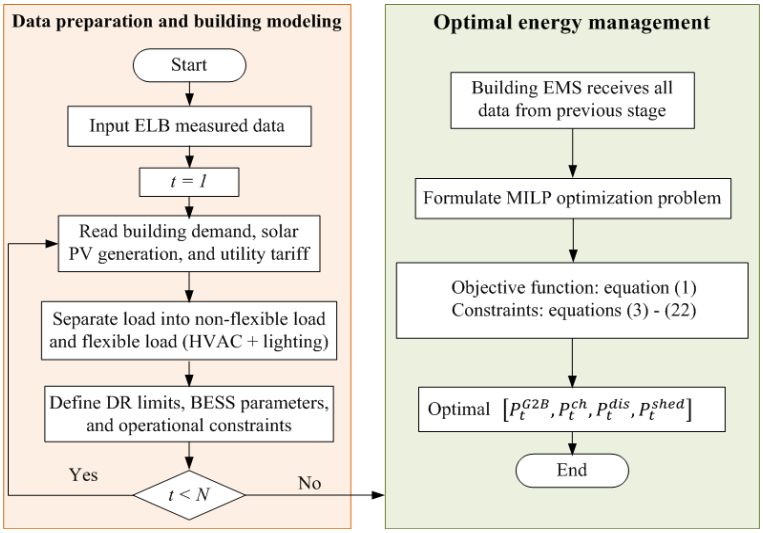

Figure 2. Flowchart for optimal operation of the campus building.

In the second stage, the building energy management system receives the complete dataset and formulates the MILP optimization problem described in Section 3. The objective minimizes total monthly electricity cost, comprising the energy charge, the battery degradation cost, and the demand charge, with the fixed service charge added to the reported bill, subject to constraints on demand response, PV utilization, BESS operation, and power balance. The optimizer jointly determines the flexible load schedule and the BESS charging and discharging schedule, from which the optimal grid import, PV utilization, and monthly billed peak demand are obtained. The final outputs are the optimal flexible load schedule, BESS charge and discharge profile, grid import profile, PV utilization, peak demand, and total monthly electricity cost.

3. Problem Formulation

The proposed framework is formulated as a mixed-integer linear program (MILP) that determines the optimal ELB schedule over a monthly billing cycle. The building is currently supplied by grid electricity and on-site solar PV generation, and a portion of the load is treated as flexible and available for demand response. Additionally, we propose a battery energy storage system (BESS) as an additional resource to assist demand response. A billing cycle is defined by a set of 15 min intervals $T = \{0, 1, \ldots, N-1\}$ of duration $\Delta t = 0.25$ h, where N is the number of intervals in a billing month (2976 for a 31-day month). Using the 15 min meter readings directly preserves short demand peaks that hourly averaging would smooth out (Section 4). We used a monthly cycle rather than a daily cycle because the demand charge tariff is based on the single highest demand within the billing period and cannot be captured in a daily window.

The objective is to minimize the total operational cost of the building. In Equation (1), starting from the left, the first term is the energy charge for power imported from the grid into the system. The second and third terms are the charging and discharging degradation costs of the BESS. The final term is the demand charge, applied once per billing period to the monthly billed peak P^{peak}. Although the demand-charge rates are constant, P^{peak} is a decision variable, so this term drives the optimizer to reduce the highest on-peak grid import. The fixed monthly service charge does not depend on any decision variable and is omitted from the objective, but it is included in the reported monthly bill. Load shed by demand response does not appear as a separate term. It reduces the power imported from the grid through the power balance in Equation (22), so its savings are already captured in the energy charge and, during on-peak intervals, in the demand charge.

$$\sum_{t \in T} \left(p_t^{G2B} c_t^{grid} + c^{ch} . p_t^{ch} + c^{dis} . p_t^{dis} \right) \Delta t + \left(c^{cap} + c^{noncap} + c^{dist} \right) P^{peak} \quad (1)$$

where

p_t^{G2B} is the power imported from the grid;

c_t^{grid} is the grid energy price;

c^{ch}, c^{dis} are the charging and discharging degradation costs of the BESS;

Δt is the interval duration (0.25 h);

p_t^{ch}, p_t^{dis} are the charging and discharging power of the BESS;

P^{peak} is the monthly billed peak demand;

$c^{cap}, c^{noncap}, c^{dist}$ are the capacity, non-capacity, and distribution demand charge rates.

The degradation cost is derived from the capital cost and rated cycle life of the battery, as given by Equation (2). Each full cycle moves the usable capacity of the battery once in charge and once in discharge, so the capital cost is spread evenly over the lifetime charge and discharge throughput.

$$c^{ch} = c^{dis} = \frac{C^{BESS}}{2N^{cyc}(E^{max} - E^{min})} \quad (2)$$

where
C^{BESS} is the capital cost of the BESS;
N^{cyc} is the rated cycle life of the BESS.

Demand response is represented by two mechanisms: load shedding, in which demand is reduced and not recovered, and load shifting, where demand is relocated to a lower-peak interval. The load shed in each interval is limited by the flexibility of the load, as given by (3). The maximum sheddable load in each interval is the sum of the flexible HVAC and lighting shares in that interval, as expressed in (4), where the HVAC and lighting load profiles are defined by (5) and (6). We also limit the shedding to a predetermined demand response event window by (7), limiting the shedding to the peak intervals.

Load shifting is modeled using two variables representing demand removed from and added to each interval. The flexible load available for shifting, F_t^{max}, consists of the same HVAC and lighting shares as (4) but is not limited to the event window. The quantity shifted out is limited by the flexibility of the system, and the quantity shifted in has additional headroom so that the specified interval can take in the shifted demand without overloading, as expressed in (8) and (9). Shifted demand must be recovered within the same day, so load moved out of an interval is served later that day, reflecting the recovery period of thermal loads such as pre-cooling, as enforced by (10).

$$p_t^{shed} \leq S_t^{max} \quad \forall\, t \in T \quad (3)$$

$$S_t^{max} = \alpha^{hvac} L_t^{hvac} + \alpha^{light} L_t^{light} \quad \forall\, t \in T \quad (4)$$

$$L_t^{hvac} = \beta^{hvac} L_t \quad \forall\, t \in T \quad (5)$$

$$L_t^{light} = L^{light,max} \phi_{h(t)} \quad \forall\, t \in T \quad (6)$$

$$S_t^{max} = 0 \quad \forall\, t \notin [t_{start}, t_{end}] \quad (7)$$

$$p_t^{out} \leq F_t^{max} \quad \forall\, t \in T \quad (8)$$

$$p_t^{in} \leq F_t^{max} + 0.25\, L_t \quad \forall t \in T \quad (9)$$

$$\sum_{t \in T_d} p_t^{out} = \sum_{t \in T_d} p_t^{in} \quad \forall d \quad (10)$$

where
S_t^{max} is the maximum sheddable load at t;
L_t is the measured building load at t;
p_t^{shed} is the amount of load shed due to demand response;
L_t^{hvac}, L_t^{light} are the HVAC and lighting load at t;
$\alpha^{hvac}, \alpha^{light}$ are the allowed shed fractions of the HVAC and lighting systems;
β^{hvac} is the HVAC share of building load;
$L^{light,max}$ is the installed lighting load;
ϕ_h is the hourly lighting occupancy profile;
$h(t)$ is the hour-of-day interval t;

https://doi.org/10.3390/a19121021

t_{start}, t_{end} are the start and end of the demand response event window (12:00 and 18:00);
p_t^{out}, p_t^{in} are the amounts of load shifted out of and into t;
F_t^{max} is the flexible load available for shifting at t;
T_d is the set of intervals in day d.

The PV power utilized by the building cannot exceed the amount of solar power generated in any given interval, as represented by Equation (11). We use Equations (12)–(19) to constrain our BESS. In (12) and (13), charging and discharging power are capped and only permitted when they are active. Equation (14) prevents a situation where we are charging and discharging the BESS at the same time. The stored energy carries over from interval to interval in Equations (15) and (16), with the first interval initialized from the starting charge. Equation (17) requires the battery to end the billing cycle at the level at which it began so that the schedule is self-contained, and Equation (18) holds the stored energy within the physical limits of the battery. Equation (19) limits the battery's monthly discharge throughput to $N^{cyc,m}$ equivalent full cycles, set to one cycle per day, consistent with the cycling assumption behind the cycle life used in Equation (2).

$$p_t^{PV} \leq PV_t \quad \forall\, t \in T \tag{11}$$

$$p_t^{ch} \leq I_t^{ch} P^{ch,max} \quad \forall\, t \in T \tag{12}$$

$$p_t^{dis} \leq I_t^{dis} P^{dis,max} \quad \forall\, t \in T \tag{13}$$

$$I_t^{ch} + I_t^{dis} \leq 1 \quad \forall\, t \in T \tag{14}$$

$$E_0 = E^{init} + (\eta^{ch} p_0^{ch} - \frac{p_0^{dis}}{\eta^{dis}})\Delta t \tag{15}$$

$$E_t = E_{t-1} + (\eta^{ch} p_t^{ch} - \frac{p_t^{dis}}{\eta^{dis}})\Delta t \quad \forall\, t \geq 1 \tag{16}$$

$$E_0 = E_{|T|-1} \tag{17}$$

$$E^{min} \leq E_t \leq E^{max} \quad \forall\, t \in T \tag{18}$$

$$\sum_{t \in T} p_t{}^{dis} \Delta t \leq N^{cyc,m}(E^{max} - E^{min}) \tag{19}$$

where
p_t^{PV} is the PV power utilized by the building at t;
PV_t is the available solar generation at t;
I_t^{ch}, I_t^{dis} are the binary charging and discharging indicators at t;
$P^{ch,max}, P^{dis,max}$ are the maximum charging and discharging power of the BESS, equal to its rated power, taken as $0.25E^{max}$;
$N^{cyc,m}$ is the maximum number of equivalent full cycles per month (one per day);
E_t is the energy stored in the BESS at t;
E^{init} is the initial stored energy of the BESS;
η^{ch}, η^{dis} are the charging and discharging efficiencies;
E^{min}, E^{max} are the minimum and maximum stored energy of the BESS.

Grid import is bounded by the service capacity of the building, as given by Equation (20). Then Equation (21) defines the billed peak demand, which is required to be as large as the grid import in every on-peak interval. Since Equation (1) is applied to these values, the optimization function uses this as a common ceiling for everything to follow. The operation of the building has to follow the power balance rule; for each interval, the amount

we input, generate through PV, and discharge from the BESS must be equal to the building load plus the BESS charging, as given by Equation (22). Here, the charging and discharging power are measured at the building bus, so conversion losses are applied only once, in the stored-energy Equations (15) and (16), avoiding double-counting of the battery efficiency.

$$p_t^{G2B} \leq P^{G2B,max} \quad \forall\, t \in T \tag{20}$$

$$P^{peak} \geq p_t^{G2B} \quad \forall\, t \in T_{on} \tag{21}$$

$$p_t^{G2B} + p_t^{PV} + p_t^{dis} = \left(L_t - p_t^{shed} - p_t^{out} + p_t^{in}\right) + p^{ch}{}_t \quad \forall\, t \in T \tag{22}$$

where
$P^{G2B,max}$ is the maximum grid connection capacity of the building;
T_{on} is the set of on-peak intervals (7:00–23:00).

4. Engineering Laboratory Building (ELB) and Dataset

This framework is validated by using the Engineering Laboratory Building (ELB) at the University of Michigan-Dearborn as a real-world case study. The ELB is a 123,000 square-foot facility including a mix of engineering laboratories and classroom space. The building is billed under the DTE tariff structure, and the building's load is monitored through dedicated electrical metering, which forms the basis of the dataset used in this study.

The data provided was recorded at 15 min intervals over a multi-year period. Eight invalid near-zero readings, at 02:00–02:45 on 8 March 2026 (the daylight-saving time change) and on 5 April 2026, were replaced by linear interpolation. The optimization uses these 15 min readings directly, since averaging them to hourly values would understate the billing peak: the highest 15 min demand was 168.7 kW in May 2026 and 94.9 kW in December 2025, 6% and 19% higher than the corresponding hourly averages. The solar PV generation was measured by the array's production meter at hourly resolution, with usable records beginning in December 2025; each hourly value was applied uniformly across its four 15 min intervals. Missing PV readings (73 h on 12–15 December 2025 and 2 h on 5 February 2026, less than 1% of production) and small negative nighttime readings were set to zero. For this study, we evaluated every month for which both measured load and PV data are available, December 2025 through May 2026, and selected two months for detailed analysis: May 2026, representing the higher-demand cooling season, and December 2025, representing the lower-demand winter season. Each month provides 2976 15 min load readings and 744 hourly PV readings, and both fall within the period covered by the PV data. Figure 3 shows the distribution of the 15 min load in May 2026, and Table 1 compares its weekday and weekend loads.

Based on the data provided, we can see that the ELB maintains a large, continuous operating base load; this is consistent with laboratory equipment, HVAC, and lighting being active even on the weekends, as they can be serving research spaces. Figure 4 shows the same distribution for December 2025, and Table 2 compares its weekday and weekend loads.

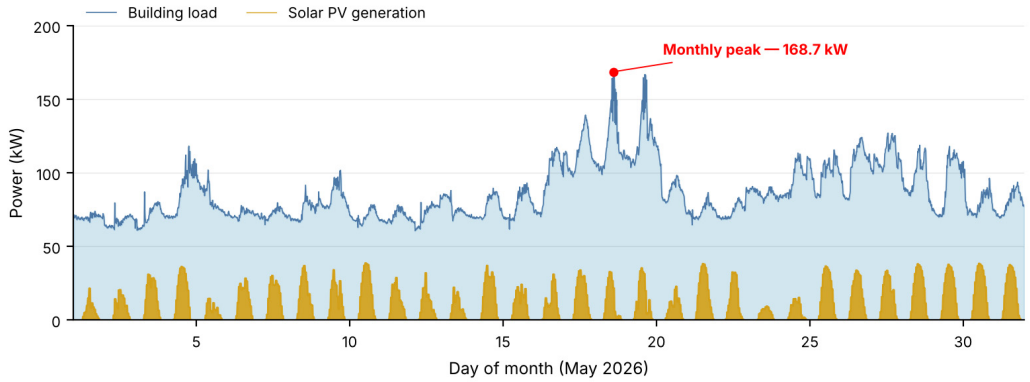

Figure 3. The monthly load distribution of the ELB for the month of May.

Table 1. Load of the ELB comparing weekends to weekdays in May.

	May Weekday	May Weekend
Days	21	10
Average Load	86.6 kW	84.3 kW
Maximum Load	168.7 kW	139.3 kW

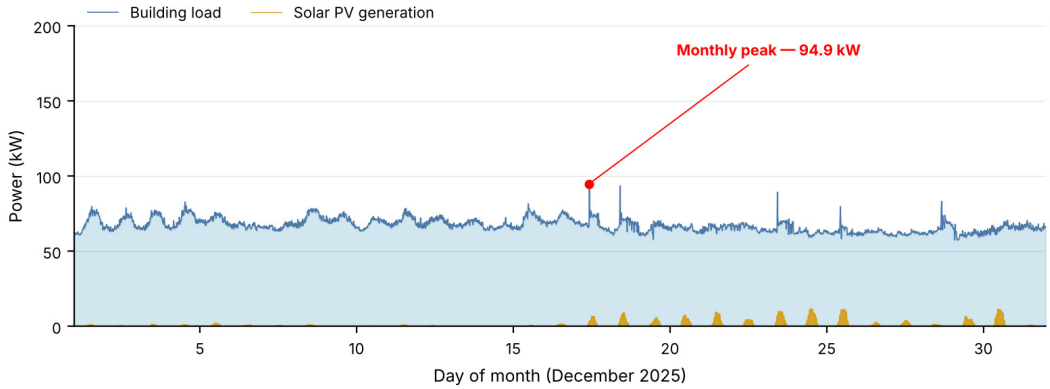

Figure 4. The monthly load distribution of the ELB for the month of December.

The rooftop PV array produced 18,796 kWh over December 2025–May 2026, ranging from 336 kWh in January to 7175 kWh in May, with a peak hourly output of 38.9 kW, equal to 5.8% of the building's electricity consumption over the same period (1.1% in December and 11.2% in May).

Table 2. Load of the ELB comparing weekends to weekdays in December.

	December Weekday	December Weekend
Days	23	8
Average Load	67.7 kW	65.7 kW
Maximum Load	94.9 kW	83.2 kW

As in May, the December weekend average (65.7 kW) was close to the weekday average (67.7 kW). However, December's load was considerably lower and flatter: its highest 15 min demand was 94.9 kW, compared with 168.7 kW in May. This flatter winter profile directly affects the value of battery storage, as discussed in Section 5.

Table 3 summarizes the measured load and PV generation for each of the six months studied.

Table 3. Monthly load and PV Generation of the ELB, December 2025–May 2026.

Month	Days	Avg Load (kW)	Max Load (kW)	Energy Use (MWh)	PV Generation (kWh)	PV Load Share
December 2025	31	67.2	94.9	50.0	534.5	1.1%
January 2026	31	66.5	103.8	49.5	335.8	0.7%
February 2026	28	66.9	100.2	44.9	1553.0	3.5%
March 2026	31	74.6	128.9	55.5	3813.1	6.9%
April 2026	30	83.3	129.6	60.0	5384.6	9.0%
May 2026	31	85.9	168.7	63.9	7174.8	11.2%
Total	182			323.8	18,795.8	5.8%

The ELB is billed under DTE Energy's Primary Educational Institution Rate (D6.2) [26], a commercial tariff that combines energy time charges with a demand charge based on the customer's highest 15 min demand during on-peak intervals. The rate components used in this study, obtained from the university's March 2026 electricity invoice, are summarized in Table 4.

Table 4. DTE energy tariff D6.2.

Parameters	Rate
Energy (On-Peak)	\$0.04535/kWh
Energy (Off-Peak)	\$0.04235/kWh
Capacity Demand Charge	\$10.34/kW
Non-Capacity Demand Charge	\$3.99/kW
Distribution Demand Charge	\$7.15/kW
Service Charge	\$70.00/month

In Table 4, the energy charge is billed per kilowatt-hour consumed and differs only slightly between on-peak and off-peak hours (\$0.04535/kWh and \$0.04235/kWh, respectively), a spread of about 7%. Because the difference is small compared to typical time-of-use rate structures seen in residential tariffs, shifting energy consumption between hours provides limited direct benefit under this tariff.

The demand charges, however, are billed on the single highest power demand recorded during on-peak hours within the billing month, independent of total energy consumed. Three components apply: a capacity demand charge of \$10.34/kW, a non-capacity demand charge of \$3.99/kW, and a distribution demand charge of \$7.15/kW, together totaling \$21.48/kW of monthly billed peak demand. A fixed monthly service charge of \$70.00 is also applied regardless of consumption or demand.

Because the demand charges are assessed on the single highest demand interval of the month while the energy charge accumulates gradually over the whole month, a short-duration reduction in peak demand can produce a cost benefit comparable to a much larger reduction in total energy consumption. This asymmetry motivates the demand-charge-aware objective function formulation presented in Section 3 and is shown in Section 5 to account for most of the cost savings achieved in this study.

5. Simulation Results and Discussion

A mixed-integer linear program (MILP) was developed in Python 3.13 using the PuLP 2.9.0 modeling library and solved with the CBC 2.10.3 solver. All of our cases were evaluated at 15 min resolution for each of the six monthly billing periods from December 2025 to May 2026, using the measured building load, metered solar generation data, and the DTE D6.2 tariff parameters; May 2026 and December 2025 are presented in detail. Each monthly problem was solved to optimality in under one minute. For our proposed BESS, we modeled a 200 kWh usable capacity as the primary case, with additional 100 kWh and 150 kWh cases used to examine how the savings change with storage capacity. We compared four different usage cases. The baseline case represented our normal operation in which no demand response or storage is applied. We obtained this by setting our shedding and shifting ceilings to zero. The next case was utilizing demand response only; this enables load shedding and shifting but provides no battery storage. The BESS-only case enables battery scheduling while following scenario one and disabling shifting and shedding. Lastly, the DR + BESS case enables both resources simultaneously.

Table 5 summarizes the parameters used across all four cases. We simulated with a BESS of 200 kWh of usable capacity and a minimum reserve of 20 kWh to prevent full discharge. The charging and discharging efficiencies were taken to be 92%, which was around 85% for a full cycle. The rated power of the BESS was taken as one-quarter of its capacity (50 kW for the 200 kWh case). Its capital cost of $93,700 is the midpoint of the commercial and industrial range reported by Lazard [27], and its cycle life of 5475 cycles corresponds to one full cycle per day over a 15-year life [28]; by Equation (2), these give a degradation cost of $0.048/kWh. The monthly cycle limit of Equation (19) was set to one cycle per day. No demand response incentive payment is included; the value of demand response is measured only through the reduction in the D6.2 bill, so any payment from a utility demand response program would add to the savings reported here. In order to keep the cycle self-contained, the battery's initial charge was set to half of the rated capacity, and at the end of the billing period it was set to return to this level. For the demand response cases, HVAC, which is often one of the largest consumers of power, was assumed to represent 45% of the total building load, and lighting was assumed to be around 35 kW, about 22% of peak demand. HVAC was permitted to be reduced by up to 30% and lighting by up to 15% during the demand response event window.

Table 5. Model parameters.

Parameters	Value
Rated Power	50 kW (0.25 × capacity)
Charging/Discharging Efficiency	92%
Capital Cost	$93,700 ($468.5/kWh)
Cycle Life	5475
Degradation Cost	$0.048/kWh
Maximum cycles	One per day
BESS Capacity	200 kWh
BESS Minimum	10% of capacity (20 kWh at 200 kWh)
Initial charge	100 kWh (50% of capacity)
HVAC Load	45%
Maximum HVAC reduction	30%
Lighting Load	35 kW
Maximum Lighting reduction	15%
Maximum grid import	250 kW

Table 6 summarizes the monthly electricity cost of each case. Looking at the baseline, we can see that the total bill was $6017, with the demand charge being around $3435, which is 57% of the bill despite being based on only a single 15 min interval. This confirms that peak management, rather than conserving energy, is the dominant cost saver.

Table 6. Monthly bill comparison for May across DR, BESS, and combined scenarios (200 kWh battery).

Scenario	Bill	Energy Charge	Demand Charge	Billed Peak	Savings (%)
Baseline	$6016.87	$2511.68	$3435.19	159.9 kW	—
DR Only	$4837.38	$2340.35	$2427.03	113.0 kW	19.6
BESS Only	$4944.54	$2513.35	$2361.19	109.9 kW	17.8
DR + BESS	$4063.34	$2344.71	$1648.63	76.8 kW	32.5

Demand response alone reduces the monthly bill to $4837, a 19.6% saving relative to the baseline. This saving comes from both billing components: shedding removes energy from the billing period, lowering the energy charge, while shedding and shifting reduce the billed peak from 159.9 kW to 113.0 kW and lower the demand charge by $1008. The BESS-only case behaves differently; although the peak rate was lower overall, the bill was still higher than with DR alone. This can be assumed to be because a battery offsets our peak load, but we are still requiring the same amount of energy without cutting down. In our last scenario, coordinated operation of both resources produces the largest saving, reducing the monthly bill to $4063, or 32.5% below the baseline. The combined savings are larger than those of either resource alone but smaller than the sum of their separate savings (19.6% + 17.8% = 37.4%), because both resources reduce the same peak. Demand response reduces the peak load by shifting and shedding, and the battery then discharges against the reduced profile that remains; this profile is flatter, so the battery lowers the peak by 36.2 kW instead of the 50.0 kW it achieves on its own.

Table 7 presents the same tests but for a 100 kWh battery. With storage alone, we see that the bill falls to $5480.09, an 8.9% saving, while the peak is reduced from 159.9 kW to 134.9 kW. When combined with demand response, the bill falls to $4301.82, corresponding to a 28.5% saving and a billed peak of 88.0 kW. Similar to the 200 kWh case, the energy charge in the BESS-only scenario remains essentially unchanged from the baseline, $2511.90 against $2511.68, confirming that storage relocates energy in time rather than reducing total consumption. All of the savings in that case are therefore due to the reduction in demand charge.

Table 7. Monthly bill comparison for May across a baseline, BESS, and combined scenarios (100 kWh battery).

Scenario	Bill	Energy Charge	Demand Charge	Billed Peak	Savings (%)
Baseline	$6016.87	$2511.68	$3435.19	159.9 kW	—
BESS Only	$5480.09	$2511.90	$2898.19	134.9 kW	8.9
DR + BESS	$4301.82	$2341.79	$1890.03	88.0 kW	28.5

Table 8 presents the results for a 150 kWh battery. Storage alone reduces the bill to $5211.97, a 13.4% saving with a billed peak of 122.4 kW, while combined operation reduces the bill to $4175.44, a 30.6% saving with a billed peak of 82.0 kW.

Table 8. Monthly bill comparison for May across a baseline, BESS, and combined scenarios (150 kWh battery).

Scenario	Bill	Energy Charge	Demand Charge	Billed Peak	Savings (%)
Baseline	$6016.87	$2511.68	$3435.19	159.9 kW	—
BESS Only	$5211.97	$2512.28	$2629.69	122.4 kW	13.4
DR + BESS	$4175.44	$2343.15	$1762.29	82.0 kW	30.6

Comparing Tables 6–8 shows two consistent trends. First, increasing battery capacity produces a reduction in the peak and the total cost; however, it is not as effective as demand response. Second, in the BESS-only cases, the peak reduction equals the battery's rated power at every size (25.0, 37.5, and 50.0 kW), so in May it is the rated power, rather than the stored energy, that limits how far the battery can shave the peak. In all three battery scenario tests, the cost savings came from the demand charge since we were shifting the energy to a different point in time, which, while effective, wasn't the best solution. Even at 200 kWh, the BESS-only case gets a 17.8% saving compared to demand response reaching 19.6%. This supports the conclusion that demand response should be the primary cost-saving measure, with storage deployed as a complementary resource.

Demand response saved 19.6% in May but 12.5% in December, and the coordinated strategy saved 32.5% against 22.8%. Both differences come from the shape of the load profile. In December, the building's highest demand was only 1.41 times its average load, compared with 1.96 times in May, so the demand charge made up a smaller share of the baseline bill (47% against 57%), and there was less peak above the base load to remove. The value of battery storage was lower in winter for the same reason. In May, the battery alone lowered the billed peak by 50.0 kW, its full rated power, but in December only by 23.0 kW, to 68.6 kW, close to the building's average load of 67.2 kW. Below this level, the base load continues through the whole on-peak window every day: under coordinated operation, grid import is held at the billed peak of 53.1 kW in 859 on-peak intervals on all 31 days of December, compared with 296 intervals on 17 days in May. Each further kilowatt of peak reduction would require the battery to discharge throughout these intervals, and the degradation cost and conversion losses of that energy exceed the $21.48/kW demand charge it would save.

With storage alone at 100 kWh, the bill falls to $3752.24, an 11.3% saving, with a billed peak reduced from 91.6 kW to 69.1 kW. Combined with demand response, the bill falls to $3268.91, a 22.8% saving, with a billed peak of 53.1 kW. As in May, the BESS-only energy charge remains close to the baseline value ($2197.28 vs. $2194.27), confirming that the savings in that case are driven almost entirely by the reduced demand charge rather than reduced energy consumption.

At 150 kWh, storage alone yields an 11.6% saving with a billed peak of 68.6 kW, while coordinated operation reaches 22.8% with a billed peak of 53.1 kW, the same as at 100 kWh. Comparing Tables 9–11 with their May counterparts (Tables 6–8) shows that demand response alone outperforms storage alone at every capacity tested in both months. Unlike May, however, a capacity above 100 kWh adds little savings in December for storage alone (11.3% to 11.6%) and none for coordinated operation, for the reason explained above. Table 9 summarizes the same four cases for December 2025 with the 200-kWh battery.

Table 9. Monthly bill comparison for December across DR, BESS, and combined scenarios (200 kWh battery).

Scenario	Bill	Energy Charge	Demand Charge	Billed Peak	Savings (%)
Baseline	$4232.44	$2194.27	$1968.17	91.6 kW	—
DR Only	$3704.35	$2054.07	$1580.28	73.6 kW	12.5
BESS Only	$3740.50	$2197.78	$1472.71	68.6 kW	11.6
DR + BESS	$3268.91	$2057.88	$1141.03	53.1 kW	22.8

Table 10. Monthly bill comparison for December across a baseline, BESS, and combined scenarios (100 kWh battery).

Scenario	Bill	Energy Charge	Demand Charge	Billed Peak	Savings (%)
Baseline	$4232.44	$2194.27	$1968.17	91.6 kW	—
BESS Only	$3752.24	$2197.28	$1484.96	69.1 kW	11.3
DR + BESS	$3268.91	$2057.88	$1141.03	53.1 kW	22.8

Table 11. Monthly bill comparison for December across a baseline, BESS, and combined scenarios (150 kWh battery).

Scenario	Bill	Energy Charge	Demand Charge	Billed Peak	Savings (%)
Baseline	$4232.44	$2194.27	$1968.17	91.6 kW	—
BESS Only	$3740.50	$2197.78	$1472.71	68.6 kW	11.6
DR + BESS	$3268.91	$2057.88	$1141.03	53.1 kW	22.8

Table 12 compares the DR-only and coordinated results for both months at each battery capacity. At every capacity, both the bill and the billed peak are consistently lower in December than in May, reflecting December's smaller baseline load. The percentage savings are also lower in December, by 7.1 points at DR-only (19.6% vs. 12.5%) and 9.7 points at 200 kWh (32.5% vs. 22.8%), since the flatter December load profile leaves less peak above the base load for demand response and the battery to remove.

Table 12. Comparison of bill, peak demand, and savings for May and December under DR+BESS at increasing battery capacity.

Capacity (kWh)	May 2026			December 2025		
	Bill ($)	Peak (kW)	Savings (%)	Bill ($)	Peak (kW)	Savings (%)
DR Only	4837.38	113.0	19.6	3704.35	73.6	12.5
100	4301.82	88.0	28.5	3268.91	53.1	22.8
150	4175.44	82.0	30.6	3268.91	53.1	22.8
200	4063.34	76.8	32.5	3268.91	53.1	22.8

To examine whether these results hold beyond the two selected months, all four cases were also solved for every month with measured load and PV data. Table 13 summarizes the results for the 200 kWh battery.

Table 13. Monthly bills and savings, December 2025–May 2026 (200 kWh battery).

Month	Baseline	DR Only	BESS Only	DR + BESS
Dec 2025	$4232.44	$3704.35	$3740.50	$3268.91
Jan 2026	$4293.57	$3754.97	$3707.06	$3246.82
Feb 2026	$4130.29	$3599.80	$3423.40	$2980.43

Mar 2026	$5013.84	$4226.58	$4432.95	$3707.81
Apr 2026	$5188.71	$4613.77	$4581.50	$3834.79
May 2026	$6016.87	$4837.38	$4944.54	$4063.34
Total	$28,875.72	$24,736.85	$24,829.95	$21,102.10

Over the six months, demand response alone reduced the electricity cost by 14.3%, the battery alone by 14.0%, and coordinated operation by 26.9%. Demand response and storage alone therefore produced similar savings overall: demand response saved more in December, March, and May, and the battery in January, February, and April. Coordinated operation produced the largest savings in every month (22.8–32.5%), and the savings were highest in May, the month with the highest peak.

To estimate the payback period, we doubled the six-month savings to approximate a full year and subtracted a fixed operation and maintenance cost of $8.2/kWh per year [27], or $1640 per year. This gives annual savings of $6452 for the battery alone and $5630 when it is added to demand response, for simple payback periods of 14.5 and 16.6 years at the $93,700 capital cost. Using the low and high ends of the Lazard cost range, the payback ranges from 9.4 to 22.5 years. Over the six months, the battery completed only 29 full cycles with demand response, about 58 per year and well under the one-cycle-per-day limit, so it would not reach its 5475-cycle life within 15 years and would not need to be replaced.

This study has some limitations. The optimization assumes the month's load and PV generation are known ahead of time, so the savings shown are an upper bound on what a real-time controller could achieve. Occupant comfort is only represented by the limits on HVAC and lighting reduction and the same-day recovery of shifted load, and the HVAC and lighting shares are assumed rather than measured. The tariff is also simplified. We evaluate demand over 15 min intervals from 7:00 to 23:00 every day, while D6.2 bills the highest 30 min demand from 11:00 to 19:00 on weekdays [26], so the billed demand in our model is equal to or higher than the actual billed demand. The demand ratchet and 12-month distribution demand in D6.2 were not modeled, since each month is solved separately. Lastly, PV data was only available from December 2025, so the summer months could not be evaluated.

6. Conclusions

This paper presented a measurement-driven energy management framework integrating demand response (DR) and battery energy storage systems (BESSs) for campus buildings, using measured electricity demand, rooftop PV generation, and utility tariff data from the Engineering Laboratory Building at the University of Michigan–Dearborn. A graphical user interface was also developed to facilitate the practical application of the framework and support decision-making by campus operators. Simulation results demonstrated that DR alone reduced electricity costs by 19.6% in May 2026, while coordinated DR–BESS operation achieved a 32.5% reduction. Over the six-month evaluation period, the corresponding savings were 14.3% and 26.9%. The results highlighted the importance of peak demand management and demonstrated that BESS benefits depend strongly on seasonal load characteristics and battery capacity. However, the estimated battery payback period of 14.5–16.6 years indicates that investment feasibility must be carefully considered. These findings provide practical guidance for campus operators, suggesting that DR should be prioritized as an initial improvement, while BESS deployment should be considered as a subsequent upgrade based on economic feasibility and building demand characteristics. Future work will focus on integrating load and PV forecasting, improving tariff modeling, and extending the framework toward real-time energy management.

Author Contributions: Conceptualization, A.B. and V.-H.B.; methodology, A.B. and V.-H.B.; software, A.B.; validation, A.B., Q.M.H. and G.V.H.; formal analysis, A.B.; investigation, A.B.; data curation, A.B.; writing—original draft preparation, A.B.; writing—review and editing, Q.M.H., G.V.H. and V.-H.B.; visualization, A.B.; supervision, V.-H.B.; project administration, V.-H.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Summer Undergraduate Research Experience (SURE) Program, University of Michigan-Dearborn.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available because they are metering data of a university building.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. International Energy Agency. Buildings. In *Energy Efficiency 2025*; IEA: Paris, France, 2025.
2. Zia, M.F.; Elbouchikhi, E.; Benbouzid, M.E.H. Microgrids energy management systems: A critical review on methods, solutions, and prospects. *Appl. Energy* **2018**, *222*, 1033–1055. https://doi.org/10.1016/j.apenergy.2018.04.103.
3. Oldewurtel, F.; Parisio, A.; Jones, C.N.; Gyalistras, D.; Gwerder, M.; Stauch, V.; Lehmann, B.; Morari, M. Use of model predictive control and weather forecasts for energy efficient building climate control. *Energy Build.* **2012**, *45*, 15–27. https://doi.org/10.1016/j.enbuild.2011.09.022.
4. Killian, M.; Kozek, M. Ten questions concerning model predictive control for energy efficient buildings. *Build. Environ.* **2016**, *105*, 403–412. https://doi.org/10.1016/j.buildenv.2016.05.034.
5. Drgoňa, J.; Arroyo, J., Figueroa, I.C., Blum, D.; Arendt, K.; Kim, D.; Ollé, E.P.; Oravec, J.; Wetter, M.; Vrabie, D.L.; et al. All you need to know about model predictive control for buildings. *Annu. Rev. Control* **2020**, *50*, 190–232. https://doi.org/10.1016/j.arcontrol.2020.09.001.
6. Palensky, P.; Dietrich, D. Demand side management: Demand response, intelligent energy systems, and smart loads. *IEEE Trans. Ind. Inform.* **2011**, *7*, 381–388. https://doi.org/10.1109/TII.2011.2158841.
7. Mohsenian-Rad, A.-H.; Wong, V.W.S.; Jatskevich, J.; Schober, R.; Leon-Garcia, A. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. *IEEE Trans. Smart Grid* **2010**, *1*, 320–331. https://doi.org/10.1109/TSG.2010.2089069.
8. Pedrasa, M.A.A.; Spooner, T.D.; MacGill, I.F. Coordinated scheduling of residential distributed energy resources to optimize smart home energy services. *IEEE Trans. Smart Grid* **2010**, *1*, 134–143. https://doi.org/10.1109/TSG.2010.2053053.
9. Wang, B.; Zhang, C.; Dong, Z.Y. Interval optimization based coordination of demand response and battery energy storage system considering SOC management in a microgrid. *IEEE Trans. Sustain. Energy* **2020**, *11*, 2922–2931. https://doi.org/10.1109/TSTE.2020.2982205.
10. Zhang, W.; Lian, J.; Chang, C.-Y.; Kalsi, K. Aggregated modeling and control of air conditioning loads for demand response. *IEEE Trans. Power Syst.* **2013**, *28*, 4655–4664. https://doi.org/10.1109/TPWRS.2013.2266121.
11. Shao, S.; Pipattanasomporn, M.; Rahman, S. Development of physical-based demand response-enabled residential load models. *IEEE Trans. Power Syst.* **2013**, *28*, 607–614. https://doi.org/10.1109/TPWRS.2012.2208232.
12. Callaway, D.S.; Hiskens, I.A. Achieving controllability of electric loads. *Proc. IEEE* **2011**, *99*, 184–199. https://doi.org/10.1109/JPROC.2010.2081652.
13. Sæle, H.; Grande, O.S. Demand response from household customers: Experiences from a pilot study in Norway. *IEEE Trans. Smart Grid* **2011**, *2*, 102–109. https://doi.org/10.1109/TSG.2010.2104165.
14. U.S. Department of Energy. *On-Site Energy Storage Decision Guide*; Better Buildings Initiative; U.S. Department of Energy: Washington, DC, USA, 2017.
15. Leadbetter, J.; Swan, L. Battery storage system for residential electricity peak demand shaving. *Energy Build.* **2012**, *55*, 685–692. https://doi.org/10.1016/j.enbuild.2012.09.035.
16. Atzeni, I.; Ordóñez, L.G.; Scutari, G.; Palomar, D.P.; Fonollosa, J.R. Demand-side management via distributed energy generation and storage optimization. *IEEE Trans. Smart Grid* **2013**, *4*, 866–876. https://doi.org/10.1109/TSG.2012.2206060.

17. Yan, Q.; Zhang, B.; Kezunovic, M. Optimized operational cost reduction for an EV charging station integrated with battery energy storage and PV generation. *IEEE Trans. Smart Grid* **2019**, *10*, 2096–2106. https://doi.org/10.1109/TSG.2017.2788440.
18. Muqeet, H.A.U.; Ahmad, A. Optimal scheduling for campus prosumer microgrid considering price based demand response. *IEEE Access* **2020**, *8*, 71378–71394. https://doi.org/10.1109/ACCESS.2020.2987915.
19. Thomas, D.; Deblecker, O.; Ioakimidis, C.S. Optimal operation of an energy management system for a grid-connected smart building considering photovoltaics' uncertainty and stochastic electric vehicles' driving schedule. *Appl. Energy* **2018**, *210*, 1188–1206. https://doi.org/10.1016/j.apenergy.2017.07.035.
20. Gao, H.-C.; Choi, J.-H.; Yun, S.-Y.; Lee, H.-J.; Ahn, S.-J. Optimal scheduling and real-time control schemes of battery energy storage system for microgrids considering contract demand and forecast uncertainty. *Energies* **2018**, *11*, 1371. https://doi.org/10.3390/en11061371.
21. Shi, J.; Ye, Z.; Gao, H.O.; Yu, N. Lyapunov optimization in online battery energy storage system control for commercial buildings. *IEEE Trans. Smart Grid* **2023**, *14*, 328–340. https://doi.org/10.1109/TSG.2022.3197959.
22. Hasan, A.S.M.J.; Enriquez-Contreras, L.F.; Yusuf, J.; Ula, S. A universal optimization framework for commercial building loads using DERs from utility tariff perspective with tariff change impacts analysis. *Energy Rep.* **2023**, *9*, 6088–6101. https://doi.org/10.1016/j.egyr.2023.05.036.
23. Yu, M.G.; Huang, B.; Ma, X.; Devaprasad, K. Multi-objective sizing and dispatch for building thermal and battery storage towards economic and environmental synergy. *Appl. Energy* **2024**, *372*, 123819. https://doi.org/10.1016/j.apenergy.2024.123819.
24. Achour, Y.; Ouammi, A.; Zejli, D. Model predictive control based demand response scheme for peak demand reduction in a smart campus integrated microgrid. *IEEE Access* **2021**, *9*, 162765–162778. https://doi.org/10.1109/ACCESS.2021.3132895.
25. Kumar, N.M.; Gupta, R.P.; Mathew, M.; Jayakumar, A.; Singh, N.K. Performance, energy loss, and degradation prediction of roof-integrated crystalline solar PV system installed in Northern India. *Case Stud. Therm. Eng.* **2019**, *13*, 100409.
26. DTE Electric Company. *M.P.S.C. No. 1—Electric Rate Book, Rate Schedule D6.2: Primary Educational Institution Rate*; DTE Electric Company: Detroit, MI, USA, 2026.
27. Lazard. *Levelized Cost of Energy+ (LCOE+)*, Version 18.0; Lazard: New York, NY, USA, 2025.
28. National Renewable Energy Laboratory. *2024 Annual Technology Baseline: Commercial Battery Storage*; NREL: Golden, CO, USA, 2024.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.