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Grid-Interactive Residential Buildings as Distributed Flexibility Providers: A Network-Constrained Energy Management Framework

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Abstract

The growing penetration of distributed energy resources, smart building technologies, and advanced control systems is transforming residential buildings from passive electricity consumers into active participants in modern power systems. This study proposes an energy management framework for grid-interactive residential buildings that integrates smart controllable loads, rooftop photovoltaic (PV) systems, battery energy storage systems (BESS), and IoT-enabled adaptive building technologies within a network-constrained optimization model. The framework coordinates building-level flexibility resources while respecting distribution-network operational constraints to enhance both occupant-side and grid-side performance. An energy-based flexibility decomposition method is introduced to quantify the relative contributions of smart loads and combined PV and BESS resources. The proposed nonlinear optimization model is evaluated on the IEEE 33-bus distribution system across multiple flexibility configurations and penetration levels. Results show that coordinated flexibility reduces household electricity costs, increases renewable-energy utilization, and improves distribution-network load profiles. The integrated PV–BESS configuration reduces household electricity costs by up to 90.6% relative to conventional residential operation while decreasing substation power imports. At 20% smart-house penetration, combined PV and BESS resources account for approximately 85% of the average energy-based flexibility contribution, while smart loads provide the remaining 15% through demand adjustments. The results also reveal a trade-off between household savings and local distribution-company profitability, highlighting important implications for tariff and flexibility program design. Overall, the proposed framework demonstrates the potential of grid-interactive residential buildings to support coordinated energy management, renewable-energy integration, and reliable smart-grid operation.

Keywords: energy management; grid-interactive buildings; energy flexibility; distributed energy resources; battery energy storage systems; demand response; smart grids

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1. Introduction

Buildings account for a substantial share of global electricity consumption and greenhouse-gas emissions, which places them at the center of the transition toward sustainable and low-carbon energy systems. The rapid deployment of distributed renewable generation, battery energy storage systems (BESS), and advanced building-automation technologies is changing the role of buildings from passive energy consumers into active participants in system operation. Residential buildings, in particular, are emerging

as important flexibility providers that can adjust their consumption patterns, integrate local renewable generation, and support grid operation through coordinated demand-side management [1–5].

Advances in Internet of Things (IoT) technologies, low-cost sensing, and building energy-management systems now enable real-time monitoring and control of residential energy resources. These technologies allow controllable appliances, adaptive building components, rooftop photovoltaic (PV) systems, and BESS to be coordinated so that buildings respond dynamically to electricity prices and grid conditions [6–9]. In parallel, occupant-centric control has attracted growing attention, as it seeks to balance energy efficiency, flexibility provision, and thermal comfort in smart residential environments [10,11].

The increasing share of variable renewable generation has intensified the need for flexibility mechanisms that can absorb the variability and uncertainty of renewable output. Building energy flexibility has therefore become a distinct research theme, formalized in coordinated international efforts on the characterization and control of flexible buildings and on grid-interactive efficient buildings (GEB) [3–5]. Reported approaches span demand-response programs, home energy-management systems, virtual power plants, and distributed-energy-resource coordination frameworks [12–16], all of which aim to align demand with renewable generation while reducing peak demand and improving overall efficiency.

A large body of work has examined demand-side management and smart building operation. Sharda et al. [17] studied load-shifting in IoT-based home energy-management systems and showed that coordinated appliance scheduling can reduce electricity costs. Mortaji et al. [18] developed a smart-home residential energy-management scheme, and Babar et al. [19] proposed optimization techniques for coordinated residential demand response. Other studies have applied IoT-enabled energy optimization and management at the smart-city and distribution-system levels, including the socio-economic management of networks with high shares of renewable generation [16,20,21]. At the system level, Rahimi et al. [22] improved the scheduling of virtual power plants by jointly considering dynamic line rating and flexible supply and demand, while Alves et al. [23] showed that demand flexibility can influence the long-term adequacy of generation systems. The joint integration of rooftop PV and battery storage in residential buildings has likewise received considerable attention: PV reduces dependence on grid-supplied electricity and increases self-consumption, whereas storage enables energy shifting between generation and consumption [24,25]. Related IoT- and storage-based demand-management schemes have also been shown to reduce demand and operating cost, for example, through IoT–fog coordination between consumers and utilities in power distribution systems [26] and micro-distributed storage for microgrid demand management [27]. Nonetheless, most of this literature optimizes either at the building level or at the network level, with limited treatment of the coupling between building flexibility and network operational constraints.

From a power-system perspective, the coordination of flexible resources has been investigated to improve operation under rising distributed-generation penetration. Krishnan and Jacob [28] proposed an IoT-based smart-grid energy-management scheme optimized with the DHOCSA technique; Balakumar et al. [29] developed a machine-learning-based demand-response scheme for an IoT-enabled, PV-integrated smart building; and Sharma et al. [30] showed, for plug-in electric vehicle charging in residential distribution systems, the importance of respecting distribution-network constraints when coordinating flexible residential loads. These studies provide valuable operational insight, but they typically focus on a single building or a single type of flexible resource, or simplify building behavior without explicitly representing advanced building technologies or occupant-driven flexibility. Consequently, there remains a need for integrated

frameworks that simultaneously capture building-level flexibility resources, occupant behavior, distributed generation and storage, and distribution-network operation within a single formulation.

Despite this progress, most existing studies optimize building-level energy use and distribution-network operation separately. Comparatively little work coordinates occupant-responsive demand, distributed PV generation, battery storage, and network operational constraints within one unified architecture, and fewer still make the resulting flexibility contribution of each resource explicit and reproducible. As distributed-energy-resource penetration continues to grow, there is a clear need for energy-management approaches that turn residential buildings from passive consumers into active flexibility providers serving both occupant and grid objectives, together with metrics that quantify how much flexibility each resource actually delivers.

To address this gap, this paper proposes an energy management framework for grid-interactive residential buildings that integrates smart controllable loads, rooftop PV systems, BESS, and IoT-enabled adaptive building technologies within a network-constrained optimization model. The framework coordinates flexible demand, local generation, and storage while maintaining compliance with distribution-network operational limits, and it is accompanied by an explicit energy-based flexibility-decomposition metric. The methodology is evaluated on the IEEE 33-bus distribution system to quantify the impact of coordinated flexibility on building energy performance, renewable-energy utilization, economic outcomes, and network operation.

This framework builds on earlier work [8], which integrated IoT-based houses into direct demand-response programs to minimize the distribution-system peak load. While the present study retains the network-constraint layer of that formulation (power-flow, feeder, substation, voltage, and peak-load limits), its flexibility model is fundamentally different. In [8], flexibility comes solely from energy-neutral demand-response load-shifting under a peak-minimization objective. Here, flexibility is instead the coordinated output of rooftop PV and battery storage, introducing a smart-house energy balance, state-of-charge dynamics, inverter limits, and reverse-power-flow constraints, under an economic objective capturing time-of-use revenue, grid-purchase cost, peak-demand charges, and flexibility payments. The two studies therefore differ in objective, resources, and the mathematical structure of the flexibility model, shifting the scope from peak-oriented demand response toward economically driven, network-constrained coordination of building-level distributed energy resources.

The main contributions of this paper are as follows:

- An energy management framework for grid-interactive residential buildings that jointly coordinates flexible demand, rooftop PV generation, BESS, and IoT-enabled building technologies under explicit distribution-network operational constraints.
- A network-constrained nonlinear optimization model that couples building-level flexibility resources with distribution-network operation, including power flow, feeder capacity, reverse power flow, substation capacity, and voltage regulation, while occupant comfort is preserved upstream in the building-simulation stage that generates the smart-load profiles, enabling joint assessment of occupant-side and grid-side benefits.
- An energy-based flexibility decomposition method that quantifies the relative contributions of smart loads and combined PV and BESS resources to residential flexibility provision.

- A full-factorial evaluation, across flexibility configurations and penetration levels, of the impact of coordinated flexibility on household electricity cost, distribution-company profit, renewable-energy utilization, peak demand, substation imports, and feeder-level performance, including an analysis of why household benefit saturates once network limits bind.
- A discussion of the distributional tension between household savings and distribution-company profit, with implications for tariff and demand-side-program design in future smart grids.

The remainder of the paper is organized as follows. Section 2 presents the proposed framework and optimization model. Section 3 describes the modeling assumptions and case study. Section 4 presents and discusses the results. Section 5 concludes and outlines future work.

2. Proposed Energy Management Framework

This section presents the proposed framework for coordinating energy flexibility in grid-interactive residential buildings. The framework integrates occupant-responsive loads, IoT-enabled adaptive building technologies, rooftop PV systems, BESS, and distribution-network operational constraints within a unified optimization architecture. Unlike conventional building energy-management approaches that focus on reducing energy use or cost at the individual-building level, the proposed framework simultaneously considers building-level flexibility and distribution-network requirements. The objective is to let residential buildings actively participate in smart-grid operation by coordinating flexible demand, local renewable generation, and storage, while maintaining occupant comfort, improving renewable-energy utilization, and supporting secure and reliable network performance.

Figure 1 illustrates the proposed framework. The framework integrates two interconnected modeling stages: a building energy model and a network-constrained energy management optimization model. The building energy model incorporates weather conditions, occupant behavior and preferences, and IoT-enabled adaptive-window operation to generate comfort-feasible smart-load profiles and characterize building flexibility availability. These outputs, together with rooftop PV generation, BESS operating parameters, electricity prices, and distribution-network information, are provided as inputs to the network-constrained optimization model within the Energy Management System (EMS). The optimization model coordinates smart-load scheduling, PV generation, and battery charging and discharging to maximize the economic performance of the local distribution company (LDC), subject to power-flow equations, voltage limits, feeder-capacity restrictions, reverse-power-flow limits, substation-capacity constraints, and resource operating limits. This integrated modeling approach connects occupant-responsive building operation with distribution-network requirements while preserving the thermal-comfort conditions established during the building-simulation stage. Through this architecture, grid-interactive residential buildings can operate as distributed flexibility providers that serve both occupant-side and grid-side objectives, yielding reduced electricity cost, higher renewable-energy utilization, improved flexibility provision, lower peak demand, and better distribution-network operation.

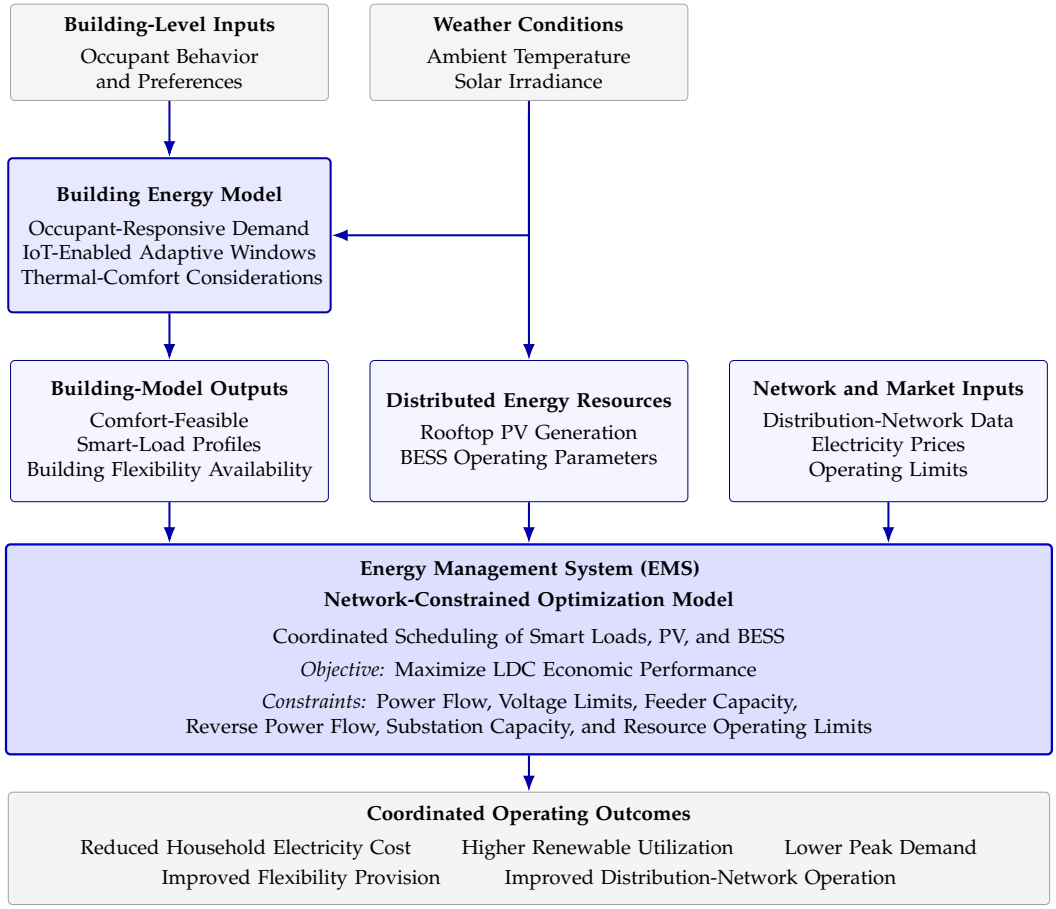


Figure 1. Proposed energy management framework for grid-interactive residential buildings.

2.1. Occupant-Centric Residential Building Modeling

Residential buildings are modeled as energy-flexible systems whose electricity consumption adapts to environmental conditions, occupant behavior, and energy-management objectives. Unlike conventional buildings that follow fixed consumption patterns, grid-interactive buildings actively adjust their demand profiles through coordinated control of flexible loads, distributed energy resources, and smart building technologies.

Occupant behavior strongly influences residential consumption and flexibility potential. Daily activities, appliance-usage patterns, occupancy schedules, and thermal-comfort preferences all shape building demand. Occupant behavior is therefore embedded in the framework to capture realistic variation in residential consumption: occupants act through smart devices, thermostat settings, appliance scheduling, and adaptive control, so that residential demand is represented as a dynamic, responsive component rather than a fixed load profile.

The building considered here is equipped with an IoT-enabled adaptive window that dynamically adjusts solar heat gains according to weather and occupancy. The smart window is a double-glazed unit with an intelligent mid-shade that regulates the Solar Heat Gain Coefficient (SHGC). During warm, unoccupied periods, the SHGC is reduced to limit solar gains and cooling demand; during colder conditions, higher solar penetration supports passive heating and reduces heating demand. This adaptive operation improves building energy performance and provides an additional degree of flexibility for demand-side coordination. Crucially, thermal-comfort preferences are enforced at this building-simulation stage: the resulting smart-load profile is comfort-feasible by construction, and it subsequently enters the network-constrained optimization of Section 2.3 as

an input. The optimization therefore coordinates flexibility without needing to re-impose comfort as an explicit constraint.

2.2. Building Flexibility Resources

The framework considers three primary sources of building energy flexibility:

1. Smart controllable loads: Flexible appliances and controllable loads whose operation can be shifted in time while respecting occupant comfort and service requirements.
2. Rooftop photovoltaic systems: Distributed solar generation that reduces net building demand and raises local renewable-energy utilization.
3. Battery energy storage systems: Residential BESS units that store excess PV generation and supply energy during high-demand or high-price periods.

Coordinated operation of these resources lets buildings provide both upward and downward flexibility. Upward flexibility corresponds to reducing net demand or exporting locally generated electricity; downward flexibility corresponds to absorbing electricity through increased consumption or battery charging. Together they enable residential buildings to support grid operation while improving their own performance. Within the framework, these resources are coordinated by the EMS to maximize economic benefit, improve self-consumption, reduce peak demand, and support network operation. Integrating local generation and storage substantially expands the flexibility available to residential buildings and allows them to act as active participants in smart-grid operation.

2.3. Network-Constrained Energy Management Optimization

The framework coordinates residential flexibility at the distribution-network level through a network-constrained nonlinear optimization model that simultaneously schedules controllable loads, battery storage, and PV generation while enforcing network operational limits.

The EMS determines optimal operating schedules by considering both building-level resources (comfort-feasible smart-load profiles, rooftop PV, and BESS) and network-level constraints (power flow, feeder loading, voltage regulation, reverse power flow, and substation capacity). The objective function in (1) maximizes the economic performance of the local distribution company (LDC) while accounting for energy transactions between residential buildings and the grid.

In the following formulation, i and j denote distribution-network buses, while h represents the hourly time interval. The symbols P, Q, V, and δ represent active power, reactive power, voltage magnitude, and voltage angle, respectively. Superscripts and subscripts distinguish the associated energy resources, network components, and operating conditions.

$$\max \sum_{i\in\mathcal{N}}\sum_{h=1}^{24} \rho_h^{TOU}\left[Pd_{i,h}\left(1-\gamma_i^{SH}\right)n_i^H + P_{i,h}^{-SH}\right] - \sum_{h=1}^{24}\rho_h^{Grid}\,P_{u,h}^{Sub} - \frac{\rho^{PLC}\,P^{PK}}{n_d} - \sum_{i\in\mathcal{N}}\sum_{h=1}^{24}\rho_h^{TOU}\,P_{i,h}^{+SH} \quad (1)$$

The first term is the net revenue from selling power to conventional and smart households; the second is the cost of purchasing power from the grid; the third is the peak-demand charge; and the fourth is the payment for power purchased from smart households (their upward flexibility). The optimization is subject to the following constraints.

Power-flow equations: The injected power at the substation bus, accounting for net load and the flexibility of smart houses, is governed by

$$P_{u,h}^{Sub} - Pd_{i,h}\left[\left(1-\gamma_i^{SH}\right) n_i^H\right] - P_{i,h}^{-SH} + P_{i,h}^{+SH} = \sum_{j\in\mathcal{N}} V_{i,h} V_{j,h} Y_{i,j} \cos(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}), \quad \forall i \in \mathcal{N},\ \forall h \tag{2}$$

$$Q_{u,h}^{Sub} - Qd_{i,h} = -\sum_{j\in\mathcal{N}} V_{i,h} V_{j,h} Y_{i,j} \sin(\theta_{i,j} + \delta_{j,h} - \delta_{i,h}), \qquad \forall i \in \mathcal{N},\ \forall h \tag{3}$$

where $Y_{i,j}$ and $\theta_{i,j}$ are the magnitude and angle of the (i,j) element of the bus admittance matrix.

Upward and downward flexibility balance: The smart-house energy balance links flexibility to local generation, storage, and load:

$$\gamma_i^{SH} n_i^H P_{i,h}^{PV} + P_{i,h}^{Disch^{ABES}} + P_{i,h}^{-SH} = \gamma_i^{SH} n_i^H P_{i,h}^{SL} + P_{i,h}^{Ch^{ABES}} + P_{i,h}^{+SH}, \quad \forall i \in \mathcal{N},\ \forall h \tag{4}$$

Battery power limits: Aggregated charging and discharging are bounded by the BESS power rating and smart-house penetration:

$$P_{i,h}^{Ch^{ABES}} \le \gamma_i^{SH}\, n_i^H\, P_{size}^{BES}, \qquad \forall i \in \mathcal{N},\ \forall h \tag{5}$$

$$P_{i,h}^{Disch^{ABES}} \le \gamma_i^{SH}\, n_i^H\, P_{size}^{BES}, \qquad \forall i \in \mathcal{N},\ \forall h \tag{6}$$

Power-conversion limits: The power converted from aggregated PV and BESS respects the inverter ratings:

$$\gamma_i^{SH}\, n_i^H\, P_{i,h}^{PV} \le \gamma_i^{SH}\, n_i^H\, P^{Inv^{PV}}, \qquad \forall i \in \mathcal{N},\ \forall h \tag{7}$$

$$P_{i,h}^{Ch^{ABES}} \le \gamma_i^{SH}\, n_i^H\, P^{Inv^{BES}}, \qquad \forall i \in \mathcal{N},\ \forall h \tag{8}$$

$$P_{i,h}^{Disch^{ABES}} \le \gamma_i^{SH}\, n_i^H\, P^{Inv^{BES}}, \qquad \forall i \in \mathcal{N},\ \forall h \tag{9}$$

Non-simultaneity of resource actions: Charging and discharging (and upward and downward flexibility) cannot occur simultaneously:

$$P_{i,h}^{Ch^{ABES}}\, P_{i,h}^{Disch^{ABES}} = 0, \qquad \forall i \in \mathcal{N},\ \forall h \tag{10}$$

$$P_{i,h}^{+SH}\, P_{i,h}^{-SH} = 0, \qquad \forall i \in \mathcal{N},\ \forall h \tag{11}$$

State of charge: The aggregated BESS state of charge evolves as

$$SOC_{i,h+1} = SOC_{i,h} + \left(P_{i,h}^{Ch^{ABES}}\, \eta^{Ch} - P_{i,h}^{Disch^{ABES}} / \eta^{Disch}\right) \Delta t, \quad \forall i \in \mathcal{N},\ h = 1,\ldots,24 \tag{12}$$

$$\underline{SOC}\, \gamma_i^{SH}\, n_i^H\, \overline{E^{BES}} \le SOC_{i,h} \le \gamma_i^{SH}\, n_i^H\, \overline{E^{BES}}, \qquad \forall i \in \mathcal{N},\ h = 1,\ldots,25 \tag{13}$$

$$SOC_{i,1} = SOC_{i,25} = 0.5\, \gamma_i^{SH}\, n_i^H\, \overline{E^{BES}}, \qquad \forall i \in \mathcal{N} \tag{14}$$

Equation (14) initializes the aggregated BESS at 50% of its energy capacity and requires it to return to the same level at the end of the 24 h horizon, so that stored energy is not depleted without being replenished.

Peak-load constraint: Used together with (1) to limit peak demand:

$$P_{u,h}^{Sub} \le P^{PK}, \qquad \forall u,\ \forall h \tag{15}$$

Reverse-power-flow limit: The upward flexibility that would cause reverse flow under minimum-load conditions is bounded:

$$\sum_{i\in\mathcal{N}} P_{i,h}^{+SH} \le \sum_{i\in\mathcal{N}} Pd_{i,h}^{Min} + 0.6\, S_u^{Subcap}, \qquad \forall u,\ \forall h \tag{16}$$

The reverse-power-flow coefficient of 0.6 adopted in Equation (16) is based on the distribution-network hosting-capacity practices documented in CIGRE Technical Brochure No. 586 [31]. Specifically, the report describes a utility practice in which permissible distributed-generation capacity is determined using 60% of the substation transformer rating plus the minimum station load.

Feeder-capacity limits: Power flow through each feeder must not exceed its capacity:

$$-V_{i,h}^2 Y_{i,j}\cos\theta_{i,j} + V_{i,h}V_{j,h}Y_{i,j}\cos(\theta_{i,j}+\delta_{j,h}-\delta_{i,h}) \le S_{(i,j)}^{Fcap}\cos\varphi_{(i,j),h}^{F}, \quad \forall (i,j)\in\mathcal{L},\ \forall h \tag{17}$$

$$V_{i,h}^2 Y_{i,j}\sin\theta_{i,j} - V_{i,h}V_{j,h}Y_{i,j}\sin(\theta_{i,j}+\delta_{j,h}-\delta_{i,h}) \le S_{(i,j)}^{Fcap}\sin\varphi_{(i,j),h}^{F}, \quad \forall (i,j)\in\mathcal{L},\ \forall h \tag{18}$$

where $\mathcal{L}$ is the set of feeder sections (lines), $S_{(i,j)}^{Fcap}$ is the apparent-power capacity of feeder (i,j), and $\varphi_{(i,j),h}^{F}$ is its power-factor angle.

The feeder-capacity constraints in Equations (17) and (18) ensure that active and reactive power flows remain within the assigned operational capacities of the distribution feeders. These constraints represent physical network limitations and prevent excessive feeder loading as distributed energy resource penetration increases. While the IEEE 33-bus benchmark provides the network topology, line impedances, and load characteristics, the feeder-capacity limits are imposed as additional operational restrictions to maintain network feasibility.

Substation-capacity limit: The apparent power drawn from the substation must not exceed its capacity:

$$\left(P_{u,h}^{Sub}\right)^2 + \left(Q_{u,h}^{Sub}\right)^2 \le \left(S_u^{Subcap}\right)^2, \qquad \forall u,\ \forall h \tag{19}$$

Voltage limits: The voltage magnitude at each bus must remain within its limits:

$$\underline{V} \le V_{i,h} \le \overline{V}, \qquad \forall i\in\mathcal{N},\ \forall h \tag{20}$$

The resulting problem is a nonlinear program (NLP). Because (10) and (11) are complementarity conditions and the power-flow terms are nonconvex, the model is nonconvex; it is solved with the Sequential Quadratic Programming (SQP)-based SNOPT solver in GAMS [32]. SNOPT returns locally optimal solutions; to improve solution quality, the model is solved from multiple starting points and the best feasible solution is retained. This formulation enables joint evaluation of building-level benefits and network impacts across penetration levels of grid-interactive residential buildings.

2.4. Flexibility Quantification and Decomposition

The energy-based contributions of smart loads and combined PV and BESS resources are quantified using the optimized schedules over the 24 h simulation period.

The flexibility contribution of smart loads at bus i is calculated as

$$F_i^{SL} = \sum_{h=1}^{24} \gamma_i^{SH} n_i^{H} \left| Pd_{i,h} - P_{i,h}^{SL} \right| \Delta t, \tag{21}$$

where $Pd_{i,h}$ and $P_{i,h}^{SL}$ represent conventional and smart-load demand per household, respectively.

The combined contribution of PV and BESS is calculated as

$$F_i^{PV+BESS} = \sum_{h=1}^{24} \left| \gamma_i^{SH} n_i^H P_{i,h}^{PV} + P_{i,h}^{Disch^{ABES}} - P_{i,h}^{Ch^{ABES}} \right| \Delta t. \tag{22}$$

The relative contribution of each resource category at bus i is determined by

$$\Phi_i^{SL} = \frac{F_i^{SL}}{F_i^{SL} + F_i^{PV+BESS}}, \qquad \Phi_i^{PV+BESS} = 1 - \Phi_i^{SL}. \tag{23}$$

The overall contribution is obtained by averaging the resource shares across the evaluated load buses:

$$\overline{\Phi}^{SL} = \frac{1}{|\mathcal{N}_L|} \sum_{i \in \mathcal{N}_L} \Phi_i^{SL}, \qquad \overline{\Phi}^{PV+BESS} = 1 - \overline{\Phi}^{SL}, \tag{24}$$

where $\mathcal{N}_L \subseteq \mathcal{N}$ denotes the set of evaluated load buses and $|\mathcal{N}_L|$ is their number.

3. System Modeling and Case Study Description

This section describes the residential-building model, distributed energy resources, occupant-behavior assumptions, electricity pricing, and distribution-network test system used to evaluate the framework. The case study combines detailed building-level modeling with a benchmark network representation to assess how grid-interactive residential buildings provide distributed flexibility while supporting secure network operation.

3.1. Residential Building Characteristics

The building represents a typical single-family detached dwelling with advanced energy-management technologies and distributed energy resources. It comprises a living room, two bedrooms, a kitchen, and a garage, and includes common appliances (refrigerator, dishwasher, washing machine, clothes dryer, electric oven) and LED lighting. These appliances contribute to demand and provide opportunities for demand-side flexibility through intelligent scheduling. HVAC service is provided by a variable-refrigerant-flow (VRF) system with heat recovery and a dedicated outdoor-air system (DOAS) for ventilation. The envelope includes an adaptive IoT-enabled window with a window-to-wall ratio of 28.2%, enabling dynamic regulation of solar heat gains according to occupancy and weather. Detailed building specifications and thermal parameters are adopted from the residential energy-simulation model in Ref. [10]. Occupant-behavior characteristics—occupancy schedules, appliance-usage patterns, comfort preferences, and interactions with smart controls—are adopted from the survey-based study in Ref. [11], yielding realistic demand profiles and flexibility availability throughout the day.

3.2. IoT-Enabled Adaptive Window Operation

A distinctive feature of the building is the adaptive IoT-controlled window that dynamically regulates the SHGC. The double-glazed unit uses an intelligent mid-shade capable of reflecting more than 95% of incident solar radiation. During warm, unoccupied periods, the SHGC is reduced to limit solar gains and cooling demand; during colder periods, higher solar penetration supports passive heating. Table 1 lists the SHGC values used for the conventional and smart windows.

Table 1. Solar Heat Gain Coefficient (SHGC) values for conventional and smart residential windows under different operating conditions.

Window Type	Warm (Occupied)	Warm (Vacant)	Cold Weather
Conventional Window	0.25	0.25	0.25
Smart IoT Window	0.41	0.07	0.41

The adaptive window is incorporated into the building energy simulation to generate the comfort-feasible smart-load profiles used in the proposed energy management framework. Its influence on residential energy demand and flexibility is discussed in Section 4.

3.3. Distributed Energy Resources, Pricing, and Model Parameters

Each grid-interactive building has rooftop PV and battery storage. The PV system is rated at 10 kW with a 12 kW inverter; PV output is computed from historical irradiance and ambient-temperature data using the performance model in Ref. [24]. The residential BESS is rated at 3 kW/6 kWh with a 6 kW inverter and 95% charging/discharging efficiency, consistent with Ref. [25]. The battery stores excess PV generation and supplies energy during peak or high-price periods. Building-flexibility scheduling responds to time-of-use (TOU) tariffs and wholesale prices following the pricing structure in Ref. [9]: high-price periods encourage battery discharge and local PV use, while low-price periods encourage charging and flexible-load operation. The key techno-economic parameters used in the study are summarized in Table 2 to support reproducibility.

Table 2. Key techno-economic and network parameters used in the case study.

Parameter	Symbol	Value
PV rated capacity	P^{PV}_{size}	10 kW
PV inverter rating	$P^{Inv^{PV}}$	12 kW
BESS power/energy rating	$P^{BES}_{size}/\overline{E^{BES}}$	3 kW/6 kWh
BESS inverter rating	$P^{Inv^{BES}}$	6 kW
Charging/discharging efficiency	η^{Ch}, η^{Disch}	95%
Minimum state of charge	$\underline{SOC}$	20%
TOU tariff (off-peak/mid/on-peak)	ρ^{TOU}_h	0.08/0.14/0.22 $/kWh
Wholesale (grid) price range	ρ^{Grid}_h	0.05–0.12 $/kWh
Peak-demand charge	ρ^{PLC}	8.0 $/kW
Days per billing month	n_d	30
Reverse-flow coefficient	—	0.6
Voltage limits	$\underline{V}, \overline{V}$	0.95–1.05 p.u.
Nominal system voltage	—	12.66 kV
Individual house peak demand	—	2.08 kW

The TOU and wholesale price values in Table 2 are representative of the tariff structure in Ref. [9]; the peak-demand charge enters the objective (1) together with the peak-load constraint (15), and the reverse-flow coefficient is used in constraint (16). Coordinated PV and storage operation increases self-consumption, reduces reliance on grid supply, and expands available flexibility; these distributed energy resources are the primary flexibility assets of the framework.

3.4. Distribution Network Model

The framework is evaluated on the IEEE 33-bus radial distribution system [33], operating at 12.66 kV with a total peak demand of about 4.4 MW. All connected loads are treated as residential customers, and individual units are modeled with a 2.08 kW peak,

consistent with Ref. [30]. Hourly demand profiles are generated from the IEEE Reliability Test System (RTS) [34]. To quantify the impact of distributed flexibility, a full-factorial set of penetration levels (0%, 10%, 20%) and flexibility configurations (Conventional; Smart Loads; Smart Loads + BESS; Smart Loads + BESS + PV) is examined, enabling the individual and combined contributions of flexibility resources to be assessed for household cost, LDC profit, renewable utilization, feeder loading, substation imports, and network performance. This combination of detailed building modeling and a benchmark network provides a comprehensive platform for evaluating grid-interactive residential buildings as distributed flexibility providers.

4. Performance Evaluation and Discussion

This section evaluates the framework across the penetration levels and configurations defined above. The analysis addresses residential energy flexibility, economic performance, distribution-network impacts, and the resource-level flexibility decomposition, providing insight into how coordinated control of smart loads, PV, and BESS improves both building-level and network-level performance.

4.1. Residential Energy Flexibility Assessment

Coordinated operation of smart loads, PV, and BESS enables buildings to actively modify their demand in response to prices and system conditions. Relative to conventional operation, grid-interactive buildings shift demand away from peak periods and increase the use of locally generated renewable energy.

Figure 2 shows the active power imported from the upstream grid under different configurations at 20% penetration. The baseline exhibits the highest dependence on utility supply throughout the day. Smart controllable loads slightly smooth the profile through load shifting. Adding BESS yields further improvement, as coordinated charging and discharging reduce peak periods and improve load distribution. The largest reduction in substation imports occurs when PV is combined with storage: during daylight, local solar supplies a significant share of demand, while excess generation is stored and used in the evening. This reduces reliance on centralized generation and raises self-consumption. Overall, distributed energy resources enhance flexibility well beyond what demand-side management alone achieves, allowing residential buildings to become active participants in system operation.

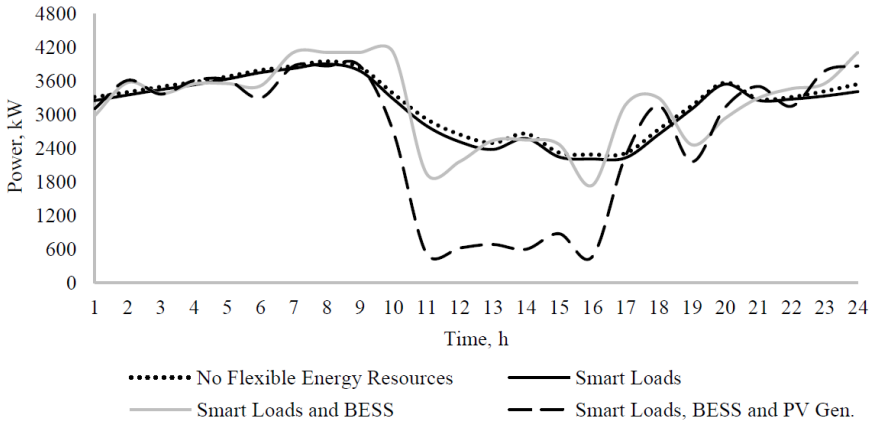


Figure 2. Impact of building flexibility resources on substation power imports under a 20% penetration level of grid-interactive residential buildings.

4.2. Economic Performance Analysis

Table 3 summarizes economic outcomes across the full-factorial set of configurations and penetration levels, reporting both household cost and LDC profit.

Table 3. Economic performance under different penetration levels and flexibility configurations.

Pen. (%)	Configuration	Household Cost (USD)	LDC Profit (USD)
0	Conventional	7.04	7184
10	Smart Loads	6.20	7052
	Smart Loads + BESS	7.72	7288
	Smart Loads + BESS + PV	0.66	6438
20	Smart Loads	6.20	7009
	Smart Loads + BESS	7.65	7343
	Smart Loads + BESS + PV	1.01	5761

Household cost is reported per representative household, whereas LDC profit is a system-wide quantity that varies with penetration. For the smart-load configuration, which does not interact with network limits, the household bill is therefore identical at the 10% and 20% levels while the corresponding LDC profit differs; for the BESS and PV–BESS configurations, the household bill also changes with penetration, as discussed below. Relative to the 7.04 USD conventional baseline, smart controllable loads alone provide moderate savings of about 12% (to 6.20 USD) through demand shifting and better use of TOU pricing. The largest household savings, however, come from deploying PV and storage together: the integrated PV–BESS configuration reduces the household bill to 0.66–1.01 USD, i.e., by up to roughly 90.6%, driven by increased PV self-consumption and price arbitrage between low- and high-price periods.

A key observation is that the household benefit is not monotonic in penetration. At the 10% level, the integrated PV–BESS bill is 0.66 USD (about 90.6% reduction), whereas at 20% it rises to 1.01 USD (about 85.7%). This saturation is a direct consequence of the network-constrained formulation: as penetration grows, the reverse-power-flow limit (16) and feeder-capacity limits (17) and (18) begin to bind during high-solar, low-load hours, so the PV energy that can be exported is restricted and the marginal household benefit declines. A purely building-level model, lacking these constraints, would incorrectly predict continued improvement; capturing the saturation is therefore one of the practical advantages of coupling building flexibility with network operation.

The standalone deployment of battery storage slightly increases the household bill (to 7.65–7.72 USD). Because the optimization maximizes LDC profit (Equation (1)), the aggregated BESS is dispatched primarily to serve system-level goals, namely reducing upstream procurement cost and peak-demand charges, rather than to minimize household expenditure. Charging is therefore scheduled when it benefits the LDC, which does not always coincide with the lowest TOU price period. Combined with round-trip conversion losses, this raises household grid purchases. Under a household-cost-minimizing objective, the 0.08–0.22 USD/kWh TOU spread would make storage arbitrage profitable for occupants. When coupled with PV, however, storage stores surplus solar generation for later use, which raises self-consumption and reduces grid purchases enough to deliver large household savings even under the LDC-oriented objective.

Table 3 also reveals a distributional tension. The configuration that is best for households (PV–BESS) is the worst for LDC profit, which falls from about 7184 USD to 6438 USD at 10% and to 5761 USD at 20%, corresponding to reductions of approximately 10.4% and 19.8%, respectively. Since the objective maximizes LDC profit subject to household flexibil-

ity being compensated, the reported outcomes represent the network-feasible optimum under this trade-off, rather than a scenario in which all participants benefit equally.

The reduction in LDC profit can be explained by the interaction of several economic components represented in the objective function in Equation (1). Increased PV self-consumption reduces electricity purchases from the distribution network, thereby decreasing retail electricity sales revenue. Furthermore, locally generated electricity exported to the network displaces conventional grid-supplied electricity, while compensation for residential flexibility introduces additional expenditure. Although coordinated PV and BESS operation can reduce upstream electricity procurement costs and peak-demand charges, these savings do not fully offset the reduction in retail revenue and associated flexibility payments under the adopted tariff structure.

These findings highlight the importance of compensation mechanisms that align the economic interests of residential customers and distribution companies. Capacity-based network tariffs could support the recovery of fixed distribution infrastructure costs independently of electricity sales, while flexibility-service remuneration could recognize the operational value of distributed energy resources in reducing peak demand, alleviating feeder congestion, and improving network utilization. Local flexibility markets could further support this alignment by allowing residential PV and BESS owners to receive compensation for providing network-support services, while enabling distribution companies to procure flexibility that could reduce operating costs or defer network investments. Performance-based regulatory mechanisms could also incentivize distribution companies to facilitate distributed energy resource integration. Although these mechanisms are not explicitly incorporated into the present optimization framework, they represent potential approaches for balancing residential economic benefits with the financial sustainability of distribution companies.

4.3. Distribution Network Performance Assessment

The operational impact of building flexibility is examined at representative buses. Figures 3–5 present feeder load profiles under different configurations. At Bus 18 (Figure 3), coordinated operation of smart loads, PV, and storage reduces feeder loading during high-demand periods and improves load distribution across the day, improving feeder-capacity utilization and reducing stress on infrastructure. At Bus 24 (Figure 4), distributed energy resources produce the largest reduction in net feeder demand; during high-solar periods, reverse-power-flow conditions arise from excess PV. Although reverse flow raises renewable utilization, it also underscores why network constraints (16)–(18) must be embedded in the optimization to keep operation secure.

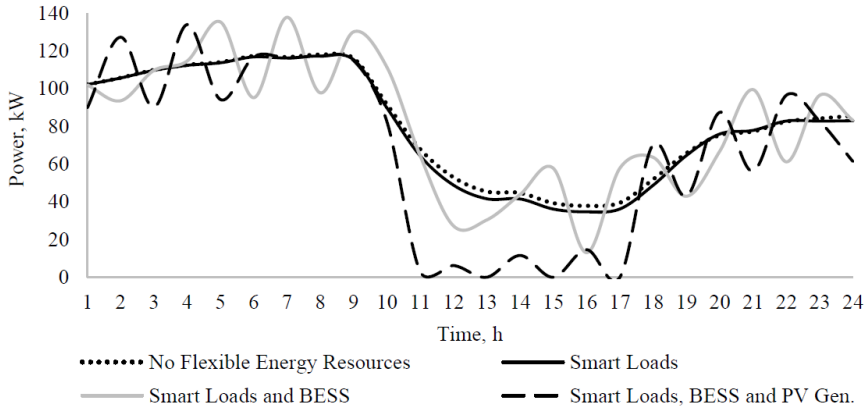


Figure 3. Feeder load profile at Bus 18 under different grid-interactive residential building configurations.

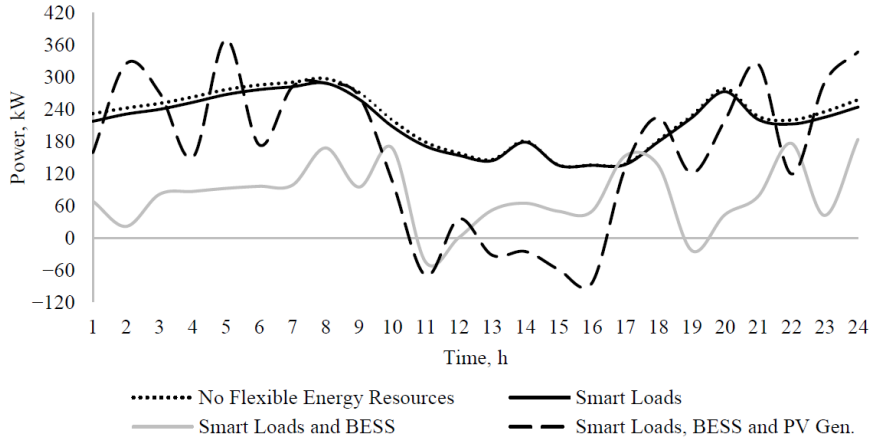


Figure 4. Feeder load profile at Bus 24 under different grid-interactive residential building configurations.

Similar trends appear at Bus 33 (Figure 5), where coordinated flexibility improves demand distribution and reduces feeder loading. These results show that building-level flexibility generates benefits beyond individual households: grid-interactive buildings support network operation by reducing peak loading, improving infrastructure utilization, and increasing the operational flexibility available to network operators—capabilities that become increasingly important as renewable penetration rises.

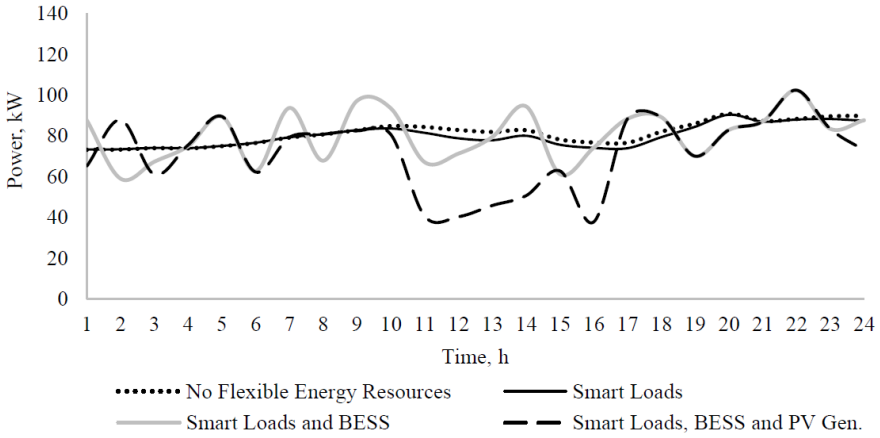


Figure 5. Feeder load profile at Bus 33 under different grid-interactive residential building configurations.

4.4. Flexibility Resource Contribution Analysis

Figure 6 illustrates the relative energy-based contributions of smart loads and combined PV and BESS resources at 20% smart-house penetration. The results indicate that PV and BESS account for approximately 85% of the evaluated flexibility, while smart loads contribute approximately 15%. These percentages represent the average resource contribution shares across the 32 load buses over the 24 h simulation period, calculated using the methodology presented in Section 2.4. The dominant contribution of PV and BESS reflects the combined ability of distributed generation and storage to reduce grid demand and shift energy across time, while smart loads provide complementary flexibility through demand adjustments.

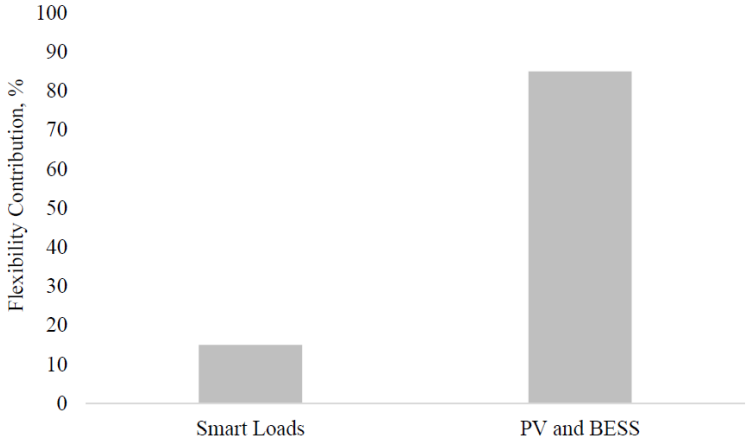


Figure 6. Relative contributions of smart loads and combined PV and BESS resources to total flexibility provision at 20% smart-house penetration.

The relatively limited contribution of smart controllable loads reflects the comfort-feasible demand profiles and appliance operating constraints considered in the building model. In contrast, rooftop PV reduces net electricity demand, while BESS provides temporal flexibility through energy shifting. These findings demonstrate that residential energy flexibility extends beyond conventional demand response and emerges from the coordinated management of demand, distributed generation, and energy storage. This integrated capability enables grid-interactive residential buildings to support both occupant-side and grid-side objectives.

Although the IoT-based adaptive window contributes relatively modestly to overall energy flexibility compared with PV and BESS, its potential value extends beyond flexibility provision. Adaptive windows may improve occupant thermal comfort and reduce heating and cooling requirements by responding to environmental conditions. Therefore, their economic justification cannot be determined solely from their flexibility contribution. A comprehensive cost–benefit assessment considering capital and maintenance costs, energy savings, and thermal comfort benefits would be required to evaluate their overall economic viability, which is beyond the scope of the present study.

The reported flexibility contributions and economic outcomes are based on deterministic PV-generation and occupant-demand profiles. Incorporating stochastic or robust optimization could alter the allocation of flexibility among PV, BESS, and controllable loads, potentially requiring additional battery reserves or adjustments to controllable-load schedules to maintain network feasibility and affecting consumer operating costs. Furthermore, the approximately 85% contribution of PV and BESS reflects the simulated operating conditions rather than a fixed proportion. Under extreme weather conditions, reduced PV generation and increased heating or cooling demand could shift the relative contributions of these resources. Although higher thermal demand may offer additional demand-side flexibility, occupant comfort and appliance operating constraints may limit its availability. Quantifying these effects would require further stochastic and seasonal simulations, including extreme-weather scenarios.

4.5. Effect of the Adaptive Window

The IoT-enabled adaptive window contributes to residential energy management by dynamically adjusting the SHGC according to weather and occupancy conditions, as described in Section 3.2. By lowering the SHGC to 0.07 during warm, unoccupied periods, the smart window limits unwanted solar gains and cooling demand, whereas increasing it to 0.41 in colder conditions supports passive heating. These adjustments are incorporated

into the building energy simulation to generate comfort-feasible smart-load profiles used in the proposed energy management framework. The adaptive window thus complements smart-load, PV, and storage resources by influencing the underlying thermal demand and supporting demand-side flexibility.

4.6. Implications for Future Smart Grids

The transition to future smart grids will require substantially more operational flexibility to accommodate rising renewable and distributed-energy penetration. The results show that grid-interactive residential buildings can serve as valuable distributed flexibility providers, coordinating occupant-responsive demand, distributed generation, and storage while respecting network constraints. Such capabilities can support demand-response programs, virtual power plants, local energy communities, and transactive energy markets. As residential systems evolve, coordinated flexibility is likely to become an essential component of distribution operation, and the proposed framework offers a scalable methodology with a reproducible flexibility metric for evaluating and deploying these resources.

5. Conclusions

This paper presented a network-constrained energy management framework for grid-interactive residential buildings that integrates smart controllable loads, rooftop PV systems, BESS, and IoT-enabled adaptive building technologies. The framework coordinates building-level flexibility resources while respecting distribution-network operational constraints, enabling residential buildings to act as distributed flexibility providers. The results demonstrated that coordinated flexibility improves residential energy performance, reduces household electricity costs, and enhances distribution-network operation. The integrated PV–BESS configuration achieved the largest household savings, reducing daily electricity costs by up to 90.6% relative to conventional operation. However, these benefits did not increase monotonically with smart-house penetration, as reverse-power-flow and feeder-capacity constraints limited additional PV utilization at higher penetration levels. The energy-based flexibility decomposition showed that combined PV and BESS resources accounted for approximately 85% of the average evaluated flexibility contribution, while smart loads contributed the remaining 15%. The analysis also revealed a trade-off between household savings and local distribution-company (LDC) profitability, highlighting the need for tariff structures that better align consumer and utility incentives.

Despite these promising results, practical implementation would require addressing communication latency, interoperability among heterogeneous IoT devices and control systems, and cybersecurity risks associated with distributed monitoring and control. Secure communication protocols, standardized interfaces, and robust control strategies would therefore be important for reliable deployment. Future work will extend the framework to multi-season and stochastic operating conditions, incorporate diverse residential building archetypes and larger building populations, and investigate alternative tariff and flexibility-remuneration mechanisms. Experimental validation using real-world building data or hardware-in-the-loop testing will also be considered to assess practical feasibility and operational robustness.

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Abbreviations

i, j	Buses, $i, j \in \mathcal{N}$
h	Hour, $h \in \mathcal{H}$
u	Location of distribution substation, $u \in \mathcal{U}$
$\mathcal{L}$	Set of feeder sections (lines)
$\mathcal{N}_L$	Set of evaluated load buses
ρ^{PLC}	Peak-load charge, \$/kW
ρ_h^{TOU}	Time-of-Use electricity price, \$/kWh
ρ_h^{Grid}	Main-grid price, \$/kWh
Δt	Duration of a time step, hour
$\underline{E^{BES}}$	BESS energy capacity, p.u.
$\underline{SOC}$	Minimum state of charge, %
n_d	Number of days in a month
n_i^H	Number of houses at bus i
η^{Ch}, η^{Disch}	Charging/discharging efficiency, %
P^{SL}	Smart load of a household, p.u.
P^{PV}	Rooftop PV generation of a smart house, p.u.
P_{size}^{PV}	PV rated capacity, p.u.
P_{size}^{BES}	BESS power rating, p.u.
$P^{Inv^{PV}}, P^{Inv^{BES}}$	PV/BESS inverter power limit, p.u.
Pd	Conventional load of a household, p.u.
Pd^{Min}	Minimum load, p.u.
Qd	Reactive load at bus i (from system data), p.u.
γ_i^{SH}	Penetration of smart houses, p.u.
P^{+SH}, P^{-SH}	Upward/downward power flexibility, p.u.
$P^{Disch^{ABES}}$	Discharge power of aggregated BESS, p.u.
$P^{Ch^{ABES}}$	Charge power of aggregated BESS, p.u.
P^{Sub}, Q^{Sub}	Active/reactive power drawn, p.u.
P^{PK}	Daily peak load imported by substation, p.u.
S^{Subcap}	Substation apparent-power capacity, p.u.
S^{Fcap}	Feeder apparent-power capacity, p.u.
φ^F	Feeder power-factor angle, rad
Y, θ	Admittance magnitude (p.u.)/angle (rad)
SOC	State of charge of aggregated BESS
F^r, Φ^r	Flexibility energy/share, $r \in \{SL, PV{+}BESS\}$
V, δ	Voltage magnitude (p.u.)/phase angle (rad)

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