Technoeconomic Analysis of Performance-Linked Business Cases in intelligent Grid-Forming Buildings*

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Abstract

The transition to sustainable energy systems requires innovative approaches for integrating buildings into the energy grid. Current business models for buildings often fail to address the role of buildings as flexibility providers to the grid and other consumers. This paper presents the Performance-Linked Energy Storage Intelligence (PLESI) business model, leveraging intelligent Grid-Forming Buildings (iGFBs) to improve energy management and economic performance. We develop a mathematical model that incorporates flexible loads, renewable generation, thermal building loads, and Battery Energy Storage Systems (BESS). Sensitivity analyses show that the internal rate of return increases with the peak load-to-BESS power ratio. Besides, economies of scale arise when increasing the number of end-users, resulting in savings up to 45% for optimal configurations.

Keywords— Clean energy Business Models, Energy Storage, intelligent Grid Forming Buildings

1 Introduction

The transition to sustainable energy systems faces challenges such as renewable energy variability, lack of load flexibility, and rising energy costs. intelligent Grid Forming Buildings (iGFBs) address these issues by integrating renewable energy sources, Battery Energy Storage Systems (BESSs), and advanced control algorithms, transforming buildings into active grid participants. iGFBs enhance grid flexibility, optimize renewable energy self-consumption, and respond to market signals, creating new revenue streams for building owners. Scalable and cost-effective business models that combine technical and economic feasibility with environmental sustainability are needed, highlighting the importance of further research into iGFB implementation. Recent studies underline the potential of iGFBs to support grid resilience by balancing supply and demand locally while contributing to ancillary services such as frequency regulation. BESSs play a pivotal role, optimizing energy use, reducing peak demand charges, and improving economic returns.

Energy Performance Contracts (EPCs) have emerged as a key business model to improve energy efficiency in various sectors. The authors in [8] identify Shared Savings schemes as the most profitable approach when considering energy contracting performance under uncertainty. Across the European Union, public-private collaboration drives EPC market growth, enabling large-scale energy efficiency projects [15]. EPC-based startups are contributing to introduce this service-based models [22] in the energy value chain with objectives such as the mitigation of carbon emissions [11]. Nevertheless, in emerging markets, structured risk management is still needed for EPC success [17]. Thus, it is crucial that financial planning and stakeholder priorities are aligned to mitigate risk [19], and that effective institutional support policies are placed to overcome EPC-based business models challenges [16].

In this sense, managing risk and uncertainty in EPC implementation is a critical challenge. Uncertainty and Sensitivity Analysis has been proposed to mitigate investment risks and improve reliability in EPCs [3]. Stackelberg game theory provides further insights into how altruistic preferences shape EPC profitability and stakeholder behaviour [12]. Specific applications with risk management of EPCs include investment models for Distributed Energy Resources (DERs) [24], and zero-carbon industrial parks profits maximization through energy storage integration [6]. The integration of BESSs into EPC and business models is another area of significant research. Studies in Finland demonstrate the feasibility of BESS-as-a-service models for revenue stacking and regulatory compliance [20]. Profitability frameworks for energy storage business models reveal their growing role in energy systems [2].

Buildings' dual role as energy consumers and flexibility providers within EPCs is often overlooked by existing business models. Although integrating BESSs into retail and wholesale markets holds potential, significant gaps remain in leveraging buildings as active energy hubs, particularly concerning the scalability and techno-economic viability of integrating BESSs within iGFBs. This paper bridges these gaps by analyzing the Performance-Linked Energy Storage Intelligence (PLESI) business model, which uses EPCs to optimize energy management. Clients share only a fraction of the achieved performance gains, as presented in Fig. 1. The main contributions are:

- Develop and evaluate a techno-economic framework for the PLESI model.

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- Analyze the model's sensitivity to different customer types, BESS parameters, and scalability factors.
- Propose economic metrics to demonstrate the financial viability of the PLESI model.

The remainder of the paper is organized as follows. Section 2 details the proposed business model. Section 3 presents the optimization formulation for evaluation of the business model. In Section 4, techno-economic results are analysed. Finally, Section 5 concludes the paper.

2 Business Model

Fig. 1 overviews PLESI business model for iGFBs sharing energy services with external users. The iGFB interacts with external assets through a Virtual Point of Common Coupling (PCC), which allows for the aggregation and sharing of profits.

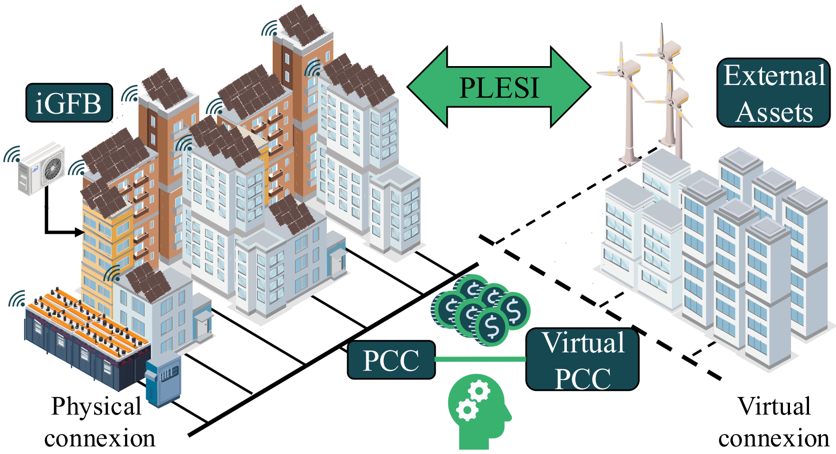

Figure 1: Overview of the PLESI business model, illustrating the iGFB's external assets cost minimization via EPC.

2.1 Lean Model Canvas

This business model addresses the challenge of demonstrating the value of EPC services to customers. The lean model canvas depicted in Table 1 outlines how the iGFB provides services based on predefined objectives, such as cost savings or performance improvement, which are periodically evaluated against a baseline. Customers are charged based on the realized performance increase, aligning with the principles of EPCs. A key advantage of this approach is the mitigation of upfront cost barriers and performance risks for customers, making it particularly suitable for large buildings or condominiums.

2.2 Energy Value Chain Analysis

The proposed PLESI business model enhances value across the energy chain, from production to end-user consumption, as illustrated in Fig. 2. In the upstream phase, iGFBs leverage BESSs, renewable energy sources, and EPCs to reduce initial investment barriers for external users and distribute financial risk among stakeholders. During the midstream phase, PLESI optimizes energy distribution and management through real-time monitoring and control systems. Performance-based pricing models align incentives between building owners and external users, ensuring efficient energy use and maximized returns. Partnerships with aggregators facilitate participation in wholesale markets if infrastructure upgrades or ancillary

Table 1: Lean Model Canvas for the proposed Business Model for intelligent Grid Forming Buildings

Problems	**Solutions**	**Value Proposition**	**Advantage**	**Customer Segments**
Unclear value of storage services.	Performance-based pricing models.	Value-based storage intelligence for customers focused on cost-saving or performance.	Risk-free for customers and adaptation to diverse markets with high storage needs.	Small/medium enterprises.
Existing Alternatives	**Key metrics**	**High-Level Concept**	**Channels**	**Early Adopters**
Flat-rate storage pricing.	Performance improvements, ROI.	Cost-effective storage services with performance guarantees.	Service agreements, utilities.	Enterprises prioritizing performance.

Cost structure	**Revenue Streams**
CAPEX: Initial investment in energy storage systems and associated intelligence platforms. **OPEX**: Maintenance and operation of storage systems, Energy management costs for evaluating performance objectives (e.g., cost savings, performance improvements).	Performance-based fees calculated as a percentage of realized savings or performance improvements (e.g., 10–20% of savings). Potential additional income from providing grid services during under-utilized periods.

services to the local Distribution System Operator (DSO) are needed. In the downstream phase, end-users benefit from reduced energy costs and enhanced energy reliability. PLESI's scalable solutions meet diverse consumer needs, especially in the residential sector. The model fosters a decentralized energy ecosystem where buildings actively contribute to energy generation and consumption, driving a resilient and efficient energy infrastructure.

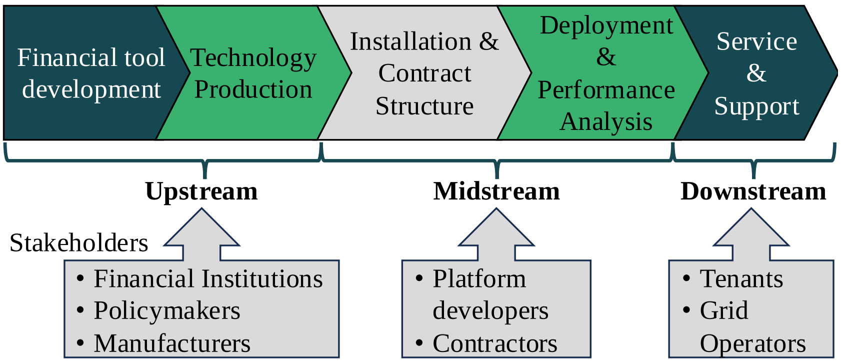

Figure 2: Energy value chain analysis for the PLESI business model, highlighting value addition stages.

3 Problem Formulation

This section defines the mathematical model for optimizing energy management in the iGFB. It integrates the operation of BESSs, Flexible Loads, Renewable Generators, and Heating, Ventilation, and Air Conditioning (HVAC) to maximize profit from internal and external assets by leveraging load flexibility, renewable generation, and BESS performance.

3.1 Flexible Loads

The power of flexible loads $p_{f,t}$ depends on baseline power $P_{f,t}^{base}$, upward flexibility $p_{f,t}^{u}$, and downward flexibility $p_{f,t}^{d}$:

$$P_{f,t}^{min} \leq p_{f,t} \leq P_{f,t}^{max} \tag{1a}$$

$$p_{f,t} = P_{f,t}^{base} + p_{f,t}^{u} - p_{f,t}^{d} \tag{1b}$$

$$\sum_{t} (p_{f,t} - P_{f,t}^{base}) = 0 \tag{1c}$$

$$\sum_{t} c_f \pi_{f,t} (p_{f,t}^{d} - p_{f,t}^{u}) \geq 0 \tag{1d}$$

$$p_{f,t}, p_{f,t}^{u}, p_{f,t}^{d} \geq 0 \tag{1e}$$

Equation (1a) bounds $p_{f,t}$ between $P_{f,t}^{min}$ and $P_{f,t}^{max}$. Equation (1b) defines $p_{f,t}$ using the baseline $P_{f,t}^{base}$ and flexibilities $p_{f,t}^{u}$ and $p_{f,t}^{d}$. Equation (1c) ensures zero net deviation from the baseline over time. Equation (1d) ensures that the extra savings generated by external demands are non-negative, where c_f is the proportion of savings paid to the iGFB and $\pi_{f,t}$ is the price per power consumption. Equation (1e) enforces non-negativity for $p_{f,t}$, $p_{f,t}^{u}$, and $p_{f,t}^{d}$.

3.2 Renewable Generation

Equation (2a) determines the power generation $p_{g,t}$ based on the renewable power $P_{g,t}^{RE}$, and curtailment $p_{g,t}^{curt}$. Equation (2b) limits curtailment $p_{g,t}^{curt}$ by the renewable power $P_{g,t}^{RE}$.

$$p_{g,t} = P_{g,t}^{RE} - p_{g,t}^{curt} \tag{2a}$$

$$p_{g,t}^{curt} \leq P_{g,t}^{RE} \tag{2b}$$

$$p_{g,t}, p_{g,t}^{curt} \geq 0 \tag{2c}$$

3.3 Dispatchable Thermal Building Loads

The thermal dynamics of the building are modelled using a first-order RC HVAC model [13]. This model captures the heating and cooling processes of the building, considering the thermal resistance R_h, capacitance C_h, outdoor temperature τ_{ht}^{out}, initial temperature $T_{h,0}$, cooling power $p_{h,co}$, heating power $p_{h,he}$, and their respective efficiencies η_h^{co} and η_h^{he}.

$$\tau_{h,t+1} = \tau_{h,t} + \frac{\Delta t}{C_h} \left[\frac{\tau_{ht}^{out} - \tau_{h,t}}{R_h} + \eta_h^{he} p_{h,t}^{he} - \eta_h^{co} p_{h,t}^{co} \right] \tag{3a}$$

$$\tau_{h,t}^{min} \leq \tau_{h,t} \leq \tau_{h,t}^{max} \tag{3b}$$

$$p_{h,t}^{co} \leq P_h^{co,max} z_{h,t} \tag{3c}$$

$$p_{h,t}^{he} \leq P_h^{he,max}(1 - z_{h,t}) \tag{3d}$$

Equation (3a) describes the temperature update rules for the initial and subsequent time steps, respectively, considering the thermal resistance R_h, capacitance C_h [13], outdoor temperature τ_{ht}^{out}, initial temperature $\tau_{h,0}$, cooling power $p_{h,t}^{co}$, heating power $p_{h,t}^{he}$, and their respective efficiencies η_h^{co} and η_h^{he}. Equation (3b) enforces the temperature bounds between $\tau_{h,t}^{min}$ and $\tau_{h,t}^{max}$. Equations (3c) and (3d) constrain the cooling and heating power based on their maximum capacities $P_h^{co,max}$ and $P_h^{he,max}$, and the binary $z_{h,t}$ indicating the HVAC state.

3.4 Energy Storage System

The BESS operation is modelled using its State of Charge (SOC) and power flows, considering charging power $p_{s,ch}$, discharging power $p_{s,dis}$, charging efficiency η_s^{ch}, discharging efficiency η_s^{dis}, time step Δt, and binary variable z_s indicating the charging state.

$$soc_{s,t} = soc_{s,t-1} + (\eta_s^{ch} p_{s,t}^{ch} - p_{s,t}^{dis}/\eta_s^{dis})\Delta t \tag{4a}$$

$$SOC_s^{min} \leq soc_{s,t} \leq SOC_s^{max} \tag{4b}$$

$$p_{s,t}^{ch} \leq P_s^{max}(1 - z_{s,t}), \quad p_{s,t}^{dis} \leq P_s^{max} z_{s,t} \tag{4c}$$

$$b_{s,t}^{cal} \geq A_{s,m} soc_{s,t} + Bs, m \tag{4d}$$

$$b_{s,t}^{cyc} \geq C_{s,m}(p_{s,t}^{ch} + p_{s,t}^{dis})/P_s^{max} + D_{s,m} \tag{4e}$$

Equation (4a) updates the SOC based on initial SOC, $\mathrm{SOC}_{0,s}$, charging and discharging power, $p_{s,t}^{ch}$, $p_{s,t}^{dis}$, charging and discharging efficiency η_s^{ch}, η_s^{dis}, and time step Δt. Equation (4b) ensures SOC remains within minimum SOC_s^{min} and maximum SOC_s^{max} limits. Equations (4c) constrain charging and discharging power by maximum power P_s^{max} and binary variable $z_{s,t}$. Equations (4d) and (4e) model an upper bound of calendar and cyclic degradation using coefficients $A_{s,m}$, $B_{s,m}$, $C_{s,m}$, and $D_{s,m}$, and variables $b_{s,t}^{cal}$ and $b_{s,t}^{cyc}$ [4].

3.5 Virtual Aggregation

Internal loads are physically aggregated within the iGFB, creating a virtual hybrid thermal and electrical battery to optimize the overall energy management strategy.

$$\sum_{s \in O_s} (p_{s,t}^{ch} - p_{s,t}^{dis}) + \sum_{f \in O_f^{int}} p_{f,t} + \sum_{h \in O_h} (p_{h,t}^{co} + p_{h,t}^{he}) + \sum_{g \in O_g} p_{g,t} + p_t^{iGFB,u,ext} = p_t^{demand} + p_t^{iGFB,d,ext} \tag{5a}$$

$$p_t^{iGFB,u,ext} = \sum_{f \in O_f^{ext}} p_{f,t}^u, \quad p_t^{iGFB,d,ext} = \sum_{f \in O_f^{ext}} p_{f,t}^d \tag{5b}$$

Equation (5a) represents the energy balance within the iGFB, aggregating the power contributions from BESSs $p_{s,t}^{ch}$, $p_{s,t}^{dis}$, internal Flexible Demands $p_{f,t}$, HVACs $p_{h,t}^{co}$, $p_{h,t}^{he}$, and Renewable Generators $p_{g,t}$. The terms $p_t^{iGFB,u,ext}$ and $p_t^{iGFB,d,ext}$ account for the virtual aggregation of external loads. Equation (5b) defines the upward and downward flexibility of external loads.

3.6 Energy acquisition: Retailing and Market Participation

Additionally, the iGFB can participate in the wholesale market as an active node when aggregating enough resources. The energy that is not obtained from the wholesale market is obtained from a retailer.

3.6.1 Day-Ahead Market Constraints

The Day-Ahead Market (DAM) constraints ensure that the minimum bid size for buying p_t^{DAMB} and selling p_t^{DAMS} energy is respected. Equations (6a) and (6b) enforce the bounds of the minimum bid requirements B_{DAM} using binary variables y_t^{DAMB} and y_t^{DAMS} and the Big enough M parameter M_{DAM}.

$$y_t^{DAMB} \cdot B_{DAM} \leq p_t^{DAMB} \leq M_{DAM} \cdot y_t^{DAMB} \tag{6a}$$

$$y_t^{DAMS} \cdot B_{DAM} \leq p_t^{DAMS} \leq M_{DAM} \cdot y_t^{DAMS} \tag{6b}$$

3.7 Objective Function

The objective function aims to maximize the overall profit from internal and external assets within the iGFB, considering battery degradation. The objective function is defined as follows:

$$\max \sum_{f \in O_f^{ext}, t} c_f \pi_{f,t}(p_{f,t}^d - p_{f,t}^u) + \sum_t \pi_t^{retS} p_t^{retS} - \sum_t \pi_t^{retB} p_t^{retB} + \sum_t \pi_t^{DAM}(p_t^{DAMS} - p_t^{DAMB}) -$$

$$- \sum_{s \in O_s, t} C_s^{DEG} (b_{s,t}^{cal} + b_{s,t}^{cyc}) \quad (7)$$

Equation (7) represents the profit from external assets, with c_f as the proportion of savings paid to the iGFB for external Flexible Demands. The retailer profit is modelled using π_t^{retS} and p_t^{retS} for selling, and π_t^{retB} and p_t^{retB} for buying power. The DAM participation includes π_t^{DAM} as the market price, p_t^{DAMS} as the power sold, and p_t^{DAMB} as the power bought. Battery degradation is penalized economically using C_s^{DEG}.

4 Business Model Analysis

4.1 Input data

Simulations are performed on a cluster with 80 TB RAM and 160 nodes, each with 2 x AMD EPYC 7H12 CPUs at 2.60 GHz, running Suse Leap 42 Linux. The optimization problem is solved using Pyomo 6.8.2 [10] with Python 3.11.4 and Gurobi 10.0.1 [9]. Each problem comprises 744,610 rows, 464,271 columns, and 1,620,577 non-zeros, including 157,036 continuous and 65,105 binary variables, solved with a MIP gap of 0.1% within 15 to 40 min.

4.1.1 Building characteristics

Three building types are analyzed: residential, commercial, and industrial. Residential and commercial buildings' flexibility is based on thermal dynamics, while industrial flexibility is modelled as deferrable loads. Residential buildings typically consume 180 kWh/m^2 and commercial buildings 280 kWh/m^2 [7]. Typical European urban blocks range from 4 to 6 stories with 3 to 6 flats per floor, and commercial buildings are 2 to 4 levels [21]. The average residential home size is 100 m^2, and commercial buildings average 30,000 m^2 [5]. It is assumed that 25% of rooftop area is available for rooftop solar photovoltaics with OPEX initially set to 18.31 €/(kWp·year) [18]. Mean temperatures and global solar tilted irradiation for 2023 are sourced from [25]. OPEX for HVAC systems is set at 4.84 €/m^2 [1].

4.1.2 Load profiles

Load profiles are derived from the SimBench dataset [14], providing real-world inspired datasets with annual load time series for industrial, commercial, and residential loads.

4.1.3 ESS characteristics

Degradation model parameters are based on [4] for a Lithium-Ion Battery. Parameters A_m, B_m, C_m, and D_m are derived from the convex hull of data points. The battery's end-of-life is set at 60% of initial capacity, with a round-trip efficiency of 90%. Capital Expenditures are set at 460.24 €/kWh, and OPEX are set at 10.857 €/kWh/year [18]. These values are based on an BESS with a C-Rate of 1. Note that higher C-Rates will proportionally increase both measures.

4.1.4 Business model parameters

According to [23], wholesale power prices will remain high until 2025, then stabilize as renewable capacity increases and reliance on natural gas decreases. OPEX for BESSs, HVACs, and renewable sources are expected to drop due to technological advancements and economies of scale. Trends used are available at [18].

4.1.5 Search Space

Table 2 shows the search space for the business model analysis, including the percentage of industrial and commercial loads, industrial flexibility, total peak load, BESS power, C-rate, percentage of savings kept by the iGFB, and the external load percentage.

Table 2: Search Space Parameters

Parameter	**Levels**
Industrial Load Percentage	[0.1, 0.2, 0.4]
Commercial Load Percentage	[0.1, 0.2, 0.4]
Industrial Flexibility	[0.1, 0.3, 0.5]
Total Peak Load (kW)	[500, 2000, 3500, 6000]
BESS Power (kW)	[500, 1500, 2000, 3500, 5000]
C-rate	[0.5, 1.0, 2.0, 4.0, 6.0]
Percentage Kept by iGFB	[0.05, 0.1, 0.15, 0.2]
External Load Percentage	[0.01, 0.05, 0.1, 0.2]
Total Search Points	43,200

4.2 Sensitivity to the ESS characteristics

Fig. 3 shows the Internal Rate of Return (IRR) variation with respect to the Peak Load-to-BESS Power and Peak Load-to-C-rate ratios for different external percentages (c_f) from 5% to 20%. The IRR generally increases with a higher Peak Load-to-BESS Power ratio, reflecting the adequacy of the battery's power capacity to handle peak demands and highlighting better financial performance with greater battery utilization. Similarly, the Peak Load-to-C-rate ratio, which evaluates the battery's ability to sustain energy output relative to peak demand over time, significantly impacts the IRR, with higher ratios indicating improved returns under specific external percentage conditions. Given their close correlation, focusing on the Peak Load-to-BESS Power ratio suffices to evaluate the BESS characteristics' impact on the business model's performance.

4.3 Sensitivity to the type of customer

Fig. 4 shows the IRR variation with the peak load to BESS power ratio and the percentage of external loads for different c_f values. Increasing c_f and external percentage significantly impacts the IRR. For a given c_f, the IRR rises with higher peak load to BESS power ratios, reflecting improved profitability from leveraging BESS flexibility. However, as the external percentage increases, the IRR initially grows and then diminishes beyond an optimal external load share. The rapid IRR increase at 10% external load is due to efficient flexibility savings allocation between internal and external loads, enabling higher revenues with lower peak load to BESS power ratios. Beyond this point, returns diminish due to competitive dynamics in distributing flexibility benefits, higher costs of engaging more external loads, and reduced efficiency in BESS utilization.

The relationship between the residential percentage in the portfolio and the peak power-to-BESS power ratio significantly influences cost savings for external loads in the PLESI model, as shown in Fig. 5. Higher residential percentages consistently enhance cost savings across all peak power-to-BESS power ratios, indicating the economic advantage of incorporating more residential customers. Lower ratios (≤ 1) yield the highest savings due to efficient storage utilization for peak demand management, while higher ratios (≥ 4) show slightly reduced savings, suggesting diminished storage efficacy. Nonetheless, higher ratios remain cost-effective due to increased economic viability, as demonstrated in Fig. 3.

4.4 Scalability analysis

The proposed business model demonstrates scalability in terms of internal cost efficiency and economic return. Figure 6 (a) shows that as the percentage of external loads increases, the ratio of internal cost difference to internal demand decreases across different peak load to BESS power ratios, indicating enhanced internal cost efficiency. Figure 6 (b) illustrates that the IRR increases with higher peak loads and peak load power to BESS power ratio, suggesting that systems designed to handle larger demand achieve more favourable economic returns.

The decrease in the internal cost difference to internal demand ratio with increasing external load percentage in Figure 6 (a) is due to the effective distribution of operational costs across a larger base, reducing the per-unit cost for internal

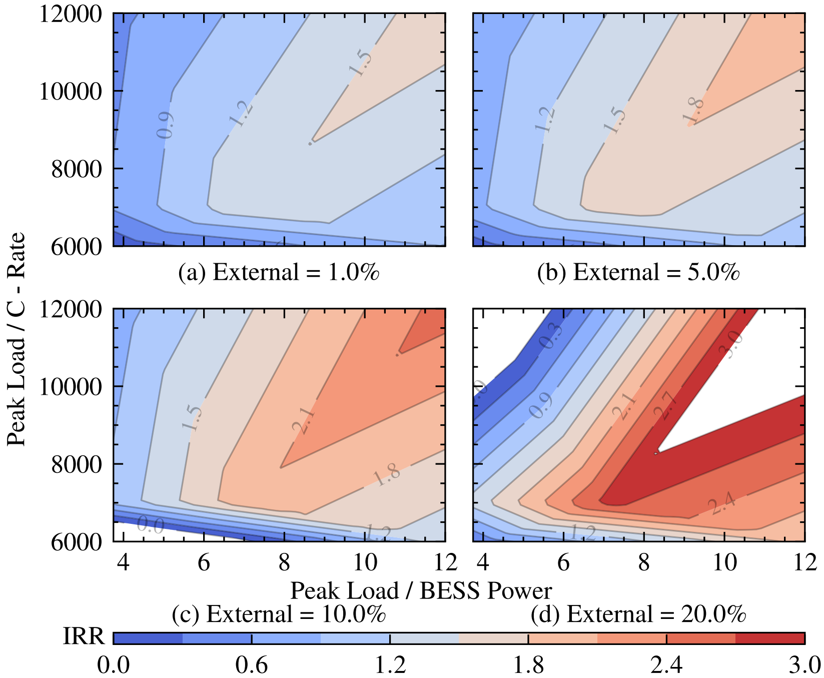

Figure 3: Impact of the Peak Load / BESS Power and Peak Load / C-rate on the IRR for different percentages of external users.

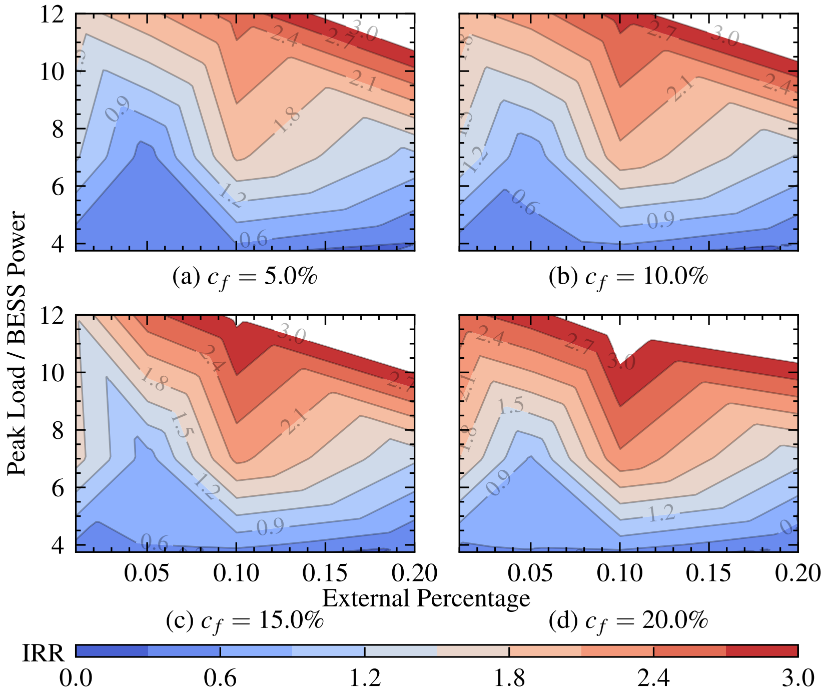

Figure 4: Impact of Flexibility Sharing Ratios, ESS characteristics, and Portfolio Composition on the IRR

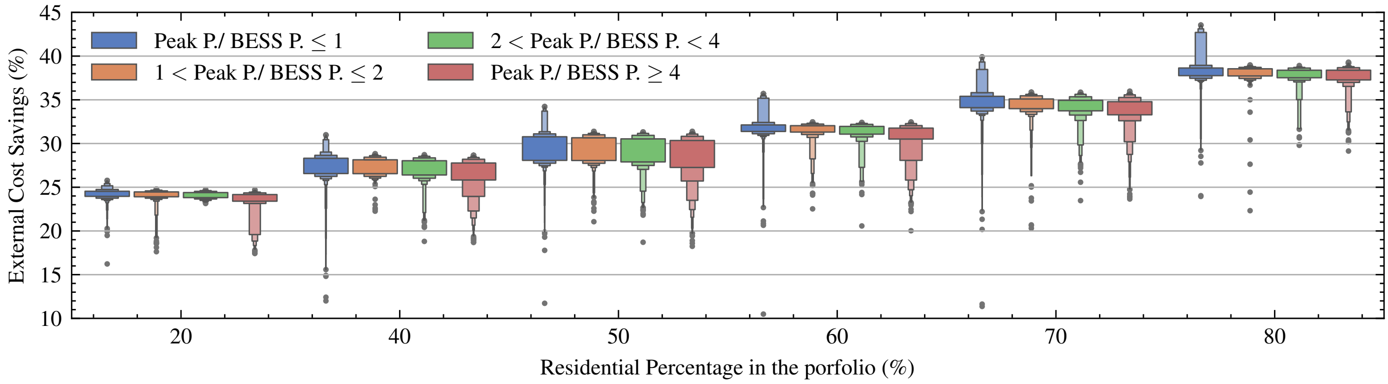

Figure 5: Impact of Residential Portfolio Percentage and Peak Power-to-BESS Power Ratio on External Load Cost Savings

demands. The rapid increase in IRR with higher peak loads in Figure 6 (b) is attributed to the improved profitability from leveraging the BESS flexibility, which allows for better management of peak demands and maximizes revenue streams.

5 Conclusion

The PLESI business model optimises energy management and economic performance by integrating flexible loads, renewable generation, thermal building loads, and energy storage systems. Sensitivity analyses reveal that BESS characteristics and customer composition significantly influence the IRR, suggesting that high ratios of peak load to BESS power increase the profitability. Scalability assessments demonstrate PLESI's applicability across diverse building portfolios and demand profiles, supporting its implementation, especially for residential portfolios, reaching up to 45% cost savings. The model scales effectively with service capacity expansion and investment flow if the external ratio of customers remains under 5% of the total internal load. These findings highlight the economic and operational benefits of performance-linked business models in iGFBs, offering scalable and cost-effective solutions for the energy transition. Future research should explore advanced forecasting methods and real-time optimisation.

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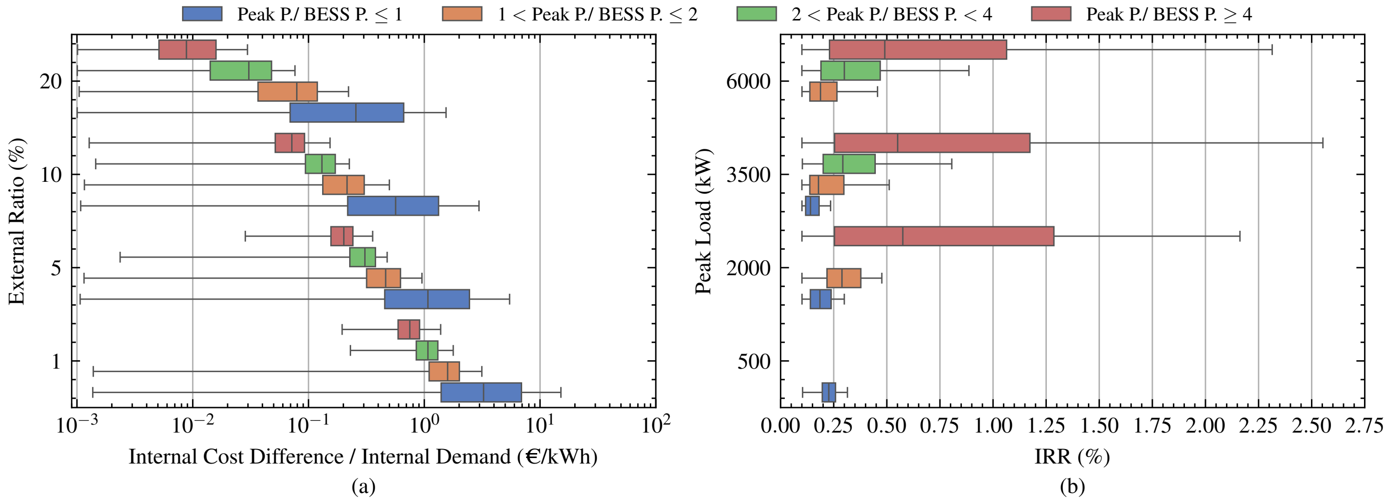

Figure 6: Scalability Analysis of the iGFB Business Model Under Varying External Loads and Peak Demands.

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