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Pricing Optimization in Shared Community Energy Storage Systems: A Bilevel Approach

Master Candidate

Alessia Ortile

Student ID 2082122

Supervisor

Prof. Roberti Roberto

University of Padova

Co-supervisor

Prof. Ghaddar Bissan

Technical University of Denmark

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To my families,
those I come from and
those I have built along the way

Abstract

This thesis explores the design of a pricing mechanism for a shared energy storage system within a residential community including diverse households, each with distinct energy consumption patterns and optional rooftop solar generation. The core objective is to develop a fair and efficient pricing strategy that enhances overall community welfare while accommodating two operational models: a profit-oriented storage operator and a nonprofit alternative. To achieve this, the system is modeled using a bilevel optimization framework. At the upper level, the storage manager sets energy prices, and at the lower level, households respond by optimizing their energy usage based on economic incentives. The model incorporates key constraints such as load flexibility, appliance scheduling, and storage limitations.

Real-world data from Waterloo, Ontario, are used to simulate realistic summer and winter scenarios. Simulations account for real-time electricity pricing, photovoltaic generation, and thermal load modeling. Different levels of household flexibility are also explored, including scenarios with restricted appliance usage windows and simplified time-of-use price tariffs.

The results reveal that while profit-driven operation can yield variable revenue for the storage operator across seasons, it also provides tangible cost savings for households. Notably, the nonprofit model further increases the households economic benefit, demonstrating up to a 1020% increase in cost savings compared to baseline grid use. Additionally, the study shows how pricing structures influence household behavior, shifting consumption patterns in ways that reduce peak demand and enhance grid stability.

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1 Introduction

1.1 Motivation

Globally demand has continued to rise since the mid-20th century due to industrial development and population growth. Urban areas now consume more than two thirds of the world's energy and are responsible for approximately 70% of global greenhouse gas emissions. Furthermore, rapid industrial and residential expansion has forced grid stations to operate near maximum capacity [1], particularly in cities such as Toronto and Ottawa, increasing the risk of power outages due to local overcapacity.

In recent decades, the electricity sector has undergone a fundamental transformation in both supply and demand dynamics. Between 1993 and 2012, global energy production and consumption increased by approximately 50%. Looking ahead, urban electricity demand is projected to rise significantly, driven by the electrification of transport, heating, and industrial processes [2]. Concurrently, the share of Renewable Energy Source (RES) in the total energy mix has also grown and is expected to continue increasing.

The increasing integration of renewable energy is largely driven by policy frameworks such as those of the European Union (EU), which aims to achieve climate neutrality. The EU has set a binding target to reduce greenhouse gas emissions by 55% by 2030 (compared to 1990 levels) and to achieve full climate neutrality by 2050. These goals are supported by initiatives to decarbonize all sectors, improve energy efficiency, and expand the use of domestic renewable sources. Increasing reliance on renewables not only helps combat climate change but also enhances energy security, reduces dependency on imported fuels, and contributes to price stability by avoiding geopolitical volatility. As part of this strategy, the EU has mandated a renewable energy share of 42.5% in the energy mix by 2030, with an aspirational target of 45% [3].

To address the surge in electricity demand and the variability of renewable sources, modern power systems are transitioning toward decentralized and flexible energy resources. These include distributed generation, energy storage, and demand-side management capabilities. Indeed, traditional transmission and distribution (T&D) networks, designed for centralized, one-directional power flows, struggle to accommodate higher shares of RES. Historically, these systems followed a radial "down-and-out" paradigm, which is now being challenged by consumers who are also becoming producers and storage managers.

Smart technologies play a crucial role in reducing energy consumption and emissions. These technologies encompass a cleaner energy mix, intelligent energy management systems, and shared resource utilization. The work presented in [4] offers a comprehensive survey of smart grid systems and developments in this area. Within such systems, households can collaborate with aggregators to enhance grid reliability and receive benefits such as value-added services and improved energy management. Although collaboration in energy management is a popular topic, limited research has explored energy sharing, particularly in the domain of Energy Storage System (ESS).

Smart grids enhance energy efficiency by addressing dynamic demand, minimizing transmission losses through localized storage [5], and enabling the integration of RES such as wind and solar. They also promote the use of microgrids, Electric Vehicle (EV) [6], and smart appliances [7].

Today, households can manage smart appliances and communicate power usage data via Home Energy Management Systems (HEMS), adjusting their consumption using Distributed Energy Resource (DER) [8, 9]. For example, when a household installs DERs like rooftop photovoltaic panels, any surplus generation can be managed by the HEMS, either stored in ESS [10] or traded through local energy markets facilitated by aggregators [11]. This setup supports economic efficiency and increases user flexibility.

However, a major limitation of most ESS remains the high investment cost. To ensure technical feasibility and economic viability, efficient system design and operation are crucial. The role of energy management is to define optimal charging and discharging schedules for ESS and related components. Such optimization ensures that integrated energy systems operate reliably and cost-effectively [12]. Moreover, not all households are equipped with smart systems, and users must be incentivized to adopt flexible consumption behaviors to benefit fully from shared energy systems. Insights from the OECDs EPIC survey [13], which covered 17,000 households across nine countries, show that while 65% of respondents are willing to make lifestyle compromises for environmental benefit, 63% are not willing to incur additional costs. This underscores the need for economic incentives that align personal financial interests with environmental goals.

For these reasons, this thesis addresses a research gap in the area of pricing systems for community-based energy storage. While most existing studies focus on operational optimization to improve energy efficiency, less attention has been given to the development of pricing mechanisms that ensure the economic viability of such systems. There is a need for research that explores how pricing strategies can make energy storage not only technically effective but also financially attractive for communities.
This project aims to optimize pricing models for community-based energy storage systems to deliver economic benefits to users while considering the high initial investment costs. The objective is to propose solutions that are both advantageous for end-users and communities and economically viable, by evaluating whether the generated profits by the Energy Storage (ES) can offset implementation and operational expenses. With the increasing integration of DER and growing interest in decentralized energy markets, pricing mechanisms play a pivotal role in shaping user behavior, ensuring system profitability, and enabling cost recovery for storage infrastructure.

1.2 Thesis Objective

The overall aim of this research is to investigate how well-designed pricing systems can support the wider adoption and efficient operation of community-based energy storage systems, in a way that balances economic sustainability with tangible benefits for end-users. Three main research questions has been identified.

- How can a pricing system be designed to meet user demand while ensuring profitability for storage managers?

- How can a pricing system be designed to provide economic advantages to the users?
- How do user participation and energy consumption behaviors change under different pricing models?

By addressing these questions, the thesis tries to contribute to the design of pricing mechanisms that can help scale up community-based energy storage in a socially fair and economically sound manner.

The thesis is structured as follows. Chapter 2 provides a comprehensive literature review, outlining the current state of research on ESS, pricing mechanism design, and bilevel optimization methods. Chapter 3 introduces the problem addressed in this work, along with its mathematical formulation. The solution approach is then detailed in Chapter 4, which describes the methodologies and techniques used to solve the optimization problem. Chapter 5 presents the real-world data used for the simulations and discusses the results obtained under various scenarios, while Chapter 6 presents a deeper analysis of the results. Finally, Chapter 7 offers a discussion of the findings, highlights the limitations of the study, and proposes directions for future research.

2 Literature Review

2.1 Energy storage

Eletric Energy Storage System (EESS) are, in general, a technically viable solution to bridge the temporal gap between production from RES and consumption. A comprehensive survey by [14] categorizes EESS applications into three main types:

Storage-only applications: EESS operate as independent systems interacting with the grid. The primary task is to determine the optimal charging and discharging schedules to meet system-level objectives.

Producer-oriented applications: In this case, EESS are integrated with renewable generation facilities (e.g., solar or wind) to improve the output quality and stability. Economic objectives typically dominate, while technical objectives such as power quality are secondary.

Consumer-oriented applications: These systems serve one or multiple consumers and may include local generation units like rooftop photovolatic (PV) panels or small wind turbines. However, the overall energy balance tends to be negative. The primary objective is typically cost reduction by shifting consumption from high-price, on-peak periods to low-price, off-peak times. Secondary goals include minimizing comfort violations or demand deviations. A limited number of studies have investigated off-grid consumer-oriented PV applications.

The survey also reveals that most publications consider uncontrollable loads; only 25 out of 202 studies incorporate controllable load profiles. Moreover, the majority rely on day-ahead scheduling (used in 74 out of 91 relevant studies), which includes forecast data for the following day.
Currently, smart households can monitor and control their energy consumption using HEMS integrated with DERs. Multiple studies focus on optimizing the coordination between DER and HEMS. For instance, [15] and [16] present mathematical models for major household appliances, including refrigerators, freezers, dishwashers, dryers, stoves, air conditioners, and heaters, along with PV and ES systems at the residential level. These models are used to optimize appliance scheduling and enhance system coordination. Similarly, [17] investigates centralized energy management in residential buildings, enabling real-time optimal decisions. Furthermore, [18] focuses on optimizing battery size to minimize electricity payments, using both stochastic and robust optimization models to handle demand uncertainty.

While these works provide valuable insights into individual household behavior, they generally overlook the collective behavior of a community. Consequently, solutions that are optimal at the household level may not be globally optimal for the entire community.

To address this limitation, some studies have started to examine small communities or multi-unit buildings. For example, [19] proposes a demand-side management model that reduces peak demand and cost while preserving user privacy, as smart meters communicate only with the utility, not between households. [20] uses Dantzig-Wolfe decomposition and column generation to optimize interactions between households and aggregators, without direct cooperation between users. In contrast, [21] focuses on optimizing load schedules under various price-based Demand Response (DR) programs, successfully reducing costs without compromising user comfort or increasing peak load. Other studies extend the scope to microgrids. For example, [22] considers the optimal battery sizing for an isolated microgrid under stochastic demand. [23] offers a comprehensive review of battery sizing criteria and approaches.

However, many of these studies still analyze systems at the individual household level and do not explore the potential benefits of shared storage within a community. The concept of community-based energy systems has only recently gained attention, grouping multiple households within a local area to collaborate on energy use and management.

Recent literature begins to highlight the economic and operational benefits of community-based approaches. For instance, [24] and [25] present the advantages of Community Energy Storage (CES), including reduced power consumption and lower energy costs. [26] proposes optimal placement of multiple CES units within a distribution network featuring PV generation, aiming to maximize net present value through optimal sizing and location. [27] determines the appropriate rated capacity and dispatch strategy of CES in residential systems with PV to improve the annual load factor.
Further, [28] identifies optimal CES system configurations based on community size and PV time-shifting capabilities. [29] classifies users based on electricity consumption using k-means clustering to facilitate Peer-to-Peer (P2P) energy trading for better supply-demand balance. [30] introduces an online algorithm for energy sharing in looped communities, minimizing costs while promoting fairness. In contrast, [31] focuses on how CES operations impact the broader electricity market.
Fairness and economic viability are also explored through various modeling frameworks. For example, [32] and [33] utilize multi-agent systems to simulate collaborative energy management. [34] proposes an auction-based approach where prices are determined through a non-cooperative Stackelberg game. Conversely, [35] applies cooperative game theory to achieve load balancing and shared benefits.
Battery sizing remains a critical aspect of CES design. [36] introduces a location-based model grouping neighboring households using real geographic and road network data to determine the optimal community-level storage size, accounting for PV generation and installation costs. Similarly, [37] proposes a scalable architecture for shared ESS, determining optimal CES size based on user stochastic demand across various network sizes.

Although this section focused on the technical and operational role of ES within residential and community-based systems, Section 2.1.1 shifts focus to an equally important dimension: the design of pricing systems that govern user behavior and economic efficiency in such energy networks.

2.1.1 Price Systems

The integration of pricing systems for shared energy resources, such as CES, is a complex topic that still requires further research. Several aspects must be considered when approaching the design of such systems.

A pricing system can be defined as a tariff structure or incentive mechanism aimed at motivating end-users to adjust their electricity consumption. This adjustment can occur in response to time-varying electricity prices or through incentive payments designed to reduce electricity use during periods of high market prices or when grid reliability is at risk [38].
DR schemes are typically classified into two categories based on the control mechanism: centralized and distributed. In centralized schemes, consumers communicate directly with the utility without interacting with each other. In contrast, distributed schemes involve user-to-user interactions, with aggregated consumption data sent to the utility [38].
When designing a pricing system, two major elements must be addressed: the structure of the pricing model and the behavioral response of users, particularly in leaderfollower dynamics.
One of the most widely adopted pricing models is Time of Use (TOU) pricing. TOU divides the day into distinct blocks, each associated with a different electricity price, typically based on demand levels at different times of the day. According to [39], TOU tariffs can effectively reduce peak demand by up to 30% and lower energy bills by at least 20%. However, they do not significantly improve metrics such as self-consumption or self-sufficiency.
Alternatively, Real-Time Pricing (RTP) provides hourly varying electricity prices that reflect real market conditions. In RTP systems, users typically receive next-day pricing information in advance. From the perspective of electric energy flexibility, RTP is considered the most favorable tariff structure [40].
A more recent model introduced in the literature is Time and Level of Use (TLOU) pricing, where prices vary not only with time but also with the level of energy consumption [41]. This structure aims to reflect both temporal and volumetric demand patterns more accurately.

To optimize these pricing frameworks, several mathematical and algorithmic methods have been proposed in the literature. For instance, [41] formulates the TLOU pricing optimization as a bilevel optimization problem. In this model, the supplier (upper level) sets prices to maximize profit within a demand response context, anticipating the behavior of a residential aggregator (lower level) that minimizes the total cost. The model explicitly considers load-shifting preferences and user acceptability constraints.
In another approach, [42] employs a Stackelberg game-theoretic model, where

the system manager acts as the leader and the users as followers. The equilibrium of this leaderfollower game is computed to determine optimal pricing and consumption strategies.
Finally, [43] proposes a reinforcement learning-based bilevel optimization framework. The upper level maximizes supplier profit, while the lower level addresses each users optimal consumption decision using individual Markov Decision Processes (MDPs). This approach enables adaptive learning of user behavior and dynamic pricing in complex and uncertain environments.

2.2 Bilevel optimization

As discussed in the previous section, the interaction between energy system operators and consumers often follows a leaderfollower dynamic. This naturally leads to the adoption of bilevel optimization frameworks, which are well-suited to capture such hierarchical decision-making structures.
Bilevel optimization is an active and growing field in applied mathematics, particularly effective for modeling hierarchical decision-making processes. It has been widely used in the context of energy price setting [44, 45, 46], offering a powerful framework to represent leaderfollower dynamics, where one decision-maker (the leader) anticipates the reaction of another (the follower).
In a bilevel optimization problem, one optimization task is nested within another. The upper-level (leader) problem makes decisions while accounting for the optimal response of the lower-level (follower) problem. This structure makes bilevel models especially suitable for energy pricing, but also computationally challenging due to their hierarchical nature and non-convex feasible regions [47, 48]. Solving them often requires advanced reformulation techniques and approximation methods.
Numerous studies apply bilevel optimization to energy systems. For instance, [49] investigates the optimal placement of electric vehicle charging stations and the corresponding pricing schemes. Similarly, [50] incorporates customer preferences and peak load reduction into a bilevel framework, while [51] presents a bilevel formulation for TLOU pricing. In their model, the supplier (leader) sets prices to maximize profit while anticipating the cost-minimizing behavior of a residential load aggregator (follower).
Bilevel optimization is not limited to the energy sector. Applications exist in transportation networks, such as highway toll design [52, 53], and in telecom-

munication systems, where network operators set tariffs [54]. A notable example from logistics is the bilevel shipping tariff problem explored by [55].
More advanced models incorporate uncertainty. In [56], the authors explore stochastic bilevel optimization for electricity network tariff design. The upper level represents a retailer that sets tariffs and manages load curtailment, while the lower level models flexible end-user behavior (both consumers and prosumers). Uncertainty is modeled using a finite set of scenarios, and the bilevel problem is transformed into a single-level problem via KarushKuhn-Tucker (KKT) conditions and Special Ordered Sets of Type 1 (SOS-1) constraints. Similarly, [57] adopts a hybrid stochastic-robust approach to determine optimal electricity supply contracts. Strong duality is used to derive a single-level reformulation under scenario-based uncertainty. Another key application of bilevel optimization in energy is the modeling of strategic bidding in wholesale electricity markets, as discussed by [58].

In this thesis, a bilevel optimization framework is adopted, where the CES operator is the leader. The operator determines the energy selling price for each hour of the day, given access to next-day market prices, and the buying price offered to prosumers who feed energy into the system. The followers are households (consumers and prosumers) who adjust their behavior in response to the set prices. They aim to minimize their electricity costs by shifting flexible loads throughout the day. This type of problem is considered pessimistic, as the leader aims to maximize profit while the followers aim to minimize costs, thus introducing a conflicting objective structure between the two agent types.
A commonly used solution strategy, also found in [41, 51], is used by reformulating the bilevel problem as a single-level optimization problem. This is done by deriving the KKT conditions for the lower-level problem and embedding them in the upper-level formulation. The resulting model includes complementarity constraints, which pose additional numerical challenges. To manage these, the well-established Big-M relaxation technique are applied to linearize the complementarity constraints and make the problem solvable with standard optimization solvers.

While the existing literature has extensively explored household-level energy optimization, pricing strategies, and bilevel formulations, little work has been done to integrate these elements within a realistic, community-based framework. This thesis addresses that gap by applying a bilevel optimization model to a CES system, where the CES operator acts as the leader and households

(prosumers and consumers) serve as followers. Additionally, the utility grid is modeled as a natural competitor to the CES, allowing users to opt out of using the CES when it is not economically advantageous.
The proposed model jointly considers the economic profitability of the CES operator and the cost-saving behavior of households, accounting for their flexibility in daily energy consumption. It incorporates both buying and selling price decisions and evaluates their impact on community welfare, energy cost distribution, and storage system profitability. The analysis is grounded in real-world energy consumption data from the city of Waterloo, Canada, enhancing the practical relevance of the results.

3 Problem Formulation

The objective of this research is to minimize the electricity costs experienced by households by considering various load configurations, including PV generation and ES setups. The operation scheduling for households is optimized under different allocation schemes of CES. The optimization is conducted for two scenarios: one in which the CES operator acts as a profit-seeking agent controlling energy prices, and another where the CES operates under a non-profit model.

To better define the objectives and scope of this study, we begin by describing the key agents in the system, households and the CES, in Sections 3.1 and 3.2, respectively. The mathematical model is then presented in Section 3.3, followed by a summary of the primary assumptions made in Section 3.4.

3.1 Households

Each household is characterized by its geographic location (coordinates), its electricity consumption profile, and its ability, or lack of, to generate energy through PV systems. Household consumption consists of two components: fixed load and flexible load.

The fixed load includes baseline electricity usage such as lighting and essential appliances like refrigerators and freezers. It also incorporates Heating, Ventilation and Air Conditioning (HVAC) system consumption, where applicable. HVAC consumption is modeled dynamically based on the difference between the desired indoor temperature and the external temperature. The energy required to maintain the desired indoor temperature, denoted by $|\theta_{d,t}|$, is calculated using the following equation:

$$\Theta_{indoor} = e^{-\frac{\Delta T}{c_d R_d}} \Theta_{indoor} + (1 - e^{-\frac{\Delta T}{c_d R_d}})(\Theta_{d,t}^{outdoor} - R_d \eta_d \theta_{d,t}) \tag{3.1}$$

The fixed load is defined on an hourly basis and is non-controllable, meaning the household cannot shift or modify this consumption.
The flexible load includes the operation of appliances such as dishwashers, washing machines, and dryers, when the household owns one or more of these devices. While this energy must be consumed within the day, the presence of smart home technology enables users to schedule the operation of these appliances at times when electricity prices are more favorable.
Households are connected both to their assigned CES and to the main electricity grid. At any hour, they can choose to purchase electricity from either source based on economic convenience. Furthermore, households that generate excess electricity via PV systems can act as prosumers by selling their surplus energy to the CES.

3.2 Community Energy Storage

The CES systems, as the name suggests, are ES units shared among a group of households. These systems are managed by a storage operator who is responsible for setting the electricity prices at which energy is sold to households and bought from households.
Each CES unit has a finite ES capacity and is subject to limitations on the maximum instantaneous power it can supply, due to transmission and distribution network constraints. In this study, three different methods are used to allocate households to CES units: Random, Diverse, and Homogeneous. The following sections describe the allocation process in detail, including the assumptions made regarding the physical connection between households and CES units.

3.2.1 Community Clustering

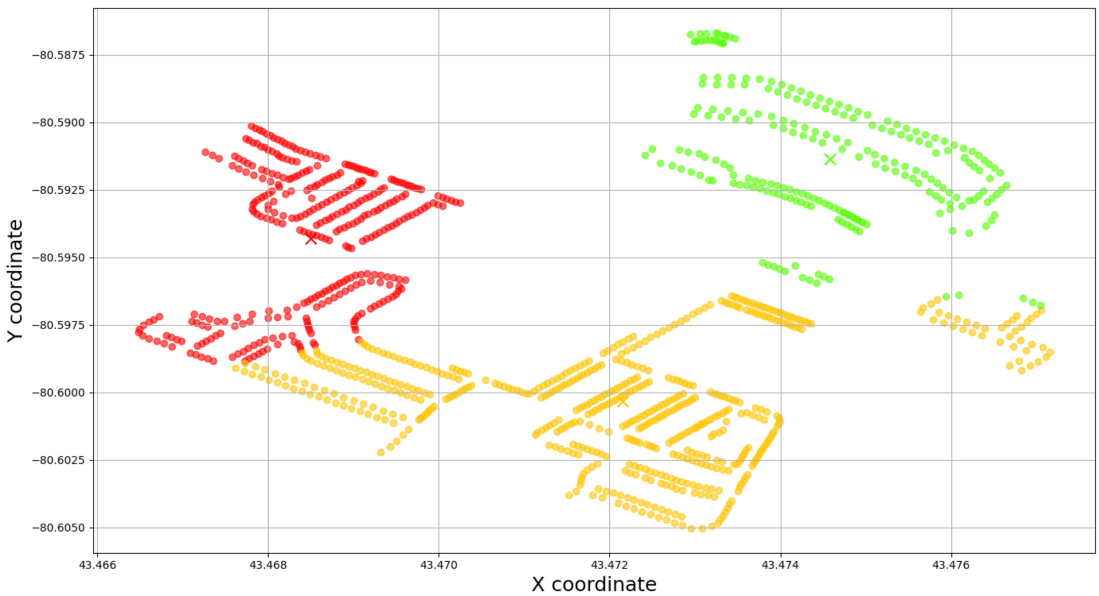


Figure 3.1: Distance based communities

Before the simulation and optimization processes, households in the region are grouped into communities based on the physical constraints of the distribution network. For example, households are not allowed to connect to ESS that are beyond a certain geographical distance.

To divide the region into communities, a k-means clustering approach is applied using the geographic coordinates of the households. This clustering captures practical constraints of ESS, such as the layout of the electric power infrastructure and distribution circuit lengths. Household locations are obtained from address data via OpenStreetMap, and it is assumed that connections to ESS units follow public roads (rather than crossing private property), reflecting realistic deployment conditions.

The k-means algorithm iteratively forms k clusters by minimizing the distance between each household and its cluster centroid. The value of k is selected based on the region's size and characteristics, ensuring the resulting clusters adhere to the physical constraints of the system.

Figure 3.1 shows the region divided into three communities, with household data based on the distribution of households in Waterloo.

3.2.2 Energy Storage Systems Allocation

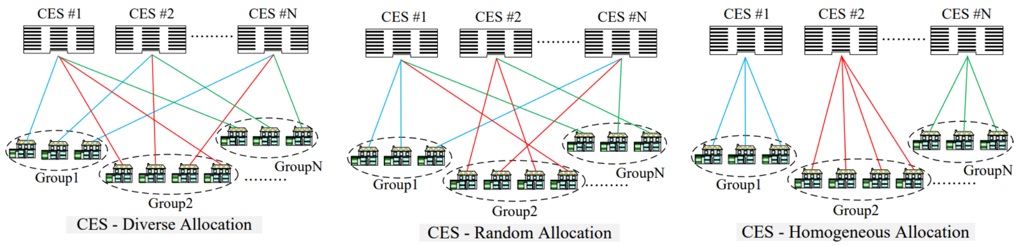


Figure 3.2: Different allocation options of the CES [59]

Once the geographic communities are established, each is further divided into local sub-communities, and CES units are assigned accordingly.
A second round of clustering is applied, again using the k-means algorithm, but this time based on household electricity consumption patterns. These patterns are derived from fixed load profiles. This process results in clusters of households with similar energy usage behaviors. The number of clusters corresponds to the number of CES units to be allocated within the community.
The clustering process ensures that each CES unit serves a comparable number of households. The research examines three different allocation strategies, which are outlined as follows and are also illustrated in Figure 3.2.

CES-Random Allocation: Households from the same consumption-based cluster are randomly assigned to any CES within the community. Each CES is assigned from a random set of households from the community.

CES-Diverse Allocation: Households from the same cluster are evenly distributed across different CES units, resulting in each CES serving households with diverse consumption profiles.

CES-Homogeneous Allocation: All households within the same cluster are assigned to the same CES unit, producing groups with similar energy usage behavior.

3.3 Mathematical Formulation

The mathematical formulation follows a bilevel problem structure, and the notation and variables used are described in Table 3.1 and 3.2. The CES operator

Nomenclature	Description
Sets	
R	Set of households
D_r	Set of devices allocated to household r
E	Set of energy storages
E_r	Set of energy storages connected to household r
R_e	Set of households which the energy storage e serves
Parameters	
T	Time horizon
ΔT	Duration of each time step (h)
Π_t	Price of electricity at time t from main grid (C$/kWh)
$\widetilde{C}_{d,t}$	Power generation of PV system d at time t (kW)
$\widetilde{U}_{d,t}$	Power consumption of fixed load d at time t (kW)
$\widetilde{S}_r$	Flexible load of household r (kW)
$\Theta_{d,t}^{outdoor}$	Outdoor temperature of thermal load d at time t (°C)
Θ_{d}^{indoor}	Desired indoor temperature by thermal load d (°C)
C_d	Thermal capacitance of thermal load d (kWh/°C)
R_d	Thermal resistance of thermal load d (°C/kW)
η_d	Working efficiency factor of thermal load d
$S^{ch\,max}, S^{ch\,min}$	Maximum and minimum charging power limitation of one household from the energy storage (kW)
$S^{dis\,max}, S^{dis\,min}$	Maximum and minimum discharging power limitation of one household from the energy storage (kW)
$S^{grid\,max}, S^{grid\,min}$	Maximum and minimum charging power limitation of an energy storage at time t from the main grid (kW)
$S_{ces}^{ch/dis/grid\,max}$	Maximum charging/discharging power limitation of all the household from the energy storage (kW)
B_e^{max}, B_e^{min}	Maximum and minimum battery state of charge of energy storage e (kWh)
$\eta_e^{ch}, \eta_e^{dis}$	Charging and discharging efficiency of energy storage e (%)

Table 3.1: Notation leader and follower models

is modeled as the leader, who determines the energy selling and buying prices offered to households. The households, acting as followers, respond to these prices by adjusting their behavior, shifting flexible loads, and choosing whether

Nomenclature	Description
Variables	
$D_{r,t}$	Actual demand from home appliances of household r at time t (kW)
$i_{r,t}$	Continuous ratio of flexible load consumed by household r at time t
$S^{ch}_{e,t}$	Charging power consumption of energy storage e at time t, representing the energy bought from the households (kW)
$S^{dis}_{e,t}$	Discharging power consumption of energy storage e at time t, representing the energy sold to the households (kW)
$S^{grid}_{r,t}$	Charging power consumption of household r at time t from the main grid (kW)
$S^{grid}_{e,t}$	Charging power consumption of energy storage e at time t from the main grid (kW)
$B_{e,t}$	Battery state of charge of energy storage e at time t (kWh)
p^s_t	Price electricity at time t for buying from energy storage
p^b_t	Price electricity at time t for buying from household

Table 3.2: Variables leader and follower models

to buy energy from the CES or the main grid.

The leader's problem is defined by its objective function (3.2) and non-negativity constraints on prices (3.3). We first consider the profit-driven CES operator, whose objective is to maximize profit from selling energy to households, minus the cost of buying energy from the main grid and the prosumers. The non-profit case is discussed in Section 3.3.2.

$$\max \sum_{e\in E}\sum_{t\in T}(S^{dis}_{et}\cdot p^s_t - S^{ch}_{et}\cdot p^b_t - S^{grid}_{et}\cdot \Pi_t) \tag{3.2}$$

$$\text{s.t } p^s_t, p^b_t \geq 0 \ \forall t \in T \tag{3.3}$$

The follower's objective is to minimize the total electricity cost, considering both energy consumption (S^{dis}_{et} and S^{grid}_{rt}) and potential rewards from selling excess harvested energy (S^{ch}_{et}):

$$\min \left(\sum_{e\in E}\sum_{t\in T} S^{dis}_{et}\cdot p^s_t - S^{ch}_{et}\cdot p^b_t + \sum_{r\in R}\sum_{t\in T} S^{grid}_{rt}\Pi_t\right). \tag{3.4}$$

A set of physical and behavioral constraints further define the system operation. Starting with the CES, the state-of-charge is updated each hour (3.5), taking into account incoming and outgoing energy flows, and conversion efficiency η. Each battery has a minimum and maximum capacity, and must start and end the simulation at 40% state-of-charge.

$$\Delta T(\eta^{ch}(S_{et}^{ch} + S_{et}^{grid}) - \frac{1}{\eta^{dis}} S_{et}^{dis}) = B_{et} - B_{et-1} \ \forall t \in T, e \in E \tag{3.5}$$

$$B_{et} \geq B_e^{min} \ \forall t \in T, e \in E, r \in R \tag{3.6}$$

$$B_{et} \leq B_e^{max} \ \forall t \in T, e \in E, r \in R \tag{3.7}$$

Next, distribution grid constraints are imposed, defining a maximum amount of total simultaneous energy flow incoming and outgoing from the ES through all the households connected. All energy flows must also be non-negative.

$$\sum_{r \in R_e} S_{ret}^{ch} = S_{et}^{ch} \ \forall t \in T, e \in E \tag{3.8}$$

$$\sum_{r \in R_e} S_{ret}^{dis} = S_{et}^{dis} \ \forall t \in T, e \in E \tag{3.9}$$

$$S_{et}^{ch} \geq S^{ch\,min} \ \forall t \in T, e \in E \tag{3.10}$$

$$S_{et}^{ch} \leq S_{ces}^{ch\,max} \ \forall t \in T, e \in E \tag{3.11}$$

$$S_{et}^{dis} \geq S^{dis\,min} \ \forall t \in T, e \in E \tag{3.12}$$

$$S_{et}^{dis} \leq S_{ces}^{dis\,max} \ \forall t \in T, e \in E \tag{3.13}$$

$$S_{et}^{grid} \geq S^{grid\,min} \ \forall t \in T, e \in E \tag{3.14}$$

From the household perspective, a user cannot simultaneously sell and buy energy from the CES. This is enforced through binary decision variables s_{ret} in equations (3.18) and (3.19). However, households may draw energy from both the CES and the grid within the same hour if needed:

$$s_{ret}^{ch} S^{ch\,min} \leq S_{ret}^{ch} \leq s_{ret}^{ch} S^{ch\,max} \ \forall t \in T, e \in E, r \in R \tag{3.15}$$

$$s_{ret}^{dis} S^{dis\,min} \leq S_{ret}^{dis} \leq s_{ret}^{dis} S^{dis\,max} \ \forall t \in T, e \in E, r \in R \tag{3.16}$$

$$s_{rt}^{grid} S^{grid\,min} \leq S_{rt}^{grid} \leq s_{rt}^{grid} S^{grid\,max} \ \forall t \in T, e \in E, r \in R \tag{3.17}$$

$$s_{ret}^{dis} + s_{ret}^{ch} \leq 1 \ \forall t \in T, e \in E, r \in R \tag{3.18}$$

$$s_{rt}^{grid} + s_{ret}^{ch} \leq 1 \ \forall t \in T, e \in E, r \in R \tag{3.19}$$

The household's energy demand must be satisfied in each hour of the day by balancing uncontrollable factors, such as the harvested solar energy $\widetilde{C}$, with the energy purchased from the grid or discharged from the ES (S^{dis}), and the energy

sold to the storage (S^{ch}), as defined in equation (3.20).
The total demand is composed of a fixed load $\widetilde{U}$ and a flexible load $\widetilde{S}$, which can be shifted across different time slots during the day, as shown in equation (3.21). The fraction of the flexible load consumed at time t is represented by the continuous variable i_{rt}.

$$\sum_{e\in E_r} S_{ret}^{dis} + S_{rt}^{grid} = D_{rt} - \sum_{d\in D_r} \widetilde{C}_{dt} + \sum_{e\in E_r} S_{ret}^{ch} \ \forall t \in T, r \in R \tag{3.20}$$

$$D_{rt} = \sum_{d\in D_r} \widetilde{U}_{dt} + i_{rt}\tilde{S}_r \ \forall t \in T, r \in R \tag{3.21}$$

$$\sum_{t=0}^{|T|-1} i_{rt} = 1 \ \forall t \in T \tag{3.22}$$

$$i_{rt} \geq 0 \, \forall t \in T, r \in R \tag{3.23}$$

3.3.1 Greedy

Currently, the subproblem is formulated to minimize the total sum of household expenses for purchasing energy. The behavior of each household is modeled to benefit the entire community by collectively reducing energy prices, rather than focusing on minimizing individual expenses. In most cases, minimizing community costs also results in lower individual household costs. However, there are scenarios where, for the storage system to offer a cheaper price than the grid, some households must make the contributive choice of purchasing electricity from the grid, even when it is more expensive than the storage option.
This kind of assumption presents limitations in real-world applications. First, it requires households to share their behavior and preferences with others, which raises privacy concerns. Additionally, the fact that collaboration may lead some households to make decisions that are not in their individual best interest can lead to user dissatisfaction and reduced participation.
For this reason, a greedy approach has been analyzed and developed to simulate non-collaborative household behavior.
This approach is implemented by enforcing greedy conditions, where each household always selects the most economical option. Specifically, households buy electricity from the source offering the lowest price at any given time. Two

constraints are added to model this behavior:

$$s_{ret}^{dis} \cdot p_t^s \leq \Pi_t \tag{3.24}$$

$$s_{rt}^{grid} \cdot \Pi_t \leq p_t^s \tag{3.25}$$

These constraints ensure that households consistently select the cheaper option at each time step. In fact, if the binary variable associated with a decision to use either the grid or storage is set to 1, the corresponding cost must be less than or equal to the alternative option.

3.3.2 No Profit

Additionally, it is of interest to analyze a scenario in which the sole objective is to maximize community welfare, and the ES operator acts as a non-profit entity. In this case, the structure of the model remains essentially the same; however, the objective of the leader changes. Instead of maximizing profit, the operator aims to maintain zero profit, covering operational costs without generating surplus revenue.

From a mathematical perspective, this is modeled by minimizing the profit while ensuring it remains non-negative. The formulation is as follows:

$$\min \sum_{e \in E} \sum_{t \in T} (S_{et}^{dis} \cdot p_t^s - S_{et}^{ch} \cdot p_t^b - S_{et}^{grid} \cdot \Pi_t) \tag{3.26}$$

$$\text{s.t.} \sum_{e \in E} \sum_{t \in T} (S_{et}^{dis} \cdot p_t^s - S_{et}^{ch} \cdot p_t^b - S_{et}^{grid} \cdot \Pi_t) \geq 0 \tag{3.27}$$

3.4 Assumptions

Furthermore, while modeling the scenario for this thesis, several assumptions have been made:

Instantaneous Energy Exchange: Energy exchange, including charging and discharging of the storage system, is assumed to be instantaneous.

Zero Energy Loss: As a starting point, we assume there is no energy loss due to transmission distance or cable resistance between storage systems and households. The only losses considered are due to the charging and discharging efficiency of the CES.

User Behaviour: Household behavior is assumed to be perfectly known and predictable. No uncertainty is considered. This assumption is difficult to satisfy in real-world applications, as it requires collecting detailed information from users, which may raise privacy concerns.

One Energy Storage: Each household is connected to one and only one community ES unit.

Complete Flexibility: The flexible load is modeled as a set of appliances whose consumption can be scheduled at any time of the day. It is assumed that these appliances have full flexibility and can operate during any hour, including nighttime. In real-world applications, this assumption does not always hold true due to user preferences or appliance constraints. Therefore, the results obtained under this assumption represent an upper bound on the optimization potential achievable with complete flexibility.

No Uninterruptible Load: More complex systems may include scenarios where appliance usage must be continuous over multiple hours (i.e., uninterruptible loads). However, in this model, all flexible load is assumed to be continuous and interruptible. Therefore, uninterruptible load scenarios are not considered.

4

Solution Methodology

The model described in the previous section introduces computational challenges that require the application of appropriate solution techniques to be effectively addressed.

4.0.1 KKT formulation

Bilevel models cannot be solved directly due to their complexity, various techniques can be used to obtain a solution. In this case, the chosen approach is single-level reformulation using the KKT conditions, which transform the follower's problem into a set of constraints that can be incorporated into the leader's problem, resulting in an equivalent single-level model. The set of constraints consists of the following:

Stationarity: $\partial f(x^*) + \sum_{j=1}^{\ell} \lambda_j \partial h_j(x^*) + \sum_{i=1}^{m} \mu_i \partial g_i(x^*) = 0$

Primal Feasibility: $h_j(x^*) \leq 0, \text{ for } j = 1, \ldots, \ell \text{ \& } g_i(x^*) = 0, \text{ for } i = 1, \ldots, m$

Dual Feasibility: $\lambda_j \geq 0, \text{ for } j = 1, \ldots, l$

Complementary Slackness $\sum_{j=1}^{l} \lambda_j h_j(x^*) = 0.$

To formulate the stationarity constraint, the first step is to define the Lagrangian function, which is presented successively.

$$\mathcal{L} = \sum_{e \in E} \sum_{t \in T} \left(S_{et}^{dis} \cdot p_t^s - S_{et}^{ch} \cdot p_t^b \right) + \sum_{r \in R} \sum_{t \in T} S_{rt}^{grid} \Pi_t$$

$$
\begin{aligned}
&+\sum_{e\in E}\sum_{t\in T}\lambda_{1\_et}\left(B_{et}-B_{et-1}-\Delta T\left(\eta^{ch}(S_{et}^{ch}+S_{et}^{grid})-\frac{1}{\eta^{dis}}S_{et}^{dis}\right)\right)\\
&+\sum_{e\in E}\sum_{t\in T}\lambda_{2\_et}\left(\sum_{r\in R_e}S_{ret}^{ch}-S_{et}^{ch}\right)+\sum_{e\in E}\sum_{t\in T}\lambda_{3\_et}\left(\sum_{r\in R_e}S_{ret}^{dis}-S_{et}^{dis}\right)\\
&+\sum_{e\in E}\sum_{t\in T}\sum_{r\in R}\lambda_{4\_ret}\left(s_{ret}^{ch}S^{ch\,min}-S_{ret}^{ch}\right)+\sum_{e\in E}\sum_{t\in T}\sum_{r\in R}\lambda_{5\_ret}\left(S_{ret}^{ch}-s_{ret}^{ch}S^{ch\,max}\right)\\
&+\sum_{e\in E}\sum_{t\in T}\sum_{r\in R}\lambda_{6\_ret}\left(s_{ret}^{dis}S^{dis\,min}-S_{ret}^{dis}\right)+\sum_{e\in E}\sum_{t\in T}\sum_{r\in R}\lambda_{7\_ret}\left(S_{ret}^{dis}-s_{ret}^{dis}S^{dis\,max}\right)\\
&+\sum_{t\in T}\sum_{r\in R}\lambda_{8\_rt}\left(s_{rt}^{grid}S^{grid\,min}-S_{rt}^{grid}\right)+\sum_{t\in T}\sum_{r\in R}\lambda_{9\_rt}\left(S_{rt}^{grid}-s_{rt}^{grid}S^{grid\,max}\right)\\
&+\sum_{e\in E}\sum_{t\in T}\sum_{r\in R}\lambda_{10\_ret}\left(s_{ret}^{dis}+s_{ret}^{ch}-1\right)+\sum_{e\in E}\sum_{t\in T}\sum_{r\in R}\lambda_{11\_ret}\left(s_{rt}^{grid}+s_{ret}^{ch}-1\right)\\
&+\sum_{t\in T}\sum_{r\in R}\lambda_{12\_rt}\left(\sum_{e\in E_r}S_{ret}^{dis}+S_{rt}^{grid}-D_{rt}+\sum_{d\in D_r}\widetilde{C}_{dt}-\sum_{e\in E_r}S_{ret}^{ch}\right)\\
&+\sum_{t\in T}\sum_{r\in R}\lambda_{13\_rt}\left(\sum_{d\in D_r}\widetilde{U}_{dt}+i_{rt}\tilde{S}_r-D_{rt}\right)+\sum_{r\in R}\lambda_{14\_r}\left(\sum_{t=0}^{|T|-1}i_{rt}-1\right)\\
&+\sum_{e\in E}\sum_{t\in T}\lambda_{15\_et}\left(S^{ch\,min}-S_{et}^{ch}\right)+\sum_{e\in E}\sum_{t\in T}\lambda_{16\_et}\left(S_{et}^{ch}-S_{ces}^{ch\,max}\right)\\
&+\sum_{e\in E}\sum_{t\in T}\lambda_{17\_et}\left(S^{dis\,min}-S_{et}^{dis}\right)+\sum_{e\in E}\sum_{t\in T}\lambda_{18\_et}\left(S_{et}^{dis}-S_{ces}^{dis\,max}\right)\\
&+\sum_{e\in E}\sum_{t\in T}\lambda_{19\_et}\left(S^{grid\,min}-S_{et}^{grid}\right)+\sum_{r\in R}\sum_{t\in T}\lambda_{20\_rt}(-i_{rt})\\
&+\sum_{e\in E}\sum_{t\in T}\lambda_{21\_et}\left(B_e^{min}-B_{et}\right)+\sum_{e\in E}\sum_{t\in T}\lambda_{22\_et}\left(B_{et}-B_e^{max}\right).
\end{aligned}
$$

Given this Lagrangian formulation, the next step is to compute the partial derivatives with respect to each variable in the problem and impose the optimality conditions by setting these derivatives equal to zero. The resulting constraints are as follows:

$$\frac{\partial L}{\partial S_{ret}^{dis}}\lambda_{3\_et}-\lambda_{6\_ret}+\lambda_{7\_ret}+\lambda_{12\_rt}=0\,\forall t\in T,e\in E,r\in R \quad \text{(A)}$$

$$\frac{\partial L}{\partial S_{ret}^{ch}}\lambda_{2\_et}-\lambda_{4\_ret}+\lambda_{5\_ret}-\lambda_{12\_rt}=0\,\forall t\in T,e\in E,r\in R \quad \text{(B)}$$

$$\frac{\partial L}{\partial S_{rt}^{grid}}\Pi_t-\lambda_{8\_rt}+\lambda_{9\_rt}+\lambda_{12\_rt}=0\,\forall t\in T,r\in R \quad \text{(C)}$$

$$\frac{\partial L}{\partial S^{grid}_{et}} - \lambda_{1\_et}\eta^{ch}\Delta T - \lambda_{19\_et} = 0\,\forall t \in T, e \in E \quad \text{(D)}$$

$$\frac{\partial L}{\partial B_{et}} + \lambda_{1\_et} - \lambda_{21\_et} + \lambda_{22\_et} = 0\,\forall t \in T, e \in E \quad \text{(E)}$$

$$\frac{\partial L}{\partial s^{ch}_{ret}}\lambda_{4\_ret}S^{ch\,min} - \lambda_{5\_ret}S^{ch\,max} + \lambda_{10\_ret} + \lambda_{11\_ret} = 0\,\forall t \in T, e \in E, r \in R \quad \text{(F)}$$

$$\frac{\partial L}{\partial s^{dis}_{ret}}\lambda_{6\_ret}S^{dis\,min} - \lambda_{7\_ret}S^{dis\,max} + \lambda_{10\_ret} = 0\,\forall t \in T, e \in E, r \in R \quad \text{(G)}$$

$$\frac{\partial L}{\partial s^{grid}_{rt}}\lambda_{8\_rt}S^{grid\,min} - \lambda_{9\_rt}S^{grid\,max} + \lambda_{11\_ret} = 0\,\forall t \in T, e \in E, r \in R \quad \text{(H)}$$

$$\frac{\partial L}{\partial D_{rt}} - \lambda_{12\_rt} - \lambda_{13\_rt} = 0\,\forall t \in T, r \in R \quad \text{(I)}$$

$$\frac{\partial L}{\partial i_{rt}}\lambda_{13\_rt}\tilde{S}_r + \lambda_{14\_d_r} - \lambda_{20\_rt} = 0\,\forall t \in T, r \in R \quad \text{(J)}$$

$$\frac{\partial L}{\partial S^{ch}_{et}} - p^b_t - \lambda_{1\_et}\eta^{ch} - \lambda_{2\_et} - \lambda_{15\_et} + \lambda_{16\_et} = 0\,\forall t \in T, e \in E \quad \text{(K)}$$

$$\frac{\partial L}{\partial S^{dis}_{et}}p^s_t + \frac{\lambda_{1\_et}}{\eta^{dis}} - \lambda_{3\_et} - \lambda_{17\_et} + \lambda_{18\_et} = 0\,\forall t \in T, e \in E \quad \text{(L)}$$

These constraints characterize the necessary conditions for optimality and will be incorporated into the single-level reformulation of the bilevel problem. Sequently the complementary slackness condition has been formulated with a big M notation instead of the standard bilinear constraint $\lambda \cdot g(x) = 0$. Although Gurobi can handle bilinear constraints, the extensive number of constraints and variables significantly increases the complexity of the problem, making it difficult to solve efficiently using the bilinear formulation. The value of M has been set to $10,000$.To ensure its validity, an initial assessment was conducted on the possible range of the primal variables. This allowed for an estimation of the order of magnitude in the first part of the equation. However, due to the lack of prior knowledge regarding the dual variables, the value of M was determined empirically by analyzing the values taken by λ in the solutions of the problem. This empirical verification confirmed that $M = 10,000$ is sufficiently large to fulfill its intended purpose.

$$S^{ch}_{ret} - s^{ch}_{ret}S^{ch\,min}_e \leq Mz_1 \quad (4.13)$$

$$\lambda_4 \leq M(1 - z_1) \quad (4.14)$$

$$s^{ch}_{ret}S^{ch\,max}_e - S^{ch}_{ret} \leq Mz_2 \quad (4.15)$$

$$\lambda_5 \leq M(1 - z_2) \tag{4.16}$$
$$S_{ret}^{dis} - s_{ret}^{dis} S_e^{dis\,min} \leq M z_3 \tag{4.17}$$
$$\lambda_6 \leq M(1 - z_3) \tag{4.18}$$
$$s_{ret}^{dis} S_e^{dis\,max} - S_{ret}^{dis} \leq M z_4 \tag{4.19}$$
$$\lambda_7 \leq M(1 - z_4) \tag{4.20}$$
$$S_{rt}^{grid} - s_{rt}^{grid} S^{grid\,min} \leq M z_5 \tag{4.21}$$
$$\lambda_8 \leq M(1 - z_5) \tag{4.22}$$
$$S_{rt}^{grid\,max} - s_{rt}^{grid} S^{grid} \leq M z_6 \tag{4.23}$$
$$\lambda_9 \leq M(1 - z_6) \tag{4.24}$$
$$1 - s_{ret}^{dis} - s_{ret}^{ch} \leq M z_7 \tag{4.25}$$
$$\lambda_{10} \leq M(1 - z_7) \tag{4.26}$$
$$1 - s_{ret}^{grid} - s_{ret}^{ch} \leq M z_8 \tag{4.27}$$
$$\lambda_{11} \leq M(1 - z_8) \tag{4.28}$$
$$S_{et}^{ch} - S^{ch\,min} \leq M z_9 \tag{4.29}$$
$$\lambda_{15} \leq M(1 - z_9) \tag{4.30}$$
$$S_{ces}^{ch\,max} - S_{et}^{ch} \leq M z_{10} \tag{4.31}$$
$$\lambda_{16} \leq M(1 - z_{10}) \tag{4.32}$$
$$S_{et}^{dis} - S^{dis\,min} \leq M z_{11} \tag{4.33}$$
$$\lambda_{17} \leq M(1 - z_{11}) \tag{4.34}$$
$$S_{ces}^{dis\,max} - S_{et}^{dis} \leq M z_{12} \tag{4.35}$$
$$\lambda_{18} \leq M(1 - z_{12}) \tag{4.36}$$
$$S_{et}^{grid} - S^{grid\,min} \leq M z_{13} \tag{4.37}$$
$$\lambda_{19} \leq M(1 - z_{13}) \tag{4.38}$$
$$i_{rt} \leq M z_{14} \tag{4.39}$$
$$\lambda_{20} \leq M(1 - z_{14}) \tag{4.40}$$
$$B_{et} - B_e^{min} \leq M z_{15} \tag{4.41}$$
$$\lambda_{21} \leq M(1 - z_{15}) \tag{4.42}$$
$$B_e^{max} - B_{et} \leq M z_{16} \tag{4.43}$$
$$\lambda_{22} \leq M(1 - z_{16}) \tag{4.44}$$

Finally, to complete the KKT optimality conditions, dual feasibility has been ensured by defining $\lambda_{[4:11]}$ and $\lambda_{[15:22]} \geq 0$, while the other λ variables are not subject to a positivity constraint since they are associated with equality constraints rather than inequalities.

4.0.2 Decomposition

This model effectively captures the behavior and interests of both the leader and the follower. However, it remains a complex problem to solve and lacks scalability. To address this issue and enable the solution of larger instances, an alternative approach is required. One possible method is decomposition.

By assuming that each household is connected to a single ES unit, the model can be rewritten as a set of submodels, one for each ES unit. In fact, all constraints establish a connection between an ES unit and the associated households and devices, but there is no interdependence between different ES units. Although the constraints do not introduce interdependence, there are two variables that remain common across all ES units: the buying and selling prices. If the problem is solved through decomposition rather than as a complete model, the result would be a pricing system that varies across ES units. Consequently, each price over time is optimized specifically for the set of households and devices linked to a particular ES unit.
The definition of each submodel remains the same as the previously defined single model, with only the following modifications:

- For each submodel, e is fixed.
- Instead of considering the full set R only the subset R_e is used.

The final solution of the overall model is obtained by summing the individual objective functions of each submodel, therefore determining the total profit across all ES units. Meanwhile, household electricity expenses can be analyzed by summing the consumption of each household according to the specific pricing system of the corresponding ES unit.

4.0.3 Flexibility Windows

An initial strong assumption was made regarding the flexibility of household appliance usage. Specifically, devices were modeled as smart appliances that can be scheduled at any time of the day. However, this assumption may lead to varying levels of discomfort for households, depending on their daily routines and preferences. To better reflect realistic usage patterns and user convenience, an additional scenario has been incorporated into the model.

A flexibility window system has been introduced to restrict the scheduling of flexible loads to a specific time window for each household. This ensures that households consume their flexible load within a designated period, rather than having full-day flexibility.

The implementation involves adding a constraint to enforce that the entire flexible load must be consumed within the selected window, as shown below:

$$\sum_{t \in \text{window}} i_{rt} = 1 \tag{4.45}$$

This modification allows for a more realistic modeling of user behavior and comfort, while still preserving the structure of the optimization problem.

5

Simulation Setup & Results

5.1 Data and Simulation Setup

5.1.1 Data

The results are simulated using a real-world use case in Canada. The selected region is located in Waterloo, Ontario, and includes 1133 households. The maximum physical distance between two households in the area is 1.2 kilometers, which is suitable for installing CES.

The simulation parameters are based on data from August 6, 2018, a typical summer day, and December 16, 2018, a typical winter day without snow in Waterloo, Ontario. The relevant parameters are listed in Table 5.2.

The simulation period is one day, with $\Delta T = 1$ and $|T| = 24$. The hourly electricity price Π_t is taken from the Hourly Ontario Energy Price [60], see Figure 5.1, while the TOU price is taken from the Ontario Energy Board [61]. The average household fixed load $\widetilde{U}_{d,t}^{avg}$ is derived from provincial load data provided by the IESO [62], see Figure 5.1. This is computed by scaling the overall Ontario daily consumption according to the household proportion in the simulated region. Home appliance loads are assumed as follows: dishwasher 1.2 kW, clothes washer 0.75 kW, and clothes dryer 1.65 kW.

In terms of thermal load, Canadians lifestyle habits are considered [63]. The indoor temperature setting for HVAC systems (Θ^{indoor}) is assumed to range from 20°C to 24°C in summer and from 18°C to 21°C in winter. The outdoor temperature record $\Theta^{outdoor}$ is taken from timeanddate.com, see Figure 5.1. Based on a

Table 5.1: Ownership rate in Waterloo, Canada

Devices	**Category**	**Ownership rate**
Dish Washer	Flexible load	60%
Clothes washer	Flexible load	87%
Clothes dryer	Flexible load	83%
HVAC system	Thermal load	60%
Rooftop solar	PV systems	0% - 100%
CES	Energy storage	100%
Others	Provincial load	100%

standard thermodynamic model, the thermal capacitance is C_d = 2.5 kWh/°C, thermal resistance is R_d = 2°C/kW, and the HVAC working efficiency is η_d = 2.5 [64].

The PV system assumes rooftop solar panels modeled after Canadian Solar CS6U-340P modules operating under NOCT conditions. Each household with PV installs 8 panels. The average harvested energy $\widetilde{C}^{avg}$ is sourced from IESO records for the Grand Renewable Energy Park in Ontario [65], see Figure 5.1.

The CES system specifications are based on eCamion Community Energy Storage units [66]. Battery parameters include a maximum capacity B^{max} = 250 kWh and a minimum of B^{min} = 0 kWh. The power transfer capacities between households and CES are defined as $S^{ch\,max} = S^{dis\,max}$ = 5 kW and $S^{ch\,min} = S^{dis\,min}$ = 0 kW. The CES itself has a rated continuous power capacity of $S_{ces}^{ch\,max} = S_{ces}^{dis\,max}$ = 500 kW. Charging and discharging efficiencies are both $\eta_{ch} = \eta_{dis}$ = 0.948, resulting in a round-trip efficiency of approximately 90%.

The initial and final battery state of charge ($B_{e,-1}$ and $B_{e,23}$) are both set to 40% of the maximum capacity.

The ownership rates of household appliances are summarized in Table 5.1. Dishwasher, clothes washer, and clothes dryer ownership rates are based on data from Statistics Canada [67], while the rates for air conditioners and hydro space heating are from the Households and the Environment Survey [63].

Finally, two flexibility windows are defined: W_1 covering the first part of the day and W_2 the second part.

Table 5.2: Parameters of home appliances in Waterloo, Canada

Category	Parameters	Data Resource, Assumptions
Period time	$\Delta T = 1,\ \lvert T\rvert = 24$	Simulating one day
Energy price	Π_t	IESO, Hourly Ontario Energy Price
Energy price TOU	Π_t^{TOU}	Ontario Energy Board
Provincial load	$\widetilde{U}_{d,t}^{avg}$	IESO, zonal demand in Ontario
Dish washer	$I_{d,t} = [1.2]$	1 hour
Clothes washer	$I_{d,t} = [0.75]$	BC Hydro, EnergyStar 2017, 1 hour
Clothes dryer	$I_{d,t} = [1.65]$	BC Hydro, EnergyStar 2017, 1 hour
Indoor temp. setting	$\Theta^{indoor} = [20, 24]$	Summer, Statistics Canada, HES 2015
Indoor temp. setting	$\Theta^{indoor} = [18, 21]$	Winter, Statistics Canada, HES 2015
Ambient temp.	$\Theta^{outdoor}$	timeanddate.com
AC or Heating	$C_d = 2.5,\ R_d = 2,\ \eta_d = 2.5$	
PV system	$C_{d,t}^{avg}$	IESO, Grand Renewable Energy Park, Ontario
		Canadian Solar CS6U-340P PV modules, 8 pcs
CES battery	$B_c^{max} = 250,\ B_c^{min} = 0$	eCamion Community Energy Storage
CES efficiency	$\eta_e^{ch} = 0.948,\ \eta_e^{dis} = 0.948$	eCamion Community Energy Storage
CES charging	$S_{ces}^{ch\,max} = 500$	eCamion Community Energy Storage
CES discharging	$S_{ces}^{dis\,max} = 500$	eCamion Community Energy Storage
CES charging	$S^{ch\,max} = 5,\ S^{ch\,min} = 0$	eCamion Community Energy Storage
CES discharging	$S^{dis\,max} = 5,\ S^{dis\,min} = 0$	eCamion Community Energy Storage
Initial and Final battery SOC	$B_{e,1} = 40\%,\ B_{e,23} = 40\%$	
Window 1	$W_1 = [0, 12]$	
Window 2	$W_2 = [12, 24]$	

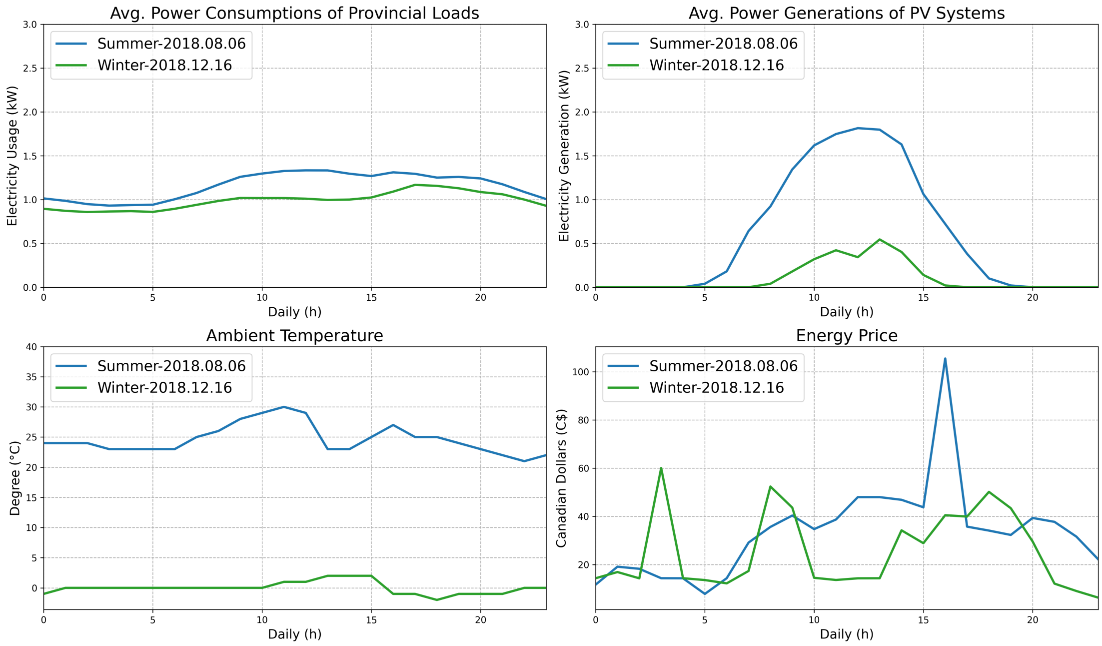


Figure 5.1: Daily charts for the parameters in Waterloo.

5.1.2 Simulation Setup

Through these simulations, we aim to compare system performance under different CES allocation strategies, solution methods, and scenario conditions. All simulations are conducted using a fixed set of system parameters. Appliance ownership is assumed as follows: 60% of households own a dishwasher, 87% a clothes washer, and 83% a clothes dryer. Each CES unit is configured with a maximum storage capacity of 250 kWh. Two main scenarios are considered: a typical summer day and a winter day in Waterloo. Each scenario is defined by specific energy consumption patterns, energy harvesting trends, daytime temperatures, and hourly energy prices.
Three clustering strategies are evaluated in the simulation: diverse, homogeneous, and random, as described in Section 3.2. Finally, three different solution methods are used: profit-collaborative, profit-greedy, and no-profit, as presented in Section 3.3.

Evaluation Metrics

To assess both the quantitative and qualitative aspects of each solution, the following metrics are employed:

Household Cost: Total monetary expense by households to meet their energy demand.

Storage Profit: Total profit earned by each ES system during the day.

% Cost Saved: Percentage of cost savings achieved by households using the hybrid gridstorage system compared to the baseline cost obtained relying solely on the grid.

Average Unit Cost: Average cost per unit of energy (kWh) over the simulation period. Which is computed as the ratio between total money spent and total energy bought.

Household Discharge Fairness: Jains fairness index computed from the ratio of energy bought from storage over total energy bought (grid + storage) per household.

Household Charge Fairness: Jains fairness index of the amount of energy sold to storage by solar panelowning households.

Storage Discharge Fairness: Jains fairness index based on energy discharged by each storage system to households.

Storage Charge Fairness: Jains fairness index computed on the ratio of energy bought from households versus total energy bought (household + grid) by the storage system.

Load Shifting: The extent to which household demand is shifted throughout the day to avoid peak consumption periods.

5.2 Results Small simulation

This first part of the simulation compares two approaches for solving the energy allocation problem: the decomposition method, which treats each ES system and its associated households as independent subproblems, and the single model, which considers all ESs and households in a unified optimization framework. The decomposition method was introduced to handle large problem instances that are computationally intractable for the single model. It assumes that each ES unit independently sets its own pricing strategy. In contrast, the single model enforces a centralized pricing scheme across all ES units. Given this fundamental difference, we evaluate whether the decomposition method provides satisfactory results in terms of both solution quality and fairness, especially since it is designed for large-scale application. Three scenarios are considered, involving 3, 3, and 4 ES systems with 100, 150, and 200 households, respectively. Households are distributed across the region, and PV ownership rate of 50% is used in all scenarios.

5.2.1 Fairness Analysis

Figure 5.2: Household Fairness with Diverse Clustering

Figure 5.2 shows the fairness results from the household perspective, comparing the decomposition and single model approaches. The decomposition method yields higher fairness for both energy charging and discharging, with an average increase of 0.131 in discharge fairness and 0.260 in charge fairness.

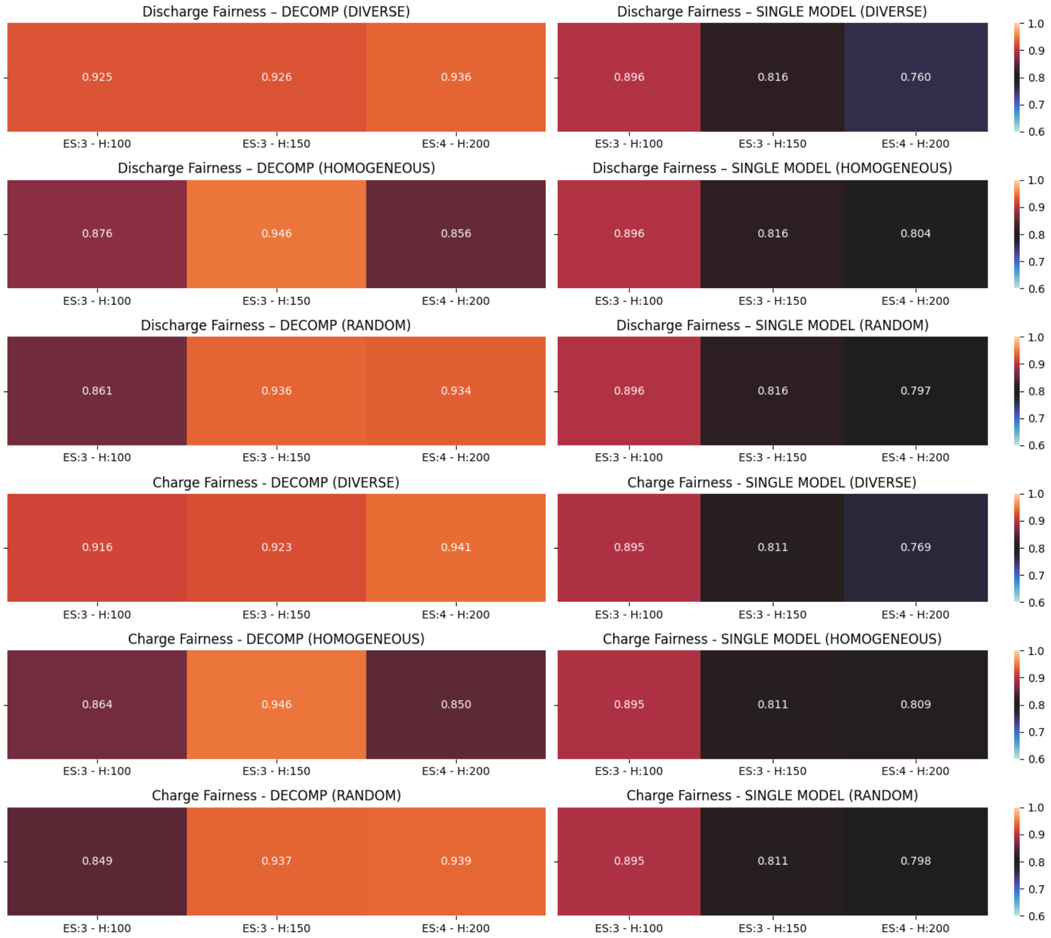


Figure 5.3: Energy Storage Fairness with Diverse Clustering

Charge fairness tends to be lower across both methods. This is because charge fairness is based on the amount of energy sold by households back to the storage systems. However, this amount depends not only on household consumption but also on PV generation, affected by solar forecasts and stochastic variations, which are independent of household behavior. Therefore, charge fairness may not fully reflect whether households had equitable opportunities to sell energy. Figure 5.3 presents fairness from the perspective of the ES units. Again, the decomposition method demonstrates better performance in both charge and discharge fairness. When examining the decomposition method across different clustering techniques, results are not entirely aligned with expectations. On average, homogeneous clustering achieves a slightly lower discharge fairness (average 0.892), while random and diverse clustering perform better with average values of 0.910 and 0.929. This is because homogeneous clustering forms

groups of households with similar consumption levels. As a result, some storage units are faced with consistently high demand while others experience very low load, leading to unequal operational levels.
Despite these issues at the ES level, homogeneous clustering can lead to fairer outcomes at the household level. This is because it is easier to ensure equal access to energy when all participating households have similar needs, reducing competition for limited energy resources. In this case, the highest household-level fairness is achieved by diverse clustering (average 0.920), while homogeneous clustering trails slightly at 0.876.
This phenomenon appears only in small-scale simulations. In such cases, the effect of the clustering method is less pronounced due to the limited number of households and the relatively small size of local communities. Each ES unit is accessible to only a small group of households, reducing the variance between clustering approaches. In larger simulations, discussed in the following section, the impact of the clustering method becomes more evident and aligns more closely with theoretical expectations.

5.2.2 Quantitative Analysis

Moving to quantitative evaluation, Tables 5.3 and 5.4 present the average cost per kilowatt-hour (kWh) experienced by each household, along with corresponding statistical values. Table 5.3 reports results obtained using the decomposition method, whereas Table 5.4 shows results from the single model approach.
Although the pricing mechanism is the same for all households regardless of PV ownership, those with PV systems incur lower average costs. This is because they can generate surplus electricity and sell it back to the storage system, effectively reducing their net energy expenditure. Across both methods, PV-owning households save approximately C$6–C$8 per kWh on average compared to non-PV owners. Comparing the two optimization methods, the decomposition model achieves lower mean and median prices, and it also shows reduced standard deviation, indicating more consistent pricing outcomes. Notably, some minimum values are negative, reflecting cases where households with minimal energy consumption and significant PV generation earn more from selling electricity than they spend, resulting in net profits.

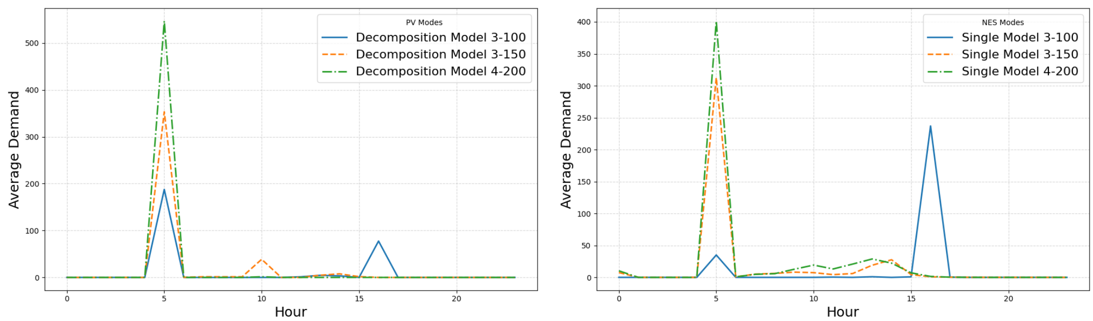
Another important performance indicator is the temporal behavior of elec-

Scenario	PV	Mean	Median	Std. Dev.	Min	Max
3-100	✓	25.157	26.502	6.671	1.245	33.754
3-100	×	33.007	33.884	2.846	24.919	38.156
3-150	✓	25.546	27.798	8.105	-72.393	34.447
3-150	×	33.950	34.106	1.920	21.563	39.736
4-200	✓	26.045	28.126	8.330	-10.491	53.794
4-200	×	33.800	34.142	3.616	22.510	65.776

Table 5.3: Average price per unit of energy (KWh) - Decomposition

Scenario	PV	Mean	Median	Std. Dev.	Min	Max
3-100	✓	29.606	28.033	12.422	-51.187	52.555
3-100	×	38.040	33.919	10.826	25.504	63.566
3-150	✓	34.462	32.083	26.232	-182.820	64.384
3-150	×	46.920	36.314	14.252	29.501	68.828
4-200	✓	37.194	34.731	18.638	-129.296	61.545
4-200	×	45.097	49.047	10.500	22.516	60.325

Table 5.4: Average price per unit of energy (KWh) - Single Model

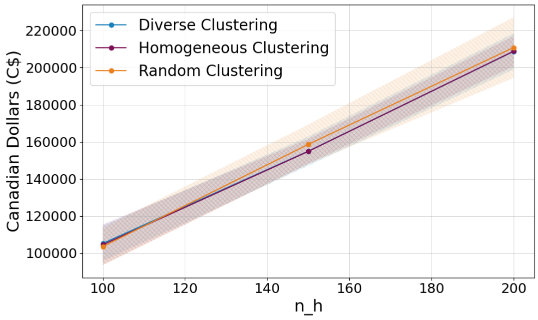


(a) Decomposition (b) Single Model

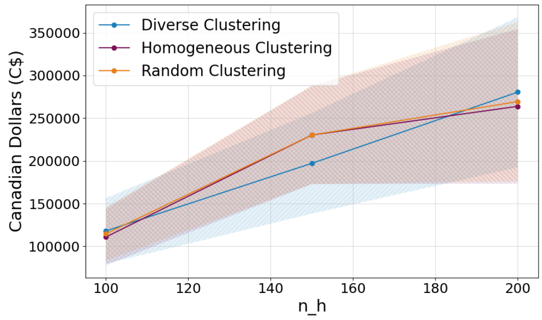
Figure 5.4: Average Hourly Demand

tricity demand. Ideally, users aim to shift flexible loads, such as appliance usage, to periods when prices are lowest. However, physical constraints of the grid can restrict the extent to which demand can be reshaped.

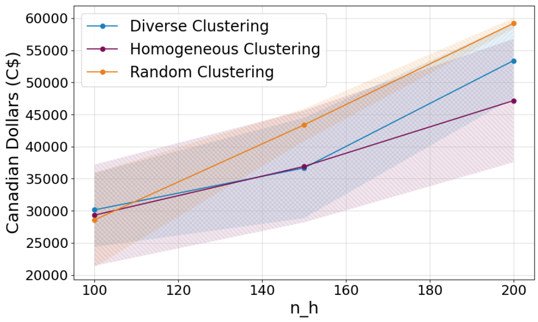
A desirable pricing system for the grid should reduce demand peaks and promote a more uniform load profile throughout the day. As shown in Figure 5.4, both the decomposition and single model methods yield broadly similar demand patterns. In Scenarios 2 and 3, peak demand occurs at hour 5 under both approaches, although the single model shows a modest shift in demand toward the later part of the day. In Scenario 1, the single model concentrates demand around hour 16, while the decomposition method results in a more evenly distributed load. However, these differences are not significant enough to conclude that decomposition alone substantially improves load balancing.



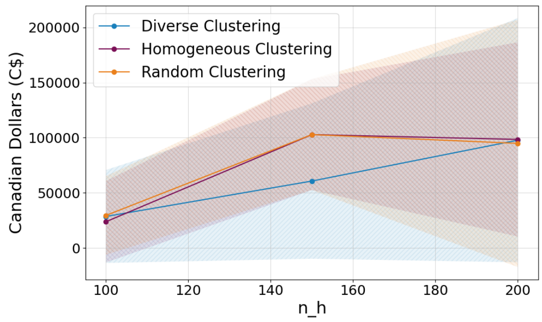
(a) Household Cost with Decomposition



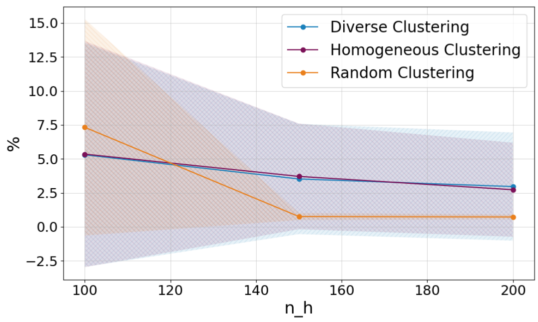
(b) Household Cost with Single Model



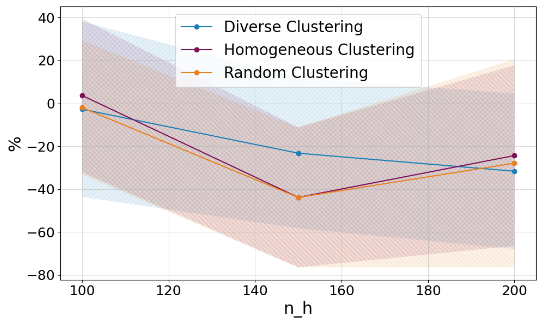
(c) Storage profit with Decomposition



(d) Storage profit with Single Model



(e) % of Cost Saved with Decomposition



(f) % of Cost Saved with Single Model

Figure 5.5: Quantitative Comparison of Clustering Methods

The remaining quantitative results from the simulations focus on the total expenditure of all households and the resulting profit for the ES systems.

First, the total cost incurred by households (Fig. 5.5a and 5.5b) aligns closely with the previously reported average cost per unit. As expected, the single model results in higher total household expenditure, with differences reaching up to C$50,000. Consistent with earlier findings, cost variability is significantly greater in the single model approach. Naturally, total household expenditure increases proportionally with the number of participating households. When using the decomposition method, total costs remain relatively consistent across clustering techniques. In contrast, for the single model, both random and homogeneous clustering result in higher average costs compared to diverse clustering in the second scenario.

Regarding ES profits (Fig. 5.5c and 5.5d), the decomposition method yields consistent and positive outcomes. In the smallest instance, total profit for ES units reaches approximately C$30,000, increasing to around C$45,000C$60,000 in larger instances. Among the clustering techniques, random clustering produces the highest average profit, while homogeneous produces the lowest. For the single model, we again observe a much wider confidence interval, with profit values ranging significantly, even occasionally dipping into negative territory, indicating potential financial losses for the storage systems.

Finally, we consider the percentage of household cost savings enabled by the system (Fig. 5.5e and 5.5f). The decomposition method delivers consistent benefits: average household savings range from approximately 5% in smaller instances to around 2.5% in larger ones. Random clustering, however, tends to deliver the lowest average savings, often closer to 1%. Conversely, the single model displays high variability, with household savings ranging from positive 40% to losses exceeding 80%. On average, the single model yields negligible or even negative net benefits for households, raising concerns about its practical viability from a user perspective.

5.3 Results Summer Simulation

The simulation setup is similar to the previous one with key difference in the scale of the problem. In this scenario, the entire set of 1133 households is considered, and simulations are conducted for varying numbers of ES units, specifically 30, 50, and 70, under a fixed PV ownership rate of 50%. Additionally, the impact of different PV ownership levels (20%, 50%, and 90%) is studied with a constant ES count of 30. This section also compares outcomes from two optimization models: a greedy, non-collaborative model and a collaborative model. All simulations use real data from a summer day in Waterloo for both energy consumption and solar energy production.

5.3.1 Fairness Analysis

Figure 5.6: Household Fairness

Fairness analysis of the collaborative model reveals that PV ownership rate does not significantly impact either charge or discharge fairness across all clustering methods. When comparing clustering techniques, homogeneous clustering consistently yields the highest household-level fairness (see Figure 5.6), with an average fairness index exceeding 0.90. This result is expected, as grouping households with similar energy consumption profiles naturally promotes more equitable energy distribution and storage interactions. Diverse clustering, on the other hand, results in the lowest fairness, averaging around 0.896. Nevertheless, all methods produce relatively high fairness values, indicating overall effectiveness in maintaining equity among households. Additionally, increasing the number of storage units improves fairness. This is attributed to the smaller size of each cluster, allowing the pricing and operational strategies of each ES unit to

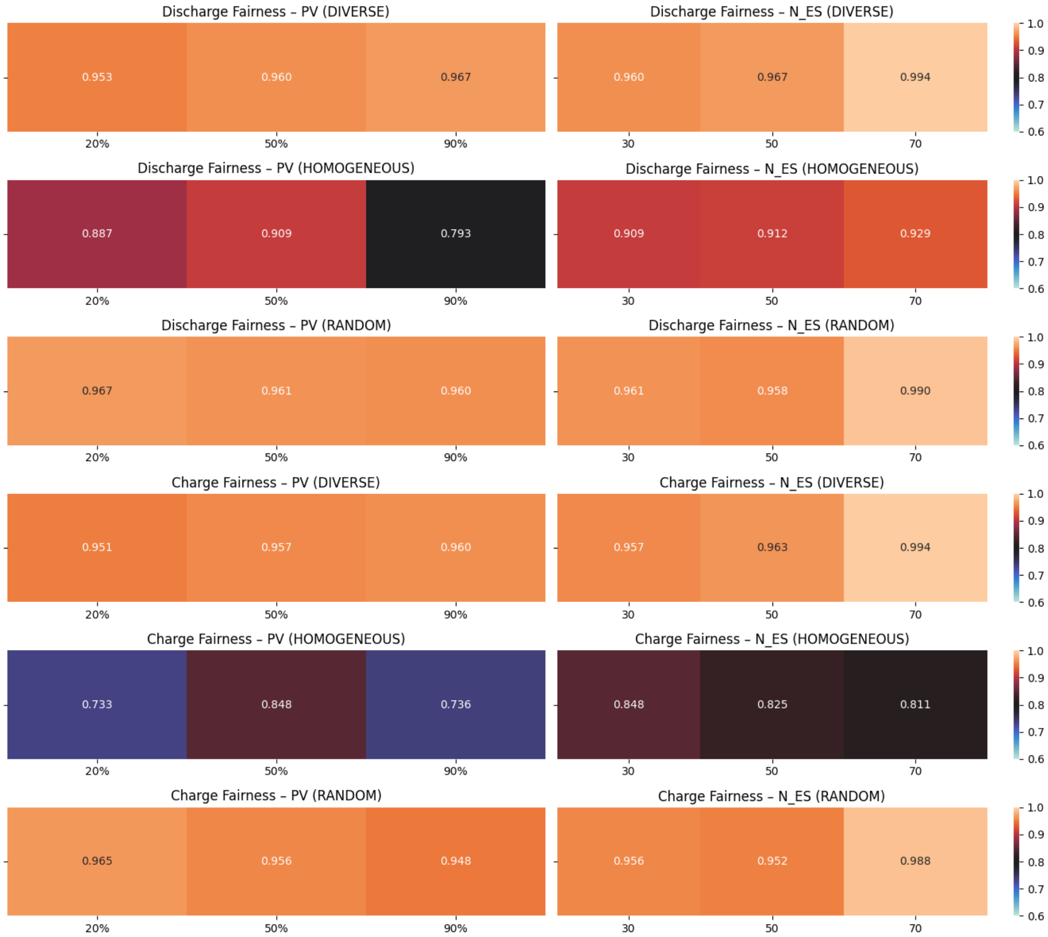
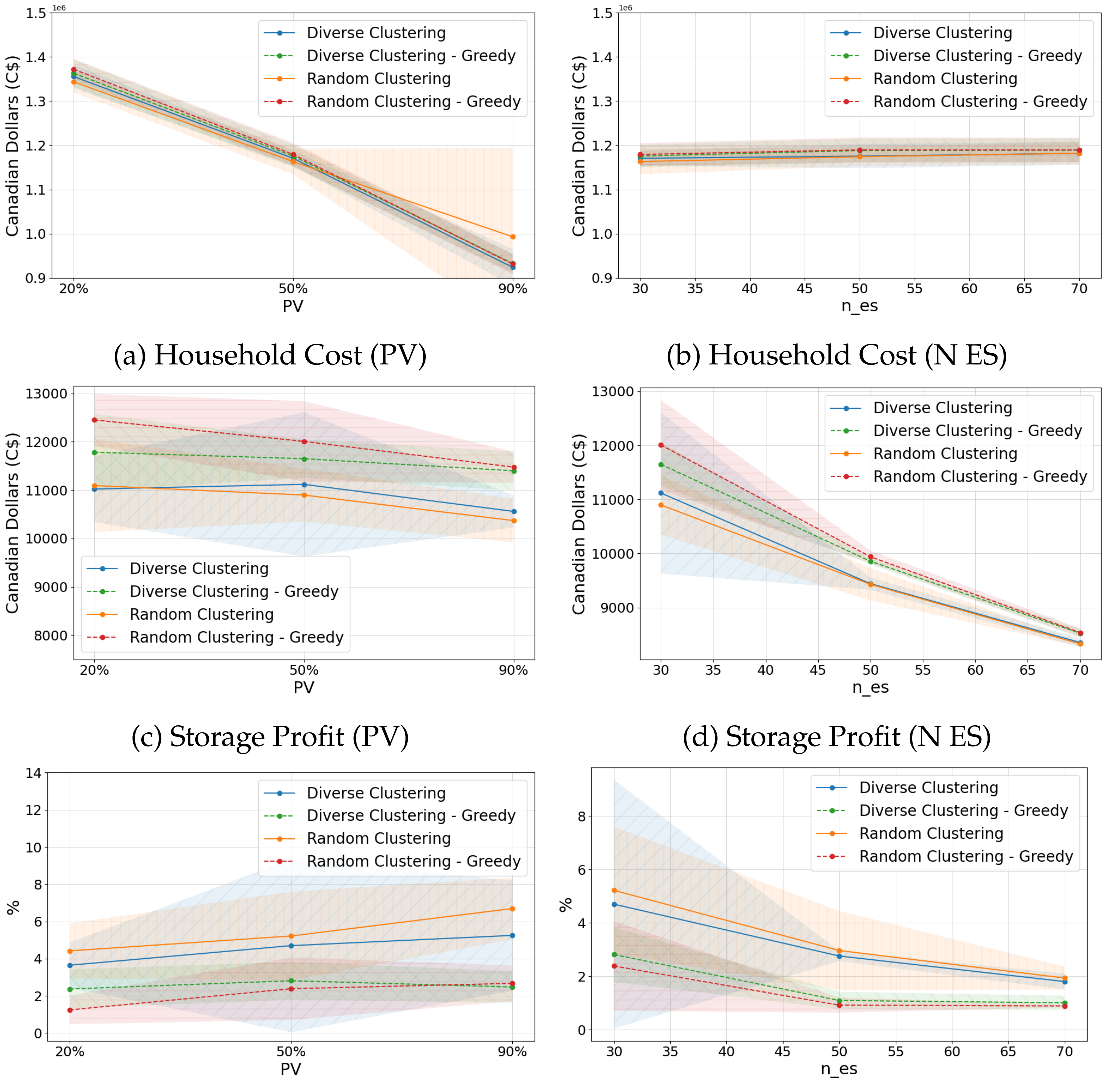


Figure 5.7: Energy Storage Fairness

be more finely tuned to the needs of a smaller household group. From the ES perspective (Fig. 5.7), the clustering method has a different impact on fairness from the ES side. Homogeneous clustering results in the lowest fairness, implying uneven utilization of ES units, some are overused while others are underutilized. In contrast, random clustering achieves the highest discharge fairness, followed closely by diverse clustering. As before, the fairness of all clustering improves with a higher number of ES units. When focusing on charge fairness, defined as the ratio of energy purchased from prosumers to the total energy procured (from both prosumers and the grid), homogeneous clustering again performs the worst. This is due to the inherent characteristics of homogeneous clusters: households with higher energy consumption place greater demand on ES systems but are less likely to generate surplus solar energy to sell. As a result, a larger share of energy must be purchased from the grid. In contrast, diverse and random clustering methods allow for more balanced distributions of surplus energy, especially when ES units are more abundant. Notably, for homogeneous clustering, increasing the number of storage units results in a decrease in charge fairness. This is likely because smaller clusters become increasingly specialized, amplifying the effects of consumption disparities on fairness metrics.

5.3.2 Quantitative Analysis



(a) Household Cost (PV) (b) Household Cost (N ES)

(c) Storage Profit (PV) (d) Storage Profit (N ES)

(e) % Cost Saved (PV) (f) % Cost Saved (N ES)

Figure 5.8: Quantitative Comparison of Clustering Methods

Tables 5.5 and 5.6 present the average cost per unit of energy for the diverse and random clustering strategies, respectively, using the collaborative model.

Scenario	**PV**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
pv: 20%	✓	25.367	28.028	8.490	-45.275	7.681
pv: 20%	×	33.341	33.672	2.152	21.727	40.069
pv: 50%	✓	25.546	27.798	8.105	-73.683	34.407
pv: 50%	×	33.123	33.581	2.360	21.173	39.264
pv: 90%	✓	25.942	28.364	7.955	-81.695	35.546
pv: 90%	×	33.598	33.911	2.365	23.429	38.914
n_es: 30	✓	25.546	27.798	8.105	-73.638	34.407
n_es: 30	×	33.123	33.581	2.360	21.173	39.264
n_es: 50	✓	25.975	28.333	7.615	-41.304	35.674
n_es: 50	×	33.434	33.795	2.180	22.163	39.475
n_es: 70	✓	26.080	28.405	7.500	-41.670	33.859
n_es: 70	×	33.623	33.927	2.052	18.865	39.475

Table 5.5: Average price per unit of energy (KWh) - Diverse Clustering

Scenario	**PV**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
pv: 20%	✓	25.133	27.893	8.918	-76.621	33.703
pv: 20%	×	33.260	33.639	2.255	21.173	40.115
pv: 50%	✓	25.636	27.710	7.543	-43.666	41.659
pv: 50%	×	33.047	33.500	2.455	19.880	39.475
pv: 90%	✓	25.719	27.992	7.580	-37.165	34.537
pv: 90%	×	33.229	33.645	2.573	21.083	38.914
n_es: 30	✓	25.636	27.710	7.543	-43.666	41.659
n_es: 30	×	33.047	33.500	2.455	19.880	39.475
n_es: 50	✓	25.861	28.183	7.448	-34.289	36.325
n_es: 50	×	33.345	33.676	2.217	21.161	38.914
n_es: 70	✓	26.255	28.363	7.218	-38.072	35.049
n_es: 70	×	33.633	33.964	2.090	21.655	39.475

Table 5.6: Average price per unit of energy (KWh) - Random Clustering

The analysis of the homogeneous clustering strategy is omitted due to its limited performance in terms of fairness. The results show that owning a PV system during the summer can yield savings of more than C$7 per kWh on average. In certain exceptional cases, PV-owning households are able to generate a net profit over the course of the day, this occurs when the revenue from selling excess solar energy surpasses the cost of the energy purchased from the storage or the grid. This behavior mirrors observations made in the smaller-scale simulations discussed earlier. There are no significant difference between diverse and random clustering results.
Figure 5.8 summarizes the overall quantitative results across different clustering techniques and optimization models (greedy vs. collaborative). As expected, total household energy expenditures decrease as the PV ownership rate increases (Fig. 5.8a). In contrast, increasing the number of ES units has a limited effect on overall household costs, which remain relatively stable (Fig. 5.8b).
Regarding storage profits, there is a slight decrease in profit as PV ownership increases (Fig. 5.8c). Nevertheless, the greedy model consistently yields higher profits, albeit within the confidence interval of the collaborative model, indicating no statistically significant difference. However, when examining profit from the ES side (Fig. 5.8b), a clear trend emerges: profit per unit declines significantly with more ES, from over C$11,000 per unit down to approximately C$7,000.
In terms of household cost savings (measured as a percentage reduction relative to a baseline), results show a wide variability, ranging approximately from 10% down to 1% (Fig. 5.8e and 5.8f). On average, the collaborative (non-greedy) method yields higher percentage savings, though with increased variability. Interestingly, higher savings are observed in scenarios with fewer ES units. For example, with 30 storage units, average savings reach 6% for the collaborative model and 3% for the greedy model. As the number of storage units increases to 70, these figures decline to around 2% and 1%, respectively.

5.4 Results Winter Simulation

The simulation setup is identical to that used for the summer scenario, with the sole difference being the use of electricity consumption, solar energy harvest, and price data from a winter day in Waterloo. This seasonal change results in lower solar energy availability, increased electricity consumption due to heating (e.g., HVAC systems), and a different price pattern throughout the day.

5.4.1 Fairness Analysis

Figure 5.10 shows the fairness results for ES usage across different clustering methods. As in the summer case, homogeneous clustering results in lower fairness for ES utilization compared to random and diverse clustering. However, a notable difference from the summer results is that fairness in the homogeneous case increases significantly as the number of ES units increases. This change is likely due to the significantly higher energy demand in winter, which creates pressure on storage systems. When only 30 storage units are available, the system struggles to meet demand in high-consumption clusters, often failing to discharge enough energy to satisfy all users and resulting in periods of empty storage and inactivity. In contrast, with 50 or 70 storage units, the system is less strained: demand per cluster is more manageable, batteries are not continuously operating at full capacity, and energy reserves are better and constantly distributed. This results in an increase in fairness as more storage units are deployed.
This overcapacity scenario also helps explain the reduced fairness observed for households in the homogeneous clustering case (Fig. 5.9). When ES cannot meet total demand, households must rely on grid electricity. Since the limited resources are not evenly distributed among households in high-demand clusters, fairness deteriorates. Regarding charging fairness, its relevance diminishes in the winter context. Due to limited solar generation and high consumption levels, most households do not generate surplus energy. Consequently, few contribute to ES charging, and only a handful of outliers sell energy back to the system. These exceptions distort the fairness index, suggesting high inequality. However, this perceived unfairness stems more from environmental constraints, i.e., differences in solar generation potential between households, than from systemic biases in the model.

5.4.2 Quantitative Analysis

Tables 5.7 and 5.8 present the average price per unit of energy experienced by households during the winter simulation. As expected, these values are lower compared to the summer results due to generally reduced grid prices, with the average grid price decreasing from 33.55C$ to 25.44C$. Among the clustering techniques, random clustering yields a slightly lower average cost

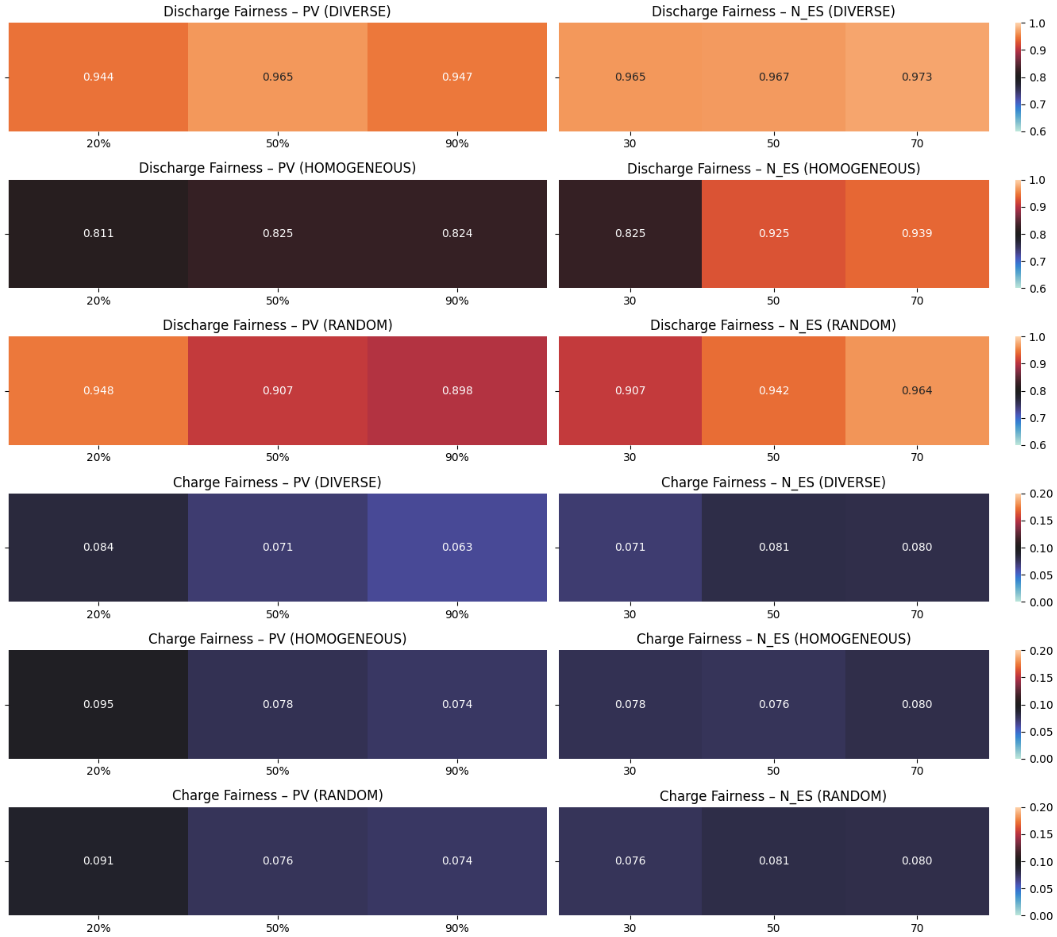


Figure 5.9: Household Fairness with Diverse Clustering

but also exhibits slightly increased variability compared to diverse clustering. Interestingly, increasing the number of ES units slightly raises the average price paid by households.
Similar to the summer scenario, the majority of flexible load usage remains concentrated within a single hour of the day, rather than being evenly distributed. This indicates a continued challenge in achieving temporal load balancing through demand-side flexibility. Figure 5.11 presents the quantitative results in the winter scenario. The total household cost slightly decreases with increasing PV ownership rates, though not as significantly as observed in the summer scenario (Fig. 5.11a). This is largely due to the limited solar energy harvested in winter. Once again, the greedy approach results in slightly higher overall costs. The total expenses remain relatively consistent across different levels of ES. Notably, when compared to the summer results, winter expenses

Scenario	**PV**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
pv: 20%	✓	24.187	24.959	2.312	8.677	33.183
pv: 20%	×	24.245	24.870	1.715	11.946	28.410
pv: 50%	✓	24.162	24.880	2.136	6.646	29.692
pv: 50%	×	24.116	24.762	1.787	12.302	27.936
pv: 90%	✓	24.206	24.938	2.136	6.651	30.104
pv: 90%	×	24.222	24.839	1.648	14.994	27.936
n_es: 30	✓	24.162	24.880	2.136	6.646	29.692
n_es: 30	×	24.116	24.762	1.787	12.303	27.936
n_es: 50	✓	24.136	25.038	2.633	6.671	29.287
n_es: 50	×	24.140	24.952	2.276	6.794	28.410
n_es: 70	✓	24.205	25.048	2.304	6.620	29.813
n_es: 70	×	24.254	24.960	1.867	12.138	28.411

Table 5.7: Average price per unit of energy (KWh) - Diverse Clustering

Scenario	**PV**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
pv: 20%	✓	24.061	24.938	2.398	6.689	27.904
pv: 20%	×	24.175	24.816	1.726	11.676	28.410
pv: 50%	✓	24.112	24.931	2.271	6.612	28.586
pv: 50%	×	24.109	24.843	1.881	12.302	28.410
pv: 90%	✓	24.080	24.928	2.312	7.809	29.387
pv: 90%	×	24.156	24.824	1.681	15.183	27.936
n_es: 30	✓	24.112	24.931	2.271	6.612	28.586
n_es: 30	×	24.109	24.843	1.881	12.302	28.410
n_es: 50	✓	24.029	25.035	2.617	7.154	29.814
n_es: 50	×	24.007	24.939	2.300	11.175	28.410
n_es: 70	✓	24.138	25.058	2.548	7.482	29.814
n_es: 70	×	24.140	24.968	2.218	8.951	28.410

Table 5.8: Average price per unit of energy (KWh) - Random Clustering

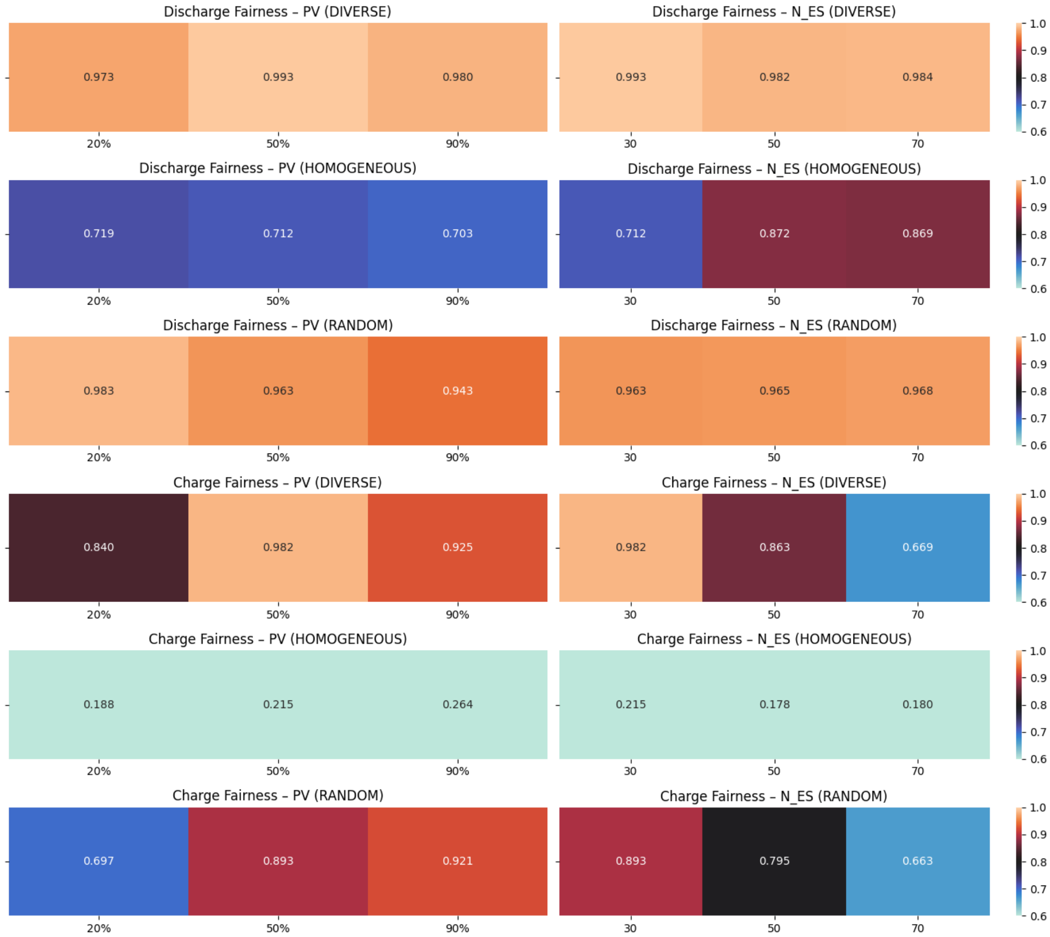
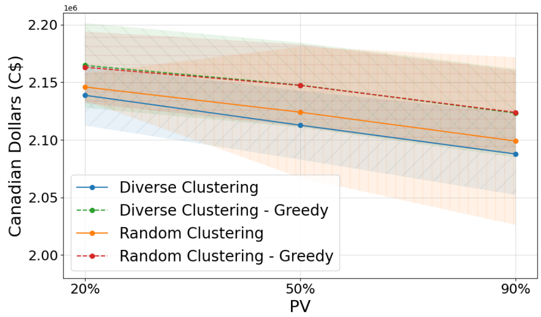


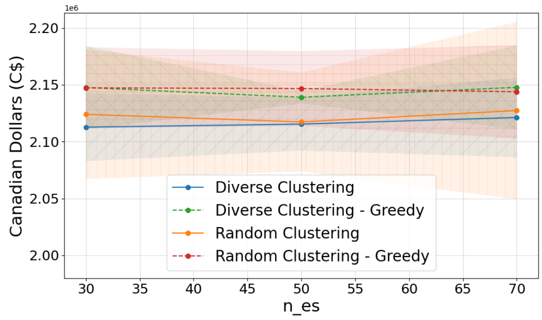
Figure 5.10: Energy Storage Fairness with Diverse Clustering

are higher despite a lower average energy price. This discrepancy is explained by the increased household energy demand, particularly for heating.

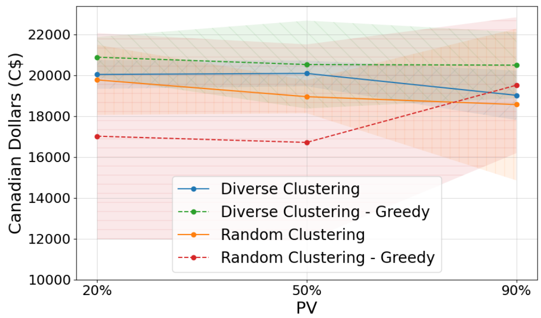
In terms of profit (Fig. 5.11c and 5.11d), the values remain relatively stable across different PV ownership rates. However, as the number of ES units increases, the profit per unit decreases. When compared to the summer scenario, there is an increase in total ES profit, rising from a maximum of C$12,000 per day to approximately C$20,000. Finally, Figure 5.11e and 5.11f show the percentage of cost saved by households remains positive but significantly lower than in summer. It stabilizes around 1–2%, and in the greedy case, it can decrease to nearly 0%.



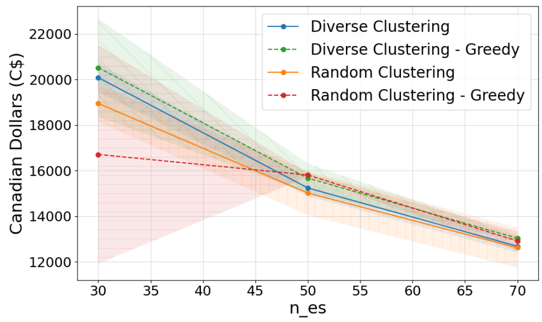
(a) Household Cost (PV)



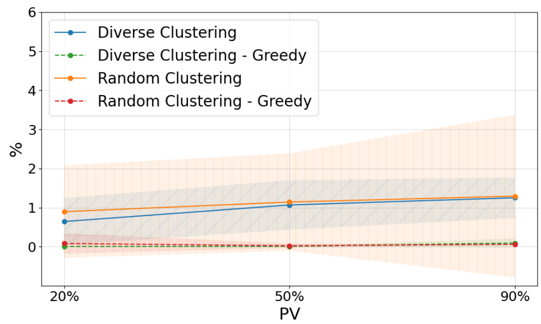
(b) Household Cost (N ES)



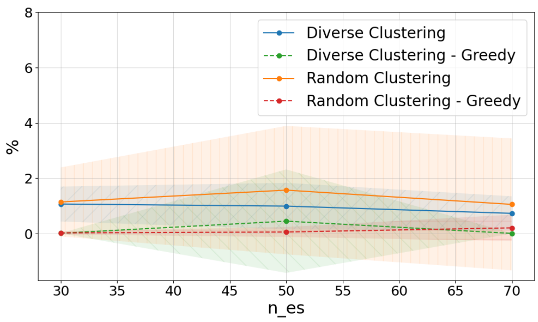
(c) Storage Profit (PV)



(d) Storage Profit (N ES)



(e) % Cost Saved (PV)



(f) % Cost Saved (N ES)

Figure 5.11: Quantitative Comparison of Clustering Methods

5.5 Results No-Profit Simulation

The simulation setup is identical to that of the summer scenario in Section 5.3, with the key difference being the implementation of a no-profit model for ES operations. In this setting, the objective is not to maximize ES profit, but rather to maintain a zero net balance, aiming solely to minimize customer energy expenses. From the fairness analysis, no substantial behavioral differences are observed when compared to the profit-driven model.

A noticeable distinction between the profit and no-profit approaches is seen

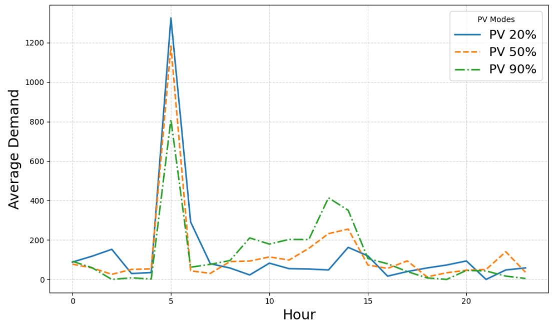


Figure 5.12: Load Shift Diverse Clustering

in the load-shifting behavior of users. Figure 5.12 shows that energy demand is more evenly distributed throughout the day, particularly around midday when solar energy production is at its peak. Furthermore, higher PV ownership rates correlate with increased load shifting toward sunny hours, indicating effective utilization of available solar power. Figure 5.13 summarize the quantitative results of the simulations.
As expected, total household costs decrease with increasing PV ownership rates (Fig. 5.13a), with an average reduction of approximately C$100,000 compared to the profit-oriented model. Additionally, costs decrease with an increased number of ES units (Fig. 5.13b). By design, the profit of ES units in this model remains close to zero.
The most significant outcome of the no-profit approach is evident in the percentage of cost savings achieved by households (Fig. 5.13c and 5.13d). These savings increase with the PV ownership rate, ranging from 7.5% for 20% ownership to as high as 20% for 90% ownership. This illustrates that the no-profit strategy can significantly enhance consumer savings, especially in high-penetration PV scenarios. An increment is shown also with the increase of the ES number.

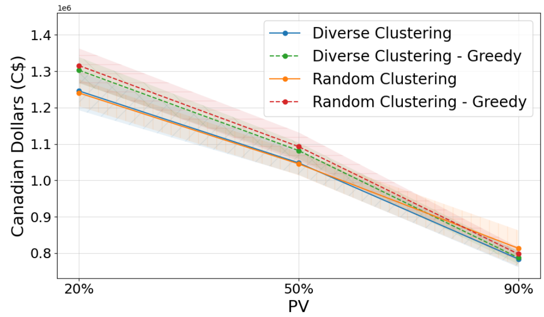
Looking at Tables 5.9 and 5.10 we can compare the actual average price per unit of energy, we observe that households owning a solar panel pay, on average, at least C$1 less per unit compared to the profit case. For those without solar panels, there is still a notable cost reduction, ranging from C$3 to C$5 per unit, particularly when 70 ES units are installed. This highlights the overall system efficiency gained through increased storage capacity, which benefits both PV and non-PV households.

Scenario	**PV**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
pv: 20%	✓	24.781	26.906	9.071	-57.701	34.750
pv: 20%	×	30.761	30.943	2.688	14.028	38.825
pv: 50%	✓	25.036	26.478	7.062	-58.230	39.118
pv: 50%	×	29.610	29.698	2.868	17.788	38.094
pv: 90%	✓	23.938	24.661	6.501	-50.505	38.895
pv: 90%	×	26.665	26.394	3.599	16.201	36.117
n_es: 30	✓	25.036	26.478	7.062	-58.230	39.118
n_es: 30	×	29.610	29.698	2.868	17.788	38.094
n_es: 50	✓	23.895	25.274	7.167	-50.673	38.715
n_es: 50	×	26.936	26.854	3.477	12.778	37.815
n_es: 70	✓	22.940	24.616	10.321	-151.909	39.420
n_es: 70	×	26.971	26.510	4.601	14.211	38.291

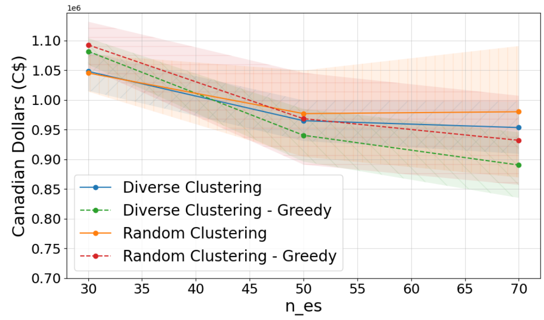
Table 5.9: Average price per unit of energy (KWh) - Diverse Clustering

Scenario	**PV**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
pv: 20%	✓	24.061	24.938	2.398	6.689	27.904
pv: 20%	×	30.105	30.279	2.689	18.108	40.115
pv: 50%	✓	24.112	24.931	2.271	6.612	28.586
pv: 50%	×	29.110	29.074	2.669	17.984	37.232
pv: 90%	✓	24.080	24.928	2.312	7.809	29.387
pv: 90%	×	27.368	27.356	3.940	17.239	35.652
n_es: 30	✓	24.700	26.001	7.182	-52.145	38.757
n_es: 30	×	29.110	29.074	2.669	17.984	37.232
n_es: 50	✓	23.977	25.334	8.067	-94.205	38.211
n_es: 50	×	26.683	26.473	3.500	14.856	37.229
n_es: 70	✓	23.530	24.886	9.339	-95.933	39.531
n_es: 70	×	26.854	26.328	4.978	11.406	37.907

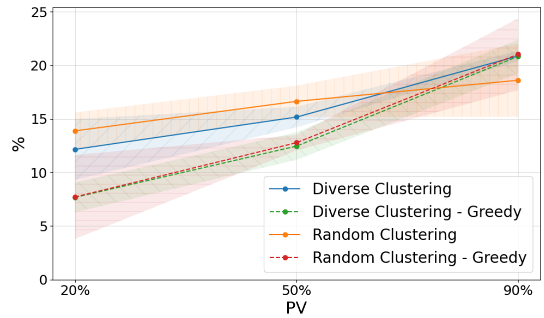
Table 5.10: Average price per unit of energy (KWh) - Random Clustering



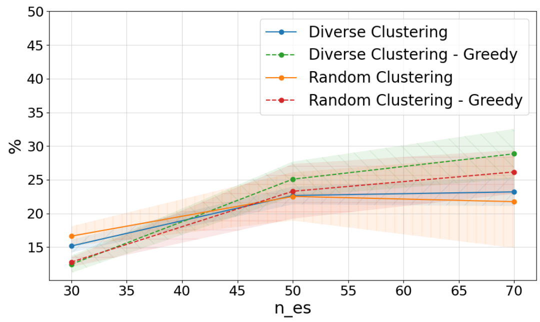
(a) Household Cost (PV)



(b) Household Cost (N ES)



(c) % Cost Saved (PV)



(d) % Cost Saved (N ES)

Figure 5.13: Quantitative Comparison of Clustering Methods

5.6 Results Time-of-Use Simulation

The previous scenarios used a RTP system, where electricity prices varied hourly based on day-ahead market data. As previously observed, the shape of the price curve significantly influences how flexible loads are scheduled, often concentrating appliance usage during the single hour with the lowest price. Such demand peaks, however, are generally undesirable from the grid operators perspective.

To explore alternative strategies that can better shape user behavior, the following analysis examines the impact of a TOU pricing scheme. In a TOU system, the day is divided into three distinct pricing periods: on-peak, mid-peak, and off-peak, each associated with a fixed rate.

Figure 5.14 shows that under the TOU pricing scheme, flexible load consumption becomes more evenly distributed across the off-peak hours rather than being concentrated in a single lowest-cost hour. This leads to a smoother load profile, which is generally more favorable for grid stability.

However, as illustrated in Figure 5.15, the benefits to households in terms of cost savings are reduced compared to the RTP model.

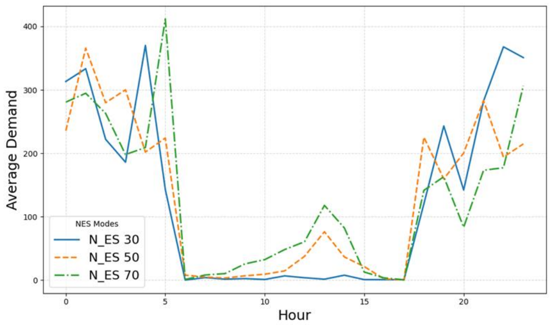


Figure 5.14: Flexible load consumption under TOU pricing

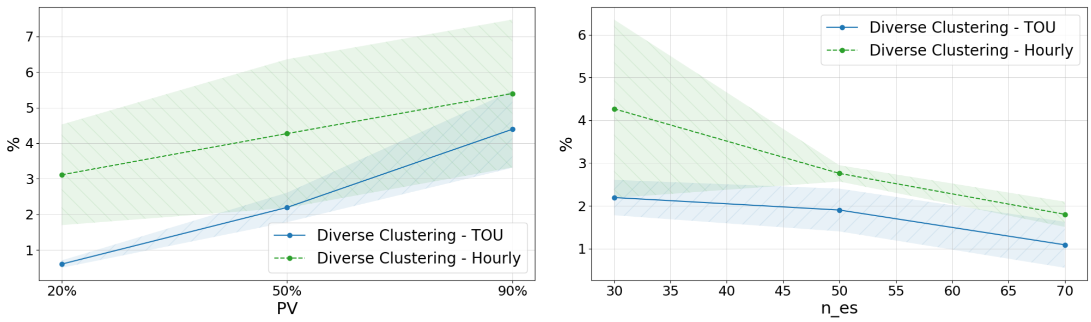


Figure 5.15: Cost savings under TOU pricing

5.7 Results two Windows Simulation

As discussed in Section 4.0.3, the final scenario simulates a more realistic assumption where households prefer to operate their appliances only within a limited time window, rather than throughout the entire day. In this case, the day is divided into two 12-hour windows:

- Window 1: Hours 0 to 11 (morning to early afternoon)
- Window 2: Hours 12 to 23 (late afternoon to night)

A random assignment is made where 40% of households operate their flexible appliances within Window 1, while the remaining 60% operate within Window 2.
This constraint on flexibility leads to a more distributed use of flexible loads across the day. Specifically, consumption now peaks during the cheapest hour

of the respective window, i.e., in the morning for Window 1 households and in the afternoon/evening for Window 2 households. This results in a more balanced load profile, reducing strain on the grid during one specific peak hour. Figures 5.16 and 5.17 show the cost savings achieved under this two-window scenario for both the profit and non-profit models. Although the savings are lower compared to the full-flexibility scenario, they remain positive. This indicates that even with reduced scheduling flexibility, households still benefit from participating in the coordinated energy system.

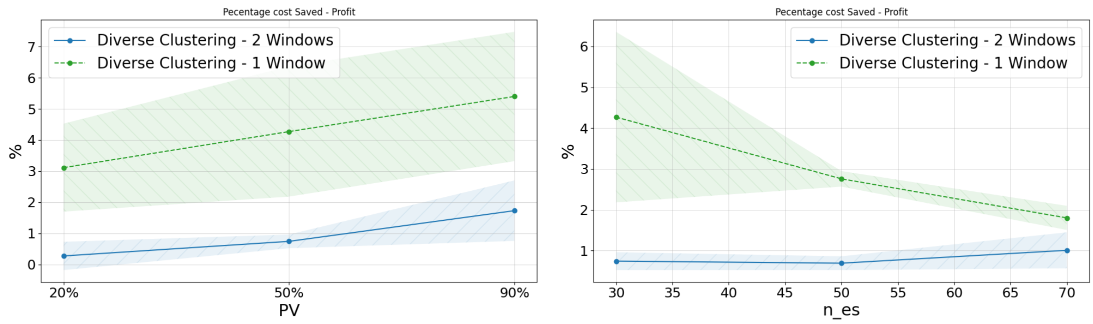


Figure 5.16: Cost savings under two windows scenario - Profit

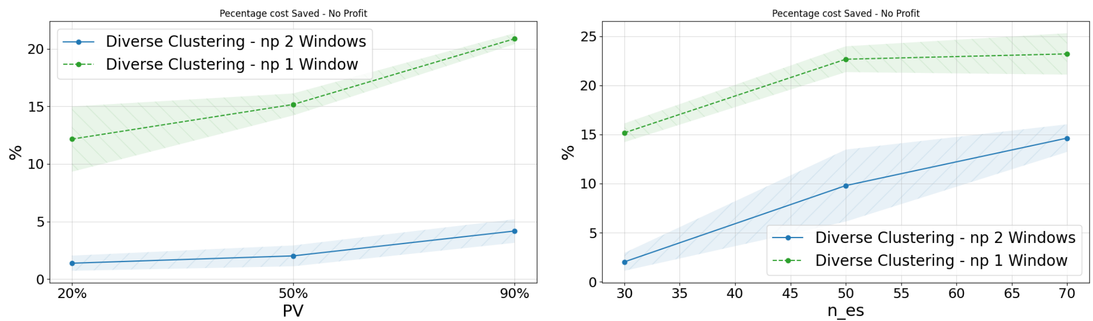


Figure 5.17: Cost savings under two windows scenario - No Profit

6 Results Discussion

The results presented in Chapter 5 highlight how different modeling assumptions, scenarios, and methodological choices significantly influence the performance and outcomes of the proposed energy-sharing system. Through a range of simulations, the study explores key trade-offs between household savings, ES profitability, and system fairness under varying pricing strategies and operational constraints. This chapter reflects on those findings, drawing connections between the quantitative results and their implications for real-world deployment.

The discussion is structured around several core themes explored in the simulations.

6.1 Decomposition vs. Single Model

The initial set of smaller-scale simulations demonstrated that the decomposition method consistently yields more balanced and stable outcomes compared to the single-level optimization model. Specifically, the decomposition approach results in lower and more consistent household energy costs, while also ensuring a fairer utilization across ES units and household demand satisfaction.

In contrast, the single-level model often leads to extreme outcomes. While it can generate higher profits for the ES operator under certain conditions, it also introduces the risk of negative profits. This instability underscores the limitations of the single-level approach, especially when fairness or long-term operational

sustainability is a concern.
Overall, the results support the use of decomposition not only as a necessary technique for scaling the model to larger instances but also as a preferred strategy in terms of solution quality. It provides both computational tractability and better system-wide outcomes, reinforcing its suitability for practical deployment. These findings not only validate the computational advantages of decomposition but also underline its potential to serve as a scalable architecture for future community-wide DR programs, where real-time optimization and fairness are dominant.

6.2 Clustering methods

In both summer and winter simulations, the choice of clustering method for forming community groups had a significant effect on system performance. Among the three methods evaluated, the homogeneous clustering consistently produced the weakest results. This method, which groups households with similar consumption profiles, led to pronounced disparities in storage utilization. Some communities experienced overuse of their storage systems, potentially shortening their lifespan, while others were significantly underutilized.
These inefficiencies were especially apparent during the winter scenario, where energy demand is higher and solar generation is limited. In such conditions, the homogeneous approach required a larger number of CES units to meet the same fairness and demand satisfaction metrics achieved by the other methods. This highlights the limitations of grouping similar consumption profiles in high-demand, low-generation settings.

The comparison between diverse and random clustering is more nuanced. In the summer, their performance alternated depending on specific metrics, with neither approach clearly dominating. In winter, however, the random clustering tended to yield slightly higher variability, with respect to the diverse scenario. In general, the random clustering obtains slightly lower average profits for the storage units and marginally higher cost savings for households. On balance, the two approaches were broadly comparable, with slight advantages depending on the scenario.
An important distinction lies in their implementation requirements. Diverse clustering relies on prior knowledge of household consumption profiles, which must be obtained before physical connections to the ES systems are made. In

contrast, random clustering does not require such data, making it easier to implement in some case.

6.3 Collaborative vs. Greedy

As expected, the adoption of a greedy strategy, resulted in slightly higher household costs and a corresponding reduction in cost savings. Depending on the scenario, this reduction ranged from 1% to 3%. In winter, the effect was even more pronounced: households saw almost no financial benefit under the greedy approach, though the storage operator continued to earn a profit.
Conversely, the collaborative scenario, in which households are assumed to coordinate their consumption to optimize collective welfare, led to lower household costs and reduced CES profit, but higher overall cost savings for users. While collaborative models offer better outcomes for the community as a whole, they also assume stronger behavioral constraints and coordination mechanisms that may be challenging to enforce in real applications.
Nonetheless, even in the absence of collaboration, particularly in the summer or in the no-profit scenario, the results show that the system remains beneficial for households. This suggests that while collaboration enhances performance, the shared ES model retains its value under less idealized behavioral assumptions.

6.4 Summer vs. Winter

From a fairness perspective, the number of CES units has a significantly stronger impact during the winter season compared to summer if using homogeneous clustering. When only 30 CES units are deployed, the level of fairness achieved in winter falls below expectations. This is primarily due to the high household energy demand for heating and the limited availability of solar energy, which places greater stress on certain storage units while using the homogeneous clustering method. These challenges are much less pronounced in summer, where energy consumption is lower and solar production is abundant, resulting in a more balanced system performance across clustering techniques.
In terms of pricing, the average price per kWh slightly increases with the number of CES units in both seasons. However, this effect is more pronounced in summer, with a maximum observed increase of C$0.619 per kWh in the worst-

case scenario. Interestingly, while winter energy prices of the grid are generally lower, total household expenses are higher due to the greater volume of energy consumed, rising from 36,101 kWh per day in summer to 85,738 kWh in winter. This higher consumption benefits the CES operator, who sees increased profits in winter as households purchase more energy from the shared system and generate less on their own. From the household perspective, however, the financial advantages of participating in the shared storage system are significantly greater in summer. Households can save up to 6% on their energy expenses in summer, compared to only 1% in winter. Ownership of PV systems also demonstrates a seasonal disparity. While having PV panels does not yield substantial monetary savings during winter, it can provide approximately C$7 discount per kWh in summer, highlighting the value of solar generation when sunshine is abundant.

6.5 Profit vs. No-Profit

As expected, operating the CES under a no-profit model significantly reduces household energy expenses. On average, there is a C$100,000 decrease in total community energy spending across the various simulated scenarios. When examining the average price per kWh with respect to the equivalent profit scenario, PV owners benefit from a roughly C$1 per kWh advantage in the no-profit case, while non-PV owners see even greater savings, ranging from C$3 to C$5 per kWh.

The most striking difference, however, lies in the percentage of expenditures saved by households. Under the profit-driven model, savings range between 1% and 6%. In contrast, the no-profit model enables savings between 7% and 30%, substantially enhancing community welfare and reinforcing the role of fair pricing in promoting energy equity.

Another notable difference emerges in the distribution of flexible load over time. In the profit-oriented scenario, household energy consumption is heavily concentrated during the lowest-price hours, leading to imbalanced load profiles and potential grid strain. In the no-profit setting, load distribution is more balanced, as households are incentivized to shift their appliance usage toward sunny hours. This behavioral change helps to improves self-sufficiency, reduces reliance on CES purchases, and aligns more closely with grid-friendly consumption patterns.

6.6 Energy Storage

From a fairness perspective, a greater number of ES units increases fairness for both the ES system and the households during the summer day. In contrast, during winter, no significant differences in fairness are observed. Specifically in summer, increasing the number of ES units also leads to a rise in the average price per kWh for households.
When examining the profit for ES operators, a decrease is observed as the number of storage units increases. In summer, the daily profit drops from approximately C$11–12k with 30 ES units to around C$8–9k with 70 units. In winter, the decrease is even more pronounced, from C$19–22k down to approximately C$13k per day.
The share of household expenditure also displays contrasting trends between the two seasons. In summer, households experience a 1–3% decrease in cost savings as the number of ES units increases. In winter, however, this metric remains relatively stable. This behavior is closely linked to the evolution of ES profit: in summer, the profit reduction is less severe and therefore results in a decline in household savings; in winter, the profit is more substantially reduced, which in turn helps to mitigate negative impacts on households.
When considering the no-profit scenario, opposite trends emerge. Household costs decrease as more ES units are introduced, and consequently, the percentage of cost savings increases. This result is expected: with a higher number of ES units, the average usage per unit is reduced, allowing for more effective optimization. Each unit can store cheaper energy during low-price hours and sell it later when demand is higher. Additionally, with fewer households connected to each ES, reliance on the energy sold later in the day, which is more expensive, is reduced, and cheaper stored energy can cover a larger portion of the demand. Since the operator is not aiming for profit, energy prices are directly tied to the cost of storage acquisition, which further benefits the household.

Finally, we compare the profit of each ES with the corresponding capital cost, based on the formula provided in [68] and the battery properties listed in Table 6.1. According to [68], the capital cost is calculated as follows:

$$\text{Capital Cost} = \text{Cell Cost} \cdot B^{\max} + \text{Init. Inverter Cost} \times \left(\frac{\text{C-rate} \cdot B^{\max}}{3} \right)^{0.7} \tag{6.1}$$

In the scenario considered, the capital cost for each storage unit is estimated at \$82,914.72, which corresponds to C\$113,698.16. Even under the lowest profit conditions observed in the simulations, this investment can be amortized within a reasonable time frame.
It is important to note that this analysis does not account for maintenance costs of the ES units or the potential investment required for appropriate grid infrastructure, where necessary.
Even with conservative profit projections, the model suggests that storage operators can recoup their investment, making CES an economically viable solution. However, the exclusion of maintenance and grid upgrade costs implies the need for careful cost-benefit analysis during implementation planning.

Property	Value
Cell Cost	\$250/kWh
C-rate	0.5
Init. Inverter Cost	\$1500

Table 6.1: Battery properties

6.7 Solar Panel Ownership

From a community-level perspective, it is not surprising to observe that, in summer, a higher percentage of households owning a PV system leads to lower total community electricity expenditures. Additionally, the average percentage of cost savings per household increases. This trend holds for both the profit and no-profit scenarios. In contrast, during winter, the difference in outcomes between scenarios with 20% and 90% ownership rates is minimal due to the limited solar generation.
Focusing on individual household outcomes, the benefits of owning a PV system vary depending on the scenario and the season. On average, in summer, a household saves approximately C\$7.71 by owning a PV system, corresponding to a 23% discount compared to non-owners. Interestingly, it is generally more beneficial for a household that owns a PV system to be part of a community with only 20% ownership, positioning them as early adopters or pioneers within the community. Conversely, for households without a PV system, it is more advan-

tageous to be part of a community with a 50% ownership rate.
In winter, owning a PV system provides no significant financial benefit due to the low amount of solar energy harvested.
In the no-profit scenario, owning a PV system enables households to save approximately 27.50% compared to grid prices. However, the cost difference between owners and non-owners is smaller than in the profit case, around C$4.60. In this setting, whether a household owns a PV system or not, it is generally most beneficial to belong to a community with a 90% ownership rate.

	Summer			**Winter**			**No-Profit**		
PV	20%	50%	90%	20%	50%	90%	20%	50%	90%
✓ **PV**	25.25	25.59	25.83	24.12	24.14	24.14	24.42	24.57	24.01
× **PV**	33.19	33.23	33.62	24.21	24.11	24.19	30.43	29.36	27.02

Table 6.2: Average price per unit of energy for scenarios

These findings collectively underscore how the system is simultaneously influenced by multiple interconnected factors, such as pricing strategy, seasonality, user behavior, and infrastructure configuration, all of which must be carefully considered when defining the system design and evaluating its real-world applicability. Building on this comprehensive analysis, the following chapter presents the overall conclusions of the research, discusses its limitations, and outlines directions for future work.

7 Conclusion

7.1 Summary and Conclusion

This research developed a model to effectively optimize a pricing system for energy distribution under multiple scenarios and parameters, aiming to increase community welfare and ensure profitability for the storage operator, at different levels depending on the scenario goals.

The proposed model adopts a bilevel optimization approach to accurately capture the interactions between the two main agents in the system: the storage manager and the households. By incorporating KKT conditions and leveraging a decomposition method, the computational complexity of the problem is significantly reduced. Moreover, the decomposition approach enables the pricing structure to be tailored to each specific community, taking into account its unique needs and constraints. This methodological framework not only ensures computational tractability for large-scale community simulations but also provides a scalable foundation for the integration of additional constraints or objectives, making it adaptable for future policy or technological developments.

Although the model allow flexibility across communities and does not explicitly enforce fairness constraints, the results consistently converge toward equitable outcomes in terms of demand satisfaction and ES utilization among households.

Considering both seasons, the shared community setting designed in this work guarantees both profit for the storage manager and economic advantages for the participating households. The profit-driven model generates higher returns for the operator while still delivering positive welfare benefits for the community. In contrast, the no-profit setting significantly enhances overall community welfare, offering greater economic savings to households.

The analysis demonstrated that within a shared energy system, the presence of PVs benefits the entire community, although the financial advantages are more substantial for households that own the panels. This economic incentive could motivate more households to invest in solar technology, promoting wider adoption within the community.

The choice of pricing scheme plays a crucial role in influencing household behavior. RTP tariffs, due to their flexibility, provide the most substantial benefits for both households and the storage operator. On the other hand, TOU tariffs, while slightly less beneficial economically, are more effective in balancing load and reducing stress on the grid.

No-profit systems significantly enhance community welfare compared to profit-driven models, although they require higher initial investments. The large gap between the two approaches in terms of profit and savings suggests that with proper regulation or predefined profit margins, hybrid models could be implemented to strike a better balance between operator profit and household welfare.

The integration of solar renewable energy introduces a strong seasonal variability in the system. This leads to notable differences in profitability and community savings between summer and winter, underlining the need for seasonal adjustments in strategy.

Household flexibility in scheduling appliance usage is a major driver of both profit and welfare. To fully realize the benefits of shared energy communities, a high degree of flexibility is essential. While there is an initial investment required to enable flexible behavior (e.g., smart appliances, control systems), the resulting economic gains justify the cost.

The use of real-world data and settings in the simulation of this model enhances the applicability of the results as a benchmark for the development of similar systems in actual municipalities and communities. This research incorporates practical constraints, such as the physical distance between households and ESs within a region of Waterloo, and addresses important aspects like clustering techniques and households with varying consumption levels. Furthermore, the results and analysis consider critical real-world factors by comparing the capital cost of ESs with their achievable profit under different scenarios,

thereby evaluating the financial feasibility of the proposed model.
Overall, these findings collectively highlight the complexity and interdependence of technical, behavioral, and economic factors in designing shared energy storage systems. A holistic approach, considering flexibility, fairness, pricing dynamics, and system constraints, is essential to realize the full potential of these systems in practice. The framework established here serves as a foundation for future enhancements, policy integration, and real-world deployment.

While the model presents promising outcomes, several aspects remain open for further exploration, as discussed in the following section.

7.2 Limitations and Future Work

This research offers valuable insights into the deployment and performance of shared ES systems. However, several limitations remain, which also point to directions for future work.

First, the model assumes that the system operator (or leader) has perfect knowledge of user behavior, specifically, how users will respond to different pricing strategies. This assumption is unlikely to hold in real-world settings, where user behavior is influenced by a variety of factors that are difficult to predict. One possible solution is to collect behavioral data directly from consumers and prosumers. However, frequent data collection can be burdensome and raises concerns regarding willingness to share information and the accuracy of self-reported behavior. A more scalable and less intrusive alternative is passive learning, which infers user preferences by observing their responses to external signals, such as price changes. While supervised learning could be used if large labeled datasets were available, such data is often scarce. Hence, future work should explore data-efficient, behavior-aware models that can learn from limited feedback.

Second, the model currently assumes idealized user flexibility, either over the full day or within a predefined time window. This simplification overlooks the role of user comfort and lifestyle preferences, which often influence appliance usage more than financial incentives alone. Future studies should incorporate models of user comfort and routine, potentially quantifying the trade-off between economic savings and perceived discomfort introduced by flexible scheduling.

Third, the optimization framework is based on deterministic inputs and does not account for uncertainty in real-world conditions. Factors such as fluctuating PV output, dynamic energy prices, varying load profiles, and potential storage degradation introduce unpredictability. Incorporating stochastic or robust optimization techniques could enhance the realism and resilience of the model, better aligning it with actual system performance.

Another limitation is the lack of a mechanism to address load balancing and grid stress, particularly during peak demand periods. While the current focus is on economic efficiency and fairness, future models could explicitly include grid impact constraints to prevent load spikes and support more stable and sustainable grid operations.

Additionally, the study highlights a significant performance gap between profit-driven and no-profit operational modes, especially in terms of profit and savings. Further work is needed to explore intermediate or hybrid market mechanisms that balance operator profitability with user equity and social welfare, potentially through regulatory incentives, pricing schemes, or cooperative governance models.

Lastly, broader socioeconomic factors such as income disparities, digital literacy, and trust in automated systems could affect user engagement and participation in flexible demand-response programs. These human-centered dimensions should be examined in future studies to ensure inclusivity and equitable access to the benefits of shared energy systems.
Exploring these factors will help bridge the gap between technically optimized models and real-world deployment challenges, ultimately supporting the development of more robust, user-friendly solutions.

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