Market Integration of Behind-the-Meter Residential Energy Storage

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Abstract

A new business opportunity beckons with the emergence of prosumers. This article proposes an innovative business model to harness the potential of aggregating behind-the-meter residential storage in which the aggregator compensates participants for using their storage system on an on-demand basis. A bilevel optimization model is developed to evaluate the potential of this proposed business model and determine the optimal compensation scheme for the participants. A realistic Texas case study confirms the year-round profitability of the model, showing that participants could earn on average nearly $1500 per year, and the aggregator could make an average profit of nearly $2000 per participant annually. The case study confirms that the proposed business model has potential, and that the main driver for a successful implementation is a suitable setting of the compensation paid to participants for using their energy storage system.

1 Introduction

With the growth in the accessibility of renewable generation technologies, the number of prosumers, i.e., consumers who can generate their own electricity [10], has been increasing worldwide, particularly in the United States [36]. Between 2018 and 2024, an increase in 85GW of residential solar PV capacity is expected worldwide [19]. This increase in solar system ownership along with the continuing drop in battery costs [20], are leading more and more residential customers to consider combining both technologies to lower their electricity bills. In the United States, residential storage deployments increased steadily in every quarter of 2020 with a 73% increase (in terms of megawatts) in the last quarter [39]. All this has led to a large untapped storage capacity residing within the households. If properly engaged with the grid, residential PV and storage owners can contribute flexibility and enhance the grid’s robustness [27]. Therefore, this integration is an essential step in the near future of electricity networks worldwide [28].

Given that prosumers seem willing to participate in providing flexibility [26], our main hypothesis for this paper is that households would be open to participate in a program that would allow them to profit from their investment in energy storage as long as it does not inconvenience them. One way to do this is to be compensated for offering services valuable to the grid, thus lowering their utility bills. As mentioned in [40], very little has been done to develop a business model that leverages the potential of distributed generation and storage at the residential level to provide services to the grid, and the market is ripe for disruption.

We consider the general framework in which prosumer households may participate in a program in which they are financially compensated for providing services to the grid. The prosumers interact with the grid through an aggregator that offers a compensation to participants in exchange for access to their energy storage capacity. Moreover, participants are allowed to sell their electricity in the

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wholesale market at the cost of sharing part of the profits with the aggregator for facilitating access to the market.

This research aims to achieve two goals. The first goal is to build a mathematical optimization model that can accurately capture the interaction between the aggregator and the participants in the context described. The solution of this model should provide insights into how to optimally handle the integration of prosumers into the electricity network. The second goal is to study under what conditions this business model would be financially viable. Our approach is to assess the optimal compensation for the participants that ensures that the business model is simultaneously profitable for the aggregator and advantageous for the prosumers. Specifically, we identify a compensation scheme that would provide an acceptable trade-off between maximizing the aggregator’s profits and minimizing the participants’ cost of electricity. The proposed business model would thus be beneficial for both the aggregator and the participants, while also providing flexibility to the grid.

To achieve these two goals, we propose a mathematical optimization model to evaluate the profitability of a combination of compensation schemes and a mechanism to operate this business model. Given the inherent hierarchical structure of the interaction between aggregator and prosumers, we model it using bilevel optimization \cite{7}. The aggregator is at the upper level, and at the lower level are multiple residential-scale prosumers connected to the grid. In optimization terms, this structure corresponds to a single-leader multi-follower bilevel optimization problem.

This paper is structured as follows. In Section 2, we provide a literature review on aggregation of residential storage, and background on bilevel optimization. In Section 3, we introduce the model designed and the algorithm used. In Section 4, we design three computational experiments to validate the model developed and discuss the results obtained. Finally, the main conclusions and future research scope can be found in Section 5.

## 2 Background and Literature Review

### 2.1 Aggregation of residential storage

There is a limited number of studies that have specifically looked at the potential for residential storage aggregation and the associated business model and compensation schemes required.

Some studies assessed opportunities for utility-scale battery storage. These tend to look at the benefits for offering a specific grid service, for example arbitrage. They concluded that, in general, it was not financially interesting to invest in energy storage in the current context \cite{35, 11, 2}. As a consequence of focusing on a single service, the battery is idle most of the day \cite{11}. Thus, the battery usage is simply not maximized making it difficult to recover the investment. In few other cases, the stacking of services was also assessed \cite{22}. A common example is the stacking of arbitrage and ancillary services. The latter typically require small volumes of electricity at specific moments in time and for short periods, and batteries are perfectly adapted to provide this important service at a low cost. Although more advantageous, the profitability of stacking is still very limited \cite{11}.

Considering energy storage at the distribution level, as done in this paper, opens the door to a multitude of new opportunities to maximize the value of the investment in battery storage \cite{11}. However, there are still major barriers to entry for investors and customers to fully maximize their return on investment, which in turns limits the benefits of storage on the grid \cite{32, 14}. The main challenge faced by most approaches and business models is the current electricity market structure. Markets in most regions do not accurately compensate flexible resources for the benefits they provide \cite{17}.

Given the limitations induced by this economical and regulatory context, most studies conducted on the topic of grid flexibility and energy storage focus solely on the complex challenges of planning, scheduling and dispatch. Only a few studies have investigated the potential of behind-the-meter energy storage and the associated business opportunities, and a limited number of economic models have assessed its value.

Within the commercial, institutional and industrial (CII) sector, some business models have been developed. These models often involve an aggregator that manages the scheduling of operations and leverages the potential of large storage systems owned or rented by CII customers. Although
innovative by considering the use of battery energy storage, these models typically leverage pricing schemes of previously existing demand response programs. Hence, they are mainly operated at the distribution level with local utilities, and are not impacted by the regulatory context of the energy markets. Specifically in relation with the topic of this paper, one study has assessed the benefits of an incentive-based model to aggregate CII battery storage and participate in the electricity market which concluded the participants could make on average 12% of extra revenues [30].

Although a growing number of households are procuring storage systems either jointly with PV generation or simply for the peace of mind they provide in case of a power outage, the financial case for a residential storage system remains largely unproven in most jurisdictions in North America [1]. Some studies have analyzed the profitability for the residential sector of solar PV and battery storage with or without market subsidies (e.g. feed-in tariffs) [6, 21, 16]. For example, one German study concluded that the profitability of residential storage increased significantly if households were given access to the wholesale market and became net producers [16].

On the compensation side, a multi-agent model was developed to define remuneration and tariff schemes for a virtual power plant including all potential players [34]. This model, however, did not specifically focus on the potential of aggregating residential storage.

A different strand of research looked at peer-to-peer trade using residential battery storage [40, 29], without considering further integration in the wholesale market. Studies show this is indeed a promising avenue. However, it ignores the larger potential of a region-wide aggregation.

One of the studies in the literature closest to our work was carried out by a group of researchers in Australia who analyzed a similar business model to ours and assessed the joint benefits for the battery owner and the retailer [13]. Although the study concluded that such a business model in the context of the Australian electricity market was beneficial to both the battery owner and the retailer, it did not assess the optimal apportionment of the benefits between the parties, which is one of the main contributions of our work.

2.2 Bilevel optimization

Bilevel optimization problems involve two different optimization problems linked by the fact that the set of admissible points for one of them, called the first level (or leader) problem, is determined at least in part by the set of optimal solutions of the other optimization problem, called the second level (or follower) problem.

Bilevel optimization provides an appropriate modelling paradigm for situations involving two decision makers, the leader and the follower, each controlling some (but not all) of the decision variables, and each having its own objective function and constraints. This decision-making process can be represented mathematically as follows:

$$\begin{align*}
\min_{v, y} & \quad F(v, \tilde{w}, y) \\
\text{s.t.} & \quad G_i(v, \tilde{w}, y) \leq 0, \quad \forall i \in \{1, \ldots, m_{\text{ineqs, upper}}\} \\
& \quad H_j(v, \tilde{w}, y) = 0, \quad \forall j \in \{1, \ldots, m_{\text{eqs, upper}}\} \\
& \quad \tilde{w} \in \arg\min_{w, z} f(v, w, z) \\
& \quad \text{s.t.} \quad g_i(v, w, z) \leq 0, \quad \forall i \in \{1, \ldots, m_{\text{ineqs, lower}}\} \\
& \quad \quad h_j(v, w, z) = 0, \quad \forall j \in \{1, \ldots, m_{\text{eqs, lower}}\}
\end{align*}$$

where $F(v, w, y)$ is the leader’s objective function and $G_i(v, w, y) \leq 0, H_j(v, w, y) = 0$ are the leader’s constraints, and analogously, $f(v, w, y)$ is the follower’s objective function and $g_i(v, w, y) \leq 0, h_j(v, w, y) = 0$ are the follower’s constraints. Note that $y$ are leader-only variables and $z$ are follower-only variables. The leader influences the follower’s decisions via $v$, and the follower’s reaction is given by $\tilde{w}$, which denotes (part of) an optimal solution of the follower problem. It is important to note that while $\tilde{w}$ impacts the leader’s objective and constraints, it is not in the direct control of the leader.

Bilevel optimization problems are fundamentally non-convex and quite difficult to solve in general. Most of the literature on this topic considers only the case of linear problems at both levels, and even under this assumption, bilevel optimization problems are NP-hard [4]. Nevertheless bilevel opti-
mization has been studied extensively and used to model numerous situations involving a hierarchical structure, such as in airline revenue management [5] or power market equilibria [3]. Dempe [8] reviews the current methods and applications for bilevel problems, and includes an extensive bibliography.

3 Business Model and Optimization Approach for Integration of Prosumers

In this section, we describe the proposed business model as well as the mathematical optimization model designed to study it. In Section 3.1, we detail the context of the business model. In Section 3.2, we present the bilevel optimization approach designed to study the business model. In particular, in Section 3.2.1 we introduce the optimization model, in Section 3.2.2 we present a simplification used for practical application, and in Section 3.2.3 we establish an extension of the formulation to account for market behaviour. Finally, in Section 3.3, we explain the algorithm used to solve the optimization model for the computational case study presented in Section 4.

3.1 Proposed Business Model

We consider an aggregator enrolling participants who agree to give access to and control of a part of their energy storage systems (ESS). This aggregator can be an independent entity or a utility, depending on the regulatory context. The aggregator wishes to maximize its profits by energy arbitrage or by providing ancillary services to the grid. In exchange, participants receive compensation for the availability and usage of their storage system. This compensation reduces their overall cost of electricity. The potential viability of this business model comes from the savings made by the aggregator through having access to energy storage without having to invest and bear the financial risk of purchasing a grid-scale storage system.

Our proposed model allows participants to decide in advance the proportion of their ESS capacity that is used by the aggregator, thus always keeping backup capacity for their exclusive use. The stored electricity must also be available for the participant in case of outages to ensure the battery still provides the main service for which it was purchased by the participant: power backup.

Our proposed model provides another mutually beneficial interaction by allowing participants to sell the electricity that they generate on the wholesale market through the aggregator. The aggregator collects a commission (i.e. percentage) of the participants’ profits for facilitating the process and access to the wholesale market. It is important to note that participants can only interact with the wholesale market by selling their electricity. If participants wish to buy electricity, then they must proceed as usual and do so on the retail market.

Figure 1 illustrates the interactions described above. The green arrows represent the aggregator’s flow of money and electricity, and the blue arrows those of the individual participating prosumer.

Figure 1: Interactions between the aggregator, participant(s), and electricity markets
3.2 Bilevel Optimization Model

3.2.1 Model Formulation

In this section we formulate a bilevel optimization model that captures the interactions described in the Section 3.1. The model is a single-leader multi-follower bilevel optimization problem. The leader is the aggregator, and each follower represents a prosumer. The upper-level problem maximizes the aggregator’s profits. The objective function of upper-level accounts for the savings from not investing in an ESS, the earnings from grid services, the commissions received for acting as an intermediary, and the costs of paying compensation to prosumers for using their ESS. Each lower-level problem minimizes the electricity bill of a prosumer by subtracting the compensations received and the wholesale market sale profits from the electricity costs.

This model achieves the two goals previously stated. First, it provides the aggregator with a tool for planning and optimizing its operations over a time horizon, i.e., to decide when and how much energy to charge or discharge from each prosumer’s ESS. Second, with the simple extension presented in Section 3.2.3 below, the model can be used for computing optimal economic parameters for the aggregator, namely how much commission to charge and how much compensation to pay prosumers to keep them engaged with the grid.

We introduce the following sets, parameters and decision variables used in the model.

Sets:

I - Set of prosumers with elements denoted as $i$

T - Set of time periods with elements denoted as $t$

Parameters:

$B_t$ - Savings by not investing in a storage system at time period $t$ [$$/kWh per time period]

$b_{i,t}$ - ESS investment cost by $i^{th}$ prosumer at time period $t$ [$$/kWh per time period]

$p_W^t$ - Electricity price on the wholesale market at time period $t$ [$$/kWh]

$p_R^t$ - Electricity price on the retail market at time period $t$ [$$/kWh]

$S_i$ - Initial state of charge of $i^{th}$ prosumer’s ESS [kWh]

$S_A^i$ - Storage space of $i^{th}$ prosumer’s ESS that the aggregator can use [kWh]

$S_P^i$ - Storage space of $i^{th}$ prosumer’s ESS that prosumer reserves for own use [kWh]

$D_{i,t}$ - Electricity demand of $i^{th}$ prosumer during time period $t$ [kWh]

$G_{i,t}$ - Electricity generation by $i^{th}$ prosumer’s PV during time period $t$ [kWh]

$\eta$ - Square root of the round-trip battery efficiency of prosumers’ ESS [%]

Leader’s decision variables:

$\pi_A^t$ - Compensation paid to prosumers for the availability of their ESS at time period $t$ [$$/kWh]

$\pi_U^t$ - Compensation paid to prosumers for usage of their ESS at time period $t$ [$$/kWh]

$\alpha_t$ - Commission collected over prosumers’ profits from wholesale market sales at time period $t$ [%]

$c_{i,t}$ - Electricity charged to $i^{th}$ prosumer’s ESS at time period $t$ for arbitrage [kWh]

$d_{i,t}$ - Electricity discharged from $i^{th}$ prosumer’s ESS at time period $t$ for arbitrage [kWh]

$e_{A,i,t}$ - Electricity stored in $i^{th}$ prosumer’s ESS at time period $t$ that belongs to the aggregator [kWh]
Followers’ decision variables:

$x_{i,t}$ - Electricity sold on the wholesale market by $i^{th}$ prosumer at time period $t$ [kWh]

$y_{i,t}$ - Electricity bought on the retail market by $i^{th}$ prosumer at time period $t$ [kWh]

$e_{i,t}^P$ - Electricity stored in the ESS space at time period $t$ that belongs to the $i^{th}$ prosumer [kWh]

The bilevel optimization problem described is defined as follows:

$$\begin{align*}
\max_{\pi^A_t, \pi^U_t, \alpha_t, c_{i,t}, d_{i,t}, e_{i,t}^A} & \quad \sum_{t \in T} B_t \left( S_{i}^A \right) \\
& + \sum_{t \in T} p^W_t \left( d_{i,t} - c_{i,t} \right) \\
& + \sum_{t \in T} \alpha_t \cdot p^W_t \cdot x_{i,t}^* \\
& - \sum_{t \in T} \pi^A_t \left( S_{i}^A - e_{i,t}^A \right) \\
& - \sum_{t \in T} \pi^U_t \cdot e_{i,t}^A
\end{align*}$$

s.t. 

$$\begin{align*}
\sum_{t \in T} c_{i,t} &= \sum_{t \in T} d_{i,t} & \forall i \in I \\
e_{i,t}^A &\leq S_{i}^A & \forall t \in T, i \in I \\
e_{i,t}^A &= e_{i,t-1} + \eta(c_{i,t-1} - d_{i,t-1}) & \forall t > 1, i \in I \\
e_{i,1}^A &= 0 & \forall i \in I \\
\pi^A_t &\leq B_t & \forall t \in T \\
\pi^U_t &\leq B_t & \forall t \in T \\
\alpha_t &\leq 1 & \forall t \in T \\
\pi^A_t, \pi^U_t, \alpha_t, c_{i,t}, d_{i,t}, e_{i,t}^A &\geq 0 & \forall t \in T, i \in I
\end{align*}$$

where $L_i(\pi^A_t, \pi^U_t, \alpha_t, c_{i,t}, d_{i,t}, e_{i,t}^A)$ is the lower-level problem representing the optimization of the $i^{th}$ prosumer’s electricity costs.
For each follower $i$, the problem $L_i$ is defined as:

$$
\min_{x_{i,t}, y_{i,t}, e_{P,i,t}} \sum_{t \in T} p_{i,t} \cdot y_{i,t} + \sum_{t \in T} b_{i,t} \cdot (S^A_i + S^P_i)
\tag{9a}
$$

$$
- \sum_{t \in T} (1 - \alpha_t) \cdot p_{i,t} \cdot x_{i,t}
\tag{9b}
$$

$$
- \sum_{t \in T} \pi^A_t \cdot (S^A_i - e_{i,t}^A)
\tag{9c}
$$

$$
- \sum_{t \in T} \pi^U_t \cdot (e_{i,t}^A)
\tag{9d}
$$

subject to:

$$
y_{i,t} \geq D_{i,t} - G_{i,t} - \frac{1}{\eta} e_{P,i,t} \quad \forall t \in T \tag{10}
$$

$$
y_{i,t} \leq D_{i,t} \quad \forall t \in T \tag{11}
$$

$$
x_{i,t} \leq G_{i,t} \quad \forall t \in T \tag{12}
$$

$$
e_{P,i,t} \leq S^P_i \quad \forall t \in T \tag{13}
$$

$$
e_{P,i,t} = e_{P,i,t-1} + \eta (G_{i,t-1} + y_{i,t-1} - D_{i,t-1} - x_{i,t-1}) \quad \forall t > 1 \tag{14a}
$$

$$
e_{P,i,1} = S_i \quad t = 1 \tag{14b}
$$

$$
e_{P,i,t} + \eta (G_{i,t} + y_{i,t} - D_{i,t} - x_{i,t}) = S_i \quad t = |T| \tag{15}
$$

$$
x_{i,t}, y_{i,t}, e_{P,i,t} \geq 0 \quad \forall t \in T \tag{16}
$$

Next we provide the interpretation of the objective functions and constraints in the model formulated above. The upper-level objective function (1a)–(1e) represents the profit of the aggregator. The term (1a) represents the savings made from not investing in an ESS of the size that is available to the aggregator at each time period. The profit made from grid services is accounted for in (1b). The third profit term (1c) shows the commission collected from prosumers for facilitating their electricity sales on the wholesale market. Finally, (1d) and (1e) detail the costs of compensations paid to prosumers for making space available in their ESS and for using their ESS to store energy, respectively. The upper-level constraints (2)–(8) enforce the following requirements:

(2) The aggregator must discharge all the electricity that has been charged during the time horizon considered.

(3) The total amount of energy in a prosumer’s ESS that belongs to the aggregator cannot exceed the maximum capacity that the aggregator can use.

(4a) The amount of energy in each prosumer’s ESS that belongs to the aggregator is updated from one time period to the next. Note that part of the energy in this process is lost due to the round-trip efficiency of the ESS.

(4b) The aggregator does not have any energy stored in the prosumers’ ESS at the beginning of the time horizon.

(5) The compensation paid for availability must not be greater than the savings realized at each time period.

(6) The compensation paid for usage must not be greater than the savings realized at each time period.

(7) The commission cannot be greater than 1, given that it represents a percentage.

(8) All the variables must be non-negative.
Consider now the lower-level problem $L_i$ for $i \in I$ that manages the ESS of the $i^{th}$ prosumer to minimize its electricity costs. These costs are described in objective function (9a)–(9e). The term (9a) accounts for the cost of the usual electricity bill according to the amount of energy bought. The term (9b) represents the cost of investing in an ESS. The parameter $b_{i,t}$ is used to account for the fact that participating in this scheme will result in extensive use of the ESS and a consequent reduction of its lifetime. The profit made from selling electricity on the wholesale market is represented in (9c), and accounts for the commission paid to the aggregator for facilitating the sale. The terms (9d) and (9e) represent the compensations received from the aggregator for the availability and usage of their ESS, respectively. The lower-level constraints (10)–(16) are interpreted as follows:

(10) The prosumer must buy at least enough energy for its net consumption.

(11) The prosumer must not buy more energy than its actual consumption.

(12) The prosumer must not sell more than the energy from its own generation.

(13) The amount of energy a prosumer stores in the ESS cannot exceed the space reserved for its own use.

(14a) The amount of own energy that the prosumer stores in its ESS is updated. Note that only the surplus of energy in a time period is stored in the ESS.

(14b) The amount of energy stored by the prosumer in its ESS at the beginning of the time horizon is $S_i$.

(15) The amount of energy at the end of the time horizon must be the same as at the beginning. This avoids that prosumers make use of free energy stored in the ESS before the optimization time horizon. This is the lower-level equivalent to (2).

(16) All the variables must be non-negative.

### 3.2.2 Model Simplification

We recall that bilevel problems are generally difficult to solve. In addition, the leader’s objective function in the model described in Section 3.2.1 is non-linear and non-concave. Consequently global optimality becomes very difficult to achieve and guarantee. For this reason, we present in this section a modification of the model that makes it easier to solve in practice and yet achieves the goals stated in Section 1. We will consider this modified version in the remainder of this paper.

The difficulties in the leader’s objective function can be avoided by setting the economic variables $(\pi_t^A, \pi_t^U, \alpha_t)$ to be parameters. By doing so, the objective function becomes linear. Transforming the compensations and commission to parameters requires these parameters to be tuned. We consider a simplification whereby these economic parameters are independent of the time period so that:

\[
\begin{align*}
\pi_t^A &= \pi^A \\
\pi_t^U &= \pi^U \\
\alpha_t &= \alpha
\end{align*}
\]

where $\alpha \in [0, 1]$ is a percentage, and $\pi^A, \pi^U \in [0, B]$ are bounded above in accordance with constraints (5) and (6), where $B$ is the average savings by not investing in an ESS:

\[
B = \frac{1}{|T|} \sum_{t \in T} B_t.
\]

The modification described transforms the problem into a linear single-leader multi-follower bilevel problem with independent followers. We note that even with this simplification, the model remains challenging to solve. The solution of a minimum non-trivial case that illustrates the model’s behaviour can be found in Section 4.2.
3.2.3 Extension to Model Market Behaviour

Because the economic variables are treated as parameters, the question arises of the specific values that should be selected to maximize the aggregator’s profit and keep prosumers engaged with the grid. Market behaviour needs to be taken into account when tuning the economic parameters. This section introduces an extension of the simplified model that is essential for tuning the economic parameters.

We model market competitiveness by introducing demand curves in each term of the objective function [25]. These curves ensure that the trivial solution for the aggregator of paying compensations of $0/KWh and receiving a commission of 100% on prosumer’s sale profits is not optimal. The demand curves are functions of the economic parameters that return values between 0 and 1. They represent the percentage of prosumers who would choose to be connected to the aggregator when a certain compensation or commission is offered in a competitive market. The leader’s objective function with demand curves thus takes the form:

\[
F(c_{i,t}, d_{i,t}, e_{i,t}^A) = \sum_{t \in T} d_3(\pi^A, \pi^U) \cdot B_t \left( S_t^A \right) \\
\quad + \sum_{t \in T} d_1(\pi^U) \cdot p_t^W \left( d_{i,t} - c_{i,t} \right) \\
\quad + \sum_{t \in T} d_2(\alpha) \cdot \alpha \cdot p_t^W \cdot \pi_{i,t}^2 \\
\quad - \sum_{t \in T} d_1(\pi^A) \cdot \pi^A \left( S_{i,t}^{max} - S_t^A \right) \\
\quad - \sum_{t \in T} d_1(\pi^U) \cdot \pi^U \cdot e_{i,t}^A.
\]

The term (1A) representing the savings from not investing in an ESS depends on both the compensation for availability and the compensation for usage because the purpose of these compensations is to reward prosumers for access to their ESS. The term (1B) is multiplied by a demand curve dependent only on the compensation for usage because the aggregator can only profit from providing grid services if a prosumers’ ESS is used for temporarily storing energy. Similarly, the demand curves of (1C), (1D), and (1E) must depend on the economic parameters \( \alpha, \pi^A \), and \( \pi^U \), respectively, since they represent the profits obtained from each of these compensation schemes.

The demand curves must satisfy some structural properties. The function \( d_1(\pi) \) models the percentage of prosumers who rent their ESS to the aggregator if a compensation of \( \pi \) is paid. Hence, the higher the compensation, the larger the percentage of participating prosumers. We assume that the prosumer behaviour is similar with respect to the two compensations \( \pi^A \) and \( \pi^U \), and model them with the same demand curve. We require the function \( d^1(\pi) : [0, B] \to [0, 1] \) to be increasing between \( (\pi, d^1(\pi)) = (0, 0) \) and \((\pi, d^1(\pi)) = (B, 1)\). This indicates that if the aggregator pays a compensation of $0/KWh, then no prosumer will want to participate, while if the aggregator pays the prosumers the amount \( B \) that is saved from not investing in an ESS, then all prosumers will rent their ESS to the aggregator.

The function \( d^2(\alpha) \) returns the percentage of prosumers who choose to sell their electricity through the aggregator if a commission \( \alpha \) is charged. Therefore, the higher the commission, the lower the percentage of participating prosumers. On this basis, we require the function \( d^2(\alpha) : [0, [0, 1] \to [0, 1] \) to be decreasing between \( (\alpha, d^2(\alpha)) = (0, 1) \) and \((\alpha, d^2(\alpha)) = (1, 0)\). This indicates that when the aggregator collects 0% commission, then all prosumers will contract with the aggregator, while a commission of 100% on prosumer’s profits will result in no prosumers contracting.

The function \( d_3(\pi^A, \pi^U) \) is a weighted combination of the impact of the compensation for availability \( d_1(\pi^A) \) and the impact of the compensation for usage \( d_1(\pi^U) \). If both compensations are $0/KWh, then no prosumer will rent its ESS, while if both compensations are set to their maximum value of $\( B \)/KWh, then all prosumers will rent their ESS.
3.3 Solution Algorithm

Both the simplified model introduced in Section 3.2.2 and its extension to include market behaviour introduced in Section 3.2.3 are linear single-leader multiple-follower bilevel problems. Because there is no solver that can directly handle bilevel optimization problems, we describe the algorithm that we used to solve these problems.

First, we reformulate the bilevel problem into an equivalent single-level formulation by replacing each linear lower-level problem with its Karush–Kuhn–Tucker (KKT) optimality conditions [15]. These conditions entail primal and dual feasibility constraints which are linear, but in addition they involve complementary constraints that link each inequality constraint with its corresponding dual variable such that:

\[ g_{i,t} \cdot \lambda_{i,t} = 0 \quad \forall t \in T, i \in I \]

where \( g_{i,t} = g(x_{i,t}, y_{i,t}, e_{i,t}^P) \leq 0 \) is a lower-level inequality constraint and \( \lambda_{i,t} \geq 0 \) is its corresponding dual variable.

We point out that this transformation yields the so-called optimistic bilevel optimal solution [9]. If there exist different lower-level optimal solutions, they may yield different upper-level objective values. In optimistic bilevel programming, the assumption is that, in this case, the leader can manipulate the follower’s decision for his benefit. Specifically in this application, given two optimal solutions for a participant, the aggregator will be able to influence that participant into choosing a lower-level solution that yields the largest upper-level profit.

Second, we reformulate the complementarity constraints as equivalent mixed-integer linear constraints by rewriting the KKT complementarity conditions as:

\[
\begin{align*}
&g_{i,t} \geq (1 - z_{i,t}) \cdot M_1 \\
&\lambda_{i,t} \leq (z_{i,t}) \cdot M_2 \\
&z_{i,t} \in \{0, 1\} \\
\end{align*}
\]

where \( M_1 \leq 0 \) is a lower bound on the possible values of \( \{g_{i,t}\}_{i \in I, t \in T} \) and \( M_2 \geq 0 \) is an upper bound on the possible values of the variables \( \{\lambda_{i,t}\}_{i \in I, t \in T} \).

Note that correctly setting the values of \( M_1 \) and \( M_2 \) is essential to obtain the global optimal solution. If these values are set incorrectly then the resulting problem might be infeasible, or the global solution of the original model might be lost. In the context of our application, we can deduce valid choices for \( M_1 \) and \( M_2 \) mathematically. The lower bounds of the inequality constraints \( M_1 \) are logically deduced from the expressions of \( g_{i,t} \). In order to deduce valid upper bounds for the dual variables \( M_2 \), we use the fact that in linear optimization, the optimal values of the dual variables represent the change in the objective function of a one-unit change in the right-hand side of the corresponding constraint. Since there are clear bounds on each lower-level decision variable \( (x_{i,t}, y_{i,t}, e_{i,t}^P) \) and the lower-level objective is linear, we can use this fact to compute bounds on the objective value. Consequently, we deduce an upper bound on the difference in the objective value of a one-unit change in the right-hand side of the corresponding constraint. This is the upper bound on the dual variables.

We have now transformed the single-level KKT reformulation into a mixed-integer linear optimization problem. The last step before solving it is to add the strong duality cut recently introduced in [23]. This cut tightens the lower-level KKT conditions and reduces the total computational time of the algorithm. Finally, we solve the resulting mixed-integer linear optimization problem using a commercial solver.

4 Computational Case Study

In this section, we report the results of a computational case study that demonstrates the potential of the proposed model. In Section 4.1, we describe our data collections and the details of our computational implementation. In Section 4.2, we present the results for a minimum non-trivial case to illustrate the suitability of the model and of the solutions obtained. In Section 4.3, we explain how we tuned the economic parameters for the larger study. In Section 4.4, we investigate how the
configuration of the ESS affects the participants’ savings, and in Section 4.5 we calculate the impact of the number of participating prosumers on the aggregator’s profitability. Finally in Section 4.6, we summarize the key findings from our study.

4.1 Data and Implementation

We base our case study on values and statistics reported for Austin, Texas, USA in the year of 2018. In order to demonstrate the profitability of the proposed business model all year round, we choose two days representative of the winter and summer seasons. This selection was made based on estimated PV generation. We used the model in [28] to estimate daily PV power output in 2018. This model uses Global Horizontal Irradiance (GHI) and ambient temperature to estimate the efficiency of a PV cell. We collected this historic solar irradiance data for Austin using the Solcast API [37], and we selected the winter day with the lowest estimated PV generation and the summer day with the highest estimated PV generation. These days are respectively 7th January and 27th June. We assume that these days represent bounds on generation profiles throughout the year.

The number of prosumers varies between 12 and 204. The capacity of a prosumers’ ESS is 6 kWh, in accordance with the typical value reported in [24]. Due to technical specifications, an ESS can never be fully charged or discharged. Therefore, we consider the maximum depth of discharge of the ESS to be 70% of its total capacity [24], this is $S_i^P + S_i^A = 4.2 \text{ KWh}$. Moreover, we assume that at the beginning of the time horizon, prosumers have no electricity stored in their own ESS: $S_i = 0 \forall i \in I$.

We consider that a residential-scale ESS costs $1426.50/kWh, as per the values reported in [24]. As a result of extensive use, the reduced lifetime of such an ESS is 5 years. Therefore, we define the investment cost in an ESS to be $0.0326/kWh per hour. Similarly, and according to the values reported in [38], we consider that a grid-scale ESS costs $380/kWh and has a lifetime of 15 years. As a result, we define the savings from not investing in a ESS to be $0.00289/kWh per hour. Also according to [38], we take the round-trip efficiency of a prosumer’s ESS to be 85%. Because energy is lost both when charging and discharging the ESS, we set the parameter $\eta$ to 0.92.

We consider a time horizon of 24 one-hour periods. The demand and generation patterns of prosumers are collected from real data reported for prosumers in Austin by the Pecan Street Project [31]. Given the data collected, we classify prosumers into three different profiles. For the data concerning the winter season, the generation excess over demand is small or nonexistent in all profiles. The main distinction between profiles happens for the data concerning the summer season. Profile A is characterised by prosumers whose generation barely surpasses their demand during peak hours. Profiles B and C both pertain to prosumers whose generation surpasses their demand during peak hours. In Profile B, the generation excess is small and only lasts for a brief period. On the contrary, Profile C denotes prosumers whose generation exceeds demand by a larger amount and during a longer period. We select a total of 12 prosumers: six prosumers for Profile A, four for Profile B and two for Profile C. Finally, larger data sets are obtained by replicating this set of prosumers while maintaining the proportions of prosumers in each profile. Figures 2, 3, and 4 show the graphs of typical demand and generation patterns for each profile for the two dates considered.

The wholesale market prices are the real-time LMP by Texas ISO ERCOT reported by the Pecan Street Dataport [31]. Furthermore, the retail electricity prices are computed based on the 12-months fixed-price plan Secure Advantage by Reliant Energy to be $0.141/kWh.

The computational experiments were performed on a Dell PowerEdge R430 with Four Intel Xeon E5-2680 v3 2.5GHz operating on Scientific Linux 7. The mixed-integer linear optimization problems were solved using the ILOG CPLEX solver [18] accessed via AMPL [12]. Finally, all the graphs are created using Python [33] and its libraries matplotlib and seaborn.
Figure 2: Demand and generation curves for a prosumer with Profile A during the selected winter and summer days

Figure 3: Demand and generation curves for a prosumer with Profile B during the selected winter and summer days
4.2 Minimum non-trivial case

This section illustrates the suitability of the model and of the optimal solutions obtained using a minimum non-trivial case with one prosumer. We solve the simplified formulation described in Section 3.2.2 with all the economic parameters set to the average between their upper and lower bounds: \((\pi^A, \pi^U, \alpha) = (0.5B, 0.5B, 0.5)\). Moreover, the prosumer keeps 50% of its ESS for own use and makes the other half available to the aggregator. We consider the data for the summer instance of 27th June 2018. The model’s optimal solution over a one-day planning period is represented in Figure 5.

Figure 5: Optimal solution of the minimum non-trivial Case with one prosumer

Figure 5a reveals the expected pattern of electricity discharges by the aggregator. The aggregator sells its electricity to the grid before the consumption peaks (around 11h and around 17h). This pattern shows evidence that the model effectively captures the aggregator’s operational reality. Moreover, the
total profit of the aggregator in this small case is $6.45$ which is a first indication that the proposed model is profitable.

Figure 5b represents the prosumer’s generation and demand profiles, and its optimal energy management decisions. We observe that between 8h and 14h, the prosumer uses its own generation to meet demand and saves on its electricity bill. The prosumer also benefits from the commission scheme by selling some of its own generated energy in the wholesale market. As can be seen in Figure 5a, this happens when the prosumer has completely filled its part of the ESS. These patterns show that the model effectively captures the prosumer’s operational reality. Moreover, the prosumer saves $6.02$ on its electricity bill which suggests that the proposed model can be advantageous for prosumers as well.

4.3 Setting the economic parameters

In this section, we explain how we tuned the economic parameters for the larger study. First, we select a representative grid of values for the economic parameters $(\pi^A, \pi^U, \alpha)$. We then solve the model for each triplet of values, and we compare the optimal values obtained.

For this purpose, we have constructed data instances with 12 prosumers. As this experiment is an economic study, the number of prosumers needs to be reasonably large and their profiles varied. As previously explained, to properly tune the economic parameters, market competitiveness needs to be represented in the objective function through demand curves. We used the following linear demand curves:

\begin{align*}
    d_1(\pi^A) &= \frac{\pi^A}{B} \\
    d_1(\pi^U) &= \frac{\pi^U}{B} \\
    d_2(\alpha) &= 1 - \alpha \\
    d_3(\pi^A, \pi^U) &= \frac{\pi^A + \pi^U}{2B}
\end{align*}

We separated the tuning process into two phases. First, the commission parameter is tuned. Second, both compensations are simultaneously tuned. This procedure is reasonable because of the objective function’s structure. The commission only appears in term (1C), and hence it can be tuned individually. By contrast, the compensations for availability and usage interact through several terms in the objective function, and consequently, a correct tuning needs to work on both simultaneously.

We tune the economic parameters assuming that prosumers keep 50% of their ESS for their own use and make the other half available to the aggregator as part of the scheme proposed. It is important to note that the parameter values obtained are independent of the percentages of battery use. For example, if instead of 50%-50% the battery was divided as 80%-20% for the aggregator and prosumer respectively, the same values would be selected for the economic parameters. This is because if a prosumer has more ESS space he will have more flexibility to act in favor or against the aggregator, but this space does not affect the decision to cooperate. This is justified by the analysis in next section.

4.3.1 Tuning of the commission

First, let us tune the commission parameter $\alpha$. We consider $\pi^A$ and $\pi^U$ fixed at their average value $B/2$. The commission changes in a grid of values between 0 and 1 with a step size of 0.1, that is, $\alpha \in \{0, 0.1, 0.2, \ldots, 1\}$. Figure 6 shows the optimal objective values obtained for the different commission parameters during the winter and summer days. Based on these results, we conclude that the optimal commission parameter is 10% in winter and 40% in summer.

We obtain further insight on the optimal commission values obtained by looking at the lower-level optimal solution. Figure 7 depicts the mean of prosumers’ optimal costs depending on the commission for the winter and summer seasons. It is clear that in both seasons, there is a turning point in the prosumers’ costs. This happens for a commission of 20% for winter and a commission of 60% for summer. This happens because it is only optimal for prosumers to sell energy on the wholesale market if the commission collected by the aggregator is sufficiently small. Otherwise, prosumers change their operational decisions and store their energy in the ESS for later use, rather than selling it for profit. These decisions affect the profit that the aggregator can make from collecting a commission on prosumers’ sales. Note that the same turning points can be observed in the aggregator’s profit in
Figure 6: Tuning of the commission parameter for the linear demand curves

Figure 6. Before and after these points, the profit follows the shape of a concave parabola due to the presence of demand curves in the objective function.

Figure 7: Mean lower-level optimal objective value per commission parameter for the linear demand curves

We note that in this analysis, we have considered prosumers as a whole. However, for prosumers with different generation profiles, the turning point of when it is no longer profitable to sell energy on the wholesale market might be different.
Furthermore, we can conclude that the correct tuning of the commission parameter has a larger impact on the aggregator’s profit in the summer scenario. This is expected since PV generation increases in summer and hence the aggregator has a better chance to make profit on prosumers’ energy sales. In fact, the difference between the optimal profits for a commission of 0% and the optimal commission indicates the potential benefit that the aggregator has from implementing this commission scheme. In this case with linear demand curves and 12 prosumers, the increase in profit due to this scheme is 0.11$ in the winter day and 21.17$ in the summer day. These bounds can be used for estimating whether the implementation of this commission scheme is profitable for the aggregator.

4.3.2 Tuning of the compensations

We now simultaneously tune the compensations for availability and for usage. We consider α fixed at its optimal value of 10% in Winter and 40% in Summer. The compensations may vary between 0 and \( B \) with a step size of 0.1\( B \), that is, \( \pi^A, \pi^U \in \{0,0.1B,0.2B,\ldots,B\} \). The surfaces displaying the optimal values with respect to each combination \((\pi^A,\pi^U)\) for January and for June are shown in Figures (8a) and (8b) respectively.

![Figure 8](image)

(a) 27th January 2020
(b) 7th June 2020

Figure 8: Tuning of the compensation parameters for the linear demand curves

The optimal compensations are \( \pi^A = 0.3B \) and \( \pi^U = B \) for both days. This optimal solution selects the maximum allowed compensation for usage. In fact, this compensation is the economic parameter with the largest impact on the objective function value. The compensation for usage affects not only its cost term (1E) but also two profit terms: the savings (1A) and the grid services earnings (1B). These two profit terms substantially contribute to high objective values. Consequently, increasing the compensation for usage will always be profitable because the profit it brings outweighs the costs incurred. Note that this phenomenon is only possible because the amount of electricity that the aggregator can provide to the grid is deemed unlimited. If there are limits on the amount of electricity that the aggregator can provide to the grid, then the outcome will likely be different.

Nevertheless, the compensation for availability is still important. It can be observed in Figure 8 that the surfaces computed are not concave, and that there are in fact two maxima: a global maximum for \( \pi^U = B \) and a local maximum for \( \pi^A = B \). This occurs because of the symmetrical shape of the demand curve \( d_3(\pi^A,\pi^U) \) selected, which equally benefits the increases in both compensations.

Furthermore, the optimal value never reaches zero because the commission \( \alpha > 0 \) is still contributing to the aggregator’s profit. The tuning of the compensations has a larger impact in the summer day than in the winter day.

Finally, similarly as was done for the commission parameter, we can estimate how the implementation of these compensations benefits the aggregator. The optimal compensations would bring the aggregator a profit of $23.69 in the winter day and $23.51 in the summer day. These values suggest that the compensation scheme is essentially equally profitable throughout the year.
4.3.3 Summary of the choices of economic parameters

In conclusion, the optimal values of the compensations using linear demand curves are \((\pi^A, \pi^U) = (0.3B, B)\) throughout the year. The optimal commission charged by the aggregator is seasonal and takes the values 10% in Winter and 40% in Summer. For the rest of the computational study, the economic parameters are set at these values.

We highlight that fact that the tuning of the compensations is generally more important because it has a larger impact on the aggregator’s profit. The tuning of the commission is more relevant during the summer season which is when the commission scheme has more potential to generate profit for the aggregator.

4.4 Impact of ESS Configuration in Participants’ Savings

In this section, we study the impact of the ESS configuration on the profitability of the proposed business model for the participants. In the proposed business model, participants decide which size of ESS to invest in and which percentage of their ESS’s capacity to make available to the aggregator. These decisions have an impact on the savings that participants can achieve by participating in the proposed scheme. In order to study this impact, we simultaneously consider the total ESS capacity and the percentage of space in their ESS that participants reserve for own use.

We consider the economic parameters fixed at their seasonal optimal values, as determined in Section 4.3. The ESS capacity varies between 0 and 20 KWh, in steps of 1 KWh. The percentage of ESS capacity that the participants keep for own use changes in a grid of values between 0 and 1 in steps of 0.1: \(\{0, 0.1, 0.2, \ldots, 1\}\). Figures (9a) and (9b) show the mean participants’ savings with respect to each ESS configuration for January and June, respectively. These savings are computed as the income received from the compensation and commission schemes minus the extra ESS investment cost. This extra cost is caused by the ESS’s reduced lifetime due to greater use. Specifically we assume that participating in this scheme reduces the ESS’s lifetime by 50%.

![Impact of ESS Decisions on Participant’s Savings](image1)

![Impact of ESS Decisions on Participant’s Savings](image2)

(a) 27th January 2020  
(b) 7th June 2020

Figure 9: Seasonal Impact of the ESS configuration on Participant’s Savings

In the worst-case winter scenario, participants with a typical ESS of approximately 4 KWh should not keep more than 40% of the capacity for own use, otherwise their investment will not be profitable. In the best-case summer scenario, the same participants will always save money.

Furthermore, in the worst-case winter scenario, when participants keep at most 30% of their ESS, their savings increase with the increase of the ESS capacity. In this case, the aggregator has access to most of the ESS and hence the compensation scheme outweighs the increase in investment cost for participants. In the best-case summer scenario, a similar phenomenon occurs when participants keep at most 20% of their ESS for own use.

In both scenarios, the larger the percentage of their ESS they keep for their own use, the smaller the savings. Moreover, when participants choose to keep a larger percentage of the battery for own use, their savings decrease.
use, they receive less income from the compensation scheme, and the benefits of participating in this scheme do not outweigh the investment costs.

Naturally, the participants will want to keep some of the ESS capacity for their own use, in particular as protection against events like black-outs. These results suggest that, regardless of their ESS capacity, participants should not keep more than 20% of their ESS for own use all year round.

We recall that we consider participants as a whole by studying the mean savings of all participants. Nevertheless, our model can be used to provide information specific to each individual participant to assist that participant’s decision-making process.

Finally, we note that the aggregator’s profit is highest when the ESS capacity is maximum and the participants give the aggregator access to all that capacity. This is because we set no limit on the amount of grid services the aggregator can provide. If such a limit were included in the model, this would likely no longer hold. While it is straightforward to set such a limit in our bilevel optimization model, determining the limit would depend on the relationship between the aggregator and the grid operator, and this is beyond the scope of this paper. Nevertheless our results suggest that a reasonable limit would not undermine the profitability for both participants and the aggregator of the proposed business model.

4.5 Impact of the Increase of Participants in Aggregator’s Profitability

In this section, we examine how the number of participants impacts the profitability of the aggregator. The economic parameters are set at the optimal values obtained with linear demand curves in Section 4.3. The ESSs of the participants have the typical capacity of 4.2 KWh as detailed in Section 4.1, and they keep 20% of this space for own use as advised in Section 4.4.

We consider 16 instances with the number of participants increasing from 12 to 204. First, we analyse the impact of the number of participants on the optimal objective value of the upper-level. Figure 10 presents the optimal values with respect to the number of prosumers for the winter and the summer data.

![Figure 10: Impact of the number of participants on the aggregator’s profit for both seasons](image)

We conclude that the aggregator’s optimal profit increases linearly with the number of prosumers. We recall that the amount of grid services that the aggregator can provide is not bounded above. Therefore, an increase in the number of prosumers is always beneficial for the aggregator. The aggregator’s profit increases by $4.03 per prosumer in the winter scenario and $6.87 in the summer scenario. Moreover, an inspection of the lower-level optimal solutions allows us to conclude that prosumers earn on average, in compensations’ revenue, $2.10 per day in the winter scenario and $6.10 per day in the summer scenario, before accounting for the extra investment cost in the ESS.
Similarly to all the results presented thus far, the optimal objective value displays greater variations for the summer instance of June. This is due to the greater solar generation typical in this season.

Taking these results into account, and assuming that the pessimistic winter scenario and the optimistic summer scenario each represent half of the year, we conclude that the aggregator could achieve profits of approximately $1989.25 per year per participating prosumer. Similarly, a participant could generate revenues of approximately $1496.50 per year from this compensations’ scheme.

Second, we study how the CPU evolves with the number of prosumers. The graph in Figure 11 depicts the computational time to solve the mixed-integer KKT formulation with respect to the number of prosumers. Similarly to previous results, the results for the winter scenario are in blue and the summer scenario in red. While Figure 11 suggests that the algorithm’s computational time increases superlinearly with the number of prosumers, all the instances are solved in under 8 seconds. This indicates our solution approach is viable for large-scale and practical application of the proposed model.

We further note that the computational times tend to be higher for the summer instances than for the winter instances. This is again likely due to the higher generation typical in the summer instances which leads to more possibilities for handling the flows of electricity, and hence a larger feasible set for the optimization model.

![Figure 11: Seasonal Computational Time per number of participants to solve the MI KKT formulation](image)

4.6 Key Findings

Our results support the following three key findings:

1) **The proposed bilevel model and solution algorithm can support the practical implementation of the proposed business model.**
   The bilevel model captures the reality of the business model both from the aggregator’s and prosumers’ perspectives. The algorithm is able to solve instances of up to 204 participants to proven global optimality in less than 10 sec which makes it efficient for practical application.

2) **The compensation for usage is the main driver for the determination of the optimal compensation scheme.**
   We considered a combination of three types of compensations: commission for wholesale market access, compensation for ESS availability, and compensation for ESS usage. The compensation for usage is the determining factor for the profitability of the model.

3) **The proposed business model is profitable all year around.**
   The results for the selected winter and summer days suggest that this business model can be
profitable throughout the year. Therefore, even if the daily profits and savings are small, they add up to interesting sums of money on a yearly basis.

5 Conclusions and Future Research

We considered a business model to leverage behind-the-meter electricity storage capacity in the residential sector. In this model, an aggregator sets up a compensation scheme in exchange for access to participants’ energy storage systems. This access allows the aggregator to provide services to the grid and hence make a profit. Moreover, participants can sell the electricity they generate in the wholesale market through the aggregator.

In order to study this interaction between an aggregator and multiple residential-scale participants, a novel mathematical optimization model was proposed. The model is a single-leader multi-follower bilevel optimization problem with a non-linear upper-level objective function. Given the complexity of the problem, a simplification is considered. The resulting model optimizes the operational aspects of the business model, that is, the flows of electricity and money between the aggregator, the prosumers and the retail and wholesale markets. Moreover, a simple extension of the model provides the ability to identify the optimal compensation scheme for participants.

The computational results confirm the validity of the model and the suitability of the algorithm used. First, the solutions obtained demonstrate that the business model is properly captured by the optimization model. Second, instances with up to 204 participants can be solved in less than 10 sec which shows that the solution approach has the potential to be deployed for practical use.

Furthermore, our results also confirm that the proposed business model has strong economic potential. Based on Texas historical data, participants could earn approximately $1496.50 per year. This is a non-negligible amount that would allow the prosumers to maximize the value of their investment in ESS technology. The business case for aggregators is even better: this business model could generate profits of approximately $1989.25 per year per participating prosumer. These potential profits seem sufficient to mitigate the important equipment costs incurred by the aggregator or utility when aggregating residential ESSs, in particular because the controllers that have to be installed in the households must meet the regulatory standards for critical infrastructure. Aggregating residential behind-the-meter storage capacity could thus provide significant value to aggregators (and hence to utilities) and to their participating customers. Given that all households with an ESS are potential participants, at the scale of an aggregator or of a utility, this is a promising business opportunity.

From the optimization perspective, future research should consider the development of a solution approach that can solve the bilevel model in Section 3.2.1 without simplifications. Note that such a solution approach must be capable of handling bilevel optimization problems with an upper-level nonlinear objective function. This challenging topic would contribute to the improvement of solution methods to bilevel optimization in general.

From the energy storage perspective, it would be interesting to extend the model to incorporate time-of-use and other retail pricing schemes used in various jurisdictions. It would also be important to study the potential benefits of the proposed business model for grid operations through congestion relief and upgrade deferral for both transmission and distribution systems, as well as via the provision of demand flexibility to the grid to support the increasing penetration of renewable energy generation.

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