Optimal Prosumer Aggregations: Design and Modeling

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Abstract

Prosumers will play an increasingly important role in the modern smart grid through their ability to modulate net consumption as well as provide excess generation back to the grid. Aggregations are a profitable model for prosumers to trade surplus energy generation and fully utilize energy resources, as well as encourage additional investment in local generation and storage resources. We present theoretical results to quantize aggregation profitability, and devise a numerical test for an optimal aggregation. We then validate these results through an agent based modeling framework built to model self-interested independent agents, using real building loads and solar generation data.

1 Introduction

Smart buildings are often equipped with energy resources in the form of local generation (photovoltaic arrays, diesel generators) and energy storage (batteries) which can be used to offset loads, reduce demand charges and optimize grid consumption. They can profit from energy production and their adaptability to changing prices, e.g. by charging their batteries during low price hours and selling excess generation to the utility during peak price hours, thus demonstrating their prosumer behavior. A *prosumer* is an entity that is capable of energy production as well as consumption through the presence of local generation and energy storage devices.

Local generation and storage is not always a profitable proposition: as net-metering programs are phased out, utilities typically buy power from distributed generation at a price lower than the price at which they sell it [1]. Buildings have to invest in over-capacity generation and storage to accommodate the variability in their loads due to fluctuating occupancy and weather conditions. These underutilized energy resources can become profitable when buildings trade their surplus energy with other buildings rather than selling to the utility, or use their energy storage to provide demand charge reduction services to other buildings. We consider prosumer aggregations where the prosumers trade energy with each other, and then present the net deficit/surplus to the utility as a single consumer. The aggregation's total cost is the cost of trading the deficit/surplus with the utility, while each individual prosumer has to pay for its internal energy trades as well as utility procurement. In general, the benefits of forming aggregations are due to more efficient utilization of energy resources and complementary demands of prosumers in the aggregation. For a prosumer, the cost benefits of joining an aggregation depend on the energy resources and demands of the other participants in the aggregation. Estimating these benefits is difficult: a closed form expression can not be formulated due to complex trading inter-dependencies between buildings. This creates the need for agent based models which can be used to assess the effects of different configurations and aggregation paradigms on the participating prosumers.

There might be conflicting interests within a prosumer aggregation during trade price negotiation, as a higher price will improve profits for the supplier while increasing costs for the consumer. One way to holistically look at aggregation welfare is through the concept of economic social welfare, where the total cost for the aggregation as a whole is minimized. The underlying idea is that the lowest social cost can be distributed in a way that minimizes each prosumer's individual cost. This is not a trivial problem, and a lot of research has been done in the area of mechanism design to implement the optimal social welfare solution [2], [3], [4], [5]. In this report, we focus on providing results on optimal aggregations and then validating them with realistic mechanisms borrowed from literature.

1.1 Contributions

We provide theoretical results on the value proposition of aggregations under different utility pricing regimes, and the optimal social welfare achievable. Our main results are on:

1. The composition of an optimal aggregation, i.e. which prosumers would form an optimal aggregation
2. A numerical test to estimate *complementarity* of prosumers which does not require them to share private information about loads, generation or storage operation

The numerical estimate can be used to prioritize aggregation expansion before further information needs to be shared for operation.

These theoretical results hold true for centrally controlled aggregations. Realistically, aggregations may employ distributed control schemes, for which these results may not hold true. We develop a virtual testbed in the form of an agent based simulation framework to test how close the actual social welfare will be to our theoretical predictions. The agent based model simulates trade between independent self-interested economic agents that have both production and consumption capabilities, and is used to validate our results with realistic market mechanisms from literature using real data of office building loads, solar generation and battery costs. The proposed agent based model can also be used to analyze other what-if scenarios: incremental investment value, comparison of control algorithms, and effects of external regulations/prices.

The report is organized as follows: Section 2 surveys related work in the area, and Section 3 introduces the prosumer model and objectives, as well as the central aggregator. Section 4 details the theoretical results, Section 5 introduces the agent based modeling framework and Section 6 uses the framework to validate results presented in Section 4. Finally, Section 7 concludes the report.

2 Related Work

The aggregation of distributed energy resources has been studied extensively in literature, and there are two main models: virtual power plants and microgrids. Virtual power plants (VPP) are a dynamic aggregation of smart loads, distributed generation and storage. They form an 'internet of energy' [6], by dynamically optimizing aggregation and including/excluding loads and generators according to the benefits they provide to the VPP. Their primary function is providing a way for smaller distributed energy resources (DER) to be visible to the larger grid [7], as individual DER do not have the capacity/generation profile to take on the risk of participating in markets on their own. Traditional microgrids, on the other hand, are a largely static set of energy resources backed by physical infrastructure that are geographically close to each other and aggregate in order to manage their loads internally. A key difference is that microgrids aim to satisfy internal loads through centralized/distributed generation, keeping minimal interactions with the grid and often maintaining the capacity to operate in islanded mode (i.e., cut off from the larger grid), whereas virtual power plants aggregate resources to provide services to the grid [8]. Microgrids are aimed at maintaining self sufficiency and increasing local consumption of energy generation, while VPPs proactively participate in energy and reserve markets in a profit seeking manner.

The aggregation that we model is closer to a microgrid than a virtual power plant, as the participants are prosumers, not just distributed energy resources (DER). The central aggregator does not directly participate in energy/ancillary services markets, and instead interacts with the utility as a single active consumer. However, the aggregation is not a static collection of centrally controlled loads and generation, and contains independent agents acting in a profit seeking manner. Dynamic membership is possible due to the virtual nature of the aggregation, and unlike in microgrids, the central aggregator can not exercise direct control over energy resources owned by buildings.

Smart Building Aggregations Self interested rational buildings will seek to join aggregations that are most beneficial for them by looking at the complementary demands and energy resources of other buildings, and the formation and operation of such aggregations has been discussed in literature. Prosumers can form coalitions to optimize a utility function, and an algorithm is proposed in [9] that makes the decision based on reduction in power losses. The effect of microgrid formation on the utility is analyzed in [10] by considering electricity prices and benefits to different stakeholders. However, since the energy cost of prosumers joining an aggregation is heavily dependent on the behavior of other participants through complex inter-dependencies, the evaluation of monetary benefit is a difficult task.

Various market mechanisms have been used in literature to model the interactions between autonomous buildings in a microgrid. The objective of the aggregation is modeled as a Nash Bargaining problem in [3] and solved by decomposing it into two sequential problems which are solved iteratively. A Vickrey-Clarke-Groves auction is modeled in [2] with the aim of minimizing social cost, i.e. net cost to the aggregation, using a quadratic utility function while imposing the condition that the aggregation be a net consumer of energy. A two stage Stackelberg-Cournot game model is developed in [11] to model the forward and spot energy markets, placing the utility in the role of the leader in the game. A mechanism is developed in [12] to enforce cooperation between buildings by punishing non cooperative behaviors by imposing a non optimal solution on the entire virtual microgrid. A mechanism to get agents to truthfully report their predicted demand is developed in [13]. Comparing the benefits of these different auction mechanisms is complicated as each one of them assumes a different market structure and has different objectives. When prosumers decide to aggregate, they need to be able to compare market mechanisms to decide which one works best for their particular objectives.

Transactive Control The traditional paradigm of microgrid control assumes a central authority dictating consumption decisions to the participants. This can not realistically be implemented in a situation where self-interested buildings want to aggregate without ceding control of their operational decisions. *Transactive control* is a strategy that uses market mechanisms such as the price of electricity to influence the operation of the virtual microgrid, and is a realistic take on the problem of influencing independent rational agents which are found in a free market. A situation where the central controller in a microgrid tries to shape the load curves of buildings is considered in [4], where buildings are priced independently and real time pricing is employed to shift demand. A retailer that tries to minimize the variance between day ahead forecast demand and real time demand using real time pricing is analyzed in [14]. A hierarchical optimization problem is discussed in [15] where buildings are modeled as having a utility function of consumption of energy, the lower level optimization problem is solved locally and a distributed algorithm is developed. Each of these control strategies can be employed in a prosumer aggregation, and participants need to compare the benefits of each.

Multi Agent Simulations An agent based model can be used to analyze the effects of different participant and control strategies on the aggregation, as well as run Monte Carlo simulations to assess the effects of uncertainty and variability in operation. The current work in agent based modeling of microgrids largely focuses on describing different modes of operation of participants as separate agents, and then analyzing distributed control methods. In [16], separate agents are modeled for generation, consumption, market clearing and coordination functions. The separation of agents by function precludes buildings from having both consumption and generation abilities. Similarly, in [17], agents are separated based on function, and the microgrid operates in distinct modes: supplier to grid, consumer from grid, etc. Agents are controlled by facilitator agents based on what mode of operation is active, which means that if a building were to have both consumption and generation capabilities it would receive separate instructions from the facilitator. In [18], agents are separated by function and interact with each other in a peer to peer fashion by giving or querying information, and proposing actions to other agents. Similarly, in [19], producers lead bargaining and proceed to iteratively settle on a price by modifying it in small increments. These agent based models differentiate between agents based on their behavior as a pure producer or pure consumer, and also impose a structure on the microgrid where buildings interact only with the buildings with whom they have direct communication/transmission links. In order to fully compare diverse aggregation paradigms for smart buildings, an agent based model needs to be general enough to include different trading models and prosumer behavior of buildings.

3 Problem Formulation

In this section we develop an agent model for the prosumers, and detail the mathematical formulation of their objectives and operating constraints.

3.1 Load, Generation and Flexibility

In any time period t, the prosumer has energy demand $d^{(t)}$, local generation $g^{(t)}$, and storage operation $u^{(t)}$. The building's net load at time t is given by

$$z^{(t)} = d^{(t)} - g^{(t)} + \eta u_-^{(t)} + \frac{1}{\eta} u_+^{(t)} \tag{1}$$

where charging storage is a net load, i.e. a positive $u^{(t)}$, and $()_+, ()_-$ represent the positive and negative parts respectively. Real batteries have some amount of energy loss during charging/discharging, which can be modeled with a one way efficiency $\eta < 1$. For every unit of energy discharged from the battery, only η of it is available for use. Similarly, for each unit charged, $1/\eta$ has to be drawn from the grid. The state of charge of the battery at any time can be obtained using the charge/discharge operations over all previous time periods, i.e.

$$\mathrm{SoC}^{(t)} = \sum_{k=1}^{t} u^{(k)} \implies \mathbf{SoC} = L_{tri}\mathbf{u} \tag{2}$$

where L_{tri} is the lower triangular matrix with all entries as 1. The operating constraints on the battery storage are given by

$$-r\mathbf{1} \leq \mathbf{u} \leq r\mathbf{1} \tag{3a}$$

$$\mathbf{0} \leq L_{tri}\mathbf{u} \leq cap\mathbf{1} \tag{3b}$$

where the first constraint is on the charging/discharging rate, and the second encodes the battery capacity. We can combine these into a set of linear constraints:

$$A\mathbf{u} \leq \mathbf{c} \tag{4}$$

3.2 Prosumer Cost

Define $\pi_b^{(t)}$ to be the time-of-use rate at which consumers buy energy from the utility, and $\pi_s^{(t)}$ as the rate at which they sell it back. These prices are typically different [1], as utilities move towards phasing out net-metering programs and include distributed energy resources in wholesale markets. A prosumer can modify its energy consumption over the course of the day to minimize its utility bill by storing energy in the battery during low price/surplus generation time periods, and discharging during peak price hours. However, battery life is affected by the number of charge/discharge cycles it goes through, and any usage of the battery costs money, which can be modeled as a per cycle amortized battery cost. The optimization problem solved by the prosumer is

$$\min_{\mathbf{u}} \sum_{t=1}^{T} \left[\pi_b^{(t)} z_+^{(t)} + \pi_s^{(t)} z_-^{(t)} + \pi_{bat}|u^{(t)}|\right] \tag{5a}$$

$$= \boldsymbol{\pi}_b^\top \mathbf{z}_+ + \boldsymbol{\pi}_s^\top \mathbf{z}_- + \pi_{bat}\mathbf{1}_T^\top |\mathbf{u}| \tag{5b}$$

$$\text{s.t.} \quad A\mathbf{u} \leq \mathbf{c} \tag{5c}$$

where $\mathbf{u}$ represents the vector of battery charge/discharge over time with positive values denoting battery charging, $\boldsymbol{\pi_b}, \boldsymbol{\pi_s}$ represent the time vectors of utility buy and sell prices, and $\mathbf{z}_+, \mathbf{z}_-$ represent the time vectors for positive and negative net demand curves respectively. The optimization objective (5a) incorporates the cost of procuring any net demand $z_+^{(t)}$ at the utility buy price, the profit from selling any net surplus energy generation $z_-^{(t)}$ at the utility sell price, as well as the cost of battery degradation evaluated with π_{bat}. The constraint (5c) encapsulates physical constraints on the state of charge for energy storage and charging speed.

If the utility had a net metering program, any sale of surplus energy to the utility would occur at the same price as the buy price, and the optimization problem in (5) would become a linear program. Without net metering, the objective (5a) is a piece-wise linear function (and convex, under the assumption that $\boldsymbol{\pi_b} \geq \boldsymbol{\pi_s}$). Any day-ahead uncertainty in load and generation can be incorporated in the objective through a stochastic optimization problem, however we do not do so for simplicity of exposition.

3.3 Central Aggregator

Instead of trading directly with the utility, prosumers can trade their surplus energy with each other and capitalize on the utility buy/sell price difference. This trade can occur in a peer-to-peer fashion

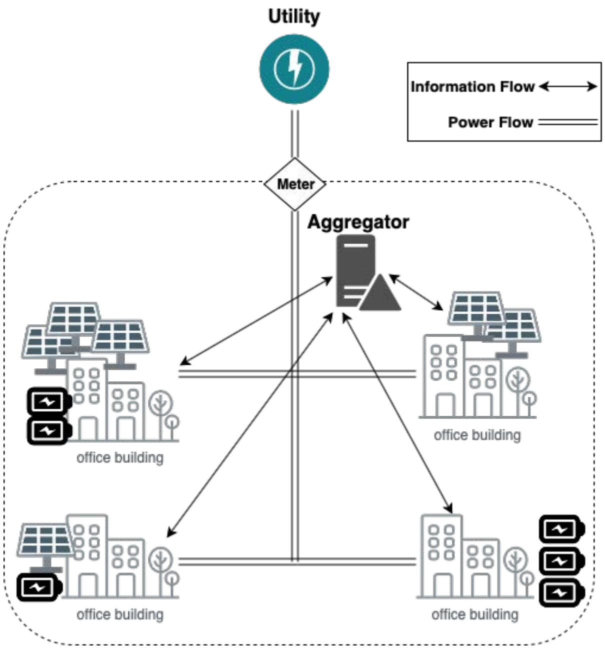


Figure 1: Social net metering in a prosumer aggregation

with independent negotiations between each potential buyer and seller, or through a central aggregator that facilitates trading within the prosumer aggregation and presents the net demand to the utility as a single active consumer. We consider the latter, and clarify that this model of aggregation does not necessarily require setting up new infrastructure. The aggregation can enter into a contract with the utility such that the net power exchange between the aggregation and utility (recorded in the meter in Fig. 1) is billed. Similar contracts for virtual net-metering exist in the United States [20], and power flow occurs only between the utility and prosumers. The aggregator and prosumers share information to settle trades and manage payments, and the aggregator does not need to balance power flow or own physical infrastructure.

3.3.1 Economic Social Welfare

Prosumers can form an aggregation with an objective of minimizing aggregate utility bills, and coordinate their energy storage operation. The social welfare problem aims to maximize the welfare of the aggregation as a whole, which is defined as the social cost, i.e. the utility bill and the battery operation costs. If a central controller has insight into prosumer loads and generation and can direct energy storage operation, it has to solve the following problem to maximize social welfare:

$$\min_{\mathbf{u_i}} J := \boldsymbol{\pi}_b^\top (\sum_i \mathbf{z_i})_+ + \boldsymbol{\pi}_s^\top (\sum_i \mathbf{z_i})_- + \pi_{bat} \mathbf{1}_T^\top \left| \sum_i \mathbf{u_i} \right| \tag{6a}$$

$$\text{s.t.} \quad A\mathbf{u_i} \leq \mathbf{c_i} \ \ \forall\, i \tag{6b}$$

3.3.2 Decentralized Control

There are a few reasons why centralized control schemes may not work in aggregations: prosumers may not be willing to cede control of privately owned resources to an external authority, and may be self-interested rational economic agents interested in minimizing their own costs rather than in contributing to social welfare. Decentralized control schemes such as transactive control can be used to facilitate virtual energy exchange between prosumers, such as in [14], [4]. *Transactive control* is a strategy that uses market mechanisms such as the price of electricity to influence the operation of storage within the prosumer aggregation, and is a realistic take on the problem of influencing independent rational agents which are found in a free market. However, decentralized schemes may not achieve the optimal social welfare (6).

4 Optimal Aggregation

We first examine the value of these aggregations under different utility pricing regimes

Remark 1. *The value of an aggregation derives from a difference in utility buy and sell prices, i.e.* $\pi_b - \pi_s$*, and the marginal benefit of an aggregation increases with the price difference. In the presence of net metering, there is no value proposition for aggregations.*

Discussion. Under net metering, $\pi_b = \pi_s$ and there is no scope for price arbitrage or trade between two prosumers. A producer has no incentive to sell at a price lower than π_s, which is the same price that a consumer already pays the utility, and hence no trade occurs.

Aggregations that aim to capture the value left on the table by utility price differences can be formed with a variety of motivations: cooperative cost savings for participants, increasing local renewable consumption, improving utilization of resources, or by profit maximizing private investors. The controls or market mechanisms used by an aggregation to facilitate virtual energy trades will determine how well these objectives are achieved, as discussed in Section 3.3.1 and 3.3.2.

Remark 2. *The maximum economic social welfare, i.e. minimum total cost is achieved when a central authority has complete insight into all participants' net loads and storage and directly controls the energy storage operation. The cost for the resulting aggregation is a lower bound for the total cost that can be achieved through any other control policy.*

Discussion. The central authority that aims to maximize social welfare solves the optimization problem in (6). By definition, this problem has as its objective the total cost (6a), and has only the physical constraints on battery operation (6b) which would exist in any other control mechanism as well. It is the least constrained problem possible with this objective, and hence achieves the lowest possible value of the objective function, i.e. the lowest total cost.

4.1 Scope of Analysis

The problem of devising a mechanism to achieve this ideal cost through decentralized control has been studied extensively in literature. In this paper, we do not consider the problem of mechanism design and instead focus on theoretical guarantees (lower bounds) for costs for centrally controlled aggregations. Any market mechanism will achieve higher costs than these bounds, but we hope the results will guide us in addressing questions of aggregation design. We test our hypotheses with simulations using a couple of decentralized control mechanisms from literature in Section 6.

We conduct the rest of our analysis for an aggregation which aims to minimize total cost. We realize that this does not capture the self interested nature of the participating prosumers, and while validating our results we will use mechanisms that use price signals to coerce socially beneficial actions from participants that are modeled as rational economic agents.

4.2 Theoretical Results

Having laid down the basis of our analysis, we now set out to answer the question: what is an optimal aggregation? i.e. given a set of buildings, which ones should cooperate and decide to form an aggregation? Our first result describes how the *grand coalition*, i.e. an aggregation comprising of all possible prosumers ensures the highest social welfare.

Result 1. *Aggregations are superadditive, i.e. larger aggregations result in higher social welfare.*

Proof. Consider two disjoint aggregations of prosumers U, V which aim to maximize social welfare. The central authority for U solves the problem (6) for $i \in U$, and likewise for V. If we consider the *grand coalition*, i.e. an aggregation of prosumers in $U \cup V$, then the objective function for the combined social welfare maximizing aggregation (6a) can be written as

$$J_{U \cup V} = \frac{\boldsymbol{\pi}_b^\top + \boldsymbol{\pi}_s^\top}{2} \sum_i \mathbf{z_i} + \frac{\boldsymbol{\pi}_b^\top - \boldsymbol{\pi}_s^\top}{2} \left| \sum_i \mathbf{z_i} \right| + \pi_{bat} \mathbf{1}_T^\top \left| \sum_i \mathbf{u_i} \right| \tag{7a}$$

$$\leq J_U + J_V \tag{7b}$$

which follows from the triangle inequality for vector addition $\left|\sum_{i \in U} \mathbf{z_i} + \sum_{j \in V} \mathbf{z_j}\right| \leq \left|\sum_{i \in U} \mathbf{z_i}\right| + \left|\sum_{j \in V} \mathbf{z_j}\right|$. Additionally, the constraints for the joint aggregation are the union of the constraints (6b) for U and V. These constraints are separable across U and V, as they apply separately on the energy storage within each disjoint aggregation subset. The combined aggregation has an optimization objective (7a) that is lower than the sum of objectives for the disjoint aggregations, and has the same constraints as the combined problems. It follows that the optimal social cost of the combined aggregation will be no greater than the sum of costs for the disjoint aggregations, for any such U, V. □

We now know that the largest possible aggregation is the one with the lowest total cost, i.e. adding a participant to an aggregation will always benefit the aggregation as a whole as well as the additional participant. However, other factors may constrain the expansion of a prosumer aggregation: communication infrastructure required, willingness of participants to share information and cede control of their storage resources, and regulatory restrictions on how large social net metering aggregations can be. In that case, an existing aggregation may have to prioritize letting in some participants, and will need to identify which prosumers are good additions to the aggregation. Our main result devises a metric to evaluate prosumers:

Result 2. *In order to maximize the marginal increase in social welfare, an aggregation should preferentially add participants that maximize the degree of complementarity to the existing participants, i.e. have optimally complementary production/consumption curves. A lower bound on the degree of complementarity can be calculated using*

$$\frac{\boldsymbol{\pi}_b^\top - \boldsymbol{\pi}_s^\top}{2} \left(\left| \sum_{i \in S} \mathbf{z_i^*} \right| + |\mathbf{z_k^*}| - \left| \mathbf{z_k^*} + \sum_{i \in S} \mathbf{z_i^*} \right| \right) \tag{8}$$

where $\mathbf{z_i^*}, \mathbf{z_k^*}$ are the optimal solutions for prosumers in an existing aggregation S and the new entrant k respectively.

Proof. Define J_S^* as the optimal social cost for a prosumer aggregation S concerned with maximizing social welfare. The marginal increase in social welfare from admitting a participant k is given by the decrease in social cost

$$J_S^* + J_k^* - J_{S \cup \{k\}}^* \tag{9}$$

J^* is obtained by solving the optimization problem (6) with the required constraints. Let $\mathbf{z_i^*}, \mathbf{u_i^*}$ denote the optimal net energy and storage operation curves for prosumers $i \in S$, and $\mathbf{z_k^*}, \mathbf{u_k^*}$ denote the same for prosumer k. These satisfy the storage constraints (6b), which are also the constraints for the combined aggregation of $S \cup \{k\}$. If we then consider the objectives defined in (7a),

$$J_S^* + J_k^* = \frac{\boldsymbol{\pi}_b^\top + \boldsymbol{\pi}_s^\top}{2}\left(\sum_{i\in S}\mathbf{z_i^*} + \mathbf{z_k^*}\right) + \frac{\boldsymbol{\pi}_b^\top - \boldsymbol{\pi}_s^\top}{2}\left(|\mathbf{z_k^*}| + \left|\sum_{i\in S}\mathbf{z_i^*}\right|\right) + \pi_{bat}\mathbf{1}_T^\top\left(\left|\sum_{i\in S}\mathbf{u_i^*}\right| + |\mathbf{u_k^*}|\right) \tag{10a}$$

$$\geq \frac{\boldsymbol{\pi}_b^\top + \boldsymbol{\pi}_s^\top}{2}\left(\sum_{i\in S}\mathbf{z_i^*} + \mathbf{z_k^*}\right) + \frac{\boldsymbol{\pi}_b^\top - \boldsymbol{\pi}_s^\top}{2}\left(\left|\mathbf{z_k^*} + \sum_{i\in S}\mathbf{z_i^*}\right|\right) + \pi_{bat}\mathbf{1}_T^\top\left(\left|\sum_{i\in S}\mathbf{u_i^*} + \mathbf{u_k^*}\right|\right) \tag{10b}$$

$$\geq \frac{\boldsymbol{\pi}_b^\top + \boldsymbol{\pi}_s^\top}{2}\left(\sum_{i\in S}\mathbf{z_i^\dagger} + \mathbf{z_k^\dagger}\right) + \frac{\boldsymbol{\pi}_b^\top - \boldsymbol{\pi}_s^\top}{2}\left(\left|\mathbf{z_k^\dagger} + \sum_{i\in S}\mathbf{z_i^\dagger}\right|\right) + \pi_{bat}\mathbf{1}_T^\top\left(\left|\sum_{i\in S}\mathbf{u_i^\dagger} + \mathbf{u_k^\dagger}\right|\right) = J_{S\cup\{k\}}^* \tag{10c}$$

where $\mathbf{z}^\dagger, \mathbf{u}^\dagger$ denote the optimal solutions for the joint aggregation $S \cup k$. (10b) follows from the triangle inequality for vector addition, and (10c) follows from the fact the expression is the objective of the optimization problem solved by the joint aggregation with optimal variable values $\mathbf{z}^\dagger, \mathbf{u}^\dagger$ under the same constraints. The gap (9) is lower bounded by the gap between (10a) and (10b), which is again lower bounded by (8). Thus the marginal improvement in social welfare will always be greater than the value predicted by the approximate metric. □

An aggregation may not have access to complete information while evaluating a new entrant, and may have to make an initial decision based on data that can be shared without privacy concerns. An example of this is metered consumption data, i.e. the energy exchanges with the utility which are denoted by $\mathbf{z_k}$. The expression in (8) can be evaluated numerically by looking at the current net consumption curves of the aggregation and the new prosumer, and can be used to predict which prosumers would be the most profitable partners to admit into the aggregation. This lower bound only holds for the centrally controlled aggregation, and a decentralized control mechanism may deviate from this- we will verify this test with real building data and decentralized transactive control schemes in Section 6.

The marginal reduction in cost (9) will be distributed within the aggregation, and a larger reduction does not necessarily mean that each individual prosumer will be better off- it just means that there is more on the table to be distributed. The metric in (8) depends on both the magnitude and timing of the net demand curves, and a test for complementarity can be designed that uses a normalized version of (8) to account for profit sharing.

5 Agent Based Modeling

The problem of forming and controlling prosumer aggregations is made complex by the fact that a transactive control scheme will modify prices based on the prosumers' operational decisions, resulting in two-way dependencies between price and storage operation (which is modeled as a bilevel optimization problem). The actions of one prosumer affect not only its own cost, but also the costs of other participants in the aggregation. The complex trading relationships between prosumers in an aggregation can not be explicitly formulated, but agent based models can be used to resolve the effects of each prosumer's actions on other participants. An agent based model can be used to analyze the effects of different prosumer operation and control strategies, as well as run Monte Carlo simulations to assess the effects of uncertainty and variability in daily generation and load curves.

Agent based models have been used widely in literature to model a variety of complex systems in transportation, logistics, manufacturing, power systems and the smart grid. They can be used in situations where the relationships between agents are not explicitly defined, and when network effects play an important role. By modeling prosumers as smart agents interacting with each other, different objectives and behaviors can be analyzed easily. The prosumer aggregation analogues of general elements of an agent based model are presented in Table 1.

Prosumer Inter-dependencies Since prosumers trade energy with other buildings through the aggregator, their costs depend on the availability of supply/demand within the aggregation. Any change in

Table 1: General elements of an agent based modeling scheme and its analogues in the prosumer aggregation model

General Element	Analogue in Prosumer Aggregation
Agent	Building, Central Aggregator
Decision Making Heuristic	Cost minimization
Adaptive Response	Response to changing electricity prices
Interaction Topology	Interactions with aggregator as in Figure 1
Environment	Utility policies and actions of other buildings in the prosumer aggregation

participant resources or addition of new participants can affect the balance of energy and market power at each hour. External factors such as battery prices influence the battery operation decisions of buildings by affecting the solution of the optimization problem in (5), and through the trading relationships between participants, may also affect costs of prosumers that do not own batteries. These changes affect costs through cost optimization problems solved by each prosumer independently, and the problem involved can not be resolved easily into an explicit expression for the optimum as a function of these factors.

5.1 Transactive Control

Transactive control is a distributed control strategy that employs market mechanisms such as the price of goods to control selfish economic rational agents. This control strategy only needs information relating to the price and quantity of the good being exchanged, in this case, the electricity demand and price. The controller has to solve an optimization problem of its own where the decision variable is the price it relays to the buildings it is aggregating.

An aggregator optimizing for social welfare through transactive control solves the following problem:

$$\min_{\boldsymbol{\pi_b}, \boldsymbol{\pi_s}} \quad J := \boldsymbol{\pi}_b^\top \left(\sum_i \mathbf{z_i^*} \right)_+ + \boldsymbol{\pi}_s^\top \left(\sum_i \mathbf{z_i^*} \right)_- + \pi_{bat} \mathbf{1}_T^\top \left| \sum_i \mathbf{u_i^*} \right| \tag{11a}$$

$$\text{s.t.} \quad \begin{aligned} \mathbf{u_i^*} = \arg\min_{\mathbf{u_i}} \; & \boldsymbol{\pi}_b^\top \mathbf{z_{i+}} + \boldsymbol{\pi}_s^\top \mathbf{z_{i-}} + \pi_{bat} \mathbf{1}_T^\top |\mathbf{u_i}| \\ \text{s.t.} \quad & A\mathbf{u_i} \leq \mathbf{c_i} \;\; \forall\, i \end{aligned} \tag{11b}$$

which is a bilevel problem. There exist many heuristic methods to solve such problems in the absence of any neat structure, and we use iterative algorithms to get close to the optimum for each transactive control scheme. In general, the aggregator has a multi-objective optimization problem, which is composed of some measure of each prosumer's welfare [21]. The controller can choose to combine these objectives in different ways, and we can simulate different controller objectives using our agent based model.

5.2 Direct Control

A central aggregator could conceivably have direct control over energy storage, especially for agents that lack control mechanisms to respond to price. For such agents, the aggregator could send a charge/discharge signal for each time period. This scenario is modeled as the centrally controlled aggregator in Section 6. Realistically, a lot of small distributed storage is not price responsive, as the prosumer does not have sophisticated control mechanisms or knowledge of prevailing utility prices.

6 Simulations

As discussed previously, implementing centralized control with independent self-interested prosumers may not be possible as prosumers may be unwilling to cede control of their privately owned resources, or to optimize for something other than their own cost. The results derived in the previous section are only applicable to a centrally controlled aggregation- however, research has been undertaken to devise transactive control schemes and market mechanisms that can influence prosumer behavior to achieve close to optimal social welfare. We use a couple of transactive control schemes to verify our results:

1. Supply-demand ratio (SDR) driven price: [5] develops a price model where the ratio of supply and demand determines the buy and sell price within the aggregation.
2. Price under perfect competition: in times of surplus supply, suppliers compete to sell at the lowest price greater than the utility alternative, i.e. π_s. Similarly, during surplus demand times, consumers purchase energy at any price lower than the utility alternative π_b [1].

These prices are dependent on the aggregation's operating status and have to be set in an iterative manner due to this inter-dependence. We design an agent based model in Python that includes the elements in Table 1 that can implement iterative pricing schemes.

Implementation: For the simulations presented in this paper, the time of use pricing is obtained from [22] and the battery costs are estimated from generic Li-ion battery data [23]. Battery one-way efficiency is taken to be 95%. The agent based simulation framework is built in Python, and the Scipy optimization package [24] is used for the participant and aggregation optimizations. The prosumers considered are commercial office buildings modeled using load data taken from [25], which is a publicly available dataset of real hourly loads of a collection of buildings across the world. A total of 10 commercial and university buildings in the Los Angeles region were chosen for simulation which are being used as office space. Their power usage is of the order of $10 - 200$ kW, and the simulations use varying levels of battery installations and PV array sizes for each of the buildings. Photovoltaic array power output is estimated using the NREL PVWatts Calculator tool [26]. The building loads and PV outputs are used as a deterministic number, but realistically will have a level of uncertainty associated with them. To build a robust estimation of cost, Monte Carlo simulations are done with data spanning a set of 100 days across the year to incorporate seasonal variations.

6.1 Effects of Utility Prices and Control Paradigms

We first validate our remarks on the optimal social welfare achieved by centralized control (Remark 2) and the value proposition of aggregations (Remark 1). The results of an agent based simulation of the set of prosumers mentioned previously with differing utility price regimes and different control mechanisms are shown in Fig 2. As can be seen in the figure, the centrally controlled aggregation has the lowest social cost, while the other decentralized transactive control schemes achieve a level between the optimal and the no aggregation case. As the price of energy sale to the utility (π_s) increases, the marginal value of aggregating reduces, and in the presence of net-metering ($\pi_b = \pi_s$) forming an aggregation results in zero cost reduction irrespective of the way in which it is controlled.

6.2 Superadditivity and Degree of Complementarity

We now examine Result 2 by comparing the numerical metric for degree of complementarity (8) with the realized marginal benefit of aggregation. We consider an aggregation of 5 office buildings (*Original aggregation* in Fig 3) and evaluate three new potential participants: A, B and C. A and C are net producers, with A having a lower (negative) cost than C. B is a net consumer with a cost similar to the aggregation. Fig 3 compares the sum of costs with the cost for the joint aggregation, i.e. when the new

Figure 2: Social costs for an aggregation under differing utility price regimes and control methods

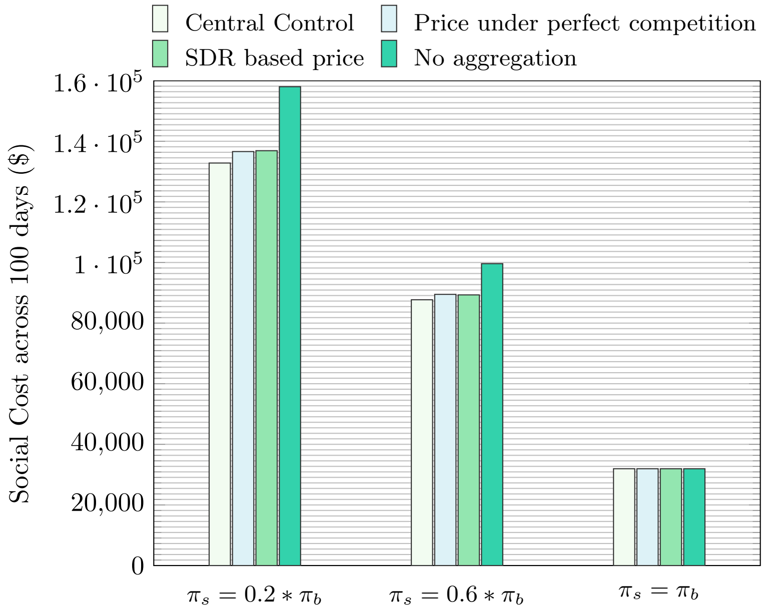


Figure 3: Comparison of degree of complementarity with the marginal increase in social welfare for a centrally controlled aggregation

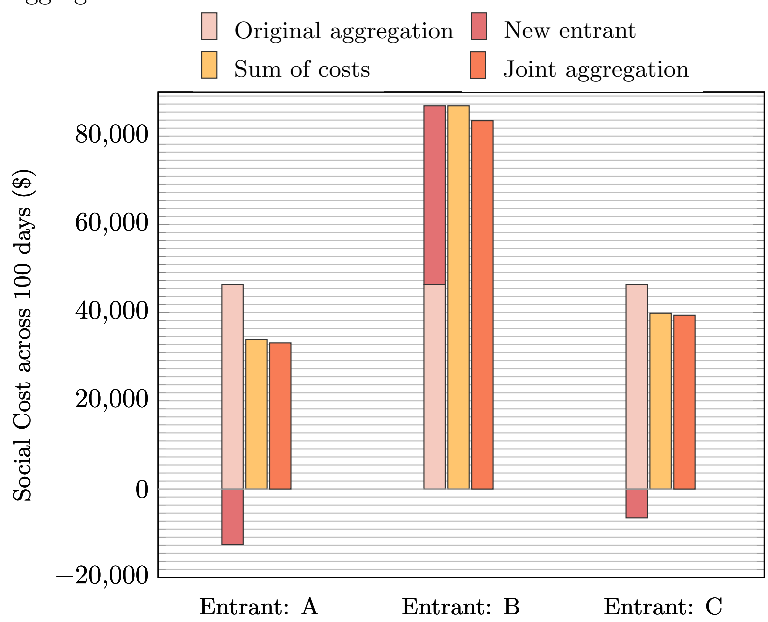
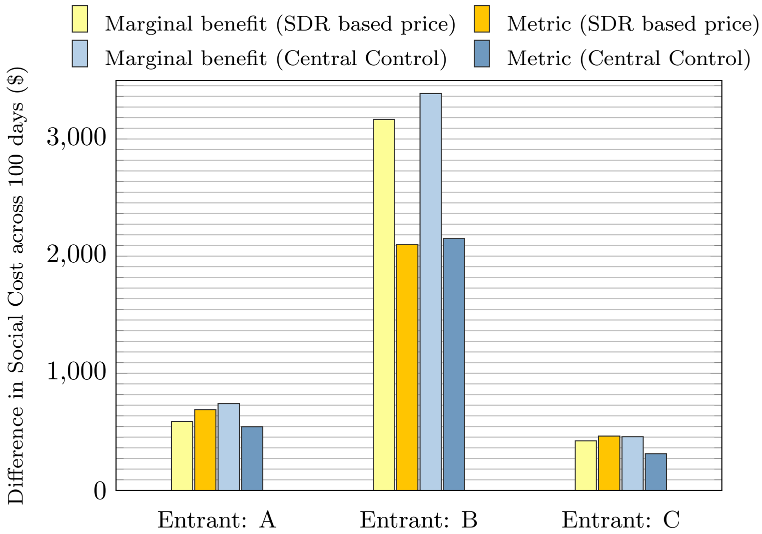


Figure 4: Comparison of marginal benefit of aggregating with the numerical metric in (8)



prosumer is added to the aggregation. As a validation of Result 1, the cost of the combined aggregation is always lower than the sum of costs of the constituents.

The marginal value of aggregating is given by the decrease in social cost (9), and Fig 4 compares the marginal value with the numerical metric for degree of complementarity (8) for two different control schemes. Even though A and C have net negative costs, it is the addition of B that provides the most marginal value for the aggregation (Fig 4). This shows that assessing a new prosumer is not a trivial task, and validates the importance of the metric we developed in (8).

As discussed previously, decentralized control schemes are not able to achieve optimal social welfare and the results derived previously may not hold for them. In Fig 4, the metric (8) for SDR based price control is not a lower bound for the marginal value of aggregation in two out of three cases, but is a close approximation of the realized value. For centrally controlled aggregations, the entry of each new prosumer causes a reduction in social cost that is lower bounded by the numerical metric for degree of complementarity (8) as predicted by our theoretical analysis.

7 Discussion

In this report, we developed ideas on when aggregations make sense and what an optimal aggregation looks like. We also developed a numerical test to prioritize the addition of prosumers, and validated our results with simulations in an agent based modeling framework with transactive control schemes and real building data.

If a profit seeking entity such as a commercial DER aggregator were to manage a prosumer aggregation, it would introduce *friction* in the system. Some of the marginal value of the aggregation would go towards profits, and any new participant would have to achieve a degree of complementarity above a minimum threshold level to guarantee a certain profit margin.

A prosumer aggregation is a way to capture some additional value. A question that naturally follows is: where does this value come from, and why do existing entities such as the utility not capture it already? As discussed in Remark 1, the value results from a difference in utility prices, and normally accrues to the utility. If an aggregation were to be formed, the utility would lose this value- however, there are many reasons a utility would still permit social/virtual net-metering as described in this paper. Prosumers do have some market power, as they could defect from the utility and form a microgrid with additional investment. More realistically, regulatory mandates could force utilities to allow such schemes as the presence of aggregations makes it profitable for prosumers to further invest in distributed generation and consume it locally, leading to a reduction in usage of carbon-emitting generation.

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