The Social Cost of Individual Privacy in Aggregated Residential Demand Response*

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Abstract— **There is an increasing body of experimental and theoretical research related to demand response using smart, connected home equipment in smart grid. However, as technologies are deployed at scale, privacy has become a major concern. One possible approach to address this concern is to model an entire home as an aggregated unit of resource for engaging in demand response. Such an approach would allow residents to participate in demand response while abstracting the specifics of the appliance usage pattern from the utility provider. The benefits of privacy-preserving demand response notwithstanding, it implies a cost in terms of wasted capacity. This paper aims to explore the privacy/capacity tradeoff by simulating a fleet of homes and comparing the results with a fleet of individual appliances. The results show that a fleet of homes only bids about 70% of available capacity, and in the presence of an aggregator this number declines to 50%. Thus, privacy of individual homes comes at a cost of sacrificing part of otherwise available capacity.**

Keywords— demand response, HEMS, aggregation, cost of privacy

I. INTRODUCTION

In the last several years, there has been significant growth in the number of intelligent electrical appliances within the residential sector. The internet of things has provided new opportunities to interface and communicate with appliances, adopt artificial learning and adaptive control, and to look at the future with highly intelligent buildings.

Intelligent appliances and home energy management systems (HEMS) can also allow utilities to manage system coincident peak and thus achieve cost reduction [1]. Further, there exists the potential for residential loads to provide ancillary services [2]. However, the growing control that utilities can exercise over specific in-home appliances can cause coordination and privacy concerns. Access to individual appliance usage history can reveal unwanted detail about user intra-day routines, thus compromising user privacy. Direct control of individual appliances may also imperfectly align with user preferences: for instance, a utility or aggregator may be interested in interrupting heating, ventilation, and air conditioning (HVAC) system operations while the users would instead be more willing to turn off a water heater. While the discussion of privacy and user preferences continues to develop, there have been a variety of suggestions about how to handle load while preserving the privacy of home energy use data (for instance, [3], [4]). One of the popular solutions that has a well-developed theoretical base [5] is to aggregate a whole-house into a single unit for demand response. As a result of aggregation, the utility only has information regarding total available capacity of a house without specific knowledge of the supporting assets. Thus, demand response service is offered to the utility without giving up any sensitive information or control over specific appliances.

This paper attempts to understand whether protection of privacy affects the provision of demand response capacity. If a certain percentage of capacity is lost under a home single bid scenario (to ensure delivery of a promised commitment), there is social cost to maintaining privacy. Further, if a significant amount of capacity is lost, bidding a whole house may be prohibitively expensive from the system standpoint.

The study is organized as follows. Section II summarizes the theoretical foundations of residential-level load aggregation. Section III provides the description of demand resource stacking and dispatch algorithm. Section IV shows simulation results for system size of IEEE 33, IEEE 69, and IEEE 123. Section V provides an additional simulation in the presence of a demand aggregator. Section VI provides the conclusion of the study.

II. CENTRALIZED VERSUS DECENTRALIZED APPLIANCE STACKS

As discussed in the introduction, there are currently two approaches to demand response. The centralized approach (e.g., direct load control) advocates that a utility or aggregator should be able to call any specific appliance if the value of calling on that appliance to provide grid service

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is sufficiently high. The main shortcoming of this approach is that third parties may be able to access and potentially use the information about individual loads, thus compromising privacy. Further, remote control of individual appliances may interfere with user comfort and eventually cause users to opt out from the demand response program. The decentralized approach allows a home energy management system to make the decision of which appliances to operate in order to offer the demand response service.

In this paper, the method of offering services to the utility is performed through a battery-equivalent model methodology. Appliances that already have an in-built physical battery, for instance a rooftop photovoltaic (PV) system with battery, are represented by their battery capacities. Thermostatically controlled loads such as water heaters and HVACs are first modeled to find state of charge (SOC) based on user setpoints and thermal capacities of the water/air temperature and forecasted outdoor temperature. This information is combined with rated power of an appliance to produce an estimated energy storage capacity and SOC. Information about individual appliances as battery equivalents are fed to the HEMS for energy use optimization. After a HEMS has selected optimal appliance operations and produce an aggregate bid, the utility can perform an optimal of available capacity as shown in Fig. 1.

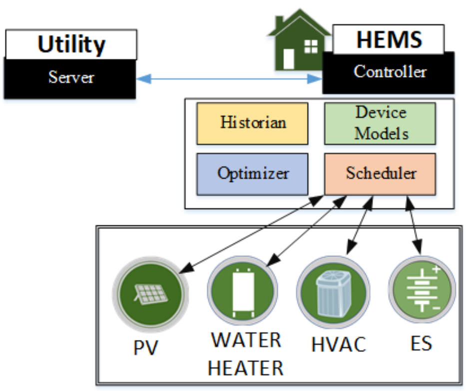


Fig. 1. Example HEMS system [10]

A robust model for aggregation of loads within a HEMS is achieved through maximization of inner Minkowski sum [6], [7], [8]:

$$E_j = \sum_i P_i \, charge_i \qquad (1)$$

s.t.

$$P_i = P_{rated\ i}$$
$$charge_i \leq charge_{max\ i}$$

where E_j is the optimal bid of house j, equivalent to its energy capacity as house battery, kWh. P_{rated} is rated power of appliance i, kW. $charge$ is the remaining charge of appliance i, h to discharge, and $charge_{max}$ is the maximum possible charge of appliance i, h.

The energy storage capacity of an appliance is affected by user settings or the nature of the appliance. For instance, the HVAC energy storage capacity is affected by the user-defined schedule or house area (thermal mass and volume of air to cool). Similarly, water heater storage capacity would be affected by the user setpoint and nameplate volume of a water heater.

The energy capacity of a house or an appliance is directly utilized to provide a demand response bid. For the purposes of this study, the utility is assumed to collect demand response bids from the control area every hour. Based on the demand response requirements, the utility clears the necessary amount of capacity and calls the selected houses to respond by acting on the controllable assets. The mechanism of selection is not the focus of this study, but the approach is compatible with both cost-based and energy-capacity based mechanisms. The final result of bidding and clearing is a signal to shed a certain load, e.g. 5 kW, for a certain period, e.g. 40 minutes, to provide 3.3 kWh of demand response at a specific site.

From an economic and physical perspective, the main difference between the two approaches is the size of the demand response capacity that is eventually proposed for dispatch. The nature of this difference is illustrated in Fig. 2. Let us suppose that there are two identical houses, each of which can curtail load on HVAC, (6 kW for 1 hour), and a water heater (3 kW for 2 hours) (Fig. 2a). If house 1 and house 2 were to bid appliances separately, the utility would get a total of $6 \times 1 + 3 \times 2 + 6 \times 1 + 3 \times 2 = 24$ kWh (Fig. 2b). But if each house bids an aggregation of loads, part of the capacity (in this instance, of the water heater) is excluded due to optimality conditions (Fig. 1c, “Trim” area shows the part of the water heater capacity excluded to create an optimal rectangle). Each house would bid the entire HVAC and only one hour of water heater, as other hours would not fit the inner Minkowski sum. The utility would then get $9 \times 1 + 9 \times 1 = 18$ kWh.

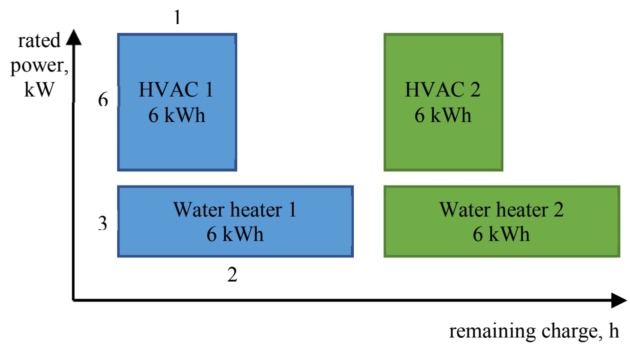


Fig. 2(a). Dimensions of available appliances.

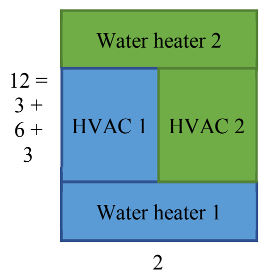


Fig. 2(b). Optimal stack when all appliances are available.

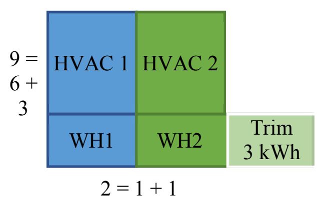


Fig. 2(c). Optimal stack when each HEMS trims part of water heater.

If the total capacity offered by a neighborhood in the form of individual appliances exceeds the total capacity offered in the form of entire home-sized bids, there is a social cost to individual privacy and user convenience. To address this question, two scenarios are formulated. In the first scenario, a utility has direct access to a fleet of appliances. In the second scenario, each house is able to decide independently on generating whole-home load shape by stacking individual appliances, as a single battery-equivalent. Once the utility receives aggregated bids, it makes a choice which bids to call for demand response. The resulting volumes are expected to differ by the social cost of privacy and user preferences.

III. Demand-side Resources Stacking and Dispatch Algorithm

Despite being recognized as a preferred approach to aggregating individual devices into a single energy storage-equivalent bid, Minkowski sum is difficult to implement. The packing optimization of the sum results in an NP-hard problem and does not account for the physical and economical nature of the problem.

First, the traditional problem minimizes the bin area (outer sum), while the objective of the HEMS system is to maximize the inner sum. The inner sum is where the homeowner observes the expected electricity cost savings.

Further, the traditional problem is very general and allows rotation and sometimes slicing of the shapes, as well as fitting shapes into multiple bins. However, the appliance rated power is not conducive to shape manipulation. The nominal power of appliances cannot be altered without additional exterior equipment (e.g. a water heater cannot run at half of manufacturer indicated power without separate hardware.) The exception is variable speed drives that can modulate power consumption such as that found in more advanced HVAC systems. Still, these tend to be much higher in cost and are not typical in residential installations. On the other hand, energy capacity can be adjusted as the number of hours of reduced operations can be controlled. As a result, each rectangle in the stack may change along x-axis, remaining charge, hours, but must be kept at nominal value along y-axis, rated power, kW.

Finally, the traditional problem allows for empty inclusions in a bin. While smoothing and derating some of the "home batteries" is possible, an accurate problem should not allow to subscribe nonexistent capacity. If a battery is allowed to have an empty corner, claiming full rated power for the full duration of charge would create over subscription of capacity and, possibly, voltage or frequency drops when the oversubscribed capacity is not able to respond.

The resulting adjusted problem is addressed using a sorted two-dimensional bin packing algorithm with partial trimming [9]. This approach permits the optimization with rectangles of fixed height and flexible width. This approach also allows packing without gaps inside the optimized space.

For implementation, the computational algorithm was designed using a python script to pre-sort the input list. In accordance with the abovementioned packing algorithm, appliances are sorted by height (rated power) as shown in Fig. 3. This approach has a strong advantage where partial trimming is needed (which is inherently true with the residential load makeup). Because rated power cannot be trimmed, in the absence of initial sorting the resulting polytope could be non-convex (for instance, when an appliance with higher rated power is placed to the right of an appliance with lower rated power). This thread of the algorithm then would have to be discarded. While the suggested algorithm reduces the potential number of combinations, it improves computational efficiency.

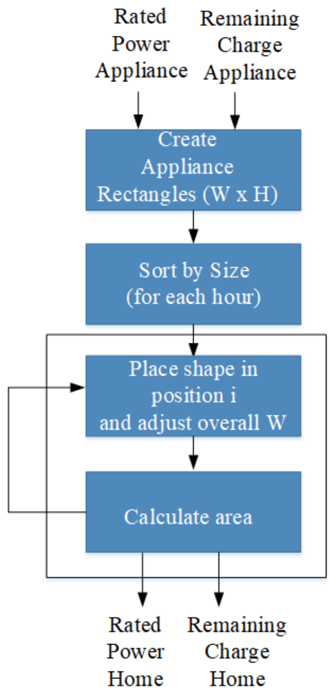


Fig. 3. Process flow for approach.

The sorted list of appliances is processed by placing each appliance either on the top or to the right of the appliances already in place. As can be seen below, this is not a "greedy" algorithm. The algorithm generates multiple search branches, such as "top-top", "top-right", "right-top", "right-right". Even if a certain combination of appliances (e.g. "top-top") gives the highest inner sum at a given moment, the branch "top-right" would still be considered while placing the next appliance. In the presence of trimming along the x-axis (hours), a "greedy" algorithm may result in rejecting potentially optimal search branches. For instance, in the presence of branch "top-right-top", and if the combined height of appliances 2 and 3 equal to height of appliance 1, a complete enumeration of positions allows to find a potentially larger inner area of the polytope. An additional comparison with full enumeration (unsorted bin packing algorithm with partial trimming) showed that the suggested approach yields 100% efficiency. Its largest inner sum of appliances is as large as the largest inner sum of appliances found by full enumeration.

If any of the capacity is left unused, the algorithm discards it. This is a limitation on the use of power and capacity of resources. If demand response capacity is not used at a given stage, the demand response potential would be diminished at later stages due to self-discharge. Hence, leaving unused capacity for later does not eliminate the potential completely, but still reduces potential.

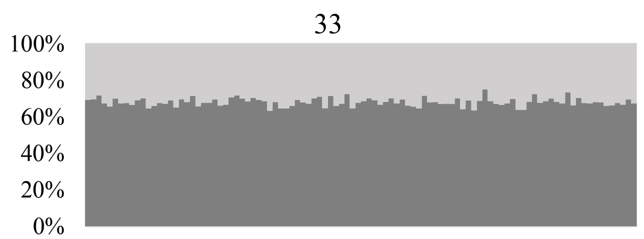
IV. Results: Battery Appliances vs Battery Houses

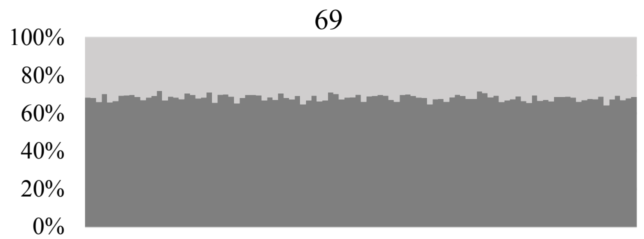
Each house is assumed to have an HVAC system, a water heater, a pool pump, and either an electric vehicle with a standard charger or a rooftop PV system with a battery. The listed appliances have been chosen because they are common for use in residential neighborhoods. The appliances were initialized with random charge between 10% and 100% of maximum SOC. This approach was developed to reflect the physical nature of a battery, which is not allowed to discharge completely. The effective average charge of a single house was found between 40% and 60%. The data for the appliances is shown in Table I.

TABLE I. Simulated Appliances

Appliance	Rated power, kW
HVAC Royalton 2.5 ton	8.2
HVAC Winchester 2 ton	7.0
Water heater Rheem 80 gal	5.0
Water heater Rheem 50 gal	4.5
Pool pump FlowXtreme II	1.1
Pool pump Hayward Super Pump	0.7
Tesla Powerwall	5.0
LG Chem	3.0
Charger	3.8

The results for simulations of 100 iterations with 33, 69 and 123 houses, 4 appliances in each, are provided in Fig. 4. As shown, when the HEMS submits aggregated bids only, about 70% of capacity is offered to the utility as demand response capacity. The results are consistent across neighborhood sizes, although variance decreases in larger neighborhoods.





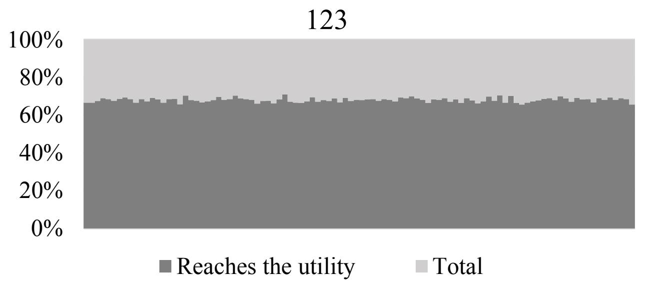


Fig. 4. A comparison of bidding of appliance fleets and house fleets, where appliance fleet represents 100% of available capacity.

This allows to conclude that the privacy-preserving mode cuts about a third of available capacity (the actual share is 31.79-31.96%), thus resulting in a suboptimal use of available resources. This, in turn, creates latent social cost.

V. Results: Effect of a Community Aggregator

In some residential settings, such as townhomes or multi-apartment buildings, or even in some instances of neighborhoods with detached houses, bidding separate homes to a utility may be infeasible. Such a situation may be found, for instance, in the event of rental housing. Then an additional intermediary appears in the form of a residential aggregator which collects bids from individual units and communicates them to a utility. The utility then sees a battery-equivalent resource behind a distribution feeder. In the presence of an intermediary the optimization problem becomes two stage (Fig 5).

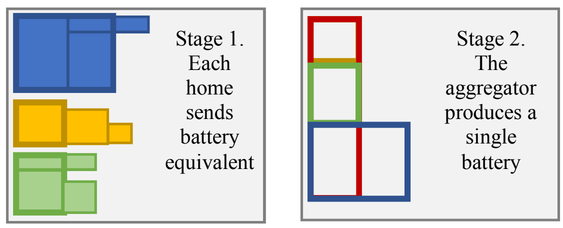


Fig. 5. Two-stage decentralized approach versus one-stage centralized algorithm.

In the first stage homes submit their bids to the aggregator, in the second stage the aggregator submits a community bid to the utility. If the aggregator wants to similarly keep a utility abstracted from the conditions behind the distribution feeder, the double packing would result in a two-stage Minkowski sum problem.

$$E = \sum_j P_j \, charge_j = \sum_j \sum_i P_i \, charge_i \tag{2}$$

s.t.

$P_i = P_{rated\ i}$
$P_j = P_{declared\ j}$
$charge \leq charge_{max}$

Where

E is optimal bid of a group of loads, equivalent to its energy capacity as a multi dwelling unit battery

$P_{declared\ j}$ is the declared capacity of house j, kW

P_{rated} is rated power of appliance i, kW
$charge$ is the remaining charge of appliance i or house j, h to discharge
$charge_{max}$ is the maximum possible charge of appliance i or house j, h.

The optimization results in similar loss of capacity at each stage, as illustrated in the previous section. However, now in the presence of an aggregator the losses are incurred twice. The first stage results in about 70% of capacity being disclosed to an aggregator, and the second stage results in about 75% of received capacity being transmitted to a utility. In a smaller simulation of 10 dwellings in a multi-unit building the total capacity that reaches the utility is around 50% (Fig. 6).

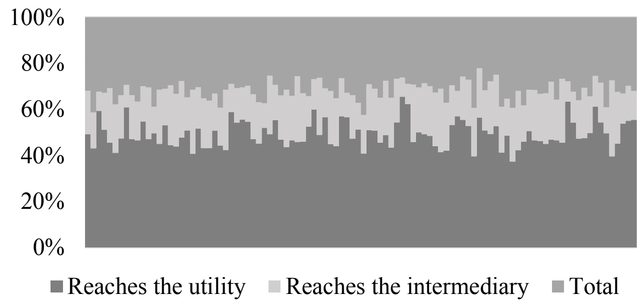


Fig. 6. A comparison of bidding appliance fleets, house fleets or multi-dwelling units, where appliance fleet represents 100% of available capacity.

Additional layers of protection, thus, generate such a high cost that they may become unacceptable. While this simulation provides an extreme example of double aggregation, this demonstrates the loss of demand response potential while considering a home aggregate level model.

VI. CONCLUSIONS

The analysis shows that about 32% of total available capacity is never offered to a utility due to the privacy preserving action of HEMS. In the presence of double optimization this number increases to about 50%. Preserving individual privacy clearly comes with a lowered demand response potential. Aggregation of the home assets though a HEMS and providing this aggregate as an energy storage block while maintaining privacy and user choice has definite drawbacks.

The simulated nature of this study leaves ample room for testing privacy-protecting bidding systems in actual neighborhoods. Additionally, this study is limited to the currently dominant approach of aggregating loads to maximize inner Minkowski sum. If alternative approaches to aggregating loads appear later, the balance of benefits and costs of aggregation may change.

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