Multi Agent Coordination for Demand Management with Energy Generation and Storage

Ronghuo Zheng[1], Ying Xu[1], Nilanjan Chakraborty[2], Michael Lewis[3], and Katia Sycara[4]

[1] Tepper School of Business, Carnegie Mellon University, Pittsburgh PA 15213, USA
ronghuoz,yingx1@andrew.cmu.edu
[2] Stony Brook University, Stony Brook NY 11794, USA
nilanjan.chakraborty@stonybrook.edu
[3] School of Information Science, University of Pittsburgh, Pittsburgh, PA 15260, USA
ml@sis.pitt.edu
[4] Robotics Institute, Carnegie Mellon University, Pittsburgh PA 15213, USA
katia@cs.cmu.edu

Abstract. In this paper, we focus on demand side management in consumer collectives with community owned renewable energy generation and storage facilities for effective integration of renewable energy with the existing fossil fuel-based power supply system. The collective buys energy as a group through a central coordinator who also decides about the storage and usage of renewable energy. produced by the collective. Our objective is to design coordination algorithms to minimize the cost of electricity consumption of the consumer collective while allowing the consumers to make their own consumption decisions based on their private consumption constraints and preferences. Minimizing the cost is not only of interest to the consumers but is also socially desirable because it reduces the consumption at times of peak demand (since differential pricing mechanisms like time-of-use pricing is usually used by electricity companies to discourage consumption at times of peak demand). We develop an iterative coordination algorithm in which the coordinator makes the storage decision and shapes the demands of the consumers by designing a virtual price signal for the agents. We prove that our algorithm converges, and it achieves the optimal solution under realistic conditions We also present simulation results based on real world consumption data to quantify the performance of our algorithm.

1 Introduction

Facing the rapid depletion of fossil fuel reserves and the increasing carbon emission, one main objective in energy industry is to reduce the usage of fossil fuels for electricity generation. This can be achieved by (a) increasing the penetration of renewable energy sources in (e.g., wind energy, solar energy) in electricity supply and (b) reducing the usage of fossil fuel-powered generators that are usually used to meet peak demand by shifting energy use of consumers at peak demand. To enhance the penetration of renewable energy sources in electricity supply, there has been several recent initiatives at using *community-owned generation facilities* for supplying part of the electricity needs of a community [1]. To reduce the variation of supply of renewable energy sources due to uncontrolled factors like weather, it is usually recommended to also have storage facilities. Therefore, in this paper, we focus on demand side management in consumer collectives with community owned renewable energy generation and storage facilities for effective integration of renewable energy with the existing fossil fuel-based power supply system.

Effective integration of renewable energy should be able to not only reduce aggregate demand for the energy generated by fossil fuel, but also to reduce peak demand from the traditional power plants. To reduce peak demand, electric utilities use differential pricing systems like time-of-use-pricing (where higher prices are charged at times of expected high load). Thus, we want to minimize the electricity consumption cost of the collective which reduces the consumption at times of peak demand and is also of interest to the consumers. In particular, we study a collective of consumers in the presence of a collectively owned renewable generation facility (e.g., solar panels) and a collectively owned storage facility (e.g., battery). The electricity demand of the group of consumers is fulfilled by renewable generation and the electricity market. A central coordinator purchases electricity from the market on behalf of the consumers and also makes decisions on the usage and storage of renewable energy. The consumers have their individual private constraints and preferences, which they may not want to share with other group members or the coordinator. The consumers make their consumption decisions based on their private constraints and preferences. Our goal is to *design coordination algorithms so that the coordinator (with knowledge of the market price of electricity and a forecast of the renewable generation) minimizes the total cost of electricity procurement of the collective by (a) managing the operation of the storage and (b) shaping the consumers' demand while allowing them to make their own decisions about their electricity usage subject to their private constraints*.

Although our problem can be formulated as an optimization problem, solving the problem becomes challenging because of the lack of knowledge of the agents about the whole problem. Each consumer only knows its own demand constraints but has no knowledge about the constraints of other agents. The no knowledge assumption has been shown to be a challenge in other group decision problems such as multi-agent negotiation(e.g., [2, 3]). The coordinator also does not have any knowledge about the agents' constraints. Thus there is no agent who has all the "data" about the problem to be solved. The only common knowledge is about the forecast of available renewable energy (which we assume to be reasonably accurate) and the market price of electricity over the planning horizon. These assumptions are reasonable for day ahead planning, where the electricity is obtained from a day-ahead market and the weather forecast is accurate enough to get a reasonable forecast. The coordinator is similar to a mediator in a negotiation among the consumer collective (e.g., [4, 5]) who needs to search for the optimal mediation protocol but also needs to decide the storage policy in our problem. The coordinator is not a market maker or a traditional demand response aggregator, but is akin to a social planner (similar to [6]). But the task of our coordinator is more complicated: in addition to coordinating consumers' demand, the coordinator has to solve the *coupled problem* of designing a method for charging and discharging storage.

To solve the coupled demand and storage management problem, we design an iterative algorithm consisting of two primary steps. In one step, the coordinator assumes a profile for charging and discharging the battery and uses virtual price signals to coordinate the consumers to obtain an optimal demand profile. In the second step, the coordinator uses the demand profile given by the consumers to compute an optimal storage solution. In step one, through the use of the virtual price signal, we ensure that (a) when each agent minimizes its own energy consumption cost, the total cost is also minimized and (b) at the optimal solution, each agent's *virtual* energy cost calculated based on its virtual signal equals its real payment. Using (a) and (b) above, we prove that our iterative algorithm converges to the optimal demand profile for the agents that minimizes the total energy cost. Furthermore (b) above ensures that the total amount that the agents pay is equal to the total electricity bill that the collective has to pay to the utility (i.e., budget-balance is achieved). The design of this provably optimal budget-balanced algorithm in the presence of limited knowledge is the key contribution of this paper. We also performed simulations based on real world consumption data. We show that the number of iterations taken for the agents to converge to the optimal solution is not sensitive to the size of the cooperative.

2 Related Work

Our work is related to two streams of research: demand side and storage management. There is extensive research about demand response programs for managing consumer side demand, either through direct load control (DLC) or indirect incentive based control, such as real time prices (RTP) (see [7] and references therein). We will restrict our discussion on how to design virtual price signals to incentivize consumer demand shifting. The design of price signal is challenged by the possibility of the *herding* phenomenon, whereby agents shift their consumptions towards the low price times simultaneously and thus cause a new spike in demand, thereby increasing the energy cost [8]. Previous work has proposed various heuristics. [9] uses an adaptive approach by sending both price and control signals to agents to control the rate and frequency of agents reacting to real-time prices so as to avoid simultaneous shifting. Unlike these papers, we study the problem from the perspective of demand schedule planning. In addition, we maintain privacy of consumers without relying on consumers learning and we keep budget balance without charging any addition fees.

Most storage management problems can be classified into two categories: storage management at the demand-side or at the supply-side. The demand-side storage management is related to how to coordinate end users each of whom owns a storage facility and makes overall decisions in terms of individual energy demand scheduling and charging/discharing of individual owned batteries; e.g., [10, 11, 12, 13]. In contrast, in our model, the storage facility is not operated at the individual level but at the aggregate level: the coordinator who operates the storage facility finds it difficult to optimize storage decisions for the whole group as he has no knowledge of the individual consumption constraints and preferences.

Prior work on the supply-side storage management has focused on how to use storage to stabilize the output of renewable energy supply when joining the conventional electricity markets (e.g., [14, 15]), or to directly satisfy consumers demand (e.g., [16, 17]). A common setting in these papers is that the energy demand is exogenous and independent of storage operations. In contrast, in our problem, the demand pattern of consumers is endogenously affected by the coordinator's storage decisions and therefore the design of storage strategy should take into account the consumers' response.

3 Problem Formulation

We consider a consumer collective with N members with the planning period divided into M discrete time slots. A central coordinator purchases electricity on behalf of the consumer collective from the market. The collective has a community owned renewable energy generation facility (e.g., solar panels, wind mills) which can only supply a part of the energy required by the collective. The collective also has a community owned storage facility. The storage capacity is also less than the amount of energy required by the collective. The coordinator is in charge of the storage and the generation facility. We assume that the forecast for the amount of generation for the planning horizon is accurate. Furthermore, the electricity prices from the market are also known. These assumptions are reasonable for a 24 hour planning period with the electricity being bought from a day-ahead market.

Let $\mathbf{g}$ be the forecast vector for the amount of electricity to be generated over the M time slots with g_j the energy generated in time slot j. There is an upper bound on the amount of electricity that the agents can draw from the market (determined by the physical constraints of the distribution infrastructure) denoted by $\mathbf{h}$. Let $\mathbf{p}$ be the market price vector which can vary over the M time slots. The component for the jth time slots of $\mathbf{h}$ and $\mathbf{p}$ are denoted by h_j and p_j respectively. The market price and the market supply capacity is common knowledge for the central coordinator and all the agents in the group. Let $\mathbf{R}$ be an $N \times M$ matrix where each row of the matrix, $\mathbf{r}_i$ is the electricity demand of the agent i, $i \in \{1, 2, \ldots, N\}$. We call $\mathbf{r}_i$ the *demand profile* of agent i. Each entry r_{ij} is the electricity demand of agent i for time slot j. The total aggregated demand in time slot j is $\rho_j = \sum_{i=1}^{N} r_{ij}$.

The demand profile $\mathbf{r}_i$ of each agent i must satisfy their individual constraints. We will assume that the constraints on the demands are given by a constraint set $\mathcal{X}_i$ which is private knowledge of the agent i. **An agent does not share this constraint set $\mathcal{X}_i$, neither with other agents nor with the coordinator.** Unless otherwise specified we will assume $\mathcal{X}_i$ to be a convex polytope, which is a fairly general model for energy consumption constraints in this setting [11, 6].

The central coordinator needs to make an energy storage decision. Specifically, in each time slot j it needs to decide whether and how much to charge or discharge. These (dis)charging decisions are represented by the (dis)charging amount at each time slot, denoted by $y_j \in [-d, d]$ for $j \in \{1, 2, \ldots, M\}$, where d denotes the maximum (dis)charging amount during each time slot, and if $y_j > 0$, at time slot j, the facility is charged with an amount of y_j; if $y_j \leq 0$, the facility is discharged by an amount of $-y_j$. The storage decision variable over the time horizon is the vector $\mathbf{y}$. Given the charging and discharging amount at each time slot, $\{y_j\}$, the storage level at the end of the time slot is $\sum_{k=1}^{j} y_k$. The storage level at the end of each time slot should be non-negative and also less than the capacity of the storage facility, denoted by $\mathbf{u}$. Therefore, the charging and discharging decision is also constrained by

$\sum_{k=1}^{j} y_k \in [0, u], \forall j \in \{1, 2, \ldots, N\}$. The constraints for storage decisions is a system of linear inequalities:

$$0 \leq \mathbf{A}\mathbf{y} \leq \mathbf{u}, \quad -\mathbf{d} \leq \mathbf{y} \leq \mathbf{d}.$$

where $\mathbf{A}$ is a lower triangular matrix with elements 1, and 0, $\mathbf{y} = [y_1, ...y_j, ...y_M]^T$, $\mathbf{u} = [u, ...u, ...u]^T$ and $\mathbf{d} = [d, ...d, ...d]^T$.

The amount of energy drawn from the market in time slot j is $\rho_j + y_j - g_j$. Thus the energy cost is $p_j \cdot (\rho_j + y_j - g_j)$. Since the objective is to minimize the sum of all agents costs, the central demand scheduling problem can be written as:

$$\begin{array}{c} \min_{\mathbf{R},\mathbf{y}} C^s(\mathbf{R}, \mathbf{y}) := \sum_{i=1}^{N} p_j \cdot (\rho_j + y_j - g_j) \\ \text{s.t. } \mathbf{r}_i \in \mathcal{X}_i, r_{ij} \geq 0 \\ 0 \leq \mathbf{A}\mathbf{y} \leq \mathbf{u}, -\mathbf{d} \leq \mathbf{y} \leq \mathbf{d} \\ 0 \leq \rho + \mathbf{y} - \mathbf{g} \leq \mathbf{h} \end{array} \tag{1}$$

The operating cost associated with the renewable energy is assumed to be constant, i.e., independent of the amount of energy produced, and is thus not a part of the objective function. Note that the above problem is defined on a convex set. Moreover, the objective function is linear. Therefore, Problem (1) is a convex minimization problem and is thus solvable optimally.

4 Solution Approach

While Problem (1) is solvable, the central coordinator could not directly determine the optimal demand profile and the storage solution because he has no knowledge of consumers' consumption constraints $\mathcal{X}_i$ for any $i \in 1, 2, ...N$. We assume that the coordinator affects the energy consumption plans of individual agents via *virtual price signals* and the individual agents *honestly* report their optimal demand based on the virtual price signals.

A simple virtual signal based on market price alone is ineffective to optimize coordination because in our problem the aggregate supply also depends on the coordinator's storage choices. The optimal storage solution and the optimal demand profile are coupled in the constraints and thus depend on each other. To address this issue, one approach is to decompose the problem into two subproblems: (1) ***optimizing the storage solution*** given the demand profile (**OSS**); (2) ***optimizing the demand profile*** given the storage solution (**ODP**). Correspondingly, we give two definitions:

Definition 1. $\sigma : \mathbf{R} \rightarrow \mathbf{y}$*: the function maps demand profile to optimal storage solution.*

Definition 2. $\delta : \mathbf{y} \rightarrow \mathbf{R}$*: the function maps storage policy to optimal demand profile.*

We design the coordination algorithm as (see Figure 1):

1. Without storage, the central coordinator finds the demand of individual agents, $\mathbf{R}^*$, that minimizes the energy cost.

2. **OSS**: Given the demand profile $\mathbf{R}^*$, the central coordinator solves the optimal storage solution, $\mathbf{y}^* = \sigma(\mathbf{R}^*)$, to minimize the energy cost.
3. **ODP**: Given the storage solution $\mathbf{y}^*$, the central coordinator coordinates the demand of individual agents, $\mathbf{R}^\sharp = \delta(\mathbf{y}^*)$, to minimize the energy cost.

Stopping Criterion If $\mathbf{R}^\sharp = \mathbf{R}^*$, stop. Otherwise, $\mathbf{R}^* = \mathbf{R}^\sharp$, and go back to step 2.

Note that step 1 is a special case of step 3 **ODP** with storage solution $\mathbf{y}^* = \mathbf{0}$. In step 2 **OSS**, only central coordinator makes decision on the storage solution. In step 3 **ODP**, the central coordinator determines virtual price signal and the agents calculate demand according to the virtual price signal.

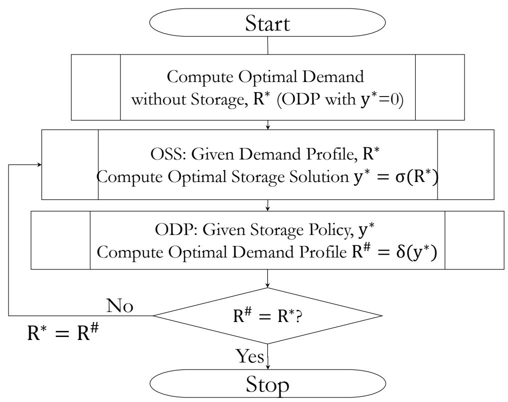

Fig. 1: Algorithm Overview

The basic intuition of the overall coordination algorithm is that after either step 2 or step 3, the aggregate energy cost is reduced. Specifically, for step 2, given the new demand profile, $\mathbf{R}^*$, the new storage solution $\mathbf{y}^* = \sigma(\mathbf{R}^*)$ should give a lower aggregate energy cost compared with the previous storage solution, because $\mathbf{y}^*$ is the storage solution minimizing the aggregate energy cost when the demand profile is $\mathbf{R}^*$. By similar argument, after step 3, the aggregate energy cost decreases too. Thus, the energy cost continues to decrease during the execution of the overall coordination algorithm. We will prove the basic algorithm keeps iterating and converges to the optimal solution to problem (1) under realistic conditions.

5 Overall Coordination Algorithm

In this section, we describe step 2 and 3 our algorithm works and prove its convergence.

5.1 Optimal Storage Solution (OSS)

Given the demand profile, $\mathbf{R}^*$, the central coordinator could optimize the storage solution by solving the problem below:

$$
\begin{aligned}
\min_{\mathbf{y}} C^s\left(\mathbf{R}^*, \mathbf{y}\right) = \textstyle\sum_{i=1}^{N} p_j \cdot \left(\rho_j^* + y_j - g_j\right) \\
\text{s.t. } \mathbf{0} \leq \mathbf{A}\mathbf{y} \leq \mathbf{u}, -\mathbf{d} \leq \mathbf{y} \leq \mathbf{d} \\
\mathbf{0} \leq \rho^* + \mathbf{y} - \mathbf{g} \leq \mathbf{h}
\end{aligned} \tag{2}
$$

Problem 2 is a linear programming problem and thus solvable. By solving the problem 2, we can get the optimal storage solution $\mathbf{y}^* = \sigma\left(\mathbf{R}^*\right)$.

5.2 Optimal Demand Profile (ODP)

In this section we discuss how to induce the optimal demand profile given a storage solution $\mathbf{y}^*$. The corresponding problem is expressed as follows:

$$
\begin{aligned}
\min_{\mathbf{R}} C^s\left(\mathbf{R}, \mathbf{y}^*\right) = \textstyle\sum_{i=1}^{N} p_j \cdot \left(\rho_j + y_j - g_j\right) \\
\text{s.t. } \mathbf{r}_i \in \mathcal{X}_i, r_{ij} \geq 0 \\
\rho + \mathbf{y}^* - \mathbf{g} \leq \mathbf{h}
\end{aligned} \tag{3}
$$

The iterative algorithm to solve Problem 3 is:

1. The central coordinator sends initial virtual price signal, denoted by s_{ij}, to the agents.
2. After receiving the virtual price signals, each agent individually calculates its optimal demand profile $\mathbf{r}_i$ by minimizing its energy cost computed based on the virtual prices and reports its profiles back to the coordinator.
3. Based on the reported demand profile $\mathbf{R}$, the central coordinator updates the virtual price signal and sends the new signal to each agent.
4. Given the new price signal, each agent chooses its new demand profile $\mathbf{r}'_i$.

Stopping Criterion If $\mathbf{R}' = \mathbf{R}$, stop. Otherwise, set $\mathbf{R} = \mathbf{R}'$ and start again from step 3.

In order to minimize the total electricity cost, the virtual price signal has to induce consumers to shift their demands from time slots with high marginal cost to those with low marginal cost and keep the aggregate demands within the capacity limits. Therefore, first of all, we need to determine the marginal cost and the capacity limit of the electricity in each time slot. In our model there are three possible electricity sources: on-site generations, storage and the market. While the marginal cost of electricity from generations and the market is well defined, we need to find a method to calculate the marginal cost of electricity from storage.

First Charging First Discharging (FCFD) We use first charging first discharging (FCFD) method to ***calculate the marginal unit cost*** of the energy discharged from storage. The FCFD policy in our setting means that the electricity charged earliest is recorded as discharged first. Below we use an example to show how the FCFD policy works. Assume there are 5 time slots, and the prices $\mathbf{p}$ are $\{10, 20, 40, 10, 30\}$. The storage solution $\mathbf{y}$ is $\{3, 8, -10, 4, -5\}$, which implies the electricity is charged in time slot $1, 2, 4$ and discharged in time slot $3, 5$. Under the FCFD policy, the electricity charged earliest is recorded as discharged first. Therefore, the 10 units of electricity discharged in time slot 3 should consist two parts, i.e., 3 units charged in time slot 1 at price $p_1 = 10$ and 7 unit charged in time slot 2 at price $p_2 = 20$. The corresponding average price for the electricity discharged in time slot 3 should be $(10\times 3+20\times 7)/10 = 17$. Similarly, the 5 units of electricity discharged in time slot 5 should consist of two parts, i.e., 1 unit charged in time slot 2 at price $p_2 = 20$ and 4 units charged in time slot 4 at price $p_4 = 10$. The corresponding average price should be $(20 \times 1 + 10 \times 4)/5 = 12$.

Thus, we can calculate the average price of electricity discharged in each time slot. The unit cost of the energy discharged in each time slot should be the average cost of the corresponding energy still in the inventory and charged earliest. We use $p_j^{FCFD}(\mathbf{R}^*, \mathbf{y}^*)$ to denote the unit cost or the price of the discharging energy in time slot j with demand profile $\mathbf{R}^*$ and storage solution $\mathbf{y}^*$.

Cost Structure Next we define the cost structure of the electricity in each time slot j, $\hat{p}_j(r)$, in an increasing order. By the following proposition 1, in each time slot, the unit cost of electricity from storage, $p_j^{FCFD}(\mathbf{R}^*, \mathbf{y}^*)$, is smaller than the unit cost of electricity from market p_j.

Proposition 1. *If the storage solution, $\mathbf{y}^*$, is the optimal storage solution given demand profile, $\mathbf{R}^*$, then $p_j^{FCFD}(\mathbf{R}^*, \mathbf{y}^*) < p_j$.*

Thus, the cost structure of the energy under the demand profile $\mathbf{R}^*$ and the storage solution $\mathbf{y}^*$ should be

$$\hat{p}_j(r) = \begin{cases} \infty & z_{3j} < r \le z_{4j} \\ p_j & z_{2j} < r \le z_{3j} \\ p_j^{FCFD}(\mathbf{R}^*, \mathbf{y}^*) & z_{1j} < r \le z_{2j} \\ 0 & z_{0j} < r \le z_{1j} \end{cases}$$

where $z_{0j} = 0, z_{1j} = g_j, z_{2j} = \max\{g_j, g_j - y_j\}, z_{3j} = h_j + g_j - y_j, z_{4j} = \infty$.

Initial Virtual Price Signal After we derive the formula of marginal cost, a straightforward approach is to set a quota for different sources in each time slot j for each agent i. Thus, the price signal is

$$s_{ij}(r) = \begin{cases} \infty & z_{3ij} < r \le z_{4ij} \\ p_j & z_{2ij} < r \le z_{3ij} \\ p_j^{FCFD}(\mathbf{R}^*, \mathbf{y}^*) & z_{1ij} < r \le z_{2ij} \\ 0 & z_{0ij} < r \le z_{1ij} \end{cases}$$

The initial quota of electricity from each resource in time slot j for agent i is proportional to agent i's demand in time slot j, r_{ij} (using aggregate demand r_i for first iteration without previous $\mathbf{R}^*$). Therefore, the corresponding thresholds in the initial virtual price signal are:

$$z_{kij} = \frac{r_{ij}^*}{\sum_{i=1}^N r_{ij}^*} z_{kj}, k = 0, 1, 2, 3, 4$$

Individual Agent's Problem After receiving the virtual price signal, each agent i computes $\mathbf{r}_i$ from

$$\min \sum_{j=1}^{M} s_{ij}(r_{ij}) r_{ij}, \text{ s.t. } \mathbf{r}_i \in \mathcal{X}_i, \; r_{ij} \ge 0. \tag{4}$$

The above problem is a convex optimization problem and thus solvable. However, due to individual constraints, some agents might not use all the quota assigned to them, while others may need more quota to further reduce their energy costs. Thus we need to update the virtual price signals accordingly.

Update Rule of Virtual Price Signal If the agent i does not fully use the quota assigned to her at time slot j, it may be due to either (a) constraints on electricity consumption or (b) lower price in other time slots. In either case, as long as the quotas on other time slots don't become smaller, which enforces agent i to shift the energy consumption from other time slots to time slot j, agent i prefers to keep the current consumption level to minimize the energy cost. Moreover, if the quotas on other time slots become larger, agent i may prefer to shift demand from time slot j to other time slot to reduce the energy cost. It is true if the prices on the time slots with larger quotas are lower than current marginal energy cost in time slot j. Therefore, to reduce the individual agent's energy cost and thus reduce the aggregate energy cost, the central coordinator needs to construct a new price signal by adjusting the quotas so as to share the excess quota among agents who use all of the quota in a time slot j. The new quotas for a demand profile $\mathbf{R}$ are determined by: let for $k = 1, 2, 3$, $\Phi_{kj} = \{i | r_{ij} < z_{kij}\}$,

$$z'_{kij} = \begin{cases} r_{ij} & i \in \Phi_{kj} \\ \frac{r_{ij}\left(z_{kj} - \sum_{i \in \Phi_j} r_{ij}\right)}{\sum_{i \in \Phi_j \cup \Psi_j} r_{ij}} & i \notin \Phi_{kj} \end{cases}$$

Under the new virtual price signal, for either electricity from generation or market supply, the agents give up their excess quota to the agents who use all of the quota with a sharing rule based on the current consumption level. Then the agents can continue optimizing their consumption schedule to reduce energy cost as they may get more quota in the time slots when they use all quota assigned to them previously.

5.3 Convergence Analysis

First, we prove the convergence of the ODP algorithm.

Theorem 1. *The ODP algorithm always converges.*

Theorem 1 is an immediate result of the two lemmas below:

Lemma 1. *The energy cost of individual agent based on the virtual price signal, $\sum_{j=1}^{M} s_{ij}\left(r_{ij}\right) r_{ij}$, is non-increasing during the execution of the iterative algorithm, so is the aggregate cost based on the virtual price signal, $\sum_{i=1}^{N} \sum_{j=1}^{M} s_{ij}\left(r_{ij}\right) r_{ij}$.*

Lemma 2. *If $\forall i, j, r_{ij} > z_{2ij}$, i.e., every agent use all quota of the electricity supply from energy generation and storage, then the aggregate cost based on the virtual price signal, $\sum_{i=1}^{N} \sum_{j=1}^{M} s_{ij}\left(r_{ij}\right) r_{ij}$, is equal to the aggregate cost based on the market price, $C^s\left(\mathbf{R}, \mathbf{y}^*\right) = \sum_{i=1}^{N} p_j \cdot \left(\rho_j + y_j - g_j\right)$.*

We now prove the convergence of the overall algorithm.

Theorem 2. *The overall algorithm always converges.*

Proof. From Definition 1, we have $C^s\left(\mathbf{R},\sigma\left(\mathbf{R}\right)\right) < C^s\left(\mathbf{R},\mathbf{y}\right)$, if $\mathbf{y} \neq \sigma\left(\mathbf{R}\right)$. Also, from Theorem 1, we have $C^s\left(\mathbf{R}^\sharp,\mathbf{y}\right) < C^s\left(\mathbf{R}^*,\mathbf{y}\right)$, if $\mathbf{R}^\sharp \neq \mathbf{R}^*$. Thus the energy cost $C^s\left(\mathbf{R},\mathbf{y}\right)$ is strictly decreasing as long as the optimal storage solution or optimal demand profile changes after each iteration. Thus, this algorithm converges.

Theorem 3. $\mathbf{R}^*$ *is optimal demand profile with storage, if* $\mathbf{y}^* = \sigma\left(\mathbf{R}^*\right)$ *and* $0 < \varrho^* + \mathbf{y}^* - g < h$.

Proof. Since $0 < \varrho^* + \mathbf{y}^* + g < h$, $0 \leq \varrho^* + y + g \leq h$ is not binding in the problem of optimal storage solution, which means $\mathbf{y}^*$ is also the solution to the following problem:

$$\begin{array}{c} \min_{\mathbf{y}} C^s\left(\mathbf{R}^*,\mathbf{y}\right) - C^s\left(\mathbf{R}^*,\mathbf{0}\right) = \sum_{i=1}^N p_j \cdot y_j \\ \text{s.t. } 0 \leq AY \leq u, -d \leq y \leq d \end{array} \tag{5}$$

Similarly, $\mathbf{R}^*$ is also the solution to the following problem:

$$\begin{array}{c} \min_{\mathbf{R}} C^s\left(\mathbf{R},\mathbf{y}^*\right) - C^s\left(\mathbf{0},\mathbf{y}^*\right) = \sum_{i=1}^N p_j \cdot \rho_j \\ \text{s.t. } \mathbf{r}_i \in \mathcal{X}_i, r_{ij} \geq 0 \end{array} \tag{6}$$

Assume C^* is the minimum cost of Problem (1) and $C^\#$ is the minimum cost of the following problem:

$$\begin{array}{c} \min_{\mathbf{R},\mathbf{y}} C^s\left(\mathbf{R},\mathbf{y}\right) := \sum_{i=1}^N p_j \cdot \left(\rho_j + y_j - g_j\right) \\ \text{s.t. } \mathbf{r}_i \in \mathcal{X}_i, r_{ij} \geq 0 \\ 0 \leq AY \leq u, -d \leq y \leq d \end{array} \tag{7}$$

Since problem (1) has more constraints than problem (7), we have $C^* \geq C^\#$. Moreover, by looking at problem (7), it actually can be decomposed to problem (6) and problem (5). Therefore, as we already show that $\mathbf{y}^*$ is also solution to problem (5) when $0 < \varrho^* + \mathbf{y}^* < h$, $\left(\mathbf{R}^*,\mathbf{y}^*\right)$ is the optimal solution to problem (7), i.e., $C^s\left(\mathbf{R}^*,\mathbf{y}^*\right) = C^\#$. As $C^* \geq C^\#$, we have $C^s\left(\mathbf{R}^*,\mathbf{y}^*\right) = C^\# \leq C^*$. Moreover, $\left(\mathbf{R}^*,\mathbf{y}^*\right)$ also satisfies all of the constraints in problem (1), which implies $C^s\left(\mathbf{R}^*,\mathbf{y}^*\right) \geq C^*$. Thus, $C^s\left(\mathbf{R}^*,\mathbf{y}^*\right) = C^*$, i.e., $\left(\mathbf{R}^*,\mathbf{y}^*\right)$ is the optimal solution to problem (1).

6 Simulation

In this section, we perform simulations to show the performance of our algorithm. We first state our assumptions on consumers' demand features, central coordinator's energy generation facility and storage facility, and the structure of market electricity price.

To reflect this diversity of the consumers' demand within the simulations, we used the Irish Commission for Energy Regulation (CER) electricity consumption data set to identify two important classes of consumers with shared characteristics. Here, Class 1 represents consumers that consume most of their electricity during the day and have a low load at night, whereas Class 2 represents consumers that have a stable consumption during the day, but have a higher consumption at night. We assume there are N agents, among them half are of Class 1 and the other half are of Class 2. Moreover, each agent

Table 1: Average Performance of Coordination Algorithm

Number of Agents	Number of rounds	Convergence Accuracy (%)
20	11.30	99.74
40	11.42	99.67
60	12.18	99.63
80	12.58	99.69
100	15.02	99.62

is defined by its total electricity requirement over the whole planning horizon, r_i, and the agent's constraints that determine the distribution of electricity consumption over the planning horizon.

For the market price, we use the real market prices from the EEX_dat_setwhich is the average hourly day-ahead spot market prices gathered from the European Energy Exchange as the price input, p. These prices are fixed across all the simulations. The capacity of the electricity contract on the other hand are not fixed. The capacity of market supply is determined by $h_j = 1.2 \sum_{i=1}^{N} x_{ij}$. The simulations were considered to converge when the cost reduction in one iteration got less than 0.001%.

Table 1 shows how the number of iterations and the convergence accuracy measured by the average share of potential cost reduction achieved changes with the number of agents. The results indicate the scalability of our algorithm with respect to the number of agents.

7 Conclusion

In this paper we proposed a novel multiagent coordination algorithm to shape the energy consumption of a consumer collective in the presence of energy generation and storage. In the collective, a central coordinator buys the electricity and decides the energy storage level for the whole group, and consumers make their own consumption decisions based on their private consumption constraints and preferences. To coordinate individual consumers under incomplete information and optimize the energy storage decision, we decompose the problem to two sub-problems: (a) optimizing demand profile of consumers given storage policy and (b) optimizing storage solution given demand profile of consumers. We proposed an iterative algorithm in which the two sub-problems above are solved alternately. We proved that our algorithm converges to the central optimal solution.

Acknowledgment This work was partially supported by NSF grant IIS-1218542

References

1. Jorgensen, J., Sorensen, S., Behnke, K., Eriksen, P.: Ecogrid eua prototype for european smart grids. In: Power and Energy Society General Meeting, 2011 IEEE, IEEE (2011) 1–7

2. Chen, S., Weiss, G.: An efficient and adaptive approach to negotiation in complex environments. In: ECAI. (2012) 228–233
3. Zheng, R., Chakraborty, N., Dai, T., Sycara, K., Lewis, M.: Automated bilateral multi-issue negotiation with no information about opponent. In: Proceedings of Hawaii International Conference on Systems Sciences. (January 2013)
4. Klein, M., Faratin, P., Sayama, H., Bar-Yam, Y.: Negotiating complex contracts. Group Decis Negot **12** (2003) 111–125
5. Lai, G., Sycara, K.: A generic framework for automated multi-attribute negotiation. Group Decis Negot **18** (2009) 169–187
6. Veit, A., Xu, Y., Zheng, R., Chakraborty, N., Sycara, K.: Multiagent coordination for energy consumption scheduling in consumer cooperatives. In: Proceedings of 27th AAAI Conference on Artificial Intelligence. (July 2013)
7. Medina, J., Muller, N., Roytelman, I.: Demand response and distribution grid operations: Opportunities and challenges. Smart Grid, IEEE Transactions on **1**(2) (2010) 193–198
8. Ramchurn, S., Vytelingum, P., Rogers, A., Jennings, N.: Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence. Communications of the ACM **55**(4) (2012) 86–97
9. Ramchurn, S.D., Vytelingum, P., Rogers, A., Jennings, N.: Agent-based control for decentralised demand side management in the smart grid. In: The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 1. (2011) 5–12
10. Vytelingum, P., Voice, T., Ramchurn, S., Rogers, A., Jennings, N.: Theoretical and practical foundations of large-scale agent-based micro-storage in the smart grid. Journal of Artificial Intelligence Research **42**(1) (2011) 765–813
11. Wu, C., Mohsenian-Rad, H., Huang, J.: Wind power integration via aggregator-consumer coordination: A game theoretic approach. In: Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES, IEEE (2012) 1–6
12. Atzeni, I., Ordóñez, L.G., Scutari, G., Palomar, D.P., Fonollosa, J.R.: Demand-side management via distributed energy generation and storage optimization. Smart Grid, IEEE Transactions on **4**(2) (2013) 866–876
13. Atzeni, I., Ordóñez, L.G., Scutari, G., Palomar, D.P., Fonollosa, J.R.: Noncooperative and cooperative optimization of distributed energy generation and storage in the demand-side of the smart grid. IEEE Transactions on Signal Processing **61**(10) (2013) 2454–2472
14. Kim, J.H., Powell, W.B.: Optimal energy commitments with storage and intermittent supply. Operations research **59**(6) (2011) 1347–1360
15. Brunetto, C., Tina, G.: Optimal hydrogen storage sizing for wind power plants in day ahead electricity market. IET Renewable Power Generation **1**(4) (2007) 220–226
16. Su, H.I., El Gamal, A.: Modeling and analysis of the role of fast-response energy storage in the smart grid. In: Communication, Control, and Computing (Allerton), 2011 49th Annual Allerton Conference on, IEEE (2011) 719–726
17. Harsha, P., Dahleh, M.: Optimal management and sizing of energy storage under dynamic pricing for the efficient integration of renewable energy. (2012)