Minimizing Electricity Costs by Sharing Energy in Sustainable Microgrids

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Abstract

Buildings account for over 75% of the electricity consumption in the United States. To reduce electricity usage and peak demand, many utilities are introducing market-based time-of-use (TOU) pricing models. In parallel, government programs that increase the fraction of renewable energy are incentivizing residential consumers to adopt on-site renewables and energy storage. Connecting on-site renewables and energy storage between homes forms a sustainable microgrid capable of generating, storing, and sharing electricity to balance local generation and consumption in residential areas. In this paper, we investigate how to minimize the costs of electricity from a utility for a microgrid under market-based TOU pricing models. In particular, we (i) present a system architecture for an energy-sharing microgrid; and (ii) develop optimal energy-sharing algorithms for homes within the microgrid. We conduct an extensive evaluation under two typical TOU pricing models that use data from more than 40 homes. Our results indicate that our system reduces the costs of Alternating Current (AC) electricity by 20%, even for homes with similar energy usage patterns.

Categories and Subject Descriptors

J.7 [**Computer Applications**]: Computers in Other Systems—*Command and control*

General Terms

Design, Measurement, Management

Keywords

Renewable Energy, Energy Sharing, Microgrids, Battery

1 Introduction

Buildings account for more than 75% of the United States' electricity use [1], with the residential sector accounting for 54% of this total. To reduce buildings' energy consumption, researchers in the sensor networks community have proposed multiple approaches.

For example, a high-fidelity wireless building energy auditing network has been built to analyze the energy consumption of a large building to identify energy waste. The Smart Thermostat [17] has been developed using occupancy sensors to save energy consumption from heating and cooling. In the Human-Building-Computer Interaction system [11], mobile sensors are deployed to interact with users to optimize energy efficiency. In [6], sensors are used to automatically turn off unused appliances (e.g., HVAC) to eliminate energy waste.

To further reduce the energy demand from the traditional power grid, homes are beginning to incorporate renewable energy sources. Because electric conversion factors and transmission and distribution losses in 2010 were as high as 32.3% [1], researchers have proposed distributed generation (DG) by deploying many small on-site energy sources in individual buildings and homes. However, in practice, DG has drawbacks that have thus far prevented its widespread adoption. For instance, DG uses solar panels that may harvest more energy than a home can consume in the middle of the day when no one is at home. As a result, today's DG deployments rely heavily on net metering, where consumers sell the unused energy they produce back to the utility company to offset their costs relative to grid energy. DG is a much less attractive option where net metering is not available. Even where net metering is available, states typically place caps on the total number of participating customers and/or the total amount of energy contributed per customer [2]. One reason for the strict laws limiting net metering's contribution is that injecting significant quantities of intermittent power from renewables into the grid can result in grid instabilities, which makes it difficult for utility companies to balance supply and demand.

On the other hand, more widespread adoption of DG is critical to meet existing goals for increasing the fraction of environmentally friendly renewable energy sources. For example, the Renewables Portfolio Standard targets 25% of electricity generation from intermittent renewables [4], while California's Executive Order S-21-09 calls for 33% of generation from renewables by 2020 [3]. Given current laws, if DG becomes more widespread, residential consumers will have to look beyond net metering to reduce costs and balance onsite energy production and consumption. We envision consumers' using a combination of on-site renewables, modest on-site energy storage units, and the electric grid to satisfy energy requirements. These on-site renewables and energy storage units are connected and form a sustainable microgrid. In parallel, we envision the adoption of market-based time-of-use (TOU) electricity pricing for residential consumers, which provides an opportunity to recoup the loss of net metering revenue, while also introducing new financial incentives for DG where net metering is not available.
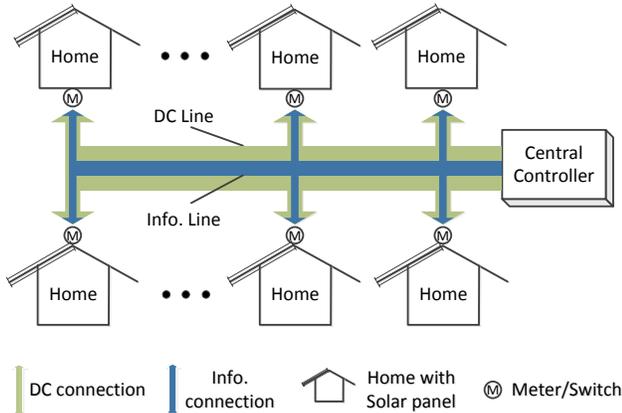
Figure 1: Architecture of Microgrids: Interconnected homes with renewable energy supply (e.g., solar panels)

In this work, we investigate how to minimize electricity costs (i.e., Alternating Current (AC) costs)[1] in a microgrid under different market-based TOU pricing models. The focus of our work is to study the theoretical, technical and economic feasibility of sustainable microgrids. Specifically, we build an energy-sharing microgrid system, which uses three types of energy-sensing data: (i) energy harvesting rate of solar panels; (ii) energy consumption rate of individual buildings; and (iii) battery charging and discharging rate. Based on the sensing data and market-based TOU pricing, our system decides how and when to share energy so that AC energy costs in the whole microgrid are minimized. The main contributions of this paper are summarized as follows:

• We design a general microgrid energy-sharing system architecture that can accurately calculate the electricity cost of individual houses under different energy consumption patterns and TOU pricing models.

• To minimize the AC energy cost in the whole microgrid, we develop (i) a spatial energy-sharing algorithm that maximizes energy shared among homes; (ii) a temporal energy-sharing algorithm that optimally stores energy in local batteries for future usage; and (iii) an AC allocation optimization algorithm that minimizes redundant AC transmission.

• To the best of our knowledge, this is the first in-depth work to investigate the feasibility of minimizing AC energy costs on a community level (i.e., microgrid). Evaluation results indicate that our system reduces (i) costs from AC lines by 20% under different TOU price models and (ii) electricity costs even in homes with similar energy usage patterns.

The paper is organized as follows. Overview of the system architecture, detailed system design, and evaluation are provided in §2, §3, and §4, respectively; related work and cost-benefit analysis are discussed in §5 and §6; finally, we conclude our paper in §7.

2 Problem Formulation

To minimize the AC energy costs of the microgrid, we propose the system architecture for energy-sharing and describe the system components and interactions between these components. Then we analyze the model of energy-sharing to formulate the problem.

2.1 System Overview

To ensure compatibility with the traditional power grid, we adopt the microgrid architecture (shown in Figure 1), which is similar to the one used in a traditional power grid. Just as the traditional

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[1]We use the term "electricity costs", or "AC costs", to refer to the costs of energy consumed from the utility company.

grid has a distribution network, our microgrid employs a similar but separate distribution network across the community of homes comprising the microgrid. Within this network, there is a power meter and a switch between every home and the central controller. The power meter is used to measure energy harvesting and consumption, while the switch is used to control energy sharing with other homes. Batteries are also deployed in each home to supply energy when there is not enough energy sharing. A centralized design is chosen to optimize AC energy costs of the microgrid and save most computation in homes. The central controller collects energy-related data from homes, arranges energy transmissions and determines the price of sharing energy among homes. Presently, our microgrid distribution network assumes a DC-based network for reasons of convenience and efficiency (e.g., to reduce conversion losses). Our system architecture and design are also compatible with an AC distribution network by considering the energy conversion loss from AC to DC and vice versa. For the sake of clarity, in the rest of the paper, we use DC distribution network to share renewable energy among homes and use traditional AC power line for distributing energy from the utility company to homes. The design goal is to minimize the cost from the AC line by optimally sharing renewable energy under different pricing models.

To realize optimal energy sharing, we propose the system design as shown in Figure 2, which includes two components: home controllers and a central controller. The home controllers have two planes: an energy sensing plane and an execution plane. The energy sensing plane senses the home's real-time energy data and makes a prediction, then forwards those data to the central controller, which includes (i) current and future energy consumption data, (ii) current and predicted energy harvesting data, and (iii) current amount of energy in the battery. For prediction of energy harvesting, we focus on solar energy in our paper as it is the predominant renewable energy source in residential DG deployment. To predict energy harvesting, a weather forecast based prediction model similar to Sharma's approach [26] is adopted. At any time t, based on the sky condition percentage $C(t)$ released by the National Weather Service (NWS), we predict the solar panel's energy harvesting rate. For prediction of home's consumption, we use historical consumption data to predict future energy consumption based on an Exponentially Weighted Moving Average (EWMA). The EWMA exploits the diurnal nature of a home's consumption, while it also adapts to seasonal variations. Note that more sophisticated models that consider changing weekend activity patterns and weather conditions can be used to improve our work. However, this is not our main contribution and from evaluation results, the following prediction models can already provide enough accuracy for our system.

In addition, homes convey their battery and solar panel capacities and cost data when they join the system. The above data will be used by the central controller for energy allocation and price decision purposes. After receiving energy-sharing instruction from central controller, the home controller's execution plane toggles the power meter and a switch to transmit a certain amount of energy. The switch controls energy flow from the following options: (i) use energy from AC line to power appliances; (ii) charge battery from AC line; (iii) charge battery from DC line; (iv) discharge battery to DC line; and (v) discharge battery to power appliances.

The central controller contains only the energy-sharing plane, which includes the spatial energy sharing, temporal energy sharing and AC allocation.

The energy-sharing plane processes data needed during energy sharing. It has three major modules: (i) the spatial energy-sharing module that uses the individual home's energy data and sharing efficiency to find energy-sharing home pairs (detailed in §3.1); (ii) the temporal energy-sharing module that yields the optimal solution on minimizing the AC energy costs of the microgrid based on TOU
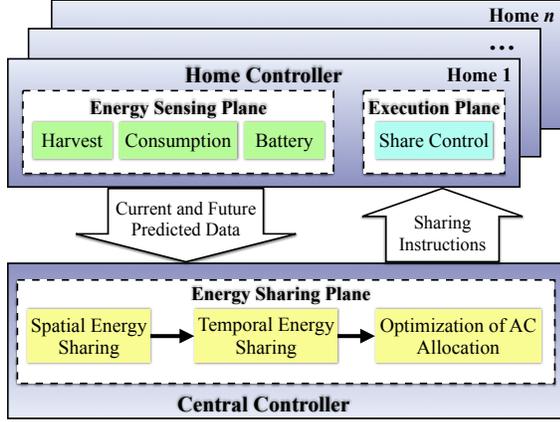
Figure 2: Overview of system architecture

Notation	Definition
w	Window size
$B_i(n)$	Amount of energy in battery of home i in window n
C_i	Battery's capacity of home i
r_i^c	Battery charging rate of home i
r_i^d	Battery discharging rate of home i
η_{ij}	Energy transmission efficiency between i to j
$C(t)$	Sky condition percentage at time t
$EC_i(n)$	Consumed energy of home i in window n
$EH_i(n)$	Harvested energy of home i in window n
$\widehat{EC}_i(n)$	Predicted consumed energy of home i in window n
$\widehat{EH}_i(n)$	Predicted harvested energy of home i in window n
$Y_{AC}(n)$	Price of AC line based on TOU in window n
$\triangle E_i(n)$	$EH_i(n) - EC_i(n)$
$\triangle B_i(n)$	Amount of energy gap of home i in window n
$E_{i \to j}(n)$	Energy transferred from i to j in window n
$EA_i(n)$	Energy from AC line of home i in window n
$ES_i(n)$	Energy surplus by sharing of home i in window n

Table 1: Definition of notations

prices and energy-sharing pairs of spatial sharing module (detailed in §3.2); and iii) the AC allocation module that optimally calculates the amount of energy each home should get from the AC line based on data from both the spatial energy sharing and temporal energy sharing module (detailed in §3.3).

In summary, our system works as follows: (i) home controllers gather consumption, harvesting and battery information and send it to central controller; (ii) central controller then decides energy-sharing sequences and sharing price; (iii) homes discharge battery to share energy to others based on central controller's instruction; and (iv) if a home still needs energy after sharing, it gets energy from AC line.

2.2 Problem Definition

With the proposed system for energy sharing, we model the energy-sharing process and formulate the problem. Because energy sharing takes time to transmit energy from one home to another home, in our system, time is divided into time slots, and the size of a slot is referred to as **window size** w. Then we can do energy sharing at window n based on energy consumption and harvesting at window $n+1$ to reduce electricity cost. Let $\triangle E_i(nw) = EH_i(nw) - EC_i(nw)$ be the difference between harvested energy $EH_i(nw)$ and consumed energy $EC_i(nw)$ for home i in the time interval $[nw, (n+1)w]$ and $n \in [1, N]$. To simplify the notation, we will use **n** to represent **nw** in rest of the paper. Let $E_{i \to j}(n)$ be the amount of energy transmitted from home i to j in window n; and η_{ji} be the transmission efficiency between homes i and j. The amount of surplus energy $ES_i(n)$ home i can get during energy sharing is as follows:

$$ES_i(n) = \sum_j (E_{j \to i}(n) \cdot \eta_{ji} - E_{i \to j}(n)) \tag{1}$$

$\sum_j E_{j \to i}(n) \cdot \eta_{ji}$ is the amount of energy home i receives from other homes and $\sum_j E_{i \to j}(n)$ is the amount of energy that home i provides to other homes. Let $B_i(n)$ and C_i be the battery level (amount of energy in battery) of window n and battery capacity of home i respectively. Table 1 summarizes the definition of parameters. Based on information of window n, we can calculate $B_i(n+1)$ as follows:

$$B_i(n+1) = \begin{cases} 0 & B_i(n) + \triangle B_i(n) < 0 \\ C_i & B_i(n) + \triangle B_i(n) > C_i \\ B_i(n) + \triangle B_i(n) & \text{otherwise} \end{cases} \tag{2}$$

where $\triangle B_i(n)$ represents the total amount of energy gap at home i in window n, which includes the difference between harvested and consumed energy, energy obtained from the AC line and energy transmission between home i and other homes in the microgrid. $\triangle B_i(n)$ can be calculated as follows:

$$\triangle B_i(n) = \triangle E_i(n) + EA_i(n) + ES_i(n) \tag{3}$$

where $\triangle E_i(n)$ is the difference between harvested and consumed energy at home i in window n; $EA_i(n)$ and $ES_i(n)$ is the amount of energy home i gets from the AC line and energy sharing in window n respectively; Based on the definition above, we can have the following lemma:

Lemma 2.1 *Home i does not have enough energy to consume if $B_i(n) + \triangle B_i(n) < 0$.*

PROOF. The equation in lemma can be rewritten by using Equation 3 to separate the energy consumption and the energy sources as follows:

$$EC_i(n) > B_i(n) + EH_i(n) + EA_i(n) + ES_i(n) \tag{4}$$

In Equation 4, the energy consumption is larger than the energy obtained from all sources, which will cause power shortages. Thus that situation should always be avoided. □

Similarly, we have the following lemma:

Lemma 2.2 *Home i wastes energy if $B_i(n) + \triangle B_i(n) > C_i$.*

Lemma 2.2 happens when the battery in home i cannot store extra energy due to its capacity limit. This situation should be avoided, but may not be eliminated. Consider the case when in the middle of a day, the harvesting overwhelms the consumption, the battery may be charged to full capacity and extra harvested energy would be wasted.

Let $Y_{AC}(n)$ be the price of the AC line based on TOU in time interval $[n, (n+1)]$. Given $\triangle E_i(n)$ and $B_i(n)$, we can formulate our design goal of minimizing the microgrid electricity cost from the AC line as follows:

$$\min \quad \sum_n \left(Y_{AC}(n) \cdot \sum_i EA_i(n) \right)$$

$$s.t. \quad 0 \le B_i(1) \le C_i \qquad\qquad\qquad\qquad (a)$$

$$EA_i(n) \ge 0 \qquad\qquad\qquad\qquad\qquad (b)$$

$$\sum_j E_{i \to j}(n) - \triangle E_i(n) - EA_i(n) \le r_i^d \cdot w \qquad (c)$$

$$\sum_i E_{i \to j}(n) \cdot \eta_{ij} + \triangle E_j(n) + EA_j(n) \le r_j^c \cdot w \quad (d)$$

$$B_i(n) + \triangle B_i(n) \ge 0 \qquad\qquad\qquad\qquad (e)$$

Constraint (a) ensures the initial battery energy level will always be no less than zero and not greater than the battery capacity. Constraint (b) means a home can only get energy from AC line, but not sell energy to utility company. Constraints (c) and (d) mean that amount of energy can be transmitted from i to j is determined by discharging rate of i, charging rate of j and window size. Constraint (e) ensures every home can have enough energy during window n. $\triangle E_i(n)$ and $B_i(n)$ are determined by users' power consumption. To minimize the total AC energy cost, we can adjust $ES_i(n)$ by choosing proper energy-sharing home pairs (i.e., home i shares $E_{i \to j}(n)$ amount of energy with j) and allocate the amount of energy $EA_i(n)$ each home gets from the AC line over time. Thus we can rewrite Constraint (e) by plugging in Equation (3) as follows:

$$ES_i(n) + EA_i(n) \ge -B_i(n) - \triangle E_i(n) \qquad (5)$$

The problem is a linear programming problem. However, for constraints (b) to (e), it needs to be valid for all windows n, thus total number of constraints is huge when number of homes and total time increases. Further, the objective function value for different windows are correlated and cannot be decomposed. Thus in our paper, we propose a spatial-temporal energy sharing design and prove that our solution is a local optimal solution.

3 System Design

In this section, we describe the detailed system design, mainly focusing on the central controller part in §3.1, §3.2 and §3.3.

3.1 Spatial Energy Sharing

The first part of central controller spatial energy sharing is introduced in this section. The goal of spatial energy sharing is to minimize AC transmission in a single window. Because in a single window, $EA_i(n)$ is needed unless home i cannot get enough energy from energy sharing, we have

$$EA_i(n) = \triangle B_i(n) - ES_i(n) - \triangle E_i(n) \qquad (6)$$

In window n, $B_i(n)$ and $\triangle E_i(n)$ are fixed values, the optimization problem can be rewritten as follows:

$$\max \quad \sum_i ES_i(n)$$

$$s.t. \quad \sum_j E_{i \to j}(n) - \triangle E_i(n) - EA_i(n) \le r_i^d \cdot w \qquad (a)$$

$$\sum_i E_{i \to j}(n) \cdot \eta_{ij} + \triangle E_j(n) + EA_j(n) \le r_j^c \cdot w \quad (b)$$

$$B_i(n) + \triangle B_i(n) \ge 0 \qquad\qquad\qquad\qquad (c)$$

$$ES_i(n) \le \triangle B_i(n) - \triangle E_i(n) \qquad\qquad (d)$$

$\sum_i ES_i(n)$ is total amount of energy sharing in window n. To maximize $\sum_i ES_i(n)$, we need to address the following two challenges:

- **Transmission Conflict**. Take Figure 3 as an example in which homes H1 and H3 need to provide energy to H2 and H4. Because all the homes are connected to same distribution network, if we do the energy sharing simultaneously, we cannot control the amount of energy from H1 to H2. Then we cannot know what amount of energy is transmitted from home i to j and cannot calculate how much j should pay to i for energy it receives. Thus, in our system, only one to multiple and multiple to one energy transmission is allowed at a time. If more transmissions are needed in microgrid, multiple one-to-multiple or multiple-to-one transmissions can be executed one by one.

- **Transmission Efficiency**. Because distances between homes are different, energy transmission losses between homes are also different. Besides, energy sharing between homes may be discharged from battery and charged to battery, which introduces battery conversion loss. Thus we need to consider different transmission efficiency between homes when designing the energy sharing algorithm. For example, transmission efficiency between $H1$, $H3$ and $H2$, $H4$ given in Figure 3 (a) includes both transmission loss and battery conversion loss.

To address the above challenges, we introduce maximum transmission speed of homes. We divide homes into an energy supplier set S and a demander set D according to whether the energy difference is positive or negative. Then we consider maximum transmission speed for two types of energy-sharing home pairs: (i) one demander with multiple suppliers in which the transmission speed is limited only by the demander's battery charging rate when there are enough suppliers; and (ii) one supplier with multiple demanders in which the transmission speed is determined by not only the supplier's discharging rate, but also by transmission loss between demanders and the supplier.

Assuming home i shares energy with home j, the discharging rate for i is r_i^d, the charging rate for j is r_j^c, and the transmission efficiency is η_{ij}, then the energy transmission rate r_{ij} during energy sharing is as follows:

$$r_{ij} = min(r_i^d \cdot \eta_{ij}, r_j^c) \qquad (7)$$

If multiple suppliers share energy to home j, the maximum transmission speed is determined by minimum value of its charging rate and total energy transmission rate available from suppliers.

$$r_j = min(\sum_k r_{kj}, r_j^c) \qquad (8)$$

If home i shares energy with multiple demanders, the maximum transmission speed is determined by discharging rate and transmission efficiency between i and demanders. To maximize transmission speed, we select demander with highest transmission efficiency until we reach discharging rate of i. Assume the demander set for maximum transmission speed is $M = \{m_1, m_2, ...\}$, $\eta_{im_i} > \eta_{im_j}$ if $i < j$. Then we have maximum transmission speed of i as follows:

$$r_i = \sum_{k \in M} r_{ik}, \quad s.t. \quad \sum_{k \in M} r_{ik} / \eta_{ik} \le r_i^d \qquad (9)$$

An example of spatial energy sharing is shown in Figure 3. Homes are divided into an energy supplier set S and a demander set D according to whether the energy difference is positive or negative. Homes H2 and H4 are in the demander set. Figures 3(a) and 3(b) show two steps of energy sharing, respectively. Figure 3(a) shows charging rate of demanders, discharging rate of suppliers and transmission efficiency between demanders and suppliers. For example,
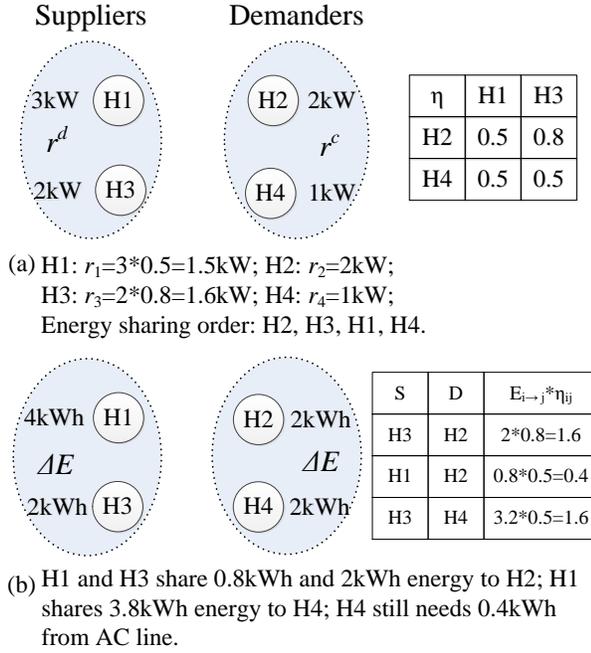
Suppliers / Demanders

(a) H1: $r_1=3*0.5=1.5$kW; H2: $r_2=2$kW;
H3: $r_3=2*0.8=1.6$kW; H4: $r_4=1$kW;
Energy sharing order: H2, H3, H1, H4.

(b) H1 and H3 share 0.8kWh and 2kWh energy to H2; H1
shares 3.8kWh energy to H4; H4 still needs 0.4kWh
from AC line.

Figure 3: An example of energy sharing between demander set D {H1, H3} and supplier set D {H2, H4}.

discharging rate of supplier $H1$ r_1^d is 3kW, charging rate of demander $H2$ r_2^c is 2kW, and transmission efficiency from $H1$ to $H2$ is 0.5. Then maximum transmission speed for four homes is calculated and energy-sharing order is determined. Because H2 has highest energy intake speed, H2 will be the first home to do the sharing. The sharing process follows the sharing order of Figure 3(a). Figure 3(b) shows energy difference of four homes and energy-sharing results.

Then we propose our spatial energy-sharing algorithm based on maximum transmission speed to maximize total energy transmission in a single window. The detail of algorithm is described as follows: The maximum transmission speed for every home is calculated at first. For demander i it is r_i^c, and for suppliers it is obtained from 9 by iterating over a list of supplier or demanders sorted by transmission efficiency η_{ij}. We then fetch home i with highest transmission speed for energy sharing (Line 2). If $i \in S$, we start energy sharing with home $j \in D$, which maximizes transmission efficiency η_{ij} (Lines 3-5). Otherwise, we start energy sharing with home $j \in S$, which maximizes transmission efficiency η_{ji} (Lines 6-9). Then energy difference of home i and j will be updated (Line 10). The energy-sharing process will continue until all homes finish energy sharing (Line 11).

The **time complexity** for Algorithm 1 is as follows: To calculate the maximum transmission rate, we need $O(n^2)$ where n is the number of homes. Then it costs $O(nlgn)$ to sort according transmission rate. For the energy-sharing process, the time complexity is at most $O(n^2)$. Note that the sorting of η_{ij} can be done once at a cost of $O(n^2)$, and we will reuse the result in the following algorithms. So all altogether, the time complexity is about $O(n^2)$.

Remark. Here we give a brief description to demonstrate that Algorithm 1 maximizes amount of energy sharing in a single window. Because we allow only one-to-multiple and multiple-to-one energy transmission, the energy transmission sequences will be like $K = \{s_1, d_2, ..., s_k\}$, s_i and d_j are the only supplier or demander in transmission. Suppose there is a optimal sequence $K^{'} \neq K$ with

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Algorithm 1 Spatial Energy Share Algorithm

Input: Supplier set S and demander set D with homes' r_i^c, r_i^d, $B_i(n)$ and $\triangle E_i(n)$; Transmission efficiency η_{ij}.
Output: Energy sharing results $E_{i \to j}(n)$.

1: Calculate the maximum transmission rate for every home;
2: Fetch home i from $S \bigcup D$ that has the maximum r_i;
3: **if** $i \in S$ **then**
4:    Fetch home j that $\eta_i = \max_{j \in D}(\eta_{ij})$;
5:    $E_{i \to j}(n) = \min(|\triangle E_j(n) + B_i(n)|, |(\triangle E_i(n) + B_i(n)) \cdot \eta_{ij}|, r_j^c \cdot w)$;
6: **else**
7:    Fetch home j that $\eta_i = \max_{j \in D}(\eta_{ji})$;
8:    $E_{j \to i}(n) = \min(|\triangle E_i(n) + B_i(n)|, |(\triangle E_j(n) + B_i(n)) \cdot \eta_{ij}|, r_i^c \cdot w)$;
9: **end if**
10: Update $\triangle E_i(n)$, $\triangle E_j(n)$;
11: Go to Line 2 if $\triangle E_i(n) == 0$, otherwise go to Line 3.

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maximum amount of energy sharing. According to Algorithm 1 s_k has lowest maximum transmission speed, there must be a home $s_i \in K^{'}$, $s_i \notin K$ with higher transmission speed. Then Algorithm 1 does not select s_i but s_k, which contradicts that it always selects the home with highest transmission speed.

3.2 Temporal Energy Sharing

With the spatial energy-sharing results, TOU model and battery capacity data, we introduce the temporal energy sharing algorithm in this section. The temporal energy sharing algorithm gathers the energy difference data and makes its charging decision in the current window to store energy for future higher price window usage. Based on the spatial energy-sharing results, for home i and window n, we can easily calculate the energy difference of i after energy sharing as $\triangle E_i^{'}(n)$:

$$\triangle E_i^{'}(n) = B_i(n) + \triangle E_i(n) + ES_i(n) \qquad (10)$$

If $\triangle E_i^{'}(n) < 0$, it means home i still does not have enough energy for its usage after energy sharing, then it has to obtain energy from AC line. Then the goal of temporal energy sharing can be formulated as follows:

$$\min \quad \sum_n \left(Y_{AC}(n) \cdot EA_i(n) \right)$$
$$s.t. \quad 0 \leq B_i(1) \leq C_i \qquad (a)$$
$$B_i(n) + \triangle E_i^{'}(n) + EA_i(n) \geq 0 \quad (b)$$
$$EA_i(n) \geq 0 \qquad (c)$$

To minimize the cost of AC energy over time, the key idea is to charge battery at windows with lower AC price and discharge battery at windows at higher AC price. To anticipate the exact amount of energy needed at window n, it is important to know how many windows to look forward. Therefore, we propose an approach called **Look Forward Window**. The next window that has a lower TOU price is the end of the look forward window, as getting energy at that time can reduce costs more than at the current window.

An example of the look forward window is shown in Figure 4. First, it looks forward to the windows in the future until it finds a window whose price of the AC line is lower than the current price
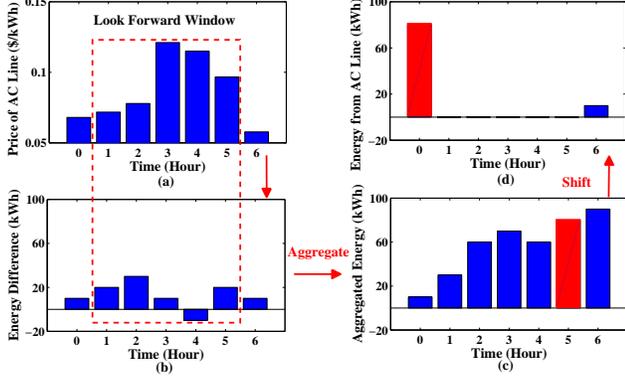
Figure 4: An example of using a look forward window to shift an energy request to a low price period to reduce cost: Energy needed from window 1-5 is shifted to window 0.

(window 6) in (a). Then it aggregates energy differences of homes before that window in (b)-(c). Finally, it shifts all the energy needed from the AC line in the future to the current window. Aggregate energy $AGG_i(k)$ can be calculated by summing up $\triangle E_i'(n)$:

$$AGG_i(k) = \sum_{n \leq l \leq k} \triangle E_i'(l) \qquad (11)$$

With $AGG_i(k)$, we then find the maximum energy needed between current window and look forward window, which is window 5 in Figure 4 (c). Note that $AGG_i(k)$ are normally negative value because homes normally need energy. In Figure 4 (c), we show the absolute value of $AGG_i(k)$, which is amount of energy needed. Then we have maximum energy we need to charge for future at window n:

$$E_{max}^-(i) = - \max_{k \in [n,m]} (-AGG_i(k)) \qquad (12)$$

However, we also need to consider two other factors: limited battery capacity and peak energy demands. If the energy obtained from the AC line after shift exceeds the battery capacity, part of the energy will be wasted. Thus, our algorithm will allow the home to obtain energy only from the AC line to fill the battery. Then the maximum energy we can charge to avoid energy waste at window n is as follows:

$$E_{max}^+(i) = C_i - \max_{l \in [n,k]} (AGG_i(l)) \qquad (13)$$

In a TOU model that same price spans over multiple windows; if the system requests all the energy it needs in the first window, there may be a peak energy demand from the AC line. To address this issue, our algorithm will distribute the energy requests evenly among these same price windows, so the energy peaks from the AC line can be smoothed out, which results in minimum impact to the grid.

The detail of the temporal energy-sharing algorithm is shown in Algorithm 2. First, it finds the look forward window m according to the TOU price (Lines 1-2). Then it computes the aggregated energy difference for windows between n and m (Lines 3-5). The maximum energy needed $E_{max}^-(i)$ is given (Line 6) and the maximum energy that the homes can charge due to battery capacity is calculated in window n (Line 7). Then it finds the number of windows with same price of AC after window n (Line 8). At last, energy from AC line $EA_i(n)$ for home i is calculated by minimum value specified by constraint (b) in the problem formulation (Lines 9-10).

Algorithm 2 Temporal Energy Sharing Algorithm

Input: Spatial energy share results $E_{i \to j}(t)$ and $\triangle E_i(t)$, $t \in [n, n+24]$; battery level $B_i(n)$; TOU AC price.
Output: Energy from AC line $EA_i(n)$.

1: **for** each home i **do**
2:     Find first window $m(m > n)$ that $Y_{AC}(m) < Y_{AC}(n)$
3:     **for** every window t from current window n to m **do**
4:         Get the $AGG_i(t)$
5:     **end for**
6:     Find window k that $E_{max}^-(i) = - \max_{k \in [n,m]} (-AGG_i(k))$;
7:     $E_{max}^+(i) = C_i - \max_{l \in [n,k]} (AGG_i(l))$;
8:     Find the number of windows num that have same price with current window
9:     $EA_i(n) = min(E_{max}^+(i)/num, |E_{max}^-(i)|/num, r_i^c \cdot w)$.
10: **end for**

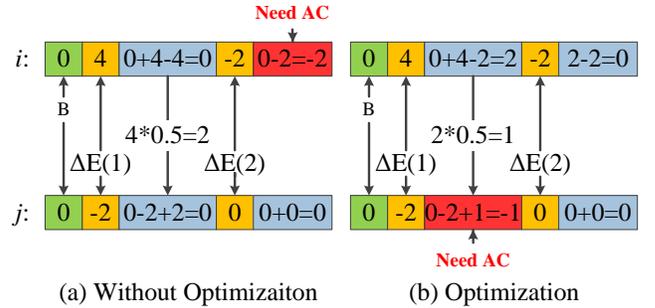(a) Without Optimizaiton   (b) Optimization

Figure 5: An example of optimization of AC allocation

The **time complexity** for Algorithm 2 is quite straight forward. Given the fact that we look forward at most 24 hours, the loop body in Lines 2-9 can be regarded as a constant time. Then multiplying the number n of homes, we get the total time complexity as $O(n)$.

Theorem 3.1 *Algorithm 2 minimizes cost of AC energy over time for a single home.*

Remark. For a single home, based on Equation (10) and (11), Algorithm 2 enables homes to charge as much energy as possible to battery for future windows. Look forward window ensures that homes only charge battery at low AC price for energy usage at windows with higher AC price. Thus Algorithm 2 minimizes cost of AC energy over time for a single home.

3.3 Optimization of AC Allocation

In §3.2, we determined an initial amount of energy needed from the AC line. The reason we need to do optimization of energy from the AC line is that spatial sharing and temporal sharing are executed separately, which may cause some unnecessary energy sharing among homes and energy requests from the AC line. In this way, we can reduce the microgrid level energy costs from the AC line.

An example is shown in Figure 5. Assume the transmission efficiency between home i and j is 0.5. At the beginning, both i and j have no energy in the battery (shown in green box); at window 1 and 2, the energy difference (shown in yellow box) between harvested and consumed is calculated for energy sharing (shown in blue box); if after energy sharing, the home still does not have enough energy, it needs to get energy from the AC line (shown in yellow box). Without optimization, home i will first transmit 4kWh energy to home j at window 1 with Algorithm 1. Then home i needs to get

2kWh energy from the AC line at window 2. With Algorithm 2, because the look forward window always has a higher AC price than the current window, home i will get 2kWh energy from the AC line at window 1. With optimization, home i will transmit only 2kWh energy to home j at window 1. Then only home j needs to get 1kWh energy from the AC line at window 1. Overall, this optimization approach can save 1kWh energy from the AC line.

Here we give the condition that we should do optimization of AC allocation for home i.

Lemma 3.1 *Optimization of Home i at window n can save the cost of AC energy if $\exists j$, $E_{i \to j}(n) > 0$, $EA_i(n+1) > 0$ and $\eta_{ij} < Y_{AC}(n+1)/Y_{AC}(n)$.*

PROOF. Before optimization, home i needs $EA_i(n+1)$ energy from AC line and the cost of AC energy is $EA_i(n+1) * Y_{AC}(n+1)$. After optimization, home i does not need energy from AC line, but ; home j needs $EA_i(n+1) \cdot \eta_{ij}$ energy from AC line and cost is $EA_i(n+1) * \eta_{ij} * Y_{AC}(n)$. Then if $\exists j$, $E_{i \to j}(n) > 0$, $EA_i(n+1) > 0$ and $\eta_{ij} < Y_{AC}(n+1)/Y_{AC}(n)$, then we have $EA_i(n+1) * \eta_{ij} * Y_{AC}(n) < EA_i(n+1) * (Y_{AC}(n+1)/Y_{AC}(n)) * Y_{AC}(n) = EA_i(n+1) * Y_{AC}(n+1)$. Thus, optimization of home i at window n can save the cost of AC energy. □

With the Lemma 3.1, we only need to find all the scenarios that fulfill Lemma 3.1 in sharing results from temporal and spatial energy sharing to minimize the electricity cost. The detail of algorithm is described in Algorithm 3. For each home $i \in S$, it checks if it both shares energy with its neighbors and gets energy from the AC line at window n (Lines 1-2). If yes, it finds home $j \in D$ that with the smallest energy transmission efficiency η_{ij} (Line 3). Then it checks if there is energy transmitted from i to j (Line 4). If yes, cancels energy transmission that causes redundant AC transmission of i (Lines 5-13).

The **time complexity** for Algorithm 3: If we implement the data structure for storing the energy-sharing results properly, either as a dictionary or as a union-set or individual lists by using home as key/index, then the checking for whether home i shares energy to other homes just takes constant time. We could reuse the sorting result in the previous algorithm for Line 3, so that Lines 3-10 also have constant time. Then the total time is $O(n)$.

Summary. In the above three sections §3.1-§3.3, we first balance energy usage of different homes in the microgrid by a spatial energy-sharing algorithm. Then based on a TOU model, energy

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Algorithm 3 AC Allocation Optimization Algorithm

Input: Energy share and AC transmission results $E_{i \to j}(n)$ and $EA_i(n)$ from Algorithm 1 and 2.
Output: Optimized $E_{i \to j}(n)$ and $EA_i(n)$.

1: **for** each home $i \in S$ **do**
2:    **if** $EA_i(n) > 0$ & $\exists j$ $E_{i \to j}(n) \neq 0$ **then**
3:       Find home j that $\min_{j \in D}(\eta_{ij})$
4:       **if** $E_{i \to j}(n) > 0$ & $\eta_{ij} > Y_{AC}(n+1)/Y_{AC}(n)$ **then**
5:          **if** $EA_i(n) > E_{i \to j}(n)$ **then**
6:             $EA_i(n) - = E_{i \to j}(n)$, $E_{i \to j}(n) = 0$;
7:          **else**
8:             $E_{i \to j}(n) - = EA_i(n)$, $EA_i(n) = 0$;
9:          **end if**
10:         remove j from D;
11:       **end if**
12:    **end if**
13: **end for**

(a) Solar Panel   (b) Energy Measurement

(c) Battery   (d) Inverter   (e) Battery Measurement

Figure 6: Experiment setup

(a) Harvesting Power   (b) Consumption Power
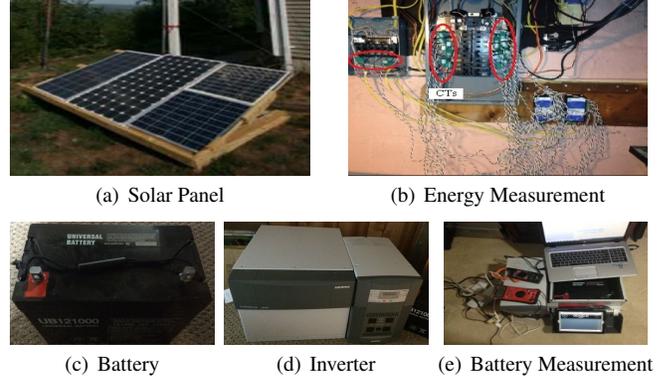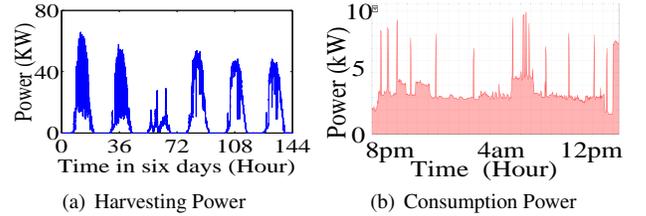
Figure 7: Sensing Data in One Home

needed from the AC line is balanced by a temporal energy-sharing algorithm. Finally, combined with two-dimensional energy-sharing results, total AC energy costs in the microgrid are minimized over time. The total time complexity for all the three algorithms is around $O(n^2)$.

Theorem 3.2 *The solution obtained from the above algorithms is a local optimal solution.*

Remark. As in our algorithms, $EA_i(n)$ and $E_{i \to j}(n)$ are determined at every window. According to Constraint (b), only $EA_i(n)$ and $E_{i \to j}(n)$ can be adjusted to reduce the total AC costs. Thus, we can prove that if any $EA_i(n)$ decreases, it will be always more expensive to fulfill Constraints (d). Due to limited space, detailed proof will not be discussed in this paper.

4 Implementation and Evaluation

In this section, we evaluate the performance of our system. We collect empirical data of (i) energy harvesting from solar panels, (ii) energy consumption from 40 homes, and (iii) charging and discharging power of a battery. We evaluate our system under two types of real world TOU price models in §4.3; we also validate that our system can work with homes with similar harvesting and consumption models.

4.1 Experiment Setup

We collect the energy consumption data of 40 homes [5]. We add current transducers (CTs) around each leg of a home's split-phase input power from the grid (shown in Figure 6(b)) to monitor all the circuits inside a home every second. Figure 7(b) shows the aggregated energy consumption data within one day in a deployed home.

We also collect energy-harvesting data from solar panels. The solar panels we use are Grape Solar 75-Watt Monocrystalline PV Solar Panels (shown in Figure 6(a)). We collect six days' worth
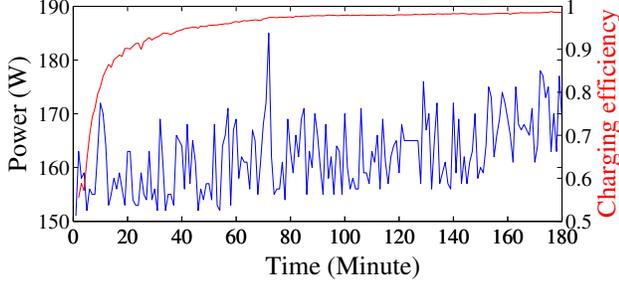
Figure 8: Battery Charging

(a) TOU in Ontario   (b) TOU in New England

Figure 9: Different TOU models

(a) TOU in Ontario   (b) TOU in New England

Figure 10: Total AC energy cost of different TOU models

of energy-harvesting data shown in Figure 7(a). In a day, the solar panel begins to harvest energy at around 7 a.m., the energy peaks around 12 p.m., and the harvesting ends around 8 p.m. However, the harvested energy on different days varies, which may be due to the varying weather conditions. Because the energy-harvesting pattern from solar panels is similar in a single area, we use the trace to produce energy-harvesting data of other homes with some randomness. Harvesting data is collected hourly. The weather forecast data we use is from the NWS (National Weather Service). The consumption data of homes consist of energy information collected every minute over six days. With empirical data, we calculate the predicted energy harvesting and consumption data over six days for our simulations.

The energy storage unit we deploy is UB12100-S Universal Battery and Xantrex PowerHub 84053 shown in Figure 6(c) and 6(d), which is a combination of an inverter/charger module capable of delivering up to 1800 watts of household power. It can work as a backup power solution to operate with solar inputs. We use iMeter Solo (an INSTEON power meter) to measure the battery energy charging and discharging rate in real time (shown in Figure 6(e)). The power consumption for charging a battery is shown in Figure 8. The average power for charging the battery is around 160W, which implies that within a one-hour window, only a limited amount of energy can be transmitted. Therefore, our design addresses the challenge of the limited energy transmission speed in § 3.1. We also verify the charging efficiency of battery. At the beginning of charging, the efficiency is relatively low. However, efficiency increases quickly with time and after 30 minutes, the efficiency is more than 95%.

4.2 Evaluation Baseline

To verify the efficiency of our system, we compare our design, which is referred to as **GSC (Global Sharing and Charging)** in latter evaluation results, with (i) **Oracle**, which uses the same energy charging and sharing algorithm as GSC but assumes real energy consumption and harvesting data in the future is available; (ii) **Individual smart charge(ISC)** [19], which only allows homes to take advantage of TOU individually with no energy sharing; and (iii) **Collective sharing (GES)** [29], which aims to share energy among homes, but not take advantage of TOU.

4.3 Evaluation Results

In this section, we will evaluate the effectiveness of our system, which includes the efficiency of our system under two kinds of TOU models. All results are simulated with the six days' empirical data of energy harvesting and consumption introduced in Section 4.1. The battery loss rate we use is 15% [25]; the average AC and DC transmission loss rate is around 22.6% and 7.6%, which varies with different distances among homes [15].

Different TOU Models: We ran our system under two different TOU models: TOU in Ontario and TOU in New England, as shown
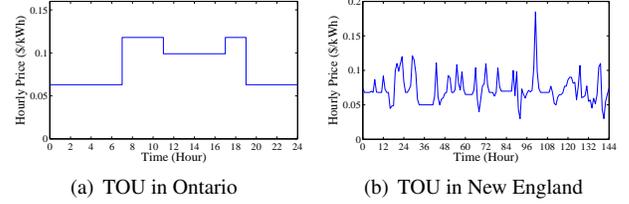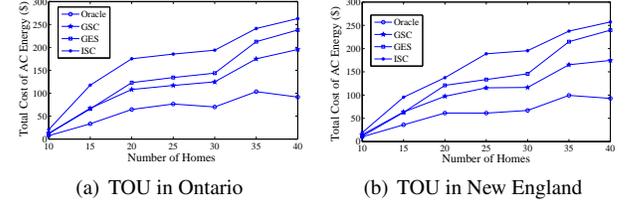
in Figures 9(a) and 9(b), respectively. These two models are carefully selected to represent a wide range of TOU models: (i) a higher price for daytime use per day (shown in Figure 9(a) for TOU in Ontario), and (ii) price dynamic changes every hour based on demand, which is also referred to as Realtime Pricing Model (RTP) in other papers (shown in Figure 9(b) for TOU in New England).

Total Cost of AC Energy: Figure 10(a) shows total cost of AC line for four different algorithms under TOU in Ontario. In all four algorithms, the total cost of the AC line generally increases with the number of homes, which is quite obvious. However, in Oracle, the total cost decreases when the number of homes increases from 25 to 30 and 35 to 40, which is due to those five additional homes having more energy surplus. Because the other algorithms do not have accurate energy information, prediction error causes the increase in total cost. Our algorithm outperforms GES by 22% and is less than Oracle by only 9.2%. ISC performs worst, which shows the importance of energy sharing among homes.

Figure 10(b) shows total cost of AC line for four different algorithms under TOU in New England. Similar to the previous TOU model, the total cost of the AC line generally also increases with the number of homes. Our algorithm outperforms GES by 37.9% and is less than Oracle by only 6.6%, which is even better than the TOU model in Ontario. The main reason for the better performance is that with the higher dynamic of the AC price, our temporal-sharing algorithm can take advantage of the TOU model more efficiently. Because the AC price changes vary frequently, the looking forward window could be relatively small, which does not need prediction for a long period. Thus, our algorithm is closer to Oracle.

Transmission Over AC Line: We also show the detailed energy transmission over the AC line per hour under TOU in Ontario in Figure 11(a). All three energy-sharing algorithms are compared to GES. For Oracle, homes seldom need energy from the AC line except when the harvested energy from a solar panel is not enough in day 3 (Hour 48 to 72). Also, because the initial battery is not fully charged, homes need to get energy from the AC at the beginning. Our algorithm is close to Oracle, in which for nearly 10 hours of one day, homes do not need to obtain energy from the AC line. However, homes need to get more energy from the AC line with ISC. For some particular time, transmission over the AC line has large peaks. That is because homes take advantage of TOU individually. If the price of the AC line is the same for every home, then all homes will try to charge at the time with the lowest TOU price. Because energy information of all homes can be achieved with GSC, central controller can simply avoid this phenomenon to reduce the

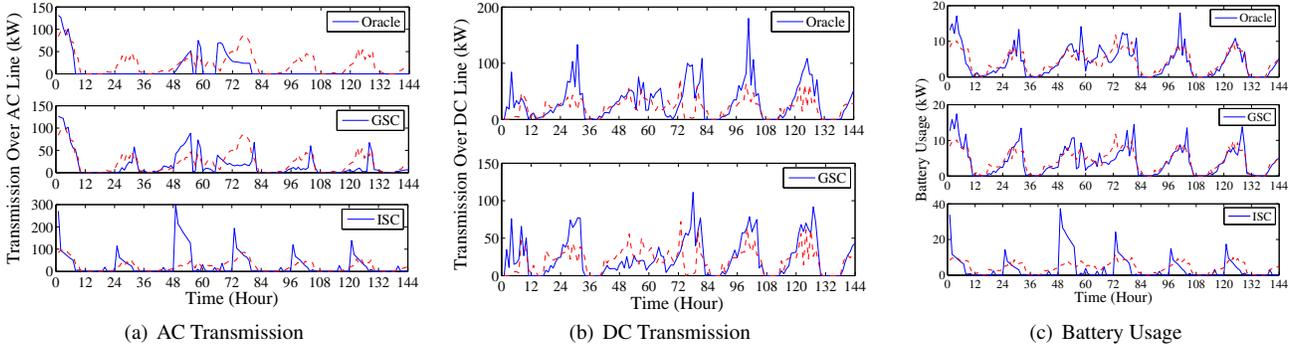| (a) AC Transmission | (b) DC Transmission | (c) Battery Usage |

Figure 11: Transmission over AC, DC line and battery usage in Ontario (red dashed line in all figures is the transmission or battery usage of GES)

peak of AC line.

Transmission Over DC Line: Transmission over the DC per hour under TOU in Ontario is shown in Figure 11(b). Oracle and our algorithm share more energy among homes to reduce AC energy cost when the price of the AC line is relatively high. Thus, their transmission of DC would be higher. Because ISC does not allow energy sharing among homes, there is no transmission over DC line.

Battery Charging and Discharging: Battery usage includes battery charging from AC or DC line and discharging to DC line and appliances' usage. Battery usage per hour under TOU in Ontario is shown in Figure 11(c). Even Oracle and our algorithm share more energy through DC line, the total battery usage of Oracle, GSC and GES is close. That means the main difference among three algorithms is the way of utilizing TOU and renewable energy but not battery. Because ISC does not allow energy sharing among homes, battery usage is only for charging from AC line and discharging to appliances' usage. Thus the curves of battery usage and AC transmission in ISC are similar. The peak demand from AC line is mainly to charge energy to battery, but not for current appliances' usage.

Summary of Different TOU Models: We have evaluated our system under two TOU models. Due to the limited space, we only show AC, DC transmission and battery usage under Ontario TOU model while the results under New England TOU model is similar. In all these scenarios, our system outperforms GES and ISC. The key observations are as follows: (i) Oracle and GSC need less AC transmission and cost compared to GES and ISC; and (ii) Oracle and GSC may cause some little peaks of AC transmission if periods with lowest price of AC are short. However, peaks of Oracle and GSC are much lower than ISC.

5 Cost-Benefit Analysis

The previous section shows that our system can reduce AC energy cost of the whole microgrid by more than 20%. In this section, we discuss our system's return on investment.

TOU	Ontario			New England		
Algorithm	Oracle	GSC	GES	Oracle	GSC	GES
Cost (10^5)	3.51			3.51		
Benefit ($10^5/yr$)	0.79	0.71	0.59	0.77	0.72	0.52
Years for Return	4.44	4.94	5.95	4.56	4.86	6.75

Table 2: Cost and Benefit

In many instances, homes already have the necessary infrastructure to implement energy sharing. More and more homes will be equipped with solar panels and batteries to generate renewable energy. To implement energy sharing microgrid, the main expense is to construct lines for distribution network, use solar panels and a larger battery to harvest and store energy. For the battery, the price is around $200/kWh. For solar panels, the price is around $0.6/Watt. The price of other equipment, such as inverter, cabling and energy monitor, is also included in total investment cost. Finally, we estimate two weeks' labor at $4000 for installation. The benefit realized with our system design is mainly due to the savings of energy transmission over AC lines. We use two types of empirical TOU price models (i.e., Ontario and New England). Based on the above pricing data, our analysis of benefit and cost is shown in Table 3. In general, our system can return the investment in less than five years. We note that the AC price is based on current TOU prices. Given the increase in electricity price, we expect that the number of years for return will be even fewer.

6 Related Work

Our work is related to three areas of previous work: energy harvesting and energy efficient systems and building energy.

• **Energy harvesting.** The renewable energy sources have become an alternative way to consume power and reduce electricity bills. However, they have limits in some instances when harvested energy availability typically varies with time in a non-deterministic manner and power systems surpass the consumption or vice-versa, which results in a mismatch [16]. To manage renewable energy, Deborah et al. [23] propose a method to exploit robotic mobility by having energy producers be mobile nodes. In [13], the authors designed perpetual environmentally powered sensor networks. Our work follows the simple idea where we build an energy sharing microgrid system in an entire community to reduce the AC energy cost, which uses the energy sensing data and market-based TOU price to decide when and who to share energy with.

• **Energy-efficient systems.** Our work is also related to energy-efficient systems [7] [27]. In energy efficient systems, researchers mainly focus on i) energy management in data centers [10] and leveraging renewable energy with carbon-aware in data centers [8], (ii) developing models to balance performance measures and energy consumption in wireless networks [9]; iii) energy management in web search by understanding the query complexity and its implications for energy-efficient web search [24]; (iv) mobile devices by empowering developers to estimate app energy, end to end energy management [22]; (v) energy-aware dispatching of parallel queues, efficient virtual machine scheduling in computer architecture [18].

• **Building energy.** This research mainly focuses on (i) energy auditing [14] [12] and design of control algorithms to reduce energy consumption inside a single building [11]; (ii) reducing the energy usage of building-wide heating, energy-efficient building automation, ventilation, and air conditioning [17] [20]; (iii) investigation

on the integration of renewable energy into power grid [31] [30]; and (iv) applying stochastic network calculus to analyze the power supply reliability with various renewable energy configurations and store that energy into very large scale batteries [21]; and v) taking model predictive control approach to schedule the workload to reduce the energy cost in the buildings [28]. Our work takes a different approach to reduce energy cost by sharing the renewable energy. Unlike these other approaches, our work opens up new approach where energy can be gained efficiently and used smartly.

Our work is built on previous works, but homes with renewable devices and small batteries are the main research focus. Most related work is [29], which tries to minimize energy transmission loss in microgrid. In this paper, we propose a holistic approach to minimize community AC cost under different TOU models. Specifically, we designed spatial and temporal energy sharing algorithms, and developed optimal AC allocation algorithm to minimize electricity cost.

7 Conclusion

In this work, we attempt to investigate how to minimize AC energy costs in a sustainable microgrid under different market-based TOU price models by exploring three types of energy sensing data: (i) sensing data of solar panels' energy-harvesting rate; (ii) sensing data of individual homes' energy consumption rate; and (iii) sensing data of battery charging and discharging patterns. Specifically, we build an energy-sharing microgrid system, which decides the energy-sharing home pairs and when to share energy based on the sensing data and market-based TOU price so that AC energy costs in the whole microgrid are minimized. We evaluate our system using empirical traces of harvested solar energy and home energy consumption. Through extensive simulations, we verify that our system can reduce AC energy costs of the whole microgrid by more than 20% under different TOU price models and can still reduce AC energy costs even when homes have similar energy consumption patterns.

8 Acknowledgments

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