iDES: Incentive-Driven Distributed Energy Sharing in Sustainable Microgrids

Weigang Zhong*[$], Zhichuan Huang[†][$], Ting Zhu[†], Yu Gu[‡],
Qingquan Zhang[†], Ping Yi[§], Dingde Jiang[¶], and Sheng Xiao[||]
[†]University of Maryland Baltimore County, *Binghamton University, [‡]IBM Research
[§]Shanghai Jiaotong University, [¶]Northeastern University, [||]Hunan University
[$] Co-primary authors

***Abstract*—Buildings consume a significant amount of electricity, which is normally generated from dirty sources causing an increase in carbon footprints. To reduce carbon footprint, distributed renewable energy generation has been proposed. However, the amount of renewable energy harvested normally does not match the amount of energy consumed in individual homes. To address this mismatch, we propose a distributed solution to share renewable energy among homes, which form a microgrid. Specifically we (i) design an incentive-driven distributed energy sharing system (iDES) in a microgrid to enable effective energy sharing and reduce the communication overhead, and (ii) develop energy sharing pricing model to incentivize energy sharing. The energy sharing price generally reflects the installation costs of on-site renewable and energy storage units, the dynamic changes of energy supply-demand relationship, and the remaining energy level of batteries. We validated the effectiveness of our system with extensive evaluations that use empirical traces. The results show that our energy sharing pricing model can effectively motivate and encourage homes to share energy.**

Keywords*—*Microgrids, Incentive, Distributed, Energy Sharing.

I. Introduction

Buildings consume over 75% of the electricity in the United States. Currently, 69.4% of U.S. electricity is generated by burning coal, petroleumor natural gas, and another 20.7% by nuclear power stations [1]. These conventional sources of energy have a number of negative environmental, economic, and geopolitical sideeffects. Therefore, different forms of renewable energy (e.g., solar and wind) have been introduced to provide energy for homes. To reduce transmission and distribution (T&D) losses and decrease carbon emissions, researchers have proposed distributed generation from many small on-site energy sources deployed at individual buildings and homes.

However, prior studies [2] show that the amount of renewable energy harvested normally does not match the amount of energy consumed in individual homes. This mismatch is usually due to the difference in the time of the energy harvest peak and user demand peak. In order to handle this mismatch, various solutions can be applied. One widely used approach is to sell the surplus energy to a utility company during energy surplus stage and get energy from the utility company during energy shortage stage . However, by using this approach, renewable energy sold on a large scale may destabilize the traditional power system.

978-1-4799-6177-1/14/$31.00

Another solution, one that brings the Time-of-Use(TOU) pricing model into play and allows the consumers to lower their electric bills is to use an intelligent charging system, such as Smart Charge [3] that uses an on-site battery array to store energy at a low cost for use during high-cost periods. This intelligent system allows consumers to reduce the electricity cost by determining when to switch the home's power supply between the grid and the battery array. Alternatively, consumers may also take part in automated demand response programs, which automatically turn off home appliances when the demand for electricity is high. These programs are increasingly offered by electric utilities [4]. The consumer's energy footprint and bill are reduced, as these intelligent load management schemes automatically disconnect the loads from power when necessary or convenient.

However, Smart Charge requires extremely large capacity batteries to store energy for an entire day's energy consumption, and the shifting appliance schedule forces users to change their energy consumption patterns. Therefore, we introduced energy sharing [5] for multiple homes, and form a microgrid. Although this approach solves the mismatch between energy supply and demand, it is a centralized approach that requires a central controller, where all the energy sharing decisions are made. However, centralized architectures require relatively high-end central controllers (which means additional investments), and like any centralized system, customer-end computing abilities are not fully utilized. Besides that, a centralized system is vulnerable to central controller failure. Moreover, homes may lack of incentives to share energy because there are no obvious profits from sharing.

To solve these issues, in this paper we propose iDES, an incentive-driven distributed method to solve the mismatch between energy harvesting and consumption in individual homes; where energy sharing decisions are made by the individual homes. We also introduce an energy selling pricing model to incentivize energy sharing among homes. Specifically, the main contributions of the paper can be summarized as follows:

• We designed an incentive-driven distributed energy sharing system (iDES) in a sustainable microgrid which is formed by homes that are willing to exchange renewable energy. Our system design is more robust and generic. It can be applied to different types of microgrids (off-grid and grid-tied microgrids).

• To incentivize energy sharing, we developed an energy sharing pricing model that effectively reflects (i) the amortized

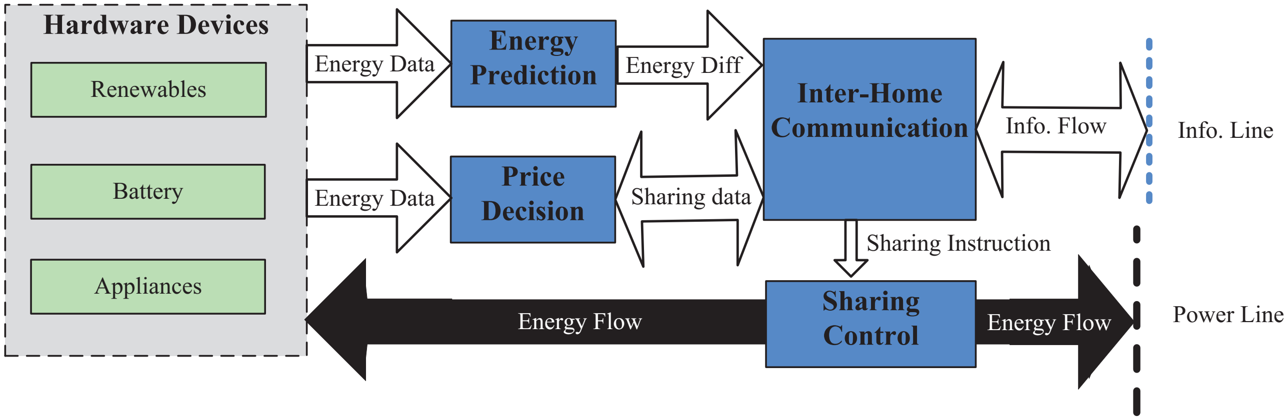


Fig. 1: Overview of iDES Design. The white arrow is the information flow. The dark arrow is the energy flow. The upper energy data flow is acquired from renewable energy sources, and the lower energy-data flow contains remaining battery energy information. The inter-Home Communication component is a distributed communication system that processes data from renewable sources and batteries to make price decisions and control energy sharing.

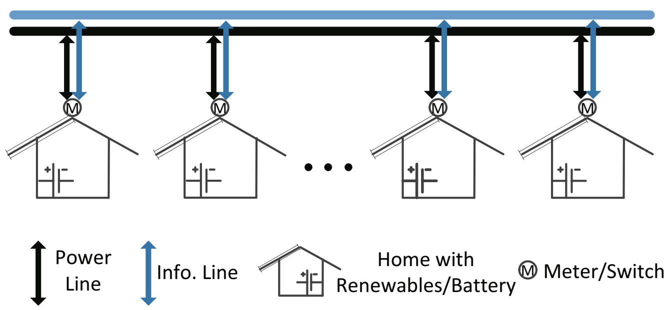


Fig. 2: Architecture of a Microgrid: Interconnected homes with renewables and batteries.

installation costs of renewable energy havesting devices (e.g., solar panels) and energy storage units (e.g., batteries), (ii) the dynamic change of energy supply-demand relationship inside the microgrid, and (iii) the batteries' remaining energy level in individual homes.

• We designed a distributed energy sharing communication protocol, which can reduce the communication overhead and effectively find the energy sharing home pairs with agreed energy sharing price between two homes.

II. System Overview

In this section we will introduce the microgrid architecture, and then describe the system components and interactions among these components.

The microgrid architecture is shown in Figure 2. Homes are connected together to form a sustainable micogrid. Renewables and batteries are deployed in homes to harvest energy and store the surplus energy, respectively. A common power line is introduced as the energy sharing media, which can use either DC (Direct Current) or AC (Alternating Current) line. An information line is used for inter-home communication. There is a power meter and a switch between every home and the power line. The power meter is used to measure energy harvesting and consumption rate, while the switch is used to control energy sharing with other homes. Each home is assigned an unique id, which is used to identify homes during the inter-home communication and sharing control. This kind of microgrid architecture is usually within community level because it is convenient to connect homes that are sharing the same power infrastructure and distance leads to cost of power transmission. However, the architecture itself has no such limitation and could be extended to more distant locations.

In order to share energy in a distributed way, we propose the system design (shown in Figure 1), which includes four components as follows:

• **Energy Prediction:** The energy prediction component collects three types of energy data including (i) the consumption data from home appliances, (ii) the harvesting data from renewables, and (iii) the remaining energy in batteries. It predicts the future energy consumption and harvesting using these collected data, then calculates whether the home has energy to share or needs energy in the near future.

• **Inter-Home Communication:** The inter-home communication component is responsible for exchanging (i) the energy data and price information during energy sharing process and (ii) the energy sharing scheduling information. Here we assume the underlying communication channel is reliable. We focus only on the information flow only.

• **Price Decision:** When home has surplus energy, the price decision component decides the energy selling price based on the energy harvesting cost, energy storage cost and the dynamic supply-demand relationship in the microgrid.

• **Sharing Control:** The sharing control component toggles the smart meter, which includes a power meter and a switch, to transmit a certain amount of energy after receiving the energy sharing instructions from the inter-home communication component.

During the energy sharing, homes are classified into suppliers (we define suppliers as homes that have surplus energy and are willing to share energy with others) and consumers

Notation	Definition
η_{ij}	Energy transmission efficiency from home i to j
$C(t)$	Sky condition percentage at time t
$P(t)$	Renewable harvesting power at time t
$EC_i(n)$	Consumption energy of home i in window n
$EH_i(n)$	Harvested energy of home i in window n
$EB_i(n)$	Remaining energy in battery of home i in window n
$E_r(n)$	Requested sharing energy in window n
$E_g(n)$	Granted sharing energy in window n
$Y(n)$	Energy selling price in window n
$\triangle E_i(n)$	Difference between available energy and consumed energy
$E_{i\rightarrow j}(n)$	Energy transferred from i to j in window n

TABLE I: Definition of notations

(we define consumers as homes that demand energy from other homes). Suppliers will share their energy to consumers, and store the remaining energy into batteries if energy is not sold out. The amount of energy obtained is measured by the power meter for accounting purpose. As we cannot control the exact energy flow if there is simultaneous energy sharing, the energy sharing is executed sequentially. If homes are not involved in the current sharing, their power switches will be left open.

III. System Design

In this section, we first introduce the energy prediction used in our system design (§III-A), then describe the energy sharing price (§III-B). The detailed information exchange during energy sharing is described in §III-C. Table I summarizes the definition of notations used in the paper.

A. Energy Prediction

In our system energy sharing is conducted periodically, therefore we divide time into "windows"; size is denoted as **window size** w. We will use ***nw*** to represent the nth window. We choose some generic models to use in our system over many other candidates, similar to [5]. Note that energy harvesting and consumption predictions are not our main contribution. More sophisticated models that consider changing weekend activity patterns, weather conditions, or other data are possible. Moreover, our design is compatible with other consumption prediction models.

Harvesting Prediction: We use a weather forecast-based prediction model [6] to predict energy harvesting. 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 $P_i(t)$ as

$$P_i(t) = P_{max} \cdot (1 - C(t)) \tag{1}$$

where P_{max} is the solar panel's maximum harvesting power. Based on Equation (1), at any time $t = n$, the harvested solar energy within the next energy-sharing window is predicted as follows:

$$\widehat{EH}_i(n+1) = \int_n^{n+1} P_i(\tau)d\tau \tag{2}$$

It is worth noting that, the algorithm is designed for solar power prediction because we are using solar panels as our testbeds. However, without loss of generality, our system could be extended to other renewable energy sources ()such as wind power) because batteries could be used for power storage in this kinds of home level renewable energy harvesting system [7].

Consumption Prediction: We use a model based on an Exponentially Weighted Moving Average (EWMA) to predict the home's consumption from historical consumption data. The EWMA exploits the diurnal nature of a home's consumption, while it also adapts to seasonal variations. Let $EC_i(n)$ denote the amount of energy consumed in $[n, n+1]$ and $\widehat{EC}_i(n+1)$ denote the predicted energy consumed in $[n+1, n+2]$, which is given by:

$$\widehat{EC}_i(n+1) = \alpha \cdot \widehat{EC}_i(n) + (1-\alpha) \cdot EC_i(n) \tag{3}$$

The value of α is chosen by using the method in [8].

As energy transmission takes time, the system shares energy for next window usage. Assuming in time interval $[n, (n+1)]$, a home consumes $EC(n)$ amount of energy and harvests $EH(n)$ amount of energy. The home is expected to have $\widehat{EH}(n+1)$ harvesting and $\widehat{EC}(n+1)$ consumption in next window by prediction, while the battery has $\widehat{EB}(n+1)$ at the beginning of window n+1. Let $\triangle E(n+1)$ be the expected energy difference between expected available energy and energy consumption as follows:

$$\triangle E(n+1) = \widehat{EH}(n+1) + \widehat{EB}(n+1) - \widehat{EC}(n+1) \tag{4}$$

Based on energy difference, homes can be classified into supplier set S and consumer set D according to whether they have surplus energy (i.e. $\triangle E(n) > 0$) or not (i.e. $\triangle E(n) <= 0$). Note that the supplier and consumer set is not fixed. A home may belong to consumer set D in window n and supplier set S in window $n+1$.

B. Energy Selling Price

In order to incentivize energy sharing, we introduce the energy selling price in this section. Suppliers set the energy selling price as they are the source of the energy sharing. There are three mainly factors that will impact the price: the energy generation cost, the supply-demand relationship and the energy selling urgency. Because in our system the renewable energy is harvested from renewables and the harvested energy for sharing is stored in a battery, the energy generation cost needs to cover the amortized cost for the renewables and battery. Meanwhile, the energy supply-demand relationship affects the price as well. When there is more harvesting than consumption in the microgrid, the suppliers need to set a low price in order to successfully sell the surplus energy with a higher probability. Otherwise, they can raise the price to increase the benefit. Another factor that impacts the price is the battery level. When a supplier's battery is nearly full and the supplier is expected to harvest surplus energy in the next window to overcharge the battery, the supplier is more likely to sell the energy at lower price to avoid energy waste. After including all these above factors, we design the pricing model as follows:

$$Y = Y_a * (1 + 1/\gamma_B) * (1 + 1/\gamma_S) \tag{5}$$

Where Y_a, γ_B and γ_S are the amortized cost, the batteries' energy level and the energy supply-demand ratio of current window, respectively. The range of γ_B is between 0 and 1. When the supplier has energy to sell, the battery will not be empty, which indicates γ_B will not be 0. γ_S is greater than 0 and less than infinity. A value of 0 or infinity means there is no supplier or no consumer, so there is no need to share energy. Note that the price is always higher than the amortized cost as homes need to at least cover the energy harvesting and storage costs for the shared energy.

The cost for the consumer is also impacted by the energy transmission loss. In time interval $[n, (n+1)]$, when a supplier home i shares $E_{i\rightarrow j}(n)$ units of energy to a consumer home j, j can receive only a fraction of $E_{i\rightarrow j}(n)$ due to energy transmission loss. The transmission loss rate is mainly determined by the transmission distance, type of power lines, and the transmission voltage. The distances between homes are known in advance by homes in the system, which is a reasonable assumption as the geometric locations of the homes are hardly changed. Based on the distance, each home can calculate the energy sharing efficiency between itself and its neighbors. Consumers can estimate the cost they need to pay after they know the transmission efficiency. For example, assuming a consumer j needs $\triangle E_j(n)$ amount of energy and gets it from a supplier i. Let η_{ij} be the transmission efficiency between home i and j, $Y_i(n)$ be the energy selling price from supplier i. Then the consumer j has to pay $\triangle E_j(n) \times Y_i(n)$ / η_{ij} to the supplier i for the energy sharing. Thus from the consumer side, the energy sharing price between homes i and j is $Y_{ij}(n) = Y_i(n) \ / \ \eta_{ij}$.

C. Energy Sharing Communication

The main challenge for the distributed energy sharing is how to design the information exchange among homes to decide the energy sharing home pairs. The design should provide necessary information for homes while avoiding information overload. In the energy sharing process, suppliers offer their surplus energy to consumers with different selling price, then consumers select the suppliers that provide the lowest sharing prices. The general steps for the energy sharing are as follows:

(i) **Broadcasting Energy Difference:** At the beginning of each time slot, homes calculate the energy difference by subtracting predicted consumption from predicted harvesting using Equation (4). The energy difference information should be known by every home in the microgrid, no matter whether it belongs to a consumer or supplier set. The reason is that consumers can get the knowledge of the amount of surplus energy each supplier has, later on they can request specific amount of energy from the suppliers. Suppliers can summarize the energy supply-demand relationship in order to decide the energy selling price. To summarize, in current phase every home broadcasts energy difference in the microgrid and keeps listening to others' broadcasted messages.

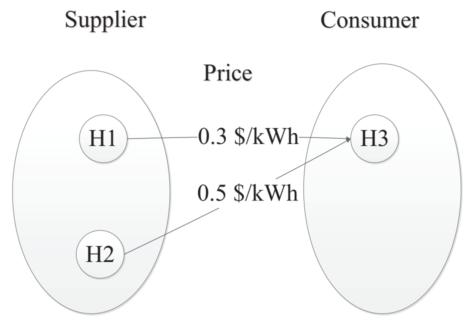


Fig. 3: An example of a consumer selecting suppliers. H3 will request energy from H1 as H1's price is lower.

(ii) **Multicasting Energy Price:** After the supplier collects the broadcasted messages, it calculates the energy selling price based on the energy generation cost and supply-consumer distribution as introduced in §III-B. In a distributed system, broadcasting the selling price is not a good design as the suppliers are competitors during energy sharing so other suppliers may take advantage of the overheard selling price to set a more competitive price. Thus all the suppliers use multicast to convey their selling price to the consumers.

(iii) **Selecting Energy Suppliers:** After consumers receive the energy selling prices from multiple supplies, they can select between these suppliers and negotiate. The selecting process may span multiple rounds due to competition among different consumers. In order to minimize the consumer's cost, the consumer sorts the suppliers in increasing order according the energy sharing price, then starts with the home with lowest sharing price $Y_{ij}(n)$. An example is shown in Figure 3. Suppliers H1 and H2 can share energy with consumer H3 with a price of 0.3$/kWh and 0.5$/kWh respectively. H3 will request energy from H1 first, then from H2 if it needs more energy.

On the supplier side, although the profit is same no matter which consumers are selected, the energy transmission efficiency is different. The supplier can grant the energy request from the consumers with less transmission loss. An example is shown in Figure 4. Because transmitting energy to H3 is more efficient than to H4, supplier H1 will grant the request from H3 to reduce the energy loss.

The detailed energy sharing algorithm for suppliers is shown in Algorithm 1. The supplier sorts the consumer set D according to the energy transmission efficiency in decreasing order (Line 1). Then it waits for an energy sharing request from consumers. When there are incoming requests, it retrieves requests based on ordered set D (Line 2). If the requested energy is less than current surplus energy, it grants the amount of requested energy; otherwise it grants the amount of surplus energy it has (Lines 4-8). The supplier sends a message to the consumer to confirm the request, adds energy sharing instructions into a list, and multicasts the remaining surplus energy to notify the consumers (Lines 9-12). It continues the process until the current phase ends (Lines 13-14). Note the supplier still keeps listening to the incoming requests even if it has granted all of its surplus energy, in this case, it replies to

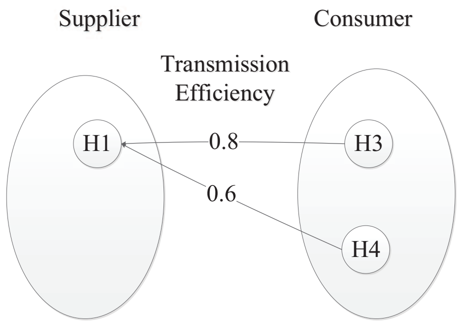


Fig. 4: An example of a supplier accepting offers from consumers. H1 will accept offer from H3 to minimize energy loss.

Algorithm 1 Energy Sharing Algorithm for Supplier i

Input: Energy consumer set D, surplus energy $\triangle E_i(n)$
Output: Energy sharing instructions list L

1: Sort D by transmission efficiency;
2: Wait for incoming requests and list them by order in D
3: **for** Incoming request (assuming from home j with energy request of $E_r(n)$) **do**
4:     **if** $|\triangle E_i(n)| \geq E_r(n)$ **then**
5:         Granted Energy $E_g(n)$ is $E_r(n)$
6:     **else**
7:         Granted Energy $E_g(n)$ is $\triangle E_i(n)$
8:     **end if**
9:     Send message to home j to grant $E_g(n)$ energy
10:     Add energy sharing instruction [j, $E_g(n)$] into list L
11:     $\triangle E_i(n)$ = $\triangle E_i(n)$ - $E_g(n)$
12:     Multicast updated $\triangle E_i(n)$ to consumers
13: **end for**
14: go to Line 1 if current phase doesn't end.

the consumer with the granted energy E_g equals 0. By doing this, the consumers are able to receive the response and try the next supplier. In this way, a deadlock on a specific supplier can be avoided. Note that when the suppliers cannot share their energy due to too many suppliers in current time, they can charge the battery using the surplus energy later.

The detailed energy sharing algorithm for consumers is shown in Algorithm 2. The consumer sorts the supplier set S according to the energy sharing price in increasing order (Line 1). Then it requests energy from the suppliers sequentially (Line 2). The amount of requested energy is limited by the supplier's surplus energy and consumer's energy shortage (Lines 3-7). After sending out the energy request, the consumer waits until it receives the response from the supplier (Lines 8-9). The supplier may grant exactly the requested amount of energy, or less due to the competition from other parallel consumers. Consumer updates its energy shortage, puts the energy sharing instructions into a list and continues the process until its energy request is fulfilled or all the suppliers are tried

Algorithm 2 Energy Sharing Algorithm for Consumer j

Input: Energy supplier set S with surplus energy and sharing price, required energy $\triangle E_j(n)$
Output: Energy sharing instructions list L

1: Sort S by sharing price;
2: **for** home i in sorted S **do**
3:     **if** $|\triangle E_i(n)| \geq |\triangle E_j(n)/\eta_{ij}|$ **then**
4:         Requested Energy $E_r(n)$ is $|\triangle E_j(n)/\eta_{ij}|$
5:     **else**
6:         Requested Energy $E_r(n)$ is $\triangle E_i(n)$
7:     **end if**
8:     Send message to home i for $E_r(n)$ energy
9:     Wait and receive message from home i for $E_g(n)$ amount of energy
10:     Add energy sharing instruction [i, $E_g(n)$] into list L
11:     $\triangle E_j(n)$ = $\triangle E_j(n)$ - $E_g(n) * \eta_{ij}$
12:     if $\triangle E_j(n)$ == 0 break
13: **end for**

(Lines 10-13). Note that the consumer will also update the amount of surplus energy once it receives the updated multicast message from suppliers.

One example of the energy sharing process between one supplier and two consumers is shown in Figure 5. Supplier H1 has 10kWh surplus energy, while consumers H2 and H3 need 3kWh and 2kWh energy, respectively. It starts with all homes broadcasting the energy difference (step 1). Then H1 multicasts the selling price to the consumers (step 2). In this example, H2 requests 3.2kWh and H3 requests 2.4kWh energy by considering transmission loss (step 3). Supplier H1 grants the requests as it has enough energy to share (step 4). In the end, H1 has 4.4kWh residual energy. Consumers H2 and H3 will pay \$0.2 $\times$ 3.2 and \$0.2 $\times$ 2.4 to H1.

(iv) **Executing Energy Sharing:** After the energy sharing home pairs are decided, homes will start energy sharing. As we cannot control or account for the exact energy flow if two energy sharing are executed at the same time on the shared bus, generally we have to use the shared bus in a sequential way, such as the approach in [5]. The limitation on the transmission speed puts a cap on the amount of energy shared within one time window. This introduces a challenge for scheduling the energy sharing. If a fixed sharing sequence is adopted, homes at the end of the sequence may be deprived of the chance of energy sharing due to the time limit, which impacts the fairness and causes either starving or energy waste in these homes.

In order to address the above issue, a dynamic token-ring approach is adopted. Homes form a virtual ring and are ordered based on their id. Only the home that holds the token is able to initiate energy sharing. At the beginning of each window, the first home that is capable of energy sharing is the last home in previous window. It will contact its counterparts to execute the energy sharing. If a home holding the token is not involved in the energy sharing in current window, it can simply yield the token to the home next in the ring. An example of this case is shown in Figure 6. Only three energy sharing processes are

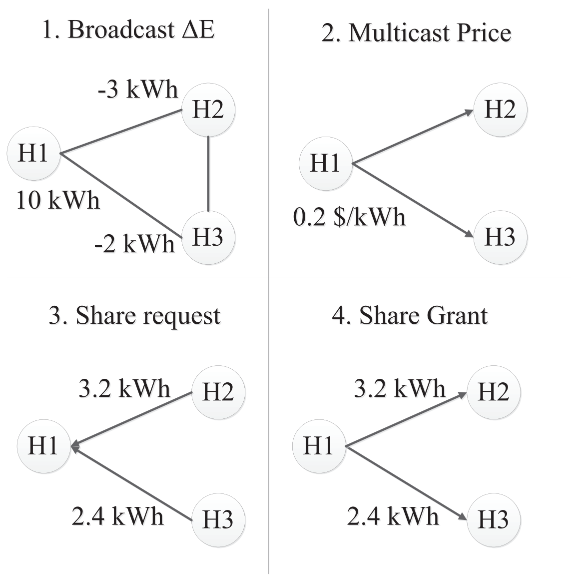


Fig. 5: An example of energy sharing communication between one supplier and two consumers. Supplier H1 shares 3.2kWh and 2.4kWh with consumer H2 and H3 respectively.

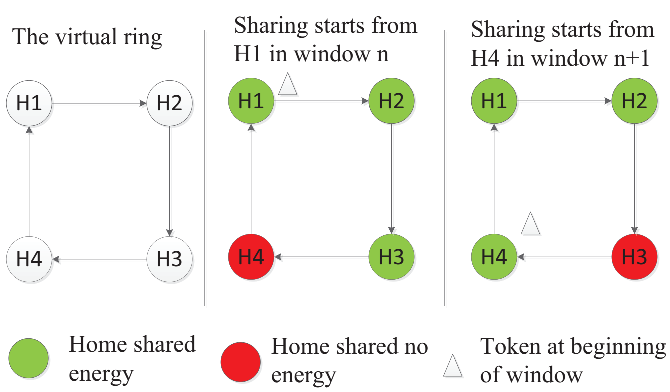


Fig. 6: An example of dynamic sharing sequence. Each window only allows three energy sharing processes. All homes shared energy at least once either in window n or (n+1).

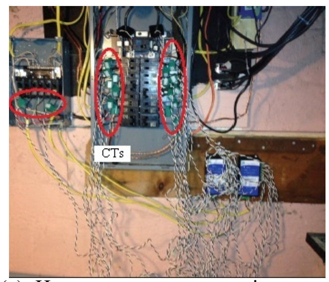
allowed within one window period. In window n, the energy sharing sequence starts from H1. H1, H2 and H3 shared energy, while H4 did not due to time limitation. In window $n+1$, the energy sharing sequence changes by starting from H4 such as (H4, H1, H2, H3), as the token is passed down to H4. The sharing ends by H4, and H1 and H2 share energy. Token is passed to H3 so H3 will share energy first in next window. In the end, all homes share energy for at least one window either in window n or $n+1$.

IV. Implementation and Evaluation

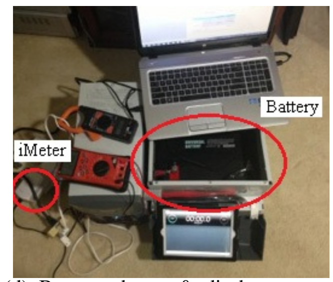
In this section, we evaluate the performance of our system. We collect empirical data from 20 homes in Amherst, MA, including:

(a) Energy storage unit (large capacity battery)

(b) Solar panel



(c) Home energy consumption measurement



(d) Battery charge & discharge measurement

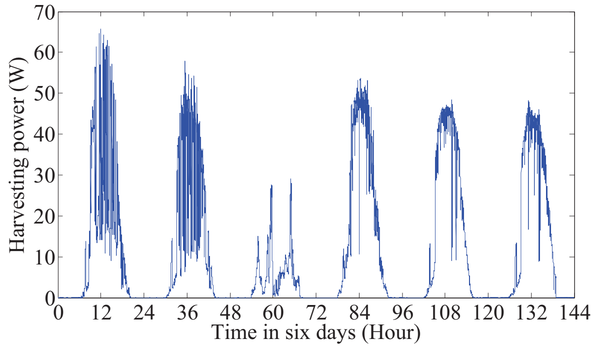
Fig. 7: Energy storage unit, renewable source and meters deployment in one home.

- **Energy harvesting data:** The renewable harvesting devices we use are Grape Solar 75-Watt Monocrystalline PV Solar Panels (shown in Figure 7(b)). Figure 8(a) shows six days of energy harvesting data. The weather forecast data we use are from NWS (National Weather Station).

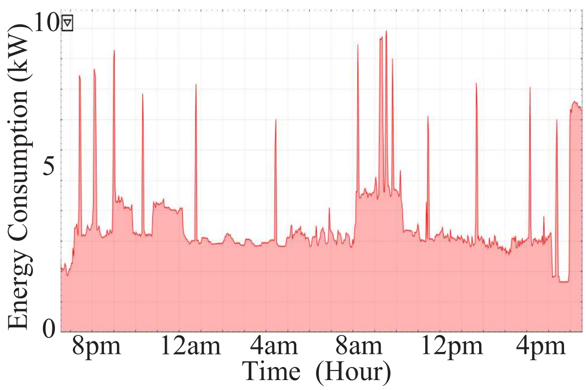
- **Energy consumption data:** Current transducers (CTs) are added (shown in Figure 7(c)) to monitor homes' consumption. Figure 8(b) shows the aggregated energy consumption data within one day in a deployed home.

- **Charging and discharging power of a battery:** The energy storage unit we use is called Xantrex PowerHub 84053. An iMeter Solo (an INSTEON power meter) is used to measure the battery charging and discharging rate. We also use a webcam to record the voltage and current readings using multimeters. Figure 7(d) shows our experiment setup. The power consumption for charging a battery is shown in Figure 8(c). The average energy that can be charged to the battery is around 160W per hour, which implies that within one hour window only a limited amount of energy can be transmitted.

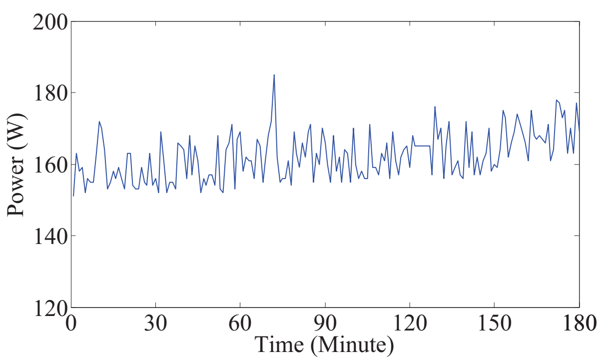
To verify the efficiency of our system, we compare our design in latter evaluation results, with (i) **Centralized energy sharing (CES)**, where a centralized energy sharing approach target minimizing the transmission loss ([5]), (ii) **No energy sharing (NES)**, where individual homes harvest and consume energy by themselves without energy sharing. In the simulation, the battery loss rate we use is 15%; power line transmission loss rate is around 7.6%, which varies with different distances among homes. The energy price for CES and NES is fixed at $0.13/kWh (the utility price in Amherst, MA). For the battery, the price is around $200/kWh. For solar panels, the price is around $0.6/kWh.



(a) Harvesting power in six days (from solar panel deployed outside of one house)



(b) Energy consumed in one house within one day (data acqiring granularity is 1 second)



(c) Power consumption for charging a battery

Fig. 8: Sensing data in one home.

The system benefit: Figure 10 shows the system cost and benefit for three systems over five years. The benefit is calculated by summing up the value of the harvested energy and the amount of money obtained from energy sharing. The benefit of our system both surpasses the system cost and show more than 17% improvement over the NES. Our system is comparable with CES, although CES is a centralized approach which can minimize the energy transmission loss.

We also show statistics of profit ratio in Table II. The

	Cost	CES	iDES	NES
Average of 20 homes ($)	5109.12	5505.82	5469.82	4643.68
STD of 20 homes	149.21	172.89	82.55	160.32

TABLE II: Cost and benefit: "Cost" is user investments for batteries and other relative devices.

	CES	iDES	NES
Average of 20 homes (Hour)	11.586	11.893	12.733
STD of 20 homes	0.696	0.315	0.622

TABLE III: Failure time

average benefits for our system and CES are very close. In our system, most of the homes could gain profit in less than five years, which provides incentive for the homes to share energy. Moreover, the STD (standard derivation) of iDES is much lower than CES, which means that all the homes in the system receive similar amount of benefit. That is because in our approach, the energy sharing scheduling is dynamic so every home is given a nearly equal chance to share energy; however, in CES the distant homes can hardly be involved in energy sharing if the energy sharing time is beyond the time window.

The average failure time: Figure 9 shows the accumulated failure time for three systems over six days. When a home runs out of energy in a window, we indicate it as a failure. The failure time in our system is almost same for all the homes, while in CES and NES it varies dramatically. For example, Homes 3, 5 17 have more than 20% longer failure time than average in CES and NES, and the failure time for home 3 is more than twice of home 4 in CES.

Table III shows the average failure time and STD for three systems. CES and iDES have similar failure time that is less than 8% compared with NES, which indicates the performance of our system is comparable with CES. The STD of iDES outperforms CES by more than 50%, which proves the effectiveness of the dynamic scheduling.

V. Related Work

Our work is related to the work of three different areas: energy harvesting, energy efficient systems, economics and network communication.

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. To manage renewable energy, Deborah et al. [9] propose a method to exploit robotic mobility by having energy producers be mobile nodes. These nodes try to keep themselves recharged by moving to locations with abundant energy supply. Once charged, they migrate to the service areas in the network for delivering energy to the (static) consumer nodes that have

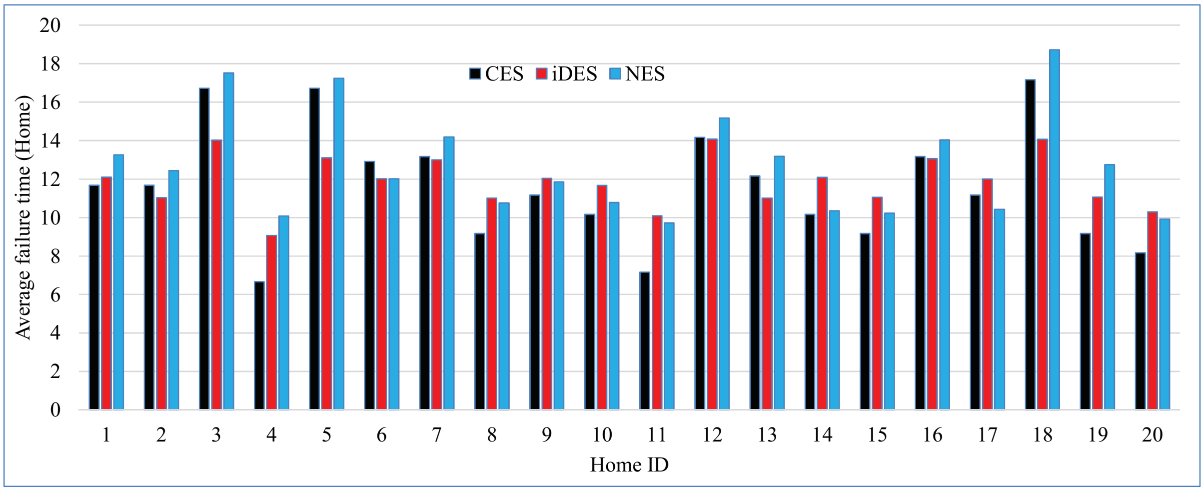


Fig. 9: Accumulated failure time of 20 homes over six days

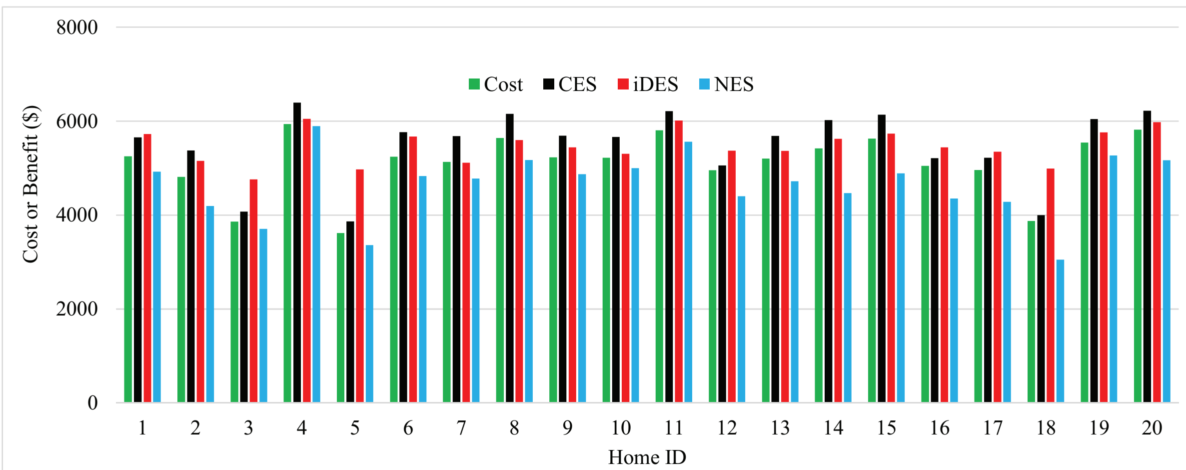


Fig. 10: Cost and benefit of 20 homes over five years

requested energy. In essence, mobile energy producers act as energy equalizers in the network by carrying energy payloads from areas where environmental ambient energy is plentiful to areas where it is either unavailable or being used faster than it can be harvested. In [10], the authors designed perpetual environmentally powered sensor networks. [11] discussed the challenges and opportunities for integrating renewable energy. [12] summarized the applications and challenges of energy harvesting for wireless sensor network in smart grid. These approaches have devices owned by single entity. However, in comparison to them, our work follows the simple idea where we build an energy sharing microgrid system to share the renewable energy, which uses the energy sensing data and novel energy sharing price to decide the energy sharing home pairs and when to share energy.

Energy efficient systems. This research mainly focuses on (i) energy auditing [13] [14] and design of control algorithms or tools to reduce energy consumption inside a single building [15] [16] [17], (ii) reducing the energy usage of system [18], energy-efficient building automation, ventilation, and air conditioning [19] [20]. In smart power grid, researchers have (i) developed models based on measurement from phase measurement units to solve the wide area control problem of large scale power systems [21], (ii) investigated the integration of renewable energy into power grid [22], (iii) optimized the packing size of large scale batteries to improve battery utilization in microgrids [23], (iv) applied stochastic network calculus to analyze the power supply reliability with various renewable energy configurations and store that energy into very large scale batteries [24], (v) combined market-based electricity pricing models with on-site batteries which are used to store renewable energy to incentivize distributed generation [25], (vi) reduced cost of purchasing batteries by smoothing demand peaks [26], and (vii) used IT technology in design and operational phases to achieve sustainability [27]. Other researchers also investigated other types of energy efficient systems such as (i) energy saving electronics [28] [29], (ii) energy efficient data centers [30], and (iii) optimal charging of plug in hybrid electric vehicles [31], (iii) wireless communication technology to maximize the network life [32]. Researches have also conducted energy management in other fields, such as mobile devices [33]–[35], sensor networks [36]–[55], and smart grids [56]–[61]. Our work is built on previous works, but homes with renewable devices and small battery are the main research focus. Also it takes a different approach to reduce energy cost by sharing the renewable energy. Unlike these other approaches, our work opens up a new approach where energy can be gained efficiently and used smartly.

Economics and network communication. Allocation optimization and fair allocation mechanisms are important factors while doing the workload scheduling. Many complex and stochastic approaches have been proposed in economics and network communication area, where allocation optimization approach is used for flow control to optimize a global measure of network performance [62] [63] and fair allocation [64]. [65] utilizes both location and time diversity of electricity price under multi-regional electricity markets to minimize the total electricity cost of IDCs. A performance modelling framework for multihop wireless networks is proposed by [66], and its network structure is adopted in this approach. Our approach is built on previous approaches, where the energy sharing price reflects the supply-demand relationship and the fairness is achieved by dynamically scheduling the energy sharing sequence.

Recent work explores reducing the peak load of main grid and storing AC energy in each homes battery, which can increase the profit to the homeowners [67]. Different from the above approach, our system can work under off-grid deployment and benefit the homes by sharing renewable energy. Most related work is [5] and [68]; the former paper minimizes energy transmission loss in a centralized fashion and does not consider the energy sharing price. The later paper designed a secure energy routing mechanism for secure and optimal sharing purpose. While in this paper, we propose a distributed solution and design the pricing model to incentivize the energy sharing.

For the energy related information and communication model, OASIS designed the Energy Interoperation standard for a smartgrid [69], while our protocol focuses on the minimum information flow needed in the smart microgrid.

VI. Conclusion

In this paper, we proposed a distributed incentive-driven energy sharing system for a sustainable microgrid. In order to incentivize energy sharing, we designed a novel pricing model. We also developed a consumer energy sharing request algorithm to minimize consumers' cost and a supplier energy sharing grant algorithm to improve the energy sharing efficiency. A dynamic token-ring sharing sequence control approach is introduced to provide fair energy sharing. To the best of our knowledge, this work is the first distributed approach to efficiently share energy in a microgrid and incentivize users by profits. We evaluated our design using real-world energy harvesting and consumption data. The results proved the effectiveness of our design compared with other approaches.

Acknowledgment

This work is supported in part by NSF grant CNS-1217791 and Singapore National Research Foundation NRF2012EWT-EIRP002-045.

References

[1] "Energy efficiency trends in residential and commercial buildings," http://apps1.eere.energy.gov/buildings/publications/pdfs/corporate/building_trends_2010.pdf, 2010.

[2] T. Zhu, A. Mishra, D. Irwin, N. Sharma, P. Shenoy, and D. Towsley, "The case for efficient renewable energy management for smart homes," in *Proceedings of the 3rd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, 2011.

[3] A. Mishra, D. Irwin, P. Shenoy, J. Kurose, and T. Zhu, "Smartcharge: Cutting the electricity bill in smart homes with energy storage," in *the third International Conference on Future Energy Systems*, 2012.

[4] "Grid friendly appliance project final report," http://cleanefficientenergy.org/sites/default/files/gfa_project_final_report_pnnl17079.pdf, 2009.

[5] T. Zhu, Z. Huang, A. Sharma, J. Su, D. Irwin, A. Mishra, D. Menasche, and P. Shenoy, "Sharing renewable energy in smart microgrid," in *IEEE 4th ICCPS*, 2013.

[6] N. Sharma, J. Gummeson, D. Irwin, T. Zhu, and P. Shenoy, "Leveraging Weather Forecasts in Energy Harvesting Sensor Systems," in *suscom*, 2014.

[7] S. H. Karaki, R. B. Chedid, and R. Ramadan, "Probabilistic performance assessment of autonomous solar-wind energy conversion systems," in *Energy Conversion, IEEE Transactions*, vol. 14, 1999, pp. 766 – 772.

[8] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power management in energy harvesting sensor networks," *ACM Transction on Embedded Computer Systems*, vol. 6, no. 4, pp. 1539–9087, 2007.

[9] M. Rahimi, H. Shah, G. Sukhatme, J. Heidemann, and D. Estrin, "Studying the feasibility of energy harvesting in mobile sensor networks," in *Proceedings of the IEEE ICRA*, 2003.

[10] X. Jiang, P. Joseph, and D. Culler, "Perpetual environmentally powered sensor networks," in *IPSN/SPOTS*, 2005.

[11] A. Krioukov, C. Goebel, S. Alspaugh, Y. Chen, D. E. Culler, and R. H. Katz, "Integrating renewable energy using data analytics systems: Challenges and opportunities." *IEEE Data Eng. Bull.*, vol. 34, no. 1, pp. 3–11, 2011.

[12] S. Ma, Y. Yang, Y. Qian, H. Sharif, and M. Alahmad, "Energy harvesting for wireless sensor networks: Applications and challenges in smart grid," in *Special Issue on Wireless Sensor Networks with Environmental Energy Harvesting*, 2013.

[13] X. Jiang, M. Van Ly, J. Taneja, P. Dutta, and D. Culler, "Experiences with a high-fidelity wireless building energy auditing network," in *SenSys*, 2009, pp. 113–126.

[14] I. Lima Azevedo, M. G. Morgan, K. Palmer, and L. B. Lave, "Reducing us residential energy use and co2 emissions: How much, how soon, and at what cost?" *Environmental science & technology*, vol. 47, no. 6, pp. 2502–2511, 2013.

[15] J. Hsu, P. Mohan, X. Jiang, J. Ortiz, S. Shankar, S. Dawson-Haggerty, and D. Culler, "Hbci: Human-building-computer interaction," in *Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, 2010.

[16] T. Weng and Y. Agarwal, "From buildings to smart buildings – sensing and actuation to improve energy efficiency," in *IEEE Design and Test, Special Issue on Green Buildings*, 2012.

[17] A. Guinard, A. M. Gibney, and D. Pesch, "A wireless sensor network design tool to support building energy management," in *Proceedings of the 1st ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, 2009.

[18] "Energy efficient digital networks," http://eetd.lbl.gov/sites/all/files/energy _efficient_digital_network_eedn.pdf, 2013.

[19] D. G. Holmberg, M. A. Raymond, and J. D. Averill, "Delivering building intelligence to first responders," in *NIST TN - 1648*, 2013.

[20] S. Goyal, H. Ingley, and P. Barooah, "Occupancy-based zone climate control for energy efficient buildings: Complexity vs. performance," in *Applied Energy*, 2013.

[21] A. Chakrabortty, "Wide-area control of large power systems using dynamic clustering and tcsc-based redesigns," in *IEEE Transctions on Smart Grid*, vol. 3, no. 3, 2012, pp. 1503– 1514.

[22] M. M. He, E. M. Reutzel, X. Jiang, R. H. Katz, S. R. Sanders, D. E. Culler, and K. Lutz, "An architecture for local energy generation, distribution, and sharing," in *Energy 2030 Conference*, 2008.

[23] F. J. Jin and K. G. Shin, "Pack sizing and reconfiguration for management of large-scale batteries," in *Proceedings of ICCPS*, 2012.

[24] K. Wang, F. Ciucu, C. Lin, and S. H. Low, "A stochastic power network calculus for integrating renewable energy sources into the power grid," *IEEE Journal on Selected Areas in Communications*, 2012.

[25] A. MISHRA, D. Irwin, P. Shenoy, J. Kurose, and T. Zhu, "Greencharge: Managing renewableenergy in smart buildings," in *IEEE Selected Areas in Communications*, vol. 31, no. 7, July 2013, pp. 1281–1293.

[26] A. Mishra, D. Irwin, P. Shenoy, and T. Zhu, "Scaling distributed energy storage for grid peak reduction," in *e-Energy '13*.

[27] C. E. Hoover, R. Sharma, B. Watson, S. K. Charles, A. Shah, C. D. Patel, M. Marwah, T. Christian, and C. E. Bash, "Sustainable it ecosystems: enabling next-generation cities," *HP Laboratories Technical Report, HPL-2010-73*, 2010.

[28] K. C. Sou, J. Weimer, H. Sandberg, and K. H. Johansson, "Scheduling smart home appliances using mixed integer linear programming," in *Conference on Decision and Control*, 2011.

[29] N. Vallina-Rodriguez, P. Hui, J. Crowcroft, and A. Rice, "Exhausting battery statistics: understanding the energy demands on mobile handsets," in *MobiHeld*, 2010.

[30] S. A. Ahmadi, I. Shames, F. Scotton, L. Huang, H. Sandberg, K. H. Johansson, and B. Wahlberg, "Towards more efficient building energy management systems," in *Proc. 7th International Conference on Knowledge, Information and Creativity Support Systems*, 2012.

[31] S. Sojoudi and S. H. Low, "Optimal charging of plug-in hybrid electric vehicles in smart grids," in *In Proceedings of the 2011 IEEE Power & Energy Society General Meeting*, 2011.

[32] K. Al Agha, M.-H. Bertin, T. Dang, A. Guitton, P. Minet, T. Val, and J.-B. Viollet, "Which wireless technology for industrial wireless sensor networks? the development of ocari technology," *Industrial Electronics, IEEE Transactions on*, 2009.

[33] Z. Dong, L. Kong, P. Cheng, L. He, Y. Gu, L. Fang, T. Zhu, and C. Liu, "REPC: Reliable and efficient participatory computing for mobile devices," in *SECON*, 2014.

[34] L. He, P. Cheng, Y. Gu, J. Pan, T. Zhu and C. Liu, "Mobile-to-mobile energy replenishment in mission-critical robotics sensor networks," in *INFOCOM*, 2014.

[35] T. Zhu, Y. Gu, T. He, and Z.-L. Zhang, "Achieving Long-Term Operation with a Capacitor-Driven Energy Storage and Sharing Network," in *ACM TOSN*, Vol. 8, No. 3, Aug. 2012.

[36] L. He, Y. Gu, J. Pan, and T. Zhu, "On-demand charging in wireless sensor networks: Theories and applications," in *MASS*, 2013.

[37] T. Zhu, A. Mohaisen, Y. Ping, and D. Towsley, "DEOS: Dynamic energy-oriented scheduling for sustainable wireless sensor networks," in *INFOCOM*, 2012.

[38] T. Zhu, Y. Gu, T. He, and Z. Zhang, "eShare: A capacitor-driven energy storage and sharing network for long-term operation," in *SenSys*, 2010.

[39] T. Zhu, Z. Zhong, Y. Gu, T. He, and Z. Zhang, "Leakage-aware energy synchronization for wireless sensor networks," in *MobiSys*, 2009.

[40] Y. Gu, T. Zhu, and T. He, "Esc: Energy synchronized communication in sustainable sensor networks," in *ICNP*, 2009.

[41] Y. Gu, L. He, T. Zhu, and T. He, "Achieving Energy Synchronized Communication in Energy-Harvesting Wireless Sensor Networks," in *ACM Transactions on Embedded Computing Systems, Vol. 13*, 2014.

[42] J. Jun, L. Cheng, L. He, Y. Gu, and T. Zhu, "Exploiting Sender-based Link Correlation in Wireless Sensor Networks," in *ICNP '14*.

[43] S. Ren, P. Yi, T. Zhu, Y. Wu, and J. Li, "A 3-hop Message Relay Algorithm for Connected Dominating Sets in Wireless Ad-hoc Sensor Networks," in *ICCC '14*.

[44] P. Yi, T. Zhu, Q. Zhang, Y. Wu, and J. Li, "Green Firewall: an Energy-Efficient Intrusion Prevention Mechanism in Wireless Sensor Network," in *GLOBECOM '12*.

[45] Q. Zhang, T. Zhu, P. Yi, and Y. Gu, "Cooperative Data Reduction in Wireless Sensor Network," in *GLOBECOM '12*.

[46] Z. Pei and T. Zhu, "A Multi-information Localization Algorithm in Wireless Sensor Networks and its Application in Medical Monitoring Systems," in *WiCOM '11*.

[47] S. Guo, S. M. Kim, T. Zhu, Y. Gu, and T. He, "Correlated Flooding in Low-Duty-Cycle Wireless Sensor Networks," in *ICNP*, 2011.

[48] T. Zhu, Z. Zhong, T. He and Z.-L. Zhang, "Exploring link correlation for efficient flooding in wireless sensor networks," in *NSDI '10*.

[49] Z. Zhong, T. Zhu, D. Wang and T. He, "Tracking with Unreliable Node Sequences," in *INFOCOM*, 2009.

[50] T. Zhu, Z. Zhong, T. He, and Z.-L. Zhang, "Achieving Efficient Flooding by Utilizing Link Correlation in Wireless Networks," *IEEE/ACM Transactions on Networking (TON)*, 2013.

[51] T. Zhu, Z. Zhong, Y. Gu, T. He, and Z.-L. Zhang, "Feedback Control-based Energy Management for Ubiquitous Sensor Networks," in *IEICE Transactions on Communications*, Vol. E93-B, No.11, pages 2846-2854, Nov. 2010.

[52] T. Zhu, Z. Zhong, T. He, and Z.-L. Zhang, "Energy-Synchronized Computing for Sustainable Sensor Networks," in *Elsevier Ad Hoc Networks Journal*, 2010.

[53] C. Zhou and T. Zhu, "Highly Spatial Reusable MAC for Wireless Sensor Networks," in *WiCOM '07*.

[54] C. Zhou and T. Zhu, "A Spatial Reusable MAC Protocol for Stable Wireless Sensor Networks," in *WiCOM '08*.

[55] C. Zhou and T. Zhu, "Thorough Analysis of MAC Protocols in Wireless Sensor Networks," in *WiCOM '08*.

[56] P. Yi, Y. Tang, Y. Hong, Y. Shen, T. Zhu, Q. Zhang, and M. M. Begovic, "Renewable energy transmission through multiple routes in a mobile electrical grid," in *ISGT*, 2014.

[57] P. Yi, T. Zhu, G. Lin, and Q. Zhang, "Routing renewable energy using electric vehicles in mobile electrical grid," in *MASS*, 2013.

[58] P. Yi, T. Zhu, G. Lin, X. Jiang, G. Li, L. Si, and M. M. Begovic, "Energy scheduling and allocation in electric vehicle energy distribution networks," in *ISGT*, 2013.

[59] P. Yi, T. Zhu, B. Jiang, B. Wang, and D. Towsley, "An energy transmission and distribution network using electric vehicles," in *ICC*, 2012.

[60] Z. Zhou, M. Xie, T. Zhu, W. Xu, P. Yi, Z. Huang, Q. Zhang, and S. Xiao, "EEP2P: An Energy-Efficient and Economy-Efficient P2P Network Protocol," in *IGCC '14*.

[61] Z. Huang, H. Luo, D. Skoda, T. Zhu, and Y. Gu, "E-Sketch: Gathering Large-scale Energy Consumption Data Based on Consumption Patterns," in *IEEE BigData*, 2014.

[62] W.-H. Wang, M. Palaniswami, and S. H. Low, "Application-oriented flow control: Fundamentals, algorithms and fairness," in *IEEE/ACM TRANSACTIONS ON NETWORKING*, vol. 14, no. 6, 2006.

[63] L. L. H. Andrew, S. H. Low, and B. P. Wydrowski, "Understanding xcp: Equilibrium and fairness," in *IEEE/ACM TRANSACTIONS ON NETWORKING*, 2009.

[64] S. Li, W. Sun, and C. Hua, "Fair resource allocation and stability for communication networks with multipath routing," in *International Journal of System Science*, 2013.

[65] L. Rao, X. Liu, M. Ilic, and J. Liu, "Distributed coordination of internet data centers under multiregional electricitymarkets," in *Proceedings of the IEEE Journals & Magazines*, vol. 100, no. 1, 2012.

[66] K. Xu, D. Tipper, P. Krishnamurthy, and Y. Qian, "A framework of efficient hybrid model and optimal control for multihop wireless networks," in *ACM Sigmetrics/Performance*, 2012.

[67] T. Carpenter, S. Singla, P. Azimzadeh, and S. Keshav, "The impact of electricity pricing schemes on storage adoption in ontario," in *e-Energy*, 2012.

[68] T. Zhu, S. Xiao, P. Yi, D. Towsley, and W. Gong, "A secure energy routing protocol for sharing renewable energy in smart microgrid," in *SmartGridComm*, 2011.

[69] "Energy interoperation version 1.0," http://docs.oasis-open.org/energyinterop/ei/v1.0/, 2012.