Monetary Fair Battery-based Load Hiding Scheme for Multiple Households in Automatic Meter Reading System

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Abstract—Automatic Meter Reading (AMR) system is expected to be used for real time load monitoring to optimize power generation and energy efficiency. Recently, it has been a serious problem that user's lifestyle may be revealed by a tool to estimate consumer's lifestyle from a real-time load profile. In order to solve this issue, Battery-based Load Hiding (BLH) algorithms are proposed to obfuscate an actual load profile by charging and discharging. Although such BLH algorithms have already been studied, it is important to consider multiple households case where one battery is shared among them due to its high cost. In this paper, a monetary fair BLH algorithm for multiple households is proposed. In presented scheme, the core unit calculates the difference between the charged amount and discharged one for each household. If the difference is bigger than the predefined threshold (monetary unfair occurs), the most disadvantageous and advantageous households are given priority to discharge and charge the battery and other households should charge to achieve monetary fairness. The efficiency of the scheme is demonstrated through the computer simulation with a real dataset.

Keywords—Automatic Meter Reading, Battery Load Hiding, Privacy for Smart Grid.

1. Introduction

In recent years, smart meters have gained much popularly with growing support from the electric power company and governments. However, smart meters pose substantial threat to the privacy of individuals [1]. Smart meters use measurement circuits that can record the load profile by a second or minute order. Recently, it has been a serious problem that user's lifestyle may be revealed by a tool, which is called Non-Intrusive Load Monitoring (NILM), to estimate consumer's lifestyle from a real-time load profile [2]–[4]. The most of NILM techniques are to detect edges in a load profile [5]–[7]. Batra *et al.* publish an open source toolkit of NILM named NILMTK [8]. However, NILM gives rise to serious user privacy concerns. Multiple studies have shown that smart meters are vulnerable to an attack that could leak fine grained usage data to third parties, e.g. an electric power industry [9]. In order to preserve individual's privacy, a Battery-based Load Hiding (BLH) technique is proposed to avoid the information leakage by NILM [10]–[14]. The basic concept of BLH is to hide actual load by wisely charging/discharging a battery. For example, in Best Effort (BE), the core unit, which is

a battery controller for BLH, charges/discharges a battery to flatten the metered load [10]. Another novel work is Non-Intrusive Load Leveling (NILL) algorithm [11]. In NILL algorithm, the core unit aims to flatten the metered load and controls the residual energy of the battery in order to continue BLH [11]. However, these schemes disclose true demand when the battery is almost empty or full. In order to solve this problem, Stepping Framework (SF) is proposed to step a metered load instead of flattening it by considering the current energy consumption level of the appliances [12].

Although many BLH algorithms have been studied in the literature, most of them do not consider the multiple households case. Privacy leakage problem is related with all regions where a real-time load measuring system is offered. According to [15], countries all over the world, e.g., US, Canada, United Kingdom, France, Spain, China and Japan, have taken the decision to roll out smart metering system. Irrespective of country, one may feel that it is expensive because a battery of 1 kWh might cost at least $1,200 [16]. Therefore it has a great importance to realize a BLH where a battery is shared among multiple households. A realistic case of the shared battery is an apartment, condominium or a set of houses [17]. In this case, inhabitants who want to avoid the privacy leakage by smart meter may cover the expenses of the development and maintenance of such a battery system. Vilardebo *et al.* propose a BLH scheme for multiple households, however, they do not consider monetary fairness [13]. That is, an unfair situation may occur when households pay a money to charge a battery by BLH but they do not use the same amount of the charged energy from it. Therefore, it is necessary to propose a monetary fair BLH scheme for multiple households.

In this paper, a monetary fair BLH scheme for multiple households by using only one battery is proposed. Authors first present a monetary fair BLH scheme for two households. In the scheme, the core unit chooses one of the following three modes based on monetary loss and residual energy on the battery: the stabilization mode, fairness mode, and normal mode. In the stabilization mode, the core unit controls the amount of residual energy and avoids the situation where BLH cannot be executed. In the fairness mode, the core unit lets an overcharged household discharge, while it lets the other charge in order to solve monetary unfairness. Finally, in the normal mode, the core unit

calculates each household's metered load at time t against every possible case and chooses the case where the residual energy approaches almost the half of battery capacity.

Authors further extend proposed algorithm to deal with more than two households is applied. If original algorithm for multiple households, the core unit would have to calculate all patterns in the normal mode and it would require heavy computation on the core unit – the order is $O(2^N)$ where N denotes the number of households. Therefore, authors propose an extended algorithm to deal with multiple households by approximating the algorithm in the normal mode. More specifically, the core unit first decides the number of charging (or discharging) households so that residual energy approaches to the target energy level (more specifically 55% of the maximum capacity). If the residual energy is less than that value, more households charge battery. Then which household charges/discharges is assigned. The efficiency of proposed scheme is shown by the computer simulation. The evaluation metrics are mutual information, which is a major indicator of how much information is leaked by BLH, and monetary loss. Authors also clarify how many households can be covered with proposed algorithm. A real electric loads dataset called Wiki-Energy is used [18] to obtain reasonable outcome.

The remainder of this paper is organized as follows. Related work regarding BLH and its shortcomings is summarized in Section 2. The proposed scheme with discussion is described in Section 3. Simulation results are shown in Section 4. The paper is concluded in Section 5.

2. Related Work

2.1. Summary of Battery Load Hiding Schemes

To protect a privacy for smart meter users, many researchers have proposed BLH algorithms considering various constraints on the battery such as capacity to minimize the amount of information leakage [10]–[14]. In BLH algorithm, the operation system controls the battery based on the demand load and previous time energy consumption observed by a smart meter (the metered load) in order to control the currently metered load.

Current BLH algorithms basically aim to flatten the metered load by wisely charging/discharging a battery. The main difference among these algorithms is how to react when the residual energy of a battery is in almost empty or full. In the BE [10], when the energy level reaches the minimum or maximum, the core unit determines whether it should be charged or discharged at the maximum rate. In the NILL [11], the core unit chooses a charging/discharging rate with respect to the energy consumption of appliances. Yang *et al.* analyze the above two algorithms and show that these two algorithms disclose the true energy consumption when the battery is too low or too high. To solve this problem, they propose SF-LS2 [12]. In SF-LS2 , instead of trying to maintain a constant load, the core unit monitors the current energy consumption level of the appliances and

chooses a target load value from a set of predefined values. Yang *et al.* verify the tradeoff between the privacy and the electricity bill and propose an online algorithm that can optimally control the battery to protect the smart meter data privacy and cut down the electricity bill [14]. Vilardebo *et al.* propose a BLH scheme that operates over multiple users by defining privacy-power function [13].

2.2. Shortcomings in Conventional BLH Schemes

Although there are many BLH algorithms, most of algorithms do not consider using one battery for multiple households. One may feel that it is expensive since a battery of a 1 kWh might cost at least $1,200 [16]. Therefore it has a great importance to realize a BLH, where a battery is shared among multiple households. Vilardebo *et al.* propose such a BLH scheme with a single battery, however, they do not consider monetary fairness (cost/profit balance between users) [13]. Without considering it for the multiple households case, one might gain or lose money by executing BLH. Here, monetary fairness denotes that the charged amount for BLH must be same as the discharged amount for each household. However, it is difficult to achieve the monetary fairness because of two constraints on the battery. The first constraint is that the battery has a limit on charge and discharge rate. The core unit needs to choose, which user and how much energy should be charged or discharged. The second one is that BLH is limited by the battery capacity. When the system deals with multiple households with one battery, it is challenging to appropriately execute BLH for each one.

3. Proposed Scheme

The paper proposed a monetary fair BLH algorithms for multiple households. Firstly, a BLH scheme for two households with a battery and then extend it to deal with more than two by approximating the computationally heaviest part in the algorithm is shown. Figure 1 shows the system
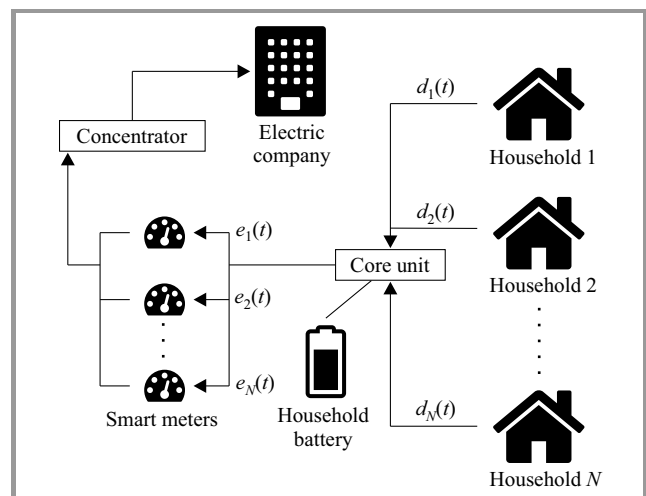

Fig. 1. The system model of BLH scheme.

Table 1
Notations used in presented scheme

Parameters	Definition
i	Index of a household
β	Quantization width
β'	$\frac{\beta}{N}$
$E_{rest}(t)$	Ratio of residual energy to the battery capacity at time t [%]
$l_i(t)$	Monetary loss caused by charging and discharging within household i
l_{th}	Threshold of $l_i(t)$
$d_i(t)$	Demand load in household i
$s_i(t)$	Charging signal. If $s_i(t) = 1$, the core unit quantizes household i's load by charging. Otherwise, the core unit quantizes household i's load by discharging.
$e_i(t)$	Metered load (the load after BLH) in household i at time t
$C_{\max}$	Battery capacity
E_{fine}	Fine level of the battery. $E_{fine} = 0.55\,C_{\max} = \frac{0.9+0.2}{2}\,C_{\max}$
p	The household which most charged during the period from 0 to $t-1$.
q	The household which most discharged during the period from 0 to $t-1$.
K_1	Difference between $0.9\,C_{\max}$ and $E_{rest}(t)$
K_2	Difference between $E_{rest}(t)$ and $0.2\,C_{\max}$
N_C	Number of charging households other than q at time t
N_D	Number of discharging households other than q at time t

model of BLH scheme. $d_i(t)$ denotes the total electric load demanded by the appliances in a household i at time t. In contrast, $e_i(t)$ is the summation of $d_i(t)$ and load charged/discharged by BLH at time t (see Table 1). In order to realize BLH for multiple households, each household's $e_i(t)$ must be calculated based on $d_i(t)$. After deciding $e_i(t)$, the core unit controls the battery in order to output $e_i(t)$ to each smart meter. After that the core unit sends each smart meter to $e_i(t)$. When each smart meter receives $e_i(t)$, each smart meter sends $e_i(t)$ to the concentrator and the concentrator sends $e_i(t)$ to the electric company.

The threshold l_{th} is defined that determines the upper bound of instantaneous monetary unfairness. When the difference between the charged amount and discharged one exceeds the predefined threshold, the core unit lets the overcharged household discharge, or vice versa. This scheme consists of three modes: stabilization, fairness, and normal mode. The control unit changes its mode based on the residual energy and the amount of loss caused by BLH. When the

residual energy is almost empty or full, the core unit transits to the stabilization mode, which is based on the state-of-the-art BLH scheme SF-LS2 [12] to avoid the situation where BLH cannot be executed. If a household charges too much, the core unit transits to the fairness mode to solve monetary unfairness. Otherwise, the core unit executes the normal mode so that the residual energy approaches almost half of its capacity. After deciding its mode, the core unit decides each household's metered load $e_i(t)$ with a quantization band β, where β is a quantization bandwidth for household i's demand load $d_i(t)$. β indicates how coarsely hides a demand load and it is given by taking into account to the battery capacity and charging/discharging rate, where charging/discharging rate denotes how much energy the battery can charge/discharge within a time unit. Finally, the core unit charges or discharges by the calculated amount.

Moreover, authors extend the algorithm to deal with more than two households. In the extended version, the core unit first decides the number of households that executes BLH by charging (and discharging), which is denoted as N_C (and N_D), based on the current residual energy $E_{rest}(t)$. After deciding the number of charging and discharging households, the core unit then assigns each household to charging or discharging group.

3.1. Three Modes of BLH Algorithm

Deciding mode. Algorithm 1 shows an algorithm for the core unit to select its operating mode. First, if the residual energy is almost empty – $E_{rest}(t-1) \leq 20\%$ or full $E_{rest}(t-1) \geq 90\%$, the stabilization mode is chosen to avoid the situation where the residual energy gets empty or full. If either of households overcharges, i.e., the charged amount is beyond the pre-defined threshold l_{th}, the control unit transits to the fairness mode to achieve monetary fairness. Otherwise, the control unit chooses the normal mode so that the residual energy approaches almost half of the battery capacity $C_{\max}$, where $C_{\max}$ is maximum battery capacity.

Algorithm 1: Deciding mode

1: Input $E_{rest}(t-1)$
2: **if** $E_{rest}(t-1)$ is almost empty $\cup$ $E_{rest}(t-1)$ is almost full **then**
3:     *mode ← Stabilization*
4: **else if** $|l_i(t)| \geq l_{th}$ for $i = 1$ and/or 2 **then**
5:     *mode ← Fairness*
6: **else**
7:     *mode ← Normal*
8: **end if**
9: Return *mode*

Stabilization mode. In the stabilization mode (Algorithm 2), the core unit lets each household charge ($s_1(t) \leftarrow 1$, $s_2(t) \leftarrow 1$) when the residual energy is almost empty (under 20%). On the other hand, the core unit lets each house-

Algorithm 2: Stabilization mode

1: Input $E_{rest}(t-1)$
2: **for** $i \in 1:2$ **do**
3:     **if** $E_{rest}(t-1) \leq 20\%$ **then**
4:        $s_1(t) \leftarrow 1$
5:        $s_2(t) \leftarrow 1$
6:     **else if** $E_{rest}(t-1) \geq 90\%$ **then**
7:        $s_1(t) \leftarrow 0$
8:        $s_2(t) \leftarrow 0$
9:     **end if**
10:    $\beta' \leftarrow \frac{\beta}{2}$
11:    **if** $s_i(t) = 1$ **then**
12:       $e_i(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta'} \right\rceil \beta'$
13:    **else if** $d_i(t) \bmod \beta \neq 0$ **then**
14:       $e_i(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta'} \right\rfloor \beta'$
15:    **else**
16:       $e_i(t) \leftarrow \left(\frac{d_i(t)}{\beta'} - 1 \right) \beta'$
17:    **end if**
18: **end for**
19: Return $e_1(t)$ and $e_2(t)$

hold discharge – $s_1(t) \leftarrow 0$, $s_2(t) \leftarrow 0$, when the residual energy is almost full (over 90%). Here, $s_i(t)$ denotes whether household i hides its load by charging or discharging at time t. That is, $s_i(t) = 1$ indicates that the core unit lets household i charge, while $s_i(t) = 0$ indicates that the core unit lets household i discharge. Then, the core unit calculates a target quantized load $e_i(t)$ for each household according to $s_i(t)$. Here, β' is set as $\frac{\beta}{2}$ so that each household equally charges/discharges.

Fairness mode. In the fairness mode (Algorithm 3), the core unit lets an overcharged household i.e. $l_i(t-1) \geq l_{th}$

Algorithm 3: Fairness mode

1: Input $l_1(t-1)$ and $l_2(t-1)$
2: **if** $l_1(t-1) \leq l_2(t-1)$ **then**
3:    $s_1(t) \leftarrow 1$
4:    $s_2(t) \leftarrow 0$
5: **else**
6:    $s_1(t) \leftarrow 0$
7:    $s_2(t) \leftarrow 1$
8: **end if**
9: **for** $i \in 1:2$ **do**
10:    **if** $s_i(t) = 1$ **then**
11:       $e_i(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta$
12:    **else if** $d_i(t) \bmod \beta \neq 0$ **then**
13:       $e_i(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta} \right\rfloor \beta$
14:    **else**
15:       $e_i(t) \leftarrow \left(\frac{d_i(t)}{\beta} - 1 \right) \beta$
16:    **end if**
17: **end for**
18: Return $e_1(t)$ and $e_2(t)$

discharge and lets the other charge to solve monetary unfairness, where $l_i(t)$ denotes the difference between charged and discharged amount of energy for a household i at time t. Then, the core unit calculates a target quantized load $e_i(t)$ for each household according to $s_i(t)$.

Normal mode. Algorithm 4 shows the algorithm of the normal mode. The fine level E_{fine} of the battery is defined and set

$$E_{fine} = 0.55 C_{\max} = \frac{0.9 + 0.2}{2} C_{\max}.$$

In the normal mode, the core unit calculates each household's metered load at time t for every possible case, i.e. $\{s_1(t),\ s_2(t)\}$ in $\{\{0,0\},\{0,1\},\{1,0\},\{1,1\}\}$. Then, the core unit chooses the case where the residual energy most approaches E_{fine}.

Algorithm 4: Normal mode

1: **for** $\{s_1(t),\ s_2(t)\} \in \{\{0,0\},\{0,1\},\{1,0\},\{1,1\}\}$ **do**
2:    **for** $i \in 1:2$ **do**
3:      **if** $s_i(t) = 1$ **then**
4:        $e_{i,s_i(t)}(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta$
5:      **else if** $d_i(t) \bmod \beta \neq 0$ **then**
6:        $e_{i,s_i(t)}(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta} \right\rfloor \beta$
7:      **else**
8:        $e_{i,s_i(t)}(t) \leftarrow \left(\frac{d_i(t)}{\beta} - 1 \right) \beta$
9:      **end if**
10:    **end for**
11:    **if** the combination of $e_{1,s_1(t)}(t)$ and $e_{2,s_2(t)}(t)$ more approaches $E_{rest}(t) = 55\%$ **then**
12:      $e_1(t) \leftarrow e_{1,s_1(t)}(t)$
13:      $e_2(t) \leftarrow e_{1,s_2(t)}(t)$
14:    **end if**
15: **end for**
16: Return $e_1(t)$ and $e_2(t)$

3.2. Extended Algorithm for Multiple Households

In the next step the algorithm was extended for more than two households. Although the modes in the extended algorithm are almost same with the algorithm for two households, each mode needs to be slightly modified to deal

Algorithm 5: Deciding mode in multiple households case

1: Input $E_{rest}(t-1)$
2: **if** $E_{rest}(t-1)$ is almost empty $\cup$ $E_{rest}(t-1)$ is almost full **then**
3:    $mode \leftarrow Extended\ Stabilization$
4: **else if** i exists that satisfies $|l_i(t)| \geq l_{th}$ **then**
5:    $mode \leftarrow Extended\ Fairness$
6: **else**
7:    $mode \leftarrow Extended\ Normal$
8: **end if**
9: Return $mode$

with more households due to the following two reasons. The first one is to require large computational complexity. The second one is the possibility that BLH cannot be executed when the battery is fully charged or empty gets higher in presence of multiple households. Therefore, some parts of operated modes are modified to take into account these difficulties.

Deciding mode. Algorithm 5 shows the algorithm to decide the operating mode. First, the core unit checks the residual energy with the same way of the deciding mode in two households. Then, if there exist households whose loss or profit is more than l_{th}, the core unit chooses the extended fairness mode to solve monetary unfairness. Otherwise, the core unit transits to the extended normal mode.

Extended normal mode. In Algorithm 6, the normal mode for two households decides each $s_i(t)$ for every possible case and thus the computation complexity is $O(2^N)$, where N denotes the total number of households. It is necessary to decrease the computation complexity when the system deals with more than two households. Therefore, authors take an approximate measure to decide each $s_i(t)$ and $e_i(t)$ in the extended normal mode. First N_C was set, which is the number of $s_i(t) = 1$, i.e. the number of households that execute BLH by charging, by taking into account the residual energy $E_{rest}(t)$. For the ease of discussion, first it is assumed each household consumes the same amount of energy. Intuitively, more households must

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Algorithm 6: Extended normal mode

1: $K_1 \leftarrow 0.9C_{\max} - E_{rest}(t)$
2: $K_2 \leftarrow E_{rest}(t) - 0.2C_{\max}$
3: $N_C \leftarrow round\left(\frac{K_1}{K_1+K_2}\right)N$
4: $N_D \leftarrow N - N_C$
5: **for** $i \in 1:N$ **do**
6:    $\text{Diff}_i \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta - d_i(t)$
7: **end for**
8: **if** $E_{rest}(t) \leq E_{fine}$ **then**
9:    indices $\leftarrow$ the indices $\{i\}$ of top N_C households that have largest Diff_i.
10: **else**
11:    indices $\leftarrow$ the indices $\{i\}$ of top N_C households that have smallest Diff_i.
12: **end if**
13: **for** $i \in 1:N$ **do**
14:    **if** $i \in$ indices **then**
15:       $e_i(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta$
16:    **else if** $d_i(t) \bmod \beta \neq 0$ **then**
17:       $e_i(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta} \right\rfloor \beta$
18:    **else**
19:       $e_i(t) \leftarrow \left(\frac{d_i(t)}{\beta} - 1\right)\beta$
20:    **end if**
21: **end for**
22: Return $e_i(t)$

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charge when the residual energy $E_{rest}(t)$ is below the target E_{fine}. More specifically, N_C was corrected by the ratio of $0.9C_{\max} - E_{rest}(t)$ to $E_{rest}(t) - 0.2C_{\max}$. Next, N_D was set, which is the number of $s_i(t) = 0$, as $N_D = N - N_C$. Therefore the number of charging households N_C and that of discharging households N_D are calculated by:

$$N_C = round\left(\frac{K_1}{K_1+K_2}\right)N, \qquad (1)$$

$$N_D = N - N_C. \qquad (2)$$

Figure 2 shows an example of calculating N_C and N_D. In Figure 2, we can obtain $K_1 = 0.9C_{\max} - 0.4C_{\max} = 0.5C_{\max}$ and $K_2 = 0.4C_{\max} - 0.2, C_{\max} = 0.2, C_{\max}$, thus $\frac{K_1}{K_1+K_2} = \frac{5}{5+2}$. Hence, when there are 7 households, the number of charging households N_C is 5 and that of discharging households N_D is 2.
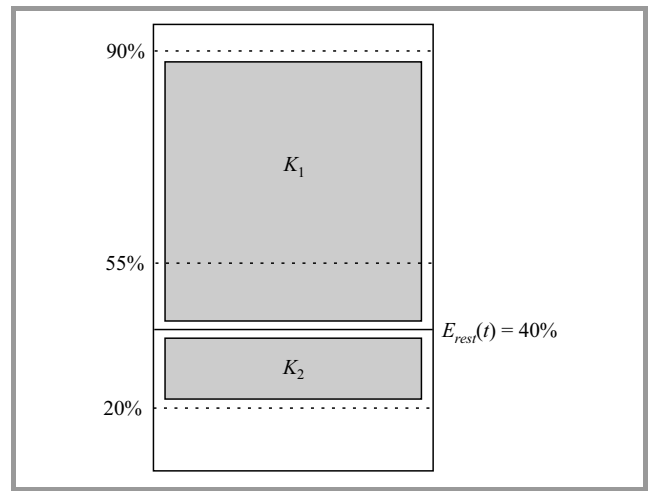

Fig. 2. Example of calculating K_1 and K_2.

After determining the number of charging/discharging households, the core unit selects, which households should charge/discharge. This is because when the residual energy is less than $E_{rest}(t)$, the more energy should be charged in order to keep the normal mode. So, the households are selected, which will charge more energy to the battery by taking difference between the quantized demand value $e_i(t)$ and the demand load in household i. In order to calculate the amount of charged energy, the core unit checks the quantized demand value $e_i(t)$ when assuming all $s_i(t) = 1$. The core unit can expect each amount of charged energy by:

$$\text{Diff}_i = \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta - d_i(t), \qquad (3)$$

where Diff_i is the amount of charged energy by a household i. When the residual battery is less than E_{fine}, N_C charging households which have larger Diff_i are chosen, because more energy should be charged to keep residual energy around E_{fine}. When the residual energy is more than E_{fine}, and vice versa. Algorithm 6 shows the algorithm of the extended normal mode.

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Algorithm 7: Extended fairness mode

1: Input $l_p(t-1)$ and $l_q(t-1)$
2: $s_p(t) \leftarrow 0$
3: $s_q(t) \leftarrow 1$
4: $K_1 \leftarrow 0.9C_{\max} - E_{rest}(t)$
5: $K_2 \leftarrow E_{rest}(t) - 0.2C_{\max}$
6: $N_C \leftarrow round\left(\frac{K_1}{K_1+K_2}\right)(N-2)$
7: $N_D \leftarrow (N-2) - N_C$
8: **for** $i \in 1:N-2$ **do**
9:    $\text{Diff}_i \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta - d_i(t)$
10: **end for**
11: **if** $E_{rest}(t) \leq E_{fine}$ **then**
12:    indices $\leftarrow$ the indices $\{i\}$ of top N_C households that have the largest Diff_i.
13: **else**
14:    indices $\leftarrow$ the indices $\{i\}$ of top N_C households that have the smallest Diff_i.
15: **end if**
16: **for** $i \in 1:N-2$ **do**
17:    **if** $i \in indices$ **then**
18:      $e_i(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta$
19:    **else if** $d_i(t) \bmod \beta \neq 0$ **then**
20:      $e_i(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta} \right\rfloor \beta$
21:    **else**
22:      $e_i(t) \leftarrow \left(\frac{d_i(t)}{\beta} - 1\right)\beta$
23:    **end if**
24: **end for**
25: Return $e_i(t)$

Extended fairness mode. Algorithm 7 shows the algorithm of the extended fairness mode. p and q denote the households that most charged and discharged during the period from 0 to $t-1$, respectively. Therefore, $l_p(t-1)$ and $l_q(t-1)$ denote the difference between charged and discharged amount of most charged household p and least charged household q during the period from 0 to $t-1$, respectively. In the extended fairness mode, the core unit first allots $s_i(t) \leftarrow 0$ to the most overcharged household, and $s_i(t) \leftarrow 1$ to the least charged household. The core unit then decides other $N-2$ households' $s_i(t)$ and $e_i(t)$ with the same way of the extended normal mode. When there are some households with loss more than l_{th}, the core unit chooses only two households, which have largest and smallest loss to reduce the complexity. The core unit checks each household's loss by interval measurements so that each loss is converged in l_{th}.

Extended stabilization mode. In the extended stabilization mode, the algorithm is almost same to the stabilization mode in two households except for changing β' to $\frac{\beta}{N}$.

3.3. Discussion

Other energy sources for BLH – although presented scheme assumes that only a battery is used for BLH, other sources such as a solar panel can also be used together with a battery. In this case, energy produced by other sources should also be taken into account for BLH. Authors do not consider the use of other energy sources in this research because the charged amount depends on the nature, which is typically difficult to model or estimate.

Initial cost to introduce BLH – a 1 kWh Li-ion battery costs at least \$1,200 [16]. By using presented scheme and sharing one battery with more than two households, the installation cost for each household can be divided.

Limitation of our scheme – the monetary fairness between two households can be reduced by the fairness mode. However, proposed scheme cannot exactly get rid of monetary unfairness between multiple households even if the core unit sets l_{th} to 0. This is because the scheme solves the monetary unfairness after observing the previous outcome of BLH.

Privacy Concern – third parties cannot estimate both household's demand loads because they cannot obtain the residual energy on real time. However, when the system deals with two households, one household may estimate the other household's demand load in real time if each household knows its own demand load, metered load, and the residual energy on real time. Household 1 can calculate the household 2's load demand $d_2(t)$ as follows:

$$d_2(t) = e_2(t) + e_1(t) - d_1(t) - (E_{rest}(t) - E_{rest}(t-1)). \quad (4)$$

To satisfy the privacy of households using proposed scheme, both households must have cooperative relationships. This issue is not important when the number of households is more than two, because a household which tries to estimate other households' demand loads needs more demand load information from several households and this could be infeasible.

4. Simulation Results

4.1. Simulation Model

During simulation a mutual information and the monetary loss are evaluated. Based on the definition in [19], the "mutual information" of household i when $t = T$ is defined as the following equation with the set of output $E = \{e_i(t)\}$ and raw measurements $D = \{d_i(t)\}$:

$$I_i(E;D) = \sum_{e \in E} \sum_{d \in D} p(e,d) \log\left(\frac{p(e,d)}{p(e)p(d)}\right), \quad (5)$$

where $p(e,d)$ denotes a joint distribution of e and $d_i(t)$ and $p(e_i(t))$ and $p(d_i(t))$ are marginal distributions of $e_i(t)$ and $d_i(t)$, respectively. Intuitively, $I_i(E;D)$ represents how much information is shared between $e_i(t)$ and $d_i(t)$ for $1 \leq t \leq T$. Therefore, if good BLH is realized, the two

variables E and D are not correlated and thus $I_i(E;D)$ will take small value. On the contrary, if the BLH is not good, the two variables E and D share similar values and thus $I_i(E;D)$ will take large value. Mutual information between two variables $e_i(t)$ and $d_i(t)$ indicates how $e_i(t)$ and $d_i(t)$ are related. If $e_i(t)$ and $d_i(t)$ are totally independent, $e_i(t)$ does not give any information about $d_i(t)$, so their mutual information is zero [12]. The monetary loss indicates the absolute value of household's loss or gain at the end of simulation.

In used simulator, electric demands $d_i(t)$ of N households are extracted from the datasets and are input into the function of core unit that to output $e_i(t)$. After all $d_i(t)$ are processed, mutual information is calculated for each household with a package "infotheo" [20]. If not stated otherwise, the simulation parameters specified in Table 2 are used and a one-minute resolution dataset named Wiki-Energy [18] for evaluation. This dataset includes totally 722 houses' data collected in the USA from 2012 to 2014: 631 in Texas, 49 in Colorado, and 42 in California [21]. The detail of 722 households is as follows: 501 single-family homes, 183 apartments, 35 town homes and 3 mobile homes. Randomly sampled 100 households' electricity data measured for one month in April 2014 was used. For the evaluation of two households case, every combination of two households from randomly sampled 100 households in the dataset were used. By referring to [12], assume the maximum battery capacity C_{max} is 1.0 kWh and its charging and discharging rate β is 1.0 kW, which means that the battery can be fully exhausted or charged in an hour.

Table 2
Parameters used in simulation

Parameters	Definition
Dataset	Wiki-Energy [18]
Interval between measurements	1 minute
Simulation duration	30 days
Maximum battery capacity C_{max}	1.0 kWh
Quantization width β	1.0 kW
Electric rate	16.341 cent/kWh
Threshold l_{th}	1, 5, 10, 25, and ∞ cent
Number of households N	2, 4, 8, 16, 32, and 64

The same flat electric rate 16.341 [cent/kWh] for all households was considered. This electric rate is cited from the one actually used in Pacific Gas and Electric Company [22]. In the two households case, the scheme was compared with SF-LS2 with the same battery capacity $C_{max} = 1$ kWh and for l_{th} as $l_{th} = 1, 5, 10, 25,$ and ∞ [cent]. Furthermore, both mutual information and monetary loss for extended algorithm were also evaluated by varying the number of households N as $N = 2, 4, 8, 16, 32,$ and 64.

4.2. Comparison of Mutual Information

Mutual information for two households. Table 3 shows mutual information against both SF-LS2 and proposed scheme in two households case. There is no significant difference between SF-LS2 and the scheme irrespective of the chosen threshold l_{th}. However, there is the difference between the best case and the worst case in SF-LS2 and this scheme. This comes from the difference in total demand for one month. That is, the total demand load is 175 kWh in the best case, whereas 2097 kWh in the worst case. This follows the intuition that more information leaks when a household uses more appliances. Here, "information leaks" means that real demand load is leaked to the electric company. From this result, one can see that the larger power a household consumes, the more difficult to realize BLH due to the limitation of battery capacity.

Table 3
Mutual information of SF-LS2 and our scheme

Scheme		Mutual information		
		Average	Best	Worst
SF-LS2		0.0135	0.0018	0.0317
Authors' scheme	$l_{th} = 1$	0.0134	0.0014	0.0368
	$l_{th} = 5$	0.0128	0.0008	0.0325
	$l_{th} = 10$	0.0127	0.0008	0.0329
	$l_{th} = 25$	0.0127	0.0007	0.0330
	$l_{th} = \infty$	0.0132	0.0007	0.0409

Mutual information for multiple households. Figure 3 shows mutual information versus N when $l_{th} = 10$. The confidence intervals represent the standard deviation of all measurements. Since every combination was simulated by choosing 2 out of 100 households, the number of measurements was $4,950 = \binom{100}{2}$ and the standard deviation was calculated from them. In Figure 3, "without BLH" indicates mutual information calculated without using BLH. One can see that as the number of households N increases, mutual information linearly increases. This is because as
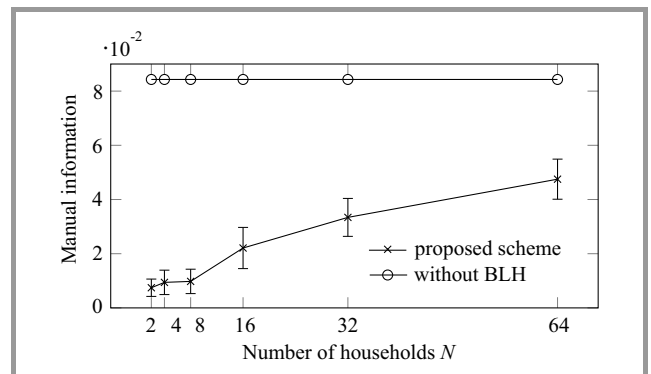

Fig. 3. Mutual information versus N.

N increases, the quantization width β' gets narrow, i.e. $\beta' = \frac{\beta}{N}$. However, the scheme still decreases mutual information by 44% even when $N = 64$. Therefore, our scheme is still effective against $N = 64$ with the battery capacity $C_{\max} = 1$ kWh.

4.3. Comparison of Monetary Loss

Monetary loss for two households. Table 4 shows the monetary loss caused by the scheme against l_{th}. In Table 4, average, best, and worst indicate the averaged, minimum, and maximum of the instantaneous loss for each l_{th} through the simulation, respectively. The average values of the monetary loss are calculated from every pair of household, i.e. 4,950 combinations, after BLH has been done. One can see that if we set $l_{th} = \infty$, which indicates the case where no

Table 4
Instantaneous loss versus l_{th}

l_{th}	Monetary loss [cent]		
	Average	Best	Worst
1	3.41	1.21	3.54
5	5.26	5.19	7.08
10	10.3	10.2	10.3
25	25.3	25.2	25.3
∞	$2.44 \cdot 10^3$	65.3	$6.78 \cdot 10^3$

Table 5
Details of processed modes when $l_{th} = 1$.

Pattern	Stabilization [%]	Fairness [%]	Normal [%]
Best	0	34.8	65.2
Worst	20.1	66.3	13.7

monetary fairness is considered, the average loss is nearly $24.46. This situation cannot be tolerant in the real case. On the other hand, when l_{th} is set as a certain value, the loss can be controlled almost within l_{th}. However, when $l_{th} = 1$, the loss is 1.22 in the best case but 3.41 on average. This indicates that even if witht $l_{th} = 1$, the core unit cannot reduce the loss by nearly 1 in most cases. Table 5 shows the details of operated modes for the best case and the worst case. When the ratio of the stabilization mode is low or that of the normal mode is high, the loss results in a small value. On the other hand, when the ratio of the stabilization mode is high or that of the normal mode is low, the loss becomes large. This is caused by the similarity of demand loads between household 1 and 2. Figure 4 shows the time series of the loss for two households in the best and worst cases when $l_{th} = 1$, respectively. Figure 4a shows that their loss values are almost symmetry. On the other hand, from Fig. 4b, their losses are asymmetric in

the worst case. From this result, when the system deals with two households, the combination of buddy households gives the difference of monetary loss.
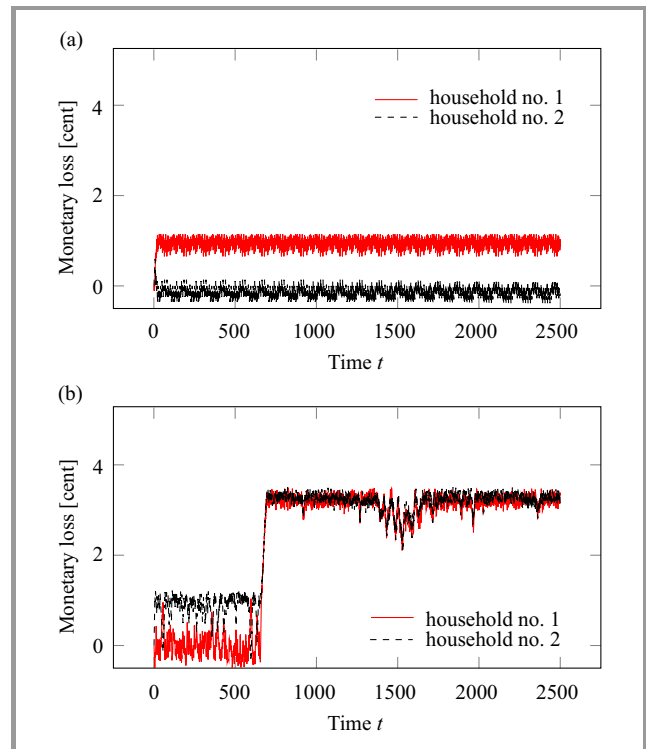

Fig. 4. Instantaneous loss versus time t ($l_{th} = 1$) for: (a) best case and (b) worst case.
(See color pictures online at www.nit.eu/publications/journal-jtit)

Table 6
Maximum instantaneous loss versus N when $l_{th} = 10$

N	Maximum loss [cent]		
	Average	Best	Worst
2	6.63	3.66	8.55
4	5.49	3.84	7.56
8	5.39	4.13	6.99
16	$1.21 \cdot 10^3$	33.2	$1.98 \cdot 10^3$
32	$2.02 \cdot 10^3$	$1.17 \cdot 10^3$	$2.42 \cdot 10^3$
64	$1.41 \cdot 10^3$	$1.08 \cdot 10^3$	$1.71 \cdot 10^3$

Monetary loss for multiple households. Table 6 shows the maximum loss caused by the scheme versus N when $l_{th} = 10$. From Table 6, one can see that the scheme maintains the monetary loss within the threshold $l_{th} = 10$ when the system deals with less than or equal to 8 households. However, when the number of households is more than 8, monetary loss suddenly exceeds $l_{th} = 10$. In order to clarify this reason, authors investigate operated modes for BLH. Table 7 shows the details of operated modes versus the number of households N when $l_{th} = 10$. As the number of households N is more than or equal to 16, the core unit

Table 7
Details of processed modes when $l_{th} = 10$

N	Stabilization [%]	Fairness [%]	Normal [%]
2	0	10.1	88.7
4	0.88	18.7	80.3
8	5.6	35.2	59.1
16	42.7	46.5	10.7
32	62.5	36.4	0.99
64	78.0	20.0	0.57

more frequently chooses the stabilization mode. From this result, when using a 1 kWh battery for more than 8 households, the core unit does not have much room to consider monetary fairness.

5. Conclusion

The paper presents a monetary fair BLH scheme for multiple households with one battery. Authors show BLH algorithm for more than two households. The proposed BLH scheme consists of three modes: the stabilization, fairness, and normal mode and the core unit changes its mode based on the residual energy and the amount of loss caused by BLH. By the computer simulation with a real electric load dataset, in two households case, authors show that when l_{th} is set to 1 cent, the scheme can achieve almost the same information leakage with SF-LS2 as well as control monetary loss less than five cents in the US currency. In the multiple households case, the paper shows that the mutual information linearly increases with the number of households. With a 1 kWh battery for BLH, the scheme can execute BLH for 8 households with preserving monetary fairness.

Acknowledgements

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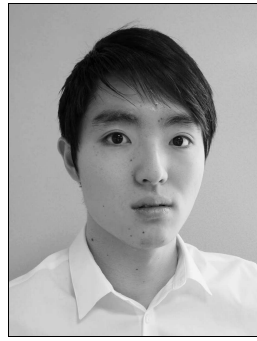3-14-1 Hiyoshi, Kohoku, Yokohama
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