Monetary Fair Battery-based Load Hiding Scheme for Two Households with One Battery in Automatic Meter Reading System

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***Abstract*—AMR (Automatic Meter Reading) system is expected to be used for real time load monitoring to optimize power generation and energy efficiency. Recently, Batra et al. propose a technique to estimate consumer's lifestyle from a real-time load profile. In order to overcome this issue, BLH (Battery-based Load Hiding) 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 because a battery is very expensive. In this paper, we propose a new BLH algorithm for two households as an example to consider monetary fairness. In our scheme, the core unit calculates the difference between the charged amount and discharged one. If the difference is bigger than the pre-defined threshold (monetary unfair occurs), the disadvantageous household is given priority to discharge the battery and the other household should charge to achieve monetary fairness. The efficiency of our scheme is demonstrated through the computer simulation with a real dataset.**

I. Introduction

In recent years, smart meters have gained much popularly with growing support from the electric power company and governments. However, smart meters pose a substantial threat to the privacy of individuals in their own homes [1]. Smart meters use solid state measurement circuits that can record the load profile every second or minute. Combined with NILM (Non-Intrusive Load Monitoring), a load value measured by a smart meter may timely reveal what appliances are used [2]–[4]. NILM is a technique for analyzing a household's net electric load profile in order to deduce what electric appliances are used. 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 and/or a data center [9], [10]. Recently, a BLH (Battery-based Load Hiding) technique is proposed to avoid the information leakage by NILM [11]–[15]. The fundamental concept of BLH is that a battery is used to store and supply power to home devices at particularly times to hide appliance loads. In the BE (Best Effort) [11], the core unit generally aims to flatten the metered load, where the core unit controls the battery based on the demand load in order to control the metered load. However, BE does not consider the case that the battery is almost empty or full. In the NILL (Non-Intrusive Load Leveling) [12], the core unit generally aims to flatten the metered load and controls the residual energy of the battery in order to continue a BLH. However, NILL discloses the true energy consumption when the battery is almost empty or full. In the SF (Stepping Framework) [13], instead of trying to flatten the metered load, the core unit chooses a metered load from a set of predefined values according to the current energy consumption level of the appliances.

Although many BLH algorithms have been studied in the literature, most of them do not consider to execute BLH against multiple households with one battery. Considering the case for multiple households is important because a battery for household use is very expensive to install. Vilardebo et al. propose a BLH scheme for multiple households, however, they do not consider monetary fairness [14]. That is, electric price that each household pays is higher than the price that they really use. In this paper, we propose a BLH scheme for two households with one battery where monetary fairness is taken into account. Our scheme achieves monetary fairness by using three modes: the stabilization mode, fairness mode, and normal mode. The core unit chooses based on monetary loss and residual energy on the battery. In the stabilization mode, the core unit stables the residual energy in order to avoid the situation that BLH cannot be executed. In the fairness mode, the household that has charged too much discharges and the other charges in order to solve monetary unfairness. 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.

We show the efficiency of our scheme through computer simulation. The evaluation metrics are maximum monetary loss and information leakage during simulation period. We use Wiki-Energy [16] which is a real electric loads dataset to obtain reasonable outcome.

The remainder of this paper is organized as follows. Section II provides the related work about BLH algorithms. We detail our scheme and give discussion in terms of pros and cons in Section III. Section IV presents experimental results of our scheme using real data. We conclude the paper in Section V.

II. Related Work

A. Privacy Preserving for Smart Meter Users by Using BLH Scheme

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 [11]–[15]. In BLH algorithm, the operation system controls the battery based on the demand load and previous time energy consumption observed by the smart meter (the metered load) in order to control the currently metered load.

B. How BLH Algorithms React

Current BLH algorithms generally aim to flatten the metered load. The main difference among these algorithms is how to react when the residual energy is too low or too high. In the BE [11], when the energy level of the battery reaches the minimum level or the maximum level, the core unit determines that the battery has to be charged or discharged at the maximum rate. In the NILL [12], instead of charging or discharging the battery at the maximum rate, 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 and propose a SF-LS2 [13]. In SF-LS2 , instead of trying to maintain a constant load, the core unit can choose a load to be seen by the smart meter from a set of predefined values according to the current energy consumption level of the appliances. Yang et al. verify tradeoff between the smart meter data privacy and the electricity bill and propose an online control algorithm that can optimally control the battery to protect the smart meter data privacy and cut down the electricity bill [15]. Vilardebo et al. propose a BLH scheme [14] that operates over multiple users by defining privacy-power function.

C. Problem of Conventional BLH Algorithms

Although there are many BLH algorithms, most of algorithms do not consider using one battery for multiple households. Although Vilardebo et al. propose a BLH scheme for multiple households with a single battery, it does not consider monetary fairness [14]. Here, monetary fairness denotes that the charged amount 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. First, the battery has a limit on charge and discharge rate. The core unit that controls the battery needs to choose appropriately which user should charge and discharge the battery based on the rate. Second, the battery has a capacity. If the residual energy is almost full or empty, the core unit cannot appropriately execute BLH for collecting electric price between users.

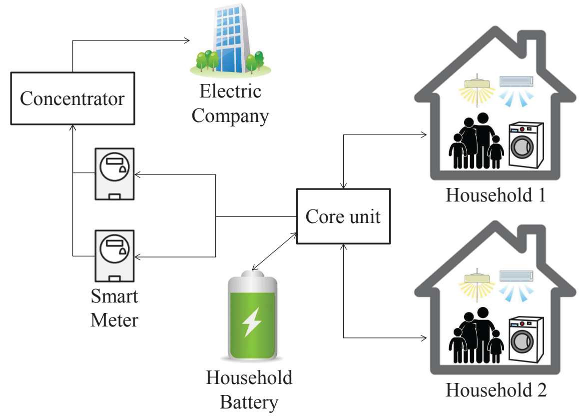


Fig. 1. The model of our BLH scheme.

TABLE I
NOTATIONS OF OUR SCHEME.

Parameters	Definition
i	Household (i = 1 or 2)
β	Quantization width
$r_{residual}(t)$	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, and vice versa
$e_i(t)$	Metered load (the load after BLH) in household i at time t

III. Proposed Scheme

Here, we propose a monetary fair BLH scheme for two households with one battery because even if there are more than three households, controls of them are based on the proposal scheme. Fig.1 shows the model of our BLH scheme. The core unit calculates each household's demand load $d_i(t)$ and decides each household's metered load $e_i(t)$, where the metered load is read by the smart meter. 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.

We define the threshold l_{th} that determines upper bound of the instantaneous monetary unfairness. When the difference between the charged amount and discharged one exceeds the predefined threshold, priority to one household is given to discharge (or charge) the battery and the other household should charges (or discharges) to achieve monetary fairness. Our scheme consists of three modes: stabilization, fairness, and normal mode. The control unit changes the mode based on the residual energy. When the residual energy is almost empty or full, the core unit transits to the stabilization mode

Algorithm 1 Deciding mode

Input $r_{residual}(t-1)$
if $r_{residual}(t-1)$ is almost empty $\cup$ $r_{residual}(t-1)$ is almost full **then**
  $mode \leftarrow Stabilization$
else if $\max(l_1(t), l_2(t)) \geq l_{th}$ **then**
  $mode \leftarrow Fairness$
else
  $mode \leftarrow Normal$
end if
Return *mode*

Algorithm 2 Stabilization mode

Input $r_{residual}(t-1)$
for $i \in 1:2$ **do**
  if $r_{residual}(t-1) \leq 20\%$ **then**
    $s_1(t) \leftarrow 1$
    $s_2(t) \leftarrow 1$
  else if $r_{residual}(t-1) \geq 90\%$ **then**
    $s_1(t) \leftarrow 0$
    $s_2(t) \leftarrow 0$
  end if
  $\beta' \leftarrow \frac{\beta}{2}$
  if $s_i(t) = 1$ **then**
    $e_i(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta'} \right\rceil \beta'$
  else if $d_i(t) \bmod \beta \neq 0$ **then**
    $e_i(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta'} \right\rfloor \beta'$
  else
    $e_i(t) \leftarrow (\frac{d_i(t)}{\beta'} - 1)\beta'$
  end if
end for
Return $e_1(t)$ and $e_2(t)$

Algorithm 3 Fairness mode

Input $l_1(t-1)$ and $l_2(t-1)$
if $l_1(t-1) \leq l_2(t-1)$ **then**
  $s_1(t) \leftarrow 1$
  $s_2(t) \leftarrow 0$
else
  $s_1(t) \leftarrow 0$
  $s_2(t) \leftarrow 1$
end if
for $i \in 1:2$ **do**
  if $s_i(t) = 1$ **then**
    $e_i(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta$
  else if $d_i(t) \bmod \beta \neq 0$ **then**
    $e_i(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta} \right\rfloor \beta$
  else
    $e_i(t) \leftarrow (\frac{d_i(t)}{\beta} - 1)\beta$
  end if
end for
Return $e_1(t)$ and $e_2(t)$

mode which is based on the state-of-the-art BLH scheme SF-LS2 [13] to avoid the situation that BLH cannot be executed. If one 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 the half of its capacity. After the core unit decides its mode, it decides each household's metered load $e_i(t)$ with a quantization band β. β is a bandwidth that the battery can quantize household i's demand load $d_i(t)$. β indicates how coarsely it hides a demand load and it is given by the battery capacity, charging rate, and discharging rate, where charging rate denotes how much energy the battery can charge within a time unit. Finally, the core unit charges or discharges to execute BLH. In the following we explain the three modes in detail.

A. Three Modes of Our BLH Algorithm

1) Deciding Mode: Algorithm 1 shows how the core unit changes its state. First, if the residual energy is almost empty ($\leq 20\%$) or full ($\geq 90\%$), we choose the stabilization mode because stabilizing a residual energy and continuing BLH is most important. Second, after checking the residual energy, if the difference between charged and discharged amount energy within household is more than the threshold, the control unit transits to the fairness mode to achieve monetary fairness. Otherwise, the control unit transits to the normal mode.

2) Stabilization Mode: Algorithm 2 shows how the stabilization mode works. In the stabilization mode, each household charges ($s_1(t) \leftarrow 1, s_2(t) \leftarrow 1$) when the residual energy is almost empty (under 20%). On the other hand, each household discharges ($s_1(t) \leftarrow 0, s_2(t) \leftarrow 0$) 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, if $s_i(t) \leftarrow 1$, it means that the core unit let household i charge while if $s_i(t) \leftarrow 0$, it means that the core unit let household i discharge. Then, the core unit calculates a target quantized load $e_i(t)$ for each household according to $s_i(t)$. Here, we use β' as $\frac{\beta}{2}$ in order to control both households' metered loads simultaneously.

3) Fairness Mode: Algorithm 3 shows how the fairness mode works. In the fairness mode, the core unit lets the household that has charged too much i.e., $l_i(t-1) \geq l_{th}$ discharge and lets the other charge to solve monetary unfairness, where $l_i(t)$ denotes the difference between charged and discharged amount energy within household at time t. Then, the core unit calculates a target quantized load $e_i(t)$ for each household according to $s_i(t)$.

4) Normal Mode: Algorithm 4 shows how the normal mode works. In the normal mode, the core unit calculates each household's metered load at time t against every possible cases, 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 55%.

Algorithm 4 Normal mode

for $\{s_1(t), s_2(t)\} \in \{\{0,0\},\{0,1\},\{1,0\},\{1,1\}\}$ **do**
  for $i \in 1:2$ **do**
    if $s_i(t) = 1$ **then**
      $e_{i,s_i(t)}(t) \leftarrow \left\lceil \frac{d_i(t)}{\beta} \right\rceil \beta$
    else if $d_i(t) \bmod \beta \neq 0$ **then**
      $e_{i,s_i(t)}(t) \leftarrow \left\lfloor \frac{d_i(t)}{\beta} \right\rfloor \beta$
    else
      $e_{i,s_i(t)}(t) \leftarrow (\frac{d_i(t)}{\beta} - 1)\beta$
    end if
    store $e_{i,s_i(t)}(t)$
  end for
  if the combination of $e_{1,s_1(t)}(t)$ and $e_{2,s_2(t)}(t)$ more approaches $r_{residual}(t) = 55\%$ **then**
    $e_1(t) \leftarrow e_{1,s_1(t)}(t)$
    $e_2(t) \leftarrow e_{1,s_2(t)}(t)$
  end if
end for
Return $e_1(t)$ and $e_2(t)$

B. Discussion

1) Initial Cost to Introduce BLH: A 1 kWh Li-ion battery costs at least US$ 1,200 [17]. By using our scheme and sharing one battery with two households, the installation cost to the battery for each household can be reduced.

2) Limitation of Our Scheme: In our scheme, monetary fairness between two households can be reduced by the fairness mode. However, our scheme cannot exactly get rid of monetary unfairness between households even if the core unit sets l_{th} to 0.

3) Privacy Concern in Our Scheme: In our scheme, third parties cannot estimate both household's demand loads because they cannot know the residual energy on real time. However, 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: $d_2(t) = e_2(t) + (e_1(t) - d_1(t)) - C_{\max} * (r_{residual}(t) - r_{residual}(t-1))$, where $C_{\max}$ means the maximum capacity of the battery. To satisfy the privacy of households using our scheme, both households must have cooperative relationships.

4) The Case for over Three Households: Our scheme is able to extend for a case with more than three households. This is because our scheme can choose the combination of two households which has charged the most and discharged the most. Even if there are more than three households, the core unit can control that two households by the fairness mode and the rest of households by the normal mode. However, the more households control with one battery, the more information leakage is increased because the battery has a capacity and relative quantization width for each household is reduced.

TABLE II
NOTATION USED IN OUR SIMULATION.

Parameters	Definition
Dataset	Wiki-Energy Dataset [16]
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]

TABLE III
MAXIMUM INSTANTANEOUS LOSS VERSUS l_{th}.

Threshold	Maximum Loss [cent]		
	Average	Best	Worst
$l_{th} = 1$	3.41	1.21	3.54
$l_{th} = 5$	5.26	5.19	7.08
$l_{th} = 10$	10.3	10.2	10.3
$l_{th} = 25$	25.3	25.2	25.3
$l_{th} = \infty$	2.44 $\times 10^3$	65.3	6.78 $\times 10^3$

IV. EXPERIMENTAL RESULT

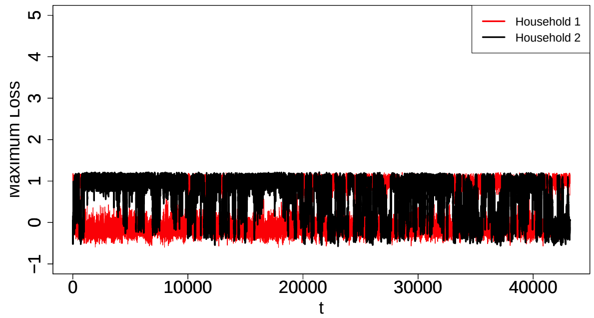
A. Simulation Model

We evaluate our scheme in terms of the loss and mutual information. Table II shows simulation parameters. We use a one-minute resolution datasets named Wiki-Energy [16]. This dataset includes electricity data measured every one-minute in over 100 households from 2012 to Apr. 2014. We use the electricity data in the dataset measured for one month in Apr. 2014. We pick every combination of two households from randomly sampled 100 households in the dataset. We assume a battery whose maximum 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 depleted and fully charged for an hour. We consider the case where both the households utilize the same flat electric rate with 16.341 [cent/kWh]. This electric rate is cited from the one actually used in Pacific Gas and Electric Company [18]. We compare our scheme with SF-LS2 with the same battery capacity. We vary l_{th} as l_{th} = 1, 5, 10, 25, and ∞ [cent].

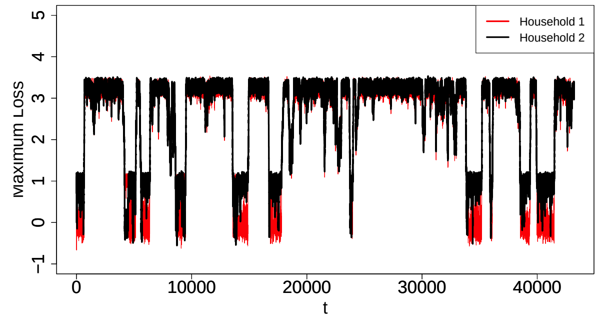
Mutual information indicates the ratio of information that is able to estimate the demand load by observing the metered load. Mutual information between two variables $e_i(t)$ and $d_i(t)$ measures the information that $e_i(t)$ and $d_i(t)$ share: it uncertain $e_i(t)$ gives the information about $d_i(t)$. For example, if $e_i(t)$ and $d_i(t)$ are totally independent, then knowing $e_i(t)$ does not give any information about $d_i(t)$, so their mutual information is zero [13].

B. Comparison of Monetary Fairness

Table III shows the maximum loss caused by our scheme for each l_{th}. In Table III, Average, Best, and Worst indicate the averaged, minimum, and maximum of the instantaneous loss for each l_{th} through the experiment, respectively. We can see that if we set $l_{th} = \inf$, which indicates the case



(a) Best case



(b) Worst case

Fig. 2. Instantaneous loss versus time t (l_{th} = 1).

TABLE IV
THE RATIO OF PROCESSED MODES WHEN l_{th} = 1.

Pattern	Stabilization (%)	Fairness (%)	Normal (%)
Best	0	34.8	65.2
Worst	20.1	66.3	13.7

where no monetary fairness is considered, the average of the maximum loss is nearly US$ 24.46. This situation cannot be tolerant in the real case. On the other hand, when we set l_{th}, the maximum loss can be almost upper-bound within l_{th}. However, when l_{th} = 1, the best of the maximum loss is 1.22 but the average one is 3.41 and the worst one is 3.54. This indicates that even if we set $l_{th} = 1$, the core unit cannot reduce the maximum loss by nearly 1 in most cases. This is caused by how the core unit chooses the mode. Table IV shows the ratio of modes both in the best case and the worst case. We can see that when the ratio of the stabilization mode is low and the normal mode is high, the maximum loss becomes small. On the other hand, when the ratio of the stabilization mode is high and the normal mode is low, the maximum loss becomes big. This is caused by the variation of the demand load between household 1 and household 2.

C. Comparison of Maximum Loss

Fig.2(a) shows the variation of the maximum loss against time t in the best case (l_{th} = 1), where the best case indicates that the maximum loss is the smallest. We can see that the variation of the maximum loss is small and the maximum loss between the household 1 and the household 2 has symmetry, where symmetry indicates that when $l_1(t) > 0$, $l_2(t) < 0$ and vice versa. On the other hand, Fig.2(b) shows the variation of the maximum loss against time t in the worst case (l_{th} = 1), where the worst case indicates that the maximum loss is the largest. In contrast to the best case, we can see that the variation of the maximum loss is large and the maximum loss between the household 1 and the household 2 does not have symmetry.

TABLE V
MUTUAL INFORMATION OF SF-LS2 AND OUR SCHEME.

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

D. Comparison of Demand Load

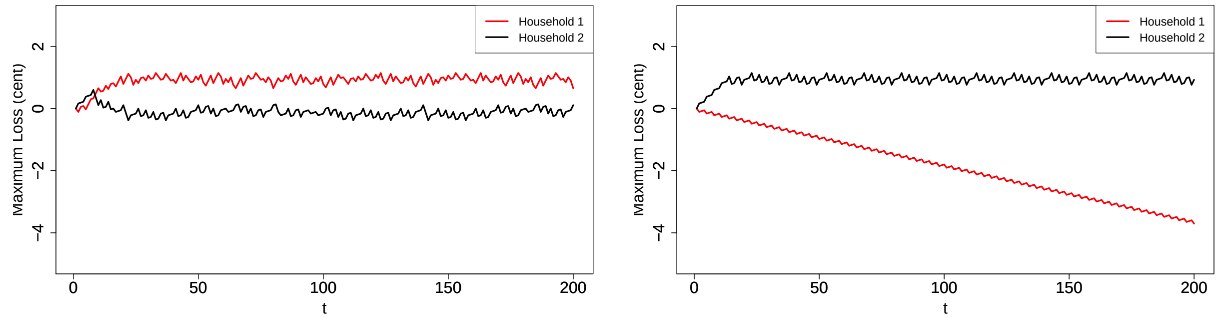
Fig.3 shows the maximum loss between household 1 and household 2 versus r_{sync}, where r_{sync} indicates the ratio that the demand loads of both household 1 and 2 are simultaneously increased or decreased over the simulation time. For example if demands of both the household 1 and 2 are always increased or decreased simultaneously, $r_{sync} = 1$. From Fig.3, we can see that there exist no monetary unfairness when $r_{sync} = 0.25$, while the maximum loss of a household continues to increase when $r_{sync} = 0.66$. This result shows that if the usage pattern of two partner households resembles, the monetary unfairness increases.

E. Comparison of Mutual Information

Table V shows mutual information against both SF-LS2 and our scheme. We can see that there is no significant difference between SF-LS2 and our scheme irrespective of the chosen threshold l_{th}. This is because our scheme assumes that a battery can be simultaneously charged and discharged. However, there is the difference between the best case and the worst case in both SF-LS2 and our scheme. This is because there is the difference in total demand for one month. The total demand load is 175 kWhin the best case, whereas 2097 kWhin the worst case. This follows the intuition that more information leaks when a household uses more appliances.

V. CONCLUSION

We have proposed a monetary fair BLH scheme for two households with one battery. Our BLH scheme aims to achieve



(a) $r_{sync} = 0.25$.

(b) $r_{sync} = 0.66$.

Fig. 3. The maximum loss between household 1 and 2.

both monetary fairness and low information leakage. Our BLH scheme consists of three modes: the stabilization, fairness, and normal mode and changes the mode based on the residual energy and the amount of loss caused by charging and discharging for BLH. From the computer simulation with a real electric load dataset, we show that when l_{th} is 1, our scheme can not only achieve almost the same information leakage with SF-LS2 but also control monetary loss less than five cents in the US currency. Through the experiment we conclude that when the threshold of the maximum loss l_{th} is 1, the maximum loss can be reduced. We also conclude that especially when the life style of households are different, the maximum loss becomes small.

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References

[1] E.L.Quinn, “Smart metering and privacy: Existng law and competing policies,” *A report for the Colorado Public Utilities Commission*, 2009.
[2] G.W.Hart, “Residential energy monitoring and computerized surveillance via utility power flows,” *IEEE Technology and Society Magazine*, pp. 12–16, June 1989.
[3] M. A. Lisovich, D. K. Mulligan, and S. B. Wicker, “Inferring Personal Information from Demand-Response Systems,” *IEEE Security & Privacy Magazine*, vol. 8, no. 1, pp. 11–20, Jan. 2010.
[4] A. Molina-Markham, P. Shenoy, K. Fu, E. Cecchet, and D. Irwin, “Private memoirs of a smart meter,” in *ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building (BuildSys)*, Nov. 2010, pp. 61–66.
[5] G. Hart, “Nonintrusive appliance load monitoring,” *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870–1891, 1992.
[6] M. Marceau and R. Zmeureanu, “Nonintrusive load disaggregation computer program to estimate the energy consumption of major end uses in residential buildings,” *Energy Conversion and Management*, vol. 41, no. 13, pp. 1389–1403, Sep. 2000.
[7] C. Laughman, R. Cox, S. Shaw, S. Leeb, L. Norford, and P. Armstrong, “Power signature analysis,” *IEEE Power and Energy Magazine*, vol. 1, no. 2, pp. 56–63, March 2003.
[8] N. Batra, J. Kelly, O. Parson, H. Dutta, W. Knottenbelt, A. Rogers, A. Singh, and M. Srivastava, “NILMTK: An Open Source Toolkit for Non-intrusive Load Monitoring,” in *e-Energy ’14*, April 2014, pp. 265–276.
[9] K.Fehrenbacher, “Smart meter worm could spread like a virus,” 2010. [Online]. Available: http://earth2tech.com/2009/07/31/smart-meter-worm-could-spread-like-a-virus/
[10] S. McLaughlin, D. Podkuiko, S. Miadzvezhanka, A. Delozier, and P. McDaniel, “Multi-vendor penetration testing in the advanced metering infrastructure,” in *ACM Annual Computer Security Applications Conference (ACSAC)*, Dec. 2010, p. 107.
[11] G. Kalogridis, C. Efthymiou, S. Z. Denic, T. A. Lewis, and R. Cepeda, “Privacy for Smart Meters: Towards Undetectable Appliance Load Signatures,” in *IEEE SmartGridComm*, Oct. 2010, pp. 232–237.
[12] S. McLaughlin, P. McDaniel, and W. Aiello, “Protecting consumer privacy from electric load monitoring,” 2011, pp. 87–98.
[13] W. Yang, N. Li, Y. Qi, W. Qardaji, S. McLaughlin, and P. McDaniel, “Minimizing private data disclosures in the smart grid,” in *ACM CCS*, New York, New York, USA, Oct. 2012, pp. 415–427.
[14] J. Gomez-Vilardebo and D. Gündüz, “Smart Meter Privacy for Multiple Users in the Presence of an Alternative Energy Source,” *iis.ee.ic.ac.uk*, 2014.
[15] L. Yang, X. Chen, J. Zhang, and H. Poor, “Optimal Privacy-Preserving Energy Management for Smart Meters,” 2014.
[16] “Pecan Street Dataport - A Universe of Data, Available Around the World.” [Online]. Available: https://dataport.pecanstreet.org/
[17] G. Frederik, T. Jeroen, R. Tom, D, T. Peter, and D. Johan, “Techno-economical and Life Expectancy Modeling of Battery Energy Storage Systems,” *International Conference on Electricity Distribution (CIRED)*, no. 1106, pp. 1–4, 2011.
[18] “Pacific Gas and Electric Company: Electric schedule A-1.” [Online]. Available: http://www.pge.com/