Combining Electric Vehicle and Rechargeable Battery for Household Load Hiding

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Abstract—**The transition from electromechanical to advanced smart meters offers great opportunities in load management, energy saving, and resource optimization. However, the fine-grained usage data collected by the smart meters also raises privacy concerns. The household load profile can be analyzed by non-intrusive load monitoring techniques to infer customer activity routines and behavioral preference. Several data obfuscation techniques based on controlling a local rechargeable battery or a controllable load have been proposed to mitigate the privacy leakage of the customers. In this paper, we introduce the use of electric vehicles (EVs) for load hiding. In particular, we propose an EV-assisted battery load hiding algorithm, which combines the use of an EV with a local rechargeable battery to achieve the dual purpose of optimal charging and measurement obfuscation. Since EVs are becoming increasingly popular and part of many households, their use renders the implementation of load hiding less costly compared to methods only using dedicated rechargeable batteries. Furthermore, EVs provide more flexibility than other household loads in terms of energy storage. We evaluate our proposed algorithm using real data for electricity price, household consumption, and EV parameters. Adopting mutual information as a measure for information leakage, numerical results show that the proposed algorithm can reduce the customer's cost while maintaining the expected privacy level.**

I. Introduction

The integration of modern information and communication technology enables smart electric power systems with advanced monitoring, automatic command control, real-time data analysis, and optimal resource allocation. One important example for the upgrade of traditional power systems is the deployment of advanced metering infrastructure (AMI), which supports two-way power flow and data communication between customers and utility companies. As an indispensable component of an AMI, smart meters that can automatically measure and report household consumption at minute or second granularity are installed at the consumer side. However, the use of smart meters has raised concerns about potential invasion of customer privacy [1]. By utilizing non-intrusive load monitoring (NILM) techniques, the fine-grained smart meter data can be exploited to detect possible operations of household appliances, which may disclose the usage profile and behavioral preferences of the customers [2], [3].

The basic idea of NILM algorithms is to identify the operation time of typical home appliances through analyzing the consumption measurements [4], [5]. Those appliance operation traces can be mapped with household activity routines, and further be exploited to infer customer preferences. Although smart meter measurement data are transmitted using dedicated networks, hackers may be able to eavesdrop and intercept customer data and usage profiles through cyber intrusion with no need of physical access. Even though data transmission can be protected from phishing and fraud by using encryption techniques and cryptography mechanisms, the utility companies still collect a significant amount of personal information, which may unwittingly be leaked to malicious third parties for unauthorized use and benefits. Moreover, built on top of the legacy power systems, smart grids are highly dependent on the existing infrastructure that is not initially designed for privacy protection. Therefore, the possible exposure of the measurement data enforces privacy preserving solutions that are specialized in the context of smart meters and smart grid.

In order to mitigate the risks of illegitimate inferring family routines and deducing personal habits, various data obfuscation techniques have been designed. The key concept is to distort the household consumption profile, usually with a local rechargeable battery [6]–[9]. Kalogridis *et al.* present a best effort (BE) algorithm which either charges or discharges the battery to shed the differences between the actual net load and desired external load whenever needed [6]. McLaughlin *et al.* design a non-intrusive load leveling (NILL) method to mask the variance of the load profile. The method exploits the battery to offset the power drawn or consumed by the appliances due to the corresponding on-off events [7]. Yang *et al.* propose a novel stepping approach, which quantifies household demand load into a step function with the step size determined by the maximum battery charging or discharging rate. The nonlinear and irreversible quantization eliminates the possibility of load profile recovery attacks [8]. The work in [9] takes the cost of electricity into consideration when addressing data privacy issues. Yang *et al.* design a cost-effective and privacy-preserving energy management system based on solving a stochastic optimization problem.

Besides those aforementioned battery-based load hiding (BLH) methods, Egarter *et al.* present a novel load-based load hiding (LLH) method for meter data obfuscation [10]. Their proposed method introduces artificial noise to the original household consumption data through controlling on-off events of the energy-intensive appliances. These devices have to be interruptible and controllable and need to be able to store energy. The available options thus are limited.

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Electric vehicles (EVs) are a promising solution for fossil fuel shortage and gas emission problems. With the fast-growing penetration level of EVs, they can benefit today's power industry when utilized as mobile, distributed energy storage by providing several ancillary services such as peak shaving, frequency regulation, and spinning reserves [11], [12]. Furthermore, EVs can be charged or discharged [13], which makes them an alternative solution for load hiding when exploited as a rechargeable battery. The only limitation is that EVs can only be scheduled when plugged-in at home, which indicates that they cannot completely substitute the role of stationary rechargeable batteries. Instead of using batteries with larger capacity or fast charging cycles, the combination of EVs and smaller capacity or lower charging power batteries can achieve load hiding at a reduced cost. In the residential sector, the peak consumption usually comes in the morning and evening hours, which is the time period requiring larger battery capacity or fast charging cycles to obscure the load. Since this often overlaps with the EV plugged-in time, the combined use of an EV and a local rechargeable battery for load hiding is possible. A smaller capacity or slow charging cycle-battery can be chosen to deal with the basic household daily consumption, while the peak load can be shed using both EV and battery.

In this paper, we employ EVs in addition to local rechargeable batteries for improving consumer privacy. In particular, we propose an EV-assisted battery load hiding method, which aims to reduce both customer's electricity cost and potential privacy leakage. We formulate a convex optimization problem to generate optimal charging and discharging strategies for both EV and local rechargeable battery, while withholding certain level of privacy leakage of the customer. The combined use of EVs and local batteries can greatly reduce the dependence on battery operations with respect to previous BLH methods [6]–[9], offering elasticity and flexibility in disguising load profile. Compared with the LLH method [10], our approach inherits the advantages of EVs that they can be discharged to shift the peak loads. We evaluate our proposed algorithm using real data for electricity price, household consumptions, and EV parameters. We exploit the mutual information measure to evaluate the privacy preserving performance of our algorithm. Results show that our algorithm can reduce the customer's cost while maintaining its expected privacy level.

The rest of the paper is organized as follows. The system model is introduced in Section II, followed by the proposed load hiding method in Section III. Section IV presents performance evaluations and simulation results. Conclusion is given in Section V.

II. System Model

The overall EV-assisted battery load hiding framework is illustrated in Fig. 1. Each house is equipped with a smart meter that can monitor and record the average residential energy consumption over typical sampling intervals of the meter. The smart meter exchanges information with the utility company for data aggregation and electricity billing. It receives the time of use (TOU) pricing information from the utility company and transmits the measured load of the household. A local control unit (LCU) is designed to schedule the household appliances based on the TOU prices without violating the specific time constraints and comfort level requirements of the customers.

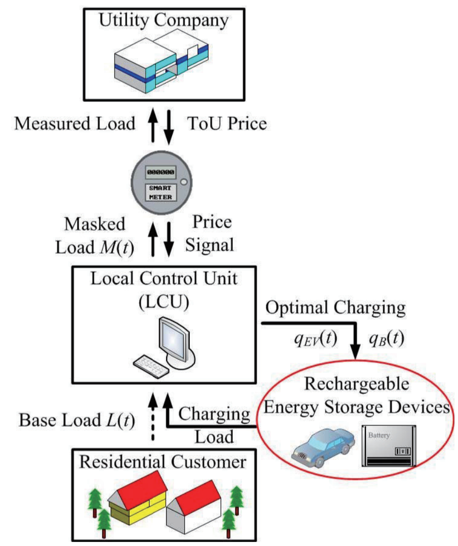

Fig. 1. An EV-assisted battery load hiding framework.

In our design, rechargeable energy storage devices, i.e., a local rechargeable battery and an EV, are connected as external electricity sources to supply the demand of the customer and alter the amount of energy drawn from the power grid. Based on the TOU prices from the smart meter, the LCU optimizes the charging strategy of those energy storage devices. The charging load is combined with the original household base load and sent to the smart meter. Thus, the measured time series usage data cannot be directly associated with the original load consumption. The proposed scheme can reduce the possibility of inferring customer privacy information. Since the charging and discharging strategy of the energy storage devices when obfuscating the load is responsive to the TOU prices, the customer's electricity cost can also be considered when masking the household demand.

We assume that the household consumption is sampled and reported by the smart meter at a fixed interval Δt. The continuous scheduling period is then divided into discrete time slots. Let $\mathcal{T} = \{1, 2, \ldots, T\}$ denote the set of time slots for one scheduling period. We denote the household base load in time slot $t \in \mathcal{T}$ by $L(t)$, which is the average amount of household appliance electricity demand during the sampled interval Δt. The masked load observed by the smart meter in time slot $t \in \mathcal{T}$ is denoted as $M(t)$, which is the actual electricity drawn from and reported to the utility company in interval Δt. In our system model, a local rechargeable battery and an EV are exploited to prevent direct correlation between $L(t)$ and $M(t)$, serving as the buffer to feed the difference in energy demand. For an arbitrary time slot $t \in \mathcal{T}$, the charging rate of the battery and the EV is denoted by

$q_B(t)$ and $q_{EV}(t)$, respectively. A positive battery charging rate (i.e., $q_B(t) > 0$) indicates the battery is charging and drawing electricity from the power grid. A negative battery charging rate (i.e., $q_B(t) < 0$) indicates the battery is discharging and supplying the partial household demand. Similarly, $q_{EV}(t) > 0$ (or < 0) indicates EV is charging (or discharging). The amount of energy provided by the battery and the EV at any time slot t is $q_B(t)\Delta t$ and $q_{EV}(t)\Delta t$, respectively. We have

$$M(t) = L(t) + (q_B(t) + q_{EV}(t))\Delta t. \tag{1}$$

The physical constraints of the battery and the EV should also be satisfied. To this end, let C_i, $SOC_i^{\min}$ and $SOC_i^{\max}$, $q_i^{\max}$ and $q_i^{\min}$, and e_i denote the capacity, the lower and upper limit for the state of charge (SoC), the maximum and minimum charging rate, and the charging efficiency factor for the battery ($i = B$) and the EV ($i = EV$), respectively. Then, we have the following constraints for charging rates $q_i(t)$ and the SoC $SOC_i(t)$ at time slot t, $i \in \{B, EV\}$:

$$q_i^{\min} \leq q_i(t) \leq q_i^{\max}, \tag{2}$$

$$SOC_i(t) = SOC_i(t-1) + \frac{q_i(t)\Delta t\, e_i}{C_i}, \tag{3}$$

$$SOC_i^{\min} \leq SOC_i(t) \leq SOC_i^{\max}. \tag{4}$$

We note that the local rechargeable battery can be scheduled during the entire period $\mathcal{T}$, while constraints (2)−(4) can be applied for the EV only for $t \in \mathcal{S} \subseteq \mathcal{T}$, where $\mathcal{S}$ is the set of time slots in which EV is plugged into the power grid. Assuming that during period $\mathcal{T}$, the EV is plugged in once at arrival time t_A and unplugged immediately before departure at time t_D, we have $\mathcal{S} = \{t_A, t_A + 1, \ldots, t_D\}$.

We assume that the initial SoC of the EV and the battery, denoted by SOC_{EV}^{init} and SOC_B^{init}, respectively, are known. The required SoC of the EV at departure, denoted by SOC_{EV}^{req}, is set by the customer. Also, the local rechargeable battery returns to its initial SoC after one scheduling period. Thus, the dynamics of the SoC of the battery and the EV are given by

$$SOC_B(t) = \begin{cases} SOC_B^{\mathrm{init}}, & t \in \{1, T\} \\ SOC_B(t-1) + \frac{q_B(t)\Delta t\, e_B}{C_B}, & t \in \mathcal{T} \setminus \{1, T\} \end{cases} \tag{5}$$

$$SOC_{EV}(t) = \begin{cases} SOC_{EV}^{\mathrm{init}}, & t = t_A \\ SOC_{EV}^{\mathrm{req}}, & t = t_D \\ SOC_{EV}(t-1) & \\ + \frac{q_{EV}(t)\Delta t\, e_{EV}}{C_{EV}}, & t \in \mathcal{S} \setminus \{t_A, t_D\}. \end{cases} \tag{6}$$

Given the above system model, our goal is to design a cost-effective load hiding method through the combined use of the local rechargeable battery and the EV.

III. EV-Assisted Battery Load Hiding

In this section, we propose an EV-assisted battery load hiding algorithm, which takes both customer's electricity cost and privacy concerns into account. To this end, an optimization problem is formulated that minimizes the customer's cost under the constraint that the privacy leakage remains within a certain acceptable range. Mutual information (MI) is a suitable privacy metric, which can measure to what extent $M(t)$ reveals information about $L(t)$. However, it is hard to directly use MI when formulating the optimization problem. Therefore, we adopt an approximate metric to represent the privacy leakage instead. Intuitively, perfect hiding would maintain $M(t)$ as a constant, which indicates that no information about $L(t)$ can be inferred from observing $M(t)$. Therefore, the deviation of $M(t)$ from a constant M_{c} is used as a substitute for the privacy measure MI in the optimization problem (MI is still used for the performance evaluation of our proposed method). In particular, we apply the constraint

$$\left\| \frac{M(t) - M_{\mathrm{c}}}{M_{\mathrm{c}}} \right\|_2 \leq \varepsilon, \tag{7}$$

where ε quantifies the maximum privacy leakage and M_{c} is the average household consumption over the scheduling period.

Minimization of the electricity cost is based on the TOU prices $p^c(t)$ and the feed-in tariff $p^d(t)$, which is the revenue that the customer earns when using the battery or EV to feed energy back to the power grid. We assume that $p^c(t) \geq p^d(t)$. Then, our optimization problem can be formulated as

$$\begin{aligned} \underset{\substack{q_B(t),\, t \in \mathcal{T}, \\ q_{EV}(t),\, t \in \mathcal{S},}}{\text{minimize}} \quad & \sum_{t \in \mathcal{T}} \left(p^c(t) \left[q_B(t) \right]^+ - p^d(t) \left[-q_B(t) \right]^+ \right) \Delta t \\ & + \sum_{t \in \mathcal{S}} \left(p^c(t) \left[q_{EV}(t) \right]^+ - p^d(t) \left[-q_{EV}(t) \right]^+ \right) \Delta t \\ & + \sum_{t \in \mathcal{T}} p^c(t) L(t) \end{aligned} \tag{8a}$$

$$\text{subject to} \quad \text{constraints (1), (2), and (4)−(7),} \tag{8b}$$

where $[x]^+ = \max(x, 0)$. Notice that the objective function (8a) is not convex. To transform problem (8) into a convex problem, we introduce the non-negative auxiliary variables $q_B^+(t)$, $q_B^-(t)$, $q_{EV}^+(t)$, $q_{EV}^-(t)$ and formulate the following convex optimization problem

$$\begin{aligned} \underset{\substack{q_B^+(t),\, q_B^-(t),\, t \in \mathcal{T}, \\ q_{EV}^+(t),\, q_{EV}^-(t),\, t \in \mathcal{S},}}{\text{minimize}} \quad & \sum_{t \in \mathcal{T}} \left(p^c(t)\, q_B^+(t) - p^d(t)\, q_B^-(t) \right) \Delta t \\ & + \sum_{t \in \mathcal{S}} \left(p^c(t)\, q_{EV}^+(t) - p^d(t)\, q_{EV}^-(t) \right) \Delta t \\ & + \sum_{t \in \mathcal{T}} p^c(t) L(t) \end{aligned} \tag{9a}$$

$$\text{subject to} \quad q_B^{\min} \leq q_B^+(t) - q_B^-(t) \leq q_B^{\max}, \quad t \in \mathcal{T}, \tag{9b}$$

$$q_{EV}^{\min} \leq q_{EV}^+(t) - q_{EV}^-(t) \leq q_{EV}^{\max}, \quad t \in \mathcal{S}, \tag{9c}$$

$$SOC_B(t) = \begin{cases} SOC_B^{\mathrm{init}}, & t \in \{1, T\} \\ SOC_B(t-1) & \\ + \frac{(q_B^+(t) - q_B^-(t))\Delta t\, e_B}{C_B}, & t \in \mathcal{T} \setminus \{1, T\}, \end{cases} \tag{9d}$$

$$SOC_{EV}(t) = \begin{cases} SOC_{EV}^{\mathrm{init}}, & t = t_A \\ SOC_{EV}^{\mathrm{req}}, & t = t_D \\ SOC_{EV}(t-1) & \\ + \frac{(q_{EV}^+(t) - q_{EV}^-(t))\Delta t\, e_{EV}}{C_{EV}}, & t \in \mathcal{S} \setminus \\ & \{t_A, t_D\}, \end{cases} \tag{9e}$$

Algorithm 1 EV-assisted battery load hiding algorithm executed by LCU at the beginning of a scheduling period

1: Obtain electricity pricing information $p^c(t)$ and $p^d(t)$, $t \in \mathcal{T}$.
2: Initialize battery parameters $C_B, SOC_B^{\min}, SOC_B^{\max}, SOC_B^{\text{init}}, q_B^{\min}, q_B^{\max}$, and e_B.
3: Collect EV parameters $C_{EV}, SOC_{EV}^{\min}, SOC_{EV}^{\max}, q_{EV}^{\min}, q_{EV}^{\max}, SOC_{EV}^{\text{init}}, SOC_{EV}^{\text{req}}, t_A, t_D, e_{EV}$, and $L(t)$, $t \in \mathcal{T}$.
4: Solve problem (9) and set $q_B(t) = q_B^+(t) - q_B^-(t)$ and $q_{EV}(t) = q_{EV}^+(t) - q_{EV}^-(t)$, $t \in \mathcal{T}$.
5: Send $q_B(t)$ to the local rechargeable battery, and $q_{EV}(t)$ to the EV, $t \in \mathcal{T}$.

$$\begin{aligned} M(t) = L(t) &+ (q_B^+(t) - q_B^-(t))\Delta t \\ &+ (q_{EV}^+(t) - q_{EV}^-(t))\Delta t, \quad t \in \mathcal{T}, \end{aligned} \tag{9f}$$

$$q_B^+(t),\ q_B^-(t) \geq 0, \qquad t \in \mathcal{T}, \tag{9g}$$

$$q_{EV}^+(t),\ q_{EV}^-(t) \geq 0, \qquad t \in \mathcal{S}, \tag{9h}$$

$$q_{EV}^+(t),\ q_{EV}^-(t) = 0, \qquad t \in \mathcal{T} \backslash \mathcal{S}, \tag{9i}$$

$$\text{constraints (4) and (7).} \tag{9j}$$

The assumption $p^c(t) \geq p^d(t)$ guarantees that at optimality, we must have either $q_B^+(t) = 0$ or $q_B^-(t) = 0$, and either $q_{EV}^+(t) = 0$ or $q_{EV}^-(t) = 0$. Otherwise, we can reduce $q_B^+(t)$ and $q_B^-(t)$ by the same amount $\delta_B(t)$, and $q_{EV}^+(t)$ and $q_{EV}^-(t)$ by $\delta_{EV}(t)$, to preserve feasibility. However, the cost will be reduced by $\delta_B(t)(p^c(t) - p^d(t)) + \delta_{EV}(t)(p^c(t) - p^d(t))$, which contradicts with the optimality condition. We can thus introduce the identities $[q_B(t)]^+ = q_B^+(t)$, $[-q_B(t)]^+ = q_B^-(t)$ and $[q_{EV}(t)]^+ = q_{EV}^+(t)$, $[-q_{EV}(t)]^+ = q_{EV}^-(t)$, which shows that problems (8) and (9) are equivalent.

The proposed EV-assisted load hiding method is summarized in Algorithm 1. At the beginning of each scheduling period, the LCU first obtains the electricity pricing information, initializes the parameters of the battery, the EV as well as the household base load. It then solves problem (9) to generate the optimal privacy preserving charging strategy. The charging rates $q_B(t)$ and $q_{EV}(t)$ are sent to the local rechargeable battery and the EV, respectively.

IV. Performance Evaluation

In this section, we evaluate our proposed method using real data for electricity price, household consumption and EV parameters. The TOU pricing information and feed-in tariffs are obtained from a utility company, Hydro One, in Ontario, Canada [14]. The residential household base load profile is obtained from MIT REDD dataset [15]. The EV related parameters are set according to the specification for Chevy Volt model [16]. In our simulation, we consider 24 hour as a scheduling period, which starts at 12 pm. We fix the meter sampling interval $\Delta t = 2$ mins. Therefore, we have $T = 720$ time slots in total. The stochastic driving pattern of EV is simulated based on the National Household Travel Survey 2009 [17]. The Gaussian distribution model is used to generate the EV's arrival and departure time [18]. The arrival time t_A follows a normal distribution with a mean of 6 pm and a standard deviation of 2 hours. The departure time t_D follows a normal distribution with a mean of 7 am and a standard deviation of 2 hours. In our simulation, we only consider one-time arrival and departure of the EV at home to simplify the discussion. However, our model can easily be extended when multiple EV arrival and departure times need to be taken into account. The initial SoC of the EV, SOC_{EV}^{init}, when plugged in is set to be uniformly distributed within [0.3, 0.9], and the desired SoC at departure is set as 0.9. The maximum EV charging and discharging rate is $q_{EV}^{\max} = -q_{EV}^{\min} = 1.44$ kW, with a capacity $C_{EV} = 8$ kWh. The lower and upper SoC limits of EV are set as $SOC_{EV}^{\min} = 0.2$ and $SOC_{EV}^{\max} = 0.9$, respectively. As for the battery, its initial SoC, SOC_B^{init}, is also set to be uniformly distributed within [0.3, 0.9]. Its lower SoC limit $SOC_B^{\min}$ and upper SoC limit $SOC_B^{\max}$ are the same as those of the EV. The maximum charging and discharging rates of the battery are set according to its capacity C_B. We fix $q_B^{\max} = -q_B^{\min} = 4C_B$ in our experiments, which means that it takes 4 hours to fully charge the battery from empty state and vice versa for discharging cycles. The charging efficiency of the battery and the EV is set as $e_B = e_{EV} = 0.9$. The privacy threshold ε is chosen based on the acceptable information leakage level of the customer. Problem (9) is solved by using CVX [19].

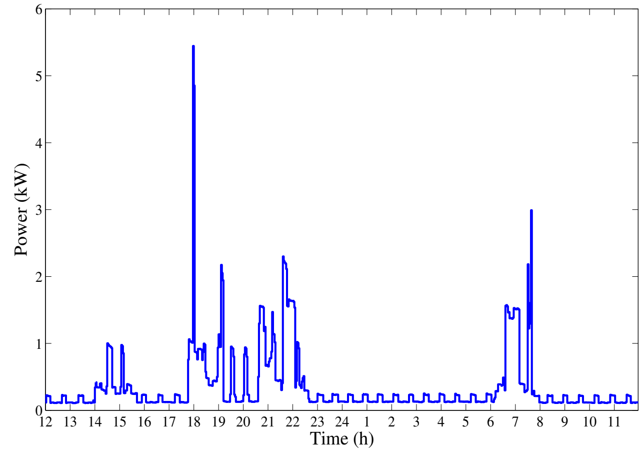

Fig. 2. The original household load profile.

A. An Example for Illustration

As an example, the one-day household consumption of a residential customer is shown in Fig. 2. Its first peak consumption comes at around 6 pm and lasts to around 10 pm. Another peak load is observed at around 6:40 am and ends before 8 am. In our simulation, we assume that the operation time of the EV, i.e., the set $\mathcal{S}$, covers the entire peak load time periods. The masked load of using the local rechargeable battery only with a capacity C_B of 10 kWh for hiding is shown in Fig. 3. It can be observed that most of the household load variances can be flattened, except for some sharp impulse points that exceed the battery operation range. The result of the EV-assisted battery load hiding is shown in Fig. 4, with the local rechargeable battery capacity C_B reduced to 5 kWh. It can be seen that a similarly flat household demand as in Fig. 3 can be maintained using a local rechargeable battery of only half the size.

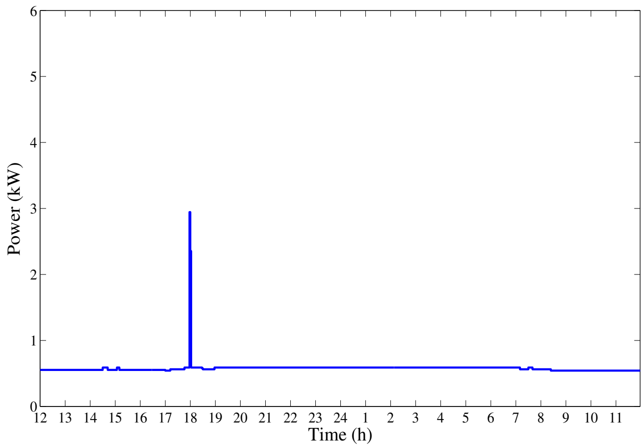

Fig. 3. The observed household load profile using a 10 kWh local rechargeable battery for load hiding.

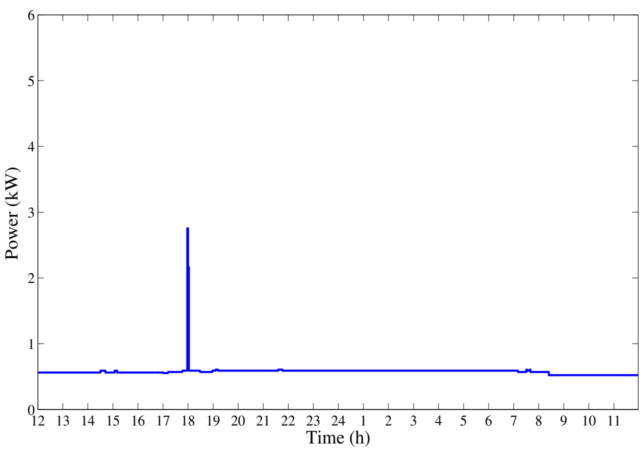

Fig. 4. The observed household load profile using a 5 kWh local rechargeable battery and an EV for load hiding.

B. Performance of EV-assisted Battery Load Hiding

Mutual information between $M(t)$ and $L(t)$ is used to evaluate our proposed EV-assisted battery load hiding method for privacy preserving performance [8]. Since the on-off status of the household appliances generally conceals in the amplitude changes of the load profile, we define the time series $\delta_{M(t)} = M(t) - M(t-1)$ for the masked load and $\delta_{L(t)} = L(t) - L(t-1)$ for the original base load, respectively. Then, we quantize $\delta_{M(t)}$ and $\delta_{L(t)}$ into n intervals ($n = 200$ in our experiments) and calculate their mutual information according to [8, eq. (1)].

Fig. 5 shows the electricity cost of the customer per scheduling period (i.e., (9a)) as a function of mutual information when only a local rechargeable battery is used. The results are obtained from (9) using different bounds ε in (7). Larger ε, which corresponds to larger MI values, generally offers more flexibility in reducing the electricity cost by taking advantage of the customer's loose requirement on privacy leakage to shift peak load. Therefore, we can observe that there is a trade-off between cost for energy consumption and level of privacy regarding consumption information. The more privacy is desired, the less storage can be used for the

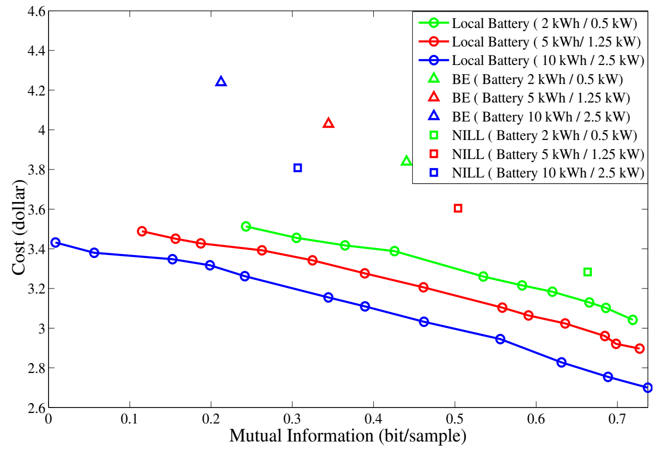

Fig. 5. Cost versus mutual information for different algorithms and batteries (maximum capacity C_B / maximum charging rate $q_B^{\max}$).

purpose of cost reduction. The figure also reveals that the cost and privacy can be improved by using a larger-capacity local rechargeable battery, which is more expensive at the time of purchase though. As points of reference, we also include the results for the BE algorithm from [6] and the NILL algorithm from [7] in Fig. 5. We note that for the same level of privacy, the proposed framework can reduce electricity cost compared to the BE and NILL algorithms. This is not entirely surprising, as we specifically consider optimizing the electricity cost when providing privacy within the customer's expectation. Furthermore, our algorithm requires knowledge of the household load profile ahead of time, which is not the case for the BE and NILL algorithms. Nevertheless, the comparative results in Fig. 5 indicate the effectiveness of our optimization approach and the meaningfulness of the absolute performance results.

Fig. 6 shows again the cost of the customer versus mutual information, now with an EV included. We compare the cases that only a local rechargeable battery is used for minimizing cost and load hiding with our proposed EV-assisted algorithm. The results for the former are different from those in Fig. 5 as the EV appears as an additional load. We observe that the EV-assisted method greatly improves the cost-privacy trade-off over local-rechargeable-battery-only based hiding. Furthermore, the acquisition cost for the local rechargeable battery can be reduced, as an example, the combined use of a 5 kWh local rechargeable battery and an EV achieves a better performance than when using a larger capacity 10 kWh local rechargeable battery without EV assistance. Clearly, the combined use of battery and EV expands the range of the charging and discharging rate that can be exploited for hiding, even if the capacity of the local rechargeable battery is reduced.

C. Peak Load Reduction of EV-assisted Battery Load Hiding

We now investigate how our proposed EV-assisted battery load hiding algorithm can help shift the peak load at an aggregate level. Three households from the MIT REDD dataset [15] are selected to simulate the aggregate load consumption,

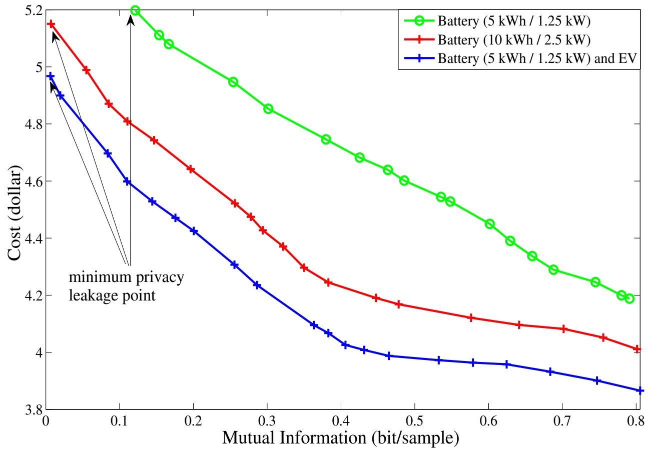

Fig. 6. Cost versus mutual information for different batteries (maximum capacity C_B / maximum charging rate $q_B^{\max}$) with and without the use of an EV for load hiding.

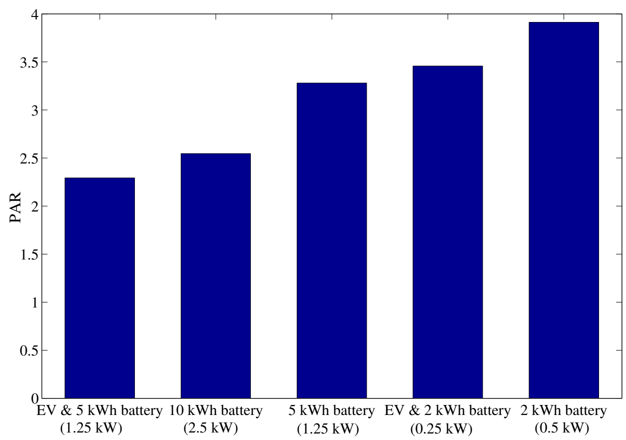

Fig. 7. Comparison of PAR for different batteries (maximum charging rate $q_B^{\max}$) with and without the use of an EV for load hiding.

with an original peak to average ratio of $\mathrm{PAR} = 6.5$. We assume that the operation time of the EV, the set $\mathcal{S}$, covers both the peak periods. The customers have the minimum amount of privacy leakage (as illustrated in Fig. 6). As shown in Fig. 7, we observe a reduction in PAR when combining the use of a smaller-capacity local rechargeable battery with an EV. The PAR is reduced to 3.3 and 2.5 when only a 5 kWh and a 10 kWh local rechargeable battery is exploited for load hiding, respectively. When an EV is added to the smaller 5 kWh battery for hiding, the PAR can further be reduced to 2.3. Similar benefits of the EV-assisted method can be seen for the case of a local rechargeable battery with only 2 kWh capacity and slower charging cycle. Thus, our proposed algorithm can be effective in peak load shaving at grid scale.

V. Conclusion

In this paper, we have proposed an EV-assisted battery load hiding method to reduce the cost for customers for battery purchase and installment, while limiting the privacy leakage of the customer within an acceptable range. The performance evaluation of our proposed algorithm has demonstrated its effectiveness in terms of privacy enhancement and cost efficiency. Our approach thus has merit for the growing number of households with EVs, which can benefit from the additional use of the EV without extra acquisition cost.

However, there are several idealizations in this initial work. We assume that the household base load is known perfectly ahead of time. Similarly, even though the stochastic driving pattern of the EVs is considered, we assume that the LCU knows the arrival time and the initial SoC of the EV, when generating the optimal privacy-preserving charging strategy. Current research is thus dedicated to extensions that account for the load uncertainty and the uncertainty of EV arrival time and SoC.

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