Real and Reactive Power Based Optimal Privacy Protection in Smart Grid Demand Response

Cihan Emre Kement and Marija Ilić

Abstract—Frequent metering of consumption data is crucial for demand side management in smart grids. However, the metered data can easily be processed with nonintrusive appliance load monitoring techniques to infer appliance usage, which provides insight about the private lives of consumers. Existing load shaping techniques for privacy focus only on hiding or altering metered real power, whereas smart meters also collect reactive power data for various purposes. In this work, we present optimizing the consumer privacy in a demand response scheme considering both real and reactive power data. Also, we consider the user cost and comfort as objectives, and build the optimization problem in such a way that the effects of optimizing sub-objectives on the others can be observed. Results show that hiding only real or only reactive power is not sufficient for ensuring privacy and they need to be altered simultaneously. Shaping real and reactive demand at the same time results in more than twofold increase in privacy in terms of mutual information.

Index Terms—Demand response, demand shaping, load shaping, multi-objective optimization, privacy, real and reactive power, smart grids, smart metering.

NOMENCLATURE

Indices and sets

- $a$: Index of appliances.
- $i$: Index of objectives.
- $s$: Index of scenarios.
- $t$, $\tau$: Indices of time slots.
- $A^{m}$: Set of power non-shiftable appliances.

Parameters

- $\alpha_a$: Operation window start of appliance $a$.
- $\beta_a$: Operation window end of appliance $a$.
- $\gamma_i$: Weight of objective $O_i$.
- $\Delta_t$: Duration of one time slot.
- $\eta^{op}_p$: Charge efficiency of the battery.
- $\eta^{dp}_p$: Discharge efficiency of the battery.
- $\eta^{op}_q$: Charge efficiency of the capacitor.
- $\eta^{dq}_q$: Discharge efficiency of the capacitor.
- $\phi_{a,t}$: Penalty cost of appliance $a$ for operating at time $t$.
- $\rho_s$: Probability of scenario $s$.
- $c^p_t$: Cost of real power at time slot $t$ ($$/\text{kWh}$).
- $c^q_t$: Cost of reactive power ($$/\text{kvar}$$).

Variables

- $O_i$: Value of the objective $i$.
- $p^s_{s,t}$: Metered real power at time $t$ in scenario $s$ (kW).
- $q^s_{s,t}$: Metered reactive power at time $t$ in scenario $s$ (kW).
- $p^{ca}_{a,s,t}$: Real power consumed by appliance $a$ at time $t$ in scenario $s$ (kW).
- $q^{ca}_{a,s,t}$: Reactive power consumed by appliance $a$ at time $t$ in scenario $s$ (kvar).
- $p^{cb}_{s,t}$: Real power charged into the battery at time $t$ in scenario $s$ (kW).
- $p^{db}_{s,t}$: Real power discharged from the battery at time $t$ in scenario $s$ (kW).
- $q^{cc}_{s,t}$: Reactive power charged into the capacitor at time $t$ in scenario $s$ (kvar).
- $q^{dc}_{s,t}$: Reactive power discharged from the capacitor at time $t$ in scenario $s$ (kvar).
- $v_{s,t}$: Real power drawn from the PV generator at time $t$ in scenario $s$ (kW).

A binary variable that takes the value 1 if power non-shiftable appliance $a$ operates at time $t$ in scenario $s$.

- $E_a$: Amount of energy that appliance $a$ has to spend to complete its operation (kWh).
- $E^{bi}_s$: Initial energy stored in the battery (kWh).
- $E^{bmax}_s$: Maximum energy that can be stored in the battery (kWh).
- $E^{ci}_s$: Initial reactive energy stored in the capacitor (kvar).
- $E^{cmax}_s$: Maximum reactive energy that can be stored in the capacitor (kvar).
- $O^*_i$: Optimal value of $O_i$.
- $P^9_{s,t}$: Real power generated by the PV generator at time slot $t$ in scenario $s$ (kW).
- $P^{max}_a$: Load capacity of the house (kW).
- $P^{min}_a$: Maximum real power that appliance $a$ can draw during operation (kW).
- $P^{min}_a$: Minimum real power that appliance $a$ can draw during operation (kW).
- $PF_a$: Power factor of appliance $a$.
- $R^{chmax}_s$: Maximum charge rate of the battery (kWh).
- $R^{dmax}_s$: Maximum discharge rate of the capacitor (kvar).
- $R^{dmax}_s$: Maximum discharge rate of the capacitor (kvar).

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I. INTRODUCTION

SMART metering is a crucial part of the smart grid (SG) structure. Frequent measurements collected from smart meters are used in accurate and personalized billing services, detecting outages and electricity theft, load forecasting, demand side management and much more [1]. However, smart meter data can also be used by adversaries to violate the privacy of the consumers [2]–[4].

The group of methods used for extracting appliance or end-use data from aggregated household meter data is called Nonintrusive Appliance Load Monitoring (NIALM) [5]. Most of these NIALM methods detect edges on the time-series meter data, and use methods such as cluster analysis to map the change in the metered data to an appliance or end-use [6]. The change in the power as well as other transient and steady-state properties such as duration and periodicity are used as features in the analysis.

There are numerous methods that aim to mitigate the privacy problem induced by smart metering and NIALM. The methods can be categorized into five: Adding noise to the metered data to achieve differential privacy, using homomorphic encryption techniques to hide sensitive data, using pseudonyms instead of consumer identification, reducing the metering frequency and shaping the consumer demand. Among these methods, load shaping (LS) (or demand shaping - DS) is one of the most promising in terms of simplicity, efficiency and applicability [7].

Numerous LS methods have been proposed in the literature [8], most of which are based on algorithms, heuristics and game theory. These methods focus on shaping the metered real power \( (P) \) consumed by the customer in such a way that it does not give away appliance-specific signatures. For shaping the real power, they use household amenities such as rechargeable batteries (RB), renewable energy sources (RES) as well as some appliances runtime and/or power consumption of which can be shifted \( (e.g. \) plug-in electric vehicles). Although the number of these LS methods are extensive, they miss a key point: smart meters do not measure only the real power. They measure instantaneous voltage and current, and hence the apparent power \( (S) \), which has both real \( (P) \) and reactive \( (Q) \) power components. Since consumers are usually billed based on the real power consumption, the reactive power is often overlooked by the smart grid privacy research community. However, reactive power is also a matter of importance for the supply side, since having a high reactive load decreases the power factor \( (P/|S|) \) and hence the efficiency of the system. Therefore, utility companies (UC) also keep track of the reactive power demand as depicted in Fig. 1.

Just like the real power, the reactive power also carries signatures of individual appliances. In fact, the change in the reactive power is one of the key features looked into by the NIALM methods [9]. Therefore, in order to ensure privacy, \( P \) and \( Q \) must be shaped simultaneously. In this study, we used the real and reactive power measurements from the Ampds2 dataset [10] to show that hiding only \( P \) or only \( Q \) is not enough to ensure privacy. In order to do that, we constructed a multi-objective optimization problem which maximizes the privacy of the consumer (by shaping \( P, Q \) or both) while also considering the cost and the comfort of the consumer. Our contributions to the literature are as follows:

1) To the best of our knowledge, this is the first study that considers real and reactive power simultaneously in preserving consumer privacy in smart grids.

2) We formulated the problem of maximizing privacy by using real and reactive power as a multi-objective mixed-integer-linear program and found optimal limits for privacy performance as well as its effect on cost and comfort.

3) Comparing the solutions which consider only \( P \), only \( Q \) and both \( P \) and \( Q \); we showed that shaping only the real load or only the reactive load is not sufficient to ensure privacy.

The rest of the paper is organized as follows: Section II presents a review of the literature on load shaping based privacy protection in SGs. Our multi-objective optimization formulation is described in Section III. Results of our analysis are presented in Section IV. Concluding remarks are made in Section V.

II. RELATED WORK

In this section, we provide a short summary of previous works on privacy protection via LS. Note that all of the studies below considered only metered real power as the data that needs to be shaped. [11] by Fan et al. is the only study that considered the reactive power and proposed using household capacitors to shape the reactive load. None of the existing studies, however, had considered hiding both real and reactive power for privacy.

Kalogridis et al. [12] (best effort algorithm), McLaughlin et al. [13] (nonintrusive load leveling algorithm), Ge et al. [14] (tolerable deviation algorithm), and Yang et al. [15] (stepping algorithm) proposed heuristic methods that laid the foundation for the LS methods. These algorithms change the load with the help of RBs, RESs and shiftable appliances.

Other studies that used various amenities to shape the load for privacy followed the aforementioned methods. Zhao et al. [16] used RBs to randomly change the metered load to ensure differential privacy. Egarter et al. [17] used shiftable appliances instead of RBs to shape the load. Giaconi et
al. [7] exploited RBs and RESs to find an optimal energy management policy. Chen et al. [18], [19] proposed using thermal storage such as water heaters instead of RBs to increase privacy. Reinhardt et al. [20] proposed a method for privacy by utilizing photovoltaic (PV) generators. Liu et al. [21] studied privacy in case of multiple RBs in a cascaded fashion. Sun et al. [22], [23] proposed utilizing plug-in electric vehicles (PEV) and household devices such as HVACs as energy storage in shaping the load for privacy. Moon et al. [24] optimized privacy and cost together in an optimization framework by using a RB. Liu et al. [25] optimized user cost, privacy and comfort with the help of shiftable appliances and RBs. Tan et al. [26] studied optimal privacy-cost trade-off with the help of household RBs. Isikman et al. [27] optimized the privacy and power usage (utility) of consumer with the help of RBs and RESs.

Further studies regarding load shaping and privacy included Li et al. [28], [29] and Erdemir et al. [30] who studied optimal RB policies by reformulating the privacy optimization as a Markov decision process (MDP). Yang et al. [31] and Chen et al. [32] proposed online algorithms for preserving privacy via using a RB and shiftable appliances. Koo et al. [33] proposed a learning based LS scheme to hide both high and low frequency load signatures for privacy. Hossain et al. [34] and Natgunanathan et al. [35] proposed online and offline heuristic methods to mitigate the problem of preserving privacy in case of prolonged high or low loads and finite capacity RBs.

All these studies and methods except [11] considered only shaping the real load, and their privacy assessments did not include the mutual information between the reactive load of appliances and the aggregated reactive load. On the other hand, [11] only considered shaping the reactive load and did not consider the effects of shaping the reactive load on the real load. We model the optimization problem that shapes both P and Q in the following section.

III. PROBLEM FORMULATION

We consider a smart-metered house with shiftable and non-shiftable appliances, a household battery for real power compensation, a household capacitor for reactive power compensation, a PV generator, and a PEV as in Fig. 1. We assume a demand response (DR) scheme where the utility company (UC) provides day-ahead real-time pricing (RTP) to the consumer, and consumers try to find an optimal schedule for their appliances according to their cost, comfort and privacy priorities. Time-shiftable appliances have certain operation windows within which they must complete their operation. Similarly, power-shiftable appliances have maximum and minimum power levels within which they can operate. We assume that the power generated by the PV can be estimated with stochastic approximation. Therefore, we use stochastic optimization to optimize the expected values of the objectives given different scenarios (s) in which the PV generator generates different outputs.

A. Stochastic Approximation of Solar Power

We used Monte Carlo sampling to generate 10000 sample vectors of PV outputs (each of size T) with the distribution in (1), (2) and then by using K-means clustering [32], reduced the number of vectors to 10. These 10 PV power output scenarios and their occurrence probabilities are then used in the stochastic optimization formulation.

The distribution of the solar irradiance was modeled as a bimodal distribution [36]. Beta distribution (1) was used for each mode.

$$f_b(x) = \frac{\Gamma(\alpha+\beta)\cdot x^{\alpha-1}(1-x)^{\beta-1}}{\Gamma(\alpha)\Gamma(\beta)}, \quad 0 \leq x \leq 1; \alpha, \beta \geq 0$$

otherwise.

(1)

Parameters $\alpha$ and $\beta$ were calculated from the mean and variance of the solar radiation data which has been provided in [36]. $\Gamma$ represents the Gamma function and $f_b(x)$ is the pdf of the solar irradiance ($kW/m^2$). The power generated by the PV was obtained by using the irradiance-to-power conversion function [36] as

$$f_{pv}(x) = \eta_{pv} \cdot \hat{g}_{pv} \cdot x,$$

(2)

where $\hat{g}_{pv}$ and $\eta_{pv}$ represent the solar panel area ($m^2$) and the efficiency of solar panels (%), respectively.

B. Objectives

Our objectives include maximizing privacy by minimizing the information leakage out of both the real and the reactive aggregated loads, as well as minimizing the user cost and discomfort. Since shaping the loads for increasing privacy would incur some monetary cost and discomfort to the consumer, these should also be considered while optimizing user privacy.

1) Maximiing the Privacy by Shaping P and Q: We define the privacy objective as a generic function $F$ which depends on the metered real and reactive powers $p_{s,t}^c$ and $q_{s,t}^c$ of the house. $F$ can be formulated depending on the method that will be used for preserving privacy. For the sake of demonstration, we adopt the best effort method [12] and extend it to consider both P and Q in (3). Note that other methods in the literature could also be formulated as in [8] and extended to include shaping the reactive load.

$$F \triangleq \sum_{s=1}^{S} \sum_{t=2}^{T} \rho_s \cdot \left( |p_{s,t}^c - p_{s,(t-1)}^c| + |q_{s,t}^c - q_{s,(t-1)}^c| \right)$$

(3)

By defining $F$ this way, we assume that the temporal differences of metered real and reactive loads have the same impact on privacy. In this study, we would like to show the difference between shaping both P and Q vs. shaping them separately. Therefore we divide (3) into two separate privacy objectives so that we can weight them accordingly to simulate different cases.

$$O_1 = \sum_{s=1}^{S} \sum_{t=2}^{T} \rho_s \cdot |p_{s,t}^c - p_{s,(t-1)}^c|$$

(4)

$$O_2 = \sum_{s=1}^{S} \sum_{t=2}^{T} \rho_s \cdot |q_{s,t}^c - q_{s,(t-1)}^c|$$

(5)
2) **Minimizing the Monetary Cost:** The monetary cost could be defined as the product of metered real power ($p_{a,s,t}^r$) and its price ($c_{a}^r$). However, since we are also considering the reactive power, its cost can also be added to the formulation.

\[
O_3 = \sum_{s=1}^{S} \rho_s \cdot \sum_{t=1}^{T} (c_{a}^r \cdot p_{a,s,t}^r + c_{a}^q \cdot q_{a,s,t}^q) .
\]

(6)

Although currently consumers are not charged for their reactive power consumption, high reactive loads induce inefficiency to the grid, which is indirectly reflected on the pricing. In addition, incurring a cost on reactive power would also eliminate the possibility of unnecessary reactive power consumption in the optimal solution. We assume a constant and relatively small cost $c_{a}^q$ for the reactive power usage.

3) **Minimizing the Discomfort:** Shaping the load demand causes a certain discomfort to the user if appliance usages are shifted. We model this discomfort by defining an exponentially increasing penalty coefficient $\phi_{a,s}$ for each appliance usage at each time slot.

\[
O_4 = \sum_{a=1}^{A} \frac{\sum_{s=1}^{S} \sum_{t=1}^{T} \rho_s \cdot \phi_{a,s,t} \cdot p_{a,s,t}^a}{\sum_{s=1}^{S} \sum_{t=1}^{T} p_{a,s,t}^a} .
\]

(7)

Note that, unlike the other objectives, here we did not use a reactive power term. The reason is that consumer comfort can be solely measured in terms of the real power usage. If there were purely reactive loads in a household environment, then it would be necessary to include $q_{a,s,t}^q$ into this objective.

**C. Constraints**

We can divide the constraints into three categories: Appliance power constraints, power balance constraints and battery/capacitor constraints. All three categories have additional constraints compared with legacy optimization formulations due to the inclusion of reactive power.

1) **Appliance Power Constraints:** Constraint (8) makes sure that the real power used by appliance $a$ is 0 outside its operation window. Constraint (9) makes sure that power-shiftable appliances run within their power limits. Constraint (10) limits the power usage of power-non-shiftable appliances to either 0 or $P_{a}^{max}$. Constraint (11) makes sure that all appliances use the exact amount of energy for completing their operation. Constraint (12) makes sure that the real and reactive power usage of appliance $a$ are proportional to its power factor.

\[
p_{a,s,t}^a = 0, \quad \forall a, s, \forall t \notin [\alpha_a, \beta_a] \quad \text{(8)}
\]

\[
p_{a,s,t}^a \leq p_{a,s,t}^a \leq P_{a}^{max}, \quad \forall a, s, t \quad \text{(9)}
\]

\[
p_{a,s,t}^a = y_{a,s,t}^p \cdot P_{a}^{max}, \quad \forall s, t, \forall a \in A^{pns} \quad \text{(10)}
\]

\[
\Delta T \cdot \sum_{t=1}^{T} p_{a,s,t}^a = E_a, \quad \forall a, s \quad \text{(11)}
\]

\[
q_{a,s,t}^q = \tan(\arccos(PF_a)) \cdot p_{a,s,t}^a, \quad \forall a, s, t \quad \text{(12)}
\]

In (12), we assumed that all the appliances have a constant power factor. Indeed, this may not be the case for some appliances with multiple components. However, these components could still be modeled as individual appliances whose operations are dependent on each other. Thus, their $P$-$Q$ relations could still be modeled in a linear way as in (12).

2) **Power Balance Constraints:** Constraint (13) along with (14) is the real power balance constraint. Constraint (15) is the reactive power balance constraint. The upper bound of household demand is enforced in (16).

\[
p_{s,t}^r = \sum_{a=1}^{A} p_{a,s,t}^a + p_{b,s,t}^b / \eta_p - p_{s,t}^d \cdot \eta_{dp} - v_{s,t}, \quad \forall s, t \quad \text{(13)}
\]

\[
v_{s,t} \leq P_{s}^d, \quad \forall s, t \quad \text{(14)}
\]

\[
q_{s,t}^q = \sum_{a=1}^{A} q_{a,s,t}^a + q_{s,t}^b / \eta_q - q_{s,t}^d \cdot \eta_{dq}, \quad \forall s, t \quad \text{(15)}
\]

\[
p_{s,t}^q \leq P_{s}^{max}, \quad \forall s, t \quad \text{(16)}
\]

3) **Battery and Capacitor Constraints:** Constraints (17), (18) make sure that at any time slot $\tau$, the capacities of the battery and the capacitor are not exceeded. Constraints (19) and (20) limit the amount of real power charged into or discharged from the battery. Similarly, Constraints (22) and (23) limit the rate at which reactive power can be stored/provided by the capacitor. Constraints (21) and (24) make sure that the amount of real and reactive power stored at the end of the day are the same with those at the beginning of the day.

\[
0 \leq E_{b}^{\tau} + \sum_{t=1}^{T} \Delta t \cdot p_{s,t}^{b} - \sum_{t=1}^{T} \Delta t \cdot q_{s,t}^{b} \leq E_{b}^{max}, \forall s, \tau \quad \text{(17)}
\]

\[
0 \leq E_{c}^{\tau} + \sum_{t=1}^{T} \Delta t \cdot q_{s,t}^{c} - \sum_{t=1}^{T} \Delta t \cdot q_{s,t}^{b} \leq E_{c}^{max}, \forall s, \tau \quad \text{(18)}
\]

\[
p_{s,t}^{b} \leq R_{s}^{bmax}, \quad \forall s, t \quad \text{(19)}
\]

\[
p_{s,t}^{d} \leq R_{s}^{dmax}, \quad \forall s, t \quad \text{(20)}
\]

\[
\sum_{t=1}^{T} p_{s,t}^{b} = \sum_{t=1}^{T} p_{s,t}^{d}, \quad \forall s \quad \text{(21)}
\]

\[
q_{s,t}^{c} \leq R_{s}^{cmax}, \quad \forall s, t \quad \text{(22)}
\]

\[
q_{s,t}^{d} \leq R_{s}^{dmax}, \quad \forall s, t \quad \text{(23)}
\]

\[
\sum_{t=1}^{T} q_{s,t}^{c} = \sum_{t=1}^{T} q_{s,t}^{d}, \quad \forall s \quad \text{(24)}
\]

**D. Multi-objective Optimization Model**

We used goal programming method for modeling our multi-objective optimization problem. One reason for using goal programming is that we can find Pareto efficient solutions for any set of weights ($\gamma_i$). Secondly, we can show the optimal results of real-power-only privacy, reactive-power-only privacy and both real and reactive power based privacy simply by arranging the weights ($\gamma_i$) accordingly.

\[
\text{minimize } Z \quad \text{(25)}
\]

\[
\text{subject to } Z \geq \gamma_i \cdot \frac{O_i - O_i^*}{O_i}, \quad \forall i \quad \text{(26)}
\]

\[
\text{subject to constraints (4) – (24)} \quad \text{(27)}
\]

In the next section we show the results for both formulations which expose the privacy leakage when shaping only the real and reactive power and show the improvement in privacy when both are simultaneously shaped.
IV. RESULTS

We used GAMS IDE to implement our mixed-integer linear program and solved it with CPLEX on a system with 4-core 8-thread core-i7 processor and 32GB of RAM.

We used the minutely real and reactive power measurement data from Ampds2 dataset [10]. We chose the data of 12/19/2012, on which day all the appliances were used in the household.

Mutual information (MI) has been used predominantly as a privacy metric in the previous studies [21]–[24], [28], [30], [33], [35], [37], [38]. Therefore, we adopted empirical MI as the privacy measure. We calculated the MI between the actual (real and reactive) power usage and metered (real and reactive) power usage. We also calculated the MI between (real and reactive) power usage of individual appliances and the metered (real and reactive) power.

A. Effects of shaping real and reactive power on privacy

We specified 6 cases along with the original appliance usage (case 0) for comparison in order to show the effectiveness of hiding both real and reactive power. Case 0 refers to the original metered data without any LS. Case 1 corresponds to the case with real-power-based-only optimal privacy preservation. In case 2, privacy is preserved optimally by only shaping the reactive power. Real and reactive power based load shaping is optimized in case 3. Case 4 represents the case where real and reactive power based privacy is optimized along with user cost and comfort. Cases 5 and 6 represents when user cost and comfort are jointly optimized with real-power-based and reactive-power-based privacy, respectively (see Table I).

TABLE I: Cases and their corresponding weights.

| Case | Weights |
|------|---------|
| #    | $\gamma_1$ | $\gamma_2$ | $\gamma_3$ | $\gamma_4$ |
| 0    | 0        | 0          | 0        | 0        |
| 1    | 1        | 0          | 0        | 0        |
| 2    | 0        | 1          | 0        | 0        |
| 3    | 1        | 1          | 0        | 0        |
| 4    | 1        | 1          | 1        | 1        |
| 5    | 1        | 0          | 1        | 1        |
| 6    | 0        | 1          | 1        | 1        |

The MI between the actual (real and reactive) loads and metered (real and reactive) loads are provided in Table II and Fig. 2. It can be seen that the amount of information in the metered load of case 3 is 79% less than case 1, where only the real power is shaped. Even in case 4, where user cost and comfort are also optimized along with privacy, there is more than twofold increase in the privacy compared to cases 2 and 3.

In Fig. 3, metered real and reactive loads of the house is plotted for different cases. Fig. 3-b and Fig. 3-c show that when only the real or only the reactive load is shaped, the other load that has not been shaped still contains information regarding the appliance usage. Fig. 3-d shows that we can successfully hide most of the information on real and reactive metered loads with small compromises from their singular optimal shapes.

| Case | MI (bits) |
|------|-----------|
| #    | real | reactive | total |
| 0    | 6.88 | 4.86     | 11.74  |
| 1    | 4.00 | 3.07     | 7.07   |
| 2    | 4.90 | 0.33     | 5.23   |
| 3    | 0.40 | 0.33     | 0.73   |
| 4    | 1.19 | 0.24     | 1.43   |

Table II shows the average MI between appliance loads and metered (real and reactive) loads. It can be seen that, shaping real and reactive load at the same time (case 3) results in more than 60% decrease in average MI compared to real power shaping only (case 1) and reactive power shaping only (case 2). When all the objectives are optimized together (case 4), the average MI is still less than 50% of the average MI in cases 1 and 2.

Table III shows the average MI between appliance loads and metered (real and reactive) loads. It can be seen that, shaping real and reactive load at the same time (case 3) results in more than 60% decrease in average MI compared to real power shaping only (case 1) and reactive power shaping only (case 2). When all the objectives are optimized together (case 4), the average MI is still less than 50% of the average MI in cases 1 and 2.

Fig. 2: The mutual information between metered and actual real (P) and reactive (Q) loads in different cases

| Case | MI (bits) |
|------|-----------|
| #    | real | reactive | total |
| 0    | 6.88 | 4.86 | 11.74 |
| 1    | 4.00 | 3.07 | 7.07 |
| 2    | 4.90 | 0.33 | 5.23 |
| 3    | 0.40 | 0.33 | 0.73 |
| 4    | 1.19 | 0.24 | 1.43 |

Fig. 3: Metered real and reactive loads of the house. a: original data (case 0), b: real-power-based LS (case 1), c: reactive-power-based LS (case 2), d: real & reactive power based LS with min. cost and max. comfort (case 4)
In this section, we compared three multi-objective cases (case 4, case 5 and case 6) to observe the effects of shaping the real power and the reactive power together.

B. Effects of shaping real and reactive power on other objectives

In this section, we compared three multi-objective cases (case 4, case 5 and case 6) to observe the effects of shaping both real and reactive power on the other objectives. It can be seen from Table IV that, shaping both the real and the reactive power (case 4) increases the cost and discomfort of the consumer more than shaping only the real power (case 5) or shaping only the reactive power (case 6) does. This is an expected result, as the privacy objectives are inherently conflicting with the cost and comfort objectives. However, the increase of the cost and discomfort in case 4 is less than 8% compared to cases 5 and 6, which is a small compromise compared with the more than twofold increase in privacy.

V. CONCLUSION

We presented the optimal privacy results in a demand response scheme by shaping both the real and the reactive metered power. Our results revealed that shaping only the real or the reactive load can result in serious data leakage for consumers. Major takeaways from this study are as follows:

1) When the real power ($P$) and the reactive power ($Q$) are shaped together, the optimal privacy is enhanced more than 50% in terms of mutual information. In other words, when $P$ or $Q$ is shaped alone, the total mutual information between the actual and metered loads increase at least twofold compared to shaping both $P$ and $Q$ together.

2) Optimizing privacy by shaping both the real and reactive power results in 30.7% and 30.5% increase in consumer cost and discomfort, respectively, from their singular optimal values. However, the additional burden of shaping both $P$ and $Q$ is less than 8% when compared to real-power-only or reactive-power-only privacy optimization.

Future research directions include using additional amenities such as PV generators for shaping the reactive load. Although currently PV generators are restricted to have unity power factors, they can be used for reactive power compensation [39] which can also help shaping the reactive load for privacy.

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