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OPTIMAL PRIVACY-ENHANCING AND COST-EFFICIENT ENERGY MANAGEMENT STRATEGIES FOR SMART GRID CONSUMERS

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ABSTRACT

The design of optimal energy management strategies that trade-off consumers' privacy and expected energy cost by using an energy storage is studied. The Kullback-Leibler divergence rate is used to assess the privacy risk of the unauthorized testing on consumers' behavior. We further show how this design problem can be formulated as a belief state Markov decision process problem so that standard tools of the Markov decision process framework can be utilized, and the optimal solution can be obtained by using Bellman dynamic programming. Finally, we illustrate the privacy-enhancement and cost-saving by numerical examples.

Index Terms— Smart metering system, privacy-cost trade-off, Kullback-Leibler divergence, Markov decision process.

1. INTRODUCTION

In future smart grids, smart meters are essential components to deliver information about consumers' energy demand to the energy provider, which enables the operator to monitor the grid and enhance the energy efficiency. However, it is at the potential cost of consumers' privacy, since the smart metering data can be used to infer on consumers' private activities. Regarding this problem, different approaches have been proposed previously. One kind of approaches are data driven methods that modify the smart metering data by obfuscation [1], anonymization [2], or data aggregation [3]. However, the main limitation of the methods that corrupt smart meter readings is that they degrade the monitoring performance.

An innovative privacy-by-design approach is to modify the actual consumer energy demand by applying privacy-enhancing energy management in the presence of an energy storage or alternative energy supplies. In [4–9], privacy leakage is measured by different information theoretic measures such as mutual information and conditional entropy. In [10], the privacy-preserving problem is evaluated under Bayesian detection setting. However, only in [6] of the aforementioned

Fig. 1. Smart metering system with a rechargeable energy storage (ES), an energy management unit (EMU) that manages the energy supply Y_t from the consumer's demand X_t , and an adversary (AD) with access to smart meter reading Y_t making an unauthorized hypothesis testing on the consumers' behavior h_0/h_1 .

works has taken the consumers' energy cost into consideration.

In this paper, we consider a smart metering system with a rechargeable energy storage at the consumer. We further use KL-divergence rate as the privacy measure, and the expected cost-saving rate as the cost measure. In order to study the trade-off between privacy and cost, a weighted sum of KL-divergence rate and expected cost-saving rate is used as our overall objective function. We show that the energy management optimization problem can be reformulated as a belief-state Markov decision process (MDP) problem, and the optimal energy management strategy is given by the solution of Bellman dynamic programming, which can be seen as the key contribution of this paper because it enables that the MDP framework can be utilized for the explicit design of optimal strategies.

Notation: We denote a random variable by a capital letter, its realization by the corresponding lowercase letter, and its alphabet by the corresponding calligraphic letter. We further denote sequence $(X_t, \dots, X_{t+k})$ and its realization $(x_t, \dots, x_{t+k})$ by X_t^{t+k} and x_t^{t+k} respectively. In particular, X^t stands for X_1^t . For a probability mass function (pmf) $P_X(x)$, we denote it as $P(x)$ if it is clear from the context. Let $D(\cdot||\cdot)$ denote KL-divergence and let $[x]_+ = \max(0, x)$.

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2. PROBLEM FORMULATION

Consider a smart metering system as shown in Fig. 1. The consumer behavior is modeled by a binary hypothesis, which can be h_0 or h_1 . At time step t , denote the consumer's energy demand by $x_t \in \mathcal{X} = \{0, 1, \dots, x_{max}\}$, the energy supply from the energy provider (EP) by $y_t \in \mathcal{Y} = \{0, 1, \dots, y_{max}\}$, and the instantaneous price by $p_t \in \mathcal{P} = \{1, \dots, p_{max}\}$, the level of the finite-capacity energy storage (ES) by $s_t \in \mathcal{S} = \{0, 1, \dots, s_{max}\}$. The instantaneous energy consumption x_t should always be satisfied by supplies from either EP or ES without wasting energy. Then, the ES level evolves following

$$s_{t+1} = s_t + y_t - x_t. \quad (1)$$

In addition, to guarantee $0 \leq s_t \leq s_{max}$, y_t should be chosen from the following feasible set

$$\bar{\mathcal{Y}}_t(x_t, s_t) = \{y_t \in \mathcal{Y} : [x_t - s_t]_+ \leq y_t \leq s_{max} + x_t - s_t\}, \quad (2)$$

where the first inequality indicates the energy supply y_t should at least provide the remaining energy when ES level s_t cannot solely satisfy the consumer demand; the second inequality follows from the constraint of the finite ES capacity.

We assume that the consumer energy demand X_t and the dynamic price P_t are independent, and follow first order Markov processes with time-invariant transition probabilities, i.e., $P_{X_{t+1}|X^t, h_i} = P_{X_{t+1}|X_t, h_i} = P_{X_t|X_{t-1}, h_i}$, $i \in \{0, 1\}$, and $P_{P_{t+1}|P^t} = P_{P_{t+1}|P_t} = P_{P_t|P_{t-1}}$. With this assumption, it can be shown that (X_t, S_t, P^t, Y^{t-1}) is a sufficient statistics for (X^t, S^t, P^t, Y^{t-1}) to decide on Y_t , which is proved in the longer version of this paper [11]. Accordingly, we consider the energy management strategy f_t that decides on the energy supply Y_t from EP following the conditional pmf $P_{Y_t|X_t, S_t, P^t, Y^{t-1}}$, i.e., $f_t = P_{Y_t|X_t, S_t, P^t, Y^{t-1}}$. Let $\mathcal{F}_t$ be the set of all conditional pmfs $P_{Y_t|X_t, S_t, P^t, Y^{t-1}}$, i.e., $f_t \in \mathcal{F}_t$. In this case, the energy management strategy over a T -time horizon can be written as $f = \{f_t\}_{t=1}^T \in \mathcal{F} = \mathcal{F}_1 \times \mathcal{F}_2 \times \dots \times \mathcal{F}_T$.

We assume an adversary (AD) has access to the smart metering data, prices, and also knows the statistics of the system. Thus, the AD can infer on the consumer's energy consumption behavior based on observations (y^T, p^T) . It is well known that KL-divergence measures the similarity of the two joint distributions of observations conditioned on different consumer behavior hypotheses. For instance, in [7], KL-divergence is used as privacy measure considering i.i.d energy demands and Neyman-Pearson hypothesis testing. Besides, due to the uncertainty about the inference behavior of the AD, we use the KL-divergence rate as the measure of privacy leakage. Over a T -time horizon, the privacy leakage induced by

$f \in \mathcal{F}$ is expressed as

$$\begin{aligned} L(f) &= \frac{1}{T} D(P_{Y^T, P^T|h_0}^f \| P_{Y^T, P^T|h_1}^f) \\ &= \frac{1}{T} \sum_{t=1}^T D(P_{Y_t, P_t|h_0, Y^{t-1}, P^{t-1}}^f \| P_{Y_t, P_t|h_1, Y^{t-1}, P^{t-1}}^f) \\ &= \frac{1}{T} \sum_{t=1}^T \mathbb{E}_{Y^t, P^t|h_0}^f \left[\log \frac{P_{Y_t, P_t|h_0, Y^{t-1}, P^{t-1}}^f}{P_{Y_t, P_t|h_1, Y^{t-1}, P^{t-1}}^f} \right], \end{aligned} \quad (3)$$

where the superscript “ f ” denotes the statistics induced by strategy f .

Besides the privacy enhancement goal, we are looking for a policy f that is also cost-efficient. Thus we use the following cost-saving rate as the measure

$$\begin{aligned} V(f) &= \frac{1}{T} \sum_{t=1}^T \{ \mathbb{E}^f[(X_t - Y_t)P_t|h_0]P(h_0) \\ &\quad + \mathbb{E}^f[(X_t - Y_t)P_t|h_1]P(h_1) \}. \end{aligned} \quad (4)$$

Taking into account the trade-off between privacy enhancement and cost-saving, the overall goal is to choose a strategy $f \in \mathcal{F}$ that minimizes the weighted sum objective

$$\min_{f \in \mathcal{F}} C(f, \lambda) = \min_{f \in \mathcal{F}} \lambda L(f) - (1 - \lambda)V(f), \quad (5)$$

where $\lambda \in [0, 1]$ controls the trade-off. And this objective function can be used as the average expected cost of the MDP problem, which is formulated in the following section.

3. MDP FORMULATION

To transform (5) into a standard MDP [12], we need to identify the states, the transition between different states, the control actions and the per-step cost which can be expressed in terms of the current states and their corresponding control action. Thus, to end up with such a per-step cost formulation, we will follow the standard approach of introducing *control actions*, which jointly with the corresponding *policies* describe the energy management strategy.

At time step t , we first define the control action as $a_t = P_{Y_t|X_t, S_t, P_t}$, where $a_t \in \mathcal{A}_t$, and $\mathcal{A}_t$ is the set of conditional pmfs $P_{Y_t|X_t, S_t, P_t}$. Thus, the control action a_t randomly decides on the energy supply Y_t based on the current state (x_t, s_t, p_t) according to the conditional pmf $P_{Y_t|X_t, S_t, P_t}$. The EMU will choose the action according to the policy $\pi_t \in \Pi_t$, where Π_t denotes the set of deterministic mappings from the historical observations, prices (y^{t-1}, p^{t-1}) to a corresponding action a_t , i.e., $\Pi_t : \mathcal{Y}^{t-1} \times \mathcal{P}^{t-1} \rightarrow \mathcal{A}_t$ with $a_t = \pi_t(y^{t-1}, p^{t-1})$. Thus, the policy over a T -time horizon is $\pi = \{\pi_t\}_{t=1}^T \in \Pi = \Pi_1 \times \Pi_2 \times \dots \times \Pi_T$. It follows that, at each time step, any energy management strategy f_t can be equivalently represented by a combination of a policy π_t and a control action a_t , since for

each $f_t = P_{Y_t|X_t, S_t, P_t, Y^{t-1}}$, we can first apply the policy $a_t = \pi_t(y^{t-1}, p^{t-1})$ to establish a mapping from the historical sequence (y^{t-1}, p^{t-1}) to action a_t that corresponds to f_t given the realization of historical sequence (y^{t-1}, p^{t-1}) , i.e., $a_t = P_{Y_t|X_t, S_t, P_t, Y^{t-1}=y^{t-1}, P^{t-1}=p^{t-1}}$. This control action a_t is then used to obtain Y_t given the current state (x_t, s_t, p_t) . Thereby, we end up with control action that itself does not depend on the historical sequence (y^{t-1}, p^{t-1}) , while however, the history decides which control action is applied at time t .

In the following, for the purpose of formulating dynamic programming as well as expanding the per-step cost in terms of state-action pairs, it is more convenient to write the policy π_t as $a_t = \pi_t(y^{t-1}, p^{t-1}, a^{t-1})$. This can be seen from the following: Since (y^{t-1}, p^{t-1}) determines $a_t = \pi_t(y^{t-1}, p^{t-1})$, they also contain the information that determines a^{t-1} . Thus, the expression $a_t = \pi_t(y^{t-1}, p^{t-1}, a^{t-1})$ is equivalent to the policy of the form $a_t = \pi_t(y^{t-1}, p^{t-1})$.

With the above definition and conclusion, we obtain an equivalent reformulation of the original problem (5) as stated in the following proposition.

Proposition 1. *Our original optimization problem (5) is equivalent to finding a policy $\pi \in \Pi$ that minimizes the following weighted sum objective*

$$C(\pi, \lambda) = \frac{1}{T} \sum_{t=1}^T \mathbb{E}_{P_{Y^{t-1}, A^{t-1}, P^{t-1}}} [C_t(\pi_t, \lambda, Y^{t-1}, A^{t-1}, P^{t-1})], \quad (6)$$

where the per-step expected cost conditioned on each possible historical sequence $(y^{t-1}, a^{t-1}, p^{t-1})$ can be specified as

$$\begin{aligned} C_t(\pi_t, \lambda, y^{t-1}, a^{t-1}, p^{t-1}) = & \lambda \sum_{y_t, p_t} P^{\pi_t}(y_t, p_t | y^{t-1}, a^{t-1}, p^{t-1}, h_0) \\ & \times \log \frac{P^{\pi_t}(y_t, p_t | y^{t-1}, a^{t-1}, p^{t-1}, h_0)}{P^{\pi_t}(y_t, p_t | y^{t-1}, a^{t-1}, p^{t-1}, h_1)} \\ & - (1 - \lambda) \sum_{x_t, p_t, y_t} \left(P(h_0) P^{\pi_t}(x_t, p_t, y_t | y^{t-1}, p^{t-1}, a^{t-1}, h_0) \right. \\ & \left. + P(h_1) P^{\pi_t}(x_t, p_t, y_t | y^{t-1}, a^{t-1}, p^{t-1}, h_1) \right) (x_t p_t - y_t p_t). \end{aligned} \quad (7)$$

And the optimal policy is given by $\pi^* = \arg \min_{\pi \in \Pi} C(\pi, \lambda)$.

Proof: To prove this proposition, we need to show $C(\pi, \lambda)$ is equal to $C(f, \lambda)$ under transition from strategy f to policy π . Thus, we need to further show the probability terms included in these two objective functions are equal. Due to the limitation of space, we only prove $P_{Y^T, P^T|h_i}^f = P_{Y^T, P^T|h_i}^\pi$ here, since the proofs for the other probability terms are similar.

After expanding $P_{Y^T, P^T|h_i}^f$ according to the strategy f ,

we obtain

$$\begin{aligned} P_{Y^T, P^T|h_i}^f(y^T, p^T) = & \sum_{x^T, s^T} P(x_1, s_1, p_1) \times \\ & \underbrace{P(y_1|x_1, s_1, p_1)}_{f_1(y_1|x_1, s_1, p_1)} \prod_{t=1}^{T-1} [P(p_{t+1}|p_t) P(x_{t+1}|x_t, h_i)] \\ & \mathcal{I}_{s_{t+1}}(y_t + s_t - x_t) \times \underbrace{P(y_{t+1}|x_{t+1}, s_{t+1}, p^{t+1}, y^t)}_{f_{t+1}(y_{t+1}|x_{t+1}, s_{t+1}, p^{t+1}, y^t)}, \end{aligned} \quad (8)$$

where $\mathcal{I}$ is the indicator function with $\mathcal{I}_{s_{t+1}}(y_t + s_t - x_t) = 1$ if $s_{t+1} = y_t + s_t - x_t$, $\mathcal{I}_{s_{t+1}}(y_t + s_t - x_t) = 0$, otherwise. By applying the equivalence between f_t and (π_t, a_t) , which is derived above, we get $P(y_1|x_1, s_1, p_1) = a_1(y_1|x_1, s_1, p_1)$ and $P^\pi(y_{t+1}|x_{t+1}, s_{t+1}, p^{t+1}, y^t) = a_t(y_{t+1}|x_{t+1}, s_{t+1}, p_{t+1})$. Thus, $P_{Y^T, P^T|h_i}^f = P_{Y^T, P^T|h_i}^\pi$ holds. $\square$

As shown in (7), the per-step conditional expected cost will depend on not only the current state and control action but also the past observations y^{t-1} , prices p^{t-1} and actions a^{t-1} . In order to formulate it into a standard MDP, we introduce belief states which will be used to replace the growing historical sequences by identifying an update rule. To this end, let $Q_t = (Y^t, P^t, A^t)$. We define a belief state $\theta_{q_{t-1}} = (\theta_{q_{t-1}}^0, \theta_{q_{t-1}}^1)$ as the posterior distributions of (X_t, S_t, P_t) conditioned on the realization q_{t-1} under the corresponding hypotheses as

$$\theta_{q_{t-1}}^i = P_{X_t, S_t, P_t | q_{t-1}, h_i}, i \in \{0, 1\}. \quad (9)$$

At time step t , for $i \in \{0, 1\}$, given any $\theta_{q_{t-1}}^i$, observation y_t and action a_t , the updating of $\theta_{q_{t-1}}^i$ is given by $\theta_{q_t}^i = \varphi(\theta_{q_{t-1}}^i, a_t, y_t)$, where the function φ is given in (10). And this evolution function can be derived by first applying Bayes rule and then substituting the corresponding terms by a_t and $\theta_{q_{t-1}}^i$.

In fact, (7) is indeed the per-step expected cost of the belief state $\theta_{q_{t-1}}$ when taking action a_t , since each realization q_{t-1} decides on a unique belief state. Thus, $C_t(\pi_t, \lambda, q_{t-1})$ can be expressed in terms of the corresponding belief state-action pairs, i.e., we have

$$\begin{aligned} P^{\pi_t}(x_t, p_t, y_t | q_{t-1}, h_i) = & \sum_{s_t} \theta_{q_{t-1}}^i(x_t, s_t, p_t) a_t(y_t | x_t, s_t, p_t). \end{aligned} \quad (11)$$

Theorem 1. *With the above formulation, according to the definition of belief-state MDP in [12, pp.150-151], the original optimization problem can be modeled as a belief-state MDP problem such that: (i) the state at time t is given by (9) and evolves according to (10); (ii) the control action at time t is specified by $a_t(y_t | x_t, s_t, p_t)$; (iii) the per-step expected cost corresponding to a state-action pair is given by (7); (iv) the optimal strategy can be derived by Bellman dynamic programming.*

$$\varphi(\theta_{q_{t-1}}^i, a_t, y_t) = \frac{\sum_{x_t, s_t, p_t} \theta_{q_{t-1}}^i(x_t, s_t, p_t) a_t(y_t | x_t, s_t, p_t) P(p_{t+1} | p_t) P(x_{t+1} | x_t, h_i) \mathcal{I}_{s_{t+1}}(y_t + s_t - x_t)}{\sum_{x_t, s_t, p_t} \theta_{q_{t-1}}^i(x_t, s_t, p_t) a_t(y_t | x_t, s_t, p_t)} \quad (10)$$

3.1. Backward Dynamic Programming

For any action a_t , according to the definition of Bellman operator in [12, pp. 152-153] define the Bellman operator B_{a_t} as

$$\begin{aligned} (B_{a_t} V)(\theta_{q_{t-1}}) = & C_t(\pi_t, \lambda, a^{t-1}, y^{t-1}, p^{t-1}) \\ & + \sum_{x_t, s_t, p_t, y_t} \left(\prod_{i=0,1} \theta_{q_{t-1}}^i(x_t, s_t, p_t) \right. \\ & \left. a_t^2(y_t | x_t, s_t, p_t) V(\varphi(\theta_{q_{t-1}}, a_t, y_t)) \right), \end{aligned} \quad (12)$$

where V denotes the value function [12, pp. 152-153]; the first part is the per-step expected cost for any given belief state $\theta_{q_{t-1}}$; and the second part denotes the corresponding expected cost-to-go. The value function is updated according to

$$V(\theta_{q_{t-1}}) = \min_{a_t \in \mathcal{A}_t} (B_{a_t} V)(\theta_{q_{t-1}}). \quad (13)$$

Thus, the optimal policy $\pi_t^*(\theta_{q_{t-1}})$ and the corresponding optimal control action $a_t^* = \pi_t^*(\theta_{q_{t-1}})$ is given by the optimizer of (13). The minimum average expected cost is given by $V(\theta^0, \theta^1)/T$, where θ^0, θ^1 are the initial joint distributions of (X_1, S_1, P_1) conditioned on user behaviors h_0 and h_1 .

4. NUMERICAL RESULTS

In this section, we consider a simple scenario over a finite horizon length $T = 5$. Furthermore, we set $P(h_0) = P(h_1) = 0.5$, $\mathcal{X} = \{0, 1\}$, $\mathcal{Y} = \{0, 1\}$, and $s_{max} \in \{1, 2\}$. The prices are fixed as follows: $p_t = 1, \forall t \in \{1, 2, 3\}$, and $p_t = 2, \forall t \in \{4, 5\}$. The transition probabilities of X_t under two hypotheses and the initial belief state are set as following

$$\begin{aligned} P_{X_{t+1}|X_t, h_0}(x_{t+1}|x_t) &= 0.5, \forall x_{t+1} \in \{0, 1\}, x_t \in \{0, 1\}, \\ P_{X_{t+1}|X_t, h_1}(1|0) &= P_{X_{t+1}|X_t, h_1}(0|1) = 0.125, \\ P_{X_{t+1}|X_t, h_1}(1|1) &= P_{X_{t+1}|X_t, h_1}(0|0) = 0.875, \\ \theta^0(x_1, s_1, p_1) &= \theta^1(x_1, s_1, p_1) = \frac{1}{2 \times (s_{max} + 1)}, \\ \forall x_1 \in \{0, 1\}, s_1 \in \{0, 1, \dots, s_{max}\}. \end{aligned} \quad (14)$$

We investigate the trade-off between privacy enhancement and cost-saving by setting $\lambda = 1, 0.8, 0.2, 0$. The variation of privacy leakage rate against expected cost-saving rate with respect to λ is shown in Fig. 2. As λ increases, both the corresponding privacy leakage rate and expected cost-saving rate increase, which means more cost-saving is achieved at a cost of more privacy leakage. Meanwhile, we further compare our strategy to the case without energy management i.e.,

Fig. 2. Trade-off between privacy leakage and cost-saving for different battery sizes, and the comparison to the benchmark scheme without energy management

$P_{Y^T|h_i} = P_{X^T|h_i}$, for $i \in \{0, 1\}$. The performance of this benchmark case is the black point on the y-axis in Fig. 2. Since the statistics of the consumer's energy demands X_t is not manipulated, the privacy leakage rate in this case is obviously the largest. The gap between our proposed strategy and the dash line shows the privacy enhancement of our strategy. Meanwhile, our strategy also saves the the consumer's energy cost compared to the case without energy management with cost-saving to be 0 at each time step.

5. CONCLUSION

In this paper, we consider the trade-off problem between smart meter privacy leakage and the energy cost of the consumer, for which we use Kullback-Leibler divergence rate and expected cost-saving rate as the measures. We have shown that the problem of designing the privacy-enhancing and cost-efficient energy management strategy can be reformulated as a belief-state MDP problem, and the optimal solution can be derived using Bellman dynamic programming. The numerical example shows that both privacy-enhancement and cost-saving can be achieved and can be traded-off compared to the case without energy management. Future work could be to find sub-optimal but computationally more efficient strategies, for which the results in the paper can serve as a benchmark.

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