On design of optimal smart meter privacy control strategy against adversarial MAP detection

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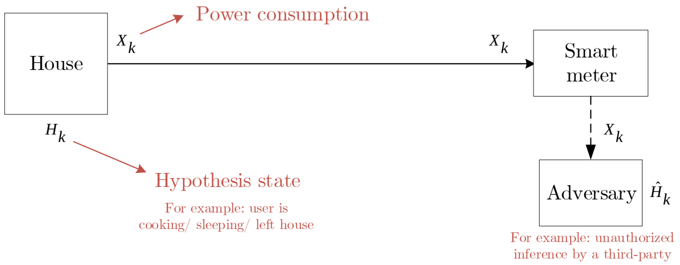
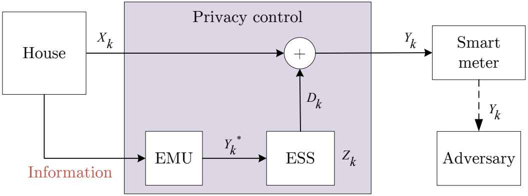
Overview

Smart meter privacy problem



- Patterns in $\{\hat{H}_k\}$ can be used to infer, for example, **religious, economic and social identities** of users.
- In Europe, GDPR regulates collecting, storing, or processing of data with sensitive personal information.

Privacy-by-design



Existing studies design EMU based on:

- **Information theory:** Variance[1], Mutual information[2,3,4] etc,
- **Detection theory:** Bayesian hypothesis testing adversary[5,6,7].

Our previous work[6,7] focused on including real ESS aspects in EMU design.

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[1] G. Kalogridis, C. Efthymiou, S. Z. Denic, *et al.*, "Privacy for smart meters: Towards...," in *SmartGridComm*, 2010.

[2] D. Varodayan and A. Khisti, "Smart meter privacy using a rechargeable battery...," in *ICASSP*, 2011.

[3] O. Tan, D. Gunduz, and H. V. Poor, "Increasing smart meter privacy...," *IEEE Jour. on Sel. Areas in Comm.*, 2013.

[4] J.-X. Chin, T. T. De Rubira, and G. Hug, "Privacy-protecting energy management...," *IEEE Tran. on Smart Grid*, 2017.

[5] Z. Li, T. J. Oechtering, and M. Skoglund, "Privacy-preserving energy flow...," in *ICASSP*, 2016.

[6] R. R. Avula, T. J. Oechtering, and D. Månsson, "Privacy-preserving smart meter control...," in *ISGT-Europe*, 2018.

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Problem formulation

- **System model:** HMM characterized by $\big(\underbrace{\mathcal{H}, \mathcal{X}}_{\text{alphabets}}, \underbrace{P_{H_k|H_{k-1}}, P_{X_k|H_k}}_{\text{HMM parameters}}\big)$.
- **Privacy model:** Adversarial maximum a posteriori (MAP) detection

$$\begin{aligned}\hat{h}_1^N(y_1^N) &= \underset{h_1^N \in \mathcal{H}^N}{\operatorname{argmax}} P_{H_1^N, Y_1^N}(h_1^N, y_1^N) \\ &= \underset{h_1^N \in \mathcal{H}^N}{\operatorname{argmax}} \sum_{k=1}^{N} \log \Big[P_{H_k, Y_k | H_{k-1}}(h_k, y_k | h_{k-1}) \Big].\end{aligned}$$

- **How to optimally control adversarial MAP detection performance?**
- **Design approach:** Stochastic optimal control of avg. detection cost, known as *Bayesian risk*, in EMU-unaware and -aware adversarial cases.

Optimal control of EMU-unaware MAP detection

- MAP estimate can be obtained using Viterbi (non-causal) algorithm.
- In the controller design, we compute a causal detection strategy ζ_k^* that achieves avg. Viterbi performance using dynamic programming:

Per-step reward: $$r_k(x_k, \hat{h}_{k-1}^k) := \max\Big[\log\Big[P_{H_k, X_k | H_{k-1}}(\hat{h}_k, x_k | \hat{h}_{k-1})\Big], r_{\mathsf{min}}\Big],$$

Aggregate reward: $$V_k(x_k, \hat{h}_{k-1}) := \max_{\hat{h}_k \in \mathcal{H}}\Big[r_k(x_k, \hat{h}_{k-1}^k) + \mathbb{E}\big[V_{k+1}(X_{k+1}, \hat{h}_k)\big]\Big].$$

- The optimal control strategy μ_k^* computed using the dynamic programming[8]:

Per-step cost: $$c_k(w_k, y_k, \zeta_k^*) := f_c(h_k, \zeta_k^*(y_k, \hat{h}_{k-1})),$$

Aggregate cost: $$J_k(w_k) := \min_{y_k \in \mathcal{Y}}\Big[c_k(w_k, y_k, \zeta_k^*) + \mathbb{E}\big[J_{k+1}\left(W_{k+1}\right)\big]\Big].$$

- Discrete state and action spaces $\implies$ **discrete optimization**.

[8] **Controller state:** $w_k = \{x_k, z_k, h_k, \hat{h}_{k-1}\}$

Optimal EMU-aware MAP detection

- The adversarial belief state $\hat{\pi}_k$ on the state $s_k = f_s(h_k, z_{k+1})$ is

$$\hat{\pi}_k = \frac{\mathbf{M}_k\Big(y_k, \hat{h}_{k-1}, \mu_k\Big)\hat{\pi}_{k-1}}{\mathbf{1}_{|\mathcal{H}|}^{\mathsf{T}}\mathbf{M}_k\Big(y_k, \hat{h}_{k-1}, \mu_k\Big)\hat{\pi}_{k-1}}; \quad [\hat{\pi}_k]_s = P_{S_k|Y_1^k}(s|y_1^k),$$

  where $\mathbf{M}_k$ is belief transformation matrix function given by the HMM.
- The optimal detection strategy $\bar{\zeta}_k^*$ computed using dynamic programming[9]:

$$\textbf{Per-step reward:} \quad \tilde{r}_k(\gamma_k, \hat{h}_k, \mu_k) := \max\left[\log\left[\frac{\mathbf{a}^{\mathsf{T}}\Big(y_k, \hat{h}_{k-1}^k, \mu_k\Big)\,\hat{\pi}_{k-1}}{\mathbf{b}^{\mathsf{T}}\Big(\hat{h}_{k-1}, \mu_k\Big)\,\hat{\pi}_{k-1}}\right], r_{\min}\right],$$

$$\textbf{Aggregate reward:} \quad \tilde{V}_k(\gamma_k, \mu_k) := \max_{\hat{h}_k \in \mathcal{H}}\Big[\tilde{r}_k(\gamma_k, \hat{h}_k, \mu_k) + \mathbb{E}\big[\tilde{V}_{k+1}(\Gamma_{k+1}, \mu_{k+1})\big]\Big],$$

  where $\mathbf{a}, \mathbf{b}$ are vector functions given by the HMM.

[9] **Control strategy** $\mu_k : \mathcal{W} \to \mathcal{Y}$; **Adversarial state:** $\gamma_k := [y_k, \hat{h}_{k-1}, \hat{\pi}_{k-1}]$

Optimal control of EMU-aware MAP detection

- Similarly, the optimal control strategy $\bar{\mu}_k^*$ computed using the dynamic programming[10]:

$$\textbf{Per-step cost:} \quad \tilde{c}_k(\lambda_k, \mu_k, \bar{\zeta}_k^*) := f_c(h_k, \bar{\zeta}_k^*(\gamma_k, \mu_k)),$$

$$\textbf{Aggregate cost:} \quad \tilde{J}_k(\lambda_k) := \min_{\mu_k \in \mathcal{U}} \Big[\tilde{c}_k(\lambda_k, \mu_k, \bar{\zeta}_k^*) + \mathbb{E}\left[\tilde{J}_{k+1}(\Lambda_{k+1}) \right] \Big].$$

- **Challenges:**
  1. γ_k and λ_k contain $\hat{\pi}_{k-1} \implies$ **continuous optimization**.
  2. The aggregate adversarial reward $\tilde{V}_k$ is piecewise concave w.r.t. $\hat{\pi}_{k-1}$.

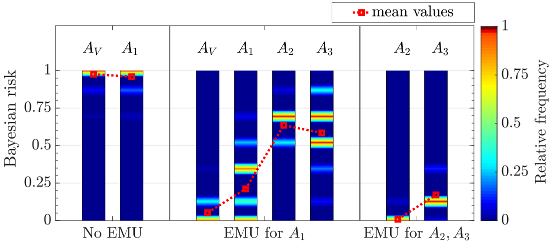
[10] **Controller state:** $\lambda_k = \{x_k, z_k, h_k, \hat{h}_{k-1}, \hat{\pi}_{k-1}\}$

Sub-optimal control: Adaptive-grid approximation algorithm

1. Find $\mathcal{Q}$, the partitions of the simplex $\Delta_{|\mathcal{S}|}$ using the hyperplanes $\{\pi \in \Delta_{|\mathcal{S}|} : (\mathbf{a}_i - \mathbf{a}_j)^\intercal \pi = 0\}$ for all possible vectors $\mathbf{a}_i, \mathbf{a}_j$ which gives per-step reward decision regions.
2. Recursively partition the simplex $\Delta_{|\mathcal{S}|}$ using $\mathcal{Q}$ and propagate them using all possible belief transformation matrices $\mathbf{M}_k$.
3. Approximate each resulting partition with a finite number of points and solve the dynamic programming equation at these finite points.

Numerical study

- Simulation study: binary states; $|\mathcal{K}| = 6$; risk = detection prob.; 2000 MC simulations, $P_{X_k|H_k} = \begin{bmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{bmatrix}$, $P_{H_k|H_{k-1}} = \begin{bmatrix} 0.01 & 0.9 \\ 0.99 & 0.1 \end{bmatrix}$.



  - EMU: Energy management unit
  - A_V : Standard Viterbi algorithm
  - A_1 : EMU-unaware causal adversary
  - A_2 : EMU-aware causal adversary (regular grid approx.)
  - A_3 : EMU-aware causal adversary (proposed suboptimal approx.)

Conclusion

- We have presented the design of an optimal control against an adversarial MAP detection.
- The optimal control strategy against EMU-unaware adversary can be computed efficiently by solving discrete optimization problems.
- Whereas, the optimal control against EMU-aware adversary becomes non-convex due to piece-wise concave structure of Bellman's equation. We presented a sub-optimal control strategy exploiting Bayesian evolution of belief state.
- Numerical study shows that the sub-optimal algorithm achieves close to the optimal performance.

Thank you!