

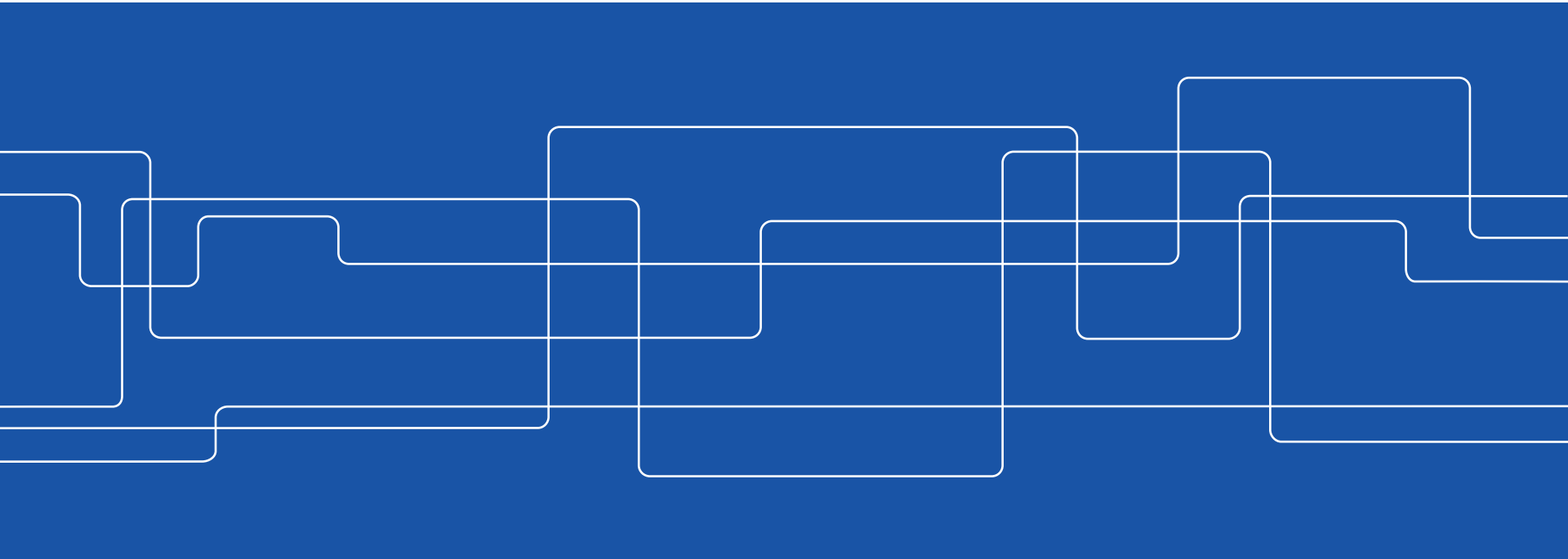


Differentially Private State Estimation in Distribution Networks with Smart Meters

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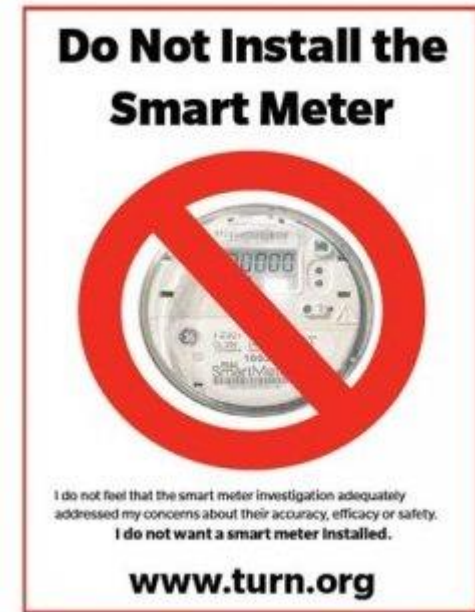
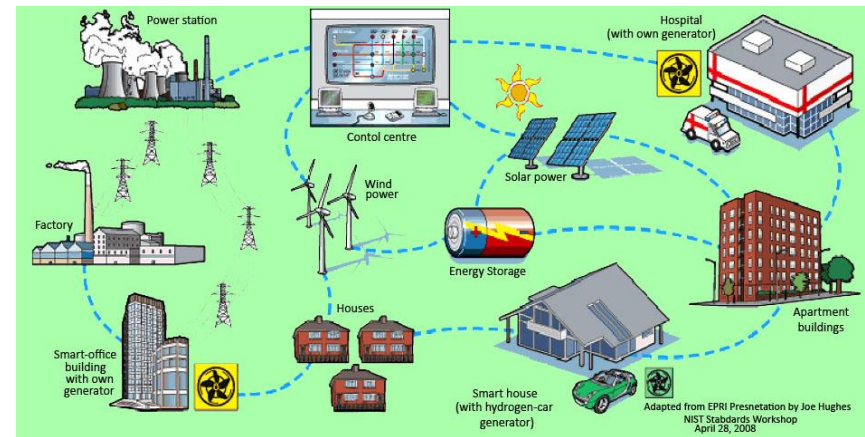
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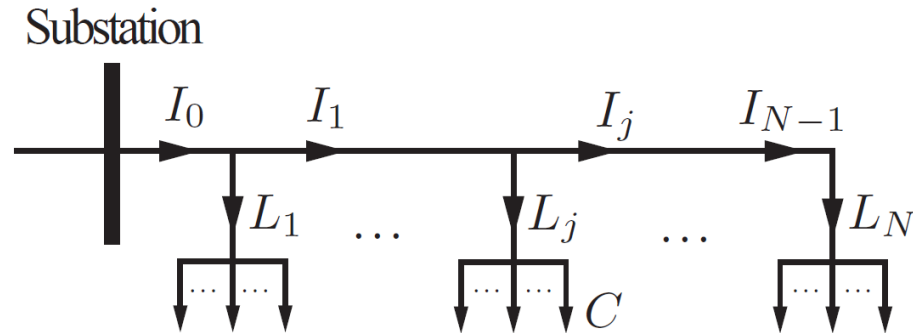


Motivation

- **The promise:** Smart meters help in demand response, billing, etc.
- Few real-time measurements in today's distribution networks → *Enabler for state estimation?*
- **The threat:** Customers' *privacy concerns* (among others)
- **The opportunity:** Privacy-preserving monitoring and control techniques



Distribution Network Model

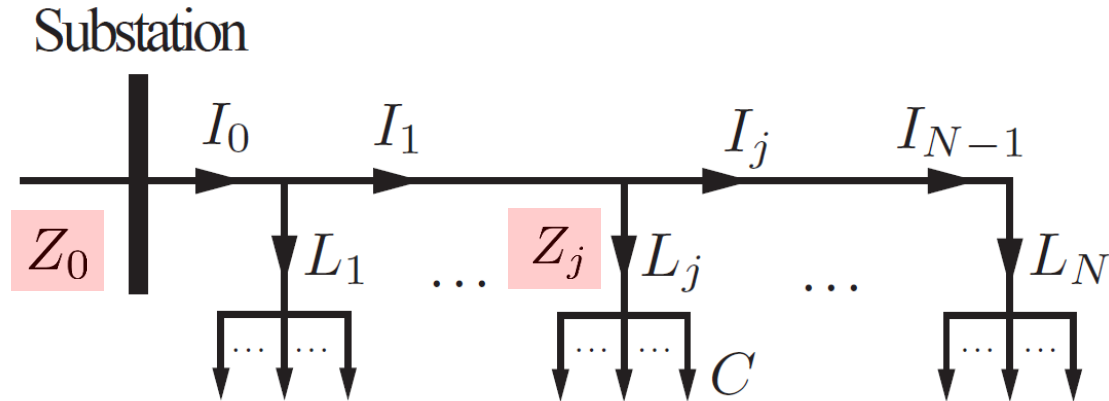


- Conservation of currents:

$$I_j = \sum_{k>j} L_k, \quad j = 0, 1, \dots, N - 1$$

- Large resistance in distribution grids → use currents
- Little dynamics in (current) distribution grids → study steady-state
- **Operator:** Desires to estimate load L_j
- **Customer C :** Desires to keep his/her real-time load private

Measurement Model



The Base Scenario – Total current with “physical meter noise”:

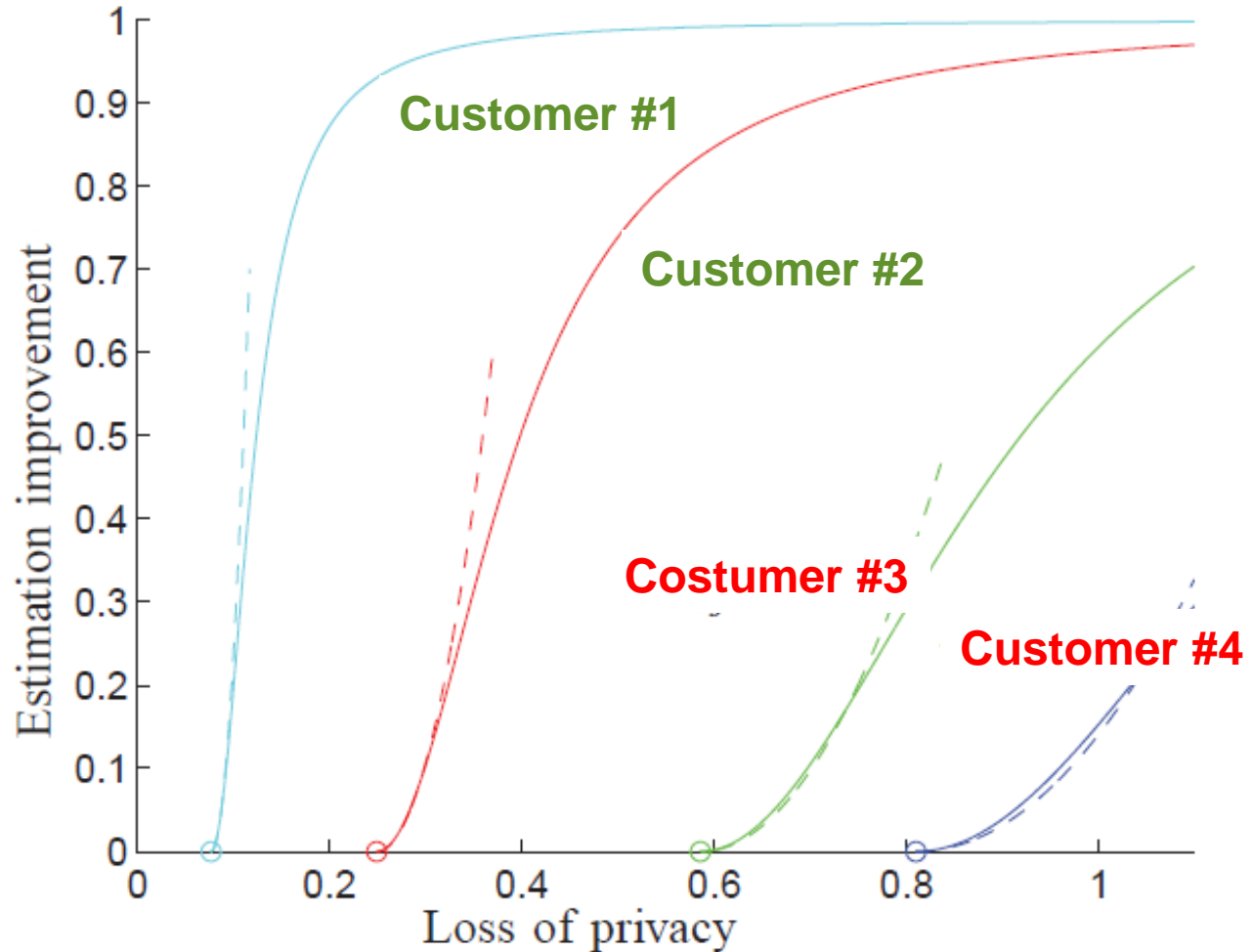
$$Z_0 = I_0 + W_0 \quad W_0 \sim \mathcal{N}(0, R_0)$$

The Smart Meter Scenario – Load current with “privacy noise”:

$$Z_j = L_j + W_j \quad W_j \sim \text{Lap}(b_j)$$

$$p_{W_j}(w) = \frac{1}{2b_j} e^{-|w|/b_j}, \quad R_j = 2b_j^2$$

Problem Formulation: Characterize Estimation vs. Privacy Trade-Offs





Related Work

- **Differential privacy:**
 - Dwork, McSherry, Nissim, Smith, 2006
- **Differential privacy in control:**
 - Le Ny, Pappas, 2014
 - Huang, Wang, Mitra, Dullerud, 2014
- **Privacy for Smart Meters:**
 - Ács, Castelluccia, 2011
 - Tan, Gunduz, Poor, 2013

Differential Privacy [Dwork *et al.*, 2006]

- Two adjacent data vectors:

$$l = (l_1 \quad l_2 \quad \dots \quad l_i \quad \dots \quad l_{m-1} \quad l_m)^T$$

$$l' = (l_1 \quad l_2 \quad \dots \quad l_i \pm \Delta \quad \dots \quad l_{m-1} \quad l_m)^T$$

- Measurement policy (q deterministic, W stoch. noise)

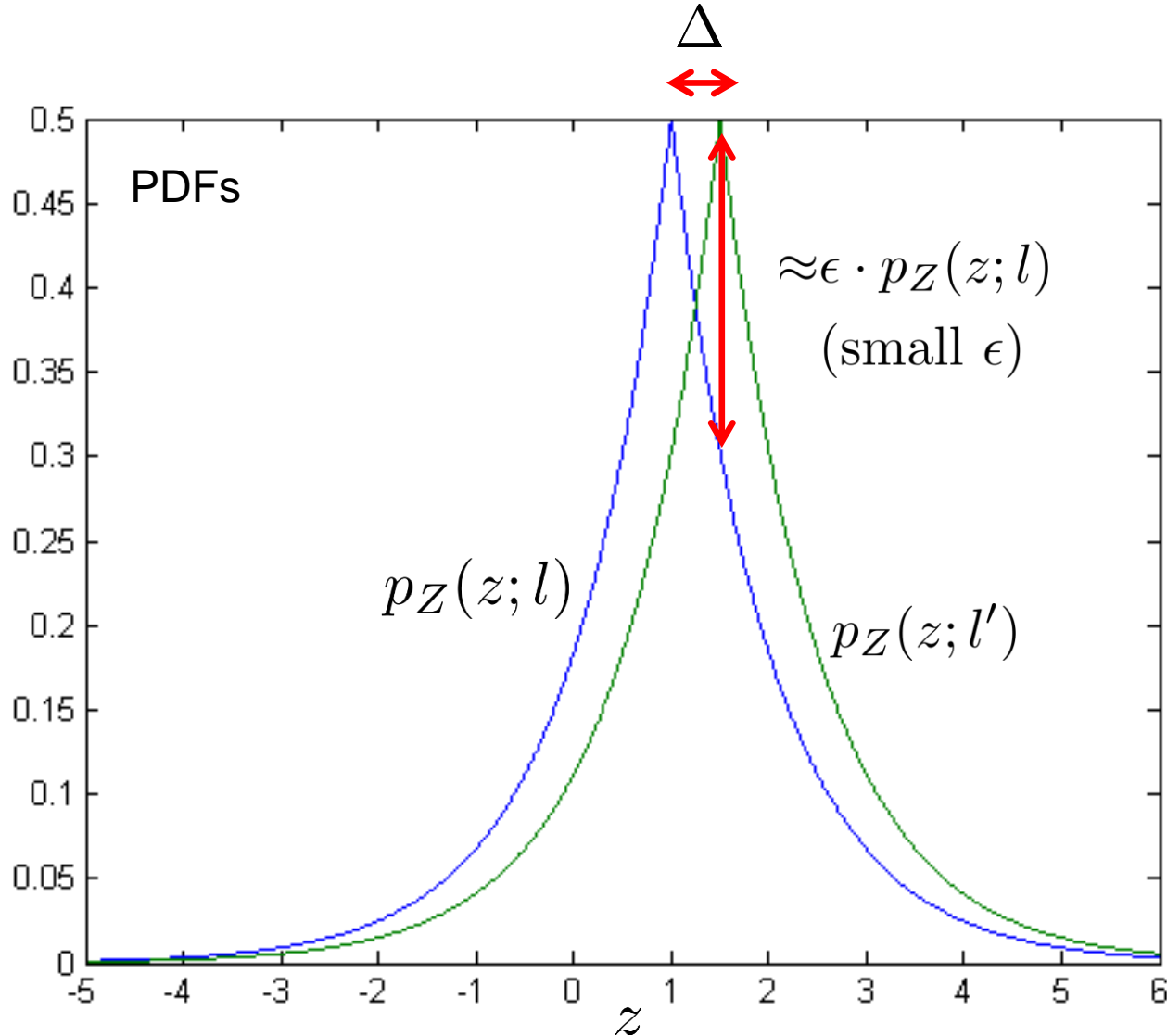
$$Z(l, W) = q(l) + W$$

(We will use $q(l) = \sum_k l_k$)

Definition: Measurement Z is (ϵ, δ) -differentially private if for all events E :

$$\Pr[Z(l, W) \in E] \leq e^\epsilon \Pr[Z(l', W) \in E] + \delta$$

Example: ϵ -Differential Privacy with Laplacian Noise

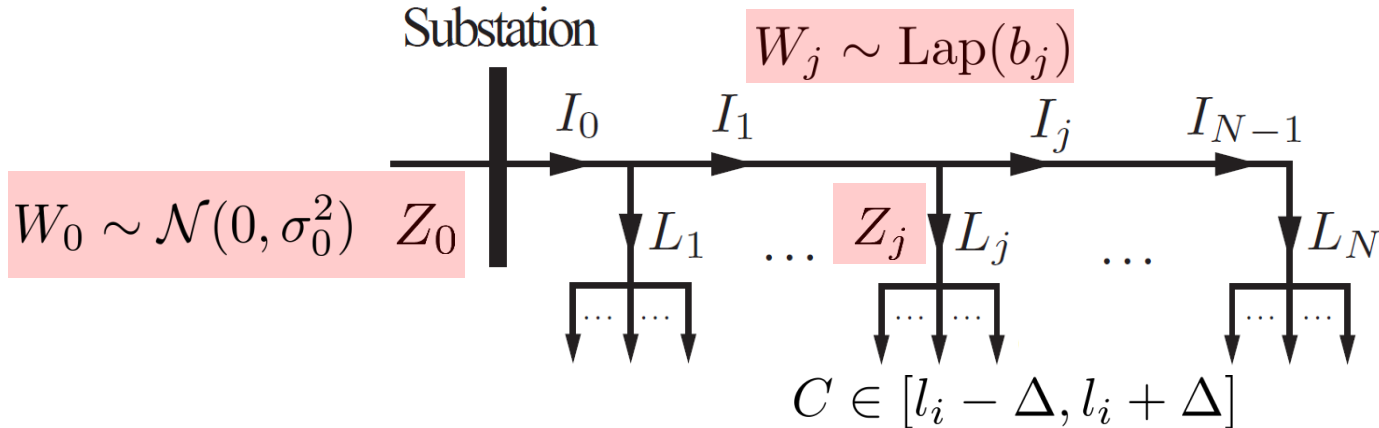


$$W \sim \text{Lap}(b)$$

$$\epsilon = \frac{\Delta}{b} = \frac{\Delta}{\sqrt{R/2}}$$

Measurements of adjacent data vectors virtually indistinguishable for small ϵ

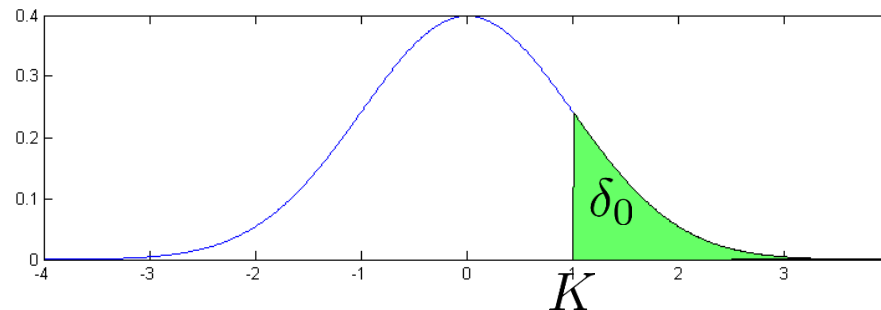
Differential Privacy in the Distribution Network



The Base Scenario (Z_0): Customer C has (ϵ_0, δ_0) -differential privacy where

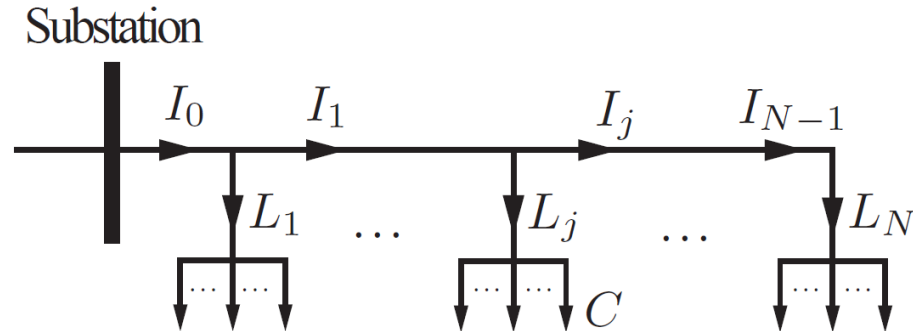
$$\epsilon_0 = \frac{\Delta K}{\sigma_0} + \frac{\Delta^2}{2\sigma_0^2}, \quad K = K(\delta_0) = Q^{-1}(\delta_0)$$

Smart Meter
privacy where



δ_0 -differential

Optimal Estimate: Load Model

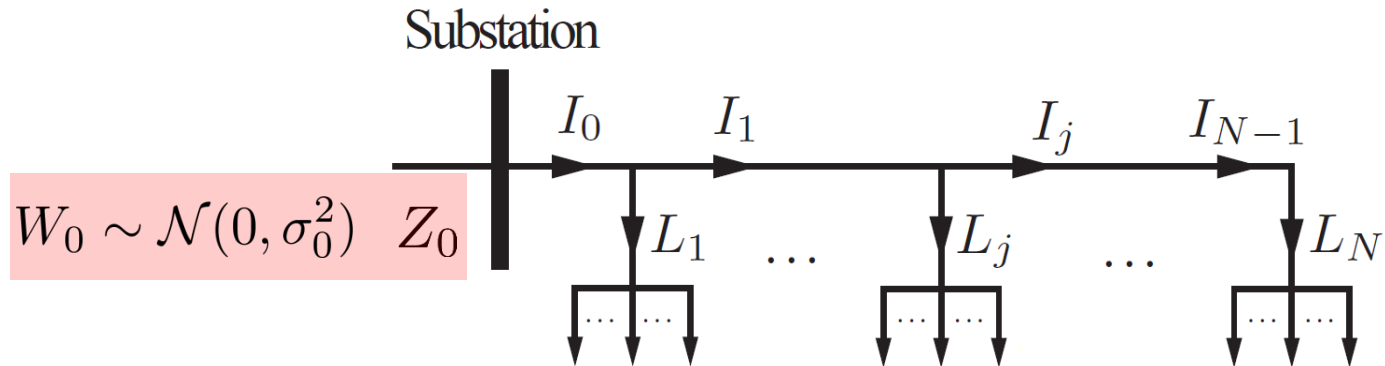


Suppose loads have a known normal distribution:

$$L \sim \mathcal{N}(m, P)$$

$$m = \begin{pmatrix} m_1 \\ \vdots \\ m_N \end{pmatrix} \quad P = \begin{pmatrix} P_{11} & \dots & P_{1N} \\ \vdots & \ddots & \vdots \\ P_{N1} & \dots & P_{NN} \end{pmatrix} \quad \begin{pmatrix} P_1 \\ \vdots \\ P_N \end{pmatrix} := \begin{pmatrix} P_{11} + \dots + P_{1N} \\ \vdots \\ P_{N1} + \dots + P_{NN} \end{pmatrix} = P\mathbf{1}$$

Optimal Estimate: Base Scenario



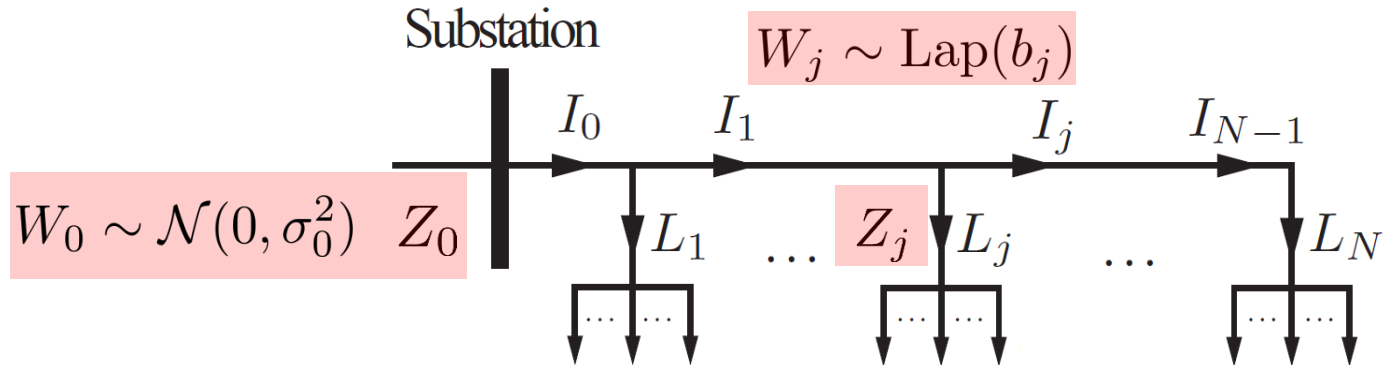
MMSE estimate:

$$\hat{L}_j^0 := \mathbf{E}[L_j | Z_0] = m_j + \frac{P_j}{P_0 + R_0} (Z_0 - m_0)$$

MMSE error:

$$Q_j^0 := \mathbf{E}[(\hat{L}_j^0 - L_j)^2] = P_{jj} - \frac{P_j^2}{P_0 + R_0}$$

Optimal Estimate: Smart Meter Scenario



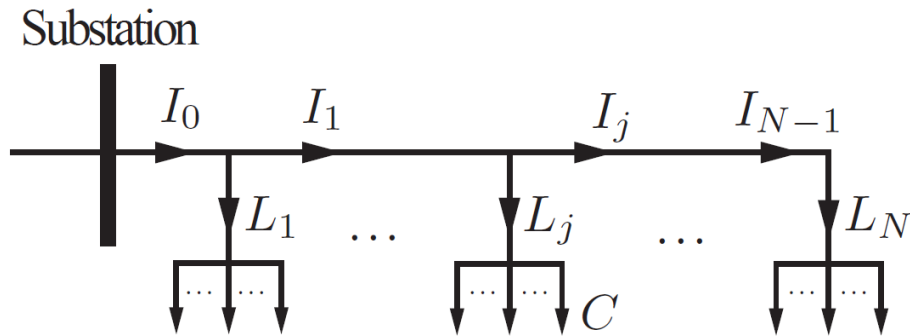
LMMSE estimate:

$$\begin{aligned} \hat{L}_j^{0,j} &:= \mathbf{E}^{\text{lin}}[L_j | Z_0, Z_j] \\ &= \hat{L}_j^0 + K_j \left[(Z_j - m_j) - \frac{P_j}{R_0 + P_0} (Z_0 - m_0) \right] \end{aligned}$$

LMMSE ei $K_j = \frac{(R_0 + P_0)P_{jj} - P_j^2}{(R_0 + P_0)P_{jj} + P_j^2} \in [0, 1]$

$$Q_j^{0,j} := \mathbf{E}[(L_j - \hat{L}_j^{0,j})^2] = Q_j^0(1 - K_j) \leq Q_j^0$$

Trade-Off: Estimation Quality vs. Privacy



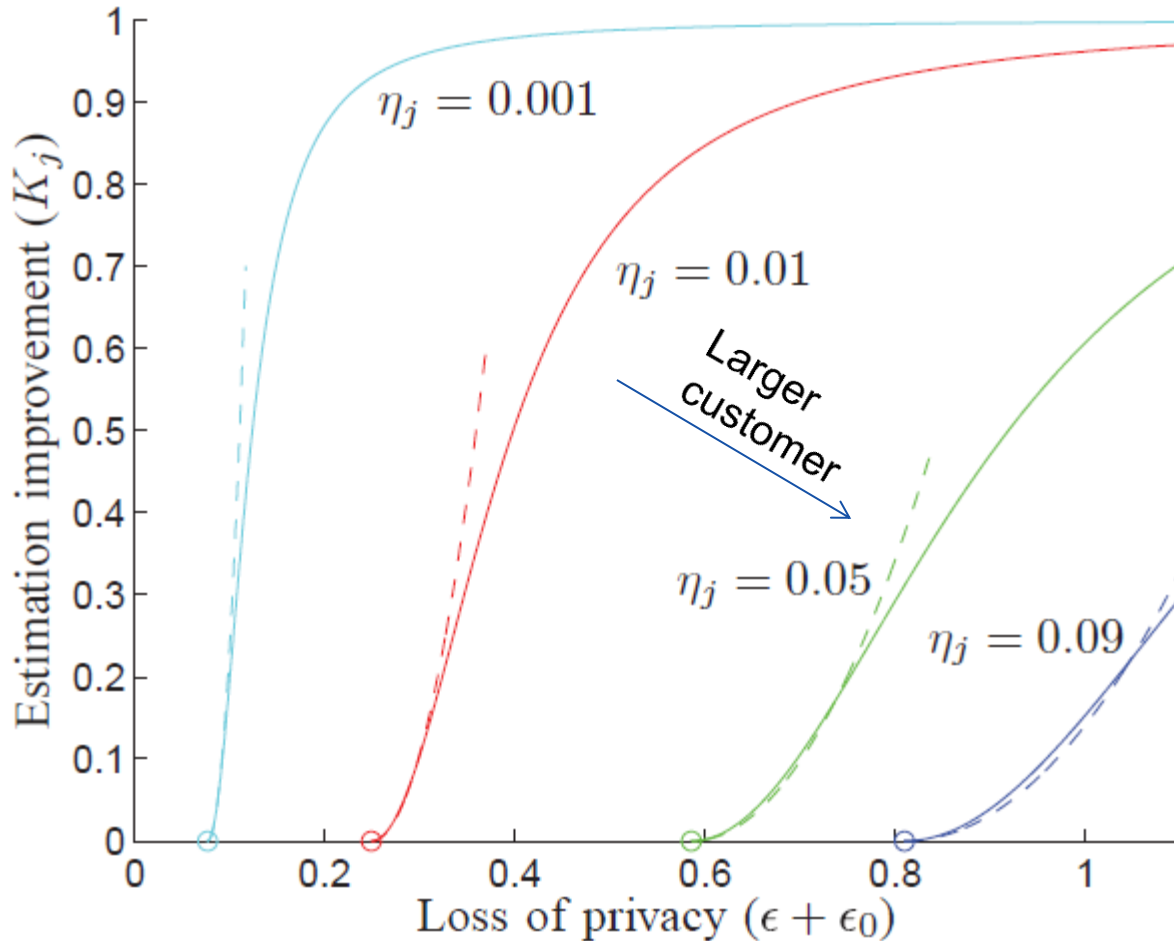
$$C \in [l_i - \Delta, l_i + \Delta]$$

$$L_j \sim \mathcal{N}(m_j, P_{jj})$$

Dimensionless quantities:

- Customers' relative importance at site j : $\eta_j := \frac{\Delta^2}{P_{jj}}$
- Site j 's relative importance on the line: $\zeta_j := \frac{P_{jj}}{P_0 + R_0}$

Trade-Off: Estimation Quality vs. Privacy



Baseline privacy:

$$\begin{aligned} \epsilon_0^2 &\approx \frac{\Delta^2 K^2}{R_0} \\ &= \eta_j \zeta_j K^2 \left(1 + \frac{P_0}{R_0} \right) \end{aligned}$$

Est. improvement:

$$\begin{aligned} K_j &= \frac{1}{1 + \frac{2\eta_j}{\epsilon^2(1-\zeta_j)}} \\ &\approx \frac{\epsilon^2(1-\zeta_j)}{2\eta_j} \end{aligned}$$

Summary

Est. improvement with Smart Meters:

$$\geq \frac{1}{1 + \frac{2\eta_j}{\epsilon^2(1-\zeta_j)}} \approx \frac{K^2}{2} \underbrace{\left(1 + \frac{P_0}{R_0}\right)}_{\text{SNR at substation}} \underbrace{\zeta_j(1 - \zeta_j)}_{\text{Site size}} \underbrace{\left(\frac{\epsilon}{\epsilon_0}\right)^2}_{\text{Norm. privacy loss}}$$

- Simple analytical treatment of trade-off between state estimation quality and customers' privacy loss ϵ
- Estimation gain $\sim \left(\frac{\epsilon}{\epsilon_0}\right)^2 \rightarrow$ Customers with high baseline privacy can make a large difference!
- Possible extensions: Dynamics, general topologies, active/reactive power flows