Sensing, Communications and Monitoring for Smart Grid

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Introduction: Smart Grid and Situational Awareness

Green Communications for Sensor Networks
  ◦ Modulation Selection
  ◦ Cooperative Relay Section

Cognitive Radio for Bandwidth Reutilization
  ◦ Non-Cooperative Spectrum Sensing (NCoS)
  ◦ Cooperative Spectrum Sensing with Soft Information Fusion (SCoS)
  ◦ Cooperative Spectrum Sensing with Hard Information Fusion (HCoS)

Phasor State Estimation with Bad Data Processing
  ◦ Equivalence between Bad Data Subtraction and Removal
  ◦ Algorithms for Bad Data Processing

Summary and Future Work
Roadmap

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• Summary and Future Work
A **smart grid** is a **digitally enabled** electrical grid that **gathers**, **distributes**, and **acts on** **information** about the behavior of all participants (suppliers and consumers) in order to improve the **efficiency, reliability, economics, and sustainability** of electricity services. [wiki]

**Support:** digitally enabled

**Actions:** gather, distribute, act

**Goals:** efficiency, reliability, economics, sustainability

**Center:** information

**Smart grid: an interdisciplinary research area**
Obtaining Situational Awareness

- **Sensing:** more advanced measurement devices
- **Communications:** achieve desired quality of service (QoS)
- **Monitoring:** more sophisticated signal processing techniques
Communications for Smart Grid

- Feature: heterogeneity [Wang-Xu-Khanna’11]
- Candidates: optical, computer networks, power line communications, wireless communications ....

- Wireless communications:
  - Pros:
    - Easy implementation
    - Low cost
  - Cons:
    - Not “green”: driven by batteries $\Rightarrow$ green communications
    - Limited wireless spectrum resources $\Rightarrow$ existing unlicensed spectrum band and cognitive radio
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• Summary and Future Work
Green Communications: Motivations

- Wireless sensor networks (WSN)
  - Powered by non-renewable batteries $\Rightarrow$ energy efficiency critical
  - Short inter-node distance $\Rightarrow$ circuit power may be non-negligible
  - Complexity constrained $\Rightarrow$ low complexity modulation scheme and communications strategy

- Ways to improve the battery energy efficiency:
  - High energy-efficient modulation schemes
  - Cooperative communications (relay networks) to combat the fading effect

- Realistic considerations
  - Nonlinear battery discharge process
  - Extra circuit power consumptions
System Model: Battery & Node Model

- Battery discharge current $i$ with PDF $f(i)$
- Average power consumption: $\mathcal{P} = \int_{I_{\min}}^{I_{\max}} V_i \cdot f(i) \cdot di$
- Linear battery model:
  - Average actual power consumption (AAPC): $\mathcal{P}_0 = \mathcal{P}$
- Nonlinear battery model [Pedram-Wu’99]:
  - AAPC: $\mathcal{P}_0 = \int_{I_{\min}}^{I_{\max}} \frac{V_i}{\mu(i)} \cdot f(i) \cdot di$ $\Rightarrow$ $\mathcal{P}_0 = \int_{t_{\min}}^{t_{\max}} \frac{V_i(t)}{\mu(i(t))} \ dt$
  - Battery efficiency factor:

$$\mu(i) = 1 - \omega i, \ \omega > 0 \Rightarrow \mu(i) \in [0.5, 1) \Rightarrow \mathcal{P}_0 > \mathcal{P}$$
System Model: the Wireless Link

• Power consumption:
  ◦ Power carried by the transmitted pulse: $E_p$
  ◦ Analog circuit power consumption: $P_{ct}, P_{cr}$
  ◦ Extra power amplifier (PA) loss: $\alpha > 0$

• Wireless channel:
  ◦ Path-loss channel gain: $G(d) = \frac{E_t}{E_r} = M_1 d^K G_1$
  ◦ Rayleigh fading
  ◦ Additive white Gaussian noise (AWGN)

• Energy requirement
  ◦ Desired energy/bit at the Rx: $E_{b,r}$
  ◦ Desired energy/bit at the Tx: $E_{b,t} = E_{b,r} G(d)$
Transmitter energy consumption for single pulse transmission

**Lemma 1:** The total battery energy consumption (BEC) for transmitting a single pulse $p(t)$ with duration $T_p$ and energy $\mathcal{E}_p$ is approximately:

$$\mathcal{E}_{0t} = \frac{\omega \gamma_p (1+\alpha)^2}{V \eta^2} \mathcal{E}_p^2 + \frac{1+\alpha}{\eta} \mathcal{E}_p + \frac{P_{ct}}{\eta} T_p$$

where: $\gamma_g = \int_0^{T_p} (g_0(t))^2 \, dt$ depends on the normalized pulse shape $g_0(t)$.

1. Second-order term: **battery nonlinearity**
2. First-order term: **pulse energy**
3. Constant term: **circuit energy consumption**

$\alpha$: effect of PA  
$\eta$: effect of DC/DC converter
Receiver energy consumption for single pulse transmission

- At receiver:
  - No PA $\Rightarrow$ no $\alpha$ term
  - Very small current $\Rightarrow$ battery nonlinearity negligible

- Circuit power on for demodulation at symbol duration: $E_{0r} = \frac{P_{cr}}{\eta} T_s$

- Only determined by the symbol duration
Modulation Schemes: PPM vs. FSK

- Both orthogonal modulation schemes: theoretically same energy efficiency
- Realistic considerations for PPM and FSK
  - **PPM at Tx:**
    - ✓ Shorter pulse: less circuit energy consumption
    - ✗ Larger current: lower battery efficiency
  - **FSK at Tx:**
    - ✗ Longer pulse: more circuit energy consumption
    - ✓ Smaller current: higher battery efficiency
  - **PPM and FSK at Rx:** exactly the same
- Intuition for selection of PPM and FSK
  - Shorter inter-node distance: circuit energy consumption dominant \( \Rightarrow \) PPM better
  - Longer inter-node distance: battery efficiency factor dominant \( \Rightarrow \) FSK better
Analytical Comparison

Lemma 2: The difference between the average battery energy consumption of FSK and PPM to achieve the same target BER can be expressed as:

$$\Delta \mathcal{E}_0^{FP} = k_2 d^{2K} + k_0$$

Where: 

$$k_2 = (1 - M) \frac{2\pi^2 M_i^2 G_1^2 \omega (1+\alpha)^2}{T_s V \eta^2 \log_2 M} \mathcal{E}_{sr} < 0$$

$$k_0 = \frac{M-1}{M^2} \frac{P_{ct} T_s}{\eta \log_2 M} > 0$$

Proposition 1: There is a critical distance $$d_c = \left(-\frac{k_0}{k_2}\right)^{\frac{1}{2K}}$$ such that when the inter-node transmission distance $$d < d_c$$, M-PPM consumes less battery energy than M-FSK and vice versa.
Numerical Results

Above the surface: PPM zone;
Below the surface: FSK zone.
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Motivation

- Battery energy consumption (BEC) is expected to be significantly reduced by...
  - Relaying vs. direct transmission
  - Multiple smaller Tx-Rx distances vs. a long link
  - Decreased path loss vs. large path loss: \( d_1^K d_2^K d_3^K < d^K \)

- Not always more energy efficient:
  - Extra circuit energy consumptions at relay nodes
  - Depending on the location of relay node
2-D 2-Hop Relay Scenario

- Source $S_1$, destination $S_2$, relay $R$
  - Direct link $S_1$-$S_2$: $d$
  - 2-hop relay link $S_1$-$R$-$S_2$, employing Decode-and-Forward (DF) Protocol
    - $S_1$-$R$D: $d_1 = \theta_1 d$
    - $R$-S2: $d_2 = \theta_2 d$

2-D arbitrary position: $\theta_1, \theta_2 > 0$, $\theta_1 + \theta_2 \geq 1$

- Performance constraint: average BER $\bar{P}_e$

- Rayleigh fading channel with K-th power path loss
  - BPSK with coherent detection at high SNR: $P_e = N_0/(4\varepsilon_r)$
  - Tx-Rx bit energy relationship: $\varepsilon_t/\varepsilon_r = M_l G_1 d^K$

$M_l$ - Link margin, $G_1$ - Gain factor at $d = 1$, $K \geq 2$ - Path loss exponent
Total BEC over Rayleigh Channel

- Total BEC of direct transmission $S_1$-$S_2$
  \[ \mathcal{E}_d = L_2 \frac{d^{2K}}{P_e^2} + L_1 \frac{d^K}{P_e} + L_0 \]

- Total BEC of relaying transmission $S_1$-RD + RF-$S_2$
  - Performance constraint at high SNR:
    \[ \bar{P}_e = 1 - (1 - P_1)(1 - P_2) = P_1 + P_2 - P_1 P_2 \approx P_1 + P_2 \]
    \[ \Leftrightarrow \quad P_2 = \bar{P}_e - P_1 \quad \text{and} \quad 0 < P_1 < \bar{P}_e \]
  - Total BEC as superposition of two consecutive direct links:
    \[ \mathcal{E}_{r,P_1} = \mathcal{E}_1(d_1) + \mathcal{E}_2(d_2) \]
    \[ = L_2 \left( \frac{d_1^{2K}}{P_1^2} + \frac{d_2^{2K}}{(\bar{P}_e - P_1)^2} \right) + L_1 \left( \frac{d_1^K}{P_1} + \frac{d_2^K}{\bar{P}_e - P_1} \right) + 2L_0 \]

Doubled distance-independent Tx/Rx circuit consumption...
Energy allocation optimization!
Optimum Energy Allocation

- Optimization problem formulation
  - Energy allocation amounts to BER assignment, i.e.,
    \[ \mathcal{E}_r = \min_{P_1} \mathcal{E}_{r,P_1}, \text{ subject to } 0 < P_1 < \bar{P}_e \]

- Optimum solution: \( \frac{\partial \mathcal{E}_{r,P_1}}{\partial P_1} = 0 \) giving rise to a quartic equation of \( P_1 \)
  \[
  \left( L_1 d_1^K - L_1 d_2^K \right) P_1^4 \\
  + \left( 2L_2 d_1^{2K} + 2L_2 d_2^{2K} - 3L_1 d_1^K \bar{P}_e + L_1 d_2^K \bar{P}_e \right) P_1^3 \\
  + \left( -6L_2 d_1^{2K} \bar{P}_e + 3L_1 d_1^K \bar{P}_e^2 \right) P_1^2 \\
  + \left( 6L_2 d_1^{2K} \bar{P}_e^2 - L_1 d_1^K \bar{P}_e^3 \right) P_1 \\
  + \left( -2L_2 d_1^{2K} \bar{P}_e^3 \right) = 0
  \]

- ✔ Quartic eq. is exactly solvable
- ☠ Root expressions are too complicated to evaluate
- ☠ Hard to obtain the optimum
Suboptimal Energy Allocation

- Suboptimum solution: discard the 2\textsuperscript{nd} order term in BEC formula
  - 1\textsuperscript{st} order BEC: \( \mathcal{E}_{1,r,P_1} = L_1 \left( \frac{d_1^K}{P_1} + \frac{d_2^K}{\bar{P}_e - P_1} \right) + 2L_0 \)
  
  - Taking derivative with \( P_1 \) and setting to 0:
    \[
    \left( d_2^K - d_1^K \right) P_1^2 + 2d_1^K \bar{P}_e P_1 - d_1^K \bar{P}_e^2 = 0
    \]
  
  - Quadratic eq. of \( P_1 \)
  
  - Related only to \( d_2/d_1 \) and BER constraint \( \bar{P}_e \)
  
  - Always has a single positive root:
    \[
    P_1^{SO} = \frac{1}{K} \bar{P}_e, \quad P_2^{SO} = \bar{P}_e - P_1^{SO} = \frac{(\theta_2/K)^2}{(\theta_1/K)^2 + 1} \bar{P}_e
    \]

  \[
  \Rightarrow \mathcal{E}_r = \frac{L_2}{\bar{P}_e^2} \left( \frac{K}{\theta_1^2} + \frac{K}{\theta_2^2} \right)^2 \left( \theta_1^K + \theta_2^K \right) d_2^K + \frac{L_1}{\bar{P}_e} \left( \frac{K}{\theta_1^2} + \frac{K}{\theta_2^2} \right)^2 d^K + 2L_0
  \]
Optimal and Sub-Optimal Allocation

\[ \bar{P}_e = 10^{-3}, \ d_2 = 200 \text{m} \]
Relay Selection Criterion

- Idea: $\Delta \mathcal{E} \triangleq \mathcal{E}_d - \mathcal{E}_r$, sign tells the more efficient one

$$\Delta \mathcal{E} = \frac{L_2}{P_e^2} \left( 1 - \left( \theta_1^K + \theta_2^K \right)^2 \right) \left( d^K \right)^2 + \frac{L_1}{P_e} \left( 1 - \left( \theta_1^K + \theta_2^K \right)^2 \right) d^K - L_0$$

**Proposition 2:** For a relay node with distances $\theta_1d$ and $\theta_2d$ apart from the primary nodes, choose direct link if $\Delta \mathcal{E} < 0$, otherwise, choose relay link.
Numerical Results

\[ d = 100 \text{ m} \]
\[ d = 150 \text{ m} \]
\[ d = 200 \text{ m} \]

Larger \( d \), bigger relay zone, more battery energy saved
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Wireless Comm.: Spectrum Scarcity

- Better QoS $\Rightarrow$ more bandwidth $\Rightarrow$ spectrum reutilization

Exhausted!!
Performance Measures in Cooperative Spectrum Sensing

- The basic performance measures and their physical interpretations:
  - Reliability: the ability to detect band in use
    - \( \Rightarrow \text{missed detection} \downarrow \)
  - Efficiency: the ability to utilize white band
    - \( \Rightarrow \text{false alarm} \downarrow \)

- The gain of cooperative spectrum sensing:
  - How to \textit{quantify} the cooperative gain?
  - What is the bound on this gain?
  - How to achieve?
Problem Formulation

- Binary hypothesis test between:
  \( H_0 \): absence of primary user \( \quad H_1 \): presence of primary user
- Rayleigh fading channel and Gaussian noise
- Average SNR information available at sensing nodes

\[
\begin{align*}
  r|H_0 &= n \sim \mathcal{CN}(0, \sigma_n^2) \\
  r|H_1 &= hx + n \sim \mathcal{CN}(0, \sigma_h^2 + \sigma_n^2) \\
  r &\text{: sensed signal;}
  n &\text{: additive white Gaussian noise (AWGN);} \\
  \sigma_n^2 &\text{: noise variance;}
  \sigma_h^2 &\text{: channel variance.}
\end{align*}
\]

After normalization:

\[
\begin{align*}
  r|H_0 &= n \sim \mathcal{CN}(0, 1) \\
  r|H_1 &= hx + n \sim \mathcal{CN}(0, \gamma + 1) \\
  \gamma &= \frac{\sigma_h^2}{\sigma_n^2}
\end{align*}
\]
System Model: Basic Sensing Strategies

- Non-cooperative sensing (NCoS)
- Cooperative sensing with soft information fusion (SCoS)
- Cooperative sensing with hard information fusion (HCoS)
Performance Metric: Diversity

- **Performance metrics:**
  - False alarm (FA) probability: $P_f$
  - Missed detection (MD) probability: $P_{md}$
  - Average detection error probability: $P_e = P_{H_0}P_f + P_{H_1}P_{md}$

- **Diversity:**
  \[
  d_\star = - \lim_{\gamma \to +\infty} \frac{\log P_\star}{\log \gamma}
  \]
  \[
  d_f : \text{false alarm diversity}
  \]
  \[
  d_{md} : \text{missed detection diversity}
  \]
  \[
  d_e : \text{detection error diversity}
  \]
  \[
  \implies d_e = \min(d_f, d_{md})
  \]
Non-Cooperative Sensing (NCoS)

- The binary hypothesis testing problem:
  \[ r | H_0 = n \sim \mathcal{CN}(0, 1) \]
  \[ r | H_1 = hx + n \sim \mathcal{CN}(0, \gamma + 1) \]

- Neyman-Pearson (NP) test:
  
  Energy Detector: \[ \lambda = |r|^2 \geq_{H_0}^{H_1} \eta \]

- Corresponding false alarm and missed detection probabilities:
  \[ P_f(\eta, \gamma) = P(\lambda > \eta | H_0) = e^{-\eta} \]
  \[ P_{md}(\eta, \gamma) = P(\lambda < \eta | H_1) = 1 - e^{-\frac{\eta}{\gamma + 1}} \]

- Minimizing the average error probability \( P_e \):
  \[ \eta^o = \left(1 + \frac{1}{\gamma}\right) \log(1 + \gamma) \]
Theorem 1: For non-cooperative sensing (NCoS):

- The threshold minimizing the average error probability is:
  \[ \eta^o = (1 + \frac{1}{\gamma}) \log(1 + \gamma) \]

- With this threshold, the diversity orders are:
  \[ d_f = d_{md} = d_e = 1. \]
NCoS: Diversity

SNR $\gamma$ (dB)

$P_e$

$P_f$

$P_{md}$

SNR $\gamma$ (dB)
Tradeoff: FA Diversity vs MD SNR

\[ P_f(\eta, \gamma) = P(\lambda > \eta | H_0) = e^{-\eta} \]
\[ P_{md}(\eta, \gamma) = P(\lambda < \eta | H_1) = 1 - e^{-\frac{\eta}{\gamma+1}} \]

- **Threshold at:** \( \eta^o = (1 + \frac{1}{\gamma}) \log(1 + \gamma) \)
  
  \[ P_f(\gamma) \sim (1 + \gamma)^{-1} \]
  
  \[ P_{md}(\gamma) \sim \gamma^{-1} \log(\gamma + 1) \]

- **Threshold at:** \( \eta' = d_0 \eta^o \)
  
  \[ P_f(\gamma) \sim (1 + \gamma)^{-d_0} \]
  
  \[ P_{md}(\gamma) \sim (\gamma/d_0)^{-1} \log(\gamma + 1) \]

- **The false alarm diversity:** \( 1 \rightarrow d_0 \)

- **The missed detection probability:** \(-10 \log d_0\) dB SNR gain
FA Diversity – MD SNR Tradeoff

dotted: \( \eta^0 \rightarrow \) solid: \( 2\eta^0 \)

\[ d'_f = d_0 = 2, \quad d'_md = 1, \quad d'_e = \min(d'_f, d'_md) = 1 \]
Cooperative Sensing with Soft Information Fusion (SCoS)

- The binary hypothesis testing problem:

  \[ r_i | H_0 = n_i \sim \mathcal{CN}(0, 1), i = 1, \ldots, N \]
  \[ r_i | H_1 = h_ix + n_i \sim \mathcal{CN}(0, \gamma + 1), i = 1, \ldots, N \]

- Neyman-Pearson (NP) test:

  Energy Detector: \[ \lambda = \sum_{i=1}^{N} |r_i|^2 \overset{H_1}{\geq} \overset{H_0}{\leq} \eta_s \]

- Corresponding error probabilities:

  \[ P_{f,s} = \int_{\eta_s}^{+\infty} f(\lambda_s | H_0) d\lambda_s = \left( \sum_{i=0}^{N-1} \frac{\eta_s^i}{i!} \right) e^{-\eta_s} \]
  \[ P_{md,s} = \int_{0}^{\eta_s} f(\lambda_s | H_1) d\lambda_s = \left( \sum_{i=N}^{+\infty} \frac{\eta_s^i}{i!(\gamma+1)^i} \right) e^{-\frac{\eta_s}{\gamma+1}} \]

- Minimizing the average error probability:

  \[ \eta_s^o = N \left( 1 + \frac{1}{\gamma} \right) \log(1 + \gamma) = N \eta_s^o \]
SCoS: Diversity

With $\eta_s^o = N(1 + \frac{1}{\gamma}) \log(1 + \gamma)$,

$P_{f,s}(\gamma) \sim (1 + \gamma)^{-N} \Rightarrow d_{f,s} = - \lim_{\gamma \to +\infty} \frac{\log P_{f,s}}{\log \gamma} = N$

$P_{md,s}(\gamma) \sim (\gamma/N)^{-N} (\log(\gamma + 1))^N \Rightarrow d_{md,s} = - \lim_{\gamma \to +\infty} \frac{\log P_{md,s}}{\log \gamma} = N$

$\Rightarrow d_{e,s} = \min(d_{f,s}, d_{md,s}) = N$

**Theorem 2:** For cooperative sensing with soft information fusion (SCoS):

- The threshold minimizing the average error probability is:

  $\eta_s^o = N(1 + \frac{1}{\gamma}) \log(1 + \gamma) = N\eta^o$

- With this threshold, the diversity orders are:

  $d_{f,s} = d_{md,s} = d_{e,s} = N$. 
SCoS: Diversity

$N = 5, \eta = \eta_s^o$

SNR $\gamma$ (dB)

- $P_{e,s}$
- $P_{f,s}$
- $P_{md,s}$

SNR $\gamma$ (dB)
Tradeoff: FA Diversity vs MD SNR

- **Threshold at:** \( \eta_s^o = N \eta^o \)
  
  \[ P_f(\gamma) \sim (1 + \gamma)^{-N} \]
  
  \[ P_{md}(\gamma) \sim (\gamma/N)^{-N}(\log(\gamma + 1))^N \]

- **Threshold at:** \( \eta'_s = d_0 \eta^o \)
  
  \[ P_f(\gamma) \sim (1 + \gamma)^{-d_0} \]
  
  \[ P_{md}(\gamma) \sim (\gamma/d_0)^{-N}(\log(\gamma + 1))^N \]

- The false alarm diversity: \( N \rightarrow d_0 \)

- The missed detection probability: \( -10 \log(d_0/N) \) dB SNR gain
FA diversity – MD SNR Tradeoff

$N = 5$, dotted: $5\eta^o \rightarrow$ solid: $2.5\eta^o$

$P_{e,s}$
$P_{f,s}$
$P_{md,s}$

Diversity decrease:
5 $\rightarrow$ 2.5

3 dB SNR gain

$d'_f = d_0 = 2.5$, $d'_{md} = 5$, $d'_e = \min(d'_f, d'_{md}) = 2.5$
Cooperative Sensing with Hard Information Fusion (HCoS)

- The binary hypothesis testing problem:
  \[ d_i | H_0 \sim \text{Bernoulli}(1 - P_{f,l}, P_{f,l}), i = 1, \ldots, N \]
  \[ d_i | H_1 \sim \text{Bernoulli}(P_{md,l}, 1 - P_{md,l}), i = 1, \ldots, N \]
  \( P_{f,l} \) is the false alarm probability for local decision
  \( P_{md,l} \) is the missed detection probability for local decision

- Neyman-Pearson (NP) test:
  \[ \lambda_h = \sum_{i=1}^{N} d_i \underbrace{\geq}_{H_1} \underbrace{\leq}_{H_0} \eta_h \]

- Corresponding error probabilities:
  \[ P_{f,h} = \sum_{\lambda_h=\eta_h}^{N} \binom{N}{\lambda_h} P_{f,l}^{\lambda_h} (1 - P_{f,l})^{N-\lambda_h} \]
  \[ P_{md,h} = \sum_{\lambda_h=0}^{\eta_h-1} \binom{N}{\lambda_h} (1 - P_{md,l})^{\lambda_h} P_{md,l}^{N-\lambda_h} \]

- Optimization mathematically intractable

- User number \( N \) required at local user

\[ \Rightarrow \text{Local optimum decision} \quad \eta_l = \eta^o = (1 + \frac{1}{\gamma}) \log(\gamma + 1) \]
**Diversity Tradeoff**

With local optimum threshold, from the result in NCoS, we know that \( P_{f,l} \sim \gamma^{-1} \) and \( P_{md,l} \sim \gamma^{-1} \), then accordingly:

\[
P_{f,h} = \sum_{\lambda_h=\eta_h}^{N} \binom{N}{\lambda_h} P_{f,l}^{\lambda_h} (1 - P_{f,l})^{N-\lambda_h} \sim \binom{N}{\eta_h} P_{f,l}^{\eta_h} \sim \gamma^{-\eta_h}
\]

\[
P_{md,h} = \sum_{\lambda_h=0}^{\eta_h-1} \binom{N}{\lambda_h} (1-P_{md,l})^{\lambda_h} P_{md,l}^{N-\lambda_h} \sim \binom{N}{\eta_h - 1} P_{md,l}^{N-(\eta_h-1)} \sim \gamma^{-(N-\eta_h+1)}
\]

**Theorem 3**: For HCoS, with locally optimum threshold \( \eta_l = (1 + \frac{1}{\gamma}) \log(1 + \gamma) \), the diversity orders are:

\[
d_{f,h} = \eta_h, \quad d_{md,h} = N - \eta_h + 1, \quad d_{e,h} = \min(\eta_h, N - \eta_h + 1)
\]

**Tradeoff in Diversities!**
Diversity Tradeoff

Solid: $\eta_h = 1$; Dotted: $\eta_h = 2$

$$d_{f,h} = \eta_h$$

$$d_{md,h} = N - \eta_h + 10^{-1}$$

$$d_{e,h} = \min (d_{f,h}, d_{md,h})$$
HCoS-1: Unknown N

If one wants to optimize the diversity of the average error probability, then \( \eta_h^o = \arg \max_{\eta_h} \min(\eta_h, N - \eta_h + 1) \).

Accordingly, we have Corollary 1.

**Corollary 1:** For HCoS, with locally optimum decision with threshold \( \eta_l = \left(1 + \frac{1}{\gamma}\right) \log(1 + \gamma) \), the optimum threshold at the fusion center to maximize the detection error diversity is: \( \eta_h^o = \left\lfloor \frac{N+1}{2} \right\rfloor \) or \( \eta_h^o = \left\lceil \frac{N+1}{2} \right\rceil \), with \( d_{e,h} = \left\lfloor \frac{N+1}{2} \right\rfloor \).

Majority Rule!

Diversity Loss! (about half)
HCoS-1: Unknown N

\[ N = 5 \]

\[ \text{SNR} \gamma \text{ (dB)} \]

\[ P_e \]

\[ \eta_h = 5, d_e = 1 \]

\[ \eta_h = 1, d_e = 1 \]

\[ \eta_h = 4, d_e = 2 \]

\[ \eta_h = 2, d_e = 2 \]

\[ \eta_h = 3, d_e = 3 \]
HCoS-N: Known N

• For local decision: $\eta_l = \eta^0 \rightarrow \eta'_l = N\eta^0$
  - The local false alarm diversity: $1 \rightarrow N$
  - The local missed detection diversity: $1 \rightarrow 1$

**Corollary 2:** For HCoS, if:

• The local threshold is: $\eta_l = N\eta^0$
  - $d_{f,h} = N\eta_h, d_{md,h} = N - \eta_h + 1$
  - $d_{e,h} = \min(N\eta_h, N - \eta_h + 1)$

• Take the fusion center threshold as: $\eta_h = 1$, Then all the diversities are maximized to $N$

**OR-Rule!**

Full diversity order achieved thanks to the known number of cooperating users!
HCoS-N: Known N

Full diversity, but SNR loss for average detection error and missed detection

dotted: soft fusion
solid: hard fusion

N = 5
Roadmap

• Introduction: Smart Grid and Situational Awareness

• Green Communications for Sensor Networks
  ◦ Modulation Selection
  ◦ Cooperative Relay Section

• Cognitive Radio for Bandwidth Reutilization
  ◦ Non-Cooperative Spectrum Sensing (NCoS)
  ◦ Cooperative Spectrum Sensing with Soft Information Fusion (SCoS)
  ◦ Cooperative Spectrum Sensing with Hard Information Fusion (HCoS)

• Phasor State Estimation with Bad Data Processing
  ◦ Equivalence between Bad Data Subtraction and Removal
  ◦ Algorithms for Bad Data Processing

• Summary and Future Work
Monitoring: State Estimation (SE)

- State: bus voltage phasors
- SE: crucial for energy management system
- Phasor measurement unit (PMU): synchronized measurement

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<th>Traditional SE</th>
<th>SE from PMU</th>
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<td>Non-synchronized voltage magnitude and active/reactive power measurements</td>
<td>Synchronized voltage and current phasor measurement</td>
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<td>Limited bad data processing technique</td>
<td>More sophisticated algorithms possible</td>
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Signal Model

\[ m = \begin{bmatrix} m_v \\ m_i \end{bmatrix} = \begin{bmatrix} I \\ Y \end{bmatrix} s + e = H s + b + \eta \]

- Synchronized voltage measurements: \( m_v : p \times 1 \)
- Synchronized current measurements: \( m_i : (q - p) \times 1 \)
- Admittance matrix: \( Y : (q - p) \times p \)
  - System topology
  - Transmission line parameters
- State to be Estimated: \( s : p \times 1 \)
  - Bus voltages
- Measurement error:
  1. Bad data: \( b : q \times 1 \)
    - Sparse: \( \|b\|_0 \leq k \)
  2. Gaussian noise: \( \eta : q \times 1 \)
    - W.L.O.G., assume to be i.i.d.
Bad Data Processing Strategies

Bad data: *location* and *value*

A. **Joint** estimation of bad data location and values: \( \hat{b} \)
   then solve: \( Hs + \eta = m - \hat{b} \)

B. **Separate**: first location estimation: \( I_b = \{i_1, i_2, \ldots, i_k\} \)
   a) Estimate the values, then subtraction:
      - Selection matrix: \( \Theta = [I(:, i_1), \ldots, I(:, i_k)] \)
      - Modified model: \( m = Hs + \Theta \hat{b}_k + \eta \)
      - Estimate, then subtraction: \( m - \Theta \hat{b}_k = Hs + \eta \)
   b) Simply removal:
      - Removal matrix: \( \Theta_\perp = (\text{null}(\Theta^T))^T \)
      - Model with reduced size: \( \Theta_\perp m = \Theta_\perp Hs + \Theta_\perp \eta \)
        \( \Theta_\perp m : (q - k) \times 1 \)
        \( \Theta_\perp H : (q - k) \times p \)
Subtraction and Removal Equivalence

The estimate and then subtraction scheme:

\[ m = Hs + \Theta b_k + \eta \]

The property of selection matrix: \( \Theta' \Theta = I_k \), thus:

\[ \Theta' m = \Theta' Hs + b_k + \Theta' \eta \]

Conditional LS estimate of bad data:

\[ \hat{b}_k(s) = \Theta' (m - Hs) \]

The LS estimate of state after subtraction:

\[ \hat{s}_S = \arg \min_S \| m - \Theta \hat{b}_k(s) - Hs \|^2 \]

Within the objective function:

\[ m - \Theta \hat{b}_k(s) - Hs = m - \Theta \Theta' (m - Hs) - Hs \]

\[ = (I - \Theta \Theta') (m - Hs) \]

Subtraction equivalent to removal!

Where:

\[ \| \Theta' \perp \Theta (m - Hs) \|^2 = \| \Theta \perp m - \Theta \perp Hs \|^2 \]

Also obtainable by oblique projection [Behren-Scharf’94]
Algorithm 1: Largest Residual Removal (LRR) [Phadke-Thorp’10]

- **Step 1:** initial LS estimate: \( \hat{s} = (H' H)^{-1} H' m \)
- **Step 2:** residual calculation: \( r = m - H \hat{s} \)
- **Step 3:** bad data detection: \( \|r\|^2 \geq \chi^2_{1-\alpha,2(q-p)} \)?
  - If no, stop;
  - If yes,
    - Bad data location identification as the largest residual: \( \hat{i} = \arg \max \|r(i)\|_2 \)
    - Remove the bad data, reduce the model size, go to step 1.
Algorithm 2: Sparsity Regularized Minimization (SRM)

Regularized minimization problem:

\[
(\hat{s}, \hat{b}) = \arg \min_{s,b} \left( \|m - b - Hs\|_2^2 + \lambda \cdot \text{spar}(b) \right)
\]

Conditional LS state estimate:

\[
\hat{s}(b) = (H'H)^{-1}H'(m - b)
\]

Bad data estimate:

\[
\hat{b} = \arg \min_b \left( \|P_H^\perp(b-m)\|_2^2 + \lambda \text{spar}(b) \right)
= \arg \min_b \left( \|H^\perp(b-m)\|_2^2 + \lambda \text{spar}(b) \right)
\]

where \(z = H^\perp m\) can be interpreted as syndrome

Formulated as a compressive sensing problem!

Final state estimate:

\[
\hat{s} = (H'H)^{-1}H'(m - \hat{b})
\]
Algorithm 3: Projection and Minimization (PM)

Iteratively remove the bad data similar as LRR

With the objective function in SRM

\[(\hat{s}, \hat{b}) = \arg \min_{(s, b)} \left( \|m - b - Hs\|^2_2 + \lambda \cdot \text{spar}(b) \right)\]

With \(\|b\|_0 = 1\), then \(b = bI(:, i)\), with syndrome \(z = H_\perp m\):

The bad data location can be identified as:

\[(\hat{b}, \hat{i}) = \arg \min_{(b, i)} \|bH_\perp I(:, i) - z\|^2_2 = \arg \min_{(b, i)} \|bH_\perp (:, i) - z\|^2_2\]

Then, remove the i-th measurement from the model. Repeat the initial state estimation and bad data detection.
Simulation Setup  [Uni. of Washington, PSTCA ]

SNR = 20 dB
Possible measurements:
• 14 voltages
• 14 injection currents
• 40 line currents: $20 \times 2$

For SRM, the compressive sensing algorithms adopted:
• LASSO: $l_1$-norm [http://sparselab.standford.edu]
• Approximated $l_0$-norm minimization [Mohimani-Babaie-Zadeh, et.al’09]
Simulation Results: Partial Redundancy

14 voltages, 14 injection line currents, 1 bad data

Bad Data to Signal Ratio (dB)

Mean Squared Error

$L_0$-SRM
LRR
LASSO-SRM
PM
Genie-Aided

$LASSO < LRR < L_0 < PM = Genie$
Simulation Results: Partial Redundancy

14 voltages, 14 injection line currents, 3 bad data

LASSO < LRR < L₀ < PM < Genie
Simulation Results: Full Redundancy

14 voltages, 14 injection line currents, 40 line currents, 4 bad data

LASSO < LRR < L₀ < PM < Genie

All good performance except LASSO
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• Summary and Future Work
**Summary**

- Smart grid: an interdisciplinary research area
- The situational awareness:
  - **Sensing:**
    - Green communications for wireless sensor networks
      - Modulation format
      - Cooperative communication links
  - **Communications:**
    - Cooperative spectrum sensing for more bandwidth to guarantee QoS
      - SCoS: full diversity, full SNR gain
      - HCoS-1: half diversity
      - HCoS-N: full diversity, but SNR loss
  - **Monitoring:**
    - Phasor state estimation from PMU measurement with bad data
      - Equivalence between bad data subtraction and removal
      - Bad data processing algorithms
Proposed Future Work 1: multi-bit cooperative spectrum sensing

- **Soft CoS**: full diversity
- **Hard CoS**: diversity or SNR loss
  - Reason: 1-bit quantization
- Could more bits help? If so, how?
- One step forward: ternary local decisions
  
  \[ |r_i|^2 \]

  \[ d_i = 0 \quad d_i = ♠ \quad d_i = 1 \]

  \[ \eta_{l,1} \quad \eta_{l,2} \]

- Issues to be investigated:
  - Local threshold selection
  - Fusion rules
  - Performance analysis
  - Generalization to more bits
Proposed Future Work 2: Parameter and Topology Error Processing

- Current bad data detection – overall residual:
  \[ r = m - H \hat{s} \]

- Finer preprocessing possible:
  - Voltage-current agreement: \[ m_i - Y m_v = 0 \]
  - KCL agreement:
    \[ \sum_j m_I(i,j) = 0 \]
  - KVL agreement:
    \[ \sum_{l \in \{\text{Loop } L\}} Y_l m_{I,l} = 0 \]
Publication List

Journal Publications:


Conference Publications


Conference Publications (cont.)


Questions?

Thank you!