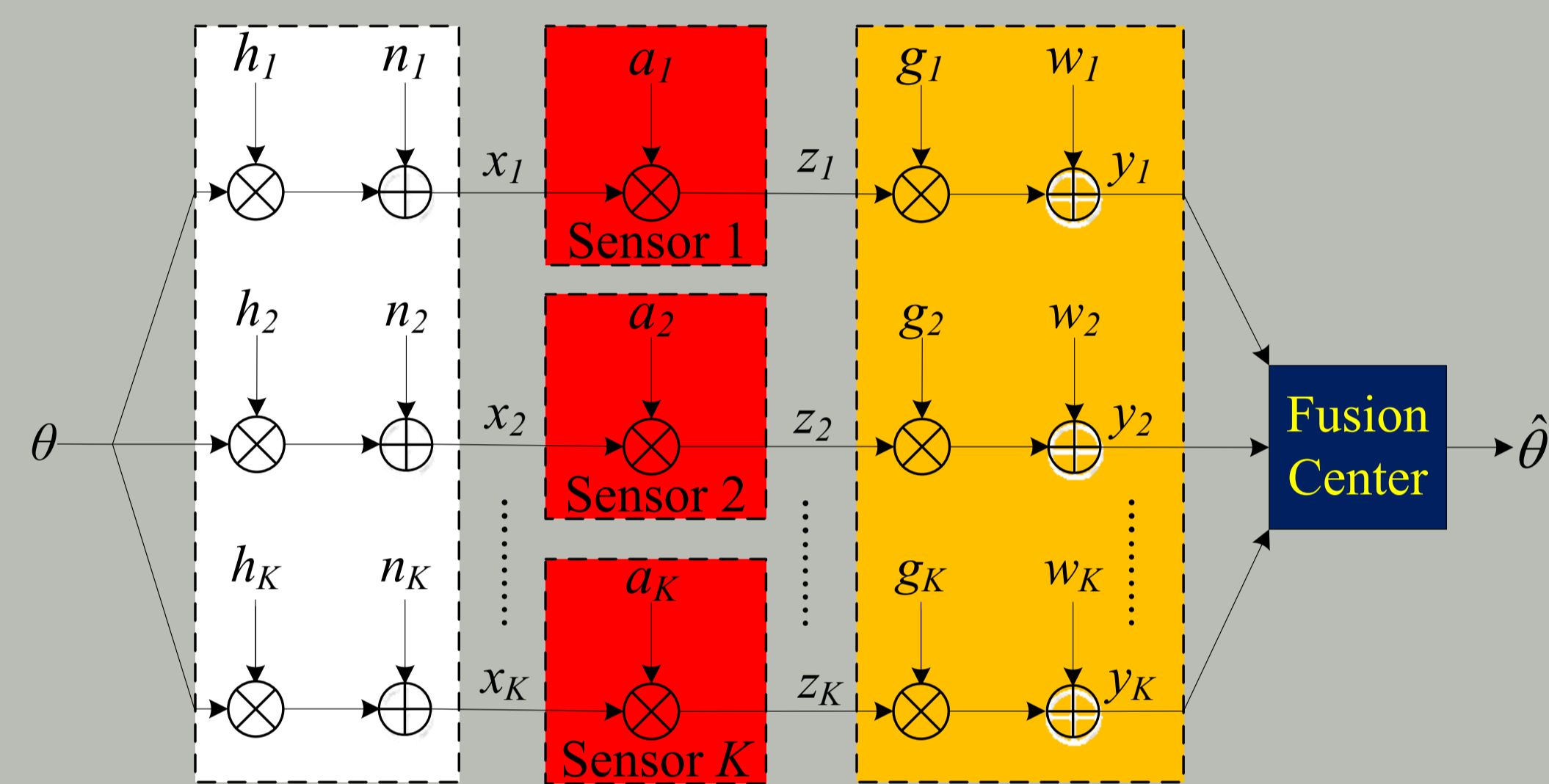


## Introduction

- One of the most important applications of wireless sensor networks (WSNs) is **distributed estimation**.
- When distributed sensors use an **amplify-and-forward** scheme to process their local noisy observations, the study of the **allocation of transmit power** to the sensors becomes important.
- Most optimal power-allocation schemes in the literature require the feedback of the exact instantaneous channel state information (CSI) from the FC to local sensors, which is **not practical**.
- We use **limited feedback** to alleviate this requirement.

## System Model



- Unknown random parameter  $\theta$  with zero mean and unit power.
- Linear observation model:  $x_i = h_i\theta + n_i$ 
  - $n_i$  is i.i.d. additive observation noise with zero mean and known variance  $\sigma_n^2$ .
  - Define **observation SNR** as  $\beta_i \stackrel{\text{def}}{=} \frac{|h_i|^2}{\sigma_n^2}$ .
- Linear amplify-and-forward local processing:  $z_i = a_i x_i$ 
  - Instantaneous transmit power of a sensor:  $P_i = a_i^2 (|h_i|^2 + \sigma_n^2) = a_i^2 \sigma_n^2 (1 + \beta_i)$
- Orthogonal coherent fading channel:  $y_i = g_i z_i + w_i$ 
  - $w_i$  is i.i.d. additive white Gaussian noise with zero mean and known variance  $\sigma_w^2$ .
  - Define **channel SNR** as  $\gamma_i \stackrel{\text{def}}{=} \frac{|g_i|^2}{\sigma_w^2}$ .
- The FC finds the best linear unbiased estimator (BLUE) of  $\theta$ : 
$$\hat{\theta} = \left( \sum_{i=1}^K \frac{h_i^2 a_i^2 g_i^2}{a_i^2 g_i^2 \sigma_n^2 + \sigma_w^2} \right)^{-1} \sum_{i=1}^K \frac{h_i a_i g_i y_i}{a_i^2 g_i^2 \sigma_n^2 + \sigma_w^2}$$
- The variance of the BLUE estimator is 
$$\text{Var}(\hat{\theta} | \mathbf{a}, \mathbf{g}) = \left( \sum_{i=1}^K \frac{h_i^2 a_i^2 g_i^2}{a_i^2 g_i^2 \sigma_n^2 + \sigma_w^2} \right)^{-1} = \left( \sum_{i=1}^K \frac{\beta_i \gamma_i a_i^2 \sigma_n^2}{1 + \gamma_i a_i^2 \sigma_n^2} \right)^{-1}$$
- Define  $\mathbf{a} \stackrel{\text{def}}{=} [a_1, a_2, \dots, a_K]^T$  and  $\mathbf{g} \stackrel{\text{def}}{=} [g_1, g_2, \dots, g_K]^T$ .

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## Problem Statement for Our Case Study

- Cui et al. [5] have derived optimal local amplification gains to minimize the BLUE-estimator variance, given a cumulative transmission-power constraint  $P_{\text{Total}}$ : 
$$a_i = \begin{cases} \sqrt{\frac{1}{\gamma_i \sigma_n^2} (\sqrt{\delta_i \rho(K_1)} - 1)}, & i \leq K_1 \\ 0, & i > K_1 \end{cases} \quad \rho(n) \stackrel{\text{def}}{=} \frac{P_{\text{Total}} + \sum_{i=1}^n \frac{\beta_i}{\delta_i}}{\sum_{i=1}^n \frac{\beta_i}{\delta_i}}$$
  - Define  $\delta_i \stackrel{\text{def}}{=} \frac{\beta_i \gamma_i}{1 + \beta_i}$  and sort the sensors so that  $\delta_1 \geq \delta_2 \geq \dots \geq \delta_K$ .
  - $K_1$ : Unique largest integer that  $\sqrt{\delta_{K_1} \rho(K_1)} > 1$  and  $\sqrt{\delta_{K_1+1} \rho(K_1+1)} \leq 1$ .
- The above optimal power-allocation scheme is based on the assumption that the complete **uplink CSI** is available at local sensors, which is **not practical** in most applications, especially in **large-scale WSNs**.

## Proposed Solution: Limited Feedback of CSI

- An **optimal codebook** is designed **offline** by quantizing the space of the optimized power-allocation vectors using the **generalized Lloyd algorithm** with modified distortion functions.
- For each channel realization, the FC:
  - Finds the optimal power-allocation scheme using the perfect **backward CSI**.
  - Feeds back the index of the closest codeword in the optimal codebook to the optimal power-allocation vector.

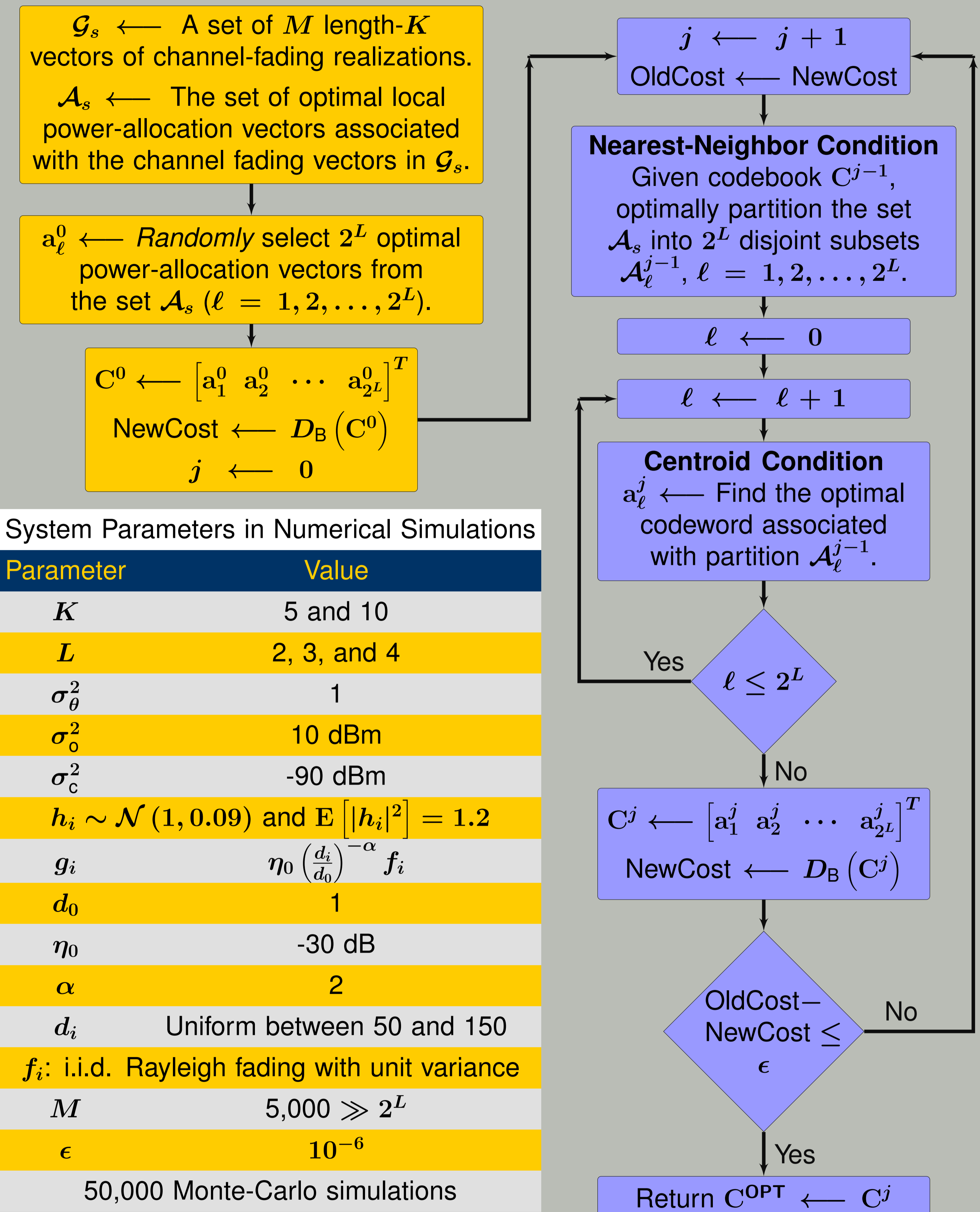
## Designing Optimal Codebook Using Lloyd Algorithm

- Define the **conditional codeword distortion** for any codeword  $\mathbf{a}_\ell \in \mathcal{C}$ , when it is used instead of  $\mathbf{a}^{\text{OPT}}$ : 
$$D_W(\mathbf{a}_\ell | \mathbf{g}) \stackrel{\text{def}}{=} |\text{Var}(\hat{\theta} | \mathbf{a}_\ell, \mathbf{g}) - \text{Var}(\hat{\theta} | \mathbf{a}^{\text{OPT}}, \mathbf{g})|$$
- Define the **average codebook distortion** for  $\mathcal{C}$ : 
$$D_B(\mathcal{C}) \stackrel{\text{def}}{=} \mathbb{E}_{\mathbf{g}} \left[ \min_{\ell \in \{1, 2, \dots, 2^L\}} D_W(\mathbf{a}_\ell | \mathbf{g}) \right]$$
  - $L$  is the number of feedback bits broadcast by the FC.
- Nearest-Neighbor Condition**
  - Find  $|\mathcal{C}| = 2^L$  optimal **Voronoi cells** of the vector space to be quantized  $\mathcal{A}$ , given a fixed codebook  $\mathcal{C}$ .
  - Each point  $\mathbf{a} \in \mathcal{A}$  is assigned to partition  $\ell$  represented by codeword  $\mathbf{a}_\ell \in \mathcal{C}$  if and only if its distance to codeword  $\mathbf{a}_\ell$ , with respect to the conditional codeword distortion function, is less than its distance to any other codeword.
- Centroid Condition**
  - Find the optimal codebook, given a specific partitioning of the vector space to be quantized  $\mathcal{A}$ .
  - The optimal codeword associated with each Voronoi cell  $\mathcal{A}_\ell \subseteq \mathcal{A}$  is the **centroid** of that cell with respect to the conditional codeword-distortion function: 
$$\mathbf{a}_\ell = \arg \min_{\mathbf{a} \in \mathcal{A}_\ell} \mathbb{E}_{\mathbf{g} \in \mathcal{G}_\ell} [D_W(\mathbf{a} | \mathbf{g})]$$

## Main Reference

- S. Cui, J.-J. Xiao, A.J. Goldsmith, Z.-Q. Luo, and H.V. Poor, "Estimation diversity and energy efficiency in distributed sensing," *IEEE Transactions on Signal Processing*, vol. 55, no. 9, pp. 4683–4695, September 2007.

## Details of Our Codebook-Design Process

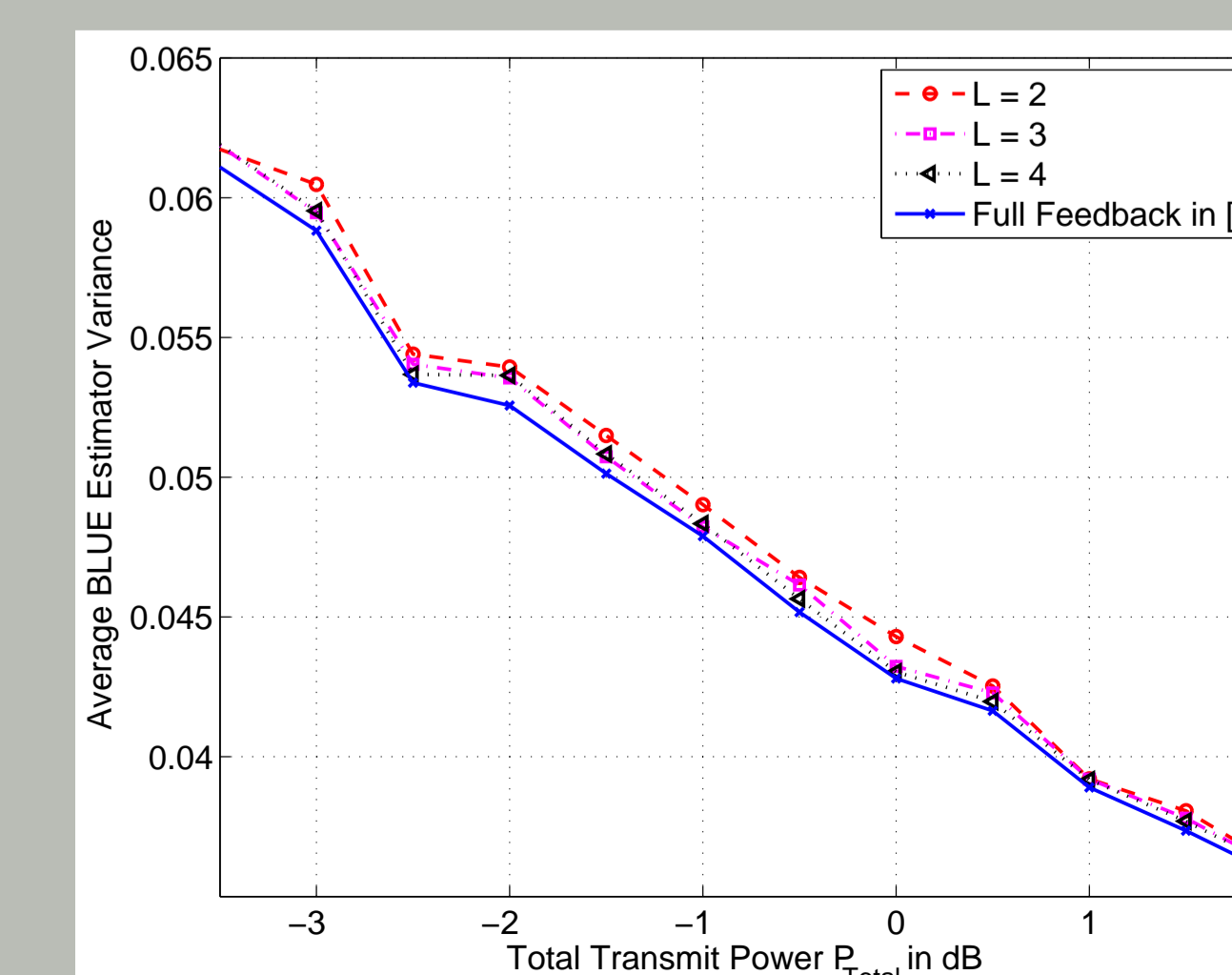


## System Parameters in Numerical Simulations

Parameter	Value
$K$	5 and 10
$L$	2, 3, and 4
$\sigma_\theta^2$	1
$\sigma_n^2$	10 dBm
$\sigma_w^2$	-90 dBm
$h_i \sim \mathcal{N}(1, 0.09)$ and $\mathbb{E}[ h_i ^2] = 1.2$	
$g_i$	$\eta_0 \left(\frac{d_i}{d_0}\right)^{-\alpha} f_i$
$d_0$	1
$\eta_0$	-30 dB
$\alpha$	2
$d_i$	Uniform between 50 and 150
$f_i$ : i.i.d. Rayleigh fading with unit variance	
$M$	$5,000 \gg 2^L$
$\epsilon$	$10^{-6}$
50,000 Monte-Carlo simulations	

## Numerical Results

For  $K = 5$  sensors in the network.



For  $K = 10$  sensors in the network.

