

A Distributed Adaptive Algorithm for Node-Specific Signal Fusion Problems in Wireless Sensor Networks

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1. Node-specific problems for spatial filtering...

... in a distributed setting

Examples:

- Minimum mean square error (MMSE):

$$\underset{X_k \in \mathbb{R}^{M \times Q}}{\text{minimize}} \mathbb{E}[\|\mathbf{d}_k(t) - X_k^T \mathbf{y}(t)\|^2]$$

- Linearly constrained minimum variance (LCMV):

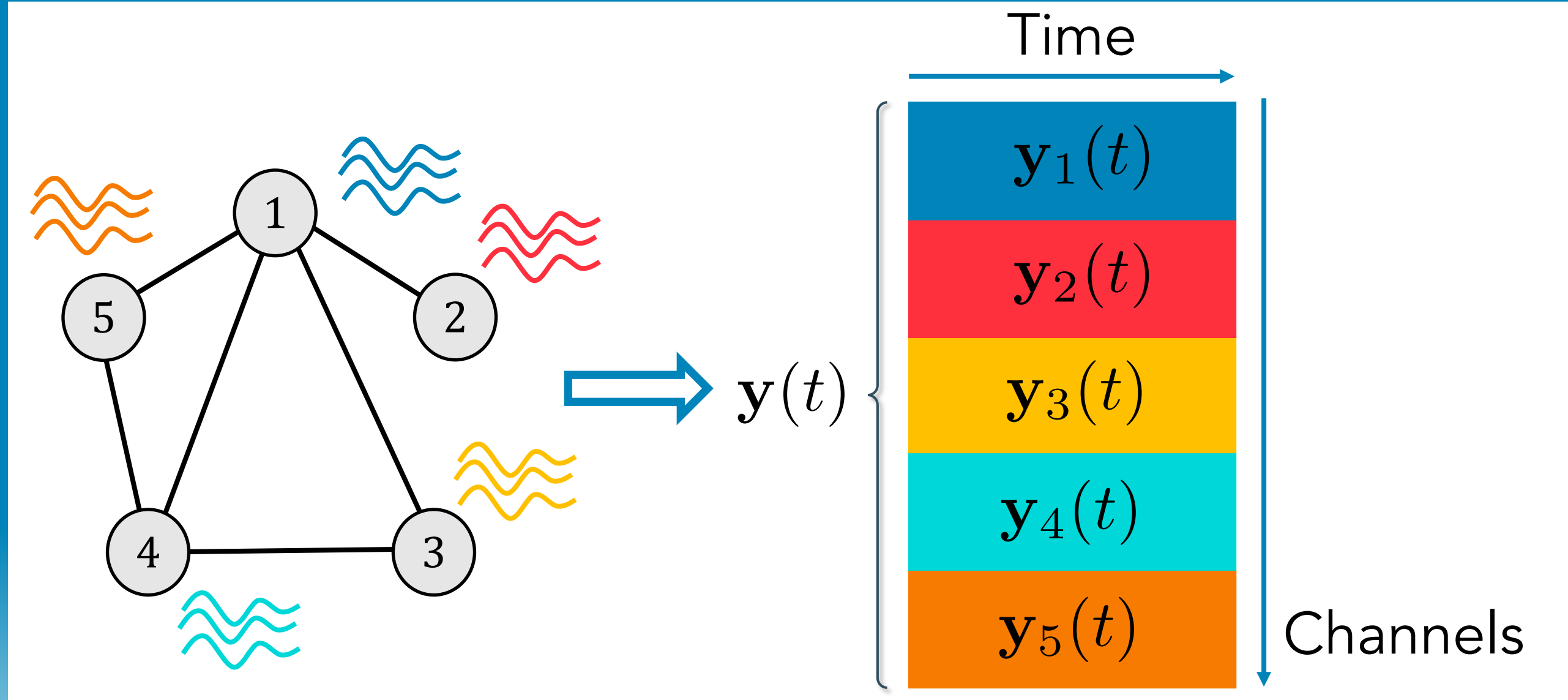
$$\underset{X_k \in \mathbb{R}^{M \times Q}}{\text{minimize}} \mathbb{E}[\|X_k^T \mathbf{y}(t)\|^2]$$

$$\text{subject to } X_k^T B = H_k$$

General form of **spatial filtering problems** with **node-specific objectives**:

$$\mathbb{P}_k : \underset{X_k \in \mathbb{R}^{M \times Q}}{\text{minimize}} f_k(X_k^T \mathbf{y}(t), X_k^T B) \\ \text{subject to } X_k \in \mathcal{S}_k$$

$$\text{Assumption: } X_k^* = X_l^* \cdot D_{k,l}$$



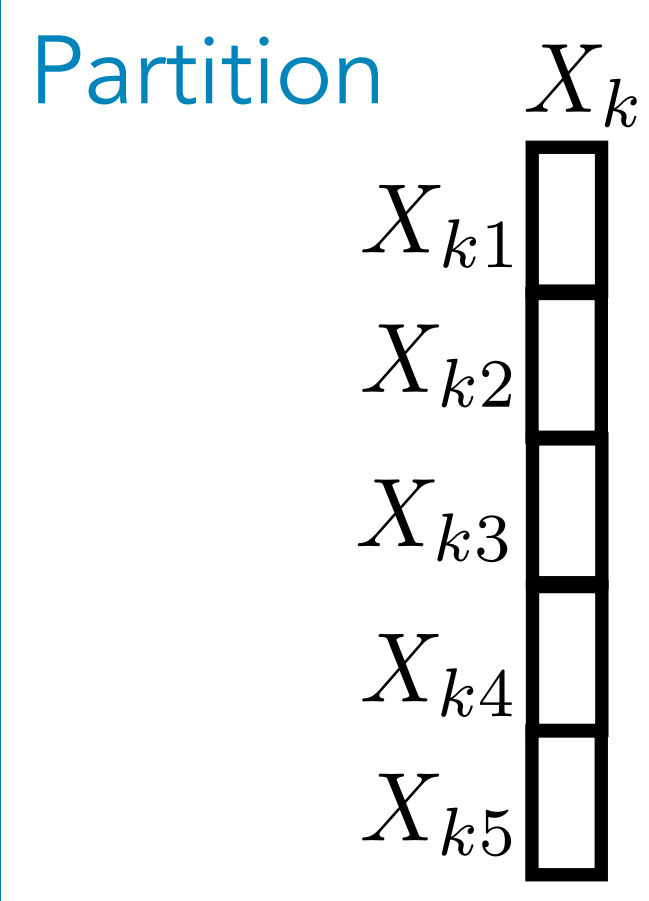
Need to exploit the correlation between all channels of \mathbf{y} but **centralization is too costly**

Goal

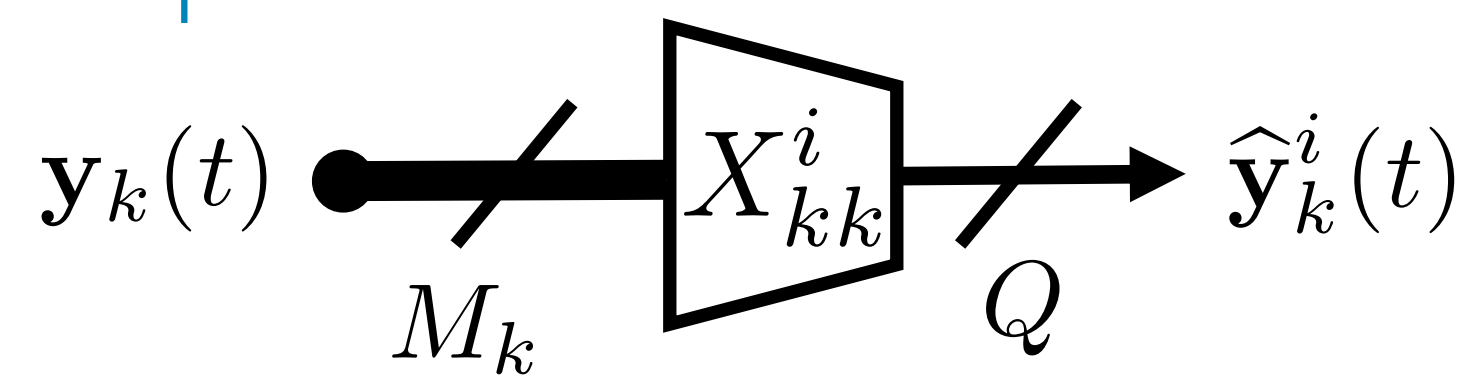
Solve **node-specific spatial filtering problems** without centralizing the data

2. Proposed method: DANSF data flow

- Compress signals measured at nodes k using current estimate X_{kk}^i of the filter: $\hat{\mathbf{y}}_k^i(t) = X_{kk}^{iT} \mathbf{y}_k(t)$

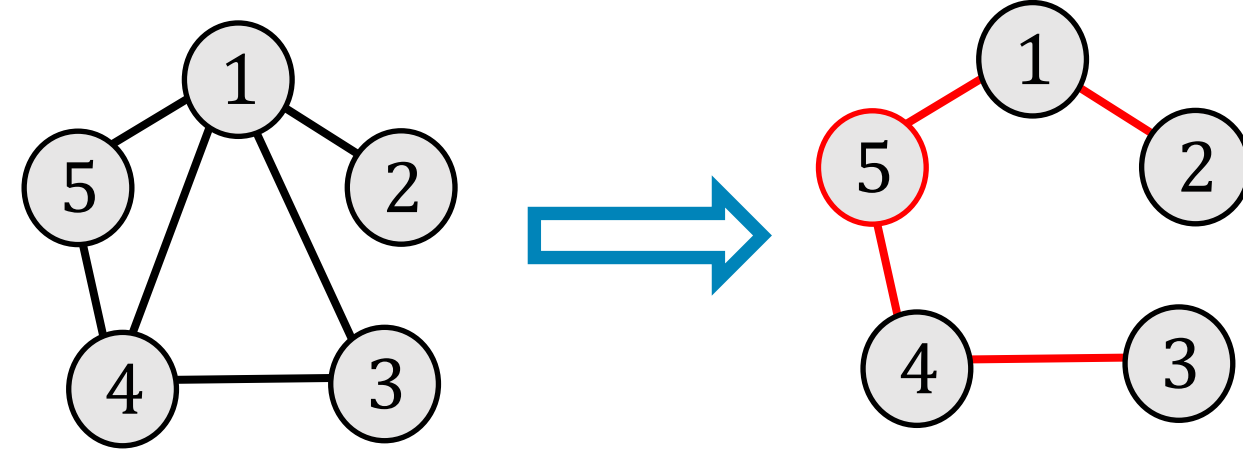


Compress

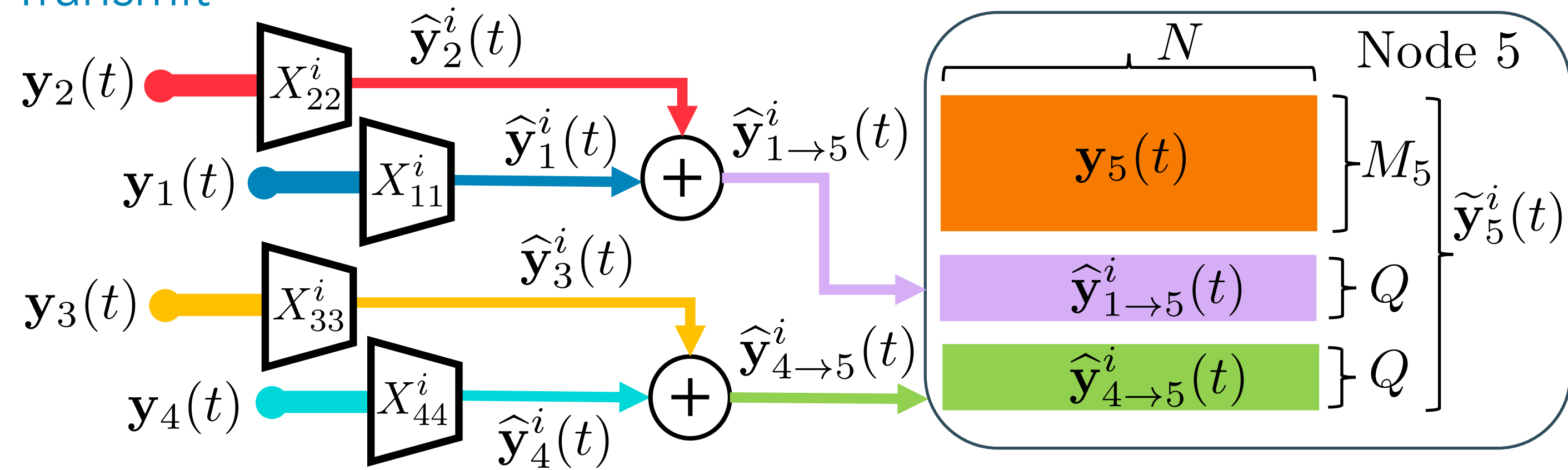


- Send N samples of compressed signals towards the updating node q after pruning the graph:

Example with $q = 5$:



Transmit



- Same procedure for the matrix B

3. Proposed method: DANSF updating

- At node q build and solve local version of the network-wide problem using $\hat{\mathbf{y}}_q^i$ instead of \mathbf{y} and \tilde{B}_q^i instead of B

Solve

$$\tilde{X}_q^{i+1} \leftarrow \underset{\tilde{X}_q \in \tilde{\mathcal{S}}_q^i}{\text{argmin}} f_k(\tilde{X}_q^T \hat{\mathbf{y}}_q^i(t), \tilde{X}_q^T \tilde{B}_q^i)$$

- Node q updates X_q as

Update

$$X_{qk}^{i+1} = \begin{cases} X_{qq}^{i+1} & \text{if } k = q \\ X_{kk}^i G_{qn}^{i+1} & \text{if } k \neq q \end{cases}$$

$q = 5$:

$$\tilde{X}_5^{i+1}$$

$$\begin{bmatrix} X_{55}^{i+1} \\ G_{51}^{i+1} \\ G_{54}^{i+1} \end{bmatrix}$$

- At node q , the filtered optimal signal is estimated as

$$X_q^{*T} \mathbf{y}(t) \approx \tilde{X}_q^{(i+1)T} \hat{\mathbf{y}}_q^i(t)$$

- Node q transmits $\tilde{X}_q^{(i+1)T} \hat{\mathbf{y}}_q^i(t)$ and $\tilde{X}_q^{(i+1)T} \tilde{B}_q^i$ to the other nodes for them to update X_k

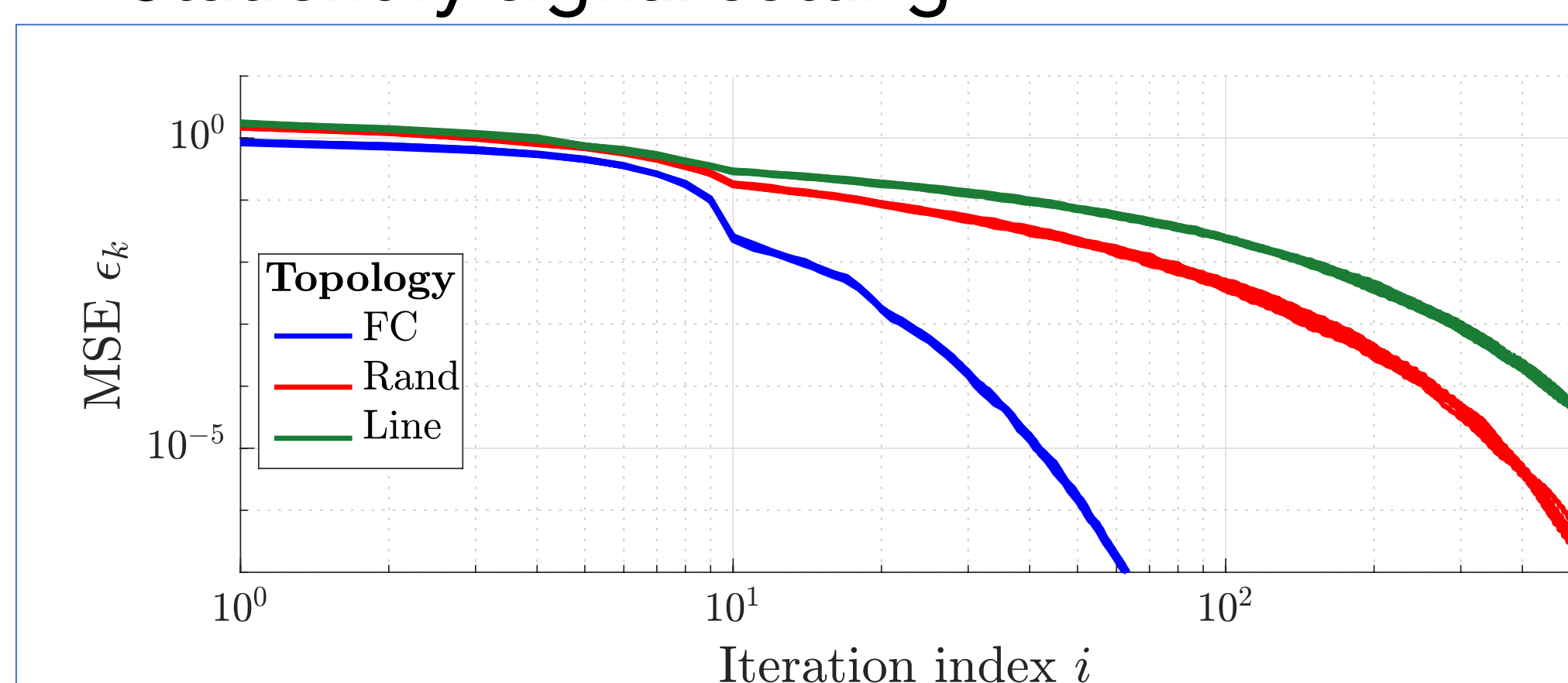
- Repeat process for other updating nodes and new signal samples

4. Results

DANSF converges to a solution X_k^* of \mathbb{P}_k for each node k under similar conditions as the original DASF algorithm^{1,2}

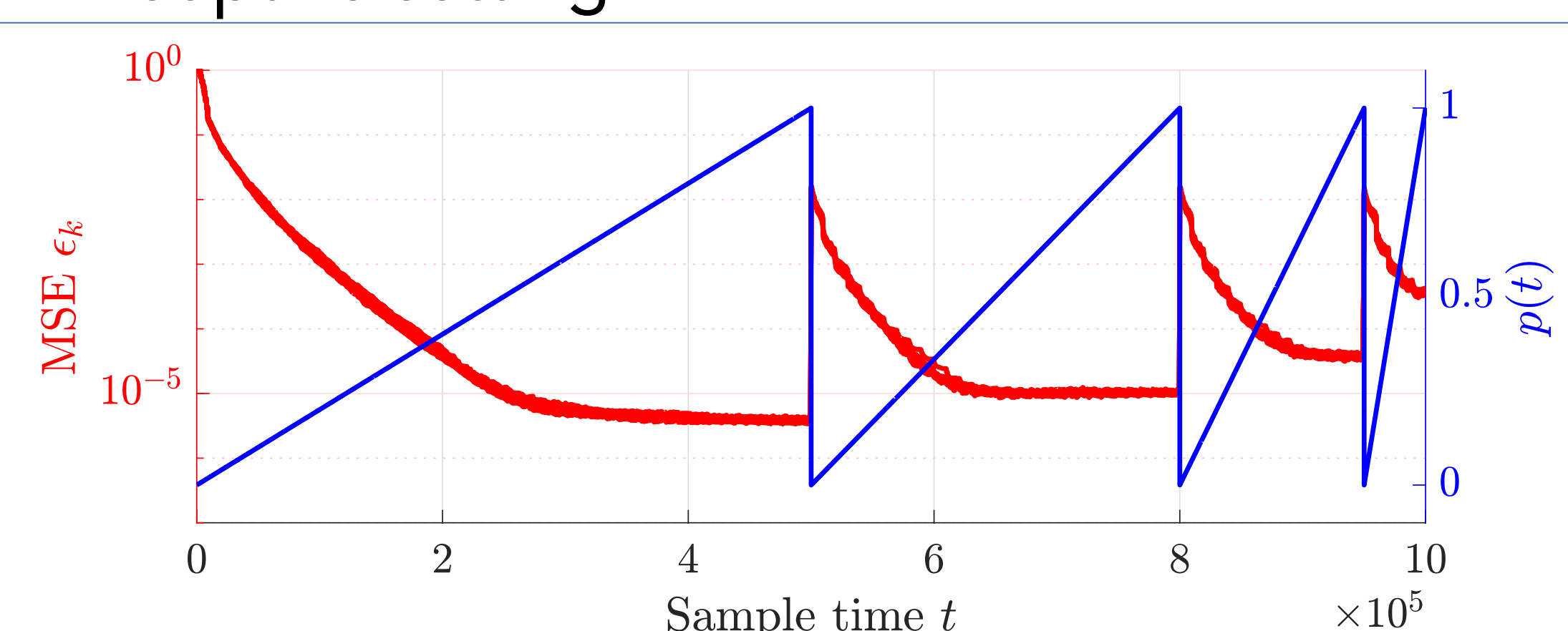
$$\text{Example problem: } \underset{X_k \in \mathbb{R}^{M \times Q}}{\text{minimize}} \text{trace}(X_k^T B_k) \\ \text{subject to } \text{trace}(X_k^T R_{\mathbf{y}\mathbf{y}} X_k) \leq 1$$

Stationary signal setting



Convergence for each node without large deviations

Adaptive setting



- Statistics of \mathbf{y} change with p
- Slow changes tracked, abrupt ones corrected

