

# Distributed In-Network Decision Making in Sensor Networks

Murat Alanyali  
Boston University

Joint work with Saligrama Venkatesh, Onur Savas, Shuchin Aeron

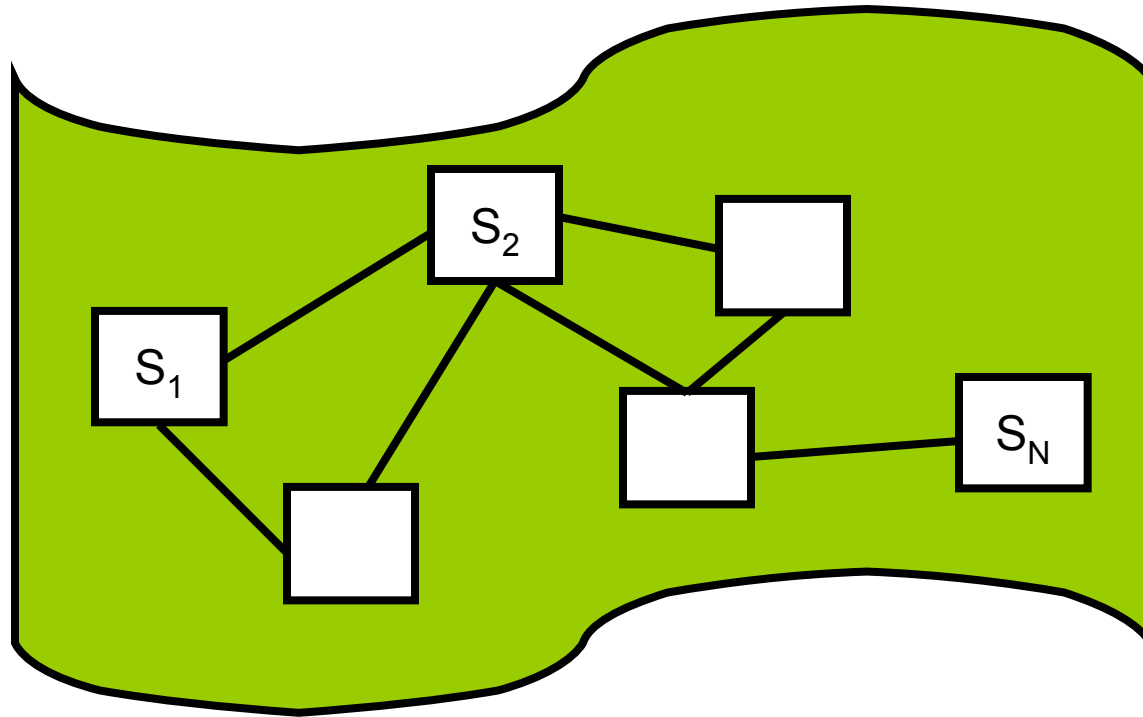
# Applications



- Habitat monitoring
- Inventory control
- Military applications
- ...

Moisture sensors on trees  
BU Sargent Camp

# Salient Features



- Spatial and temporal variability of sensed data
- Low-resolution / inexpensive sensors
- Multiple sensing modalities (e.g. moisture, light, ...)
- Wireless communication links (topology depends on geographical proximities)

# Features Contd

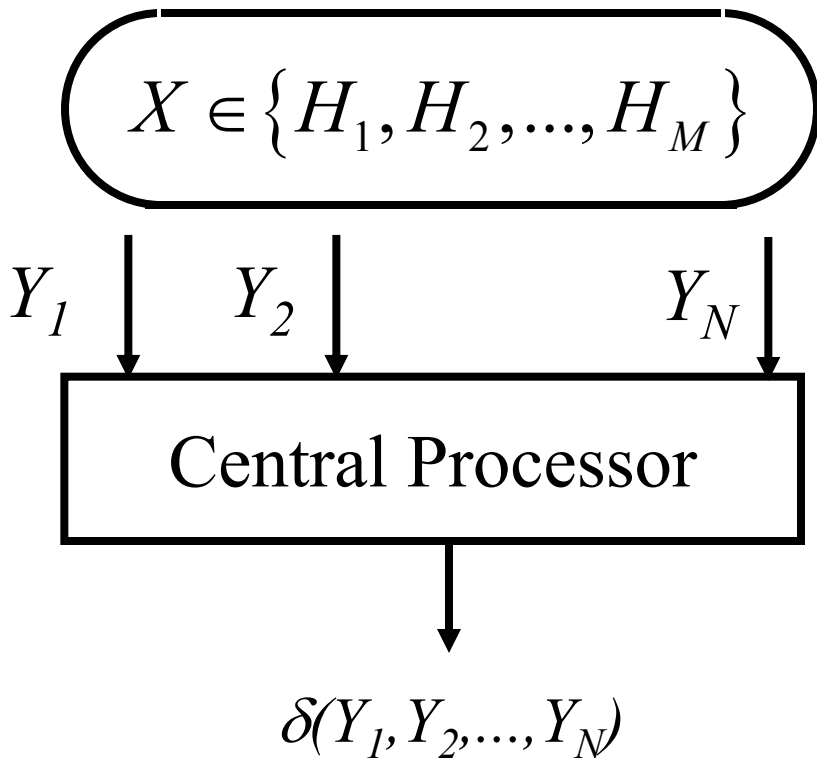
## Sensing Tasks:

- Classification
- Parameter Estimation
- Localization
- Tracking

## Requirements:

- Scalable architecture
- Power efficiency
- Robustness to failures
- Ad-hoc operation
- Graceful response to quantization & errors

# Centralized Detection



$Y_i$  : Measurement of sensor  $i$

$\delta$  : Decision rule

- Model:

$$P(Y_1, Y_2, \dots, Y_N | X)$$

- Formulation:

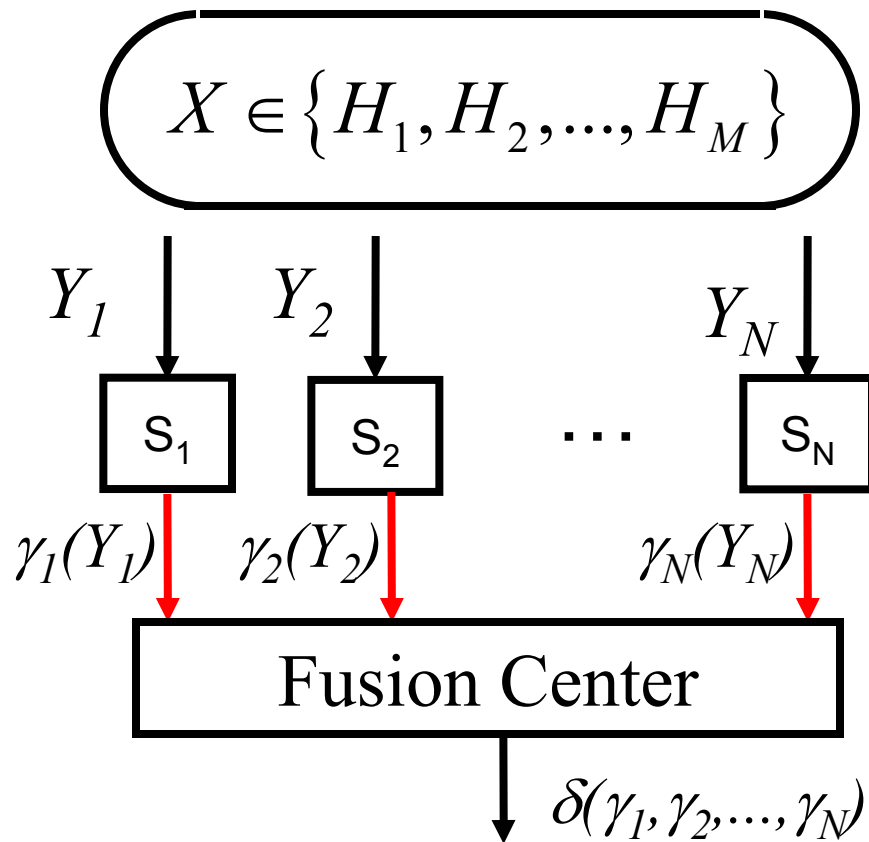
Bayesian, Minimax,  
Neyman-Pearson, ...

(Van Trees 1968)

- Maximum Likelihood (ML)  
estimator:

$$\max_m P(Y_1=y_1, \dots, Y_N=y_N | H_m)$$

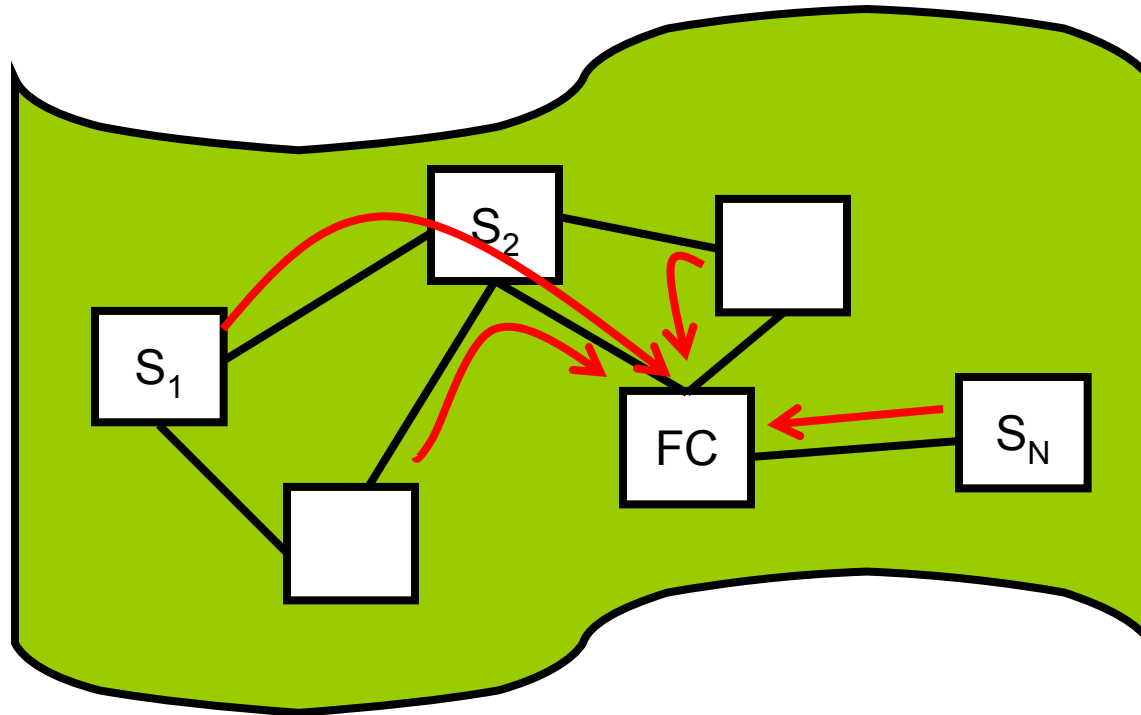
# Decentralized Detection



$\gamma_i \in \text{Finite Alphabet}$

- Finding optimal rules is hard (Papadimitriou & Tsitsiklis 1986)
- Special cases:  
Forms of optimal  $\gamma_i, \delta$  are known but depend on other sensors' measurement models. (Tsitsiklis 1993)
- The CEO problem:  
Minimize distortion between  $X$  and  $\delta$  subject to rate constraint on **channels** (Berger et al., 1996)

# Accounting for the Network

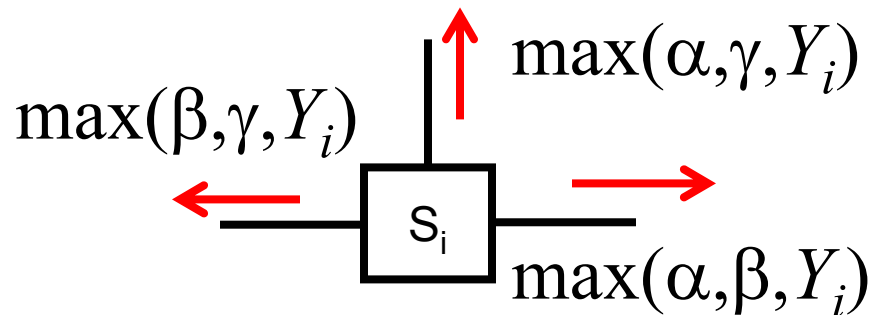
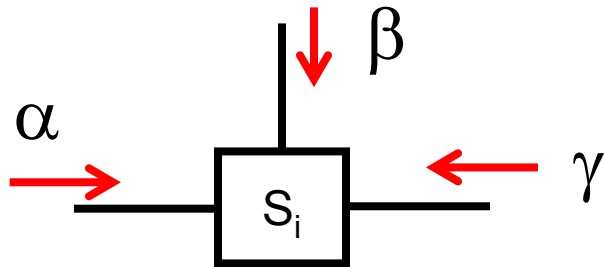


## Issues:

- Limitations due to network transport capacity (Gupta & Kumar 2000)
- Is out-of-network processing efficient?

# In-Network Processing

- Ex: Find  $\max\{Y_1, \dots, Y_N\}$



Related work:

In-network data aggregation (TinyDB, Cougar, TiNa, Galore):

- Distributed Query processing
- Hierarchical topologies

# Our Goal

General approach to distributed in-network  
{detection, estimation, tracking,...}

Essential Components:

1. Modeling spatial correlations in data
2. Local message passing techniques

# 1. Modeling Sensed Medium

- Markov Random Fields:

$X=(X_1, X_2, \dots, X_N)$  is a MRF wrt graph  $(N,E)$  if

$$P(\underline{x}) \propto \prod_{i \in N} \phi_i(x_i) \prod_{(i,j) \in E} \mu_{i,j}(x_i, x_j)$$

$\phi_i(x_i)$  Self potential

$\mu_{i,j}(x_i, x_j)$  Pair potential

Models in image processing, coding, statistical mechanics,...

- Example:

$$X_i \in \{H_1, H_2, \dots, H_M\}$$

$$\phi_i(H_m) = P(Y_i = y_i | H_m)$$

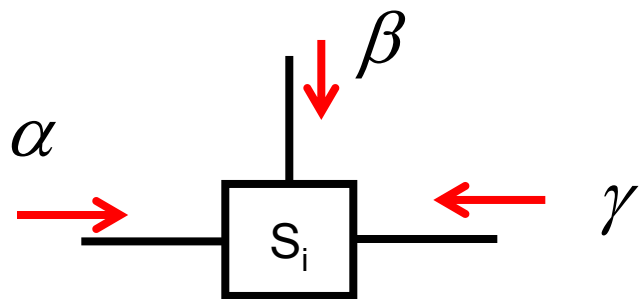
$$\mu_{i,j}(H_i, H_j) = 1 \{H_i = H_j\}$$

$$P(\underline{x}) \propto \prod_i P(Y_i = y_i | H_m)$$

If  $x_1 = \dots = x_N = H_m$

## 2. Local Message Passing

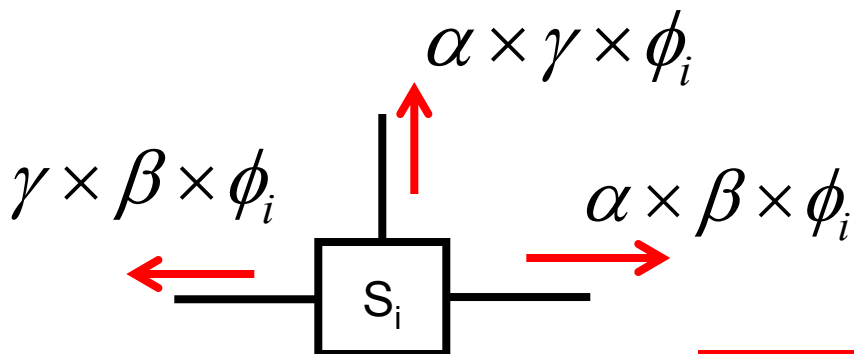
- Belief propagation (Pearl 1988)
- Example continued: Pearl's sum-product algorithm



“Belief” of sensor  $i$ :

$$\pi_i(H_m) \propto \alpha \times \beta \times \gamma \times \phi_i(H_m)$$

If network topology is a tree, then eventually



$$\pi_i(H_m) \propto \prod_j P(Y_j = y_j | H_m)$$

Cond. Independent observations:  
ML estimate =  $\arg \max_m \pi_i(H_m)$

# Robustness: Loopy Graphs

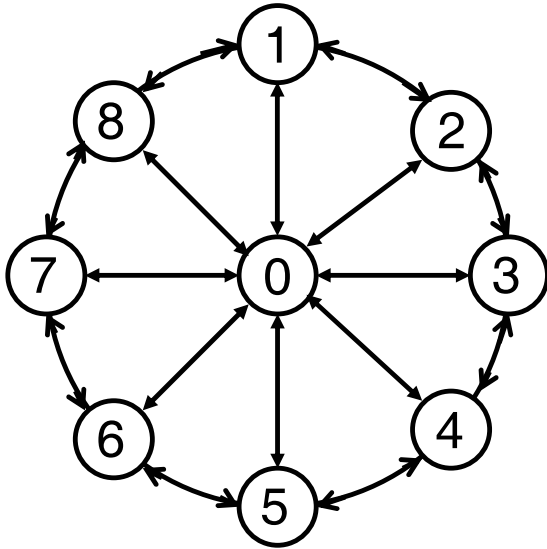
$$\pi_i(H_m) \rightarrow 0 \Leftrightarrow m \notin \arg \max_{\hat{m}} \prod_j P(Y_j = y_j | H_{\hat{m}})^{\lambda(j)}$$

- $\lambda(j)$  depends on how well-connected sensor  $j$  is.
- If  $\lambda(j) = \text{constant}$  and  $m^*$  is the unique ML estimate, then

$$\pi_i(H_{m^*}) \rightarrow 1$$

- Final configuration is a consensus: All sensors share the same belief.

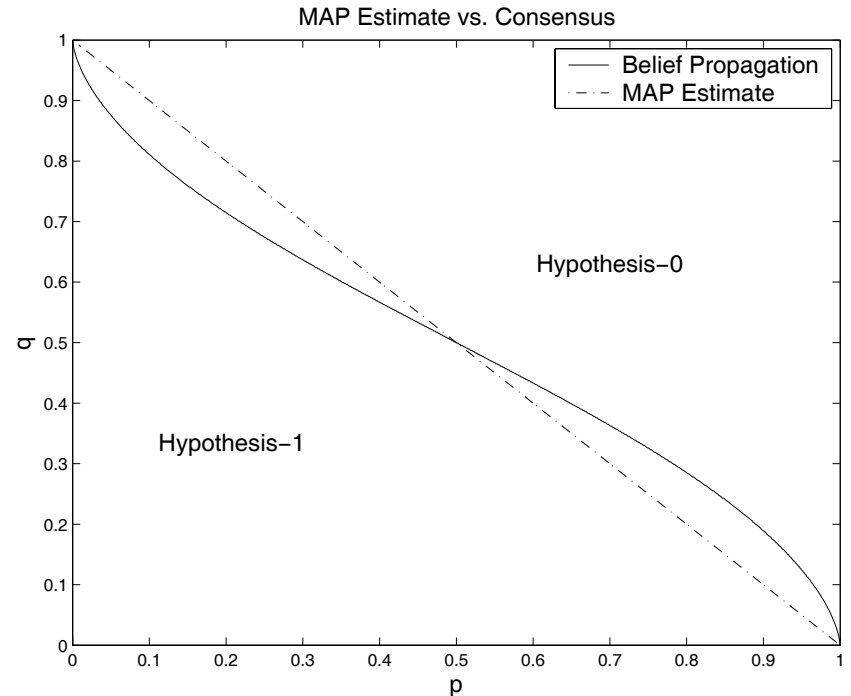
# Example: Star topology



$$\frac{\lambda(0)}{\lambda(1)} = 1.5091$$

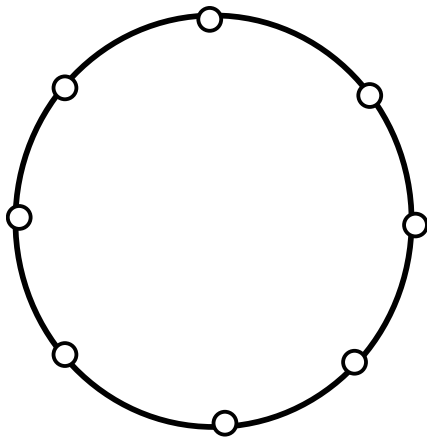
Initial Beliefs

	$H_0$	$H_1$
$S_0$	$q$	$1-q$
$S_1$	$p$	$1-p$
$S_2-S_8$	$0.5$	$0.5$

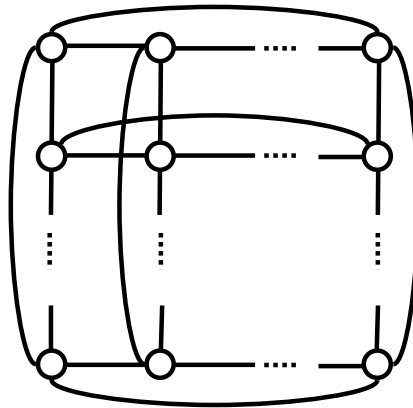


# Balanced Topologies

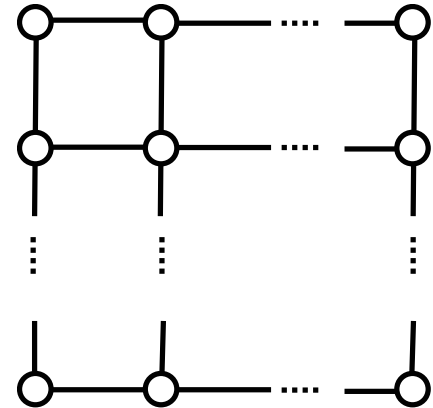
Ring



Torus



Grid

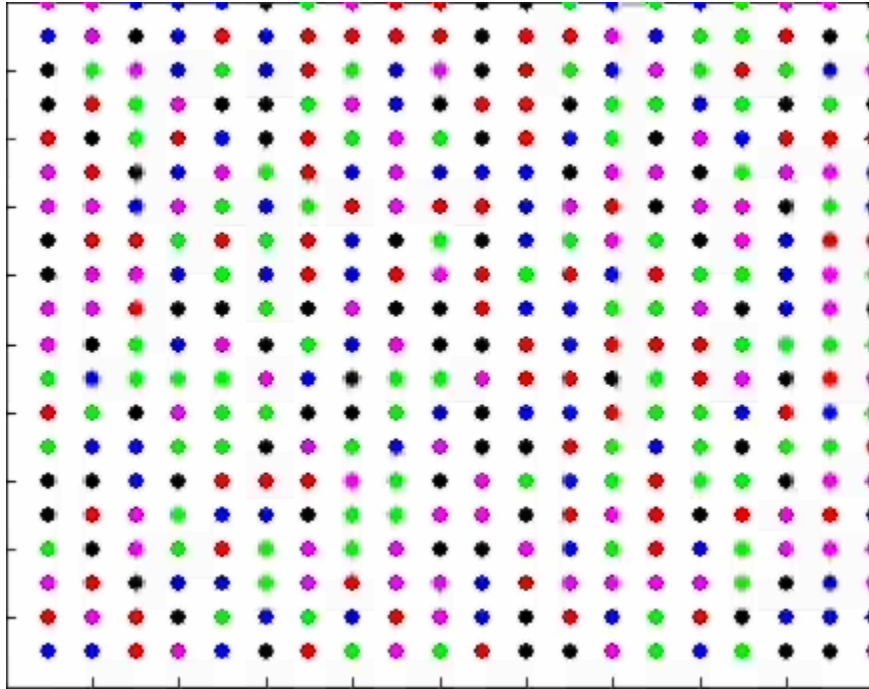


Regular Graphs:

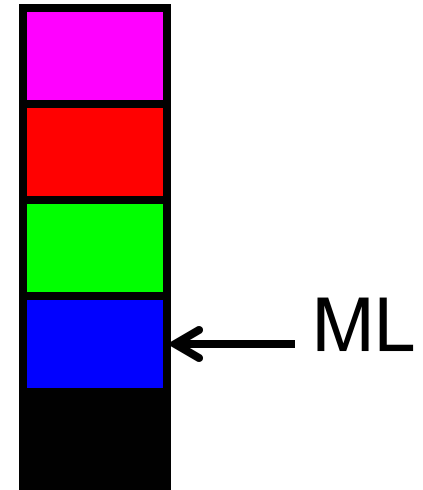
$$\frac{\lambda(i)}{\lambda(j)} = 1 \text{ for all nodes}$$

$$\frac{\lambda(i)}{\lambda(j)} \approx 1 \text{ for most nodes}$$

# Example: 20x20 Grid



5 Hypotheses



Most likely hypothesis by sensor

# Summary

- In-network inference via local messages
- Network-wide consensus that reflects centralized solution
- Ongoing work: continuous parameter estimation & tracking
- Energy efficiency and sensor actuation strategies
- Testbed: BU Sargent Camp test field for ecological applications