# Sensor Management For Estimation in Wireless Sensor Networks

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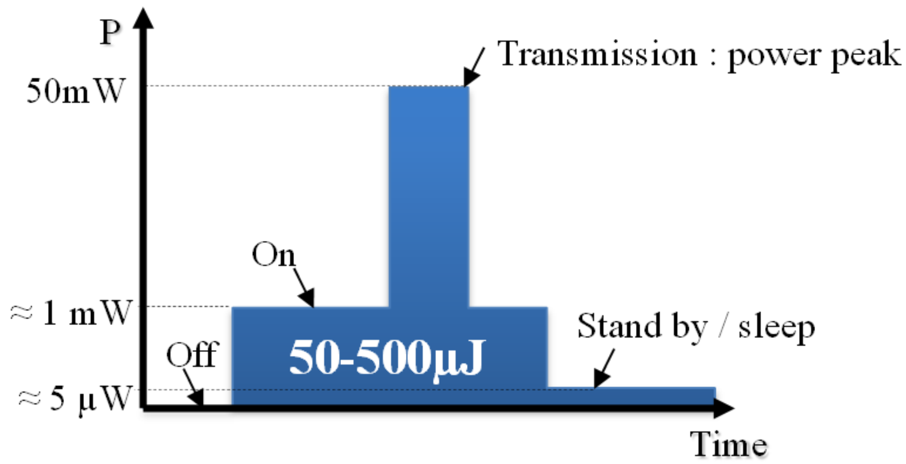
# OUTLINE

- Introduction
  - Sensor management: Motivation and problem formulation
  - State of the art
- Sensor management approaches
  - Sensor management in WSNs
    - Multi-objective optimization (MOP) based sensor management for target tracking with uncertainty
  - Sensor management in crowdsourcing based WSNs
    - Cloud sensing enabled target localization
- Concluding remarks

# Sensor Management in WSNs

- Power consumption profile of sensor nodes

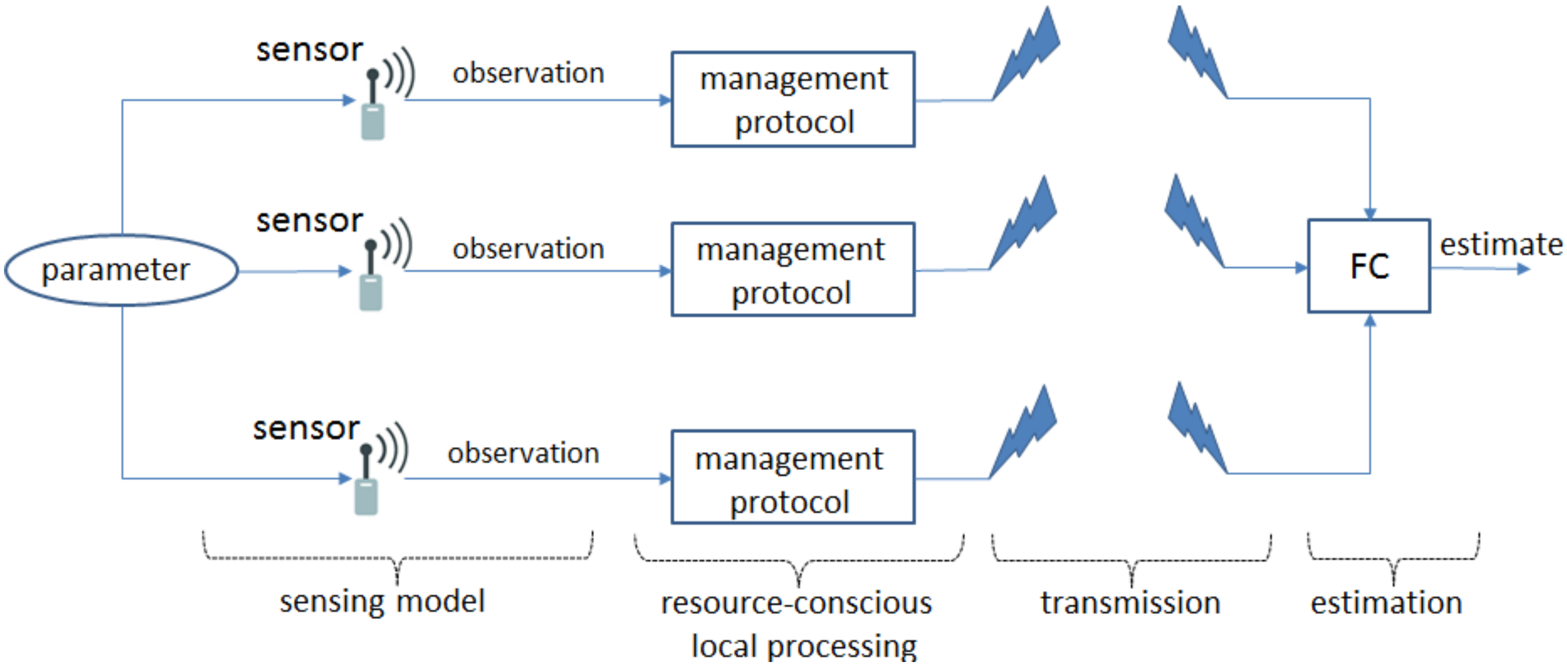



- Limited resources (energy, bandwidth, etc.)
- Proper management
  - Energy: conserve to prolong lifetime of the WSN
  - Bandwidth: more efficient transmission



http://www.intechopen.com/books/small-scale-energy-harvesting/electrostatic-conversion-for-vibration-energy-harvesting

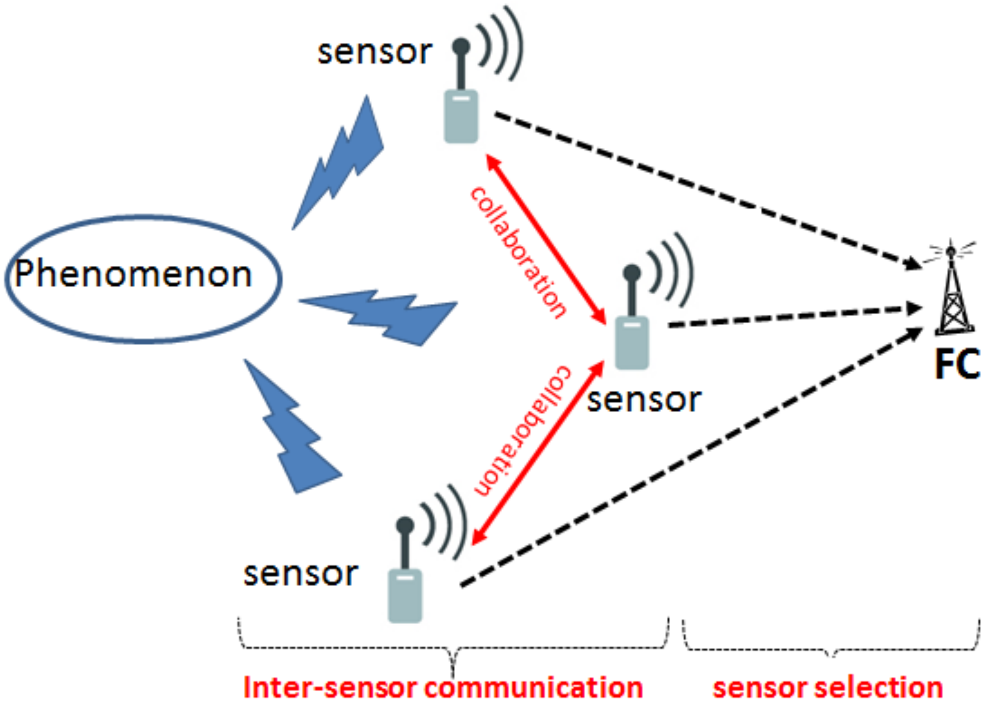
# Sensor Management for Estimation in WSNs




- **Sensor networks for estimation:** Environment/health monitoring, target localization and tracking
- **Limited network resources:** Sensor battery power, communication bandwidth, storage and computing capacity
- **Resource management:** Optimal sensor selection/scheduling, optimal inter-sensor collaboration

# Sensor Management for Estimation in WSNs

- **Resource management:** Optimal sensor selection/scheduling, optimal inter-sensor collaboration
  a) **Sensor selection/scheduling:** Find optimal tradeoff between estimation accuracy and sensor activations over space and/or time
  b) **Sensor collaboration:** Find optimal inter-sensor communication topology and power allocation scheme



# SENSOR SELECTION

- **Sensor selection (myopic/one-time ahead):** Select optimal subset of sensors in space to minimize estimation error (or other performance measure) subject to energy constraints (or other constraints)
- **Example:** sensor selection for field estimation

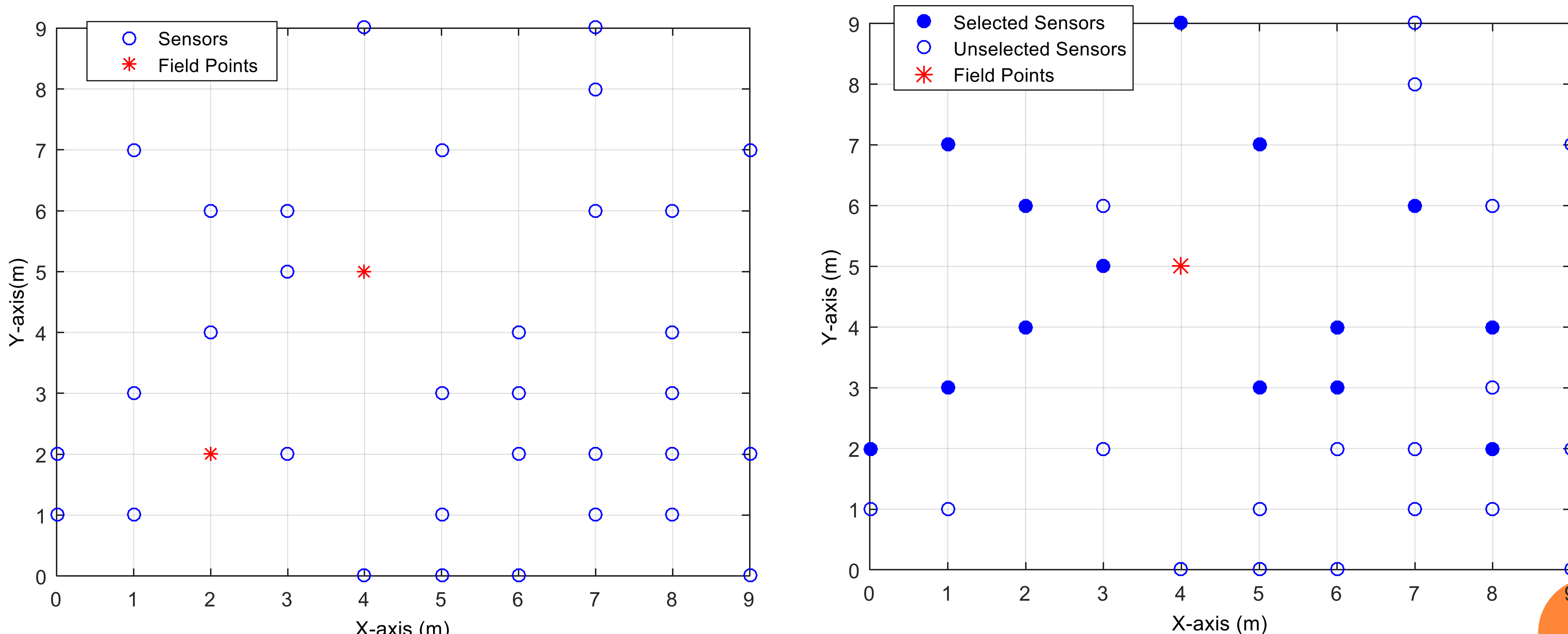



Figure: sensor network for field estimation (left); 14 selected sensors (right)

# Sensor Scheduling

- **Sensor scheduling (multiple-time ahead/non-myopic):** Seek optimal sensor schedules in *both space and time*
- For example, sensor scheduling for target tracking

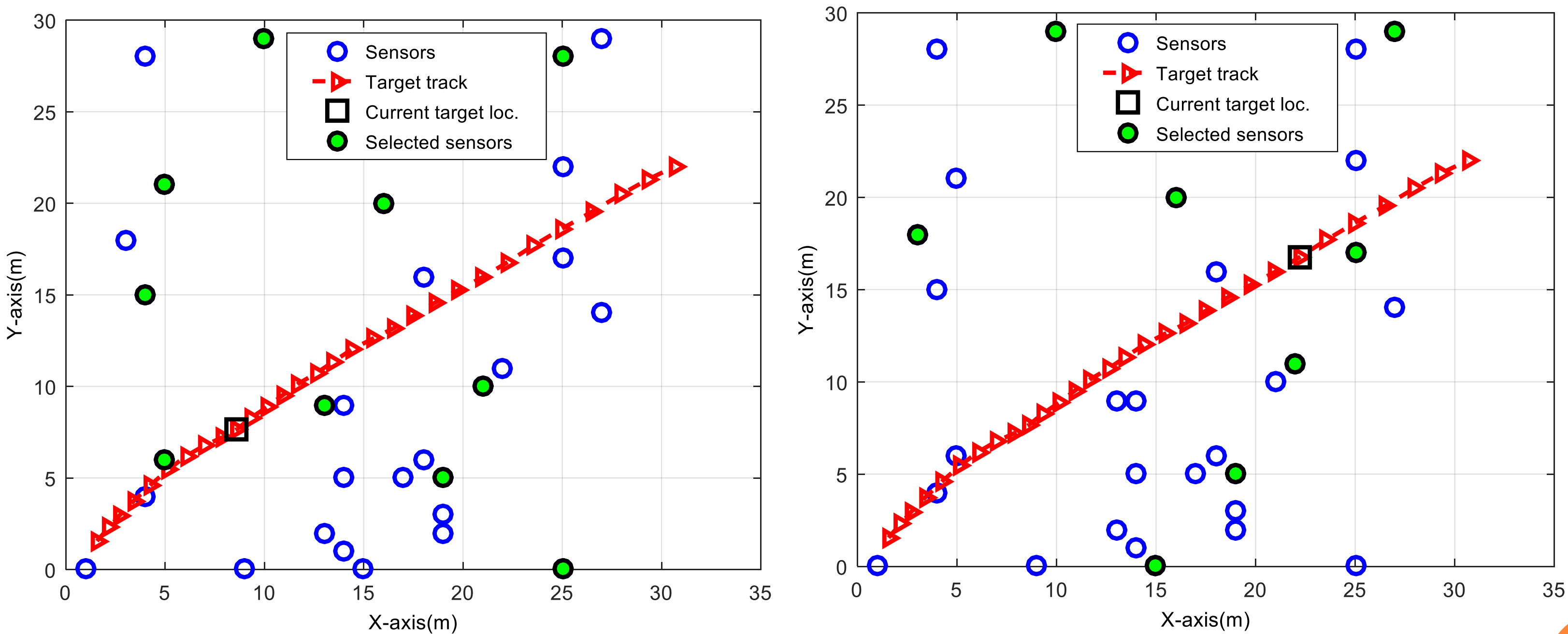



Figure: sensor schedule at t = 10 (left); sensor schedule at t = 24 (right)

# State of the art: Sensor Selection/Scheduling

- **Sensor selection/scheduling:** several *variations* of the problems have been addressed according to types of *measurement models*, *cost/utility functions*, *energy and topology constraints*, *and length of time horizon (one-time ahead, finite time, infinite time)*

# State of the art: Sensor Selection

- **Sensor selection for different types of measurement models:**
  a) **Linear measurement model (commonly studied):** *closed form* of estimation distortion (namely, mean squared error) w.r.t. sensor selection variables [JoshiBoyd'09] (and many others)

  b) **Non-linear measurement model**: *No closed form* of estimation distortion w.r.t. selection variables; *alternative performance* measure of sensor selection: entropy, mutual information, Fisher information (inverse of Cramér-Rao lower bound on estimation error) [JWFisher'03, WangEstrin'04, ZuoPKV'07, ShenLiuPKV'14, ChepuriLeus'15]

  c) **Quantized measurement:** *No closed form* of estimation distortion w.r.t. selection variables; alternative performance measure used while incorporating the effect of quantization [ZuoPKV'08, MasazadePKV'10]

# State of the art: Sensor Selection

- **Sensor selection Under Noise/Signal correlation:**
  a) **Uncorrelated measurement noise (commonly studied):** observations are *conditionally independent* given the underlying parameter; each sensor contributes to Fisher information in an *additive* manner [JoshiBoyd'09, ChepuriLeus'15] (and many others)

  b) **Weakly correlated measurement noise:** noise covariance matrix has small off-diagonal entries; assumption of weak noise correlation facilitates problem formulation and has computational merits [Jamali-Rad'14, ShenPKV'14]

  c) **Arbitrary noise correlation:** involved formulation but efficient solution has been found recently [LiuPKV'16]

# State of the art: Sensor Selection

- **Sensor selection for different cost/utility functions and constraints:**
  a) **Choice of cost/utility function relies on types of measurement models:**
     - Mean squared error: linear measurement model
     - Information measures including Shannon and Fisher: non-linear measurement model [Zhao'02, JWFisher'03]

  b) **Constraints on sensor selection:**
     - Number of selected sensors (commonly used)
     - Sensor Coverage: geographically distributed sensor nodes to ensure network-wide sensing coverage [Wang'11]
     - Energy harvesting constraints: sensors with energy harvester subject to causality constraints of power flow [LiuWangPKV'16, Calvo-Fullana'16]

# State of the art: Sensor Scheduling

a) **Sensor scheduling for linear dynamical systems (finite time horizon)**
- Scheduling continuous/discrete-time Kalman filters [MoSinopoli'11]
- Sensor scheduling via design of sparse Kalman filter gain matrices [MasazadePKV'12]
- Compressive sensing based probabilistic sensor scheduling for target tracking [CaoPKV'15]

b) **Sensor scheduling for non-linear dynamical systems (finite time horizon)**
- Recursive Fisher information or Posterior Cramér-Rao lower bound as surrogate performance measure for nonlinear systems [ZuoPKV'07, ShenPKV'14, ChepuriLeus'15]

# State of the art: Sensor Scheduling

**c) Sensor scheduling for linear dynamical systems (infinite time horizon)**

- Optimal sensor schedule for an infinite horizon problem can be approximated arbitrarily well by a periodic schedule with a finite period [Shi’11, Tomlin’12]
- Periodic switching policy using lower bound on the performance of scheduling sensors over an infinite time [Ny’11]
- Determine optimal periodic sensor schedules by designing optimal sparse Kalman filter gain matrices under periodicity conditions [LiuPKV’14]

## State of the art: Distributed Algorithms

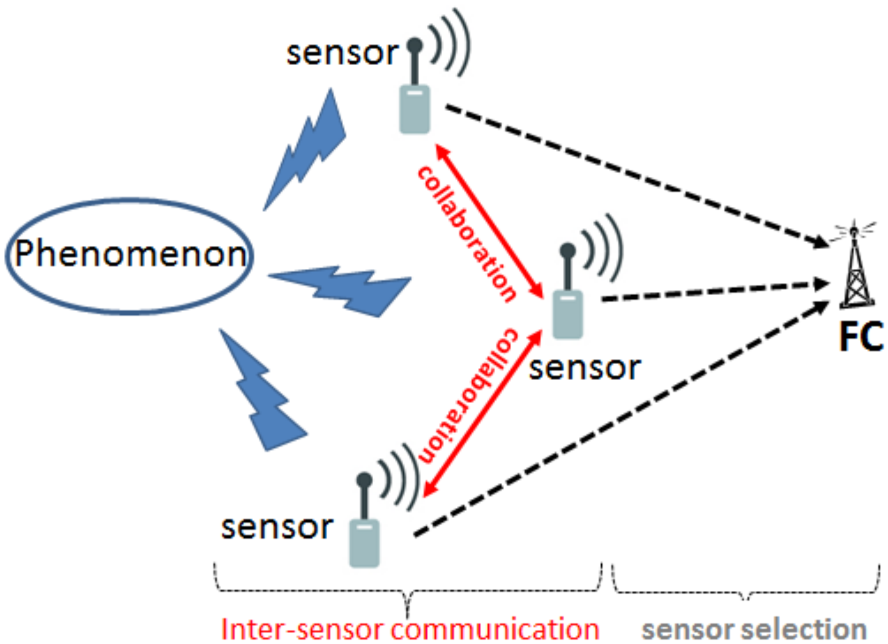
- **Distributed sensor selection:** In the absence of the fusion center, sensor selection is carried out in a distributed way and by the sensors themselves
- **Why is this important?** Robust to failure of FC, low communication burden between sensors and FC
- **Why is this difficult?** Each sensor has access only to the information in its neighborhood; Make a global decision based on local data & local communications

# State of the art: Distributed Algorithms

- Distributed algorithms
  - Greedy algorithm based on submodular utility function (with diminishing return property) [Krause'10]
  - Distributed sensor selection for parameter estimation under linear Gaussian model with weakly correlated measurement noise [Jamali-Rad'15]
  - Distributed sensor selection for estimation of spatially-correlated random field [LiuHero'16]

# Sensor Collaboration

- **Sensor collaboration:** Determine optimal inter-sensor communication strategies (namely, collaboration links) in order to enhance the estimation performance under limited network resources



# STATE OF THE ART: SENSOR COLLABORATION

- **Approaches for sensor collaboration**
  - Power allocation for communication systems with *fully-connected* collaboration network[Fang'09, Fanaei'14]
  - Sensor selection and power allocation under *given network topologies: tree, branch, linear* [Mitra'06, Mitra'08]
  - Linear coherent estimation with spatial collaboration under *arbitrary known network topologies* [KarPKV'13]
  - Sensor collaboration with *unknown* network topologies: jointly optimize sensor-to-sensor (collaboration) and sensor-to-FC (selection) schemes [LiuPKV'15]
  - Sensor collaboration in the presence of temporal dynamics: determine inter-sensor communication strategy while tracking a random process rather than estimating a static parameter [KarPKV'12, LiuPKV'16]

# CROWDSOURCING BASED WSNS

Almost everyone has devices with built-in sensors

Crowdsourcing

# CROWDSOURCING BASED WSNS

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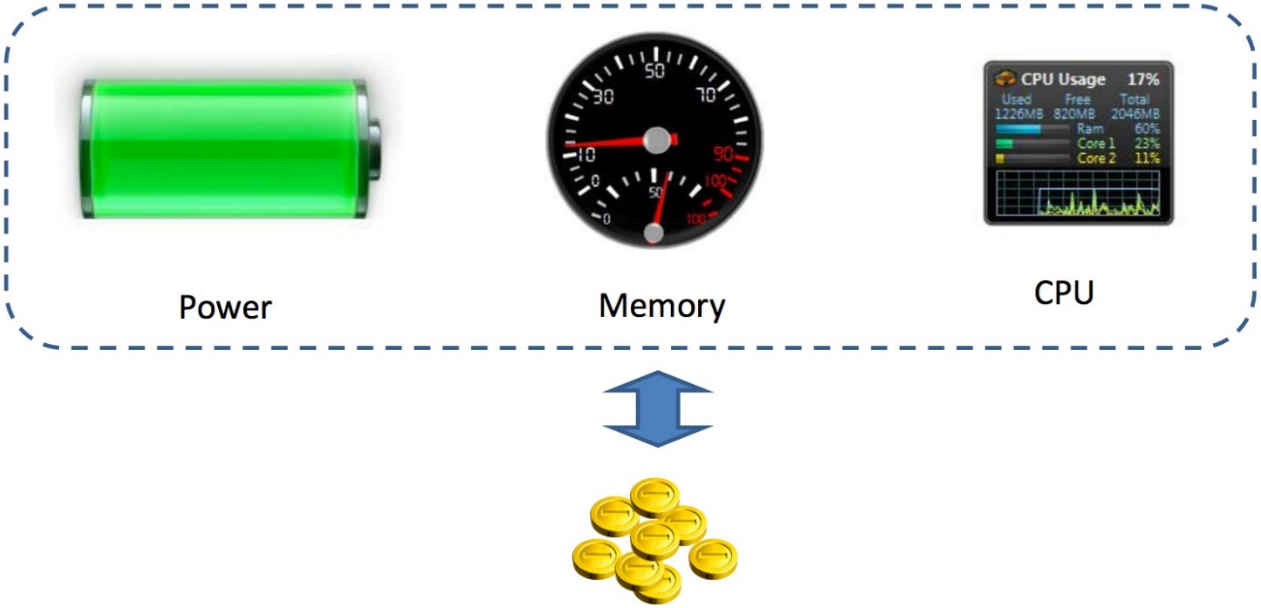


The users may not participate in sensing and inference tasks unless suitable incentives are provided to them.

**Sensor management**

http://optimization.asu.edu/papers/XUE-CNF-2012-MOBICOM-MPSensing-Slides.pdf

# State of the art: Crowdsourcing based WSNs

Sensor management in crowdsourcing based WSNs

- Concept [Mullen'06]
- Walrasian equilibrium based sensor management [Chavali, Nehorai'12],[Masazade, Varshney'13]
- Auction design for resource management [Yang'16], [Chen'16]

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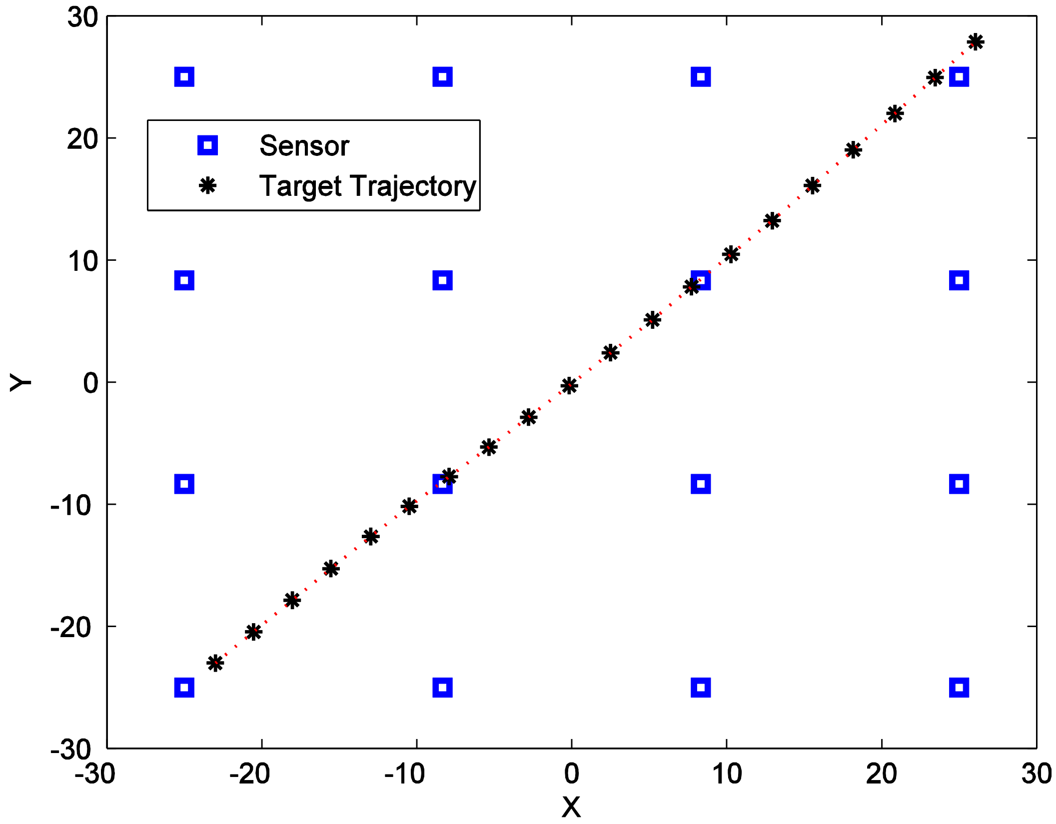
# Target Tracking in Wireless Sensor Networks



# Target Tracking
## Target Dynamics

- Target motion dynamics: $\mathbf{x}_{t+1} = \mathbf{F}\mathbf{x}_t + \underbrace{w_t}_{\text{i.i.d Gaussian noise}}$

$$\mathbf{x}_t = [\underbrace{x_t \;\; y_t}_{\text{Target location}} \;\; \underbrace{\dot{x}_t \;\; \dot{y}_t}_{\text{Target velocity}}]^T$$

- Isotropic power attenuation model of target:

$$P_{i,t}(\mathbf{x}_t) = \frac{P_0}{1 + \alpha d_{i,t}^n}$$

$P_0$ → Power at distance 0

$d_{i,t}$ → Distance between target and sensor $i$

- Signal amplitude received by sensor $i$ at time step $t$: $h_{i,t}(\mathbf{x}_t) = \sqrt{P_{i,t}(\mathbf{x}_t)}$

# Target Tracking
## Sensor Measurements

- **Uncertainty** in wireless sensor networks
  - Random interruptions in the channel
  - Sensor failures
  - Jamming or interference
  - Obstacles
- Unreliable analog sensor measurements

$$z_{i,t} = \begin{cases} h_{i,t}(\mathbf{x}_t) + v_{i,t}, & \text{with probability } p_s^{(i)} \\ v_{i,t}, & \text{with probability } 1 - p_s^{(i)} \end{cases}$$

- Probabilistic model:

$$p(z_{i,t}|\mathbf{x}_t) = p_s^{(i)}\, \mathcal{N}(h_{i,t}(\mathbf{x}_t), \sigma^2) + (1 - p_s^{(i)})\, \mathcal{N}(0, \sigma^2)$$

# Target Tracking
## Sensor Measurements

- Quantized sensor measurements:

$$D_{i,t} = \begin{cases} 0 & -\infty < z_{i,t} < \eta_1 \\ 1 & \eta_1 < z_{i,t} < \eta_2 \\ \vdots & \\ L-1 & \eta_{(L-1)} < z_{i,t} < \infty \end{cases}$$

- Probabilistic model

$$\begin{aligned} p(D_{i,t} = l|\mathbf{x}_t) &= \Pr(\eta_l \leq z_{i,t} \leq \eta_{l+1}|\mathbf{x}_t) \\ &= p_s^{(i)} \ \Pr(\eta_l \leq z_{i,t} \leq \eta_{l+1}|z_{i,t} \sim \mathcal{N}(h_{i,t}(\mathbf{x}_t), \sigma^2)) \\ &\quad + (1 - p_s^{(i)}) \ \Pr(\eta_l \leq z_{i,t} \leq \eta_{l+1}|z_{i,t} \sim \mathcal{N}(0, \sigma^2)) \end{aligned}$$

# Target Tracking Filter

- Estimation of the target location is based on the posterior probability density function (pdf)

- Recursive filter for estimation:
  - Predict the target location with posterior pdf
  - Update the estimate using the sensor measurements

# Particle Filtering

- Particle filter: $f(\mathbf{x}_t|\mathbf{D}_{1:t}) \approx \sum_{s=1}^{N_s} w_t^s \delta(\mathbf{x}_t - \mathbf{x}_t^s)$

$$w_{t+1}^s \propto f(\mathbf{D}_{t+1}|\mathbf{x}_{t+1}^s) \text{ (Updating weights)}$$

$$w_{t+1}^s = \frac{w_{t+1}^s}{\sum_{s=1}^{N_s} w_{t+1}^s} \text{ (Normalizing weights)}$$

$$\hat{\mathbf{x}}_{t+1} = \sum_{s=1}^{N_s} w_{t+1}^s \mathbf{x}_{t+1}^s$$

$$\{\mathbf{x}_{t+1}^s, N_s^{-1}\} = \text{Resampling}(\mathbf{x}_{t+1}^s, w_{t+1}^s)$$

# Sensor Management

- Weights in particle filtering are updated through measurements from selected sensors

- Sensor management criteria: estimation lower bound, Fisher information, mutual information…

# Fisher Information

- Cramer-Rao lower bound (CRLB): lower bound for estimation performance

- Fisher information (FI): inverse of CRLB

$$E\left\{[\hat{\mathbf{x}}_t - \mathbf{x}_t][\hat{\mathbf{x}}_t - \mathbf{x}_t]^T\right\} \geq J_t^{-1}$$

$$\begin{aligned}\mathbf{J}_t &= E[-\Delta_{\mathbf{x}_t}^{\mathbf{x}_t} \log p(\mathbf{D}_t, \mathbf{x}_t)] \\ &= E[-\Delta_{\mathbf{x}_t}^{\mathbf{x}_t} \log p(\mathbf{D}_t|\mathbf{x}_t)] + E[-\Delta_{\mathbf{x}_t}^{\mathbf{x}_t} \log p(\mathbf{x}_t)] \\ &= \mathbf{J}_t^D + \mathbf{J}_t^P\end{aligned}$$

  - FI for analog sensor measurement model
  - FI for quantized sensor measurement model

# Mutual Information

- Mutual information (MI) for analog sensor measurement model

$$I(\mathbf{z}_t;\mathbf{x}_t) = H(\mathbf{z}_t) - H(\mathbf{z}_t|\mathbf{x}_t)$$

- Mutual information for quantized sensor measurement model

$$I(\mathbf{D}_t;\mathbf{x}_t) = H(\mathbf{D}_t) - H(\mathbf{D}_t|\mathbf{x}_t)$$

- Mutual information upper bound (MIUB)

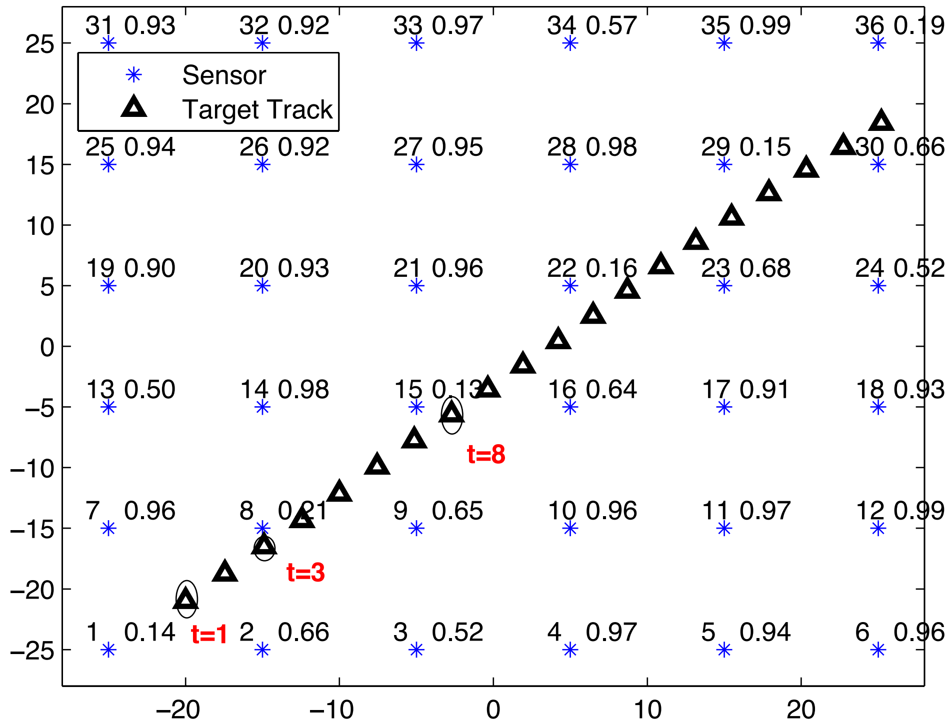
$$I(\mathbf{z}_t;\mathbf{x}_t) = \sum_{i=1}^{N} \boxed{I(z_{i,t};\mathbf{x}_t|z_{i-1,t},\cdots,z_{1,t})}$$

$$\Downarrow$$

$$\leq I(z_{i,t};\mathbf{x}_t|z_{i-1,t},\cdots,z_{2,t})$$

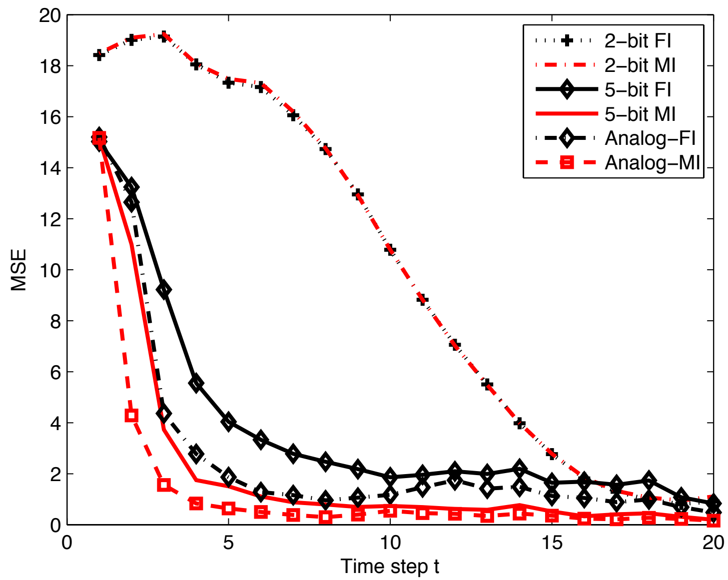
$$\leq I(z_{i,t};\mathbf{x}_t).$$

# Simulation: WSN

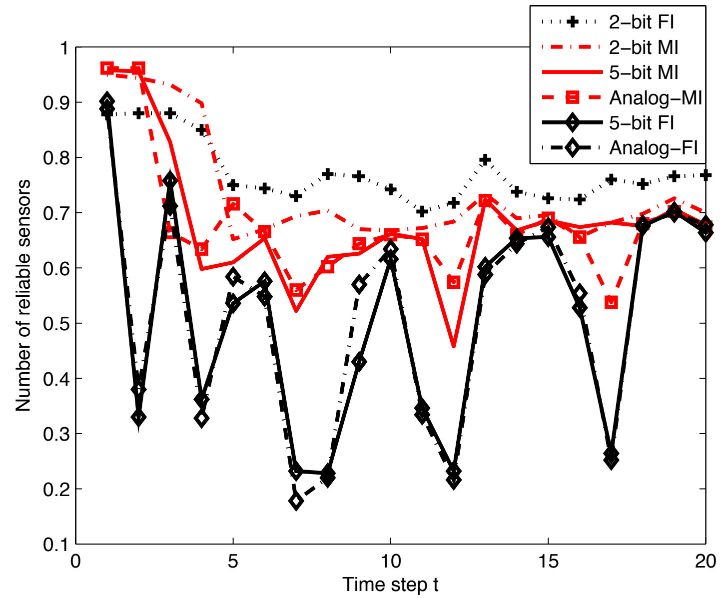


# SIMULATION: ANALOG DATA, 5-BIT QUANTIZED DATA, AND 2-BIT QUANTIZED DATA

Target tracking performance with analog data, 5-bit quantized data, and 2-bit quantized data, (a) MSE performance;
(b) average percentage of reliable sensors selected.




(a)



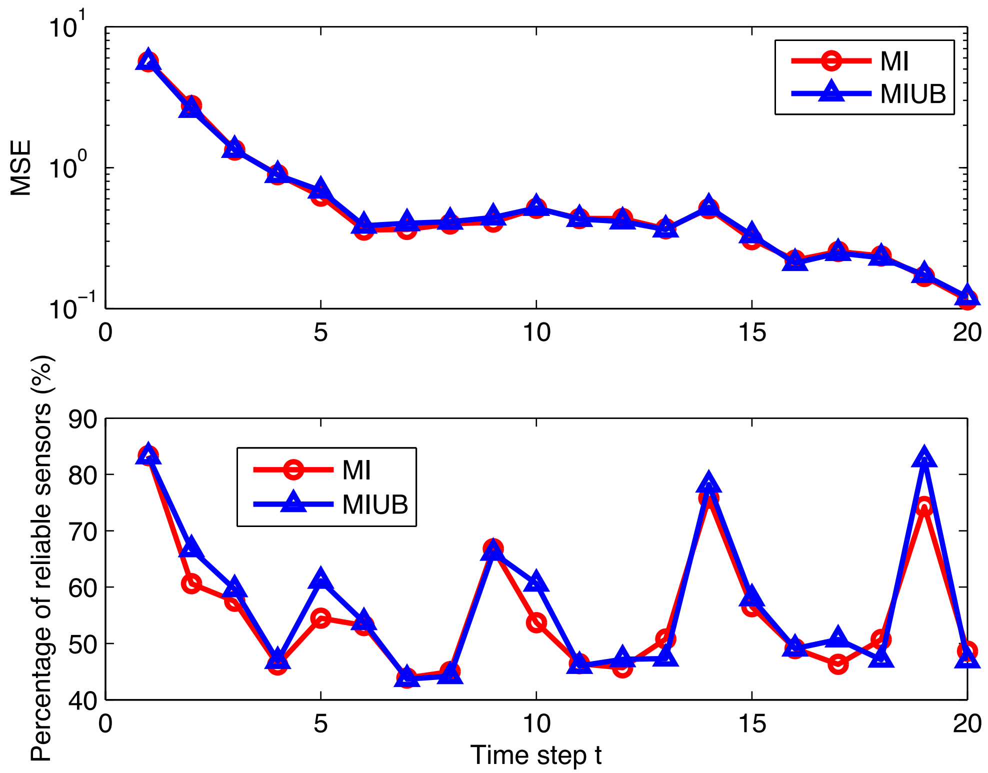

(b)



MI selects more reliable sensors – better MSE

# SIMULATION: MI AND MIUB

Target tracking performance for MI and MIUB, $A=2$.



# MOP based Sensor Management

- Number of sensors to be selected not predetermined

- **Multiple** objectives:

| | |
|---|---|
| Lifetime (max) | Energy costs (min) |
| Detection capability (max) | Communication costs (min) |
| Information gain (max) | Deployment costs (min) |
| Estimation error (min) | |

Conflicting

# MOP based Sensor Management

- Sensor management in existing literature:
  - Maximize information gain (or minimize error metric), subject to a constraint on the number of sensors

$$\underset{\boldsymbol{\alpha}}{\text{maximize}} \quad \log\det\left(\sum_{i=1}^{N} \alpha_{i,t}\mathbf{J}_{i,t}^{D} + \mathbf{J}_{t}^{P}\right)$$

$$\text{subject to} \quad \sum_{i=1}^{N} \alpha_{i,t} \leq A$$

Selection state of sensor $i$ at time step $t$

- MOP based sensor management
  - Determines the **optimal** sensor set (the number of sensors and which sensors)
  - Saves **resources**: use more or less sensors as needed

# MOP based Sensor Management
## Objective functions

- FI based objective function

$$f_1(\boldsymbol{\alpha}_t) = \frac{\log\det\left(\sum_{i=1}^{N} J_{i,t}^{D} + J_t^{P}\right) - \log\det\left(\sum_{i=1}^{N} \alpha_{i,t} J_{i,t}^{D} + J_t^{P}\right)}{\log\det\left(\sum_{i=1}^{N} J_{i,t}^{D} + J_t^{P}\right)}$$

- MIUB based objective function

$$f_1(\boldsymbol{\alpha}_t) = \frac{\sum_{i=1}^{N} I^{(i)} - \sum_{i=1}^{N} \alpha_{i,t} I^{(i)}}{\sum_{i=1}^{N} I^{(i)}}$$

Information gap between all sensors and selected sensors

- Sensor cardinality based objective function

$$f_2(\boldsymbol{\alpha}_t) = \frac{1}{N}\sum_{i=1}^{N} \alpha_{i,t}$$

# Multiobjective Optimization Problem (MOP)

- $n$ objective optimization problem:

$$\min_{\boldsymbol{\alpha}} \quad \{\mathrm{f}_1(\boldsymbol{\alpha}), \mathrm{f}_2(\boldsymbol{\alpha}), \ldots, \mathrm{f}_n(\boldsymbol{\alpha})\}$$

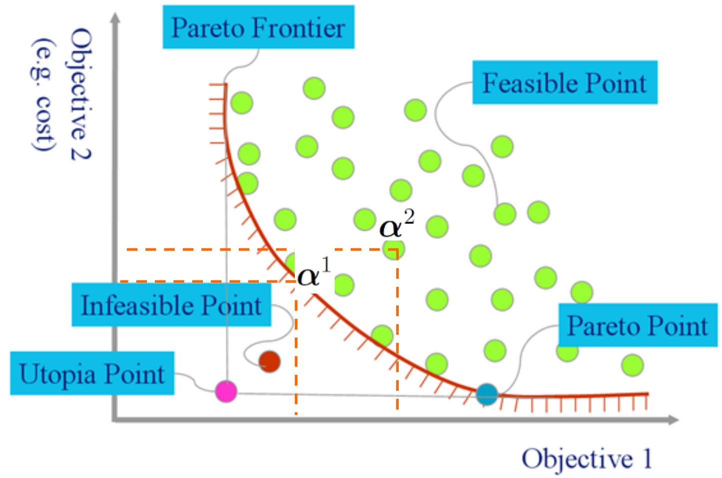
$$\text{subject to} \quad a \le \alpha_i \le b, \mathrm{h}(\boldsymbol{\alpha}) = 0, \mathrm{g}(\boldsymbol{\alpha}) \le 0$$

- Feasible solutions: those that satisfy constraints
- Solution $\boldsymbol{\alpha}^1$ dominates $\boldsymbol{\alpha}^2$ ($\boldsymbol{\alpha}^1 \succ \boldsymbol{\alpha}^2$) if and only if

$$\mathrm{f}_u(\boldsymbol{\alpha}^1) \le \mathrm{f}_u(\boldsymbol{\alpha}^2) \quad \forall u \in \{1, 2, \ldots n\}$$

$$\mathrm{f}_v(\boldsymbol{\alpha}^1) < \mathrm{f}_v(\boldsymbol{\alpha}^2) \quad \exists v \in \{1, 2, \ldots n\}$$

- $\boldsymbol{\alpha}^*$ is called a Pareto optimal solution if and only if there is no $\boldsymbol{\alpha}$ that dominates $\boldsymbol{\alpha}^*$

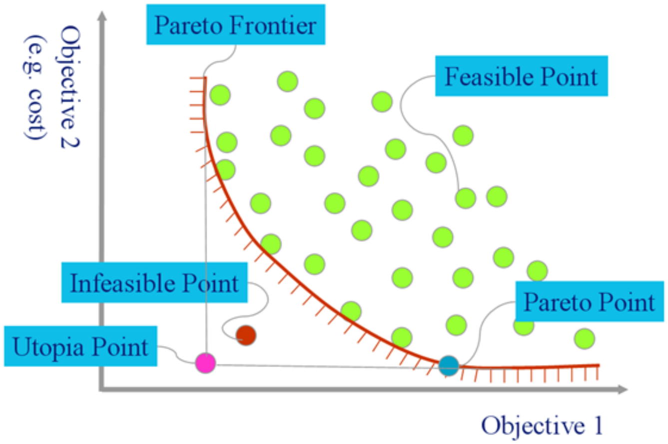



- Utopia point: at which all objectives are minimized

1. http://www.noesissolutions.com/Noesis/sites/default/files/Pareto_Front.png

# Solving MOP

- Weighted sum: $w_1 \mathrm{f}_1(\boldsymbol{\alpha}_t) + (1 - w_1)\mathrm{f}_2(\boldsymbol{\alpha}_t)$
  - Uniform spread of Pareto solutions not guaranteed
  - Reduce design alternatives [1]
- Nondominating sorting genetic algorithm-II (NSGA-II)[2]
  - Sort individuals according to level of nondomination
  - Store nondominated solutions
  - Guarantee diversity



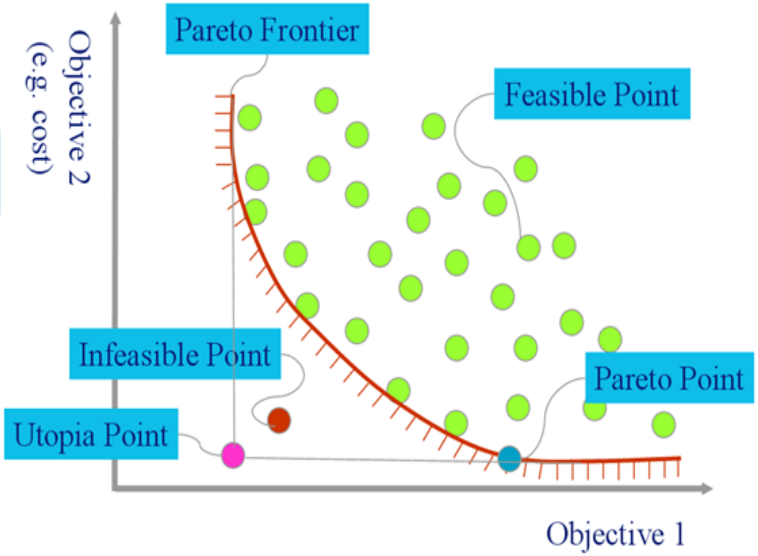

1. R. T. Marler et al., 2004
2. K. Deb et al., 2002

# Solution Selection

- Knee point solution
  - Small sacrifice in one objective results in a large gain in another

$$\boldsymbol{\alpha}_t = \arg \max_{\boldsymbol{\alpha}^2,\ldots,\boldsymbol{\alpha}^P} \text{slope}\{\boldsymbol{\alpha}^\rho\}$$

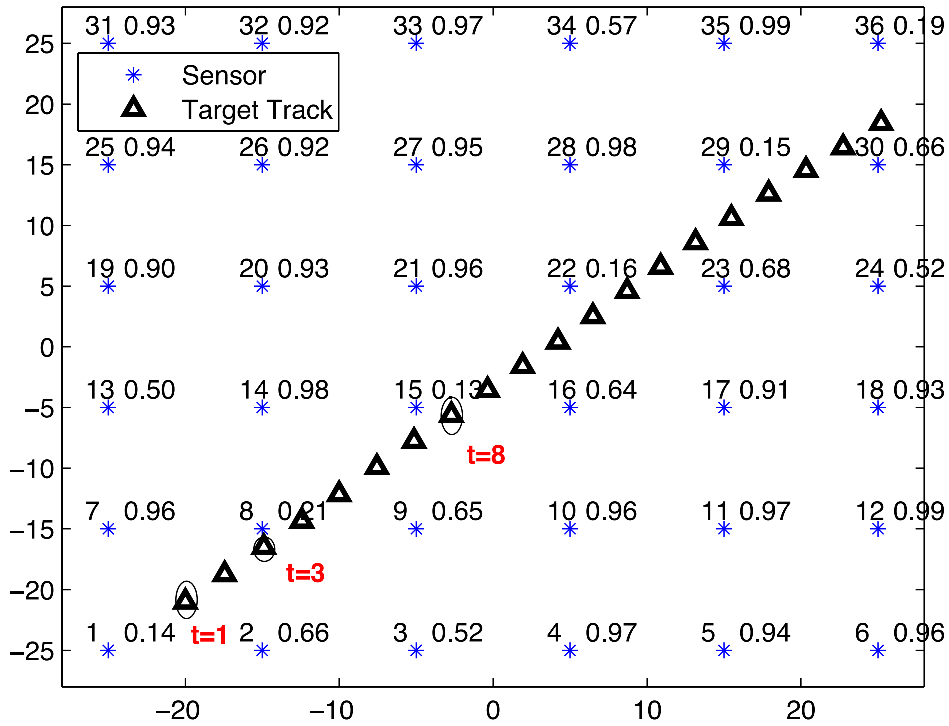
$$\text{slope}\{\boldsymbol{\alpha}^b\} = 180 - \left[\arctan\left(\frac{\mathrm{f}_1(\boldsymbol{\alpha}^a) - \mathrm{f}_1(\boldsymbol{\alpha}^b)}{\mathrm{f}_2(\boldsymbol{\alpha}^a) - \mathrm{f}_2(\boldsymbol{\alpha}^b)}\right)\frac{180}{\pi}\right]$$




- Compromise solution (CS)
  - Closest to Utopia point

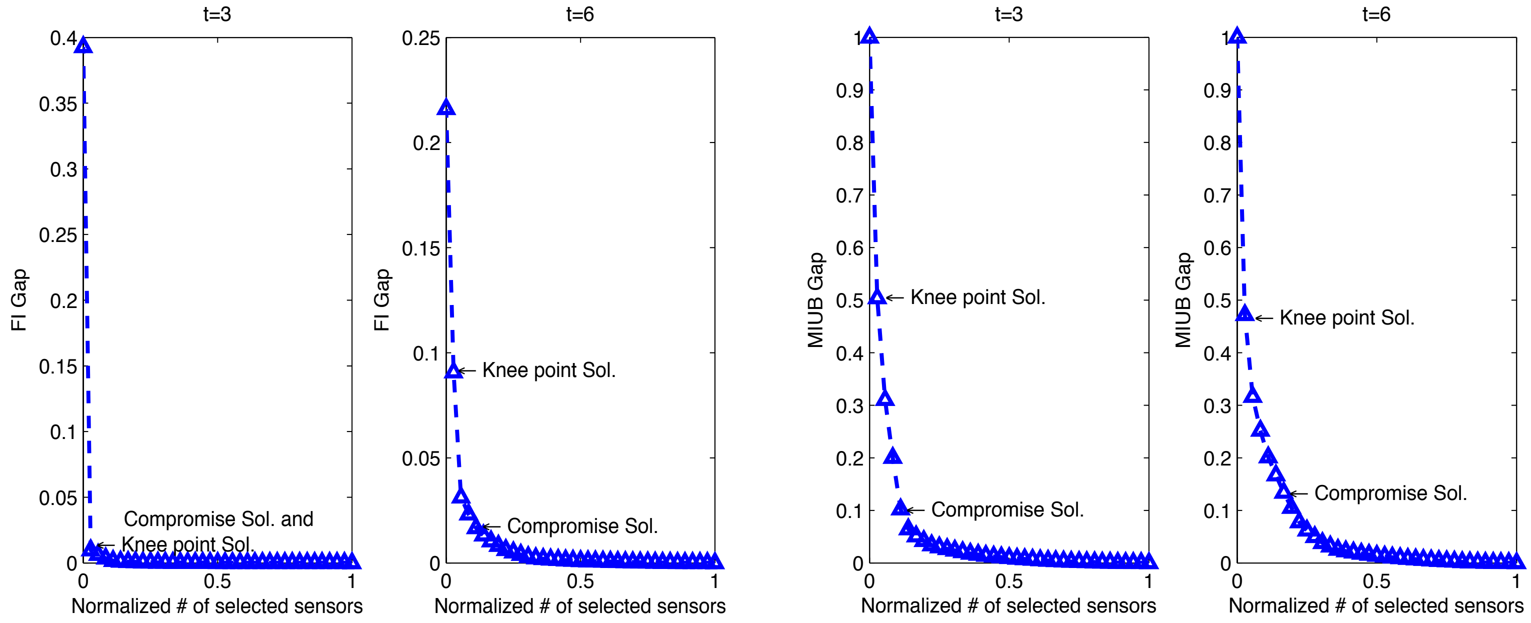
$$\boldsymbol{\alpha}_t = \arg \min_{\boldsymbol{\alpha}^1,\ldots,\boldsymbol{\alpha}^P} \sqrt{\sum_{j=1}^{n} \left(\mathrm{f}_j^* - \mathrm{f}_j(\boldsymbol{\alpha}^\rho)\right)^2}$$

# Simulation: WSN



# SIMULATION: PARETO FRONT

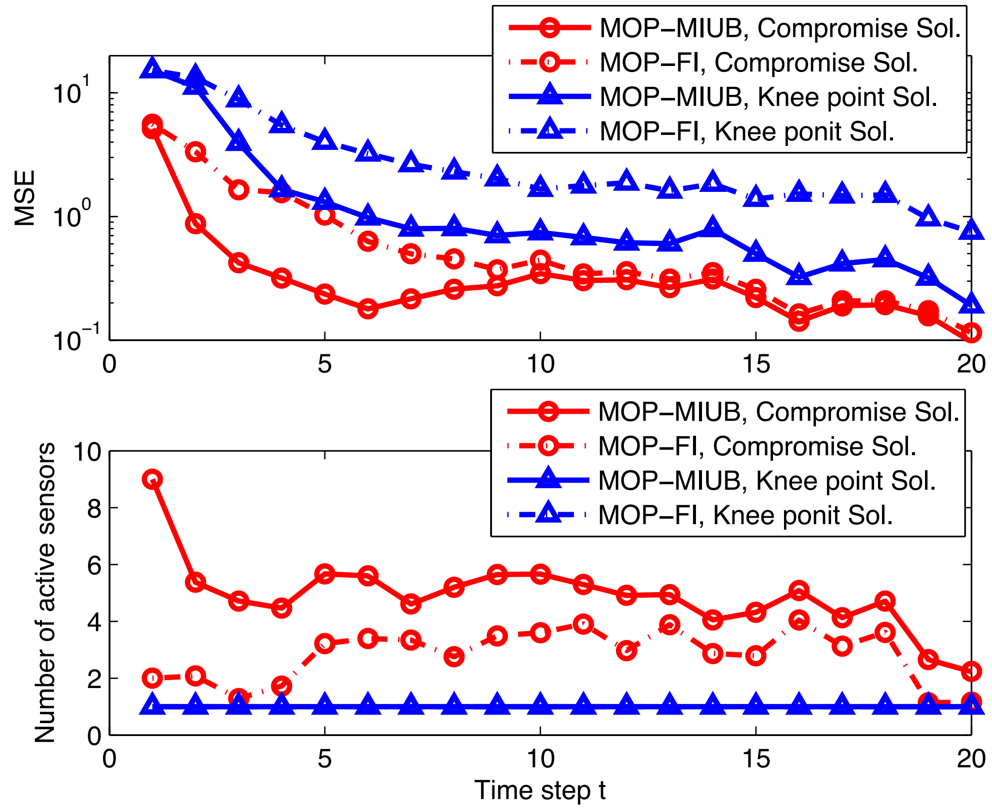
Pareto optimal front obtained by using NSGA-II at time step t=3 and t=6, (a) FI; (b) MIUB




(a) (b)

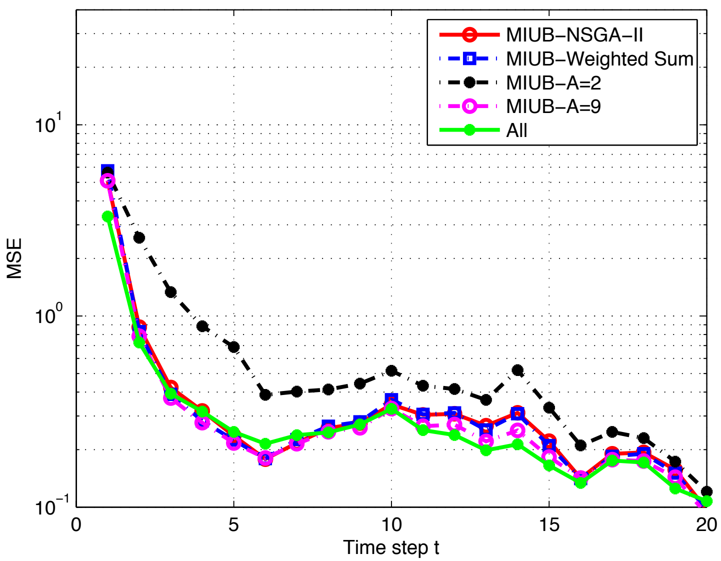
# Simulation: Solution Selection

Tracking performance at each time step with different solution selection methods.

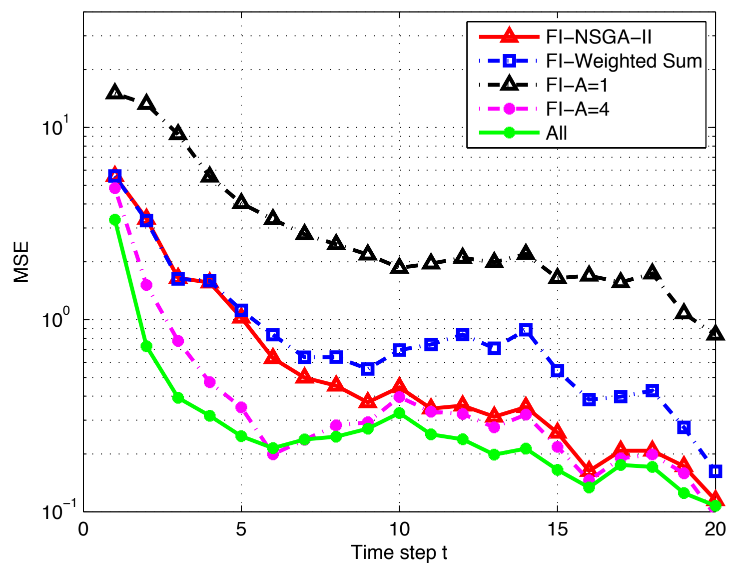


# SIMULATION: NSGA-II, CVX, WS

Tracking performance for MOP with NSGA-II, convex relaxation, and weighted sum methods (a) MSE for MIUB; (b) MSE for FI.




(a)




(b)

WS rarely produces a uniform spread of points on the Pareto front with a uniform spread of weights

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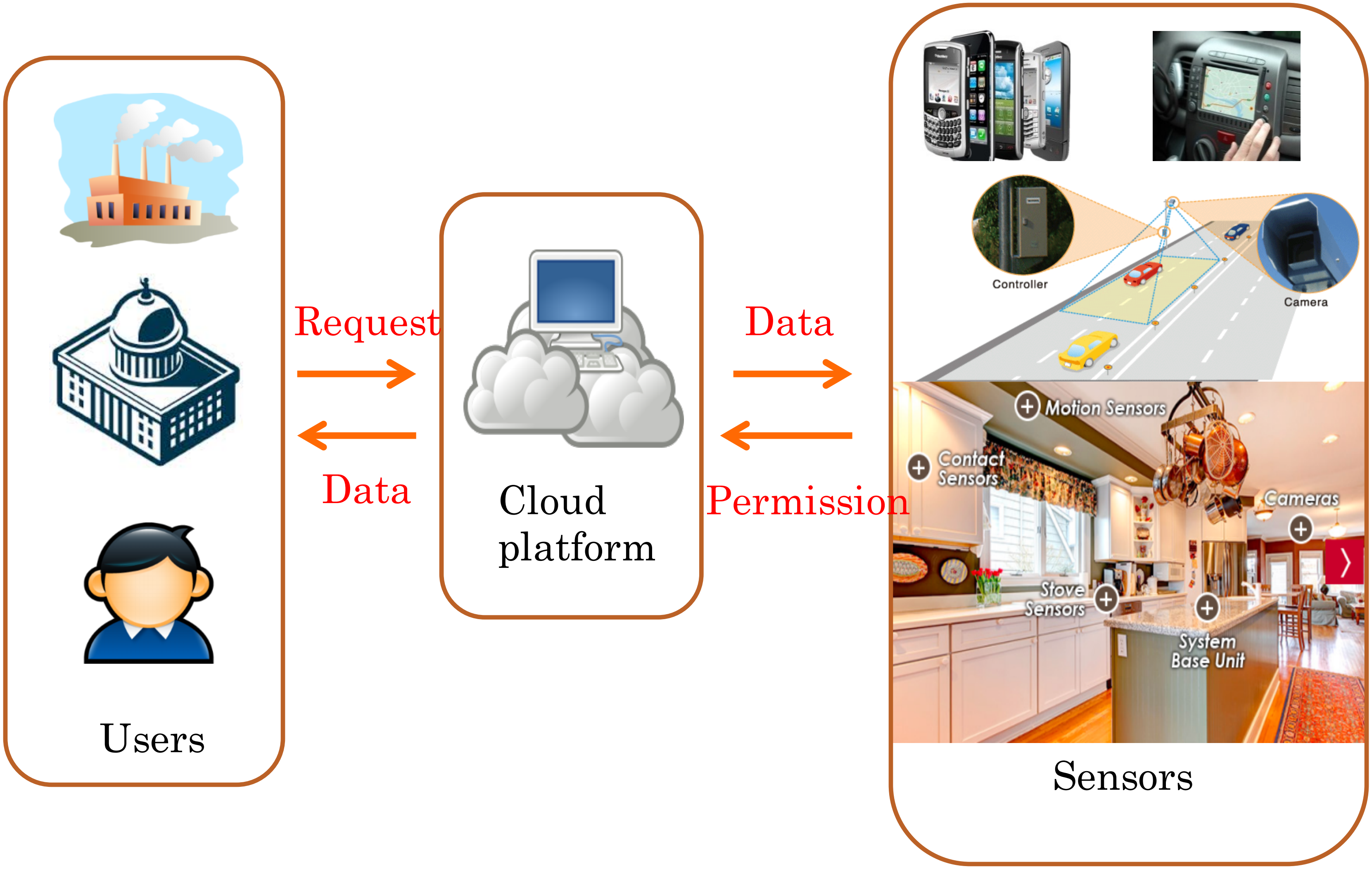
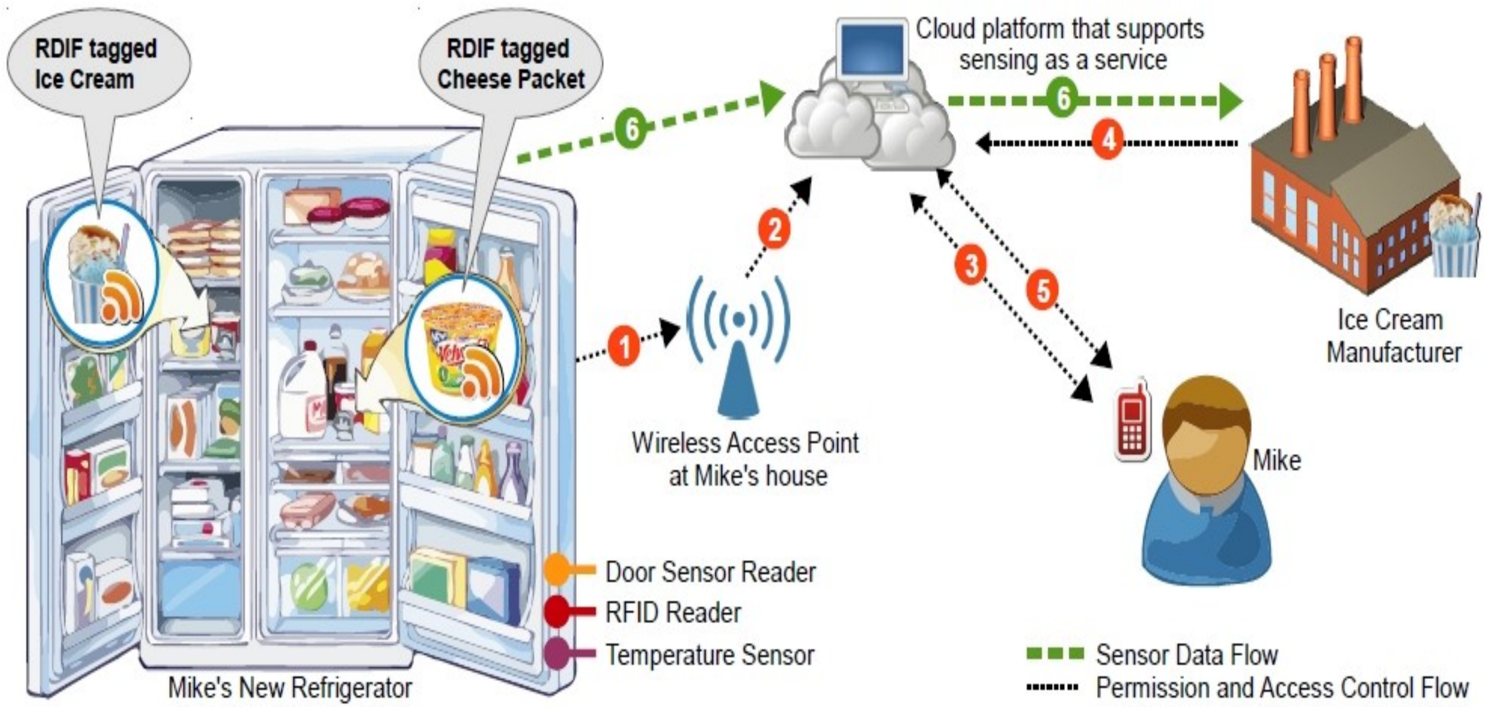
# Cloud Sensing



# A Few Cloud Sensing Examples

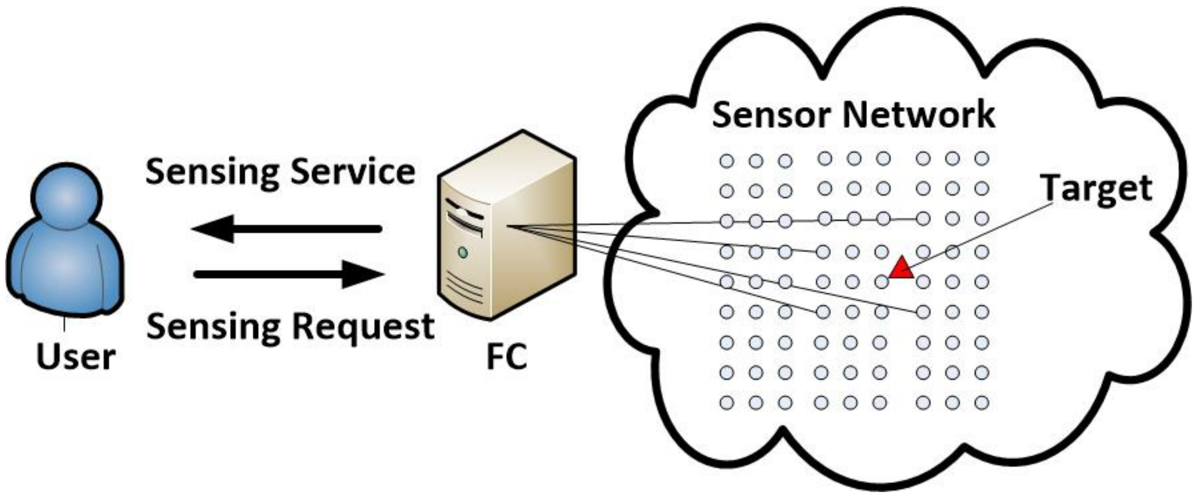
- Find lost/stolen items
- Spectrum Sensing in Cognitive Radio nets.
- Customer need assessment using embedded sensors
- Smart Cities

# Cloud Sensing Example




Perera, Charith, et al. "Sensing as a service model for smart cities supported by internet of things". *Transactions on Emerging Telecommunications Technologies* 25.1 (2014): 81-93.

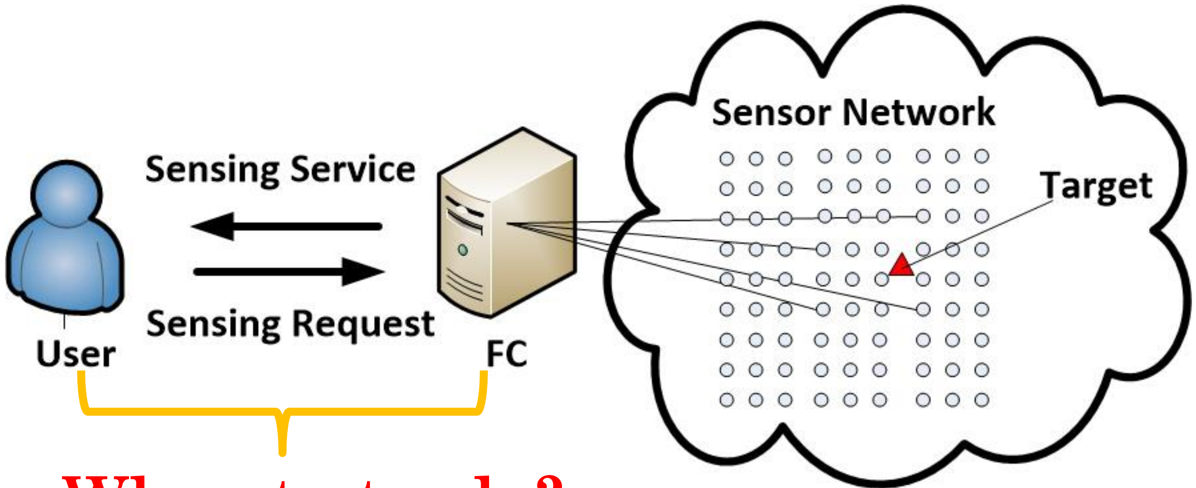
# Bilateral Mechanism Framework




**FC**: provides the service of finding the target in the WSN
**User**: wants to find the target by paying the FC for the service

**Problem encompasses Signal Processing and Economics.**

# BILATERAL MECHANISM FRAMEWORK




**When to trade?**

**How much to pay?**

**How to define the utilities?**

**How to manage the sensors in the WSN?**

# Mechanism Design Factors

i. Individual rationality (IR)
   - Non-negative utilities.
   - Guarantees the participation of the users.

ii. Incentive compatibility (IC)
   - Utility of telling truth $\geq$ Utility of lying.
   - Ensures honest reporting.

# Mechanism Design Factors

iii. Ex post efficiency

- Buyer gets the service whenever his/her total gain is greater than the cost of service provisioning.
- Seller does not provide the service whenever the cost of service provisioning is greater than the buyer's gain.

# Mechanism Design Factors

- Maximize the social welfare – the total expected utilities of the FC and the user
  - Need to define utility functions
- Investigate the IR, IC and ex post efficiency properties of the mechanism
  - Need to define IR, IC and ex post efficiency
- Formulate the optimization problem

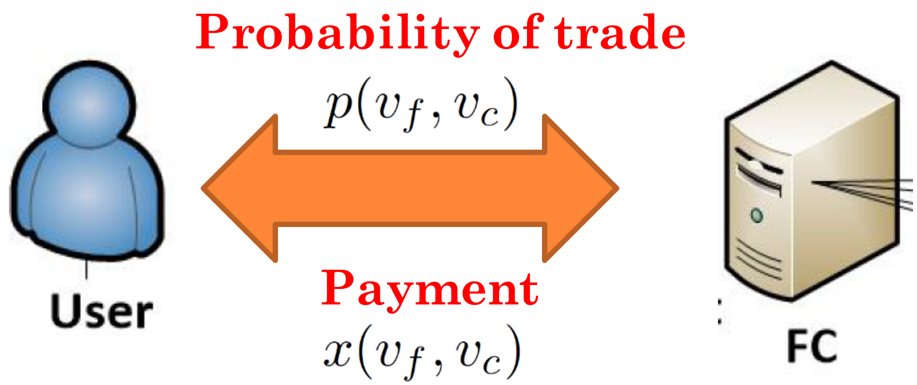
# Utility Definition

*Sensor selection state*

$\mathbf{z} = [z_1, z_2, \ldots, z_N]$

*Cost* $C(\mathbf{z})$

*Gain* $G(\mathbf{z})$




**Private valuations** $v_c$ (Per unit gain) $\qquad v_f$ (Per unit cost)

$$v_c \sim f_c : [a_c, b_c] \to \mathbf{R}_+ \qquad v_f \sim f_f : [a_f, b_f] \to \mathbf{R}_+$$

---

**Expected utility**

$U_c(v_c)$

$$\bar{p}_c(v_c)\,\underbrace{[v_c G(\mathbf{z})]}_{\text{Value of gain}} - \underbrace{\bar{x}_c(v_c)}_{\text{Payment}}$$

$U_f(v_f)$

$$\underbrace{\bar{x}_f(v_f)}_{\text{Payment}} - \bar{p}_f(v_f)\,\underbrace{[v_f C(\mathbf{z})]}_{\text{Value of cost}}$$

# DEFINITION OF IR AND IC

**IR condition**

**User:** $U_c(v_c) \geq 0$

**FC:** $U_f(v_f) \geq 0$

**IC condition**

**User:** $\underbrace{U_c(v_c)}_{\text{Utility if honest}} \geq \overbrace{\bar{p}_c(w_c)\left[v_c \underbrace{G(\mathbf{z})}_{\text{Gain}}\right] - \bar{x}_c(w_c)}^{\text{Utility if lying}}$

**FC:** $\overbrace{U_f(v_f)}^{\text{Utility if honest}} \geq \underbrace{\bar{x}_f(w_f) - \bar{p}_f(w_f)\left[v_f \overbrace{C(\mathbf{z})}^{\text{Cost}}\right]}_{\text{Utility if lying}}$

| | | |
|---|---|---|
| **Private valuation** | **User:** $v_c$ | **FC:** $v_f$ |
| **Untruthful valuation** | **User:** $w_c$ | **FC:** $w_f$ |
| **Utility** | **User:** $U_c(v_c)$ | **FC:** $U_f(v_f)$ |

# Definition of Ex Post Efficiency

- For an ex post efficient bilateral mechanism, the trading probability is

$$p(v_f, v_c) = \begin{cases} 1 & \text{if } \overbrace{v_f C(\mathbf{z})}^{\text{FC's valuation of cost}} < v_c G(\mathbf{z}) \\ 0 & \text{if } v_f C(\mathbf{z}) > \underbrace{v_c G(\mathbf{z})}_{\text{User's valuation of gain}} \end{cases}$$

**Private valuation** **User:** $v_c \in [a_c, b_c]$ **FC:** $v_f \in [a_f, b_f]$

# Optimization Problem

**Total social welfare**

$$\begin{aligned} \text{maximize} \quad & \underbrace{\int_{a_f}^{b_f} U_f(v_f) f_f(v_f) dv_f + \int_{a_c}^{b_c} U_c(v_c) f_c(v_c) dv_c}_{\text{Total social welfare}} \\ \text{subject to} \quad & U_f(b_f) + U_c(a_c) \geq 0 \\ & \bar{p}_f \text{ is decreasing, } \bar{p}_c \text{ is increasing} \end{aligned}$$

**IR and IC**

**Objective**

Impossibility of ex post efficiency has been proved

$p(v_f, v_c)$ $\quad$ $x(v_f, v_c)$

**Design trading probability and payment function using KKT conditions**

| | | |
|---|---|---|
| **Private valuation** | **User:** $v_c \in [a_c, b_c]$ | **FC:** $v_f \in [a_f, b_f]$ |
| **Utility** | **User:** $U_c(v_c)$ | **FC:** $U_f(v_f)$ |

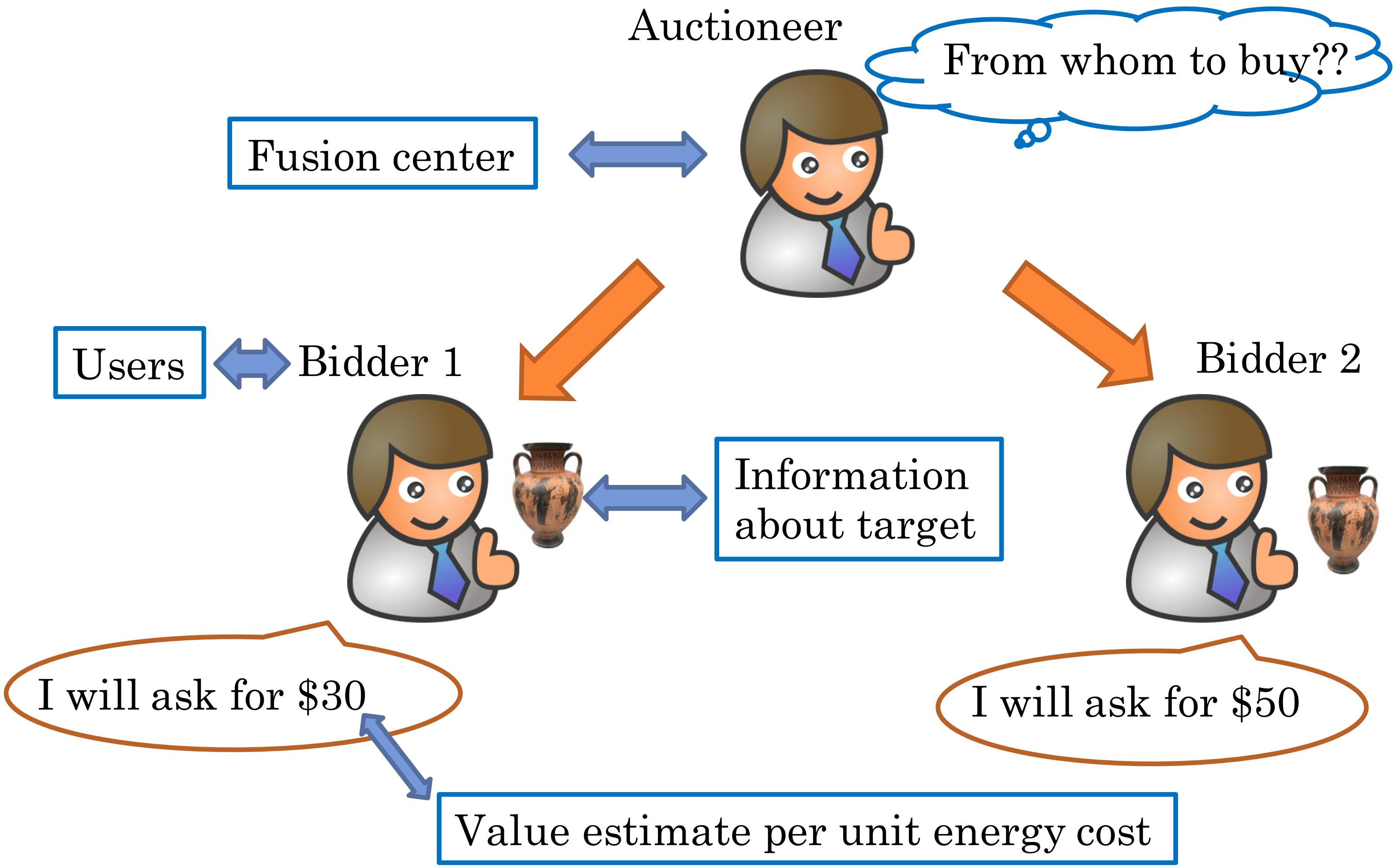
# OUTLINE

- Introduction
  - Sensor management: Motivation and problem formulation
  - State of the art
- Sensor management
  - Sensor management in WSNs
    - Multi-objective optimization (MOP) based sensor management for target tracking with uncertainty
  - Sensor management in crowdsourcing based WSNs
    - Cloud sensing enabled target localization
    - Optimal auction design for sensor management in target localization and tracking problems
- Concluding remarks

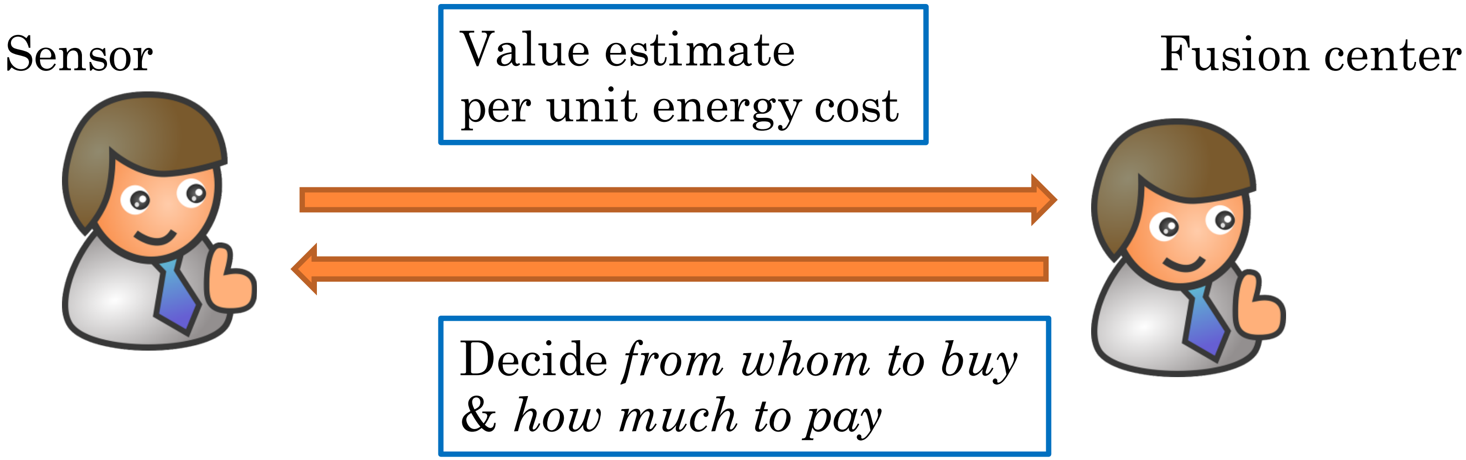
# Introduction

- Crowdsourcing
- Energy consumption – incentive is needed
- Fusion center designs optimal auction mechanism to buy data from users – gets the optimal solution of *from whom to buy data* and *how much to pay to the winning user*

# Introduction
## Reverse Auction



# INTRODUCTION
## REVERSE AUCTION

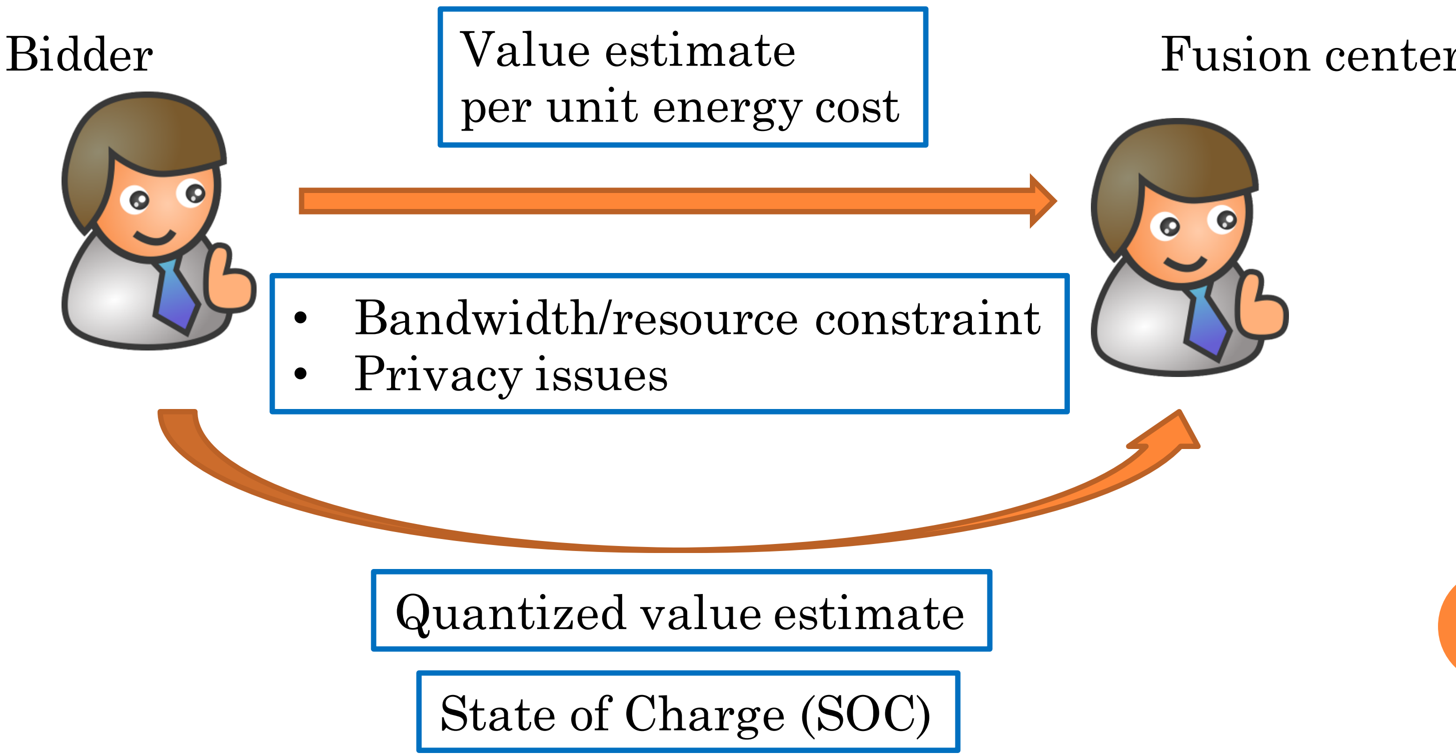


# MECHANISM DESIGN

- Optimization
  - Maximize expected utility of FC ⟺ Profit
  - Subject to IR, IC, and resource constraints
- Analyze the constraints
- Find an equivalent optimization problem
- Solve the optimization problem through dynamic programming method or convex optimization method

# AUCTION DESIGN WITH OTHER CONSIDERATIONS

- Sensors send quantized bids to the FC (Because of limited resources or privacy issues)



# Summary

- Overview of sensor management problems including state-of-the-art discussion
- Multi-objective optimization problem based sensor management
  - Dynamic sensor selection
- Optimal auction design for sensor management problems
  - Crowdsourcing
  - Optimization

# SUMMARY

- Open research problems
  - Joint distributed sensor management and parameter estimation
  - Non-parametric sensor selection based on online streaming data
  - Scalable methods for large-scale networks
  - Other inference problems: detection and classification
  - Graph signal processing problems such as topology design/inference for suitable objective functions
  - Privacy issues need to be considered in crowdsourcing based WSNs
  - Sensor management in fully autonomous sensor networks

Thank You!