



Scheduling Resource-Bounded Monitoring Devices

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Monitoring Cyber-Physical Systems

- * Being able to detect **faults** and **failures** before suffering substantial or irreversible physical damage is fundamental to the resilient operation of cyber-physical systems
- * In many spatially-distributed cyber-physical systems, faults and failures may only be detected by **monitoring devices** deployed over the system



Resource-Bounded Monitoring Devices

- * Using **battery-powered** devices can reduce deployment costs
 - * in some cases, battery power is the only feasible option
- * Battery-powered devices have limited lifetime
 - ↔ cyber-physical systems may require extended lifetime
- * **Sleep scheduling**
 - * only a subset of monitoring devices are active at any given time
 - * “sleeping” devices conserve battery power
 - * however, some events may not be detected
- * Finding an **optimal schedule** is challenging:
tradeoff between system lifetime and detection performance

Contributions

1. Monitoring networks
2. Simultaneous placement and scheduling
3. Minimizing detection delay

1. Monitoring Networks

- * Many spatially-distributed cyber-physical systems can be naturally modeled as **networks**
 - * water, wastewater, gas, and oil pipelines
 - * electric networks
- * Physical topology and device capabilities determine the **set of failures** a monitoring device can detect
- **Optimal sleep schedule** must take the physical topology of the system into account



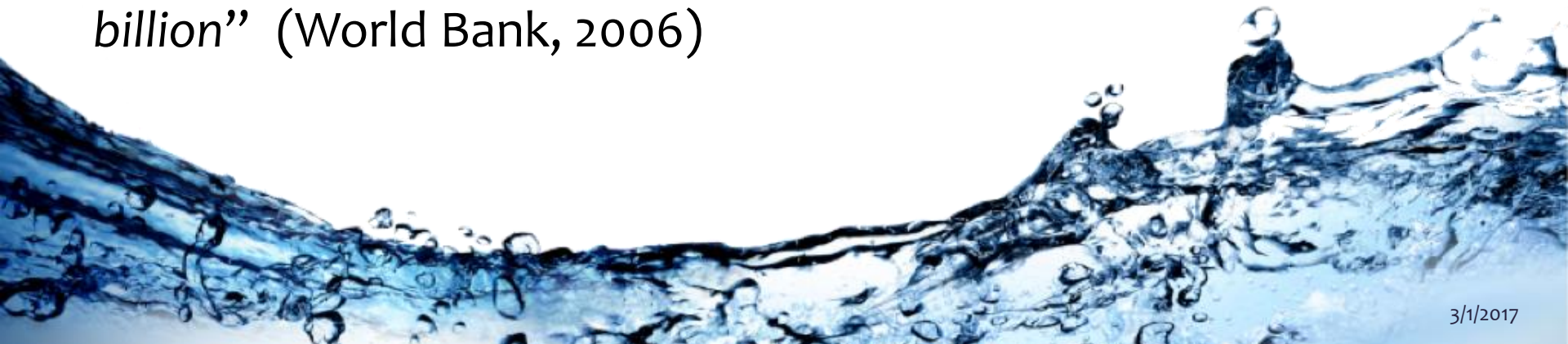
Wastewater pipeline network
of Norfolk, VA

Example Application: Water-Distributions Networks

- * Leakages in water-distribution networks can cause
 - * significant economic losses
 - * extra costs for final consumers
 - * third-party damage and health risks
 - * ...

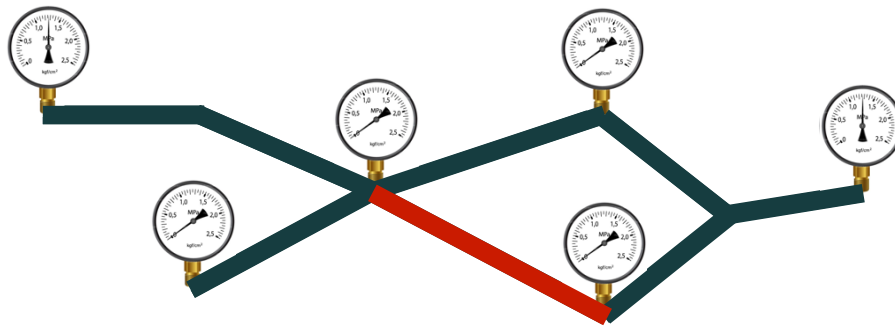
“6 billion gallons of water per day may be wasted in the U.S.”
(Center for Neighborhood Technology, 2013)

“worldwide cost of physical losses is over \$8 billion” (World Bank, 2006)

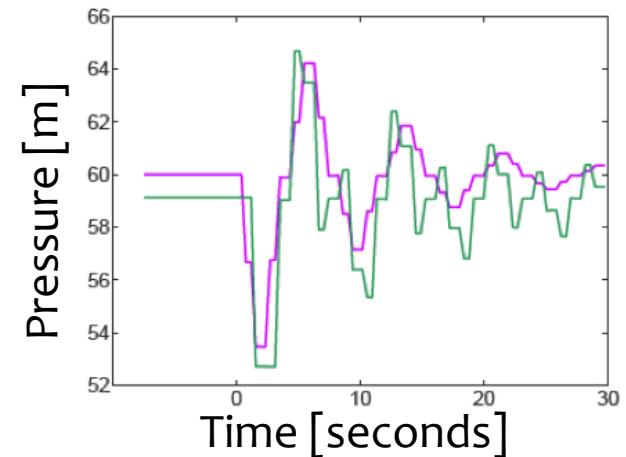


Physical Leakage Detection Model

- * Pressure sensors can detect nearby events, such as leakages and pipe bursts



Measurements of Nearest Sensors



- * Continuous monitoring through sensors can significantly reduce physical damage and financial losses
- * However, battery-powered sensors have limited lifetime

Network and Monitoring Model

- * Network: $G(V, E)$
 - * set of monitoring devices: $X \subseteq V$
 - * set of targets: $Y \subseteq (V \cup E)$
- * Distance-based monitoring model

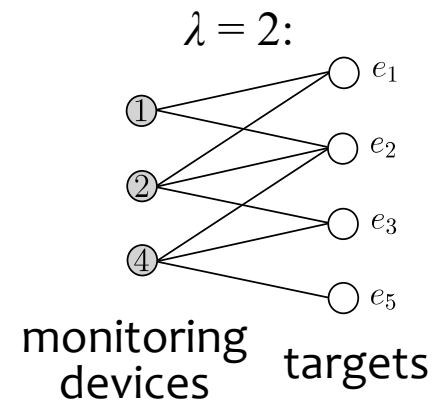
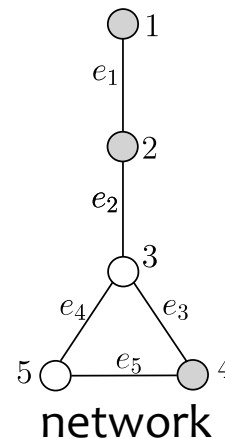
- * distance $d(x, y) =$

- * between nodes x and y :
number of hops between x and y
- * between node x and edge $y = (u, v)$:
 $\max\{d(x, u), d(x, v)\}$

- * range of monitoring devices = λ

- * device u can monitor all nodes and edges within λ distance:

$$\{v \subseteq V : d(u, v) \leq \lambda\} \cup \{e \subseteq E : d(u, e) \leq \lambda\}$$



Schedules and Detection Performance

- * Limited battery power
 - * network lifetime = k time intervals
 - * active monitoring time = $\sigma < k$

* Schedule: (S_1, \dots, S_k)

* every $S_i \subseteq X$

* for every monitoring device s :

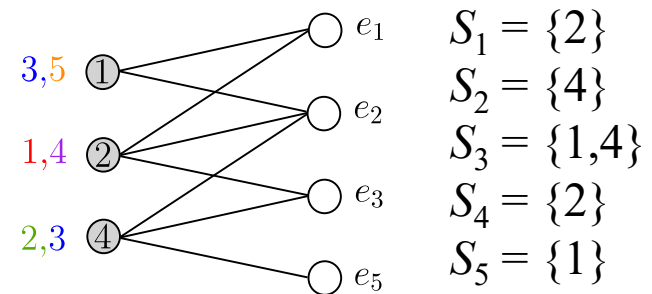
$$|\{S_i \mid s \in S_i\}| \leq \sigma$$

* Average detection performance:

$$\mathcal{D} = \frac{1}{k} \sum_{i=1}^k \frac{m_i}{|Y|}$$

* where m_i is the number of monitored targets in time interval i

Optimal schedule for $k = 5$ and $\sigma = 2$:



Detection performance:

$$m_1 = 3$$

$$m_2 = 3$$

$$m_3 = 4 \rightarrow \mathcal{D} = 0.75$$

$$m_4 = 3$$

$$m_5 = 2$$

Computational Complexity

- * Number of feasible schedules
 - * example: 10 monitoring devices, 30 time intervals, each device may be active in 10 intervals $\rightarrow 847,660,528^{10} \approx 10^{89} >$ number of atoms in the observable universe

Theorem: Given an instance of the scheduling problem, finding a feasible schedule that maximizes the average detection performance is an **APX-hard** problem.

\rightarrow no polynomial-time approximation scheme

- * Proof: reduction from the Maximum Cut Problem

Special Case: Continuous Complete Monitoring

- * Continuous complete monitoring: detection performance $\mathcal{D} = 1$
→ objective: maximizing lifetime k
- * Dominating-set based solution:
 - * every set of active monitoring devices S_i is a dominating set

Theorem: Let G be a graph such that

- G has a minimum degree of at least two,
- no subgraph of G is isomorphic to $K_{1,6}$, and
- $G \neq \{ \text{diamond}, \text{two diamonds}, \text{diamond with diagonal}, \text{square}, \text{square with diagonal}, \text{square with both diagonals}, \text{square with one diagonal and a vertex}, \text{square with one diagonal and two vertices} \}$.

Then, there exists a schedule for any $k < \frac{5}{2} \sigma$ such that $\mathcal{D} = 1$.

- * Proximity graphs are always $K_{1,6}$ -free

Potential Game Formulation

- * Game $\Gamma(\mathcal{P}, \mathcal{A}, \mathcal{U})$:
 - * $\mathcal{P} = \{1, 2, \dots, n\}$: set of players
 - * $\mathcal{A} = \mathcal{A}_1 \times \mathcal{A}_2 \times \dots \times \mathcal{A}_n$: actions spaces
 - * $\mathcal{U} = \{\mathcal{U}_1, \mathcal{U}_2, \dots, \mathcal{U}_n\}$: utility functions
- * Potential game: $\Gamma(\mathcal{P}, \mathcal{A}, \mathcal{U})$ is a potential game if there exists a potential function $\phi: \mathcal{A} \rightarrow \mathbb{R}$ such that

$$\mathcal{U}_x(a_x, a_{-x}) - \mathcal{U}_x(a'_x, a_{-x}) = \phi(a_x, a_{-x}) - \phi(a'_x, a_{-x})$$

- * Potential games are extensively used for distributed control optimization problems

Scheduling Problem as a Potential Game

- * **Scheduling game** $\Gamma(\mathcal{P}, \mathcal{A}, \mathcal{U})$:

- * players $\mathcal{P} = X$ monitoring devices

- * actions space $\mathcal{A}_i = \sigma$ -subsets of $\{1, 2, \dots, k\}$

- * utility functions:
$$U_x(a_x, a_{-x}) \triangleq \sum_{j=1}^k a_{xj} \left| N(x) \setminus \bigcup_{z \in S_j \setminus \{x\}} N(z) \right|$$

where $N(x)$ is the set of targets in range of device x , and a_{xj} is 1 if device x is active in time interval j and 0 otherwise

- * Potential function:
$$\phi(a) \triangleq \sum_{j=1}^k \left| \bigcup_{x \in S_j} N(x) \right|$$

Theorem: The scheduling game is a potential game.

Binary Log-Linear Learning

* Algorithm

- * start with random actions
 - * in each iteration, a player and an action is chosen at random
 - * action is updated with some probability, which depends on the resulting utilities
- * Only the joint action profiles that **maximize the potential function** form stochastically stable equilibria
→ algorithm will converge to a global optimum
- * Polynomial running time

Algorithm 2 Binary Log-Linear Learning

- 1: **Initialization:** Pick a small $\epsilon \in \mathbb{R}_+$, an $a \in \mathcal{A}$, and total iterations.
 - 2: **While** $i \leq$ iterations **do**
 - 3: Pick a random node $x \in \mathcal{X}$, and a random $a'_x \in \mathcal{A}_x$.
 - 4: Compute $P_\epsilon = \frac{\epsilon^{U_x(a'_x, a_{-x}(t))}}{\epsilon^{U_x(a'_x, a_{-x}(t))} + \epsilon^{U_x(a_x, a_{-x}(t))}}$.
 - 5: Set $a_x \leftarrow a'_x$ with probability P_ϵ .
 - 6: $i \leftarrow i + 1$
 - 7: **End While**
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Simple Heuristic: Greedy Algorithm

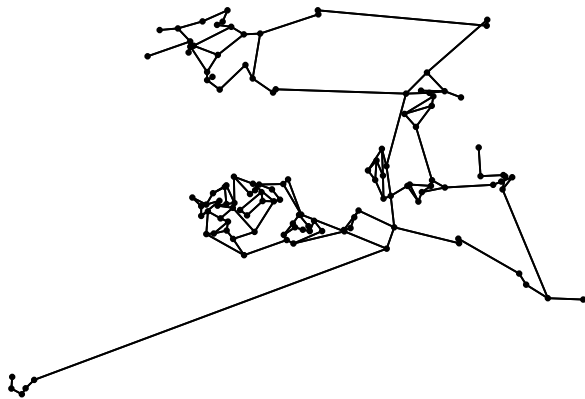
- * Scheduling problem resembles set covering since we have to “cover” targets with monitoring devices in every time interval
- * Algorithm
 - * start with an empty schedule ($S_1 = S_2 = \dots = S_k = \emptyset$)
 - * in each iteration, activate an additional monitoring device x in interval l (i.e., add x to S_l)
 - * choose (x, l) such that the increase in detection performance is maximum
- * Polynomial running time

Algorithm 1 Greedy Heuristic

```
1: Given:  $\sigma, \mathcal{K} = \{1, 2, \dots, k\}$ 
2: Initialization:  $\mathcal{X}' \leftarrow \mathcal{X}, f(x) \leftarrow \emptyset, \forall x \in \mathcal{X}$ 
3: While  $|\mathcal{X}'| \neq \emptyset$  do
4:    $(x, l) \leftarrow \operatorname{argmax}_{x \in \mathcal{X}', l \in \mathcal{K}} \sum_{y \in \mathcal{Y}} |f(y)|$ 
5:    $f(x) \leftarrow f(x) \cup \{l\}$ 
6:   If  $|f(x)| = \sigma$  do
7:      $\mathcal{X}' \leftarrow \mathcal{X}' \setminus \{x\}$ 
8:   End If
9: End While
```

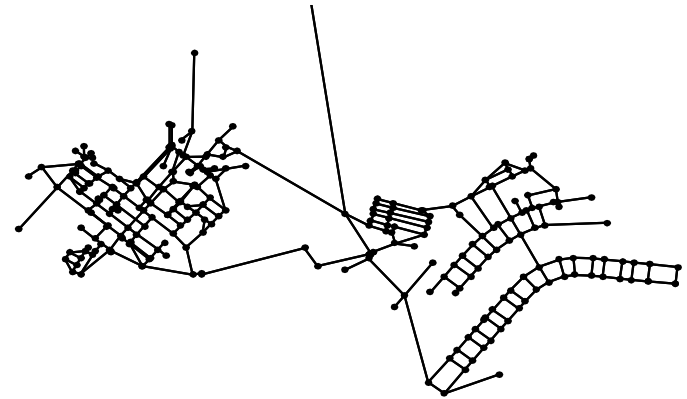
Numerical Evaluation – Water Networks

* Real-world water-distribution networks



Water network 1:

- 126 nodes, 168 links, one reservoir, one pump, and two storage tanks
- extensively studied in the sensor placement literature



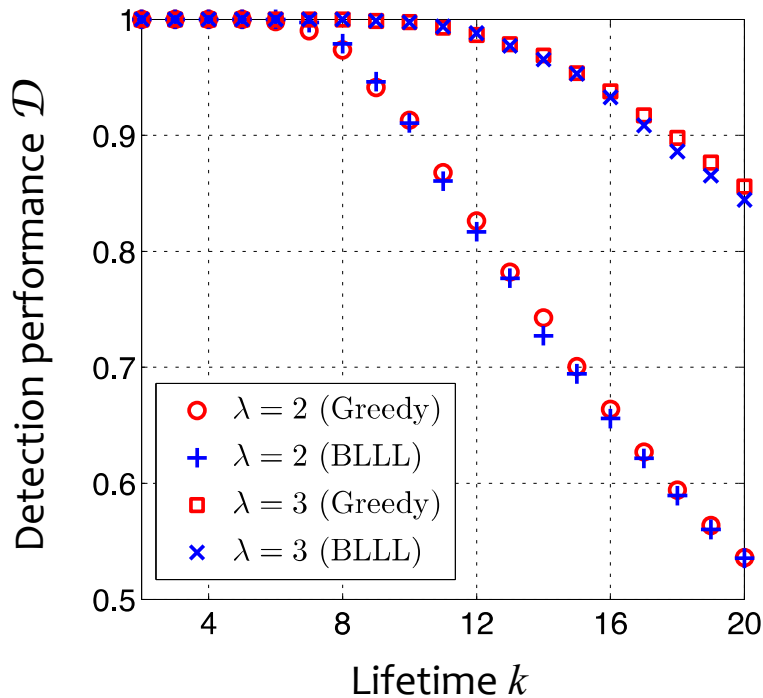
Water network 2:

- 270 nodes, 366 links, three tanks, and five pumps
- grid system in Kentucky

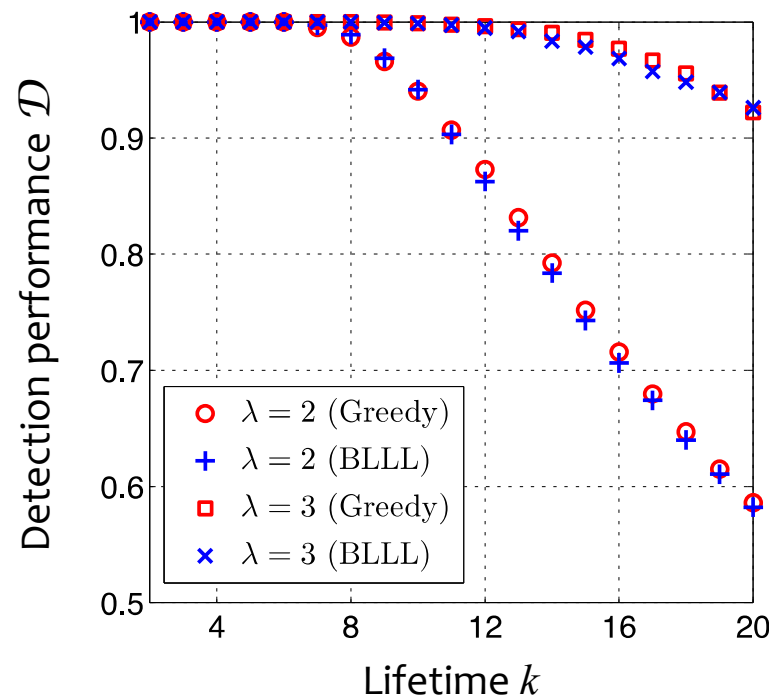
* For both networks, we let $X = V$, $Y = E$, and $\sigma = 2$

Numerical Results – Water Networks

Water network 1

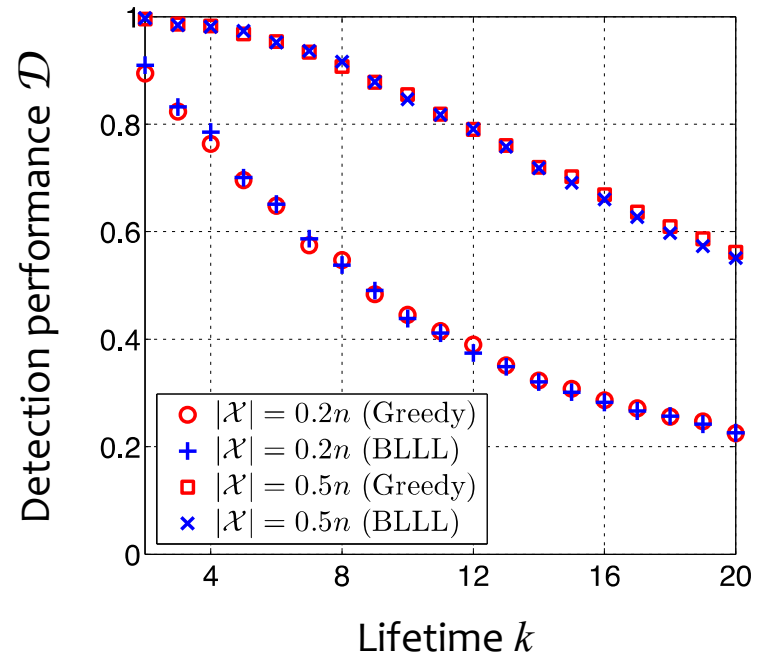


Water network 2



Numerical Results – Geometric Graphs

- * Random geometric graphs
 - * 100 nodes are distributed uniformly at random in a unit square
 - * nodes are connected if their Euclidean distance is at most 0.2
 - * certain fraction (either 20% or 50%) of the nodes are selected to be monitoring devices
- * We let $X = Y = V$ and $\sigma = 2$



2. Simultaneous Placement and Scheduling

- * So far, we assumed that the set of monitoring devices X is given
- * Placement problem:
 - where to place monitoring devices in a network?*
- * Simple “solution”:
 1. find a placement maximizing some “target coverage” metric
 2. find a schedule (e.g., greedy algorithm or BLLL)
- * Simultaneous placement and scheduling
 - * find a placement and schedule **simultaneously**
 - * advantage: placement can take the feasible schedules into account
→ higher detection performance or longer lifetime

Problem Formulation

- * Input
 - * network $G(V, E)$, range λ , lifetime k , power σ
 - * number of monitoring devices: n
 - * feasible monitoring device **locations**: $S \subseteq V$
- * Solution: placement and schedule (X, S_1, \dots, S_k) ,
where $X \subseteq S$, $|X| = n$, and every $S_i \subseteq X$
- * Objective: detection performance \mathcal{D}
- * Complexity:
at least as hard as the scheduling problem

Adapting Binary Log-Linear Learning

- * Action space \mathcal{A}_i of scheduling game Γ : σ -subsets of $\{1, 2, \dots, k\}$
- * **Scheduling and placement game $\Gamma^*(\mathcal{P}, \mathcal{A}^*, \mathcal{U})$:**
 - * we extend each action space with a position: $\mathcal{A}_i^* = \mathcal{A}_i \times S$
 - * everything else is the same as in the scheduling game
- * Scheduling and placement game is a potential game
→ convergence properties still hold

Algorithm 3 Simultaneous Placement and Scheduling

- 1: **Initialization:** Pick a small $\epsilon \in \mathbb{R}_+$ and the number of iterations. Select randomly a subset of nodes $\mathcal{X} \subseteq \mathcal{S}$, and assign labels to nodes in \mathcal{X} , i.e, select $a \in \mathcal{A}$.
 - 2: **While** $i \leq$ iterations **do**
 - 3: Randomly select a node $x \in \mathcal{X}$.
 - 4: Randomly select a node $s \in (\mathcal{S} \setminus \mathcal{X}) \cup \{x\}$, and $a_s \in \mathcal{A}_s$.
 - 5: Compute $P_\epsilon = \frac{\epsilon^{U_s(a_s, a-x)}}{\epsilon^{U_s(a_s, a-x)} + \epsilon^{U_x(a_x, a-x)}}$.
 - 6: With probability P_ϵ , set $\mathcal{X} \leftarrow (\mathcal{X} \setminus \{x\}) \cup \{s\}$, and select a_s for node s .
 - 7: $i \leftarrow i + 1$
 - 8: **End While**
-

Numerical Evaluation

- * **Baseline: individual optimization**

1. select a set of monitoring devices $X \subseteq S$ maximizing the number of targets that are monitored by at least one device
2. find a schedule using Algorithm 2 (BLLL)

- * **Networks**

- * **Water network 1:**

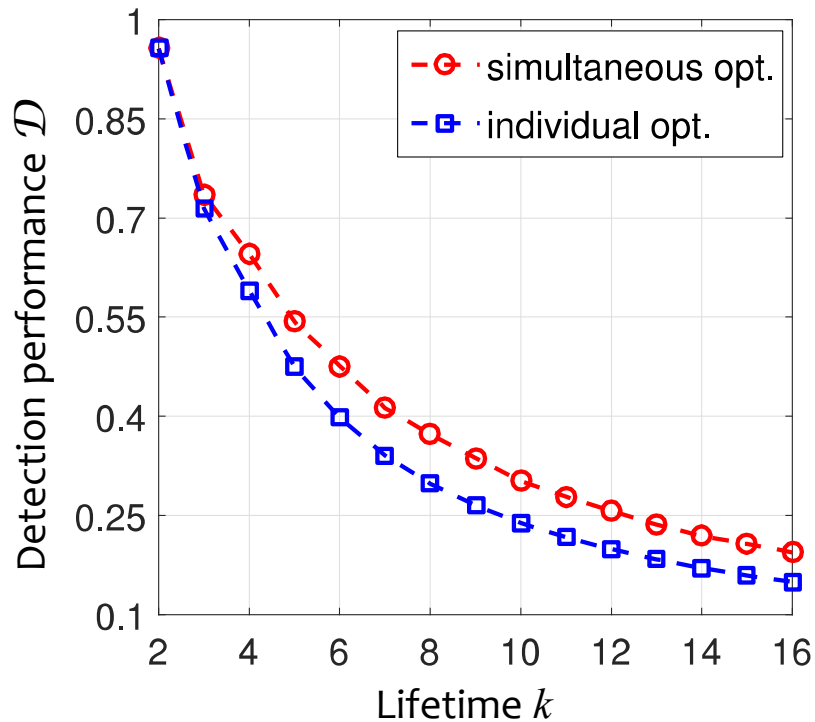
- place monitoring devices at 25 nodes (out of 126 total)

- * **Random geometric graph:**

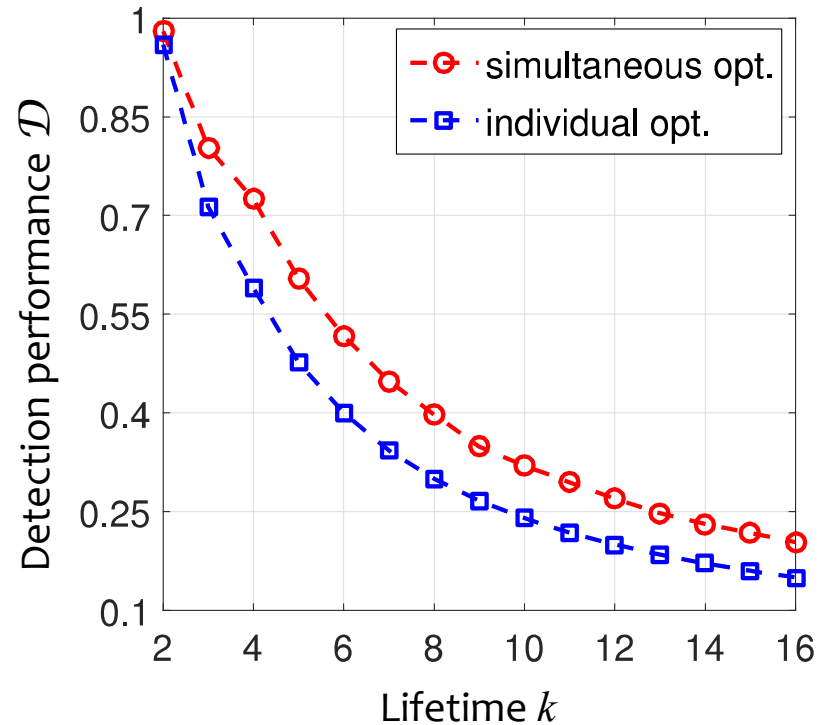
- place monitoring devices at 10 nodes (out of 50 total)

Numerical Results

Real-world water network



Random geometric graph



3. Minimizing Detection Delay

- * Maximizing detection performance \mathcal{D}
 - = maximizing the **number of time intervals** in which each target is monitored
 - * without considering **which time intervals**
- * Detection performance does not guarantee timely detection
 - * example: if a target could be monitored in 5 out of 10 intervals,
 $\{1, 2, 3, 4, 5\} \rightarrow \mathcal{D} = 0.5$, and average time until detection is 1.5
 $\{1, 3, 5, 7, 9\} \rightarrow \mathcal{D} = 0.5$, but average time until detection is 0.5
- * When losses depend on the time between a failure and its mitigation, we need to minimize the average time until detection

Problem Formulation

- * Detection delay \mathcal{T} :

expected number of time intervals until a failure at a uniformly randomly chosen target in a uniformly randomly chosen time interval is detected

$$\mathcal{T} = \frac{1}{k} \sum_{i=1}^k \frac{1}{|Y|} \sum_{y \in Y} \left[\min \left\{ j \mid j \geq i \wedge y \in \bigcup_{x \in S_{(j \bmod k)}} N(x) \right\} - i \right]$$

- * Computational complexity

- * minimizing detection delay is an **APX-hard** problem
- * using the same argument as for maximizing detection performance

Numerical Evaluation

- * **Simulated annealing**

- * start with a random schedule
- * in each iteration, choose a random monitoring device and a new σ -set of time intervals, and switch to the new assignment with probability depending on the difference in detection delay \mathcal{T}

- * **Baseline solution:**

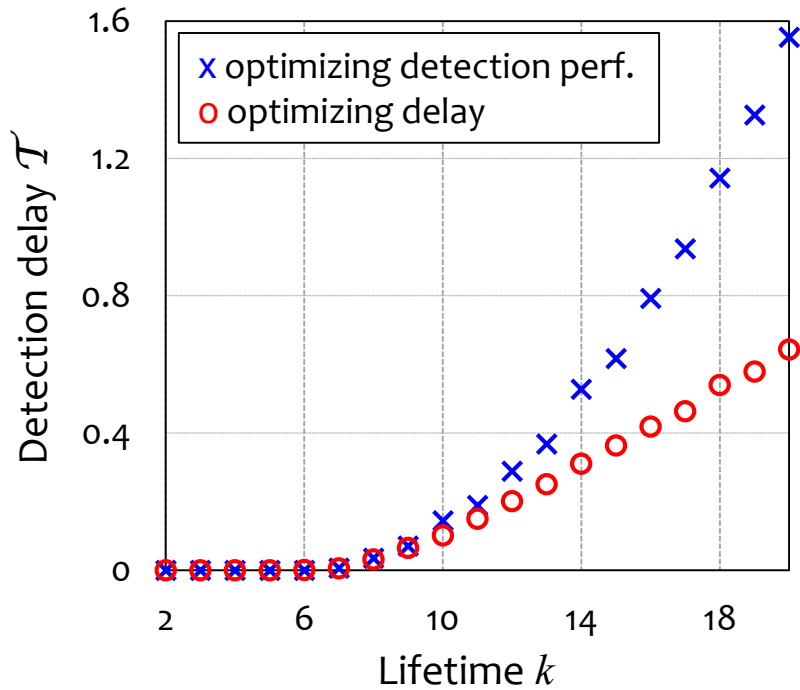
maximizing detection performance \mathcal{D} (using BLLL or greedy)

- * **Networks:**

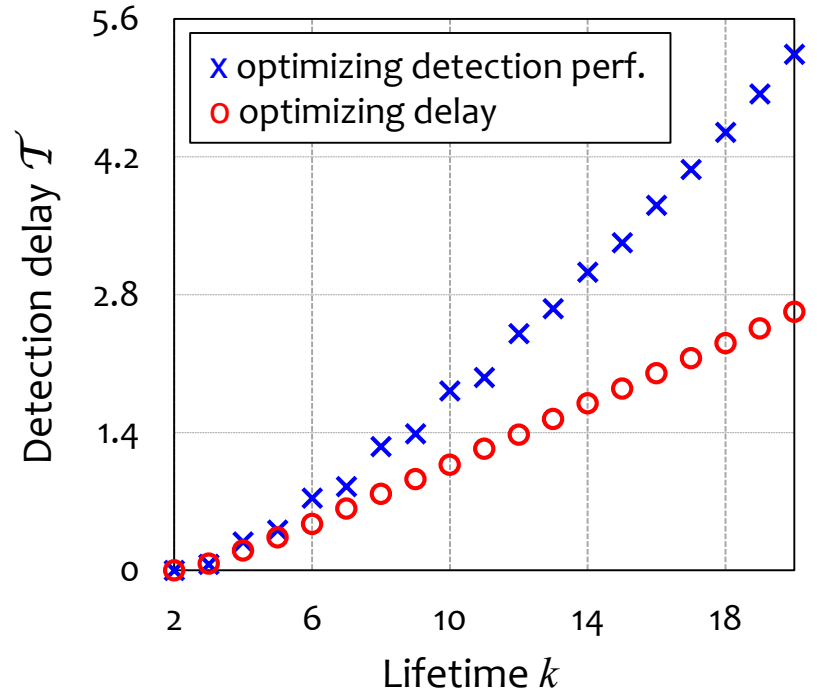
- * Water network 1 with $X = V$, $Y = E$, $\sigma = 2$, and $\lambda = 2$
- * Random geometric graph with $X = Y = V$, $\sigma = 2$, and $\lambda = 1$

Numerical Results

Real-world water network



Random geometric graph



Summary

- * Sleep scheduling enables prolonging the lifetime of battery-powered monitoring devices
- * When detection depends on the physical topology of a cyber-physical system, optimal sleep schedules must take the **physical topology** into account
- * **Simultaneous placement and scheduling** of monitoring devices may lead to a substantial increase in detection performance
- * For certain applications, **minimizing detection delay** can lead to significantly better schedules

Thank you for your attention!
Questions?

Numerical Results – Water Networks

