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Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Adaptive Sensor Selection Algorithms for Wireless Sensor Networks

Silvia Santini

PhD defense

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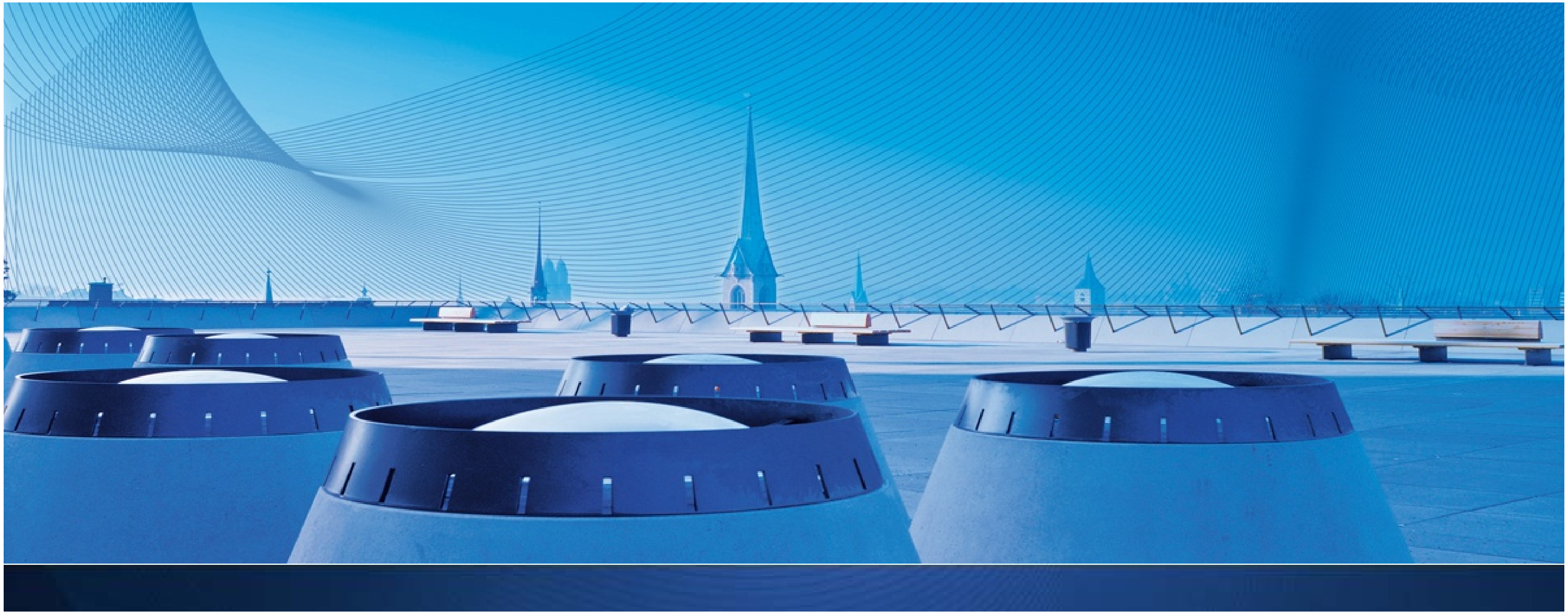
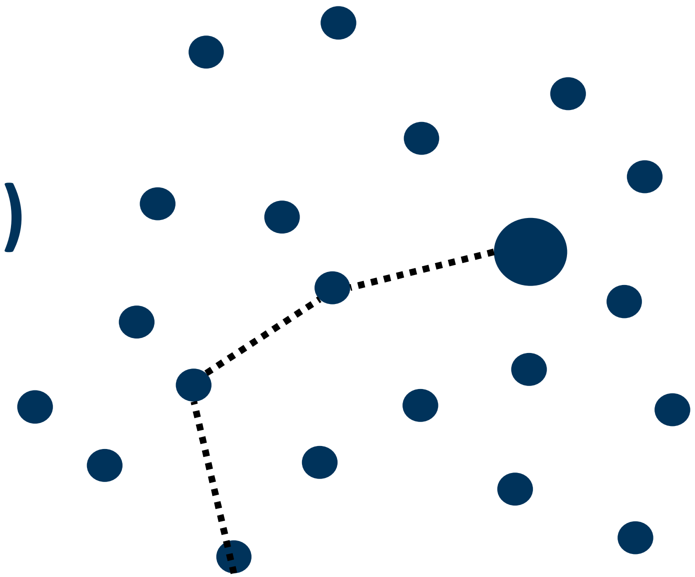


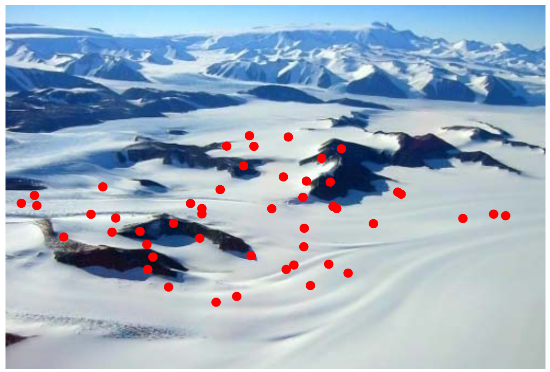
Wireless Sensor Networks (WSNs)



- WSN: compound of sensor nodes

- Sensor nodes
  - Computation
  - Wireless communication
  - Sensing
  - Tiny size, low cost
  - Power supply

- Challenge: Minimize energy consumption
  - One approach: Only subset of nodes active
  - Helps to reduce overall communication



The Sensor Selection Problem

- Which nodes, out of those deployed, should actively collect/transmit sensor readings?
  - Spatial sensor selection algorithms
- When should a node collect/transmit sensor readings?
  - Temporal sensor selection algorithms
- Challenges
  - Reduce communication
  - Guarantee data accuracy
  - Cope with limited resources

Contributions

1) Prediction-based data collection (Temporal sensor selection)

- **1a)** Algorithm based on least mean square (LMS) adaptive filter
- **1b)** Adaptive model selection (AMS) algorithm

2) Coverage preserving algorithms (Spatial sensor selection)

- **2a)** Optimization of the coverage configuration protocol (CCP)
- **2b)** Adaptive random sensor selection (ARS) algorithm

3) Application scenario: Environmental noise monitoring

- **3a)** Analysis
- **3b)** Evaluation of platforms

Outline

- Prediction-based data collection in WSNs
  - The adaptive model selection algorithm (AMS)
    - Rationale, implementations, experimental results
    - Limitations and outlook
- Spatial coverage in WSNs
  - Optimizing the coverage configuration protocol (CCP)
    - Adaptive sensor ranking, experimental results
    - Limitations and outlook
- Conclusions

Prediction-Based Data Collection in WSNs

- Sensor nodes
  - Read sensor(s) at regular time intervals (e.g., 10 minutes)
  - Compute and transmit prediction model to the sink(s)
- Sink nodes
  - Uses prediction model to estimate future sensor readings
  - Receives updates from nodes when prediction error higher than application-specific threshold (E.g., ± 0.5°C for temperature readings)
- Dual prediction scheme (DPS)
  - Performance measure: Update rate $U_k = \frac{\text{\# of transmitted samples up to time step k}}{\text{\# of collected samples up to time step k}}$

DPS – Challenges

- Choosing the “right” prediction model
  - Constant model [Olston et al., 2003], Kalman filter [Jain et al., 2004], Dead reckoning [Tilak, 2005], LMS adaptive filter [Santini et al., 2006], Autoregressive models [Tulone et al., 2006]
- Limited resources
  - Computation and memory
- Adapt to actual (changing) signal dynamics
  - Lack of a priori knowledge
  - Need for online model update procedures

Adaptive Model Selection (AMS) Algorithm

(Contribution 1b)

- Set of N arbitrary candidate models
  - E.g., linear models corresponding to different sets of parameters
- Online performance estimation
  - Update rate (or variants thereof)
- Model selection
  - Each time an update is required
  - Model minimizing the performance measure is sent to the sink
- Other features
  - Racing mechanism to prune poor performing models

AMS – Implementation

- Composition of set of models
  - Determines computational overhead and memory footprint
- Autoregressive (AR) models (AR-AMS)
  - Order p -> number of parameters
  - Recursive least square (RLS) procedure to compute parameters
- Exponential smoothing (ES) models (ES-AMS)
  - Linear predictors, smoothing constants α and β ($0<\alpha \leq 1$, $0\leq \beta \leq 1$)

AMS – Datasets for Simulation Study

N°	Data set name	Sensed variable	Sampling	Period
1	S Heater	Temperature	3 seconds	2h30min
2	I Light	Light	31 seconds	8 days
3	M Hum	Humidity	10 minutes	30 days
4	M Temp	Temperature	10 minutes	30 days
5	Midra ST1	Soil temperature	10 s	3 months
6	Midra ST2	Soil temperature	10 s	3 months
7	Midra ST3	Soil temperature	10 s	3 months
8	Monte ST3a	Soil temperature	< 1min	2 months
9	Monte ST3b	Soil temperature	< 1min	2 months
10	Monte ST3c	Soil temperature	< 1min	2 months
11	NDBC WD	Wind direction	1 hour	1 year
12	NDBC WSPD	Wind speed	1 hour	1 year
13	NDBC DPD	Dominant wave period	1 hour	1 year
14	NDBC AVP	Average wave period	1 hour	1 year
15	NDBC BAR	Air pressure	1 hour	1 year
16	NDBC ATMP	Air temperature	1 hour	1 year
17	NDBC WTMP	Water temperature	1 hour	1 year
18	NDBC DEWP	Dewpoint temperature	1 hour	1 year
19	NDBC GST	Gust speed	1 hour	1 year
20	NDBC WVHT	Wave height	1 hour	1 year

[Stenman et al., 1996]

Intel Lab data

Good Food project deployments

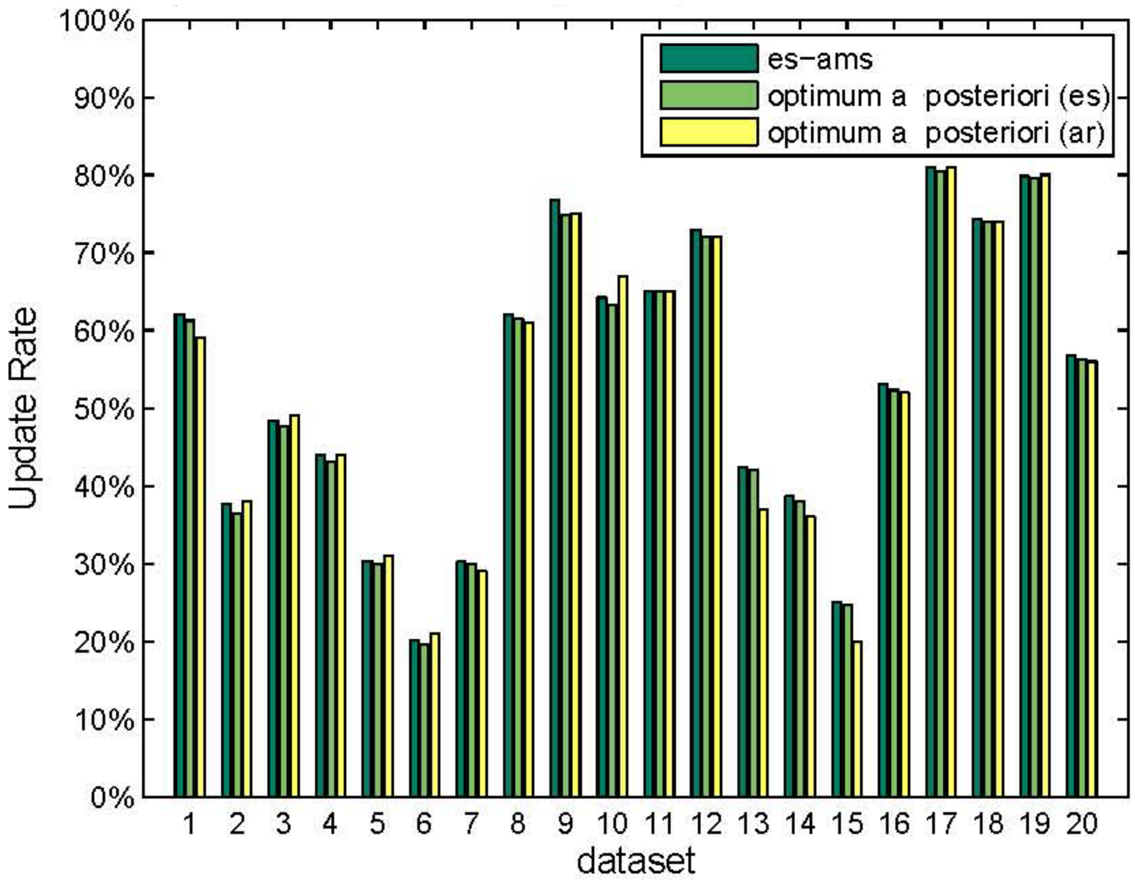
USA - National Data Buoy Center

Performance of AR-AMS

	CM	AR1	AR2	AR3	AR4	AR5	AMS
S Heater	74	75	61	**59**	**59**	**59**	AR3
I Light	**38**	40	39	40	40	39	CM
M Hum	53	53	**49**	**50**	**49**	**49**	AR4
M Temp	48	48	**45**	**45**	**44**	**44**	AR4
NDBC DPD	**65**	85	80	80	80	80	CM
NDBC AWP	**72**	**73**	**73**	**73**	**73**	**73**	CM
NDBC BAR	51	50	39	39	39	**37**	AR5
NDBC ATMP	39	39	**36**	**36**	**36**	**36**	AR3
NDBC WTMP	27	27	**21**	**21**	**21**	**20**	AR5
NDBC DEWP	57	**52**	**52**	**52**	**52**	**52**	AR3
NDBC WSPD	**74**	84	82	83	83	83	CM
NDBC WD	85	**81**	**81**	**81**	**81**	**81**	AR1
NDBC GST	**80**	81	**80**	**80**	**80**	81	CM
NDBC WVHT	58	**56**	**56**	**56**	**56**	**56**	AR3

- Model set
  - Constant model (CM) and AR models of order 1 to 5
- Performance
  - Update rate
- Error threshold
  - 1% of signal dynamic
- Simulator
  - Matlab

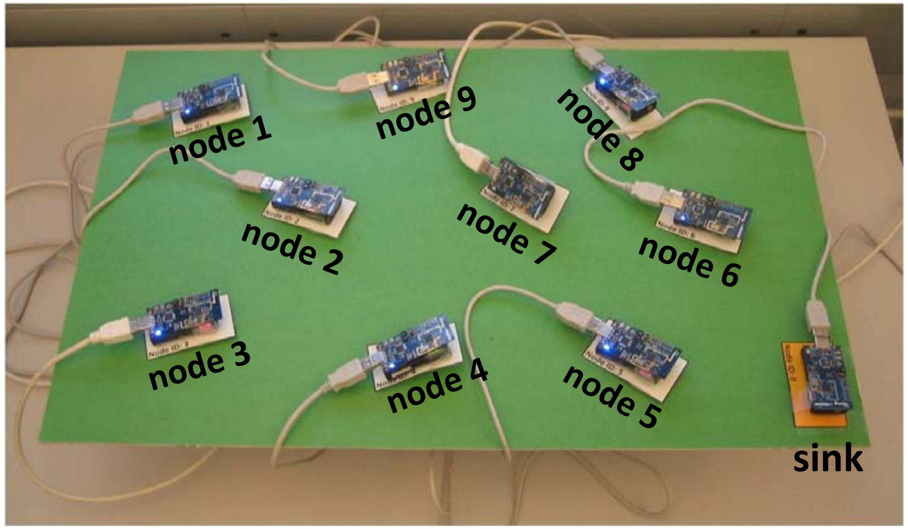
Performance of ES-AMS



- Model set
  - Exponential smoothing models
    α =0.1:0.1:1
    β=0:0.1:1
- Performance
  - Update rate
- Error threshold
  - 1% of signal dynamic
- Simulator
  - Matlab

ES-AMS as TinyOS Library

- TinyOS
  - De-facto standard operating system for WSNs
- Test deployment: 9 Tmote Sky nodes
  - Sensor: temperature
  - Sampling interval: 5 – 15 seconds
  - Error threshold: 0.1 – 1 °C
- Model set
  - Exponential smoothing models
  - α =0.1:0.1:1, β=0:0.1:1



AMS – Limitations and Outlook

- DPS generally assumes reliable communication
  - Need to take into account communication failures
- Update rate computed over the whole observation period
  - Inertia in reacting to changes in best performing model
  - Moving average would make AMS more reactive

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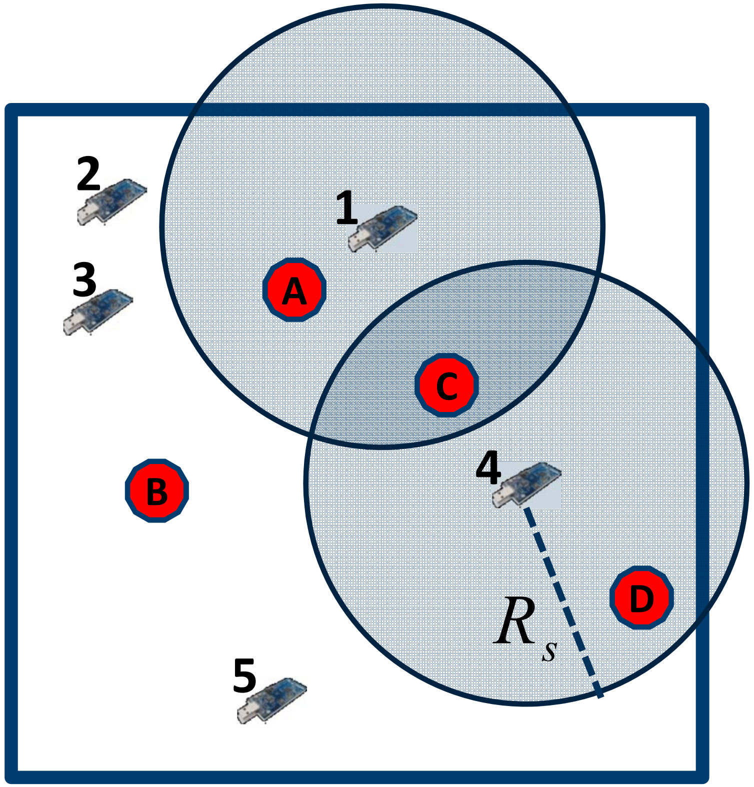
Spatial Coverage in WSNs

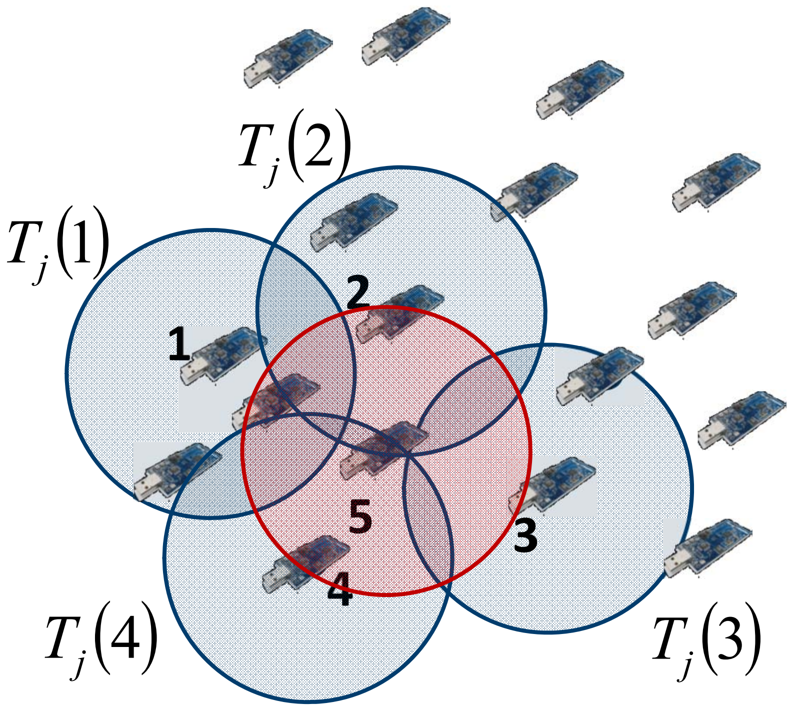
- Point covered if within sensing range R_s of at least one node
- Coverage preserving algorithms
  - Spatial sensor selection
- Coverage configuration protocol [Xing et al., 2005]



Coverage Configuration Protocol (CCP)

- Listen phase
  - Collect information on communication neighborhood
- Activation phase
  - Join timer $T_j(i)$ for each node i
  - Random value between 0 and $T_j^{\max}$
- Withdrawal phase

- Potential for optimization
  - Reduce number of withdrawals to reduce communication
  - Adaptive values for timers $T_j(i)$



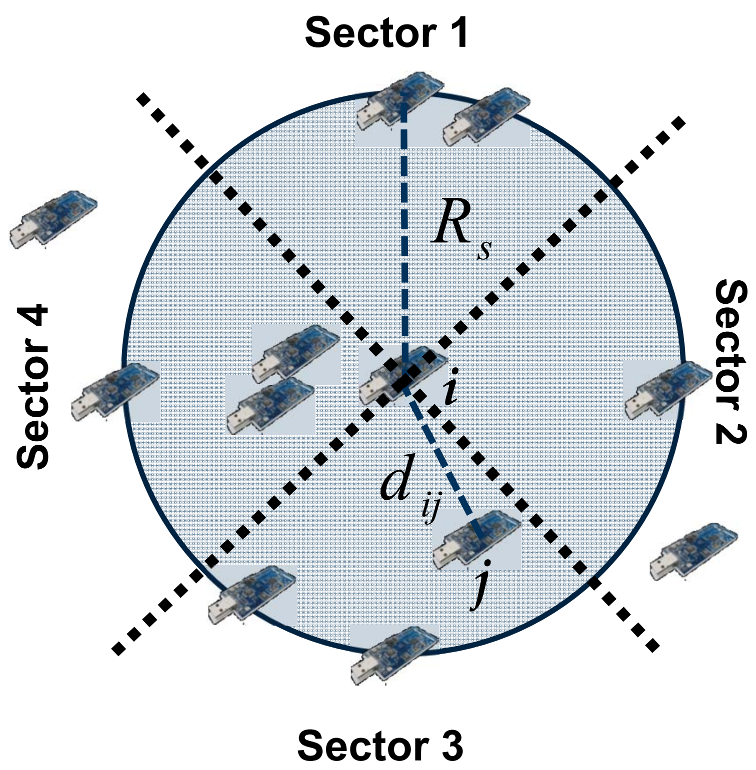
Reducing Communication Overhead of CCP

(Contribution 2a)

- Length of $T_j(i)$ depends on probability that the node i must become active
  - E.g., nodes with less neighbors should activate first
  - Determine "rank" ψ_i for every node i
- Adaptive sensor ranking strategy
  - Local network topology
  - IDW: Inverse distance weighting [Shepard, 1968]

Adaptive Sensor Ranking

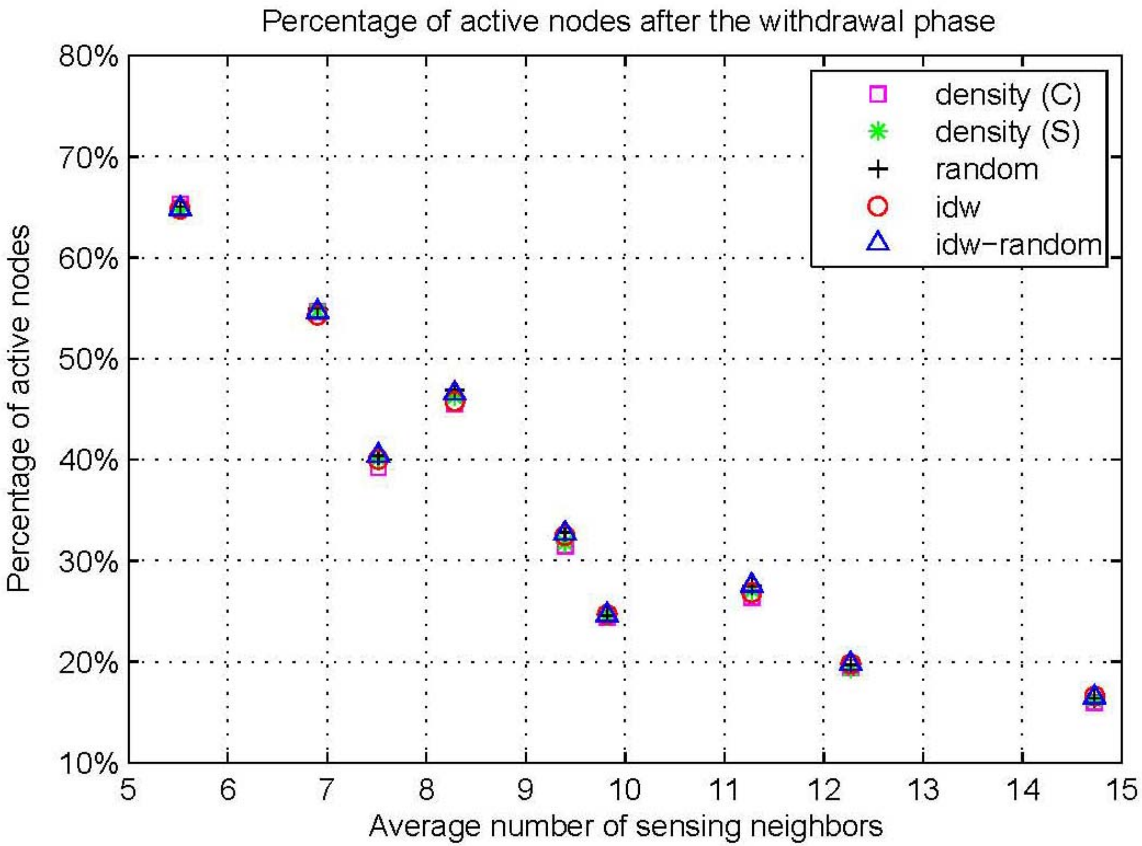
- Rank of node i
  - For each neighbor j: $\phi_{ij} = 1 - \frac{d_{ij}}{R_s}$
  - For each sector k: $\psi_{ik} = \frac{1}{1 + \sum_j \phi_{ij}}$
  - Sensor rank: $\psi_i = \frac{1}{N_{sets}} \sum_{k=1}^{N_{sets}} \psi_{ik}$



Strategies to Set the Activation Timers

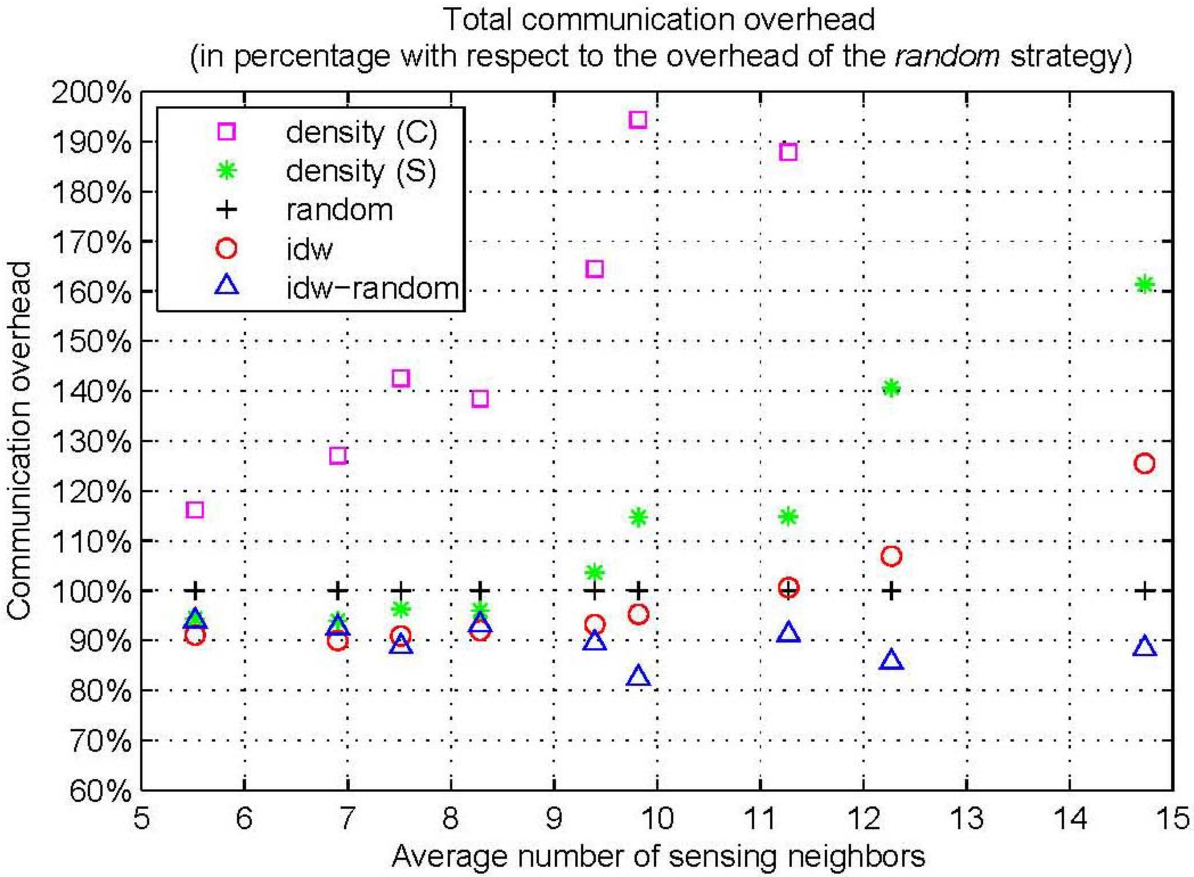
- IDW strategy
  - $T_j(i)$ proportional to $1-\psi_i$
- IDW-random strategy
  - $T_j(i)$ proportional to a random value between 0 and $1-\psi_i$
- Density (C) strategy
  - $T_j(i)$ proportional to the density of neighbors within communication range
- Density (S) strategy
  - $T_j(i)$ proportional to the density of neighbors within sensing range
- Random strategy (CCP)
  - $T_j(i)$ random value between 0 and $T_j^{\max}$

CCP + Adaptive Sensor Ranking – Results (I)



- Field
  - 100m x 100m
- Transmission range
  - 25 m
- Sensing range
  - 9.4m, 11.5m, 12.5 m
- Number of nodes
  - 200, 250, 300
  - Deployed uniformly at random (25 networks)
- Simulator
  - Matlab

CCP + Adaptive Sensor Ranking – Results (II)



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Limitations and Outlook

- Performance evaluation based on Matlab
  - Need to include realistic communication/energy model (E.g., Castalia WSN simulator)
  - Quantify savings in terms of activation time
- Open challenge: Integration with routing
  - Use sensor ranking to influence nodes' availability as data routers

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Conclusions

- Sensor selection problem
  - Solutions needed to optimize energy consumption in WSNs
- Our contributions
  - Temporal: LMS-DPS algorithm / **AMS algorithm**
  - Spatial: **CCP optimization** / ARS algorithm
  - Application scenario: Noise monitoring
- Results demonstrate importance of adaptability
  - Adapting to data dynamics
  - Adapting to local topology
  - Considering resource constrained implementations

Selected Publications

S. Santini and U. Colesanti. Adaptive Random Sensor Selection for Field Reconstruction in Wireless Sensor Networks. In Proceedings of the 6th International Workshop on Data Management for Sensor Networks (DMSN 2009), August 2009.

S. Santini, B. Ostermaier, and R. Adelmann. On the Use of Sensor Nodes and Mobile Phones for the Assessment of Noise Pollution Levels in Urban Environments. In Proceedings of the Sixth International Conference on Networked Sensing Systems (INSS 2009), June 2009.

S. Santini, B. Ostermaier, and A. Vitaletti. First Experiences Using Wireless Sensor Networks for Noise Pollution Monitoring. In Proceedings of the Third ACM Workshop on Real-World Wireless Sensor Networks (REALWSN 2008), April 2008.

Y. Le Borgne, S. Santini, and G. Bontempi. Adaptive Model Selection for Time Series Prediction in Wireless Sensor Networks. *International Journal for Signal Processing*, Special Issue on Information Processing and Data Management in Wireless Sensor Networks, 87(12):3010–3020, December 2007.

S. Santini and K. Römer. An Adaptive Strategy for Quality-Based Data Reduction in Wireless Sensor Networks. In Proceedings of the 3rd Intl. Conf. on Networked Sensing Systems (INSS 2006), Chicago, IL, USA, June 2006.

Thank you!