Emerging Techniques for Energy Management in Practical WSNs

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PerLab

Based on work carried out in cooperation with

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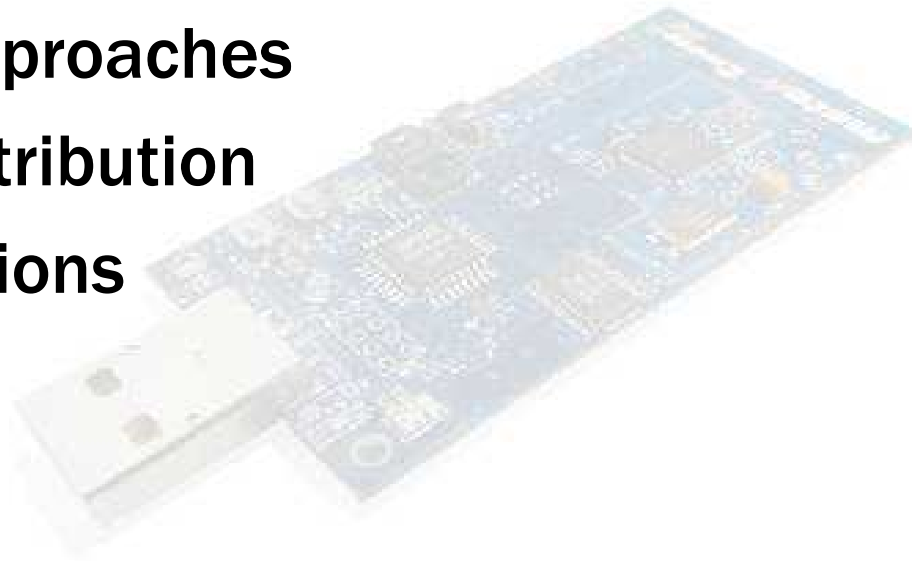
Mario Di Francesco (University of Pisa)

Outline

- **Energy-efficient data acquisition**
  - **Motivations**
  - **Main approaches**
  - **Our contribution**
  - **Conclusions**



Current snapshot

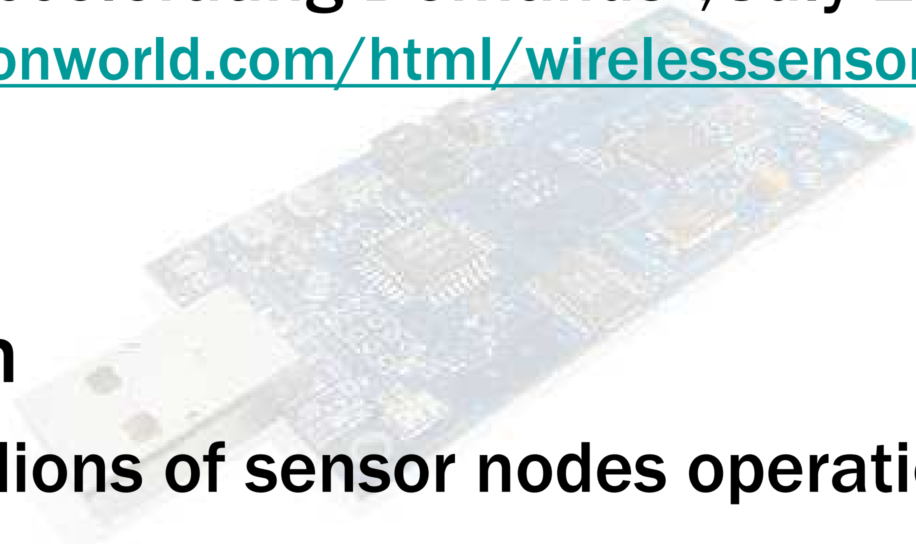
- Increasing number of sensor network deployments for real-life applications

- Progressive diffusion of commercial devices
  - sensors
  - sensor nodes

WSNs cannot be regarded any more as an interesting research topic only

Future perspectives

ON World Inc., “Wireless Sensor Networks – Growing Markets, Accelerating Demands”, July 2005
http://www.onworld.com/html/wirelesssensorsrprt2.htm



- Prediction
  - 127 millions of sensor nodes operational in 2010
  - particularly in the field of industrial applications

Future perspectives

Embedded WiSeNTs project (funded by the European Community, FP6) roadmap, November 2006.
http://www.embedded-wisents.org/dissemination/roadmap.html

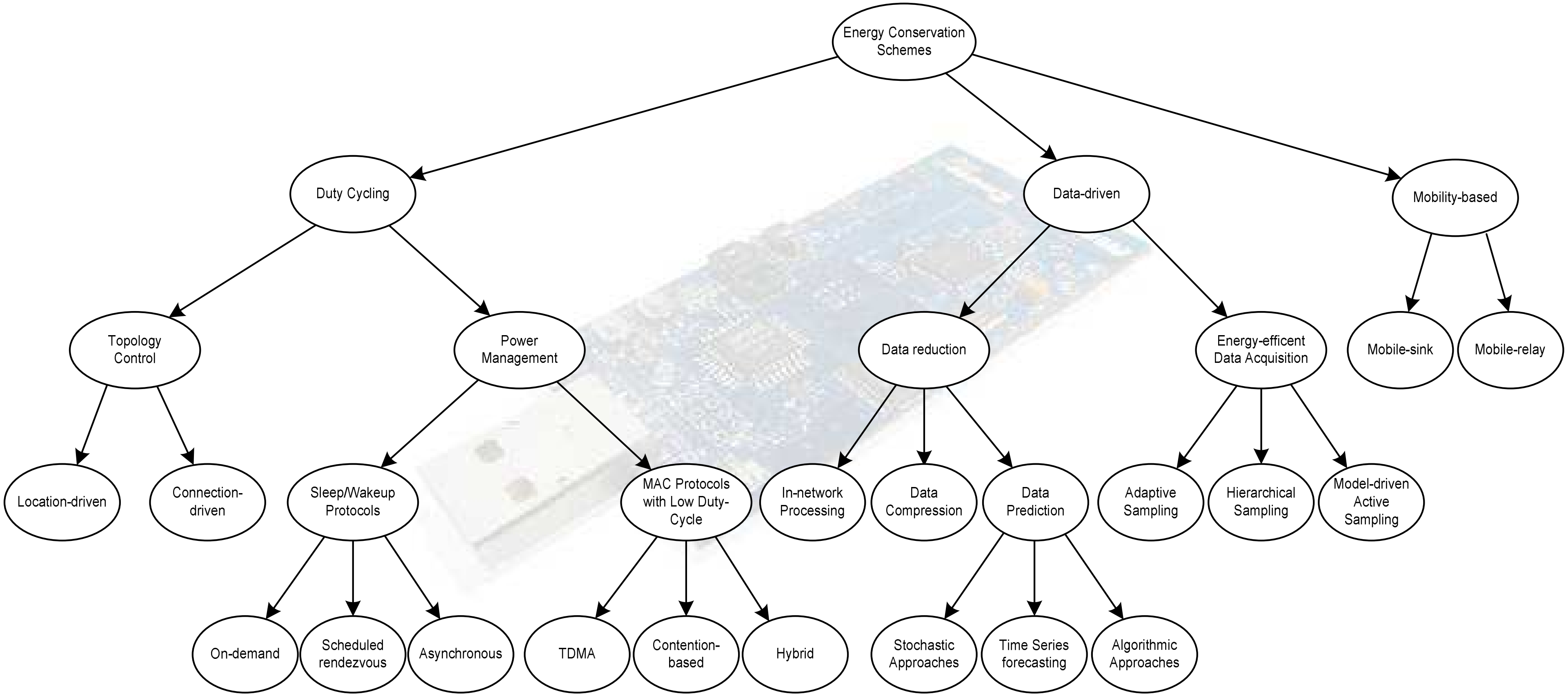
- Prediction
  - The WSN market share will grow considerably up to 2015
  - especially in the fields of logistics, automation and control

Limitations

Energy limitation remains the main barrier to the diffusion of this technology

- **Main approaches**
  - **Low-power design**
  - **Energy harvesting**
  - **Energy conservation**
  - **Energy efficient networking protocols**
  - **Energy-efficient application design**
  - **Cross-layering**
  - **…**

Energy Conservation Schemes



G. Anastasi, M. Conti, M. Di Francesco, A. Passarella, ***Energy Conservation in Wireless Sensor Networks***, ***Ad Hoc Networks Journal***, **submitted for publication**

A common assumption

- Traditional assumption about energy consumption

data transmission is much more expensive than data sensing and processing

- Recent deployments have highlighted that this assumption doesn't hold in many practical application scenarios

Power Consumption of Common Radios

Radio	Producer	Power Consumption	
		Transmission (at 0 dBm)	Reception
CC2420 (Telos)	Texas Instruments	35 mW	38 mW
CC1000 (Mica2/Mica2dot)	Texas Instruments	42 mW	29 mW
TR1000 (Mica)	RF Monolithics	36 mW	9 mW

J. Polastre, **A Unifying Link Abstraction for Wireless Sensor Networks**, Ph.D. Thesis, University of California at Berkeley, 2005.

Power Consumption of Some Sensors

Sensor	Producer	Sensing	Power Consumption
STCN75	STM	Temperature	0.4 mW
QST108KT6	STM	Touch	7 mW
iMEMS	ADI	Accelerometer (3 axis)	30 mW
2200 Series, 2600 Series	GEMS	Pressure	50 mW
T150	GEFRAN	Humidity	90 mW
LUC-M10	PEPPERL+FUCHS	Level Sensor	300 mW
CP18, VL18, GM60, GLV30	VISOLUX	Proximity	350 mW
TDA0161	STM	Proximity	420 mW
FCS-GL1/2A4-AP8X-H1141	TURCK	Flow Control	1250 mW

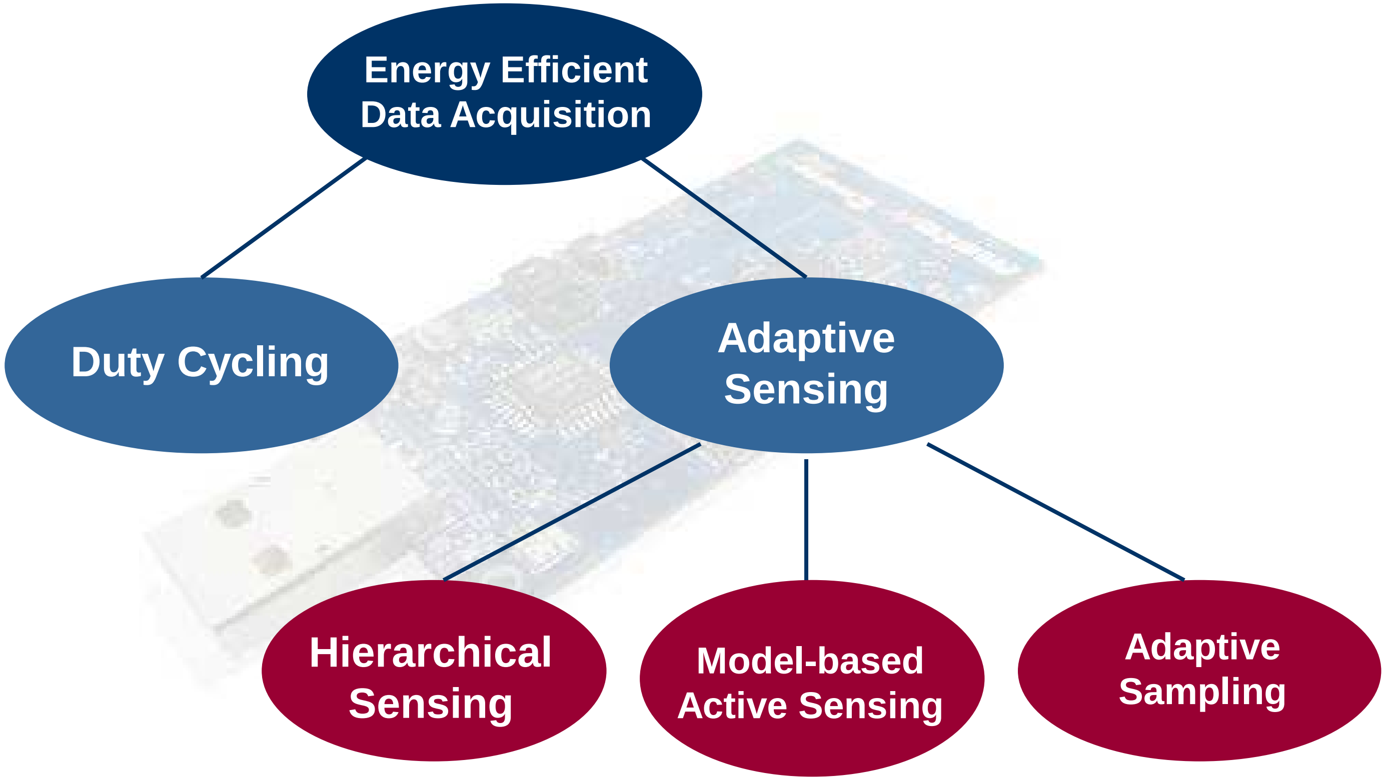
Sensor Energy Consumption

- Energy for sensing cannot be neglected due to
  - use of active transducers
    - ⇨ e.g., sonar and radar
  - need of highly energy consuming A/D converters
    - ⇨ e.g., acoustic or seismic sensors
  - presence of sensing arrays
    - ⇨ e.g., CCD or CMOS image sensor

  - acquisition time much longer than transmission time

Schemes for effective management of sensor energy consumption must be devised

Management of sensor energy consumption



V. Raghunathan, S. Ganeriwal, M. Srivastava, Emerging Techniques for Long Lived Wireless Sensor Networks, *IEEE Communication Magazine*, April 2006.

Hierarchical Sensing

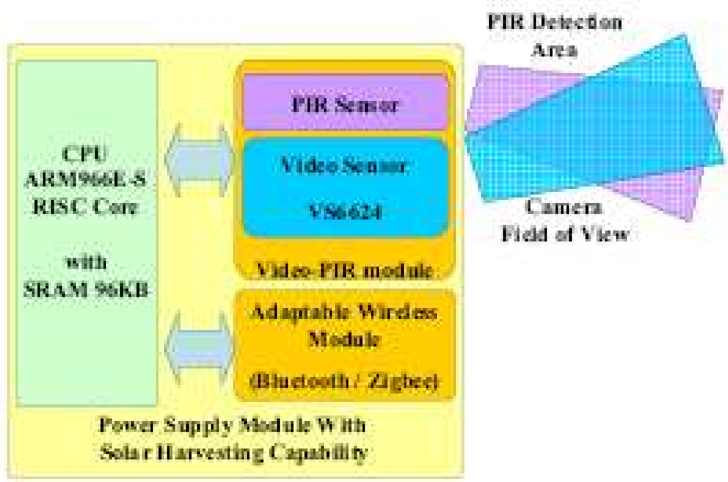
- **Basic idea**
  - ⇨ Using different sensors with different power consumption and resolution properties
  - ⇨ Accuracy/energy consumption trade-off

- **Triggered sensing**
  - ⇨ Low-power low resolution sensors trigger high-power high-accuracy sensors

- **Multi-scale sensing**
  - ⇨ Low-resolution wide area sensors are used to identify areas of interests
  - ⇨ High resolution sensors are, then, switched on for more accurate measurements

Triggered Sensing: An example

- **Low-power Low-cost Video sensor [DSD 2008]**
  - Video surveillance, traffic control, people detection, ...
  - CMOS video camera (550 mW)
  - Pyroelectric InfraRed (PIR) sensor (2 mW)
  - Bluetooth/ZigBee module (100 mW)
  - Energy harvesting system (solar cells)

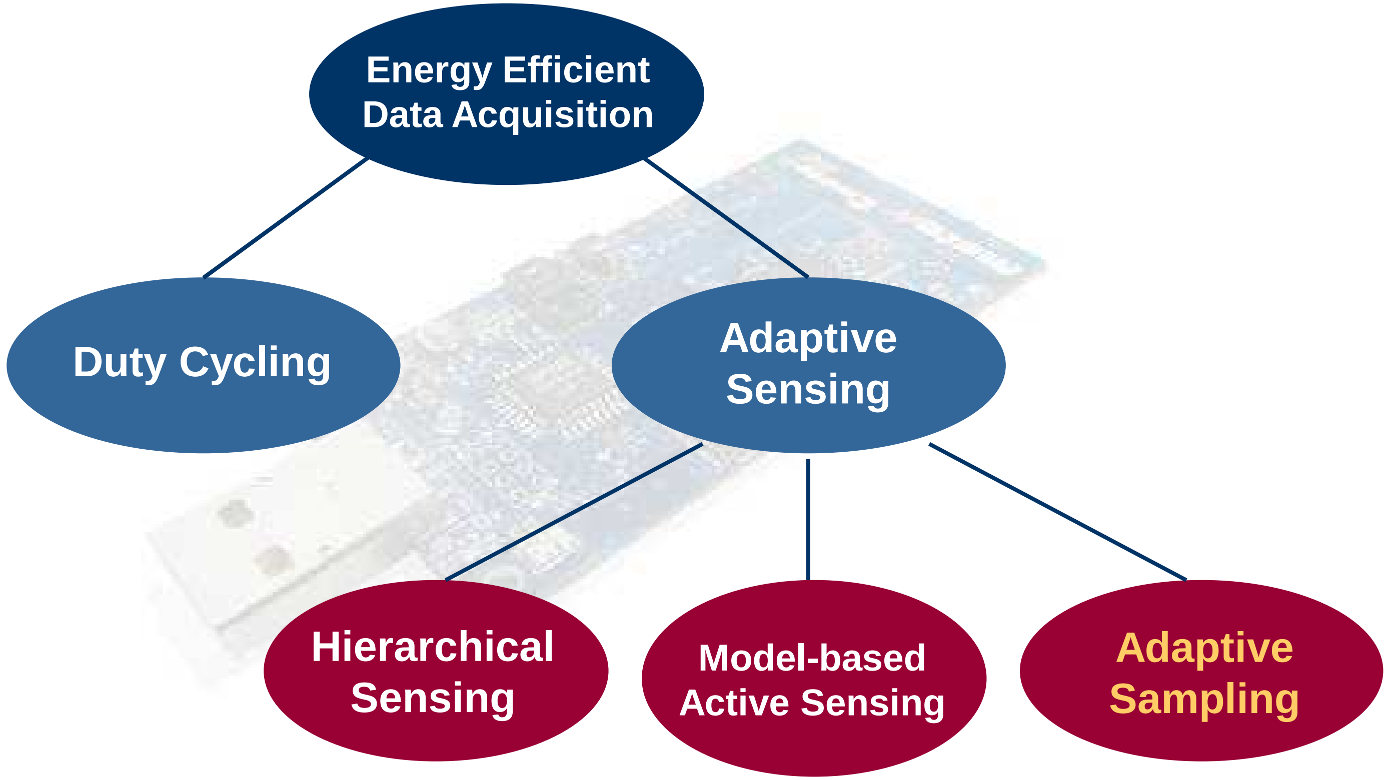


Multi-scale sensing: an example

- I-Mouse [Tseng 2007]
  - Fire detection system
  - Static sensor monitors the temperature
  - Anomaly detected in a given region ➔
    - ⇨ Mobile sensors are sent for deeper investigation
    - ⇨ They collect data (take snapshots)
    - ⇨ Then, come back to the control center
    - ⇨ Appropriate actions are taken by the control center

Y.-C. Tseng, Y.C. Wang, K.-Y. Cheng, Y.-Y. Hsieh, iMouse: An Integrated Mobile Surveillance and Wireless Sensor System, *IEEE Computer*, Vol. 40, N. 6,June 2007.

Management of sensor energy consumption



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Adaptive Sampling

- **Adapts the sampling rate to the dynamics of the phenomenon under monitoring**

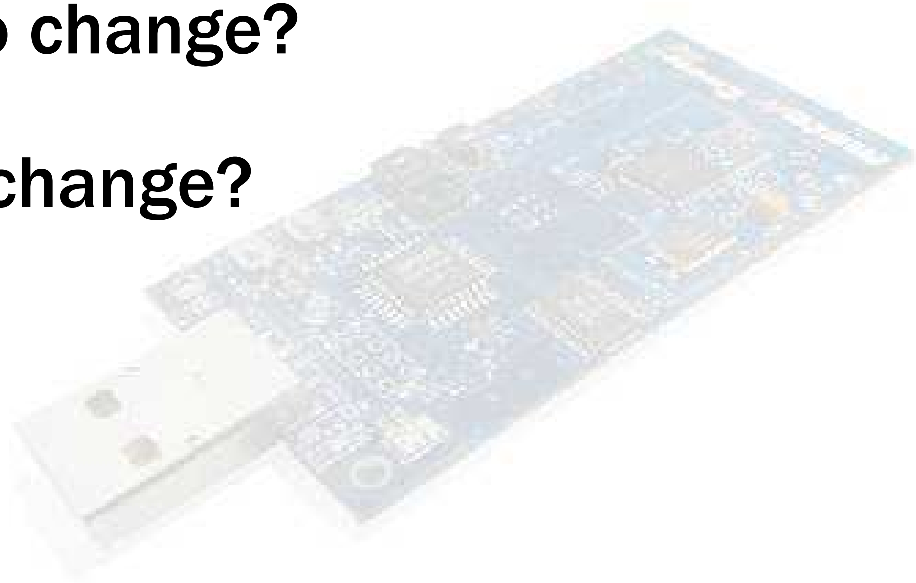
- **Exploits**
  - **Temporal Correlation**
  - **Spatial Correlation**
  - **The available energy may also be considered**

- **Reduces at the same time the energy consumption for data acquisition and communication**
  - **Lower amount of data to transmit**
  - **Lower number of sensor nodes to activate**

Adaptive Sampling (cont'd)

Key Questions

- **When to change?**
- **How to change?**



Adaptive sampling (cont'd)

- Correlation-based reliable event transport [Akan 2003]
  - Distortion vs. reporting frequency model: D(f)
  - Goal: achieve the desired distortion level D* with the minimum reporting frequency
  - Event to Sink Reliable Transport (ESRT) protocol
  - Achieves reliable event detection with minimum energy expenditure and congestion (centralized approach)
- Adaptive Sampling – [Jain-Chang, 2004]
  - Nodes adapt their sampling rate within a certain range
    - ⇨ Kalman Filter used to predict future activity
  - If the desired modification exceeds the allowed range, nodes ask for additional bandwidth
  - Decentralized adaptation scheme + (centralized) bandwidth allocation mechanism
  - Goal: bandwidth/energy usage optimization

Adaptive sampling (cont'd)

- FloodNet Adaptive Routing (FAR) [Zhou 2007]
  - Adaptive sampling + energy-aware routing
  - Adaptive sampling is based on a flood prediction model
  - Centralized approach

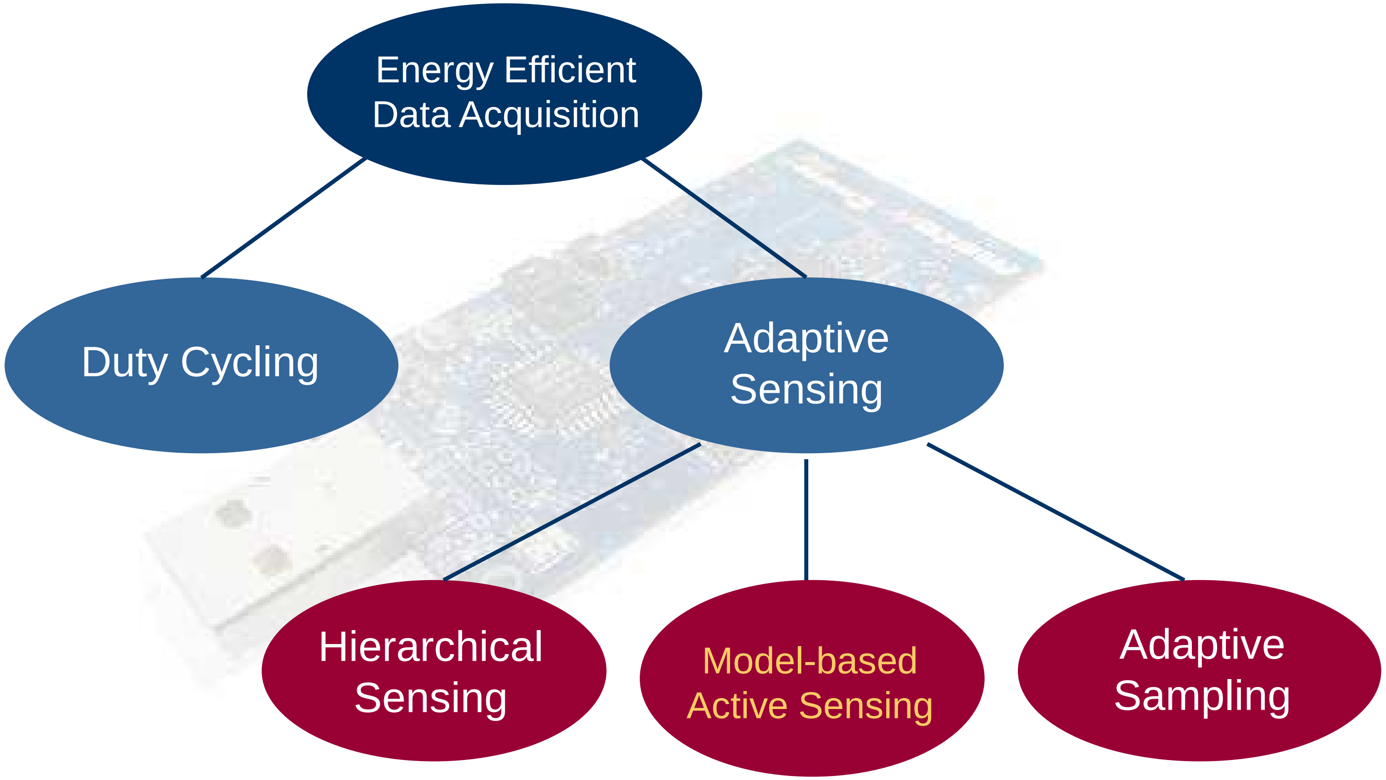
- Decentralized Adaptive Sampling [Kho 2007]
  - Sampling rate adapted on the basis of the available energy
    - ⇨ Nodes are powered by solar cells
  - Goal: minimize the total uncertainty error, given that the sensor can take a maximum number of samples on that day

Adaptive sampling (cont'd)

- Backcasting [Willet 2004]
  - More nodes should be active in regions where the variation of the sensed quantity is high
  - Preview phase: only a subset of nodes are activated for an initial estimate
  - Refinement phase: the control center can activate more nodes in regions where the spatial correlation is low

- Correlation-based Collaborative MAC (CC-MAC) [Vuran 2006]
  - Minimizes the number of sampling nodes while achieving the desired level of distortion D*
  - The base station derives the *correlation radius* (based on distortion level D* and spatial correlation model) and broadcasts it to sensor nodes
  - Only a single node within the radius samples and reports data

Management of sensor energy consumption



V. Raghunathan, S. Ganeriwal, M. Srivastava, Emerging Techniques for Long Lived Wireless Sensor Networks, *IEEE Communication Magazine*, April 2006.

Model-based Active Sensing

- **Basic idea**
  - Learn the spatio-temporal relationships among measurements
  - and use this knowledge to make the sensing process energy efficient
  - A model of the phenomenon to be monitored is built
    - ⇨ And updated dynamically, based on measurements from sensor nodes
  - The sensor node decides whether
    - ⇨ To acquire a new sample through a measurement
    - ⇨ To estimate this new sample, with the desired accuracy, through the model
- **Different kind of models**
  - Probabilistic models, Regressive models, ...
  - The most appropriate model is application specific

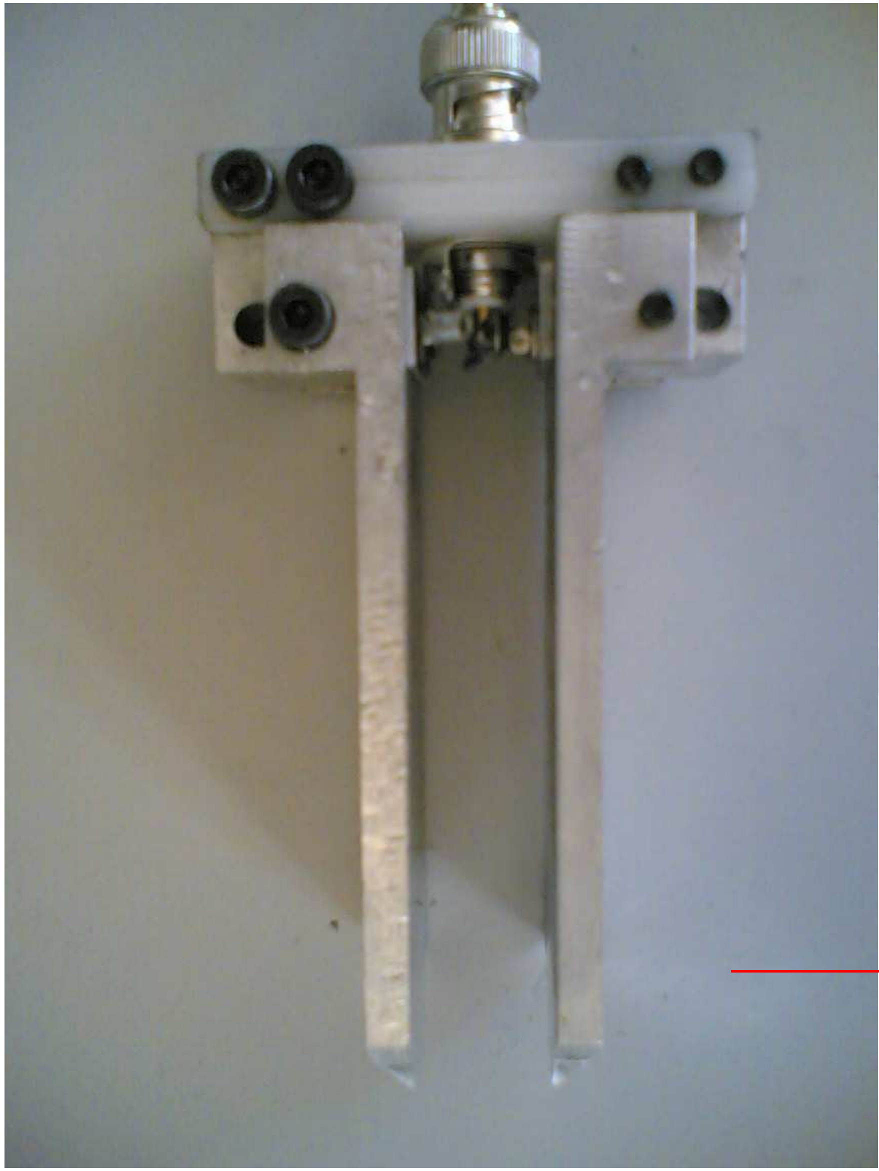
Model-based Active Sensing (cont'd)

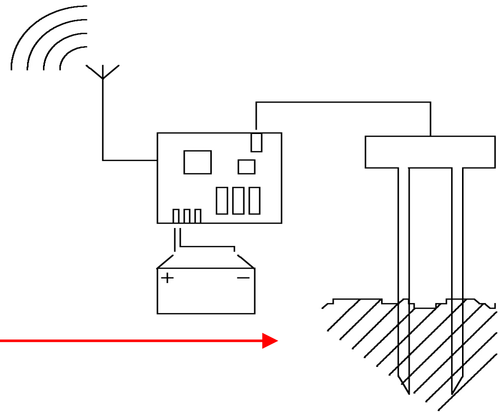
- **Barbie-Q (BBQ) Query System [Deshpande 2004]**
  - **Probabilistic model (based on time-varying multivariate Gaussians) and query planner (base station)**
  - **The model is built and updated dynamically based on sensor reading**
  - **Using this model, the system decides the most efficient way to answer the query with the required confidence**
    - ⇨ **Some values are acquired from sensors, some others are derived from the model**

- **Utility-based Sensing and Comm. (USAC) [Padhy 2006]**
  - **Glacial environment monitoring**
  - **Linear regression model (sensor node)**
    - ⇨ **data are expected to be piecewise linear functions of time**
  - **If the next observed data is within the CI the sampling rate is reduced for energy efficiency**
  - **Otherwise, the sampling rate is set to the maximum to incorporate the change in the model**

Our Contribution

Snow Sensor

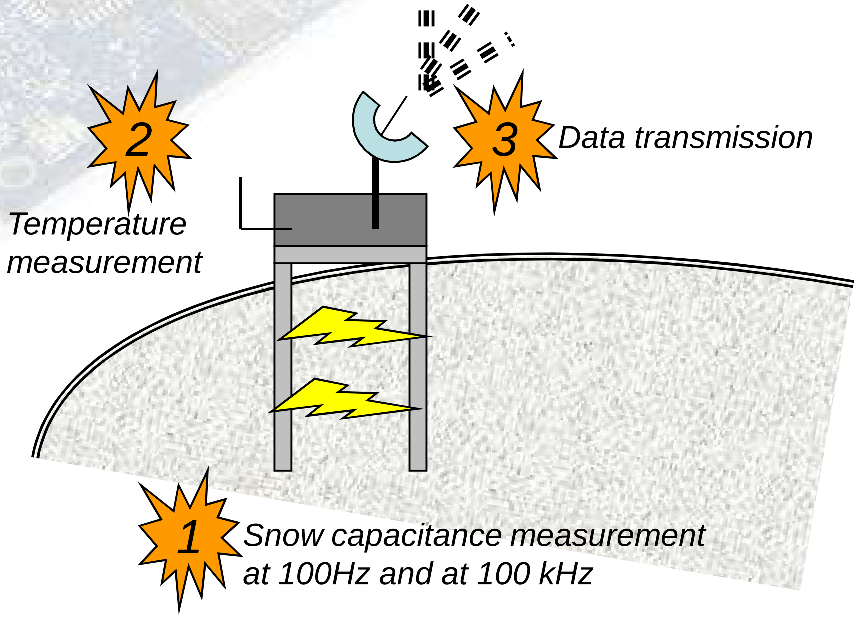




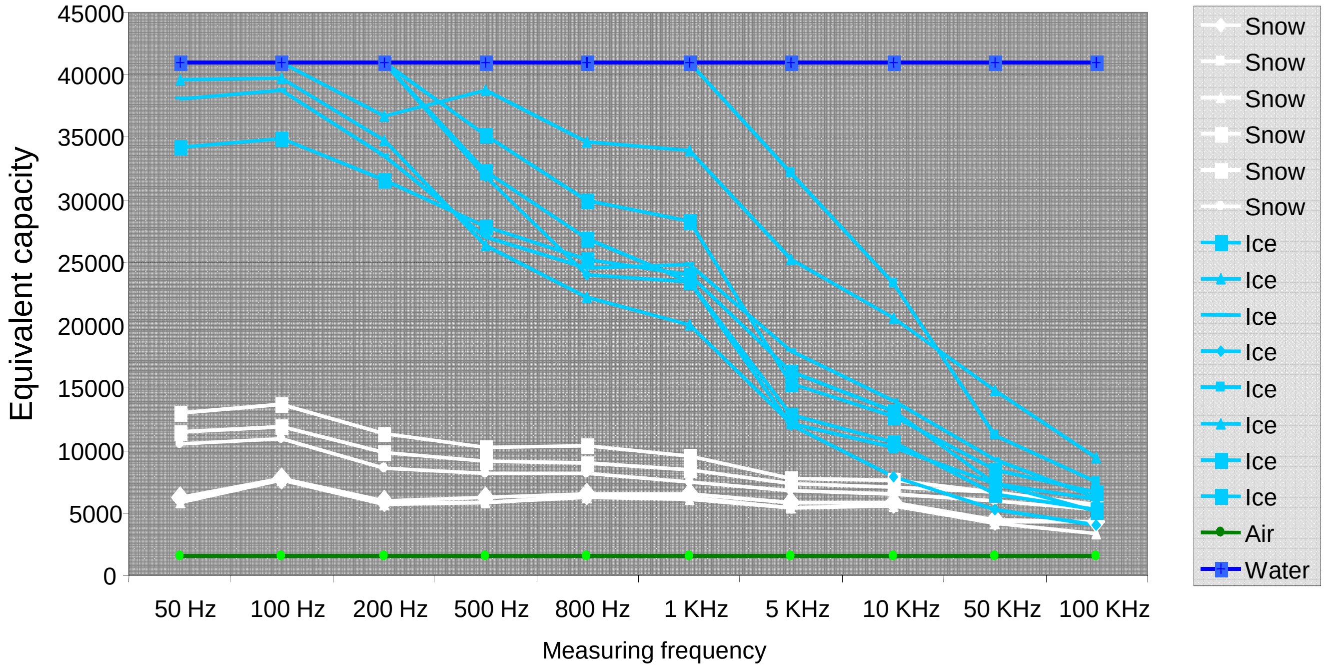
Power Consumption: 59 mW

Snow Sensor Node

- **Multi-frequency capacitive measuring unit composed by**
  - **a probe**
  - **multi-frequency injection board capable of measuring capacity of the dielectric at different frequencies**
- **Temperature sensor**
- **Mote Sensor node**
  - **Processing**
  - **Wireless communication**



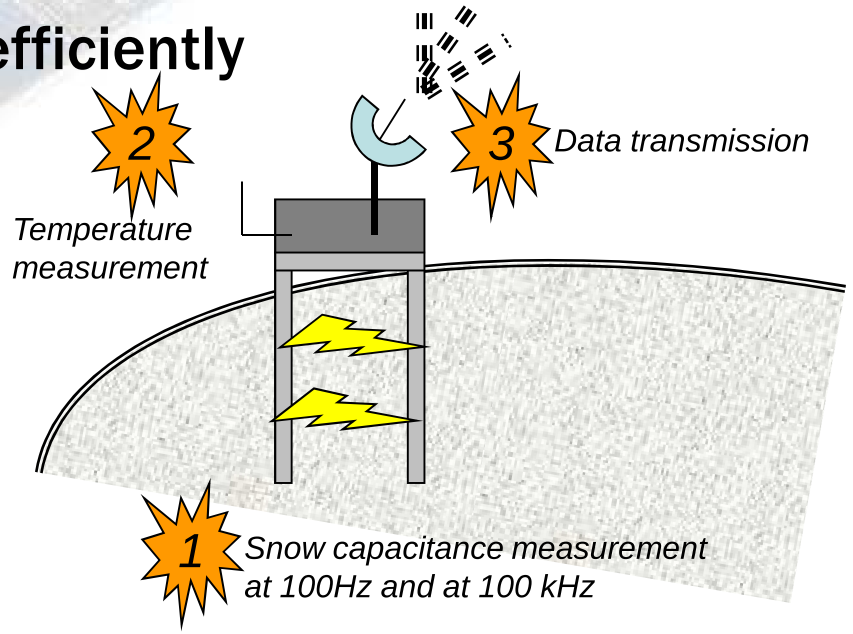
Snow Monitoring Applications



Measure the snow dielectric constant → *Quantify the presence of water, ice and air in the snow* → *Monitor the snow coverage status*

Snow Sensor

- The sensing activity is very power consuming
  - Three readings for each measure are done to achieve a stable and reliable value
  - Power Consumption: 59 mW
- The system is powered by a rechargeable battery pack
- An energy harvesting may also be present
- Energy must be managed very efficiently



Energy Conservation

- **Twofold Approach**
  - **switch off the sensor between consecutive samples**
    - ⇨ **Trivial solution**
    - ⇨ **Reduce the energy consumption by 83%**
  - **adapt the sampling frequency to the process under monitoring**

Adaptive Sampling Algorithm

- **The idea: find dynamically the minimum sample rate compatible with the monitored signal**
  - **↓ sample rate → ↓ sampling energy consumption**
    ↓ transmission energy consumption

Our proposal

- **Nyquist Theorem:**

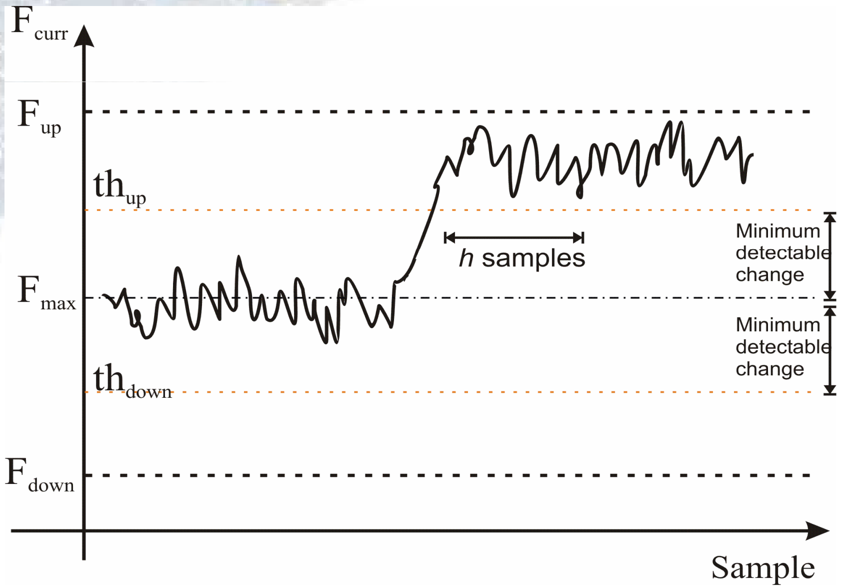
$$F_{max} \Rightarrow F_s > 2\ F_{max}$$

- **F_{max} is not known in advance and changes over time**
- **Track the dynamics of the process under monitoring and adapt the sampling frequency accordingly**
- **Modified CUSUM change detection test**
  - *We modified the traditional CUSUM test to* ***assess the non-stationarity of the maximum frequency*** *in the signal's power spectrum.*
- **General approach**
  - **Not only for snow monitoring**
  - **Suitable for slowly varying processes**

Frequency Change Detection

- ## Modified CUSUM test

1. Estimate the maximum signal frequency F_{max}
   - *W*-sample training set
   - $F_s = c * F_{max}$, $c > 2$
2. Define two alternative thresholds F_{up} and F_{down}
3. If the current estimated maximum frequency F_{curr} is closer to F_{up} / F_{down} than F_{max} for *h* consecutive samples, a change is detected in the maximum frequency of the signal
4. A new sampling frequency F_s is defined ($F_s = c * F_{curr}$, $c > 2$)

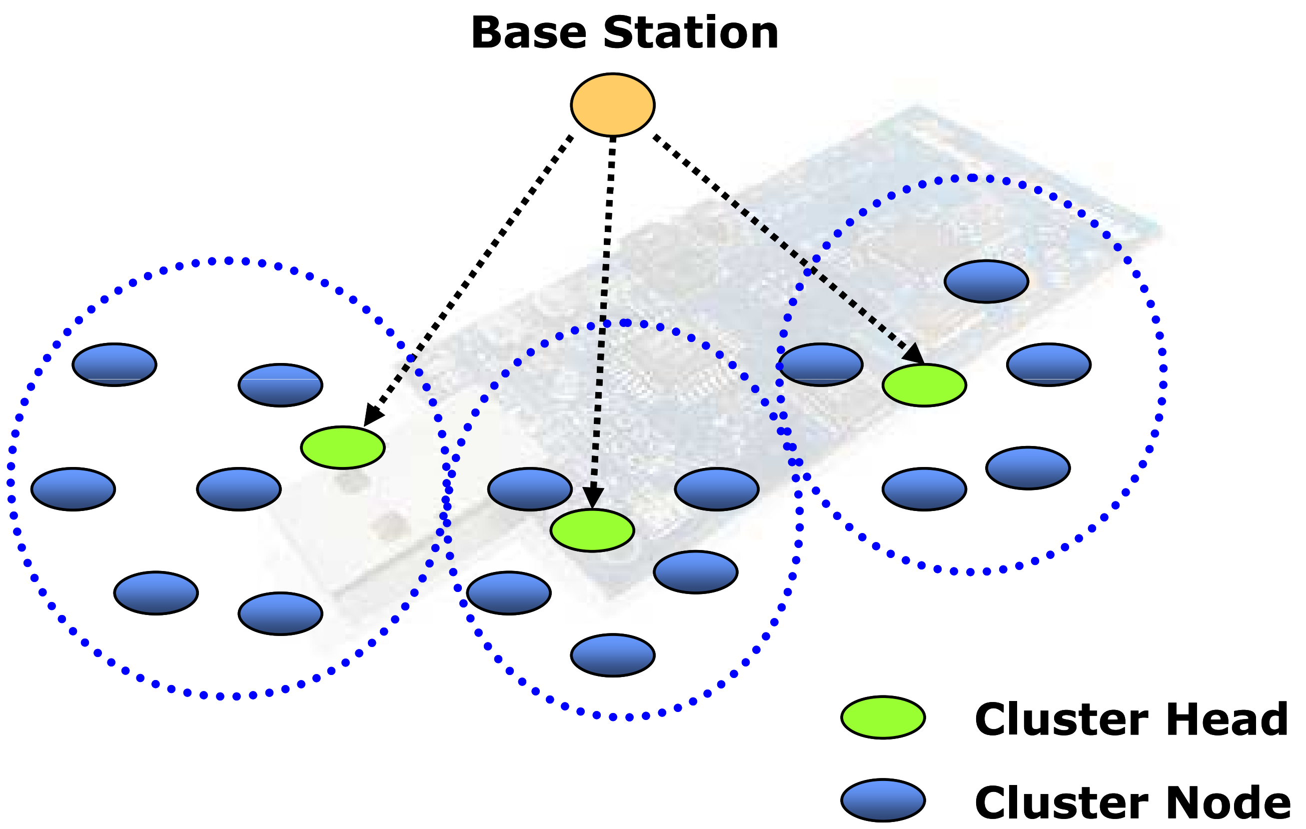


Algorithm Sampling Algorithm

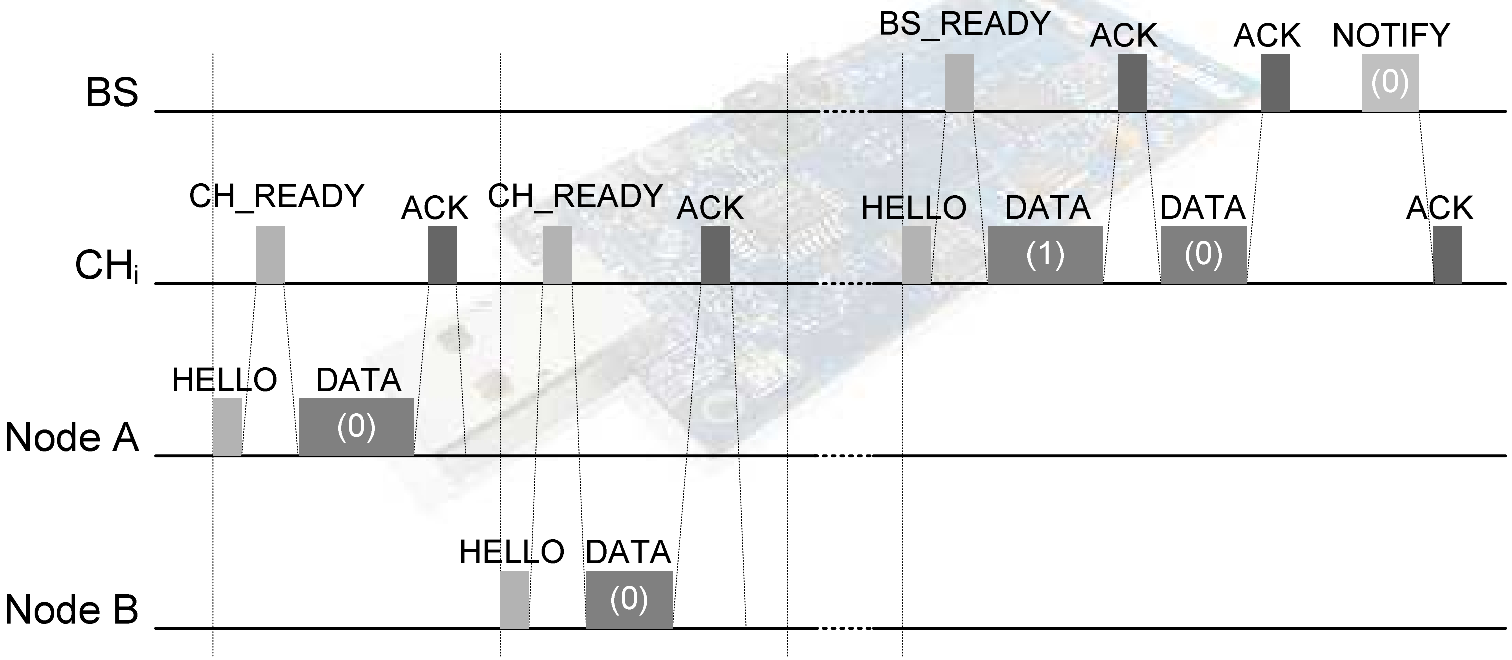
Estimate F_{max} by considering the initial W samples and set $F_s = c * F_{max}$.;
Define $F_{up} = (1 + (c\text{-}2)/4) * F_{max}$ and $F_{downp} = (1 – (c\text{-}2)/4) * F_{max}$;
$h_1=0$ and $h_2=0;$
for (i=W+1; i < DataLength; i++) {
  Estimate the current maximum frequency F_{cur} on the subsequence (i-W, i)
  if ($| F_{curr} - F_{up} | < | F_{curr} - F_{max} |$)
    $h_1 = h_1+1;$
  else if ($| F_{curr} - F_{down} | < | F_{curr} - F_{max} |$)
    $h_2 = h_2+1;$
  else {
    $h_1=0;$
    $h_2= 0;$
  }
  if $(h_1 > h) || (h_2 > h)$ {
    $F_s = c * F_{curr}$.;
    $F_{up} = (1 + (c\text{-}2)/4) * F_{curr}$;
    $F_{down} = (1 – (c\text{-}2)/4) * F_{curr}$;
  }
}

C. Alippi, G. Anastasi, C. Galperti, F. Mancini, M. Roveri, Adaptive Sampling for Energy Conservation in Wireless Sensor Networks for Snow Monitoring Applications, Proc. *IEEE MASS 2007*, MASS-GHS Workshop, Pisa (Italy), October 8, 2007.

Cluster-based Architecture



Data Collection Protocol



Simulation Setup

- **Network scenario**
  - Cluster-based architecture
  - Adaptive Sampling Algorithm executed at BS

- **Dataset: real snow measurements**
  - 4 datasets derived in different days
  - 6000 samples acquired with a fixed period of 15s
    - ⇨ about 24 hours

- **Message loss:**
  - Bernoulli process
  - Loss compensation
    - ⇨ Missed samples are replaced by the previous ones

Figures of Merit

- ***Sampling Fraction***, number of samples acquired by the Adaptive algorithm w.r.t. the number of samples acquired using fixed-rate

provides an indication of the energy saved wih the Adaptive Sampling Algorithm

- ***MRE***: $$\frac{1}{N}\sum_{i=1}^{N}\frac{\left|\overline{x_i}-x_i\right|}{\left|x_i\right|}$$

gives a measure of the relative error introduced in the data sequence reconstructed at the BS

Parameter selection: c, *h* and *W*

- Parameter *c*: confidence parameter for the maximum frequency detection (*c* > 2, Nyquist)

- Parameter *h*: critical to the robustness of the algorithm
  - low values (e.g., 1 or 2): quick detection but possible false positives
  - high values (e.g., 1000): few false positives but less prompt in detecting the changes

- Parameter *W*: critical to the accuracy of the algorithm
  - low values: not accurate estimation but low energy consumption
  - high values: accurate estimation of F_s but high energy consumption

- A-priori knowledge about the process, if available, can be used for a proper parameter setting

Parameters

- **Algorithm parameters**

$$W = 512,\ h = 40,\ c = 2.1$$

Radio Parameters

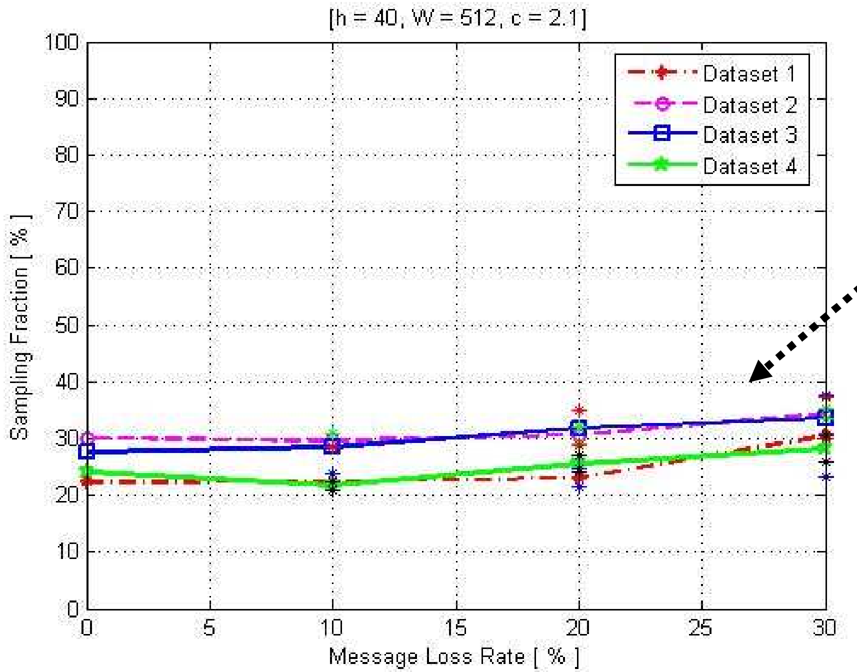
Parameter	Value
Radio	CC1000
Frame size	36 bytes
Bit rate	19.2 Kbps
Transmit Power (0 dBm)	42 mW
Receive Power	29 mW
Idle Power	29 mW
Sleeping Power	0.6 μW

Communication Protocol Parameters

Parameter	Value
hello message size	6 bytes
ch-ready/bs-ready message size	10 bytes
data message size	21 bytes
ack message size	2 bytes
notify message size	13 bytes
Frame size	15 s
Slot size	1 s
Retransmission timeout (t_out)	150 ms
Max number of retransmissions (max_rtx)	2

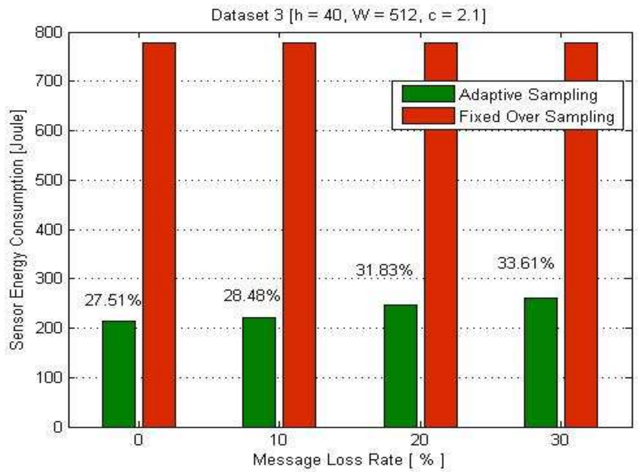
Simulation Results

- **Sampling Fraction (Energy Saving)**



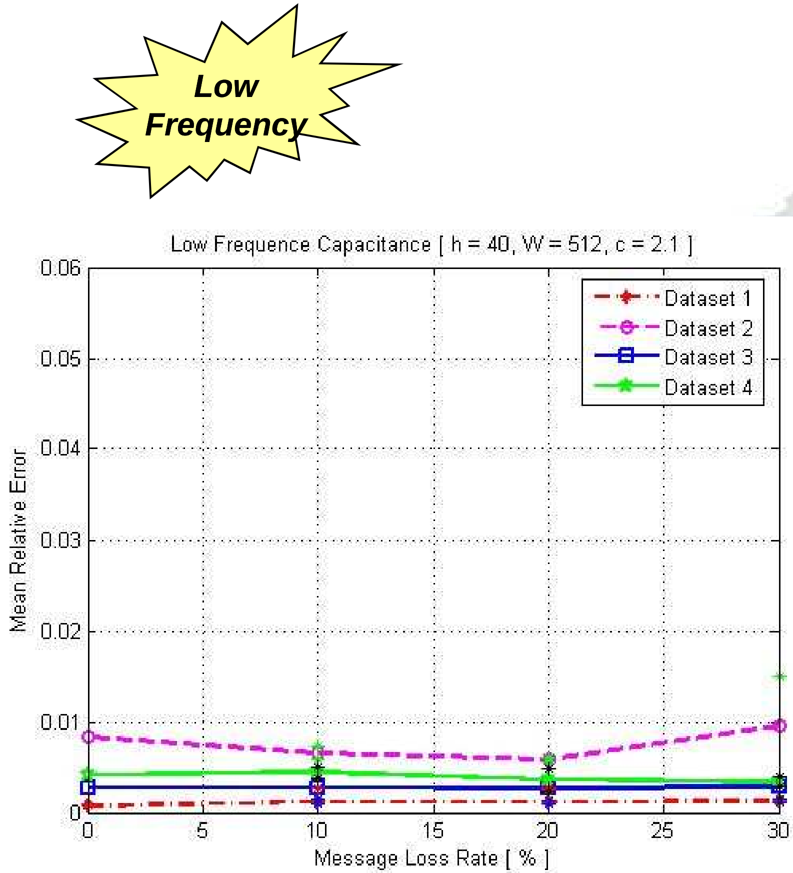
The Adaptive Sampling Algorithm reduces significantly the number of samples the snow sensor has to acquire (67-79%)

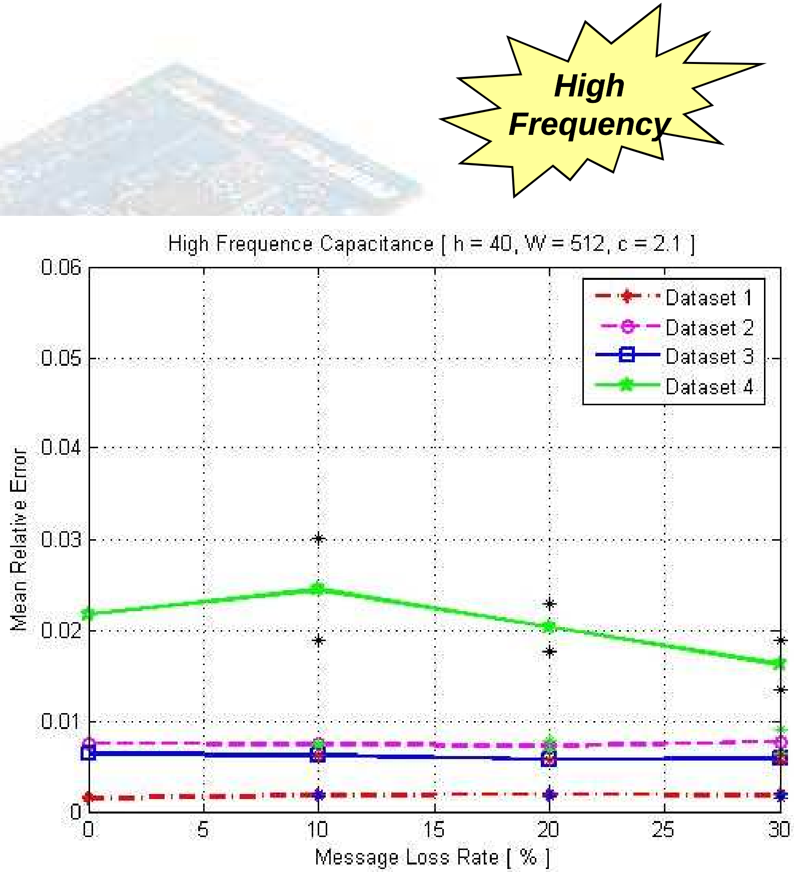
The algorithm can save a lot of energy consumed by both the sensor and radio subsystems



Simulation Results (2)

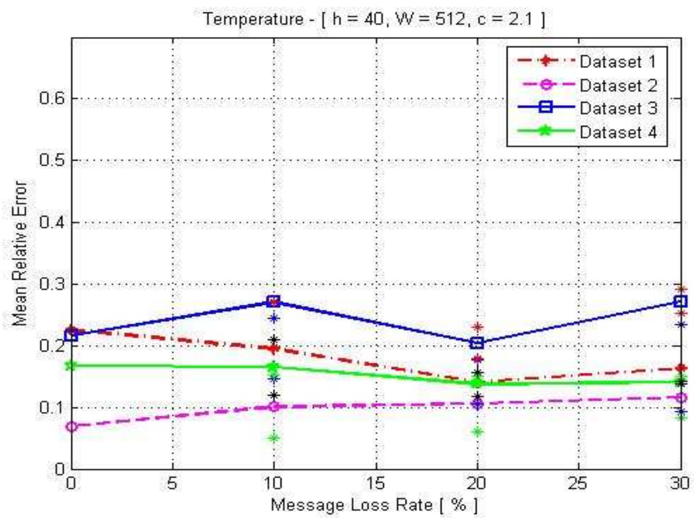
- **MRE for Low/High Frequency Capacity**



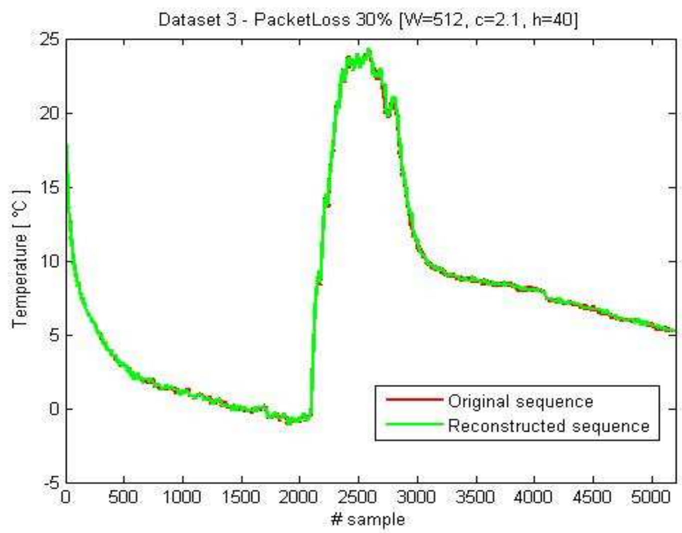


Simulation Results (3)

- **MRE for the temperature**



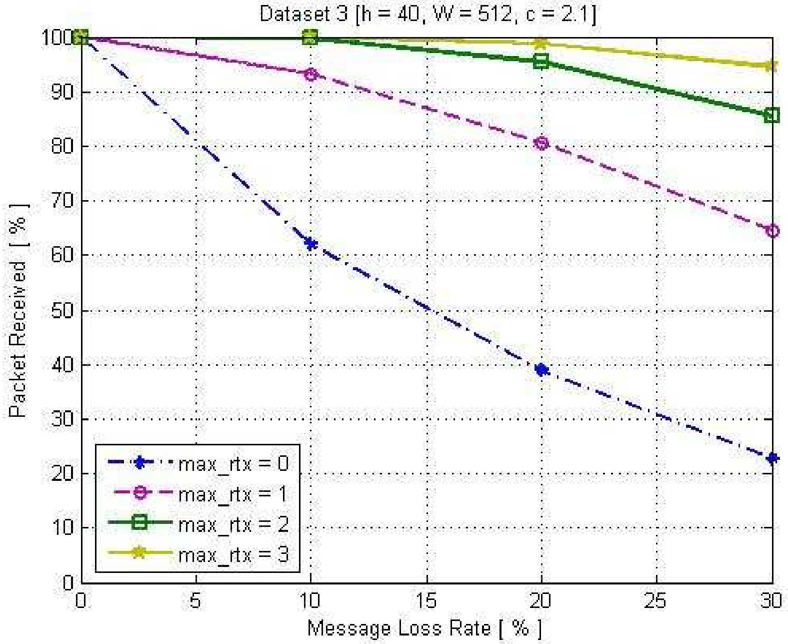
- **Original and reconstructed sequences**



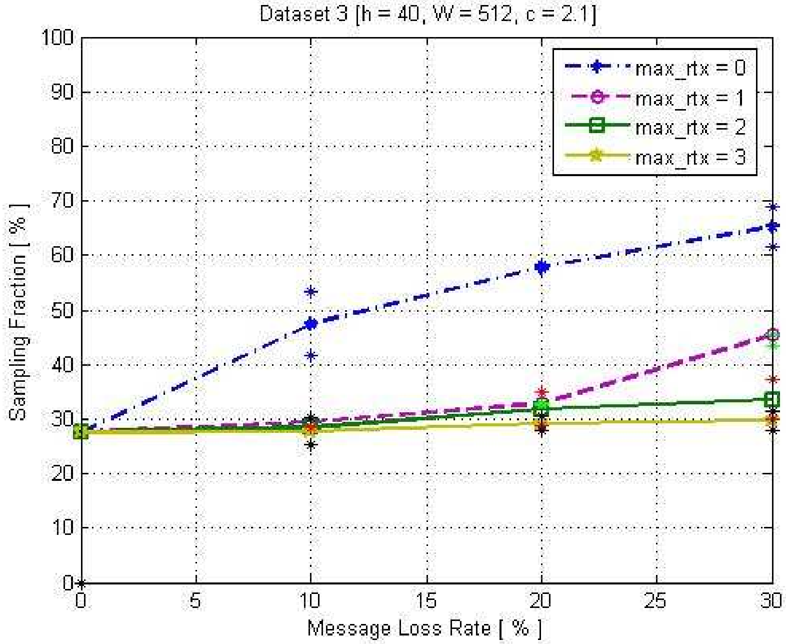
The MRE for ambient temperature is high in all the scenarios. This is because temperature values ranges from -3 to 23 C. Small absolute values can cause an high error

Impact of delivery ratio

Delivery Ratio

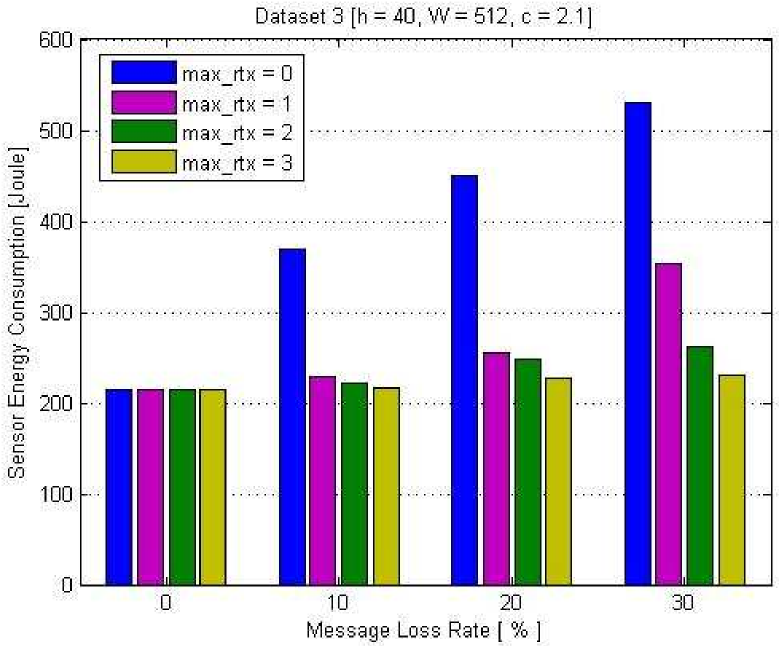


Sampling Fraction

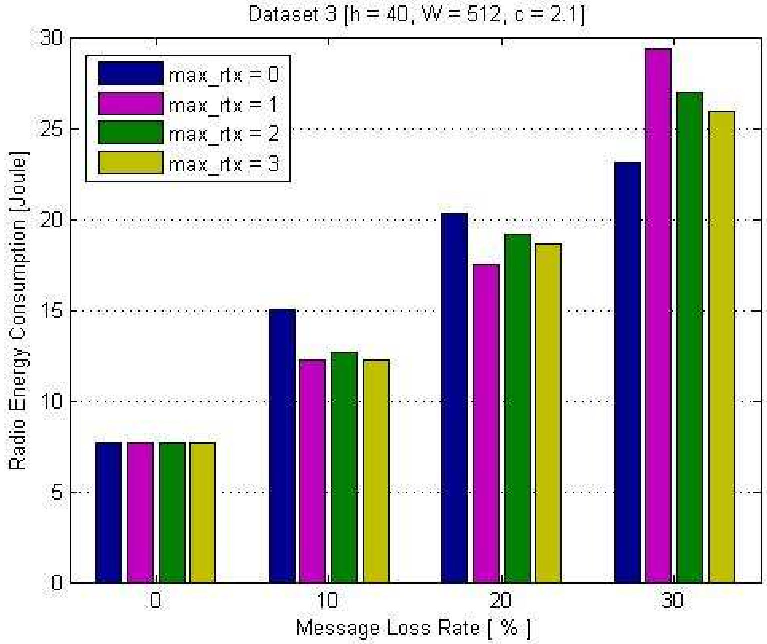


Impact of delivery ratio

Energy consumed by the sensor



Energy consumed by the radio



Energy Consumption

Power management scheme	Power cons.	Activity ratio
No Power Management (Always On)	880 mJ/sample (1 sample every 15 sec)	100%
Duty-cycle	150 mJ/sample (1 sample every 15 sec)	17%
Duty-cycle + Adaptive Sampling		3.5-5.5%

Conclusions

- The Adaptive Sampling Algorithm reduces the % of samples
  - by 67-79% with respect to fixed over-sampling (1 sample every 15 sec)
- and, correspondingly, the energy consumption
  - for sensing and communication
  - The MRE remains at acceptable values
- General methodology
  - Can be used for slowly changing phenomena

Conclusions

- **Hierarchical Sensing**
  - Very energy efficient
  - Application specific
- **Adaptive Sampling**
  - Quite general and efficient
  - Often centralized due to the high computational requirements
  - Usually a single direction (time or space) is explored
- **Model-based Active Sensing**
  - Very promising approach
  - Should be improved in the direction of decentralization
  - Key question: which is the optimal class of models for a specific application scenario?

Questions?