Wireless Sensor Networks

Paul Ferrand

April 2018

Huawei Technologies France

Synopsis

In class:

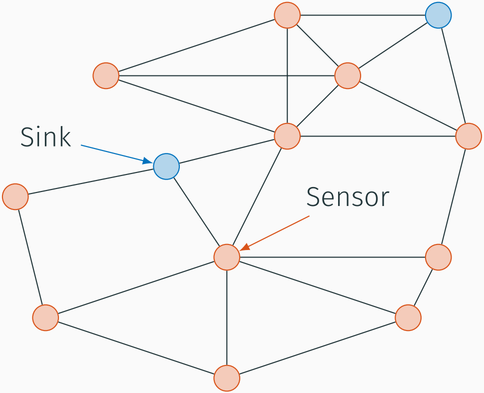
- Wireless sensor network (WSN) overview
- Energy harvesting
- Energy constraints in WSN
- Application example: distributed estimation

In the lab:

- IEEE 802.15.4 PHY layer
- Jamming and jamming avoidance

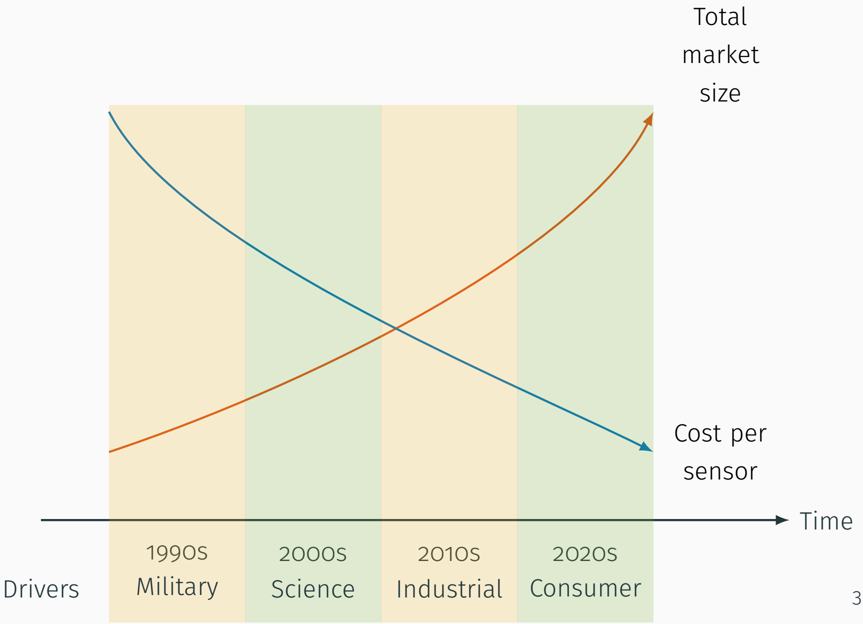
Overview

Wireless Sensor Networks

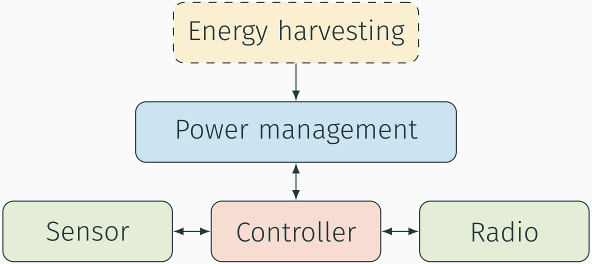


- Low energy
- Low computational power
- Cheap hardware
- Long duty cycles

History


Total market size
Cost per sensor
Time
1990s
Military
2000s
Science
2010s
Industrial
2020s
Consumer
Drivers

Sensor architecture

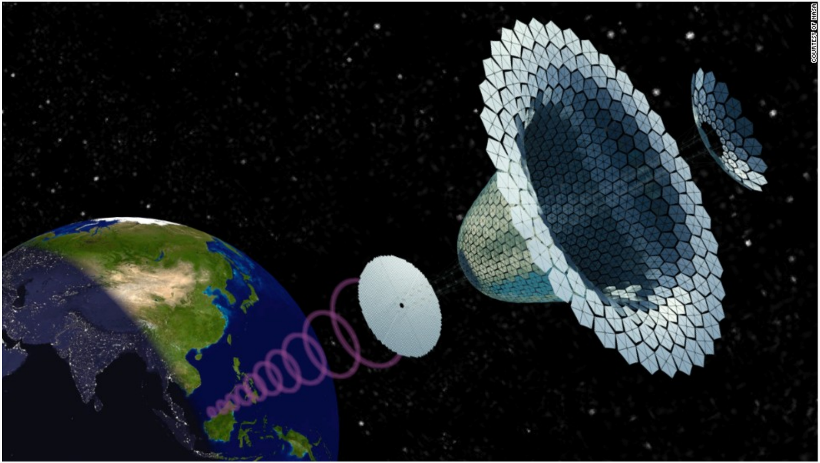


Energy harvesting technologies

Prominent candidates or technologies for harvesting:

- **Solar**: electrons are excited inside a silicon cell
- **Vibrations**: energy can be scavenged through EM transduction or piezo-electricity
- **Thermoelectric**: thermal gradient produces a potential and can thus be exploited
- **Wind**: power electrical generator
- **Wireless EM**: induction, resonant coupling, or far field

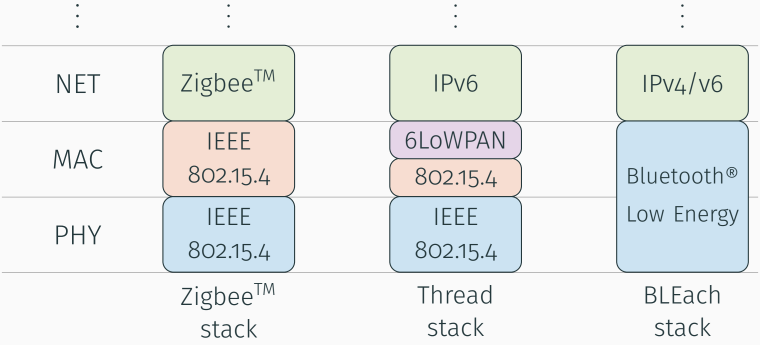
Microwave transmission of gigawatts of solar power



Energy harvesting technologies

From M. Maso, Wireless Energy Transfer and Harvesting, 2017

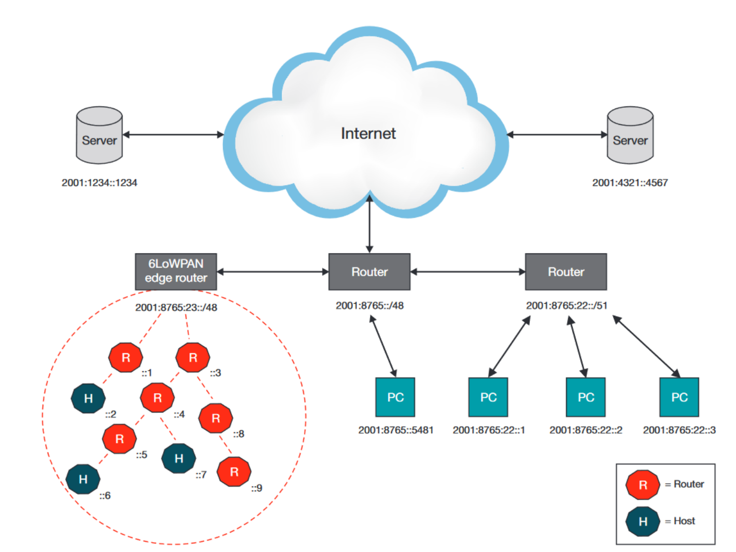
Protocol stacks



Physical layer

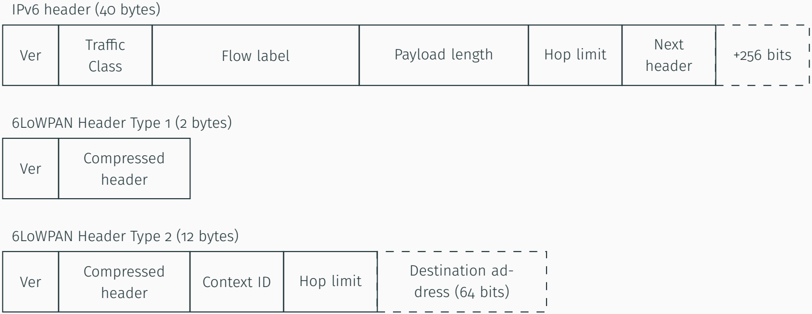
Name	Bluetooth	Bluetooth LE
Range	100m	50m
Rate	1-3 Mbit/s	1 Mbits/s
Throughput	up to 2.1 Mbits/s	0.27 Mbits/s
Active slave	7	Undefined
Robustness	Adaptive hopping, fast ACK, FEC	Adaptive hopping, lazy ACK, CRC
Latency	100ms	6 ms
Voice capable	Yes	No
Topology	Star	Star
Power consump.	1 (reference)	0.01 to 0.5
Peak current	30 mA	15 mA

Network layer



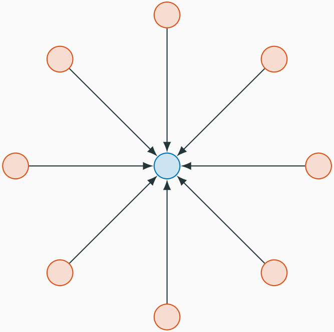
From Texas Instrument, "Demystifying 6LoWPAN", 2014.

Network layer

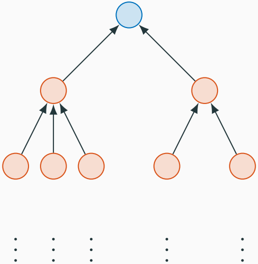


Data flow and aggregation

Star topology



Tree topology

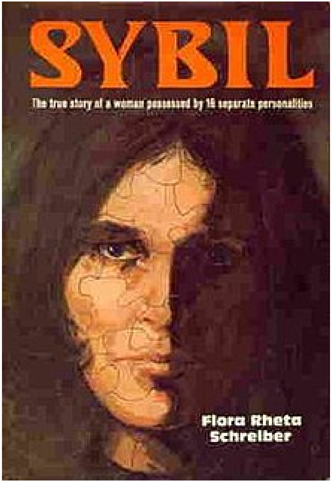


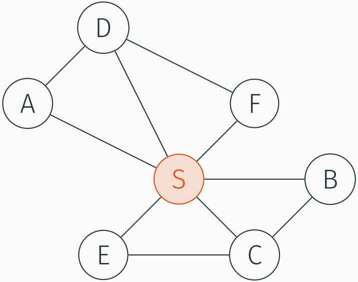
Security

Basic security needs in networking:

- Confidentiality
- Integrity
- Identity
- Trust
- Non-repudiation

Sybil attacks

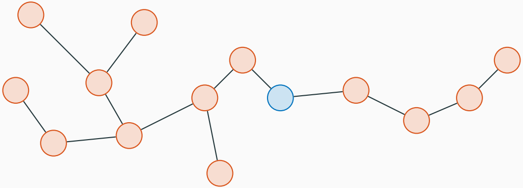




Energy constraints

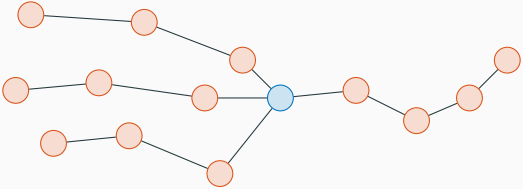
Energy constraints in routing

Imbalanced routing can impact the node lifetime greatly

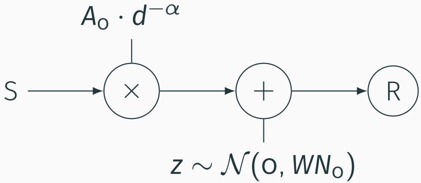


Energy constraints in routing

Nodes close to the sink will still die earlier



Spectral Efficiency–Energy Efficiency



Start from normalized TX and RX SNR

$$\gamma_e = \frac{P}{WN_0} \qquad \gamma_r = A_0 d^{-\alpha} \frac{P}{WN_0} = A_0 d^{-\alpha} \gamma_e$$

Shannon's theoretical channel capacity is

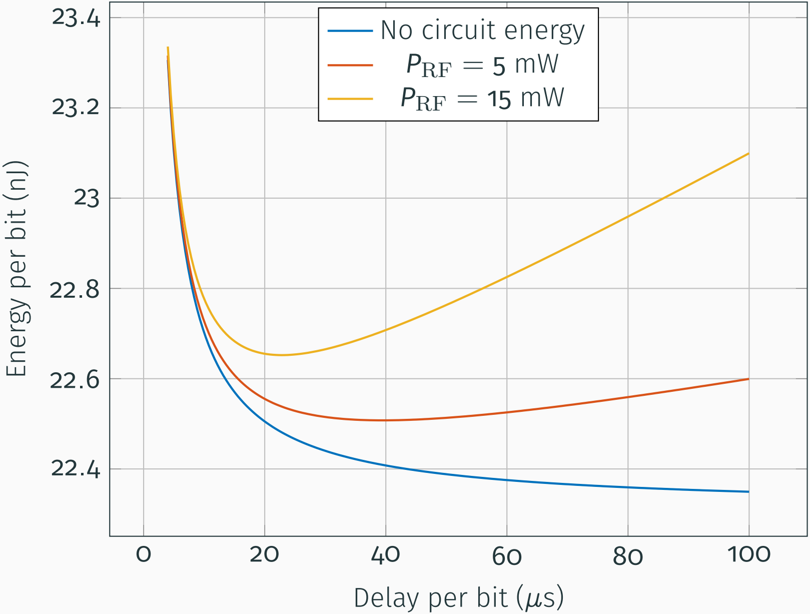
$$C(\gamma_r) = W \log_2(1 + \gamma_r)$$

Spectral Efficiency–Energy Efficiency

Delay and energy per bit

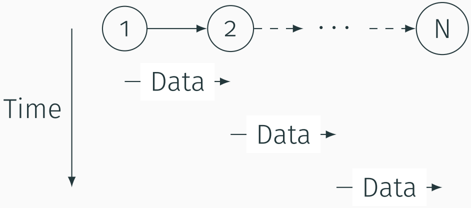
$$D_b = \frac{1}{C(\gamma_r)} \qquad E_b = \gamma_e W D_b N_o + E_Q + P_{\mathrm{RF}} \cdot D_b$$

Spectral Efficiency–Energy Efficiency



Energy–delay tradeoffs in routing

How to apply this result to route constructions?



Normalized the metrics by the distance

$$\tilde{E}_b = \frac{E_b}{d} \qquad \tilde{D}_b = \frac{D_b}{d}$$

Separability of the energy and delay optimization in γ_e and γ_r

$$\tilde{E}_b = \frac{\gamma_e N_0 + E_{\mathrm{RF}}}{(A_0\gamma_e)^{\frac{1}{\alpha}}} \cdot \frac{\gamma_r^{\frac{1}{\alpha}}}{\log_2(1+\gamma_r)} \qquad \tilde{D}_b = \frac{1}{(A_0\gamma_e)^{\frac{1}{\alpha}}} \cdot \frac{\gamma_r^{\frac{1}{\alpha}}}{\log_2(1+\gamma_r)}$$

Distributed estimation

Bias and variance

$$\text{Parameter } \theta \longrightarrow \text{Samples } \{x_n(\theta)\}$$

An estimator is a function of the samples

$$\hat{\theta} = f(\{x_n(\theta)\})$$

Bias How far it is the true value in average

Variance How spread it is around its mean

Estimation in Gaussian noise

Noisy observations:

$$x_n = \theta + z_n \qquad n = 1, \dots, N$$

Sample mean estimator: $\bar{x} = \frac{1}{N} \sum_{n=1}^{N} x_n$

Quantize with a single bit:

$$b_n = \mathbf{1}_{x_n \in (\tau_n, +\infty)}$$

b_n is Bernoulli distributed with $q_n(\theta) = \Pr\{b_n = 1\} = F_z(\tau_n - \theta)$

Assume that all the thresholds are equal, i.e. $\tau_1 = \cdots = \tau_N = \tau_c$.

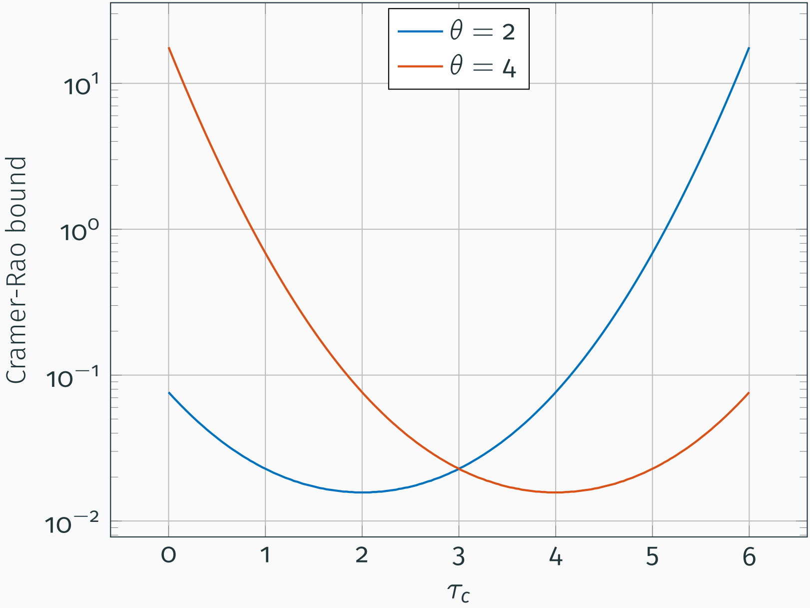
Maximum likelihood estimator for the distributed case with 1-bit quantization:

$$\hat{\theta} = \tau_c - F_z^{-1}\left(\hat{q}(\theta)\right) = \tau_c - F_z^{-1}\left(\frac{1}{N}\sum_{n=1}^{N} b_n\right)$$

Cramer-Rao bound on the unbiased estimator variance:

$$\mathrm{var}(\hat{\theta}) \geq \frac{1}{N} \cdot \frac{F(\tau_c - \theta)(1 - F(\tau_c - \theta))}{p^2(\tau_c - \theta)}$$

Distributed estimation variance



Tracking performance