Energy-Neutral Wireless Sensor Networks

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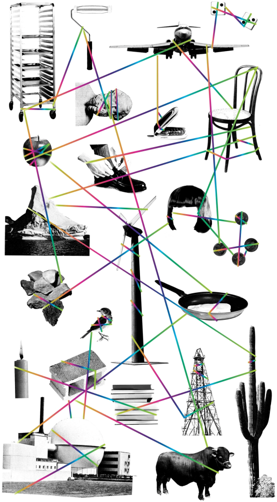
FTW, Dec. 21, 2011



The New York Times

The Internet Gets Physical

December 17, 2011

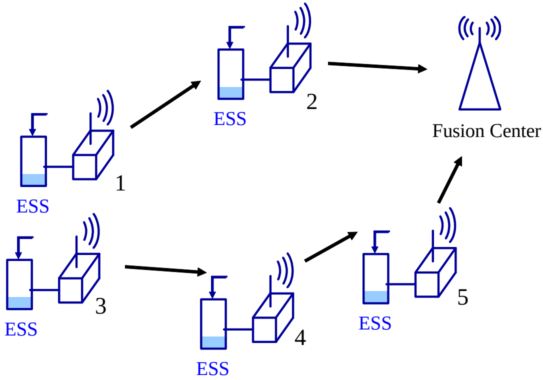
Low-cost sensors, clever software and advancing computer firepower are opening the door to new uses in energy conservation, transportation, health care and food distribution.

... The concept has been around for years, sometimes called the Internet of Things or the Industrial Internet.

... "the sensor-aware planetary computer."

Introduction

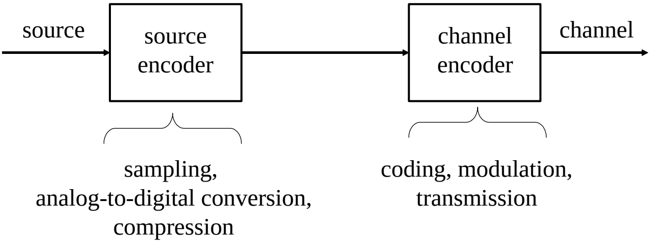
- Energy-harvesting enables new applications for sensor networks (e.g., monitoring flocks of animals, structural health monitoring, ...)



- Energy neutrality requires to balance the use of available and predicted energy

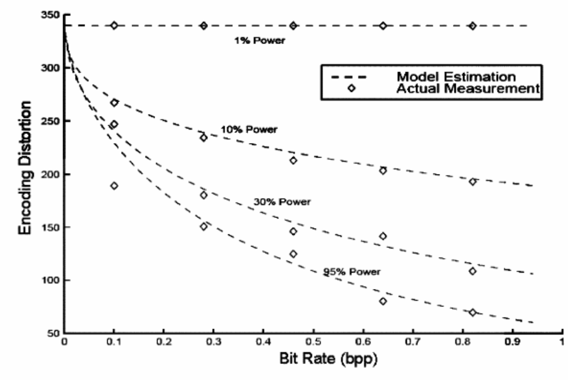
Introduction

- Wireless sensor networks have source-channel coding capabilities



Introduction

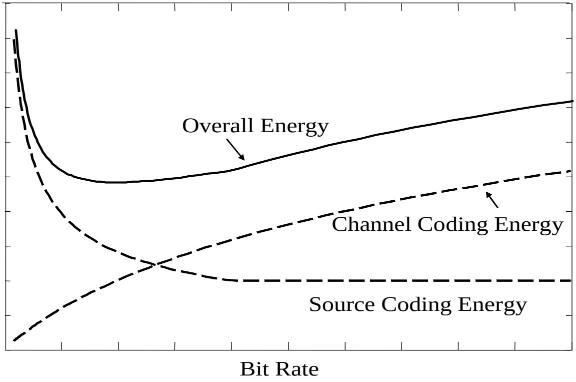
- The energy spent for *source digitization* is comparable that used for communication [Lu et al 03] [He and Wu 06] [Barr Asanovic 06]



[He and Wu 06]

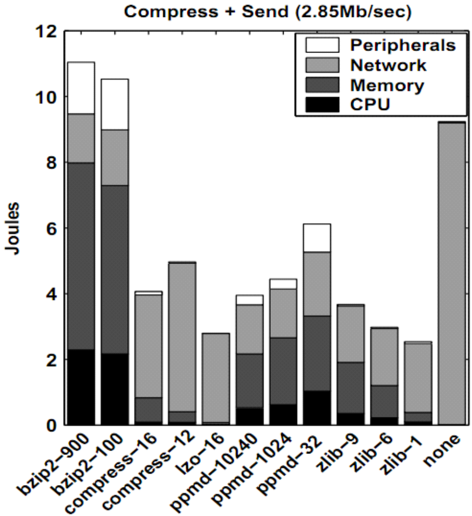
Introduction

- The energy spent for *source coding* is comparable to that used for channel coding [Lu et al 03] [He and Wu 06]



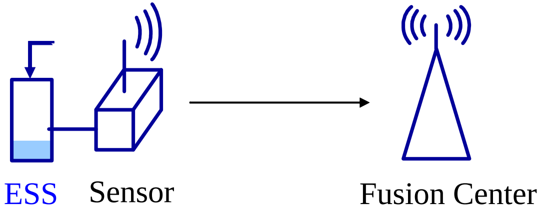
[Lu et al 03]

- Ex.: WLAN card with web data [Barr Asanovic 06]



Overview

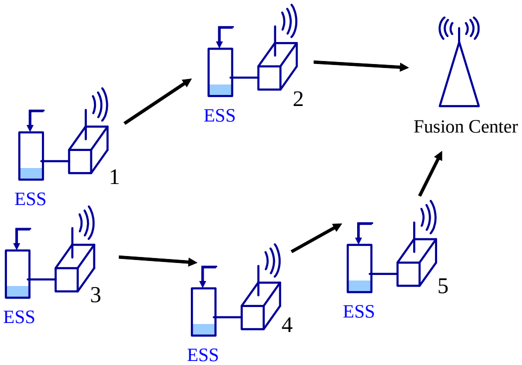
- Energy-neutral wireless sensor networks with source digitization and transmission costs



1. Point-to-point link:

- Optimal energy management policies (long-term average distortion) with arbitrarily large battery and data queue
- Trade-off distortion vs. data queue and battery sizes

Overview

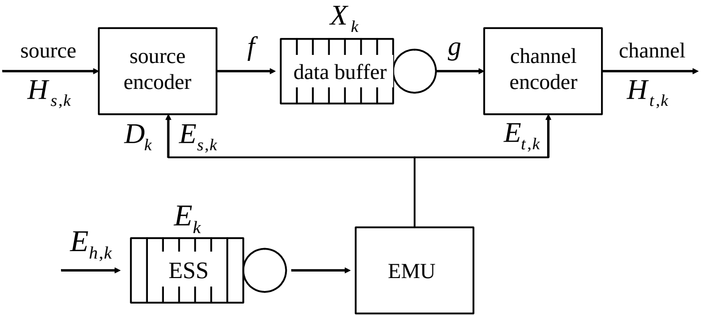


- **2. Multi-hop network:**
  - Optimal joint routing and energy management policies (long-term average distortion) with arbitrarily large battery and data queue
  - Trade-off distortion vs. data queue and battery sizes

Related Work

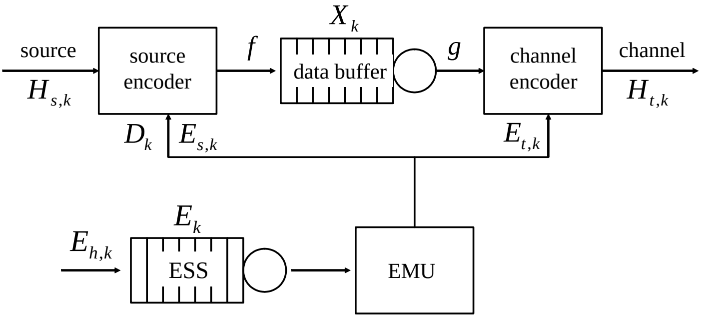
- *Energy-harvesting, transmission energy only*:
  - Information theory [Sharma et al 10][Ozel and Ulukus 10][Ozel et al 10][Devillers and Gunduz 11]
  - Medium Access Control [Iannello et al 10][Jeon and Ephremides 11]
  - Routing and queuing [Kansal et al 06][Lin et al 07][Gatzianas et al 10][Huang and Neely 10]
- *Battery-Powered, source digitization and transmission energy*: [Neely and Sharma 08][Mastronarde and van der Schaar 10]

Point-to-Point Link: System Model



- M samples of a given source measured in each slot
- *Source state* $H_{s,k} \in \mathcal{H}_s$ stationary ergodic process $\sim p_{H_s}(h_s)$
- Bits/source symbol generated by the *source encoder*: $f(D_k, E_{s,k}, H_{s,k})$ (separately continuous convex and non-increasing in D_k and $E_{s,k}$)

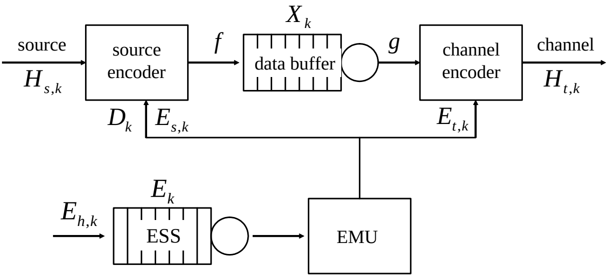
System Model



- *Channel state:* $H_{t,k} \in \mathcal{H}_t$ stationary ergodic $\sim p_{H_t}(h_t)$
- N channel uses ($b = N/M$ bandwidth ratio)
- Bits per channel use delivered successfully to the destination: $g(H_{t,k}, E_{t,k})$ (continuous, concave and non-decreasing in $E_{t,k}$)
- Data queue evolution (*infinite size*):

$$X_{k+1} = \left[X_k - g\left(H_{t,k}, E_{t,k}\right)\right]^+ + f\left(D_k, E_{s,k}, H_{s,k}\right).$$

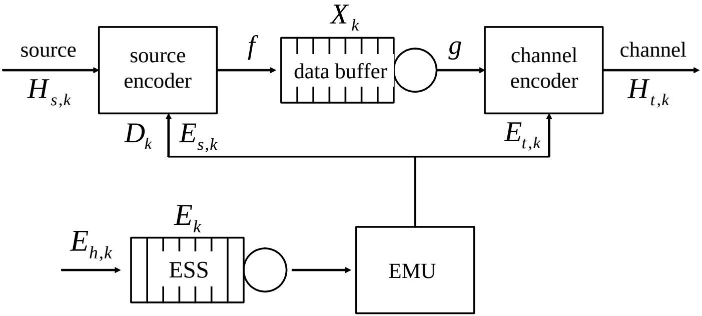
System Model



- Energy arrival $E_{h,k}$ stationary ergodic process $\sim p_{E_h}(e)$ [joule/channel use]
- Energy Storage System (ESS) of *infinite size*:

$$E_{k+1} = [E_k - (E_{s,k} + E_{t,k})]^+ + E_{h,k+1}$$

Definition of Policy



- Policy of Energy management unit (EMU):
  $\pi := \{\pi_k\}_{k\geq 1}$, where $\pi_k := \left\{D_k\left(S^k\right), E_{s,k}\left(S^k\right), E_{t,k}\left(S^k\right)\right\}$ dependent on past system states $S^k = \{S_1, \ldots, S_k\}$, where $S_i = \{E_i, X_i, H_{s,i}, H_{t,i}\}$

Minimization of Long-Term average Distortion

- Minimize over π

$$\bar{D} = \limsup_{n\to\infty} \frac{1}{n} \sum_{k=1}^{n} \mathbb{E}[D_k]$$

subject to data queue is stability

- Data queue (steady state) stability: Distribution of X_k is asymptotically *stationary* and *proper* (so that $\Pr(X_k = \infty) \to 0$)

Optimal Policy

Theorem

The minimum distortion $\bar{D}$ under stability constraints is lower bounded by the solution of the convex problem

$$\bar{D} \geq \bar{D}^* = \arg\min \sum_{h_s} p_{H_s}(h_s) D^{h_s}$$

$$\text{s.t.} \quad \begin{array}{l} \sum_{h_s} p_{H_s}(h_s) f^{h_s}\left(D^{h_s}, E_s^{h_s}\right) \leq \sum_{h_t} p_{H_t}(h_t) g^{h_t}\left(E_t^{h_t}\right), \\ \sum_{h_s} p_{H_s}(h_s) E_s^{h_s} \leq (1-\alpha)\,\mathbb{E}\left[E_{h,k}\right], \\ \sum_{h_t} p_{H_t}(h_t) E_t^{h_t} \leq \alpha \mathbb{E}\left[E_{h,k}\right], \end{array}$$

where minimization is done over the parameters $D^{h_s} \geq 0$, $E_s^{h_s} \geq 0$ for $h_s \in \mathcal{H}_s$, $E_t^{h_t} \geq 0$ for $h_t \in \mathcal{H}_t$, and $0 < \alpha < 1$.

Proof: Based on G/G/1 queuing results and on identifying appropriate variables.

Optimal Policy

Theorem

A policy π that achieves a distortion arbitrarily close to optimal *is given by*

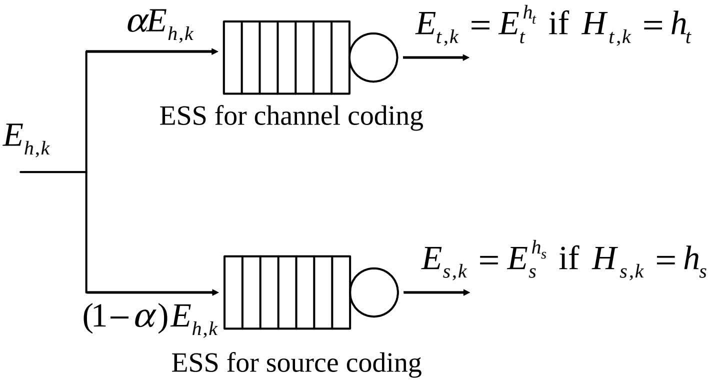
$$\begin{cases} D_k = D^{h_s} & \text{for } H_{s,k} = h_s \\ E_{s,k} = \min\left[(1-\alpha)\,E_k,\ E_s^{h_s}\right] & \text{for } H_{s,k} = h_s \\ E_{t,k} = \min\left[\alpha E_k,\ E_t^{h_t}\right] & \text{for } H_{t,k} = h_t \end{cases},$$

where parameters D^{h_s}, $E_s^{h_s}$, $E_t^{h_t}$ and $0 < \alpha < 1$ are obtained by solving the problem in the Theorem above with the three constraints modified by subtracting a parameter $\epsilon > 0$ arbitrarily small to the right-hand sides.

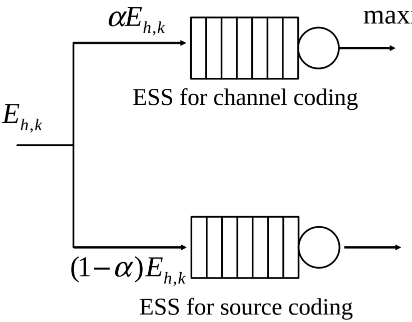
Optimal Policy: Comments

- *Stationary and separable* policy:
- *Source coding parameters* $E_s^{h_s}$,D^{h_s} *adapted only to the source quality* $H_{s,k} = h_s$
- *Channel coding parameter* $E_t^{h_t}$ *adapted only to the fading state* $H_{t,k} = h_t$

Optimal Policy: Comments

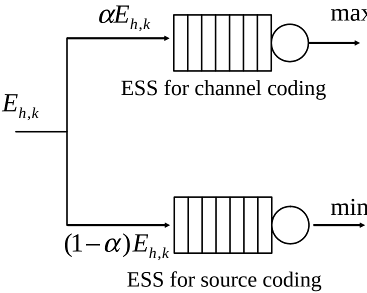


Optimal Policy: Comments



$$\text{maximize } \sum_{h_t} p_{H_t}(h_t) g^{h_t}\left(E_t^{h_t}\right)$$
$$\text{s.t. } \sum_{h_t} p_{H_t}(h_t) E_t^{h_t} \leq \alpha \mathbb{E}[E_{h,k}] - \epsilon$$

Optimal Policy: Comments



$$\text{maximize } \sum_{h_t} p_{H_t}(h_t) g^{h_t}\left(E_t^{h_t}\right)$$

$$\text{s.t. } \sum_{h_t} p_{H_t}(h_t) E_t^{h_t} \leq \alpha \mathbb{E}[E_{h,k}] - \epsilon$$

$$\text{minimize } \sum_{h_s} p_{H_s}(h_s) D^{h_s}$$

$$\text{s.t. } \sum_{h_s} p_{H_s}(h_s) E_s^{h_s} \leq (1-\alpha) \mathbb{E}[E_{h,k}] - \epsilon$$

$$\sum_{h_s} p_{H_s}(h_s) f^{h_s}\left(D^{h_s}, E_s^{h_s}\right) \leq g_{\max} - \epsilon$$

Optimal Policy: Comments

- Average energy used $\leq \mathbb{E}\left[E_{h,k}\right] - \epsilon$
- $\epsilon > 0 \rightarrow$ no underflow (as k grows large)
- This result hinges on infinite ESS

The Role of ESS: Suboptimal Policies

- Policies that do not use the ESS, or use it only partially
- *No ESS with adaptation:* For an optimized fraction $0 \leq \alpha^{h_s,h_t} \leq 1$

$$\begin{cases} D_k = D^{h_s,h_t} \\ E_{s,k} = \alpha^{h_s,h_t} E_{h,k} \\ E_{t,k} = (1-\alpha^{h_s,h_t}) E_{h,k} \end{cases} .$$

- *No ESS with no adaptation*: $\alpha^{h_s,h_t} = \alpha$
- *Source-only ESS*
- *Channel-only ESS*
- ... *non-separable* policies

Numerical Results

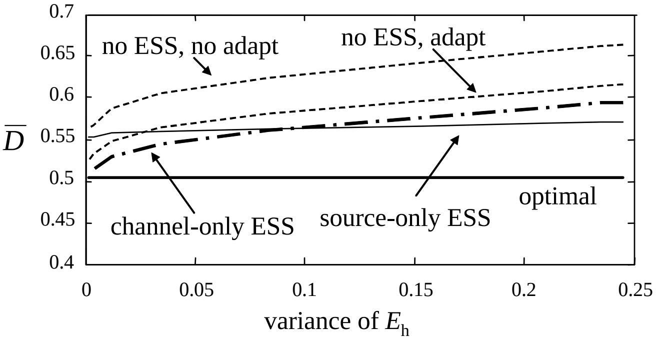
- *Source model*:
  i.i.d. source $U_{k,i} \sim \mathcal{N}(0, D_{max})$ with $i = 1, ..., M$
  measurement $\sqrt{H_{s,k}} U_{k,i} + Z_{k,i}$ where $Z_{k,i} \sim \mathcal{N}(0, 1)$ i.i.d.
  Rate-distortion-energy function is given [He and Wu 06]

$$f^{h_s}(D_k, E_{s,k}) = \frac{1}{b} \log_2 \left(\frac{D_{max} - D_{mmse}}{D_k - D_{mmse}} \right) \xi(E_{s,k}),$$

  (indirect) rate-distortion function with $D_{mmse} = (h_s + 1/D_{max})^{-1}$,
  $\xi(T_{s,k}) = \zeta \max\left[(bE_{s,k}/E_{s,max})^{-1/\eta}, 1\right]$, with $\zeta > 1$, $\eta > 1$ and
  $E_{s,max}$ being design parameters
- *Communication model*: AWGN with channel SNR $H_{t,k}$,
  $g^{h_t}(E_t) = \log(1 + h_t E_t)$
- $H_{s,k}$ and $H_{t,k}$ can take two possible values in $\mathcal{H}_s = \mathcal{H}_t = \{1, 10\}$ independently and with equal probability

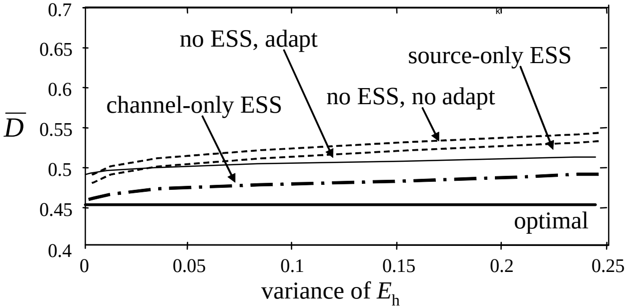
Numerical Results

- Beta distribution for $E_{h,k}$ with mean $\mathbb{E}[E_{h,k}] = 0.5$
- $E_{s,max} = 1$, $b = 1$ and $\eta = 3/2$



Numerical Results

- $\eta = 3$ ($f^{h_s}(D_k, E_{s,k})$ less convex in $E_{s,k}$)



Finite ESS and Data Queue

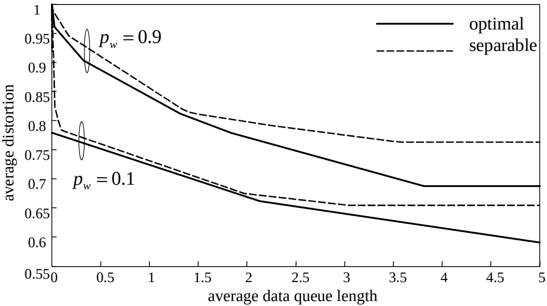
- Stability criterion does not provide any guarantee on the queue length (and thus, indirectly, on the delay)
- At the stability limit, the queue length becomes arbitrarily large
- Here we assume finite ESS and data queue
- Minimize *expected total discounted cost* ($0 \leq \lambda < 1$ is the discount factor and $0 \leq \gamma \leq 1$)

$$\lim_{n \to \infty} \sum_{k=0}^{n} \lambda^k \left[\gamma \mathbb{E}[D_k] + (1-\gamma) \mathbb{E}[X_k] \right],$$

- Dynamic programming

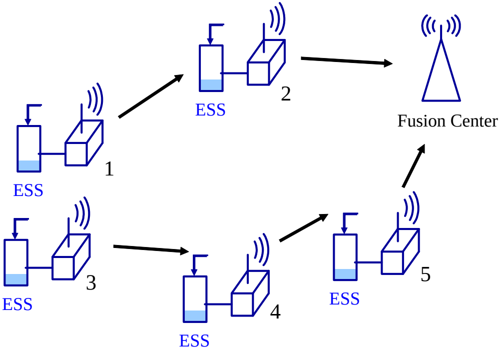
Numerical Results

- Data buffer length equal to 6, unit battery capacity, $D_k \in \{0.55, 0.75, 1\}$
- $p_{E_h}(0.5) = p_{H_t}(1) = p_{H_s}(1) = p_w$



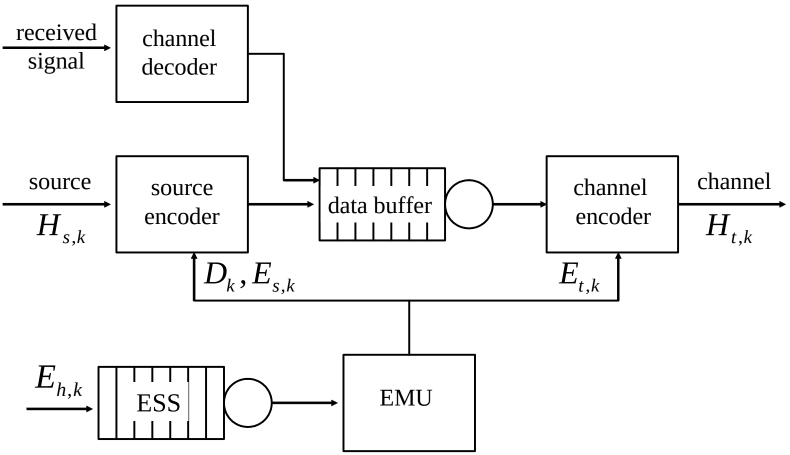
- Separable policy with two ESSs (assumes that the other encoder provides a constant and optimized rate in each slot)

Multi-hop Network: Introduction

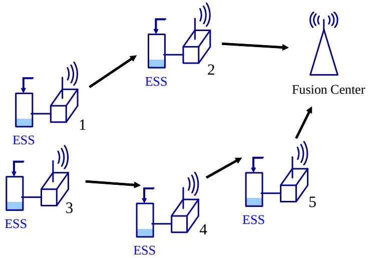


- Spatially correlated sources
  –> Distributed source coding
  –> In-network processing
- Interference
- Spatially correlated harvesting

System Model

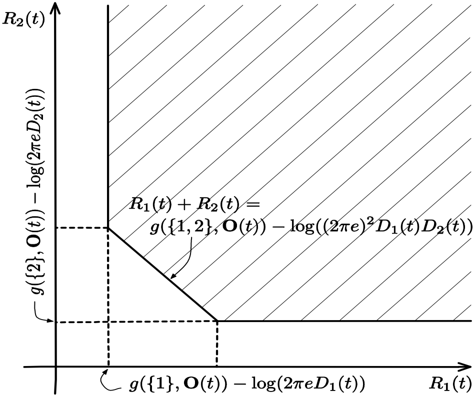


Source Coding Model



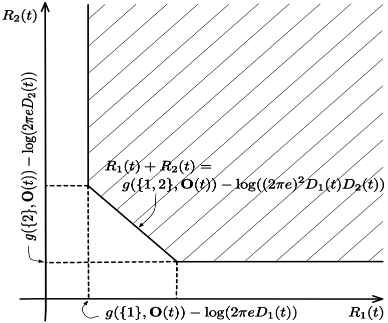
- Source state $\mathbf{O}(t) \in \mathcal{O}$ (finite) i.i.d.: joint spatial distribution of the sources $\sim \rho_{o_i}$
- ex.: $\mathcal{N}(0, \mathbf{O}(t))$
- Source coding rate (bits per source symbol): $R_n(t) \leq R_{\max}$
- Distortion: $D_{\min} \leq D_n(t) \leq D_{\max}$, with $0 < D_{\min} \leq D_{\max} < \infty$

Source Coding Model: Distributed Source Coding



- Trade rates of different users for fixed distortion levels

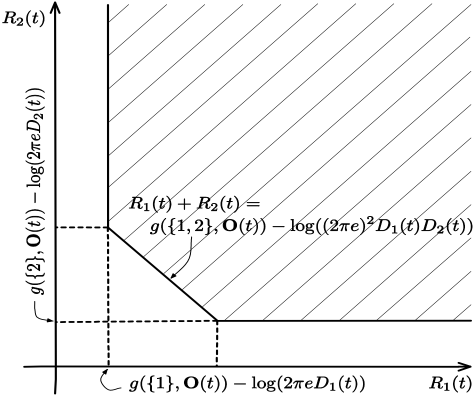
Source Coding Model: Distributed Source Coding



- High-resolution *rate-distortion constraints* [Zamir Berger 99]:

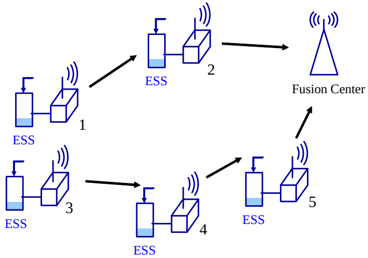
$$\sum_{n \in \mathcal{X}} R_n(t) \geq h(\mathcal{X}, \mathbf{O}(t)) - \log_2 \left((2\pi e)^{|\mathcal{X}|} \prod_{n \in \mathcal{X}} D_n \right)$$

Source Coding Model: Distributed Source Coding



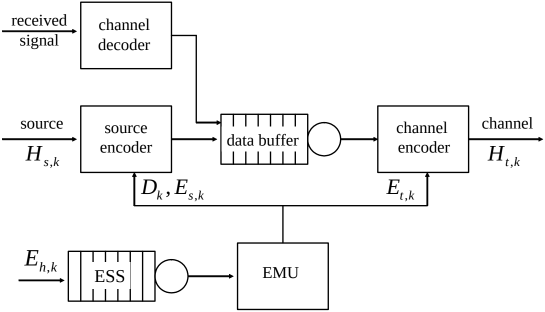
- Assume efficient distributed source codes: $\mathrm{P}_c(R_n(t)) = \alpha_n R_n(t)$, $\alpha_n \geq 0$

Transmission Model [Georgiadis et al 06]



- Transmission power (per channel use) on (n, m) link: $P_{n,m}(t)$
- Channel state $\mathbf{S}(t) \in \mathcal{S}$ (finite set) i.i.d. $\sim \rho_{s_i}$
- Transmission rate $C_{n,m}(\mathbf{P}(t), \mathbf{S}(t))$ (bit per channel use) non decreasing in $P_{n,m}(t)$
- *Interference* is detrimental: $C_{n,m}(\mathbf{P}(t), \mathbf{S}(t)) \leq C_{n,m}(\mathbf{P}'(t), \mathbf{S}(t))$ if $P_{a,b}(t) = 0$ with $(a, b) \neq (n, m)$
- Ex: $\mu_{n,m}(t) = C_{n,m}(\mathbf{P}(t), \mathbf{S}(t)) = \log\left(1 + \frac{P_{n,m}(t)S_{n,m}(t)}{N_0 + \sum_{l \neq n} P_l(t)S_{l,n}(t)}\right)$

Data Queues



- Data received by other nodes: $\mu_{in}(t) = \sum_{m \neq n} \mu_{m,n}(t)$
- Data transmitted: $\mu_{out}(t) = \sum_{n \neq m} \mu_{n,m}(t)$

$$U_n(t+1) \leq \max\left\{U_n(t) - \mu_{n,*}(t), 0\right\} + \mu_{*,n}(t) + \frac{R_n(t)}{b}$$

Energy Model [Huang and Neely 10]

- Energy harvestable $H_n(t) \in \mathcal{H}$ (finite) i.i.d. $\sim \rho_{h_i}$
- Energy harvested: $0 \leq \tilde{H}_n(t) \leq H_n(t)$
- Battery evolution: $E_n(t+1) = E_n(t) - P_n(t) - \mathrm{P}_c(R_n(t)) + \tilde{H}_n(t)$
- *Energy availability constraints* $P_n(t) + \mathrm{P}_c(R_n(t)) \leq E_n(t)$

Problem Definition

- Policy $\pi := \{\pi(t)\}_{t\geq 1}$, where $\pi(t) := \{\mathbf{D}(t), \mathbf{R}(t), \mathbf{P}(t)\}_{\Theta(t)}$
- History of current and past states: $\Theta(t) = (\mathbf{U}(t'), \mathbf{E}(t'), \mathbf{S}(t'), \mathbf{O}(t'))_{t'\leq t}$
- Minimize over π

$$\limsup_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \sum_{n} \mathbb{E}\left[f_n(D_n(t))\right]$$

- $f_n(D_n(t))$ convex and non-decreasing
- Strong stability constraint:

$$\limsup_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \sum_{n} \mathbb{E}\left[U_n(t)\right] < \infty$$

- Energy availability and rate-distortion constraints

Lower Bound

- By *relaxing* stability constraint to *mean rate* stability

$$\limsup_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\sum_{n}\mathbb{E}\left[\mu_{*,n}(t)+\frac{R_n(t)}{b}\right]\leq\liminf_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\sum_{n}\mathbb{E}\left[\mu_{n,*}(t)\right]$$

and the energy availability constraint as

$$\limsup_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\sum_{n}\mathbb{E}\left[P_n(t)+\mathrm{P}_c(R_n(t))\right]=\liminf_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\sum_{n}\mathbb{E}\left[\tilde{H}_n(t)\right]$$

constrained Markov decision process

- Optimal strategy is randomized stationary [Ross 95]
- Policy depends on $(\mathbf{S}(t),\mathbf{O}(t))$

Lower Bound

- Using Lagrangian relaxation: For any $V > 0$, $\boldsymbol{\lambda} \in \mathbb{R}_+^{L(2^N-1)}$, $\boldsymbol{\nu} \in \mathbb{R}_+^N$, $\boldsymbol{\chi} \in \mathbb{R}^N$

$$VF_0^* \geq d(\boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\chi})$$

with

$$d(\boldsymbol{\lambda}, \boldsymbol{\nu}, \boldsymbol{\chi}) = \sum_{o_i \in \mathcal{O}} \rho_{o_i} \sum_{s_j \in \mathcal{S}} \rho_{s_j} \sum_{h_k \in \mathcal{H}} \rho_{h_k} d_{o_i, s_j, h_k}(\boldsymbol{\lambda}^{(o_i)}, \boldsymbol{\nu}, \boldsymbol{\chi}),$$

Lower Bound

- with the definition $d_{o_i,s_j,h_k}(\boldsymbol{\lambda}^{(o_i)},\boldsymbol{\nu},\boldsymbol{\chi}) =$

$$\inf_{\mathbf{R}^{(o_i)},\mathbf{D}^{(o_i)},\mathbf{P}^{(s_j)},\tilde{\mathbf{H}}^{(h_k)}} \sum_n Vf_n(D_n^{(o_i)})$$
$$+ \sum_{m=1}^{2^N-1} \lambda_m^{(o_i)} \left[h(\mathcal{X}_m, o_i) - \log\left((2\pi e)^{|X_m|} \prod_n D_n^{(o_i)} \right) - \sum_{n\in\mathcal{X}} R_n^{(o_i)} \right]$$
$$+ \sum_n \nu_n \left[\frac{R_n^{(o_i)}}{b} + \mu_{*,n}(\mathbf{P}^{(s_i)}, s_i) - \mu_{n,*}(\mathbf{P}^{(s_i)}, s_i) \right]$$
$$+ \sum_n \chi_n \left[P_n^{(s_j)} + \alpha_n R_n^{(o_i)} - \tilde{H}_n^{(h_k)} \right],$$

under constraints $R_n^{(o_i)} \leq R_{\max}$, $D_{\min} \leq D_n^{(o_i)} \leq D_{\max}$ and $\tilde{H}_n^{(h_k)} \leq h_{n,k}$

Lyapunov Optimization [Georgiadis et al 06] [Neely 10]

- Consider the problem:

$$\text{minimize} \limsup_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}[f(x(t), \phi(t))]$$

$$\text{s.t.} \begin{cases} \limsup_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}[Q(t)] \leq \infty \\ x(t) \in \mathcal{X}_{\phi(t)} \end{cases}$$

- $\phi(t)$ (state) i.i.d.
- Queue: $Q(t+1) = \max\{Q(t) + g(x(t), \phi(t)), 0\}$

Lyapunov Optimization [Georgiadis et al 06] [Neely 10]

- Lyapunov function: $L(t) = \frac{1}{2}Q(t)^2$
- Average drift: $\Delta(t) = \mathbb{E}[L(t+1) - L(t)|Q(t)]$
- Minimize

$$\begin{aligned} & \Delta(t) + V\mathbb{E}[f(x(t), \phi(t))|Q(t)] \\ \leq \quad & B + Q(t)\mathbb{E}[g(x(t), \phi(t))|Q(t)] + V\mathbb{E}[f(x(t), \phi(t))|Q(t)] \end{aligned}$$

- Minimize

$$Q(t)g(x, \phi) + Vf(x, \phi) \text{ s.t. } x \in \mathcal{X}_\phi$$

(no need to know statistics of state $\phi(t)$)

Lyapunov Optimization [Georgiadis et al 06] [Neely 10]

- Relax the stability constraint: $\phi^* \leq VF^*$, where ϕ^* optimal solution of

$$\text{minimize} \limsup_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} V\mathbb{E}[f(x(t),\phi(t))]$$
$$\text{s.t.} \quad \begin{cases} \limsup_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}[g(x(t),\phi(t))] \leq 0 \\ x(t) \in \mathcal{X}_{\phi(t)} \end{cases}$$

- Lagrange dual (weak duality): $d^* \leq \phi^* \leq VF^*$, where d^* is the solution of

$$\text{minimize}\ V\mathbb{E}[f(x(t),\phi(t))|Q(t)] + \lambda\mathbb{E}[g(x(t),\phi(t))|Q(t)]$$
$$\text{s.t. } x(t) \in \mathcal{X}_{\phi(t)}$$

Lyapunov Optimization [Georgiadis et al 06] [Neely 10]

- For the considered policy

$$\begin{aligned} & \Delta(t) + V\mathbb{E}[f(x(t),\phi(t))|Q(t)] \\ \leq\ & B + Q(t)\mathbb{E}[g(x(t),\phi(t))|Q(t)] + V\mathbb{E}[f(x(t),\phi(t))|Q(t)] \\ \leq\ & B + VF^* \end{aligned}$$

- Averaging over $Q(t)$ and summing over t

$$\begin{aligned} & \frac{1}{T}L(T) + \frac{1}{T}\sum_{t=1}^{T} V\mathbb{E}[f(x(t),\phi(t))] \\ \leq\ & B + VF^* \end{aligned}$$

- By taking the limit, $\limsup_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \mathbb{E}[f(x(t),\phi(t))] \leq \frac{`B}{V} + F^*$

Perturbation-based Lyapunov Optimization

- Use Lyapunov based optimization with queues $\{U_n(t)\}$ and $\{E_n(t)\}$
- *Perturbed* Lyapunov function $\frac{1}{2}(E_n(t) - \theta_n)^2$
  ... drive the battery to a desired value so as to avoid underflow [Huang Neely 10]

Proposed Policy

Fix a weight $\boldsymbol{\theta} = [\theta_1, \ldots, \theta_N] \in \mathbb{R}_+^N$ and a parameter $V > 0$. At each time-slot t,

- *Energy Harvesting:* For each node n, if $(E_n(t) - \theta_n) < 0$ set $\tilde{H}_n(t) = H_n(t)$; otherwise, $\tilde{H}_n(t) = 0$;
- *Rate-Distortion Optimization:* Choose the rate vector $\mathbf{R}(t)$ and the distortion levels $\mathbf{D}(t)$ as

$$\text{minimize} \sum_n \left[U_n(t) r_n - (E_n(t) - \theta_n)\alpha_n r_n + V f_n(d_n) \right]$$

subject to the rate-distortion region constraint and to $0 \leq r_n \leq R_{\max}$ and $D_{\min} \leq d_n \leq D_{\max}$;

Proposed Policy

- *Power Allocation:* Define the weight of a link (n, m) as

$$W_{n,m}(t) = (U_n(t) - U_m(t) - \delta)^+,$$

where $\delta = l_{\max}\mu_{\max} + R_{\max}$, and choose the power matrix $\mathbf{P}(t)$ as

$$\underset{\mathbf{p}}{\text{maximize}} \sum_n (E_n(t) - \theta_n)p_n + \sum_{m \neq n, m} W_{n,m}(t) C_{n,m}(\mathbf{p}, \mathbf{S}(t)),$$

where $p_n = \sum_{m \neq n} p_{n,m}$, subject to constraints $0 \leq p_{n,m} \leq P_{\max}$;

- *Queues Update*

Distributed Implementation

- Rate-Distortion Optimization and Power Allocation require centralized optimization
- Distributed implementation of Power Allocation [Hoepman 04][Chen et al 06]
- Distributed implementation of Rate-Distortion Optimization: dual decomposition and subgradient

Performance Analysis

- Define the parameters $\beta_n = \min\{\alpha_n, 1\}$, $\gamma_n = \sup_{D_{\min} \leq d_n \leq D_{\max}} \left[\frac{f_n(d_n) - f_n(D_{\max})}{\log(d_n / D_{\max})} \right] < \infty$
- With $\theta_n = \alpha_n (H_{\max} + R_{\max}) + \frac{\gamma_n}{\beta_n} V + I_{\max} P_{\max}$,

1 Bounded energy and data queues for all t:

$$
\begin{aligned}
0 \leq E_n(t) &\leq \theta_n + H_{\max}, \\
\text{and } 0 \leq U_n(t) &\leq \alpha_n H_{\max} + \gamma_n V + R_{\max}
\end{aligned}
$$

2 Cost function:

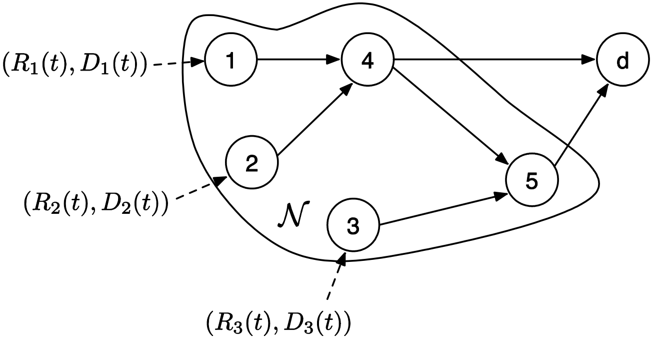
$$\sum_{n=1}^{N} f_n^{\pi} \leq F_0^* + \frac{B}{V},$$

where $B = N\left(\mu_{\max}(\mu_{\max} + R_{\max}) + R_{\max}^2/2\right) + N/2(H_{\max}^2 + \alpha_n^2 R_{\max}^2 + P_{\max}^2 + 2\alpha_n R_{\max} P_{\max}) + N\delta l_{\max}\mu_{\max}$

3 No battery underflow: If $P_n(t) > 0$ and/or $R_n(t) > 0$, we have that

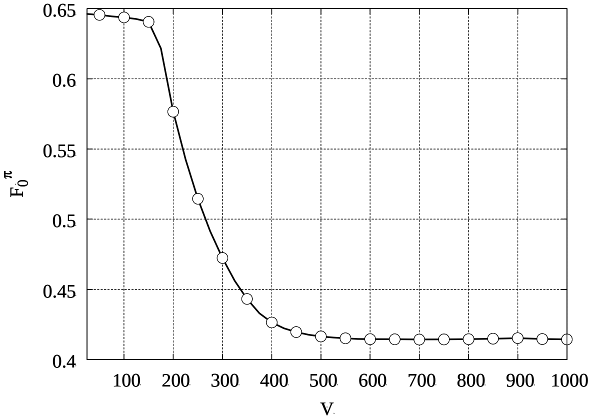
$$E_n(t) \geq \alpha_n R_{\max} + l_{\max} P_{\max}$$

Numerical Results



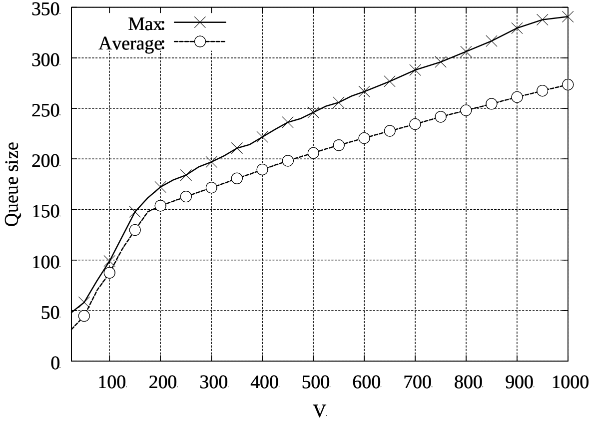
- $f_n(D_n) = D_n$ (sum-distortion)
- $S_{n,m}(t) \sim U(0,1)$, $H_n(t) \sim U(0,1)$
- Gaussian sources with correlation ρ
- $\alpha_n = 2$, $P_{\max} = 3$

Numerical Results: Impact of V



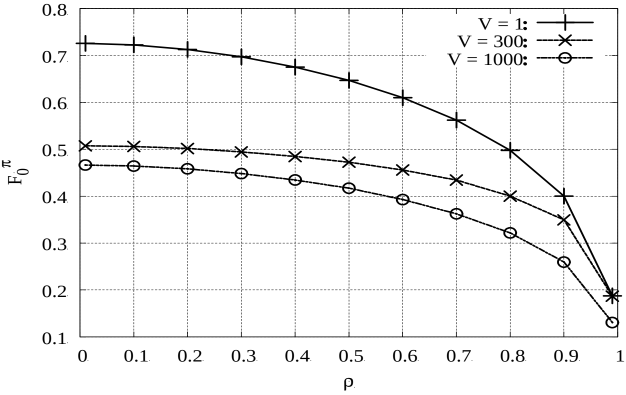
- $\rho = 0.5$

Numerical Results: Impact of V

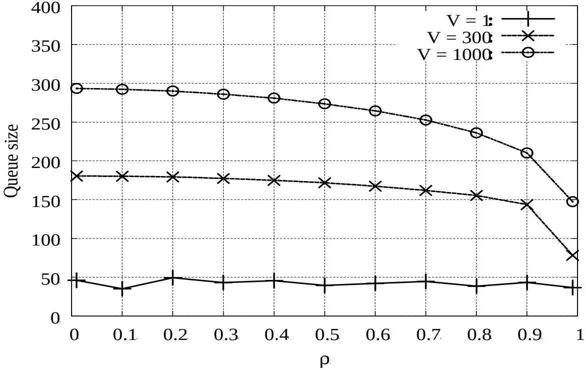


- $\rho = 0.5$

Numerical Results: Impact of Source Correlation



Numerical Results: Impact of Source Correlation



Conclusions

- Wireless sensor networks are a key component of cyber-physical systems
- Energy-harvesting enables new applications of wireless sensor networks
- Energy requirements of source and channel coding
- Point-to-point – With infinite data and energy buffers: separable policy is optimal
- With sufficiently large data and energy buffers: separable policy is approximately optimal
- Trade-off buffer sizes and performance