Energy Harvesting Wireless Sensor Networks

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Definitions

harvest

the act or process of gathering a crop

scavenge

to search for (anything usable) among discarded material

energy harvesting/scavenging (EH)

take advantage of previously "wasted" environmental energy

The self-winding pocket watch (1777)
"...15 minutes walking was necessary to wind the watch sufficiently for 8 days"

- An EHD harvests energy from the environment to collect, process and transmit/receive information
- The environment is a power reservoir: light, vibration, motion, pressure, heat, radio, human activity
- Applications: autonomous networked systems where providing line power or maintaining batteries is inconvenient
  - Ad hoc, sensor, machine-to-machine networks
  - Consumer electronics
  - Structural monitoring
  - Medical systems
  - Homes, offices, factories, roadways, hospitals, humans, animals

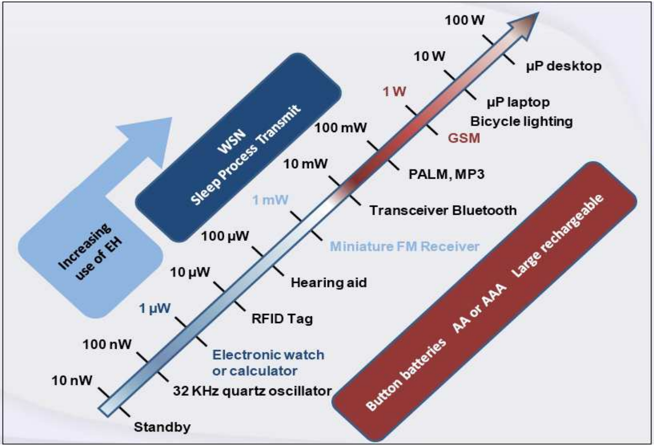
Energy harvesting estimates

Source	Type	μW/cm
Vibration/motion	Human	4
	Industry	100
Temperature difference	Human	25
	Industry	10^3-10^4
Light	Indoor	10
	Outdoor	10^4
RF	GSM	0.1
	WiFi	0.001

- Same order of magnitude as carefully designed low-power circuits typically consume
- Duty cycling, highly efficient sleep mode

Raju and Grazier, ULP meets energy harvesting, White Paper, Texas Instruments, 2008

Enabling technologies: energy harvesters



IDTechEx, Energy Harvesting and Storage, Cambridge 2009

Enabling technologies: storage

Rechargeable batteries

- High energy density (large capacity)
- Wear-out fast with charge/discharge cycles

Super-capacitors

- High power density, large number of charge/discharge cycles
- Self-discharge, temperature-dependent equivalent series resistance (ESR)

Solid-state batteries

- High energy density, large number of charge/discharge cycles, minimal self-discharge, thin-film form, eco-friendly

- Ultra-low power microprocessors (μP)
- Low standby current, low active current, low operating voltage, low pin leakage
- Low-power RF transceivers
- Energy consumption: μP with fast processing core
- Integration adds value: reduced package size and cost, fewer losses

EHD Operation

Pros

- Increased lifetime
- No battery replacement, minimal/no maintenance
- Ecological

Challenges

- Power is scarce (μW $\sim$ mW) and intermittent
- Storage limited and leaky
- Stringent constraints on size and complexity

Paradigm shift

Ultimate promise

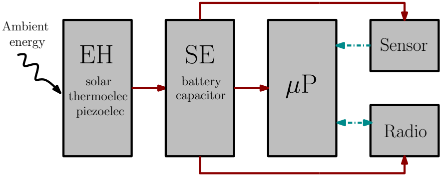
Self-sustainable, maintenance-free network of perpetually communicating devices

Up to now

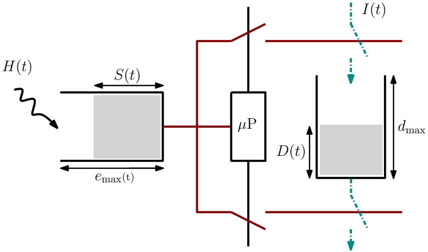
- Advances in EH, storage, μP technology... but there is a need to integrate these solutions
- Holistic system design

energy efficiency $\rightarrow$ intelligent energy management

Model



Typical EHD block diagram



Mathematical model

Energy management policy

Rules that determine decisions of μP to activate switches at a given time t

Goal

Optimize a utility function over a given time period

Solution depends on

- characteristics of $H(t)$ and $I(t)$
- degree of knowledge of μP about $H(t)$ and $I(t)$
- physical constraints

Approaches

Offline optimization

μP knows values of $H(t)$ and $I(t)$ in advance at the μP for duration of operation

Online optimization

μP knows past values of $H(t)$ and $I(t)$ but has only statistical knowledge of their future values

Learning-theoretic optimization

μP learns characteristics of $H(t)$ and $I(t)$ and adapts policy accordingly

- Energy and data arrival processes are known in advance
  - Deterministic processes (e.g. solar harvesters for given time of the day and season of operation, vibration based harvester on train tracks)
  - Serves as a bound for the general problem
  - Provides heuristics for low-complexity online algorithms
- No randomness
- Optimization problem

- Point-to-point data backlogged system
- Energy arrives in packets at discrete time instants
- Focus on transmission energy: long-range communication
- A rate-power function: r(P) bits/sec
  - $r(0) = 0$
  - $r(\cdot)$ is monotonically increasing
  - Strictly concave
- Examples:
  - Shannon capacity for AWGN channel: $r(P) = \frac{1}{2}\log\left(1 + \frac{P}{N}\right)$
  - BPSK signalling with hard-decisions: $r(P) = 1 - h\left(Q\left(\sqrt{\frac{P}{N}}\right)\right)$

Energy Efficient Communication

- Battery-limited system: Energy H_0 available at $t = 0$
- Given $r(\cdot)$ and deadline T
- How many bits can you transmit?
- Variable to optimize: Transmission power $P(t)$ for $t \in [0, T]$
- Optimization problem:

$$\max_{P(t), t \in [0, T]} \quad \int_0^T r(P(t))\, dt$$

$$\text{such that} \quad \int_0^T P(t) \leq H_0.$$

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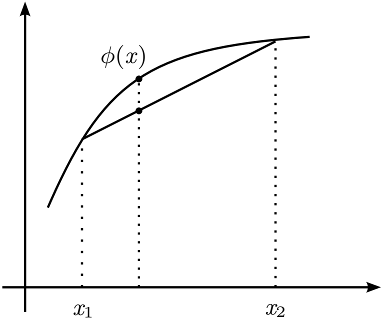
Theorem (Jensen's inequality)

Let $\phi(\cdot)$ be a concave function on the real line, then

$$\phi\left(\frac{\sum_{i=1}^{n} a_i x_i}{\sum_{j=1}^{n} a_j}\right) \geq \frac{\sum_{i=1}^{n} a_i \phi(x_i)}{\sum_{j=1}^{n} a_j},$$

with strict inequality if $\phi(\cdot)$ is strictly concave.



Jensen's inequality in integral form

Theorem (Jensen's inequality)

Let $f : [a, b] \to \mathbb{R}$ be a non-negative real valued function, and $\phi(\cdot)$ be a concave function on the real line, then

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with strict inequality if $\phi(\cdot)$ is strictly concave, $a \neq b$, and f is not constant over the interval $[a, b]$.

$$f(t) = \frac{P(t)}{T}, a = 0, b = T, \phi(\cdot) = r(\cdot)$$

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$$f(t) = \frac{P(t)}{T}, a = 0, b = T, \phi(\cdot) = r(\cdot)$$

$$r\left(\int_0^T \frac{P(t)}{T}\,dt\right) > \int_0^T \frac{r(P(t))}{T}\,dt$$

$$T \cdot r\left(\frac{H_0}{T}\right) > \int_0^T r(P(t))\,dt$$

- Constant power transmission is optimal!
- $T \cdot r\left(\frac{H_0}{T}\right)$ increases with T: Zero-power transmission is optimal (well-known minimum energy-per-bit)

Energy efficient communication

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Design principles for multiple energy packets

- Better to transmit over longer time periods (with low power)
- No silent periods
- Finish all available energy by deadline
- Constant power transmission between energy arrivals
- Energy causality condition: Energy cannot be used before it arrives

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Cumulative energy curves

- **Harvested Energy Curve, $\bar{H}(t)$:** Total energy harvested in $[0, t]$, i.e., $\bar{H}(t) = \int_0^t H(\tau) d\tau$
- **Transmitted Energy Curve, $E(t)$:** Total energy used in $[0, t]$, i.e., $E(t) = \int_0^t P(\tau) d\tau$
- Energy causality constraint: $E(t) \leq \bar{H}(t)\ \forall t \in [0, T]$
- **Minimum energy curve, $\bar{M}(t)$:** Total energy that must be used by t, i.e., $\bar{M}(t) \leq E(t)$
- Admissible if $\bar{M}(t) \leq E(t) \leq \bar{H}(t)$

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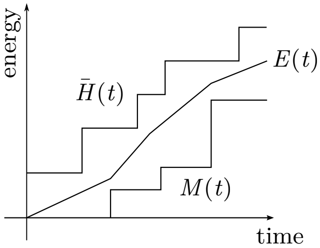
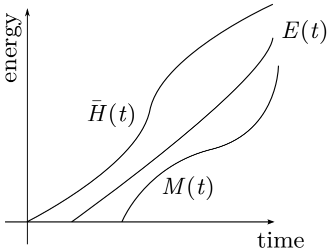
Offline optimization problem

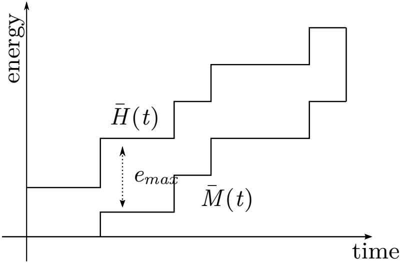
$$\max_{E(t),\, t\in[0,T]} \quad \int_0^T r(E'(t))\,dt$$

$$\text{such that} \quad \bar{H}(t) \geq E(t) \geq \bar{M}(t), \forall t \in [0, T],$$





Example 1: Limited battery capacity

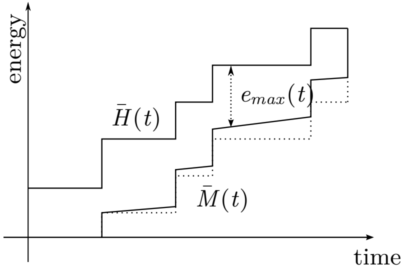


- Battery capacity: e_{max}
- Use energy for transmission rather than wasting:

$$\bar{H}(t) - E(t) \leq e_{max} \quad \longrightarrow \quad E(t) \geq \bar{H}(t) - e_{max}$$

$$\text{i.e.} \qquad \bar{M}(t) = \max\left(\bar{H}(t) - e_{max}, 0\right)$$

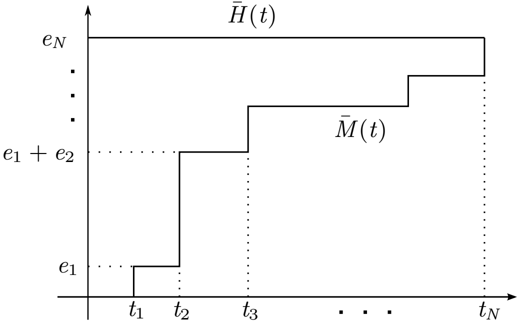
Example 2: Time-varying battery size



- Battery size decreases with multiple discharges: $e_{max}(t)$

$$\bar{M}(t) = \max\left(\bar{H}(t) - e_{max}(t), 0\right)$$

Example 3: Dying Batteries



- N batteries (all full at $t = 0$)
- battery i has e_i units of energy and dies at time t_i
- Question: maximum data that can be transmitted until last battery dies?

Optimality Conditions

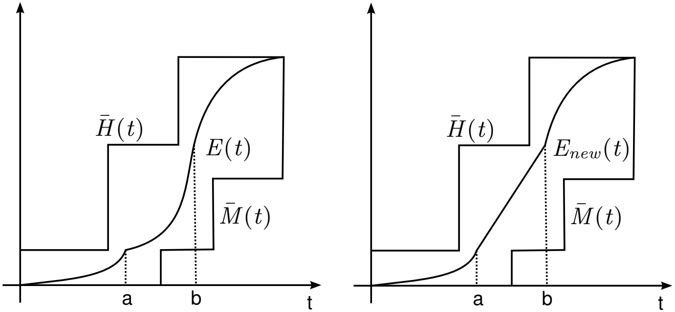
- $E(t)$: admissible transmit energy curve
- $S(t)$: straight line over $[a, b]$ joining $E(a)$ and $E(b)$, $0 \leq a < b \leq T$
- Let $\bar{M}(t) \leq S(t) \leq \bar{H}(t)$ and $S(t) \neq E(t)$
- Construct:

$$E_{new}(t) = \begin{cases} E(t) & t \in [0, a) \\ S(t) & t \in [a, b] \\ E(t) & t \in (b, T] \end{cases}$$

- We have:

$$\int_0^T r(E'_{new}(t))\,dt < \int_0^T r(E'(t))\,dt$$

- Take any admissible curve $E(t)$
- Connect any two points with a straight line
- If it doesn't violate admissibility constraints, replacing that part with a straight line increases transmitted data!



- Strictly concave rate function $r(\cdot)$
- $E(t)$ is an admissible transmitted energy curve
- No two points of $E(t)$ that can be connected by a distinct admissible straight line

Then, $E(t)$ is unique and optimal

Uniqueness of the Optimal Curve

- Strictly concave rate function $r(\cdot)$
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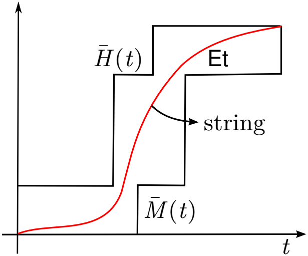
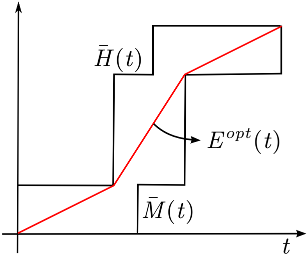
Then, $E(t)$ is unique and optimal

Optimal departure curve $E_{opt}(t)$ has the shortest length among all admissible curves. It minimizes the metric

$$length(E(t)) \triangleq \int_0^T \sqrt{(1 + (E'(t))^2)}dt$$

String visualization:



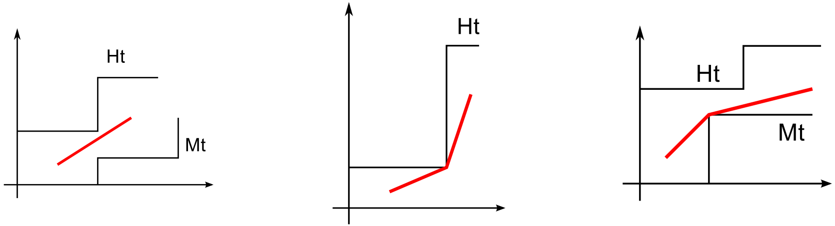


Behaviour of the optimal curve

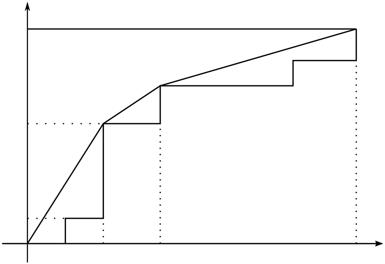
$E_{opt}(t)$: optimal transmitted energy curve
t_0: any point at which transmission power changes

- at t_0, $E^{opt}(t)$ intersects either $\bar{H}(t)$ or $\bar{M}(t)$
- if $E_{opt}(t_0) = \bar{H}(t_0)$, then slope change must be positive
- if $E_{opt}(t_0) = \bar{M}(t_0)$, then slope change must be negative

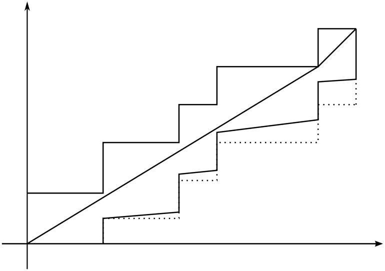
- No change in $\bar{H}(t)$ or $\bar{M}(t)$: constant power tx
- Increase tx power only when battery is empty
- Decrease tx power only when battery is full



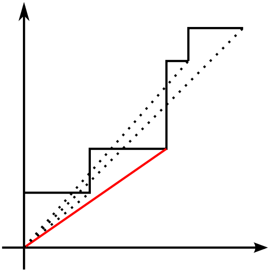
N dying batteries



Degrading battery



1. Packetized energy arrivals
2. N energy packets $H_0, \ldots, H_{N-1}$ at times $t_0, \ldots, t_{N-1}$
3. $\tilde{H}_i$: total energy harvested just before t_i
4. Starting $t = 0$, consider line segments from $(0, 0)$ to $(t_i, \tilde{H}_i)$
5. Choose the one with minimum slope
6. First transmission power: $\min_i \frac{\tilde{H}_i}{t_i}$
7. Continue recursively



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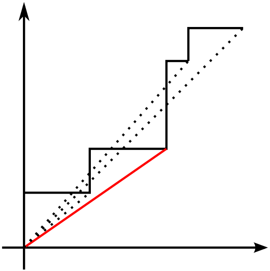
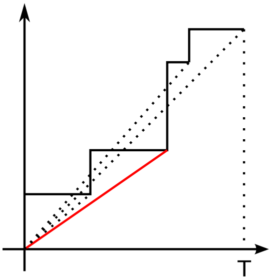
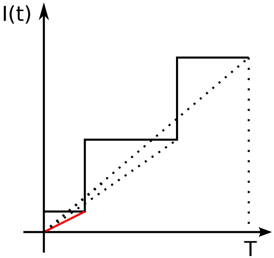


1. Both energy and data arrive in packets (Yang&Ulukus'12)
2. Both energy and data causality constraints
3. Assume unlimited battery
4. Minimize transmission time, or maximize remaining battery by a deadline





- In practice batteries are non-ideal and leak energy
- **Energy Leakage Curve, $L(t)$:** Total energy that has leaked in $[0, t]$
- Consider a constant-rate leakage

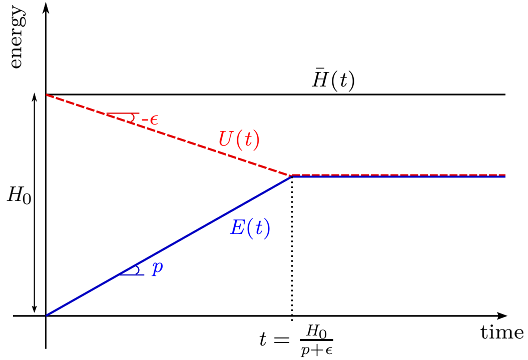
$$L'_{+}(t) = \begin{cases} \epsilon, & \text{if} \quad E(t) < \bar{H}(t) - L(t) \\ 0, & \text{otherwise} \end{cases}$$

- Similar to a maximum energy curve :

$$U(t) = \bar{H}(t) - L(t)$$

- But, leakage curve depends on transmitted energy curve

→ Previous framework does not hold

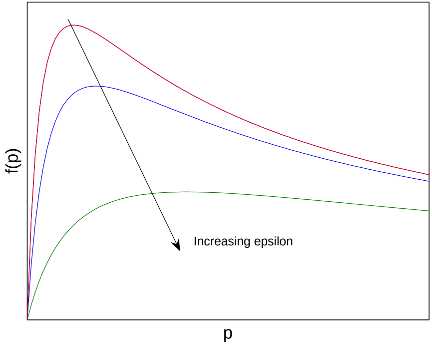


- Constant power transmission is optimal as before
- low power $\rightarrow$ more energy efficient
- high power $\rightarrow$ less leakage

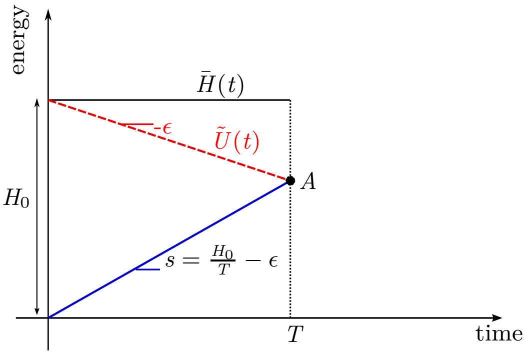
$$\max_{p \geq 0} \int_0^T r(E'(t))\,dt = \frac{H_0}{p+\epsilon}\; r(p)$$

Single Energy Packet (no deadline)

- $\max_{p\geq 0} \int_0^T r(E'(t))\,dt = \frac{H_0}{p+\epsilon}\ r(p) = H_0 f(p)$
- $f(p) \triangleq \frac{r(p)}{p+\epsilon}$:



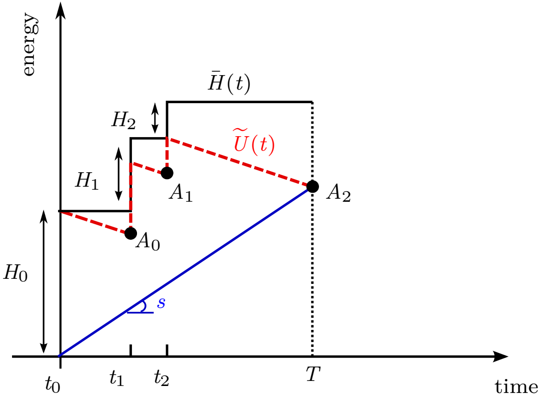
- Unique optimal transmission power $p^* = \max f(p)$ (does not depend on H_0)



- Optimal transmission power

$$\tilde{p} = \max\{p^*, s\}$$

with $p^* = \max f(p)$, $s = \frac{H_0}{T} - \epsilon$

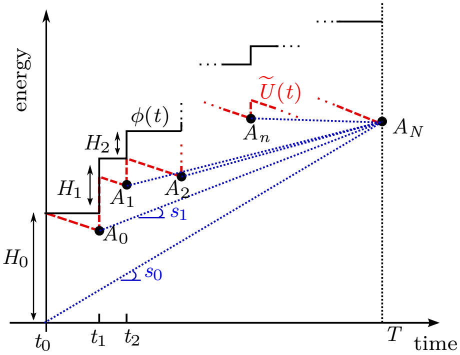


Multi-packet solution can be obtained from single-packet problem: Having all energy packets at $t = 0$ is at least as good as having them arrive over time.

Proof

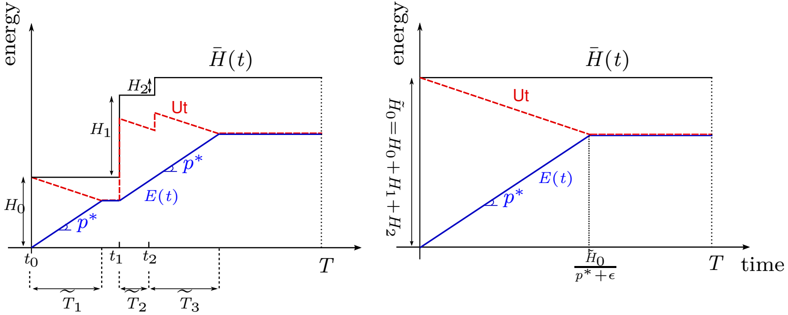
- Equivalent to single-packet problem with $H_0 = \sum_{n=0}^{N} H_n$
- Consider solution of multi-packet problem:
  - Consider epochs $[t_0, t_1]$, $[t_1, t_2]$, $\ldots$, $[t_N, \infty]$
  - In each epoch: $p_i > 0$ for period $0 \leq a_i \leq t_i$ and remain silent when no energy left
- Emulate with a single packet by transmitting for $a_1, a_2, \ldots, a_N$ with powers $p_1, \ldots, p_N$

If the line segment from origin to A_N does not cross $\widetilde{U}(t) = E(t) - \epsilon t$, then single-packet solution with $\tilde{H}_0 = \sum_{n=0}^{N} H_n$ can be obtained from multi-packet solution.



In that case,

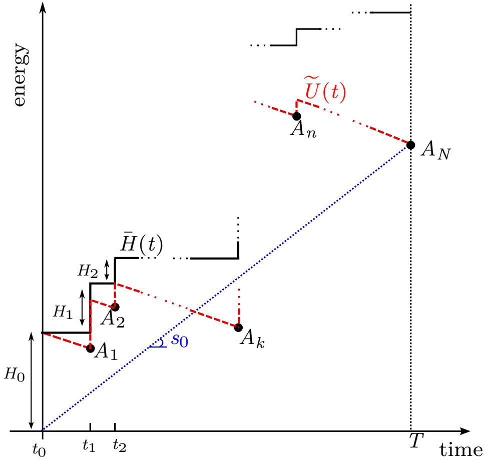
- equivalence between multiple- and single-packet problems
- Multi-packet solution: transmit with $\tilde{p}$ whenever battery is non-empty; remain silent otherwise. $\tilde{p}$ evaluated from single-packet problem: $\tilde{p} = \max\{p^*, \frac{\tilde{H}_0}{T} - \epsilon\}$



(a) multiple-packet problem

(b) equivalent single-packet problem

General algorithm: find the rightmost end-point that is “seen” from the origin, and solve the k-packet problem. Proceed recursively.



Future Directions

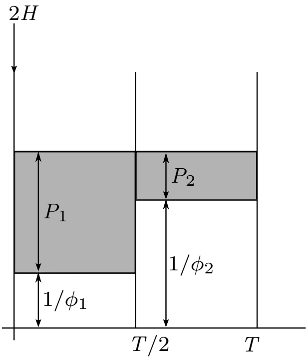
- More complicated and realistic leakage models
- Multiple batteries: serial/ parallel connections
- Leakage over transmission
- Battery state depended leakage
- Modeling information regarding battery state

Enter Fading

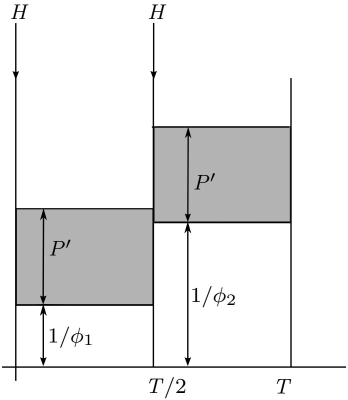
- Channel gain (ϕ) changes over energy harvesting epochs
- Rate-power function: $r(t) = \log\left(1 + \phi(t)P(t)\right)$
- Maximize transmitted data by T
- Offline optimization: channel states are known in advance

Example

- Battery operated model: $\bar{H}(t) = \bar{H}(0) = 2H$
- Two epochs of equal length
- First epoch has better channel: $\phi_1 > \phi_2$
- Problem: power allocation over parallel Gaussian channels
- Solution: Waterfilling

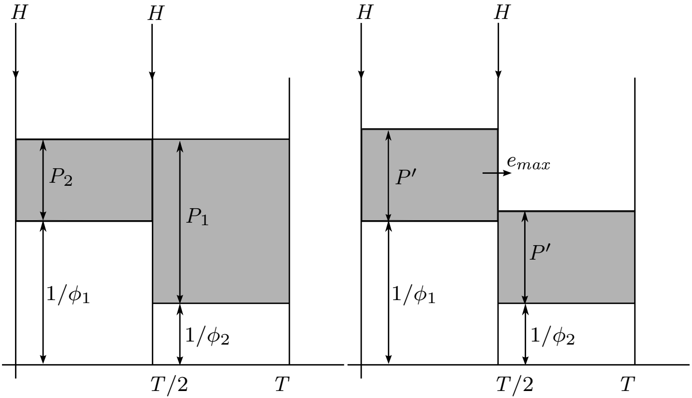


- Waterfilling allocates more than half to first epoch
- What if that much energy is not yet available?

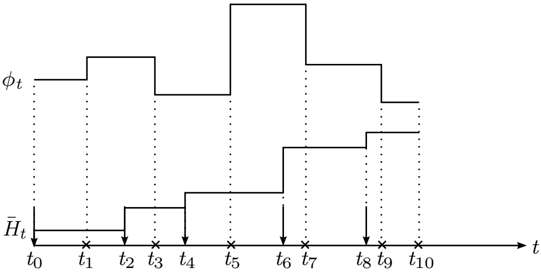


Limited Battery Capacity e_{max}

- Waterfilling solution ignores the finite SE capacity e_{max}
- Assume: $\phi_2 > \phi_1$
- We can allocate at most e_{max} to the second epoch



(a) (b)



- N epochs
- Channel gains: $\phi_1, \ldots, \phi_N$
- Durations: $\tau_1, \ldots, \tau_N$, where $\tau_i = t_i - t_{i-1}$
- Transmission power in each epoch: p_i

A less intuitive formulation

$$
\begin{aligned}
\max_{p_i} \quad & \sum_{i=1}^{N} \frac{\tau_i}{2} \log(1 + \phi_i p_i) \\
\text{s.t.} \quad & \sum_{j=1}^{i} \tau_j p_j \leq \sum_{j=1}^{i} H_{j-1}, i = 1, ..., N, \\
& \sum_{j=1}^{i+1} H_{j-1} - \sum_{j=1}^{i} \tau_j p_j \leq e_{max}, i = 1, ..., N, \\
& 0 \leq p_i, \quad i = 1, ..., N.
\end{aligned}
$$

Convex optimization problem!

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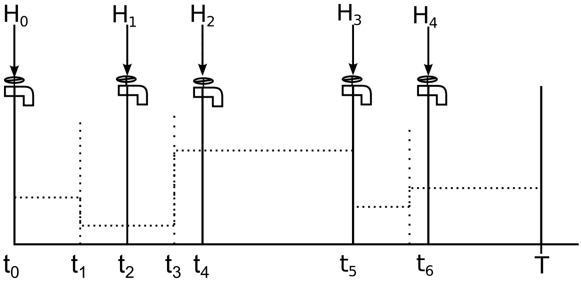
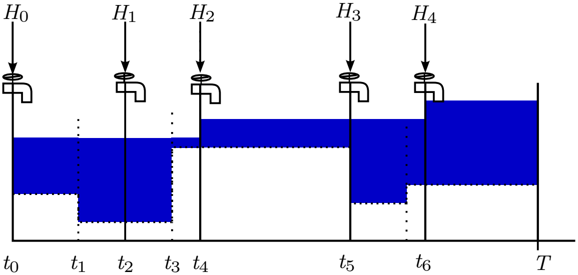
Convex optimization problem!

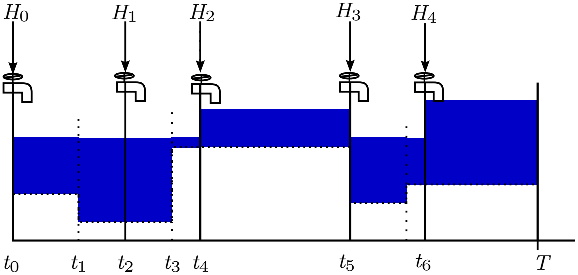
Directional Waterfilling



$e_{max} = \infty$



e_{max} is finite



Processing Energy Costs

- Processing circuitry consumes energy:
  - Static energy drawn by the transmitter,
  - Energy consumed for coding/signal processing (A/D conversion, filters, mixers, etc.)
  - Also: protocol overhead, power amplifier inefficiencies
- For sensors, even the startup energy of the transceiver may exceed transmission energy

Processing Energy Costs

- ϵ joules per unit time: only when transmitting
- Discrete events: $t_0 = 0 < t_1 < \cdots < t_{N-1} < T$
- Duration of epoch i: $\tau_i \triangleq t_i - t_{i-1}$
- Energy harvest at t_i: H_i
- Channel state in epoch i: ϕ_i
- Battery capacity: e_{max}
- Rate-power function: $\frac{1}{2}\log(1 + \phi(t)p(t))$

- Transmission power in each epoch: p_i
- Transmission time in each epoch: θ_i

$$\max_{p_i,\Theta_i} \quad \sum_{i=1}^{N} \frac{\Theta_i}{2}\log(1+\phi_i p_i)$$

$$\text{s.t.} \quad 0 \le \sum_{j=1}^{i} (H_{j-1} - \Theta_j(p_j+\epsilon)), i = 1, ..., N,$$

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- Non-convex optimization

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- Non-convex optimization

Convexification

- $\alpha_i \triangleq \Theta_i p_i$: energy consumed by power amplifier in epoch i

$$\max_{\alpha_i, \Theta_i} \quad \sum_{i=1}^{N} \frac{\Theta_i}{2} \log\left(1 + \frac{\phi_i \alpha_i}{\Theta_i}\right)$$

$$\text{s.t.} \quad 0 \leq \sum_{j=1}^{i} (H_{j-1} - \alpha_j - \epsilon\Theta_j), \quad i = 1, ..., N,$$

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- $\frac{\Theta_i}{2} \log(1 + \frac{\phi_i \alpha_i}{\Theta_i})$: perspective of $\frac{1}{2} \log(1 + \phi_i \alpha_i)$
- Strictly concave function
- Perspective operation preserves concavity
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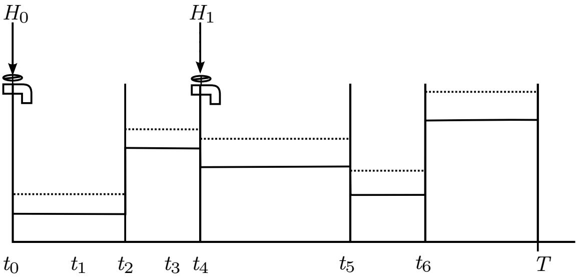
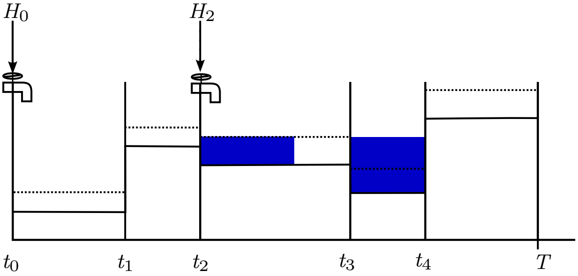
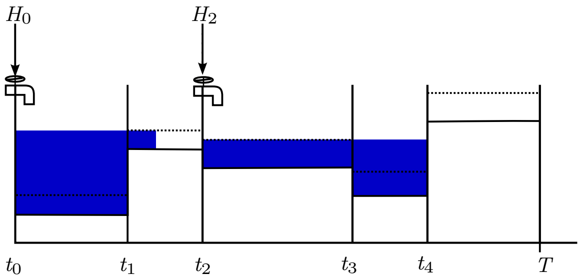
- Each epoch has a threshold value: v_i^*



- Glue Pouring
- Sleep periods



Optimal Solution



Effect of Processing Energy Cost

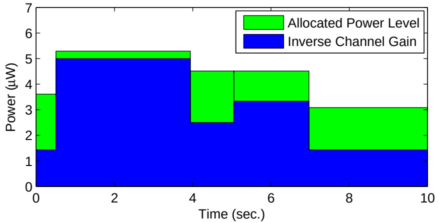


Figure: processing cost $= 0$

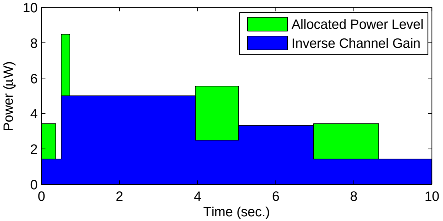


Figure: processing cost $= 1\ \mu W$

Future Directions

- More realistic models for processing cost: rate/bandwidth dependence
- Cost for memory
- Cost of sleep/wake cycles
- Battery level dependent sleep/wake optimization

- Offline optimization: all processes are known in advance
- Deterministic optimization problem
- A general upper bound on the performance
- Provides heuristics, general principles
- Studied progressively more realistic models
- Many more open problems

Online Optimization

- $H(t)$ and $I(t)$ are not known or accurately predictable
- More appropriate to model $H(t)$ and $I(t)$ as random processes
- μP must make decisions in online fashion
- Knowledge of past values of $H(t)$ and $I(t)$ and statistical description of future values
- Goal: optimization of expected outcome of decisions

- Markov decision processes: discrete-time stochastic control
- Policy: a set of decision rules based on system state
- Can be solved numerically with well known algorithms (linear programming, value iteration, policy iteration)
- But: complexity explodes with size of state space
- We can also use offline heuristics in online context: ignores statistics

- Energy sources are sporadic
- Even the statistics of energy arrivals depend on sensor location, time of day or season
- Online/offline require calibrating sensor operation before deployment
- Why not learn harvesting/ data arrival/ channel processes, and adapt accordingly?

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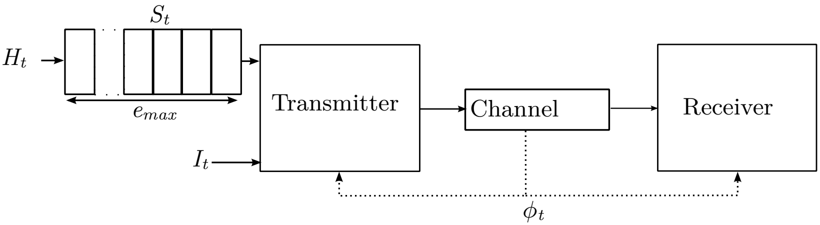
- Point to point system
- Transmitter has a rechargeable battery of size e_{max}.
- H_t: harvested energy at timeslot t
- I_t: size of data packet arriving at timeslot t
- Channel state : ϕ_t
- Decision made at each timeslot: transmit or drop incoming packet



- Energy/ data arrivals and channel state Markov processes
- At each timeslot sensor dies with probability $1-\gamma$.
- Either transmit $(X_t = 1)$ or drop $(X_t = 0)$ a packet
  - No data buffer
  - (I_t, ϕ_t) pair requires E_t energy units
- Energy constraints:
  - Available energy is limited: $X_n E_t \leq S_t$.
  - Battery has finite capacity: $S_{t+1} = \min\{S_t - X_t E_t + H_t, e_{max}\}$.

Objective: Maximize average total data within activation time:

$$\max_{\{X_i\}_{i=0}^{\infty}} \lim_{N\to\infty} E\left[\sum_{t=0}^{N} \gamma^t X_t I_t\right],$$

$$\begin{aligned} \text{s.t. } & S_{t+1} = \min\{S_t - X_t E_t + H_t, e_{max}\}, \\ & X_t E_t \leq S_t, \\ & X_t \in \{0, 1\} \end{aligned}$$

	Assumptions	Solution methods
Offline	**Non-causal knowledge** Finite horizon optimization	Branch and bound
Online	**Causal knowledge** of current values **Statistical knowledge** of the Markov processes Infinite horizon optimization	Dynamic Prog.
Learning	**Causal knowledge** of current values Feedback from the receiver (i.e., ACK) Infinite horizon optimization	Reinforcement Learn.

We use Q-learning algorithm (a Reinforcement Learning technique):

- Q-learning by performing actions and observing their rewards arrives at an optimal policy which maximizes the expected discounted sum reward accumulated over time
- Q-learning assumes
  - State is known causally
  - The immediate reward value is known after taking an action
- Q-learning estimates iteratively the action-value function

- **Two state EH** and **data** arrival process: $I_t = \{1, 2\}$ and $H_t = \{0, 2\}$.
- **Channel** can be either in **good** or in **bad** state (i.e. the energy required to tx a packet is doubled in the bad state).
- p_H: prob. of harvesting 2 energy units in epoch $n + 1$ given that 2 energy are harvested in epoch n
- **Upperbound**: in the **LP-Offline** the transmitter can partially transmit packets and has non causal knowledge.
- **Lowerbound**: in the **Greedy** algorithm the transmitter transmits a packet whenever there is enough energy in the battery.

Numerical Results - Parameters

- **Two state EH** and **data** arrival process: $I_t = \{1, 2\}$ and $H_t = \{0, 2\}$.
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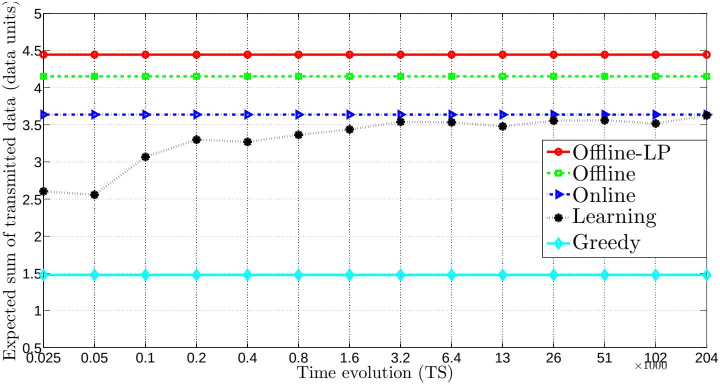
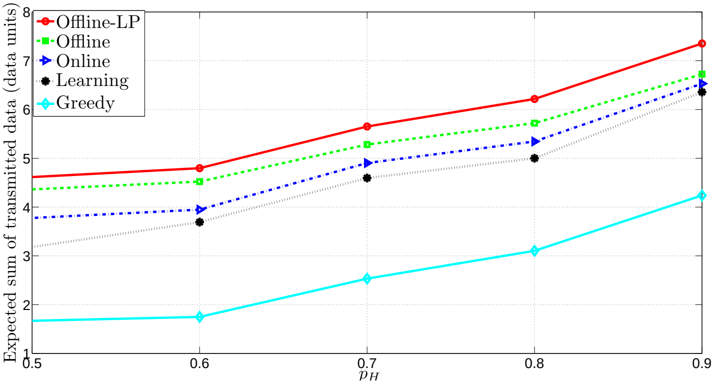

Expected sum of transmitted data (data units)
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0.025
0.05
0.1
0.2
0.4
0.8
1.6
3.2
6.4
13
26
51
102
204
×1000
Time evolution (TS)
Offline-LP
Offline
Online
Learning
Greedy


Offline-LP
Offline
Online
Learning
Greedy
Expected sum of transmitted data (data units)
1
2
3
4
5
6
7
8
0.5
0.6
0.7
0.8
0.9
p_H

- Learning theoretic framework: Appropriate for time-varying/unknown energy sources
- Sensor learns harvesting/data arrival/channel state parameters and adapts transmission policy
- Future directions:
  - Distributed learning for multi-user systems
  - Partially observable models/ Bandit problems

In summary

Offline approach

- Well predictable environments, performance upper bounds
- Tools: cumulative curves, convex optimization

Online approach

- Random (stationary) enviroments, design based on statistical information and knowledge of past values
- Tools: stochastic optimization, steady-state analysis

Learning-theoretic approach

- Unknown environments, very limited information on energy and data processes
- Tools: Reinforcement learning

What next?

EH networks

- Hard to study: we saw this even for simple cases
- Offline results for broadcast, multiple access, interference channels
- General networks? Local information?
- Characteristics of a multi-agent system
- Additional parameter: energy sharing/transfer, simultaneous transmission of energy and information
- Interesting resource allocation problems in many layers of the stack

Bridging theory and practice

- Measurement campaigns for EH models
- Implementation/testing of energy management algorithms in prototypes: Columbia's EnHants project
- Realistic models that "capture" key characteristics of underlying circuitry
- Realistic storage models: e.g., "degradation-aware" policies

MAC Protocols

- MAC protocols for wireless sensor networks typically designed for maximum network lifetime
- EH networks: not energy-limited
- Goal: energy neutral MAC protocol design
- EnOcean Alliance: ALOHA-based
- Intel WISP: EPC Class-1 Generation-2 (similar to slotted ALOHA)
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MAC Protocols

- Energy sources are correlated: best-effort policies will lead to collisions
- Correlation in harvested energy can provide coordination
- EH processes can be asymmetrical over network
- Adapt ALOHA, framed-ALOHA, dynamic framed-ALOHA to EH networks (Iannello et al.,'12)

- EnOcean Wireless Standard (ISO/IEC 14543-3-10): first standard optimized for ultra-low power and EH systems
- Standardization will aid EH market development: forecasted to 1894.87 million dollars by 2017

Global Forecast and Analysis of EH Market (2012-2017)

Closing remarks

- An exciting research field
- Many open questions at the intersection of algorithm, circuit and network design