Energy Harvesting Communication Network Design

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Scope

- Energy harvesting wireless communication systems
- Analytical models that capture fundamental challenges
- Performance optimization taking into account:
  - Intermittent nature of harvested energy
  - Capacity and leakage of storage devices
  - Complexity constraints

Organization

1. Introduction
2. Offline optimization framework
3. Online optimization framework
4. Learning theoretic framework
5. Conclusions

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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

Abraham-Louis Perrelet (1729-1826)

The self-winding pocket watch (1777)

"...15 minutes walking was necessary to wind the watch sufficiently for 8 days"

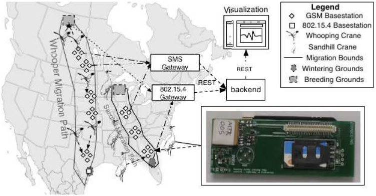
Solar powered calculator

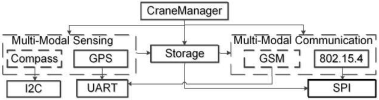
Introduced at the end of the 70's

Wireless EH Device (EHD)

- 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

CraneTracker: monitoring the *Grus Americana*

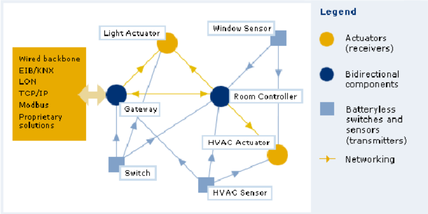


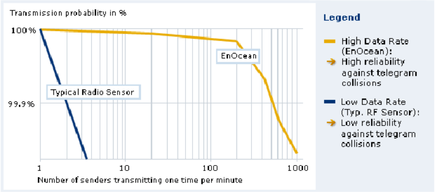


- Sustainable, continental-scale information delivery during migration (4000 km)
- Weight: < 120 gr, GPS: 2 samples/day, Compass: 0.5 Hz, Latency: < 24 h, Autonomy: 5-7 years (!)
- Flexible solar panel, lithium polymer battery, 512 kB memory

Anthony et al., Sensing Through the Continent: Towards Monitoring Migratory Birds using Cellular Sensor Networks, 2012

EnOcean: building automation





- Wireless switch: operating energy generated by pressure
- TX power: 6 dBm, Range: 30 m indoor, 300 m outdoor
- Data rate: 125 kHz, packet duration: 1 ms
- Small probability of collision: simple MAC

EnOcean Technology - Energy Harvesting Wireless, White Paper, 2011

MicroStrain 802.15.4 EH-Link™ network

- Onboard accelerometer, humidity and temperature sensor
- Measurement rate: 1 sample/hour to 2048 Hz
- Input voltage: $\geq$ 20 mV, TX power: 0 dBm, LOS range: 70 m
- Base station: node discovery, calibration, synchronization and data collection.

Enabling technologies 1: energy harvesters

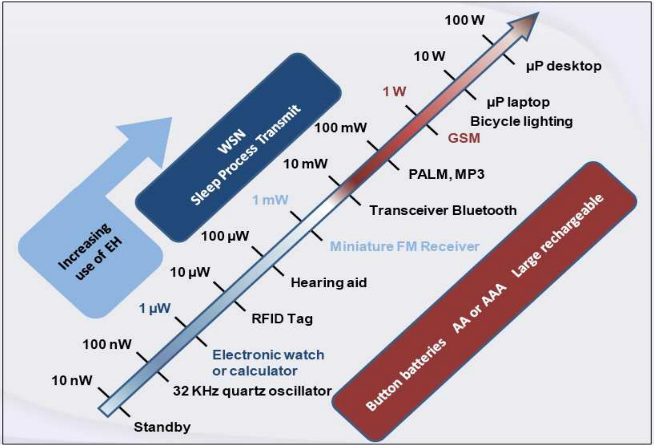
Energy harvesting estimates*

Source	Type	μW/cm^2
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

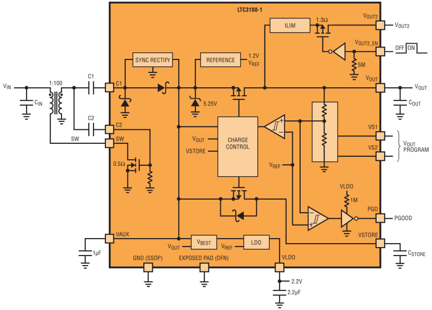
Enabling technologies 1: energy harvesters



IDTechEx, Energy Harvesting and Storage, Cambridge 2009

Enabling technologies 2: power converter

- Electrical output is unregulated, cannot be used directly to power electronic circuits
- Power converter: produce regulated output voltage
- Main components: transformer, switching converter



LTC3108*: $V_{\mathrm{IN}} \geq 20$ mV, selectable V_{OUT} of 2.35, 3.3, 4.1, 5 V

*Salerno, Ultralow voltage EH for battery-free wireless sensors, LT Journal of Analog Innovation, 2010

Enabling technologies 3: 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

Enabling technologies 4: low-power electronics

- 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

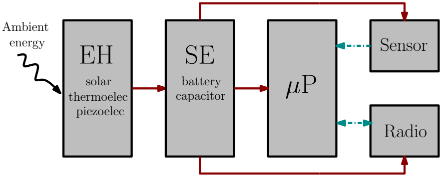
Self-sustainable, maintenance-free network of perpetually communicating devices

Up to now

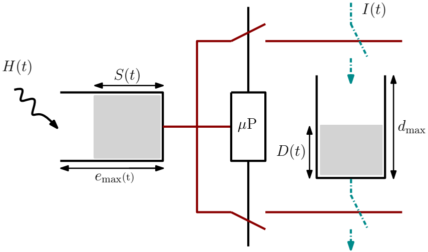
- Advances in EH, storage, μP technology... but there is a need to integrate these solutions
- Holistic system design

energy efficiency $\rightarrow$ intelligent energy management

Model



Typical EHD block diagram



Mathematical model

Energy management

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

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2. Offline Optimization

- 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

Simplified Model

- Point-to-point data backlogged system
- 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?

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:

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

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

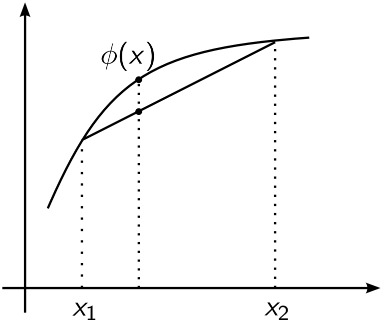
Jensen's inequality

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

$$\phi\left(\int_a^b f(t)dt\right) \geq \int_a^b \frac{\phi((b-a)f(t))}{b-a}dt,$$

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

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

Energy efficient communication

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

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- Constant power transmission is optimal!

Energy efficient communication

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

- 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)

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

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- 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

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., $E(t) = \int_0^t P(\tau)d\tau$

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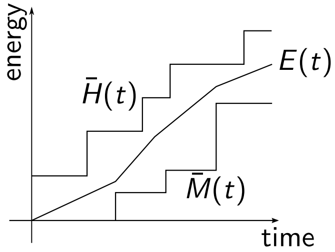
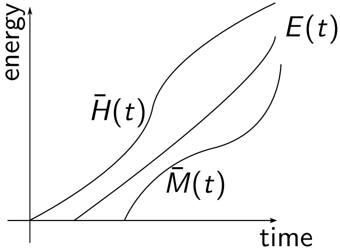
- Energy causality constraint: $E(t) \leq \bar{H}(t)\ \forall t \in [0, T]$
- **Minimum energy curve, $\bar{M}(t)$:** Total energy that must be used by t, i.e., $\bar{M}(t) \leq E(t)$
- Admissible if $\bar{M}(t) \leq E(t) \leq \bar{H}(t)$

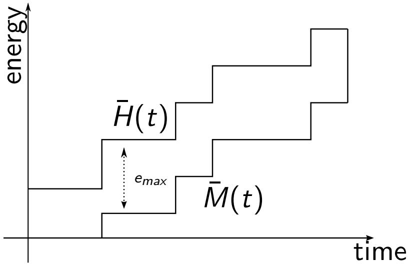
Offline optimization problem

$$\max_{E(t), t\in[0,T]} \quad \int_0^T r(E'(t))dt$$
$$\text{such that} \quad \bar{H}(t) \geq E(t) \geq \bar{M}(t), \forall t \in [0, T],$$





Example 1: Limited battery capacity

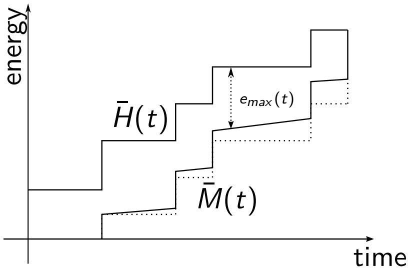


- Battery capacity: e_{max}
- Use energy for transmission rather than wasting:

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

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

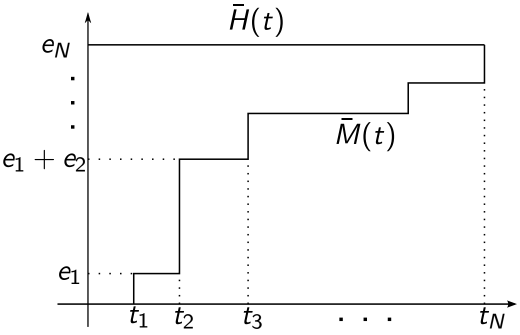
Example 2: Time-varying battery size



- 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:

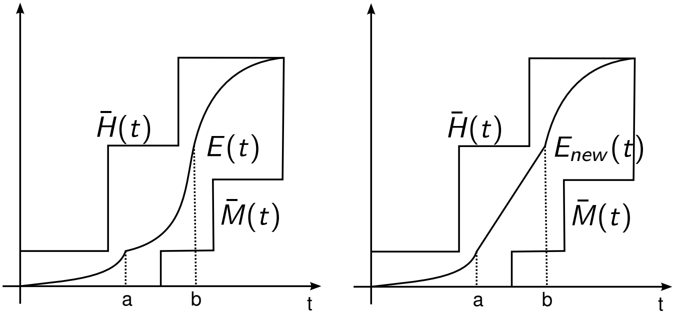
$$E_{new}(t) = \begin{cases} E(t) & t \in [0, a) \\ S(t) & t \in [a, b] \\ E(t) & t \in (b, T] \end{cases}$$

- We have:

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

Optimality conditions

- 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!



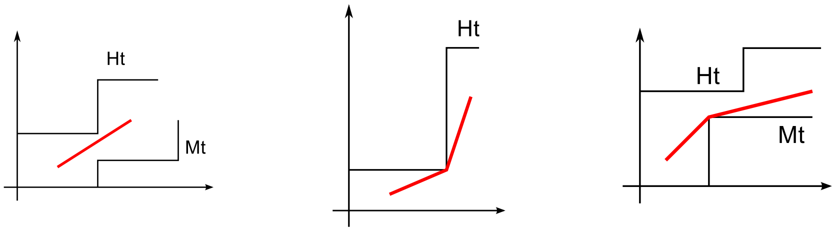
Behaviour of the optimal curve

$E_{opt}(t)$: 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

Interpretation

- 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



Uniqueness of the Optimal Curve

- 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

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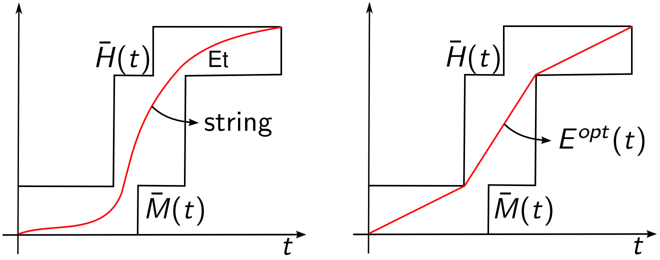
Then, $E(t)$ is unique and optimal

Shortest length

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

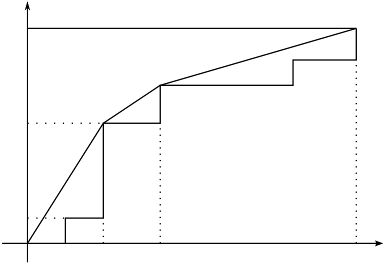
$$length(E(t)) \triangleq \int_0^T \sqrt{(1 + (E'(t))^2)}dt$$

String visualization:

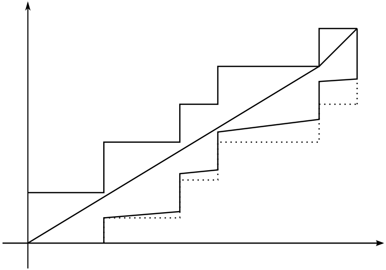


Examples

N dying batteries



Degrading battery



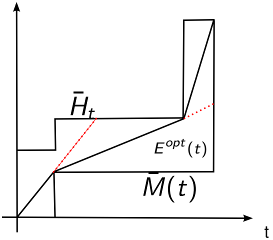
Constructing $E^{opt}(t)$

- For (t_0, α), $\mathcal{E}$ is the set of straight lines that remain admissible for some duration, i.e., line $L(t)$ s.t. $\bar{M}(t) \leq L(t) \leq \bar{H}(t)$ for $t \in [t_0, t_0 + \epsilon)$.
- Partition $\mathcal{E}$ into two:
  - $\mathcal{E}_H$: lines that intersect first $\bar{H}(t)$,
  - $\mathcal{E}_M$: lines that intersect first $\bar{M}(t)$.
- $\mathcal{S}_H$ and $\mathcal{S}_M$ are slopes of lines in $\mathcal{E}_H$ and $\mathcal{E}_M$.
- Define $\beta_0 \triangleq \inf \mathcal{S}_H = \sup \mathcal{S}_M$
- β_0: optimal slope, L_0: optimal line

Constructing $E^{opt}(t)$

Let $t_0 = 0$ in the first iteration.

1. Obtain β_0 and L_0
2. Obtain the first instance t_1 s.t.
   (a) $L_0(t_1) = \bar{M}(t_1)$, or,
   (b) $L_0(t_1) = \bar{H}(t_1)$ or $L_0(t_1) = \bar{H}(t_1^-)$.
   Set $E^{opt}(t) = L_0(t)$, $t \in (t_0, t_1]$.
3. Terminate if $t_1 = T$. If not, start with $(t_1, E^{opt}(t_1))$ as starting point.

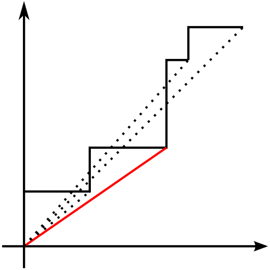


Algorithmic Construction

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

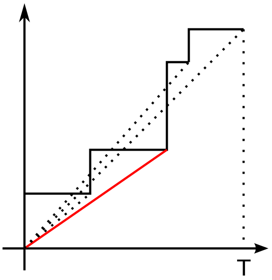
Algorithmic Construction

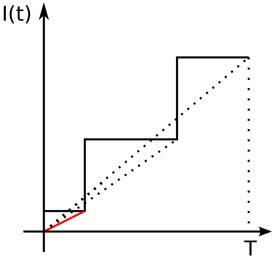
1. Packetized energy arrivals
2. N energy packets $H_0, \ldots, H_{N-1}$ at times $t_0, \ldots, t_{N-1}$
3. $\tilde{H}_i$: total energy harvested just before t_i
4. Starting $t = 0$, consider line segments from $(0, 0)$ to $(t_i, \tilde{H}_i)$
5. Choose the one with minimum slope
6. First transmission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



Joint Energy and Data Arrival

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



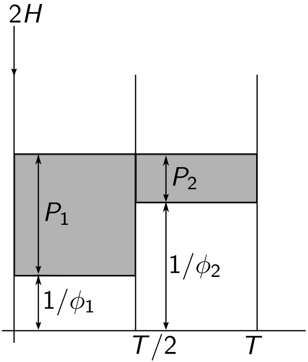


Enter Fading

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

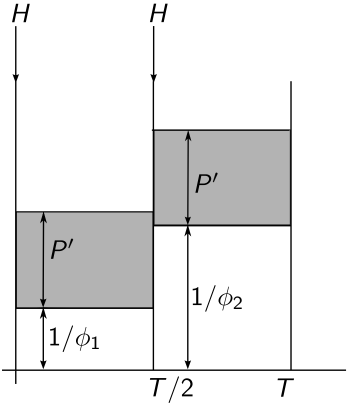
Example

- 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



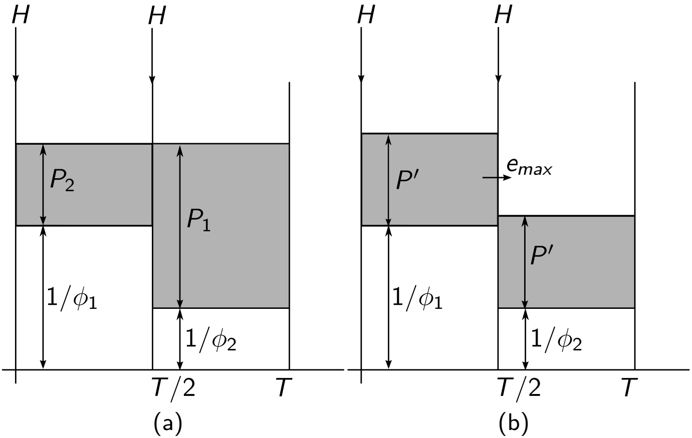
Energy Harvesting

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

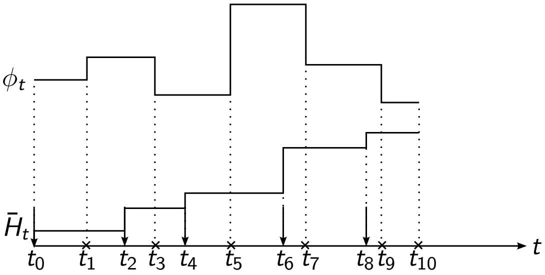


Limited Battery Capacity e_{max}

- 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



Max Throughput over a Fading Channel



- 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

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

A less intuitive formulation

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& 0 \leq p_i, \quad i = 1, ..., N.
\end{aligned}
$$

Convex optimization problem!

Lagrangian

$$\mathcal{L} = \sum_{i=1}^{N} \frac{\tau_i}{2} \log(1 + \phi_i p_i) - \sum_{i=1}^{N} \lambda_i \left(\sum_{j=1}^{i} \tau_j p_j - \sum_{j=1}^{i} H_{j-1} \right)$$

$$- \sum_{i=1}^{N} \mu_i \left(\sum_{j=1}^{i+1} H_{j-1} - \sum_{j=1}^{i} \tau_j p_j - e_{max} \right) + \sum_{i=1}^{N} \eta_i p_i$$

Lagrangian

$$\mathcal{L} = \sum_{i=1}^{N} \frac{\tau_i}{2} \log(1 + \phi_i p_i) - \sum_{i=1}^{N} \lambda_i \left(\sum_{j=1}^{i} \tau_j p_j - \sum_{j=1}^{i} H_{j-1} \right)$$

$$- \sum_{i=1}^{N} \mu_i \left(\sum_{j=1}^{i+1} H_{j-1} - \sum_{j=1}^{i} \tau_j p_j - e_{max} \right) + \sum_{i=1}^{N} \eta_i p_i$$

Complementary slackness conditions:

$$\lambda_i \left(\sum_{j=1}^{i} \tau_j p_j - \sum_{j=1}^{i} H_{j-1} \right) = 0, \forall i$$

$$\mu_i \left(\sum_{j=1}^{i+1} H_{j-1} - \sum_{j=1}^{i} \tau_j p_j - e_{max} \right) = 0, \forall i$$

$$\eta_i p_i = 0, \forall i$$

Lagrangian

Optimal power allocation:

$$p_j^* = \left[\upsilon_j - \frac{1}{\phi_j} \right]^+$$

$$\upsilon_j = \frac{1}{\sum_{i=j}^{N} \lambda_i - \sum_{i=j}^{N} \mu_i}.$$

Lagrangian

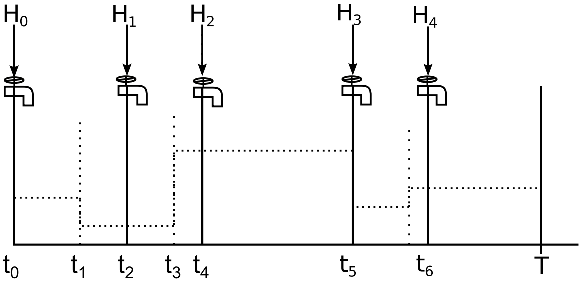
Optimal power allocation:

$$p_j^* = \left[\upsilon_j - \frac{1}{\phi_j} \right]^+$$
$$\upsilon_j = \frac{1}{\sum_{i=j}^{N} \lambda_i - \sum_{i=j}^{N} \mu_i}.$$

If $e_{max} = \infty$:

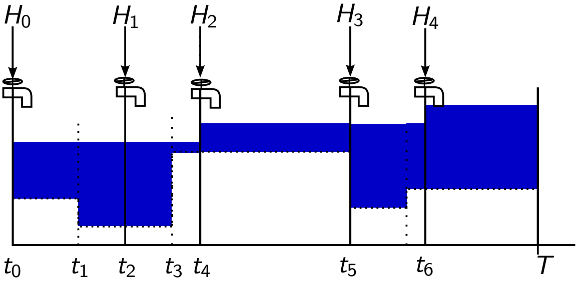
- $\mu_j = 0, \quad \forall j$
- Since $\lambda_j \geq 0$, we have $\upsilon_{i+1} \geq \upsilon_i$
- Optimal water level is monotonically increasing!
- If ϕ_i is constant, optimal power is monotonically increasing

Directional Waterfilling



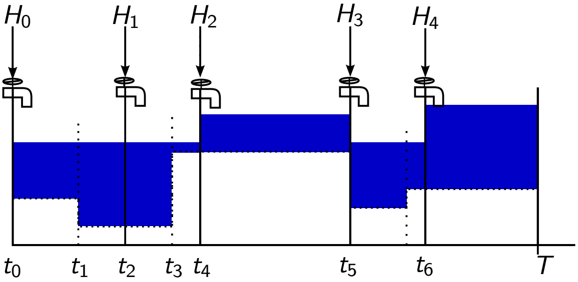
Directional Waterfilling

$e_{max} = \infty$

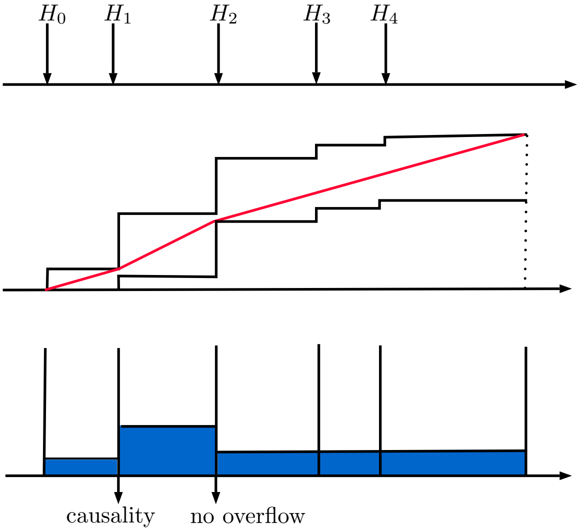


Directional Waterfilling

e_{max} is finite



Directional Waterfilling vs. Shortest Path



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: $\frac{1}{2}\log(1 + \phi(t)p(t))$

Optimization

- Transmission power in each epoch: p_i

Optimization

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

Optimization

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

$$
\begin{aligned}
\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 \leq \sum_{j=1}^{i} (H_{j-1} - \Theta_j(p_j + \epsilon)), i = 1, ..., N, \\
& \sum_{j=1}^{i+1} H_{j-1} - \sum_{j=1}^{i} \Theta_j(p_j + \epsilon) \leq e_{max}, i = 1, ..., N, \\
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Optimization

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- Non-convex optimization

Convexification

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

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& \sum_{j=1}^{i+1} H_{j-1} - \sum_{j=1}^{i} (\alpha_j + \epsilon\Theta_j) \leq e_{max}, i = 1, ..., N, \\
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Convexification

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

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

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$$\sum_{j=1}^{i+1} H_{j-1} - \sum_{j=1}^{i} (\alpha_j + \epsilon\Theta_j) \leq e_{max}, i = 1, ..., N,$$

$$0 \leq \Theta_i \leq \tau_i, \quad \text{and} \quad 0 \leq \alpha_i, \quad i = 1, ..., N.$$

- $\frac{\Theta_i}{2} \log(1 + \frac{\phi_i \alpha_i}{\Theta_i})$: perspective of $\frac{1}{2} \log(1 + \phi_i \alpha_i)$
- Strictly concave function
- Perspective operation preserves concavity

Convexification

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

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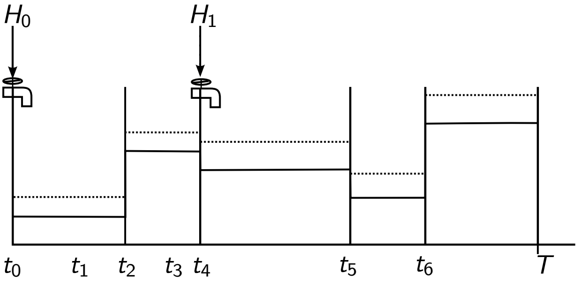
\end{aligned}$$

- $\frac{\Theta_i}{2} \log(1 + \frac{\phi_i \alpha_i}{\Theta_i})$: perspective of $\frac{1}{2} \log(1 + \phi_i \alpha_i)$
- Strictly concave function
- Perspective operation preserves concavity
- Convex optimization problem

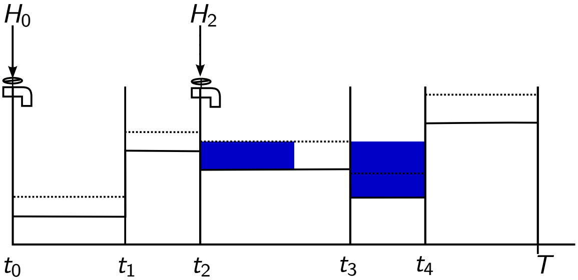
Optimal Solution

- Each epoch has a threshold value: υ_i^*

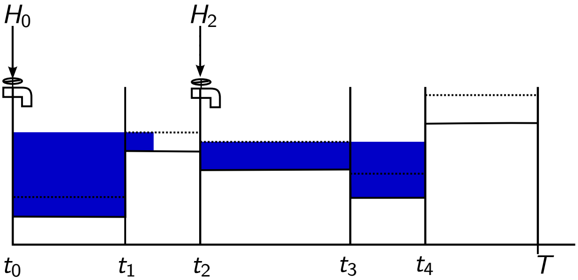


Optimal Solution

- Glue Pouring
- Sleep periods



Optimal Solution



Effect of Processing Energy Cost

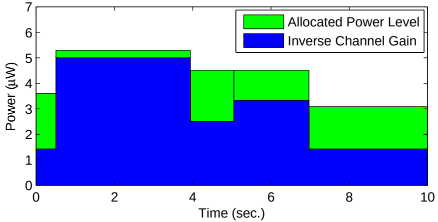


Figure: processing cost $= 0$

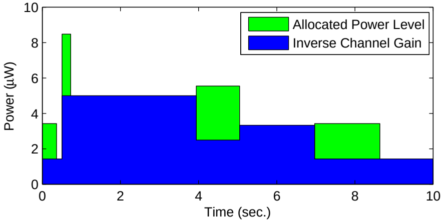


Figure: processing cost $= 1\ \mu W$

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 framework - Conclusions

- 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

Offline framework - References

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O. Ozel et al., Transmission with Energy Harvesting Nodes in Fading Wireless Channels: Optimal Policies, IEEE JSAC, Sep. 2011.

J. Yang et al., Broadcasting with an Energy Harvesting Rechargeable Transmitter, IEEE Trans. Wireless Comms., Feb. 2012.

R. Gangula et al., Optimization of energy harvesting MISO communication channels, IEEE JSAC, Mar. 2015.

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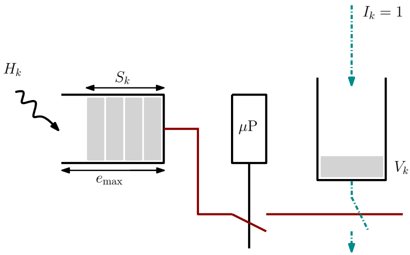
Setting

- $H(t)$ 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

Tools

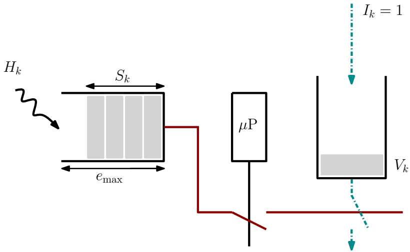
- Markov decision processes: discrete-time stochastic control
- Policy: a set of decision rules based on system state
- Can be solved numerically with well known algorithms (linear programming, value iteration, policy iteration)
- But: complexity explodes with size of state space, no insight!
- We can also use offline heuristics in online context: ignores statistics
- A good compromise: appropriately optimize simple "energy-balancing" policies

System Model



- Slotted-time: slot k is interval $[k\tau, (k+1)\tau)$, $k \in \mathbb{Z}^+$, $\tau > 0$
- Time k: new data packet of importance $V_k \geq 0$; $\{V_k\}$ are iid.
- TX: reward V_k; consume one energy quantum
- DROP: no reward; no energy consumed

System Model



- EH process: H_k iid Bernoulli with mean $\beta \in (0, 1)$
- Energy level evolution:

$$S_{k+1} = \min\{S_k - Q_k + H_k, e_{\max}\}$$

- Transmit: $Q_k = 1$; drop: $Q_k = 0$

Why is this scenario interesting?

General

- Temperature sensor: importance $\leftrightarrow$ temperature
- Relay: importance $\leftrightarrow$ priority
- Rate adaptation to fading: importance $\leftrightarrow$ achievable rate

Representative

- Intermittence of harvested energy
- Basic energy management question
- Each slot corresponds to one cycle

System state and policy definition

- System state at time k: $(S_k, V_k) \in \mathcal{S} \times \mathbb{R}^+$, where $\mathcal{S} = \{0, \ldots, e_{\max}\}$ is energy level set
- Energy outage: $S_k = 0$
- Energy overflow: $(S_k = e_{\max}) \cap (H_k = 1) \cap (Q_k = 0)$
- Policy μ determines $Q_k \in \{0, 1\}$
- $\mu(1; s, v)$: prob of TX
- $\mu(0; s, v) = 1 - \mu(1; s, v)$: prob of DROP
- Formally: μ probability measure on action space $\{0, 1\}$ parametrized by state (S_k, V_k)

Optimization problem

Long-term average reward per slot

$$G(\mu, s_0, v_0) = \liminf_{K \to \infty} \frac{1}{K} \mathbb{E}\left[\sum_{k=0}^{K-1} Q_k V_k \,\middle|\, S_0 = s_0, V_0 = v_0 \right]$$

Find optimal policy

$$\mu^* = \arg\max_{\mu} G(\mu, s_0, v_0)$$

Threshold policies

- μ^* has a threshold structure

$$\mu^*(1; s, v) = \begin{cases} 1 & v \geq v_{\mathrm{th}}(s) \\ 0 & v < v_{\mathrm{th}}(s) \end{cases}$$

- Average TX prob

$$\eta(s) = \int_{v_{\mathrm{th}}(s)}^{+\infty} f_V(\nu) \, \mathrm{d}\nu = \bar{F}_V(v_{\mathrm{th}}(s))$$

- Average reward $= g(\eta(s))$

$$g(x) = \int_{\bar{F}_V^{-1}(x)}^{+\infty} \nu \; f_V(\nu) \, \mathrm{d}\nu, \;\; x \in [0, 1]$$

- $g(x)$ is strictly increasing and concave

Admissible policies

- $\mu \leftrightarrow v_{\mathrm{th}}(\cdot) \leftrightarrow \eta(\cdot)$
- Transition probs of Markov chain $\{S_k\}$ depend only on η
- Admissible policy: unique steady-state distribution

$$\pi_\eta(s),\ s \in \mathcal{S}$$

- For admissible policy η, the long-term reward is

$$G(\eta) = \sum_{s=0}^{e_{\max}} \pi_\eta(s) g(\eta(s))$$

Markov decision process

- Optimization problem becomes

$$\eta^* = \arg\max_{\eta} G(\eta)$$

- (S_k, V_k, Q_k) is a Markov Decision Process (MDP)
- Optimal policy can be easily evaluated numerically
- We seek properties of the optimal policy
- Approach: evaluate analytically $\pi_\eta(s)$ (and $G(\eta)$)

A bound

- By Jensen's inequality

$$G(\eta) = \sum_{s=0}^{e_{\max}} \pi_\eta(s) g(\eta(s)) < g\left(\sum_{s=0}^{e_{\max}} \pi_\eta(s)\eta(s)\right)$$

- In addition

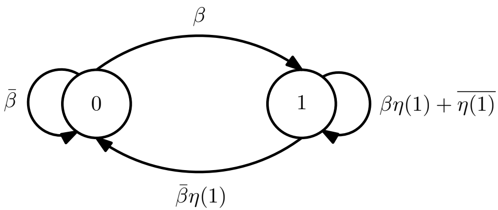
$$\sum_{s=0}^{e_{\max}} \pi_\eta(s)\eta(s) \leq \beta$$

- Therefore

$$G(\eta) < g\left(\sum_{s=0}^{e_{\max}} \pi_\eta(s)\eta(s)\right) \leq g(\beta)$$

- Bound achievable by Balanced Policy for $e_{\max} \to \infty$

Example: $e_{\max} = 1$



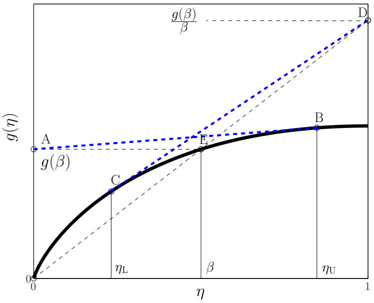
$$\pi_\eta(0) = \frac{\bar{\beta}\eta(1)}{\beta + \bar{\beta}\eta(1)}$$

$$\pi_\eta(1) = \frac{\beta}{\beta + \bar{\beta}\eta(1)}$$

$$G(\eta) = \frac{\beta}{\beta + \bar{\beta}\eta(1)}\, g(\eta(1))$$

- $\eta^*(1)$ is the unique solution of $\partial G(\eta)/\partial\eta(1) = 0$

Properties of optimal policy: $e_{\max} > 1$ [MichelTA12]



- $\eta^*(s)$ is strictly increasing
- $\eta^*(s) \in (\eta_L, \eta_U)$, $\forall s \in \mathcal{S} \setminus \{0\}$
- $\eta_L \in (0, \beta)$, $\eta_U \in (\beta, 1)$ solve

$$g(\eta_L) + \overline{\eta_L} g'(\eta_L) = \frac{g(\beta)}{\beta}$$
$$g(\eta_U) - \eta_U g'(\eta_U) = g(\beta)$$

Interpretation

- The more energy available in the battery, the larger the incentive to transmit
- η_L and η_U consequence of concavity of $g(\eta)$
- If η is too low, the policy is too conservative
- If η is too high, returns are diminishing

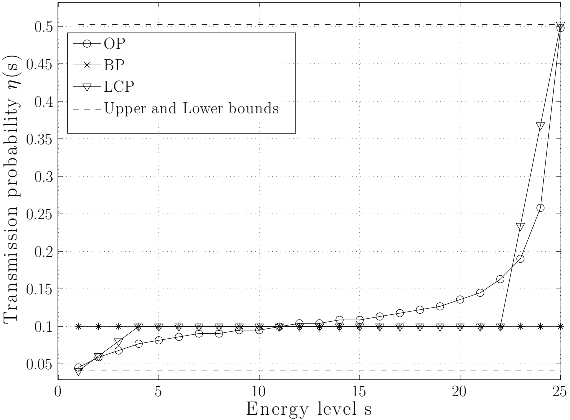
Example: rate adaptation for Rayleigh fading

$$V_k = \ln(1 + \mathrm{SNR} H_k)$$
$$g(\eta(s)) = \int_{h_{\mathrm{th}}(s)}^{+\infty} \ln(1 + \mathrm{SNR} h)\, \mathrm{e}^{-h} \mathrm{d}h$$
$$\eta(s) = \int_{h_{\mathrm{th}}(s)}^{+\infty} \mathrm{e}^{-h}\, \mathrm{d}h = \mathrm{e}^{-h_{\mathrm{th}}(s)}$$

Policies

- Optimal Policy (OP): solved for numerically
- Balanced Policy (BP): $\eta(s) = \beta \; \forall s \in \mathcal{S} - \{0\}$
- Greedy Policy (GP): $\eta(s) = 1 \; \forall s \in \mathcal{S} - \{0\}$
- Low Complexity Policy (LCP): based on proved properties

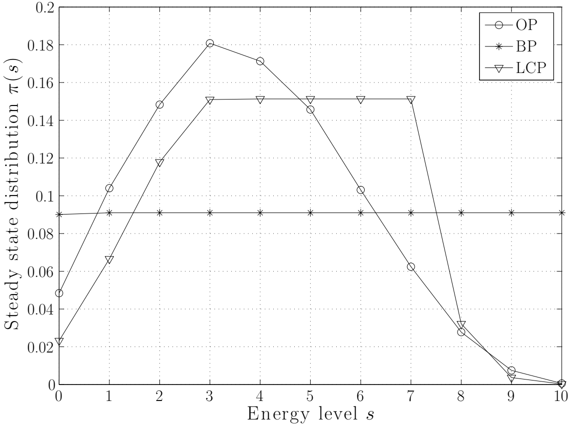
Average transmission probability



LCP "follows" OP: conservative for small s, aggressive for large s

($\beta = 0.1$, SNR $= 10\,\mathrm{dB}$, $e_{\max} = 25$)

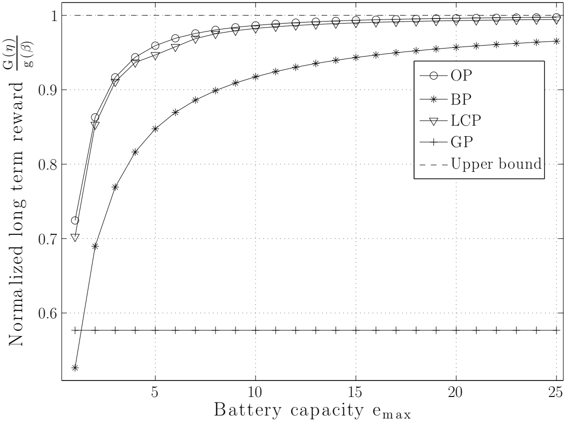
Steady-state distribution



LCP and OP maintain energy level away from outage/overflow regions

($\beta = 0.1$, SNR $= 10\,\mathrm{dB}$, $e_{\max} = 10$)

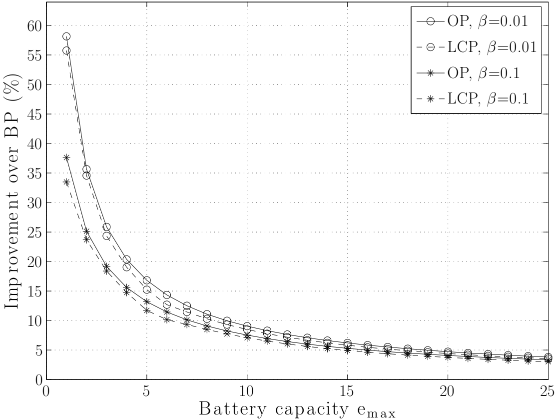
Reward



LCP performs very close to optimal. BP asymptotically optimal

($\beta = 0.1$, SNR $= 10\,\mathrm{dB}$)

Improvement over BP



Adaptation pays more for decreasing β or $e_{\max}$

(SNR $= 10\,\mathrm{dB}$)

Take-away points

- The reward of the BP is

$$G(\eta_{\mathrm{BP}}) = \frac{1}{1 + \frac{\bar{\beta}}{e_{\max}}} g(\beta)$$

- For $e_{\max}/\bar{\beta} \geq 3$, $G(\eta_{\mathrm{BP}})/g(\beta) \geq 0.75$
- Roughly: if I can store enough energy for 3 TX pulses, a balanced policy performs very well
- Why: energy arrivals are iid! Outage and overflow occur, but not for prolonged periods.
- Insight from OP: increase (decrease) TX prob as stored energy level increases (decreases)

Online framework - References

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Learning Theoretic Framework

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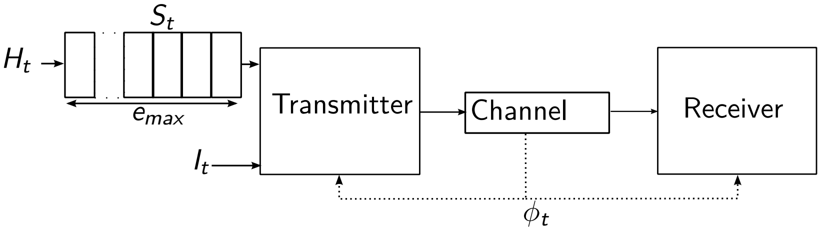
Learning Theoretic Framework

- Energy sources are sporadic
- In many cases knowing energy arrivals in advance (offline optimization) not possible
- Even the statistics 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?

System Model

- 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



System Model

- 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: $S_{t+1} = \min\{S_t - X_t E_t + H_t, e_{max}\}$.

Optimization problem

Objective: Maximize average total data within activation time:

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

$$\text{s.t. } S_{t+1} = \min\{S_t - X_t E_t + H_t, e_{max}\},$$

$$X_t E_t \leq S_t,$$

$$X_t \in \{0, 1\}$$

Optimization methods

	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.

Learning Theoretic Optimization

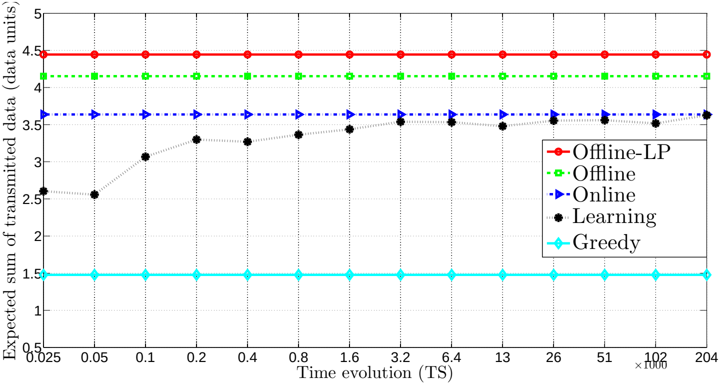
We use Q-learning algorithm (a Reinforcement Learning technique):

- 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

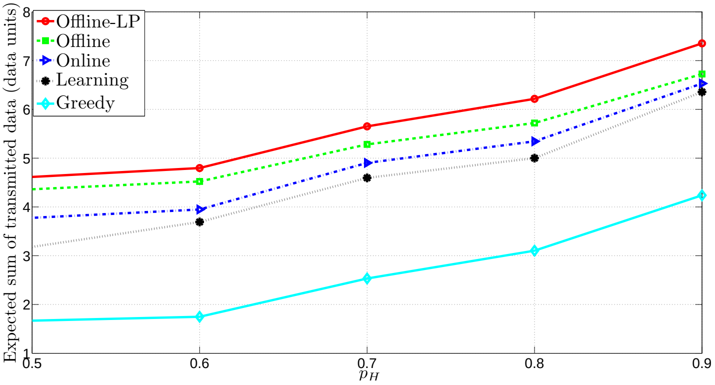
Numerical Results - Parameters

- **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.

Q–learning convergence



Energy harvesting



Learning theoretic framework - Conclusions

- 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

Learning theoretic framework - References

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Table of Contents

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 [Gorla11]
- Implementation/testing of energy management algorithms in prototypes: Columbia's EnHants project [Gorla11]
- Realistic models that "capture" key characteristics of underlying circuitry
- Realistic storage models: e.g., "degradation-aware" policies [MicheInf13]

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

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)
- : Need protocols adapted to EH sensors

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 [Iannello12], [MichelCC13]

Standards and Market

- 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), marketsandmarkets.com, August 2012

Closing remarks

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

THANK YOU!

Further References

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