Challenges of energy-aware operation in sensor nodes with energy harvesting capabilities

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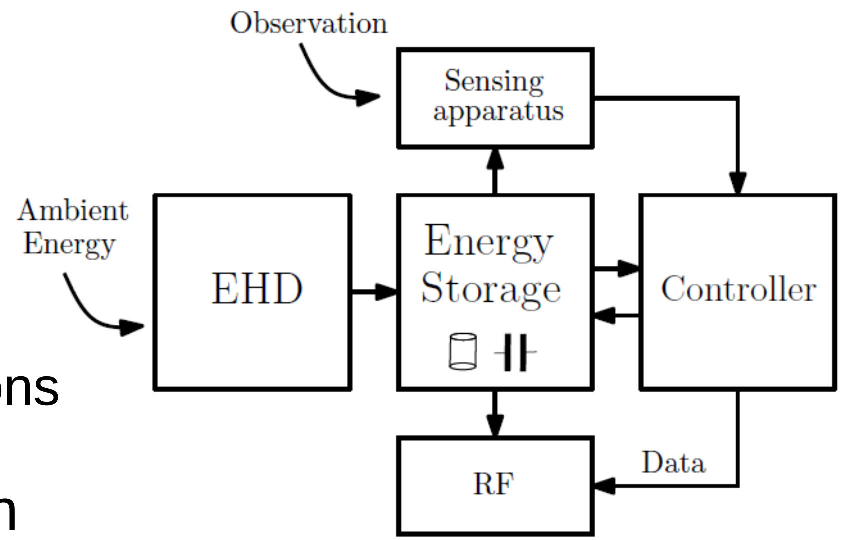
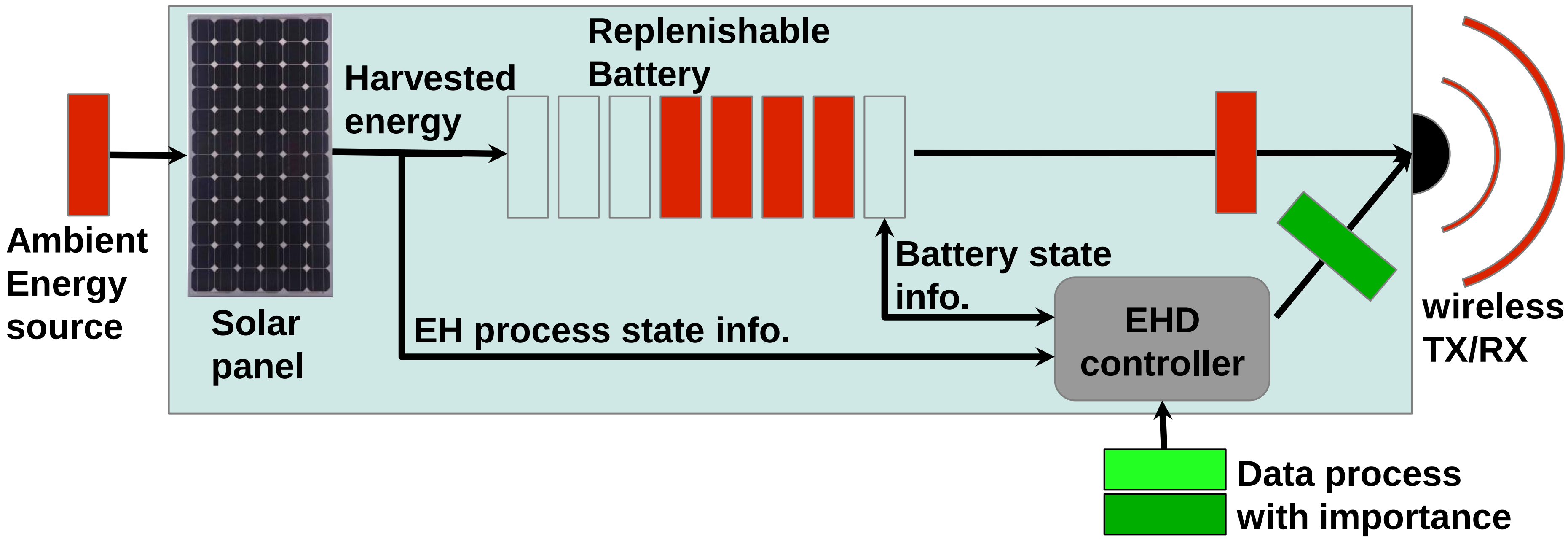
Rationale and Challenges

- Traditional sensors
  - Battery powered
    - Finite energy supply and lifetime
    - Replacement costly or prohibitive
  - Energy efficiency is the primary goal
- Energy Harvesting is a new paradigm
  - Ambient energy is harvested
    - Nearly perpetual operation
    - Challenge: Erratic energy supply
  - EH-aware energy management solutions coping with random energy supply
- Focus shifts from energy conservation and efficiency (traditional sensors) to energy management and transmission policies.



EH model with data importance

- Energy: harvested → stored in a battery → used to power the device
- Data: arrive → queued in a buffer → transmitted
- Energy quanta arrivals: Bernoulli i.i.d. process with probability β
- Data have *importance*: i.i.d. process with continuous distribution
  - *e.g.*, importance of sensed events, packet priority, fading



EHD controller

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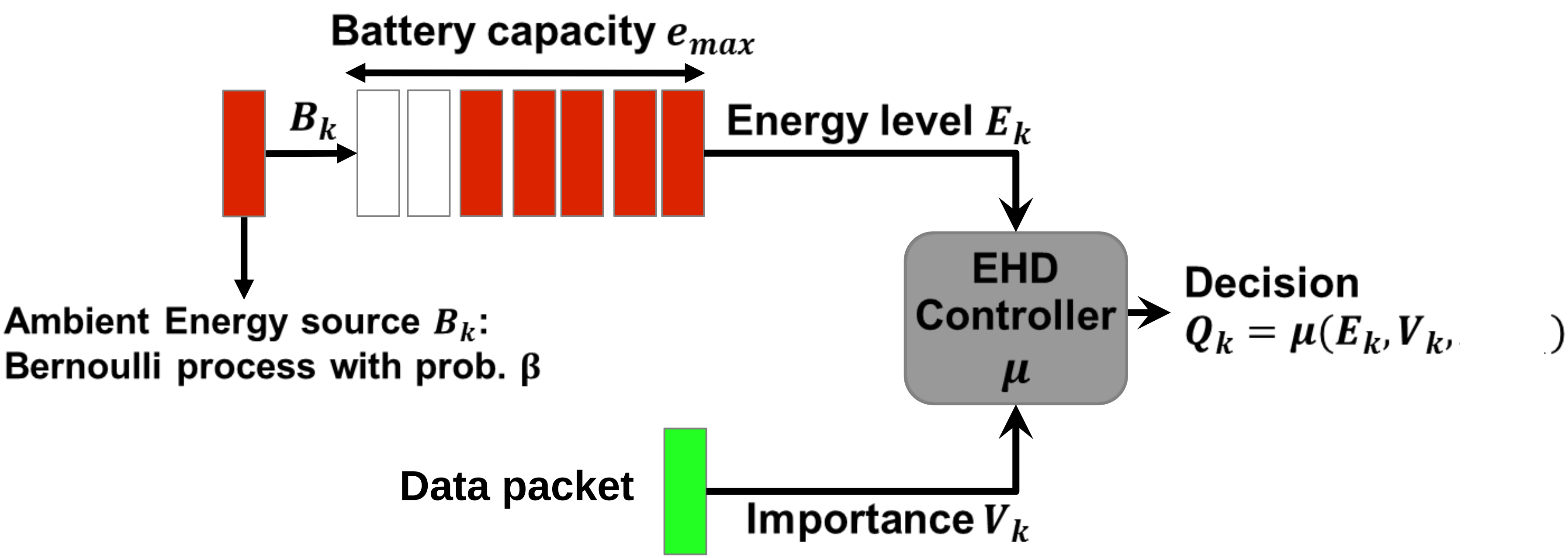


- **IDLE ($Q_k = 0$)**
  - no reward accrued
  - no energy consumed
- **TX ($Q_k = 1$)**
  - reward V_k accrued
  - 1 energy quantum used

Optimization Problem

- Long-term average data importance reported to Fusion Center (FC)

$$G(\mu, e_0) = \lim_{N\to\infty} \mathbb{E}\left[\frac{1}{N}\sum_{k=0}^{N-1} V_k \mu(E_k, V_k) \,|E_0 = e_0\right]$$

- Optimization problem

$$\mu^* = \arg\max_{\mu} G(\mu, e_0)$$

- Under mild conditions on μ, $G(\mu, e_0)$ is independent of initial state e_0
  - μ^* satisfies these conditions

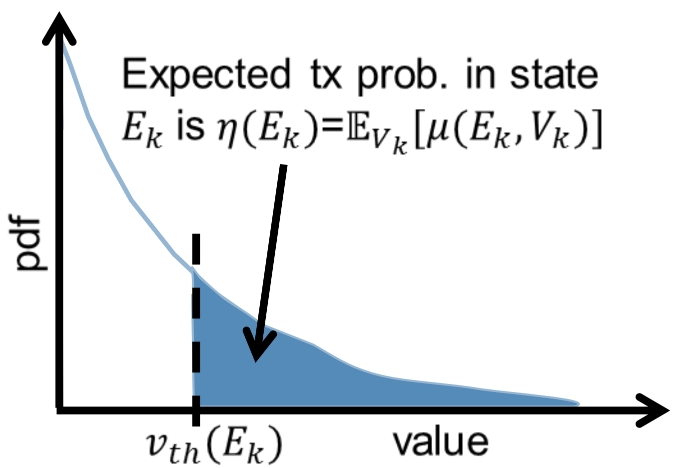
Threshold structure

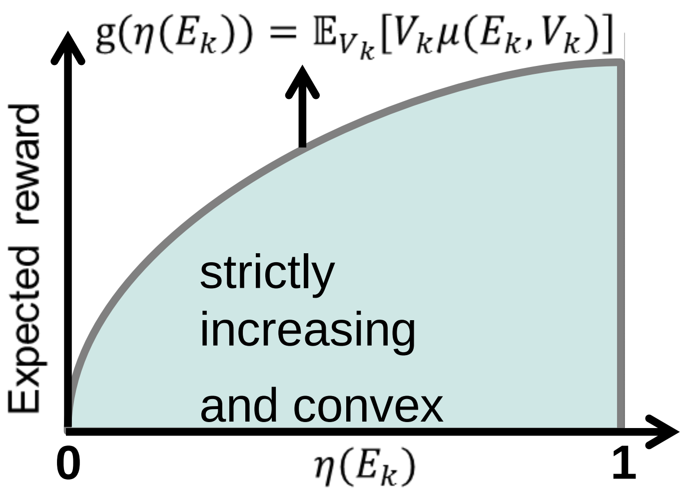
- Transition probabilities of process $\{E_k\}$ depend on data importance only through the average tx probability $\mathbb{E}_{V_k}[\mu(E_k, V_k)]$

$$\mu^*(e_k,\cdot) = \underset{\mu(e_k,\cdot):\mathbb{R}^+ \mapsto \{0,1\}}{\arg\max} \mathbb{E}_{V_k}[V_k \mu(e_k, V_k)]$$

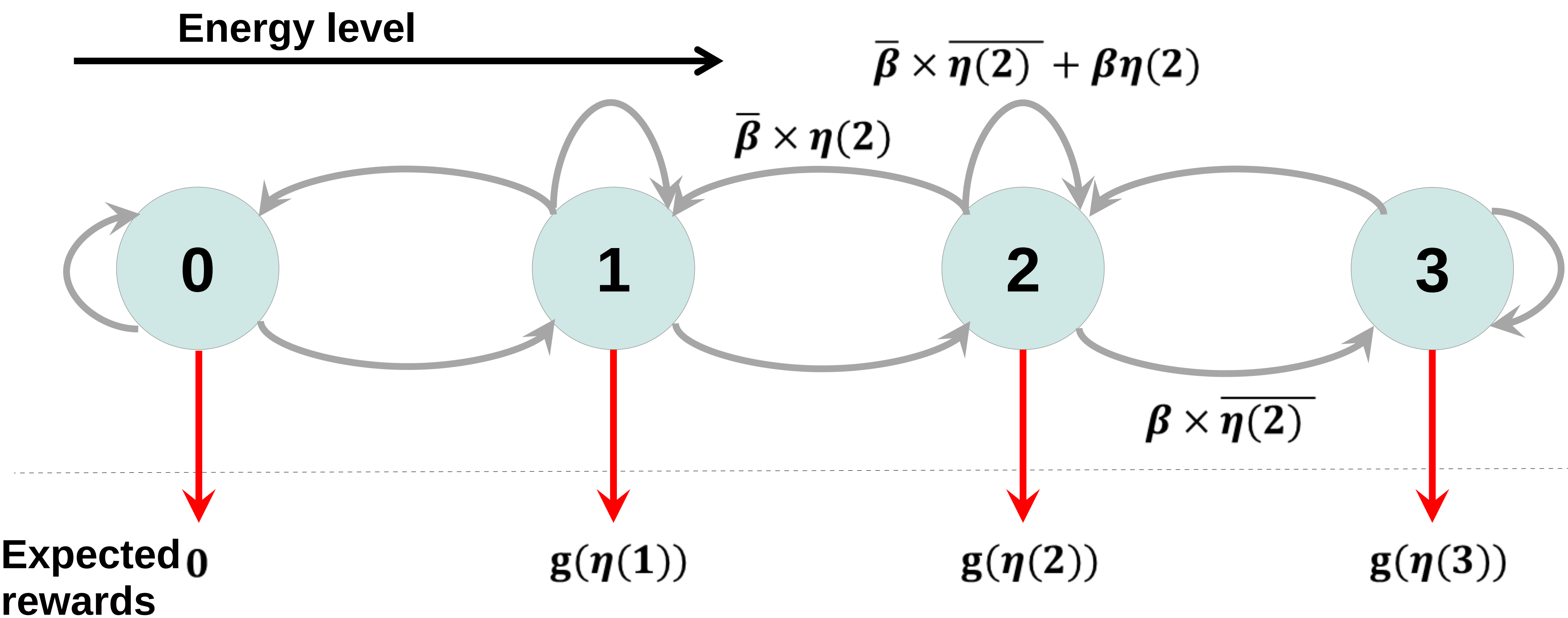
such that $\mathbb{E}_{V_k}[\mu(e_k, V_k)] = \eta(e_k)$

- μ^* has a threshold structure with respect to data importance
  - $\forall E_k$, only data with importance $> v_{th}(E_k)$ are reported





Markov Decision Process



Outage: no transmission is possible due to lack of energy (state 0)

Overflow: harvested energy cannot be stored (state emax if no tx)

Formulation under threshold structure

- Average long-term data importance

$$G(\eta) = \sum_{e=1}^{e_{max}} \pi_\eta(e) g\big(\eta(e)\big)$$

- Optimization problem

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

- Can be solved by standard optimization tools, e.g., *policy iteration* [Bertsekas'07]
  - However, we seek low-complexity policies attaining close to optimal performance

Numerical Results

- Scenario: throughput maximization
  - Rayleigh fading channel with gain $H_k \sim \mathcal{E}(1)$
  - Data importance: achievable capacity

$$V_k = \log_2(1 + \mathrm{SNR} H_k)$$

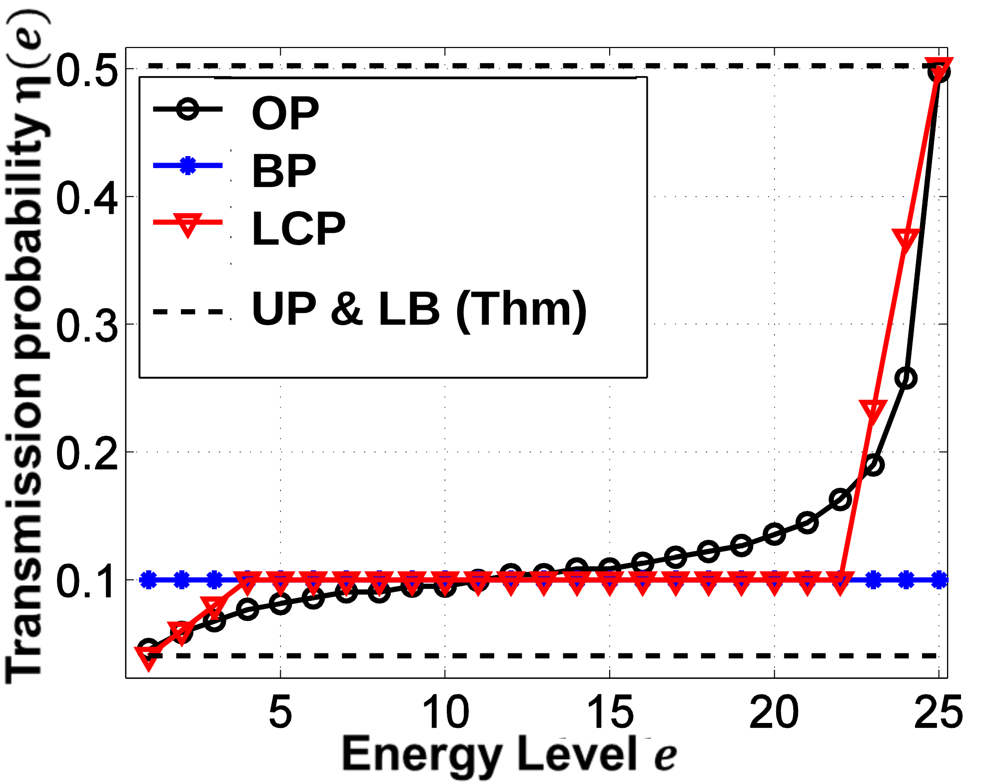
  - Channel threshold $h_{th}(e)$ employed

$$\eta(e) = \int_{h_{th}(e)}^{\infty} e^{-h} \mathrm{d}\, h = e^{-h_{th}(e)}$$

$$g(\eta(e)) = \int_{h_{th}(e)}^{\infty} \log_2(1 + \mathrm{SNR} h)\, e^{-h} \mathrm{d}\, h$$

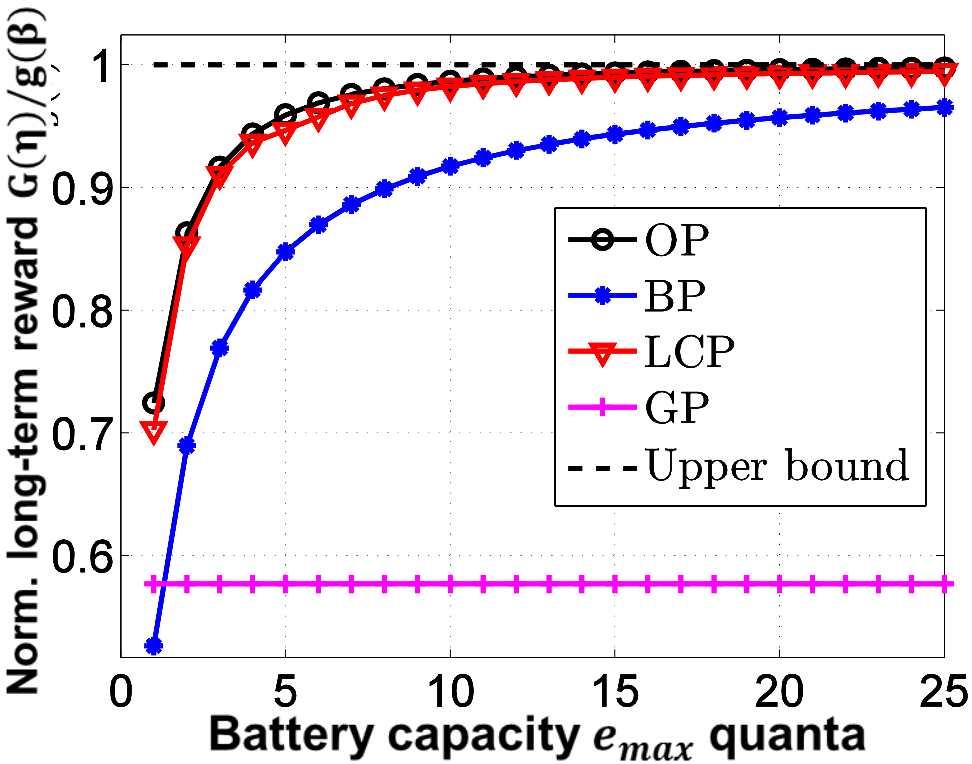
Policy Comparison

- We seek a low-complexity sub-optimal policy with good performance
- ***Conservative*** in low energy levels
  - Linear increase from LB (Thm) to β
- ***Balanced*** in intermediate energy levels
  - Tx prob. Constant equal to β
- ***Aggressive*** in high energy levels
  - Linear increase from β to UB (Thm)



Numerical Results

- SNR=8dB, $\beta = 0.1$
- Policies
  - **OP**: optimal policy, via policy iteration algorithm
  - **BP**: Balanced Policy
  - **GP**: Greedy Policy, transmits whenever energy is available
  - **LCP**: Low Complexity Policy
- **LCP** performs close to **OP** (60% better than BP with small battery capacity)
- Significant loss incurred with **BP** and **GP**



Time-correlated EH process

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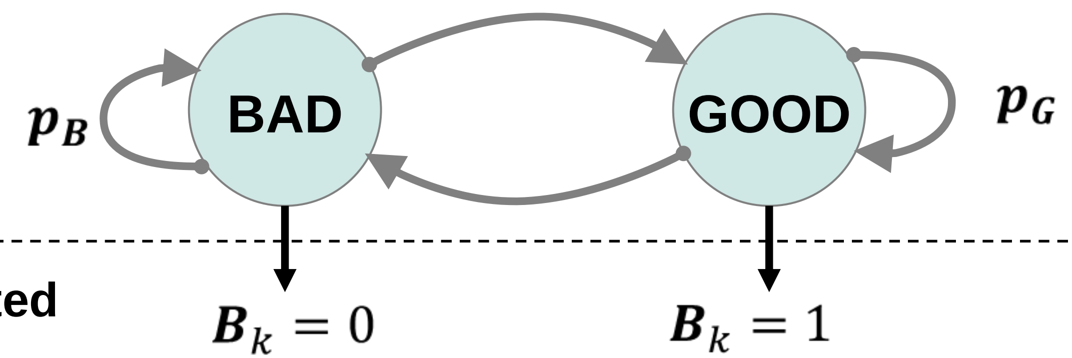
- Two-state Markov EH process (*e.g.*, solar energy source)

EH state S_k:

Energy harvested in time-slot *k*



- $D_B = \frac{1}{1-p_B}$: Average duration of BAD EH period
- $D_G = \frac{1}{1-p_G}$: Average duration of GOOD EH period
- $\beta = \frac{D_G}{D_G+D_B}$: Average EH rate
- However, in practice, the probability that $B_k = 1$ in BAD and GOOD EH states is > 0 and < 1, respectively→future work

EHD controller

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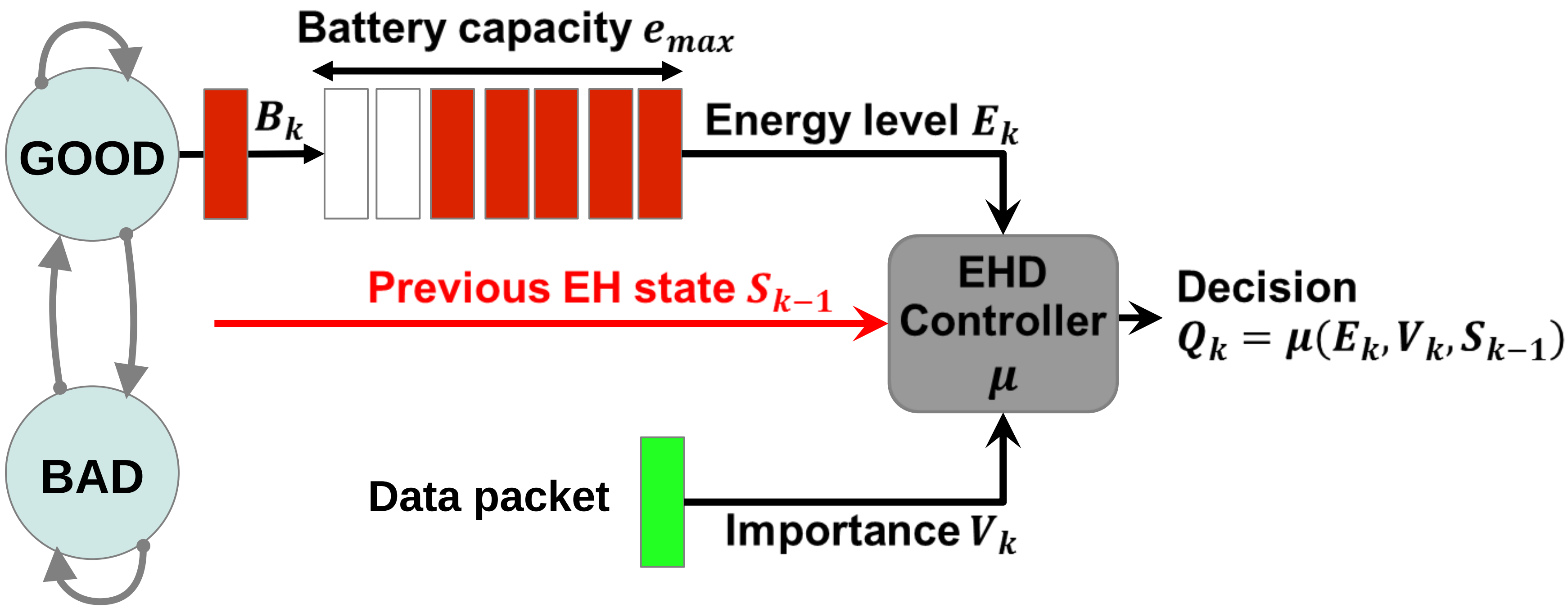

- Controller decision at time k is also based on the EH state observed in the previous time-slot *k-1*, S_{k-1}
  - From our model, one-to-one mapping between S_{k-1} and B_{k-1}
  - S_{k-1} is known by measuring B_{k-1} harvested during time-slot $k-1$

Optimization Problem

- Long-term average data importance reported to Fusion Center

$$G(\mu, e_0, s_{-1}) = \lim_{N\to\infty} \mathbb{E}\left[\frac{1}{N}\sum_{k=0}^{N-1} V_k \mu(E_k, V_k, S_{k-1}) \,|E_0 = e_0, S_{-1} = s_{-1}\right]$$

- Optimization problem $\mu^* = \arg\max_{\mu} G(\mu, e_0, s_{-1})$
- As before, μ^* has a threshold structure wrt the data importance→We focus on optimizing the tx prob. η

$$G(\eta) = \sum_{e=1}^{e_{max}} \left[\pi_\eta(e, \mathrm{G}) g\big(\eta(e, \mathrm{G})\big) + \pi_\eta(e, \mathrm{B}) g(\eta(e, \mathrm{B}))\right]$$

Balanced Policies (BPs)

- η_G: Transmission prob. in the GOOD EH state
- η_B: Transmission prob. in the BAD EH state
- Energy Balanced operation

$$\beta\eta_G + (1-\beta)\eta_B = \beta$$

  - Consumed energy equals harvested energy
- $\theta \in \{0,1\}$: Overflow avoidance parameter:
  - $\theta = 1$: energy overflow is avoided by always transmitting when battery full
- Tx prob. depends (almost) only on EH state
  - Low complexity policy
  - State-of-Charge of battery may be costly and difficult to estimate (Part II)

Performance of BPs

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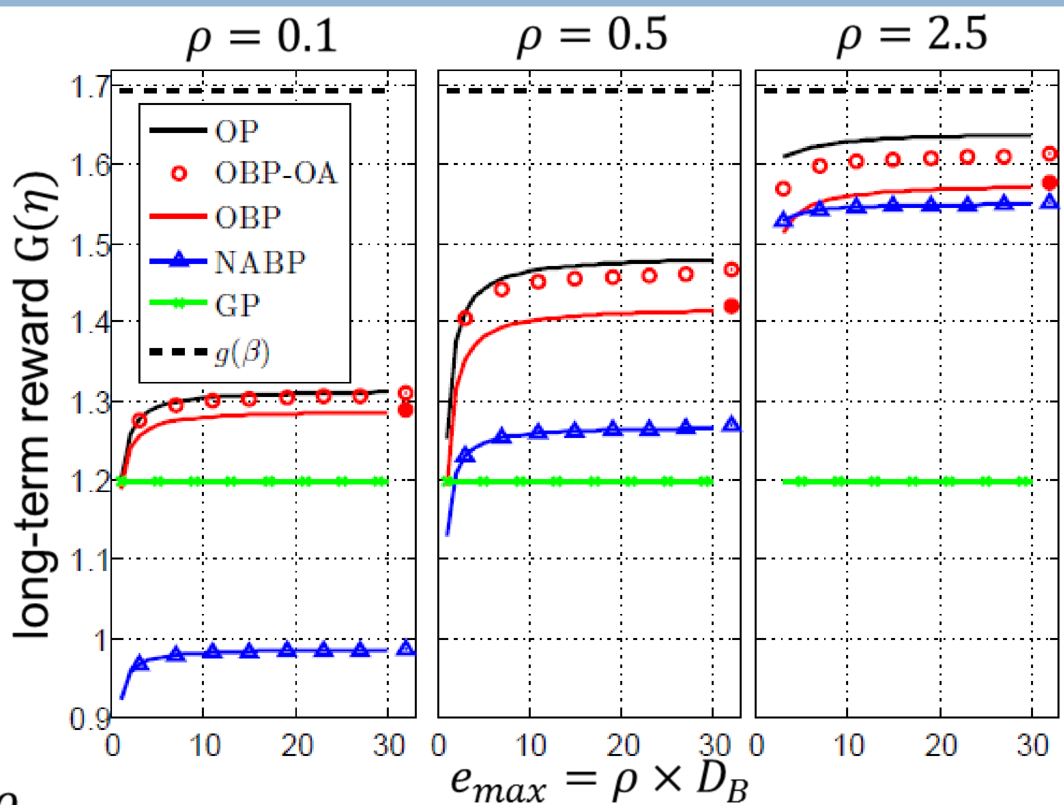
- SNR=8dB, $\beta = 0.5$
- Relative battery capacity $\rho = \frac{e_{max}}{D_B}$
  - ρ relates battery size to duration of BAD EH period
- ρ is the dominant parameter!
  - performance only mildly depends on e_{max}, for fixed ρ



OP: Optimal policy, Policy Iteration
OBP-OA: Optimal BP with OA
OBP: Optimal BP without OA
NABP: Non-adaptive BP, $\eta_G = \eta_B = \beta$
GP: Greedy BP, $\eta_G = 1$, $\eta_B = 0$

Conclusions

- Maximization of average long-term data "Importance" in an EH device
  - Importance of sensed events in WSNs, packet priority, channel fading
  - i.i.d. and two-state Markov EH process
  - Design of low complexity policies
- Performance largely depends on ratio between battery size and duration of BAD EH period
- A simple Balanced Policy, which only adapts to the EH state, achieves close-to-optimal performance

State-of-charge knowledge

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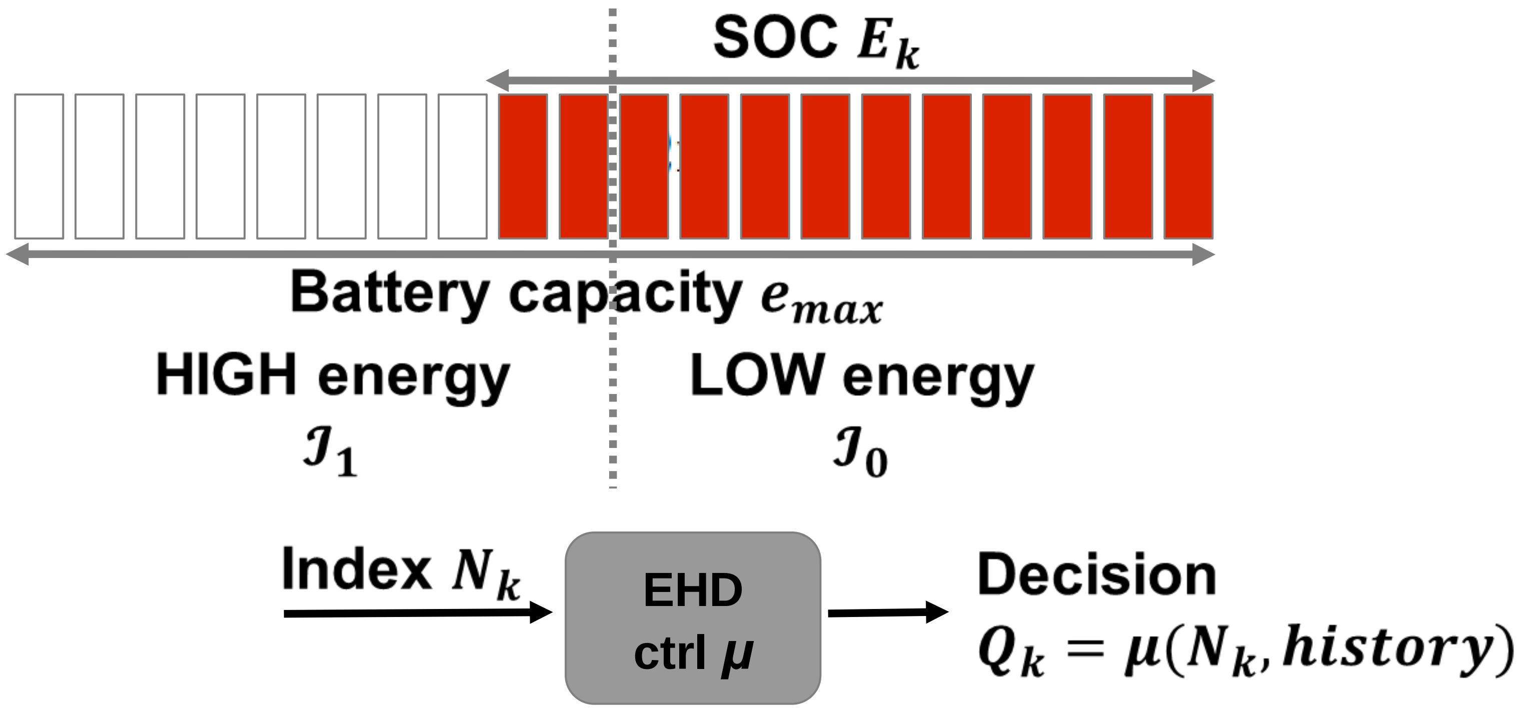
- So far, perfect knowledge of the state-of-charge (SOC) of the battery.
- Is this realistic? Battery SOC estimations are:
  - imprecise (up to 30% of errors)
  - time-consuming / energy-consuming
- New model: $[0, e_{max}]$ is quantized in intervals
  - it is just known which interval SOC e belongs to
  - e.g., two intervals: $\mathcal{I}_0$, $\mathcal{I}_1$ (LOW-HIGH)
  - we also generalize $Q_k > 1$
    - tasks consuming a variable amount of energy
    - generic i.i.d. energy arrival distribution (possibly, more than one energy quanta are harvested)
  - However, no data importance model

EHD with uncertain SOC

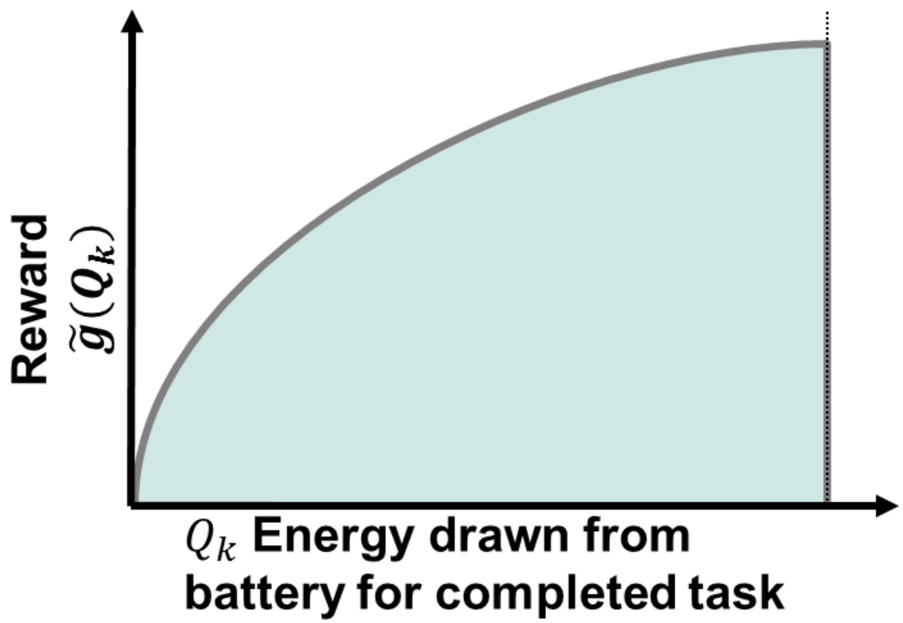
- Model of the EHD at time k



- The controller requests a number of energy quanta, Q_k, from the buffer. Reward is $g(Q_k, E_k)$

Reward

- The EHD-controller, in each time-slot, requests a certain amount of energy to perform specific tasks
- If $Q_k > E_k$, task cannot be completed, reward is 0
- If $Q_k \leq E_k$ reward $\tilde{g}(Q_k)$ is a concave increasing function of Q_k
  - E.g., achievable capacity



Optimization problem

- Maximize long-term reward

$$G(\mu, e_0) = \lim_{N\to\infty} \mathbb{E}\left[\frac{1}{N}\sum_{k=0}^{N-1} g(Q_k, E_k) \,\middle|\, E_0 = e_0\right]$$

$$\mu^* = \arg\max_{\mu} G(\mu, e_0)$$

- Reward function $g(Q_k, E_k)$

$$g(Q_k, E_k) = \begin{cases} 0, & Q_k > E_k \\ \tilde{g}(Q_k), & Q_k \leq E_k, \end{cases}$$

outage

concave increasing function of Q_k

Controller

- The controller may be informed on the past history (all past Q_k's, intervals, outages)
  - POMDP framework: the optimal controller decides based on the entire history

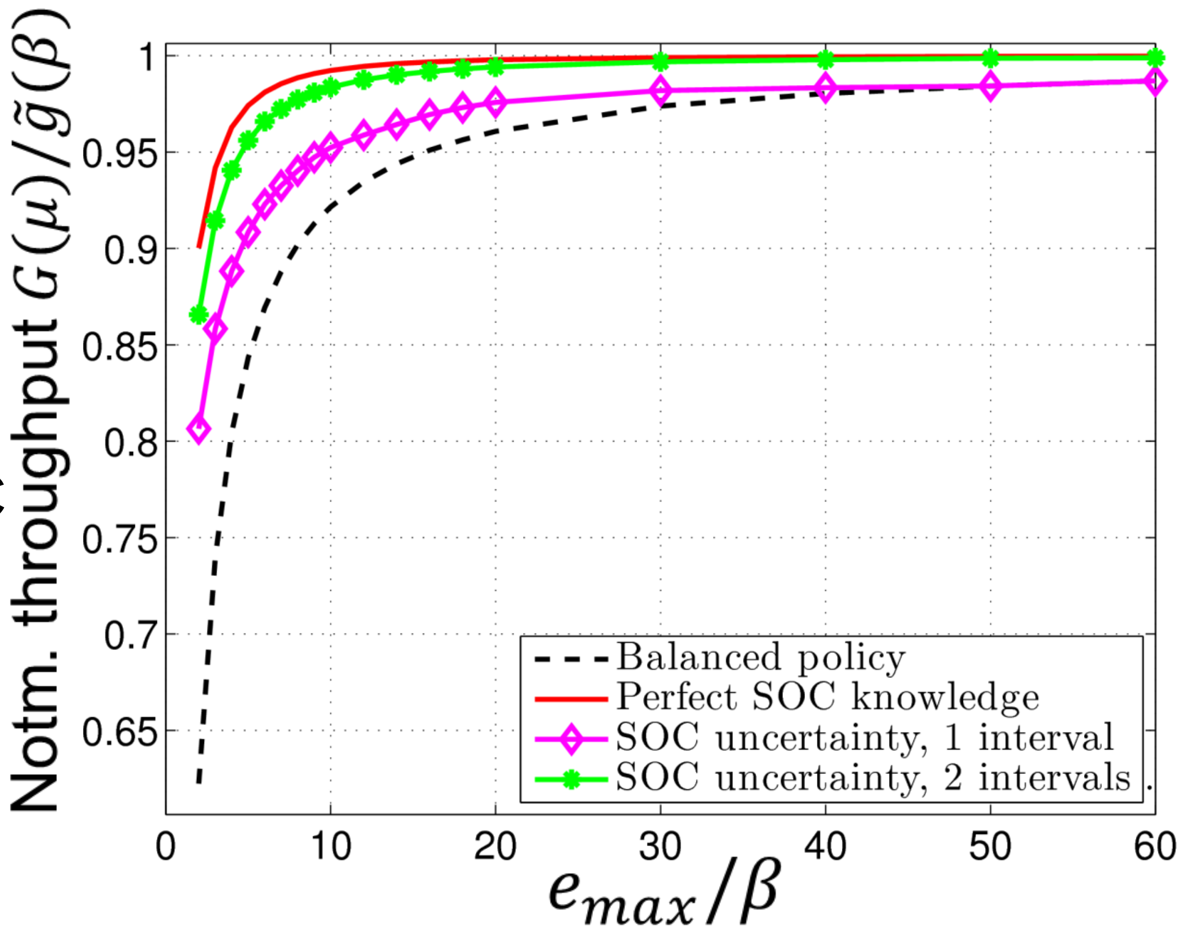
Index N_k $\longrightarrow$ **EHD ctrl $\boldsymbol{\mu}$** $\longrightarrow$ **Decision**

$$\boldsymbol{Q_k = \mu(N_k, history)}$$

- However, we seek low-complexity policies which depend only on current index N_k
  - POMDP framework cannot be employed
  - $\mu(N_k)$ is independent of history and only depends on N_k
  - Solution by exhaustive search

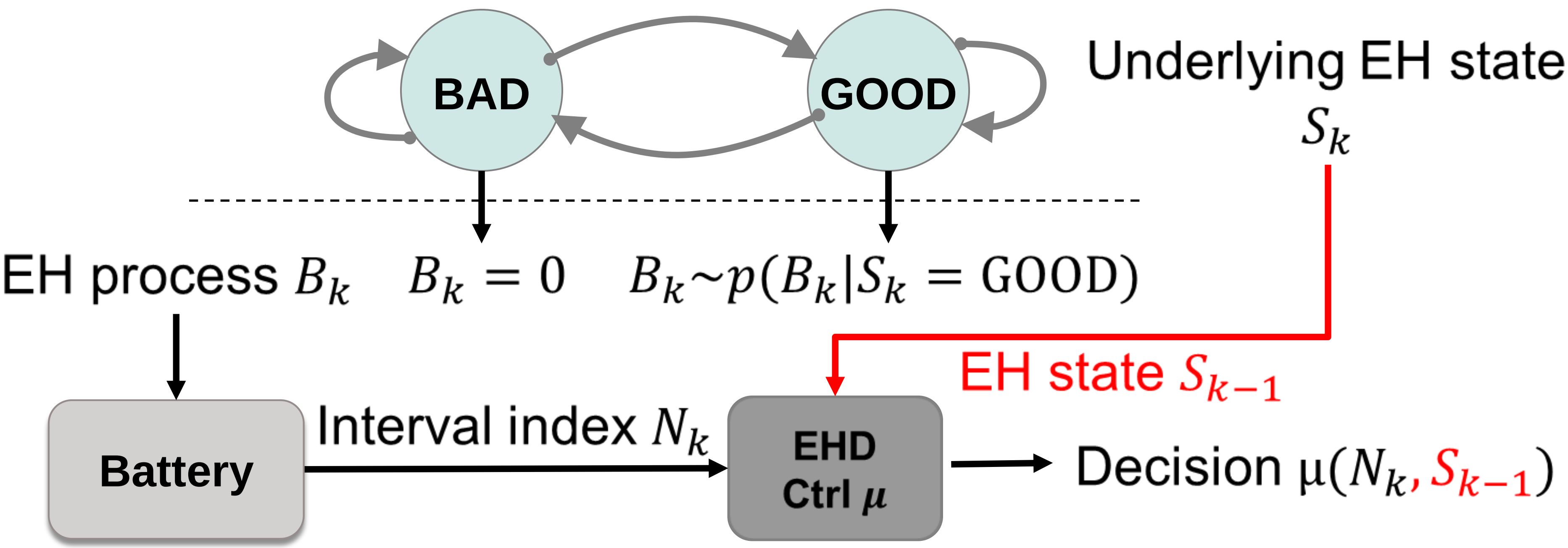
Performance vs battery capacity

- Only small degradation with 2 intervals uncertainty (within 5%)
- More significant degradation when SOC is completely unknown (but within 10%)



Time-correlated EH process

- Now, we consider a time-correlated EH process
- Can we overcome the loss due to imperfect SOC knowledge by adaptation to the EH state?



- Decision is also based on the EH state in the previous time-slot (assumed perfectly known for simplicity)

Policies considered

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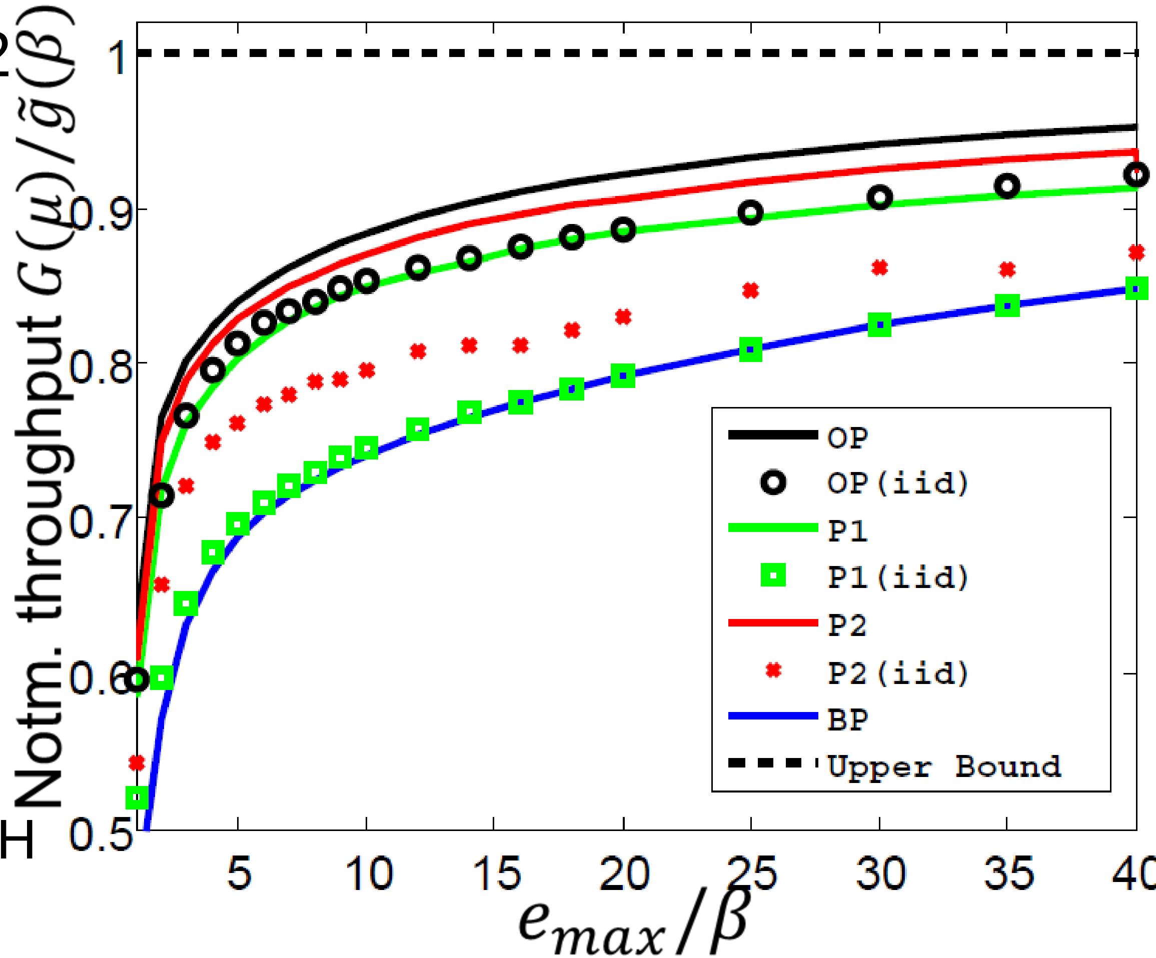
- **OP**: perfect SOC knowledge, via Policy Iteration
- **P1**: unknown SOC, 1 interval
  - Local search algorithm
- **P2**: imperfect SOC knowledge, 2 intervals (HIGH/LOW)
  - Local search algorithm
- **BP**: balanced policy $Q_k = \mathbb{E}[B_k] = \beta$
- Policies labeled with "iid": neglect time-correlation and assume i.i.d. EH process

Interplay between SOC and EH state knowledge

- Small degradation with 2 levels uncertainty (**P2**, within 2-5% of **OP**)
- Adaptation to SOC only (**OPiid**) or to EH state only (**P1**) yields similar loss (within 10% of **OP**)
  - EH state and SOC knowledge equally important
  - When neither SOC nor EH state are known, poor performance (**P1iid**)



Conclusions

- Analysis of sensors with EH capability
  - Modeled as an “energy queue” system
  - Various degrees of SOC knowledge
  - iid vs time-correlated EH process
- Interesting conclusions:
  - Performance depends on ratio battery/bad state
  - Balanced policy works well for large batteries, better policies can be devised otherwise
  - Knowledge of the EH state is important to achieve good performance, SOC knowledge much less so

Extensions

- Multi-user case
  - Distributed vs. centralized, overall energy
- Battery degradation
  - Perpetual operation is not possible due to aging
- Queueing analysis for random packet arrivals
  - Presented yesterday
- Energy transfer for unequal energy arrivals
  - Energy-rich node sends to energy-poor peer
- Higher-layer networking issues
- Check the upcoming JSAC special issue

Big picture

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- EH poses new challenge
  - Shift from energy efficiency/conservation (traditional WSNs) to energy management
- We have collected results on optimal policies
  - Structural results, investigation of good policies
  - However, models used are still simplified
- Future work
  - Extend approach to more general models
  - Study estimation techniques for EH state
  - Impact of imperfect knowledge of EH state, and controller design
  - Better models for battery degradation in time