

# Modeling and optimizing the operation policies of energy harvesting devices under realistic assumptions

Leonardo Badia

University of Padova, Dept. of Information Engineering  
leonardo.badia@gmail.com

Brixen SSIE seminar, 20130705

# Outline



- Energy harvesting models for wireless sensors
- Optimization problems
- Introduction of realistic modeling
- Conclusions
  
- Special thanks for this presentation to:
  - ▣ Nicolò Michelusi, Kostas Stamatiou, Michele Zorzi
  - ▣ Consorzio Ferrara Ricerche
  - ▣ SWAP exchange project and WSAN local project

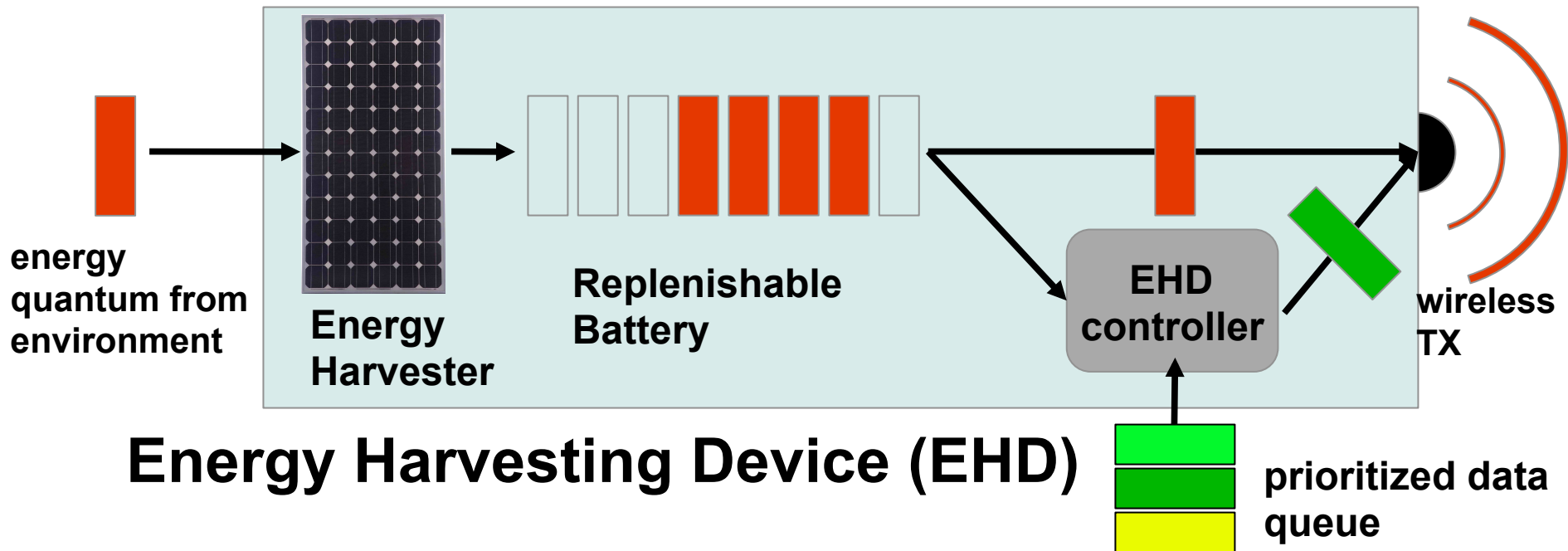
# Energy harvesting



- Sensors have limited energy supply (batteries)
  - ▣ → sensor networks have limited lifetime
- Energy harvesting can solve the problem but:
  - ▣ the capacity of the battery is limited
  - ▣ the energy source is erratic
- The system model is inherently different from that of “traditional” energy-aware protocols.

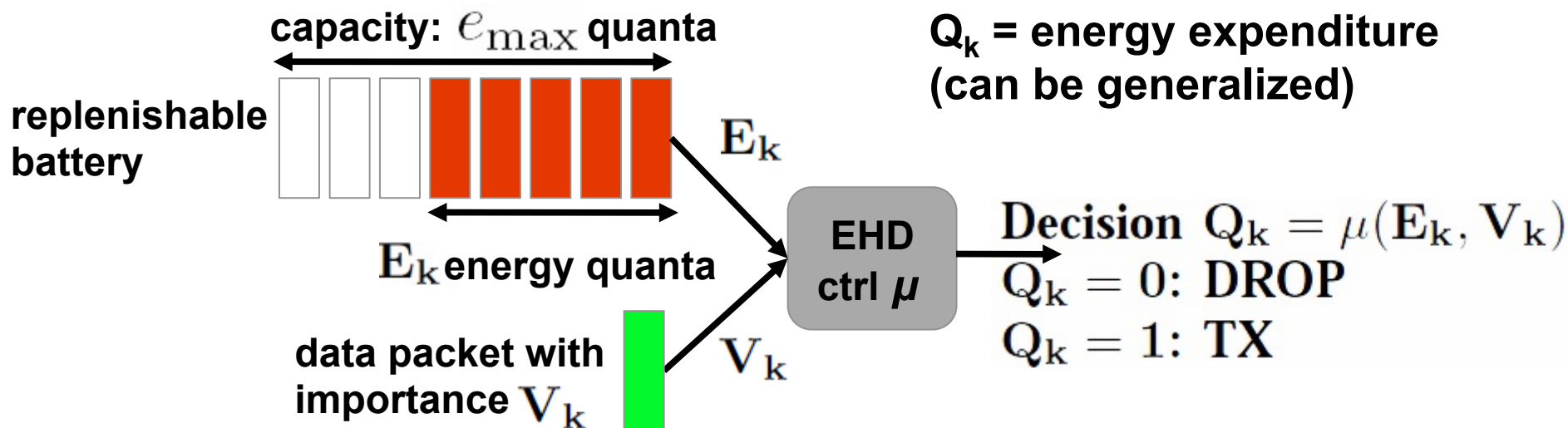
# System model

- Slotted time: Bernoulli energy arrivals (average  $\bar{b}$ ) to a battery of maximum capacity  $e_{\max}$
- Packet priorities are i.i.d.



# EHD controller model

- The EHD controller, at time  $k$ :
  - ▣ knows energy level and data packet importance
  - ▣ given this, decides TX ( $Q_k=1$ ) or DROP ( $Q_k=0$ )



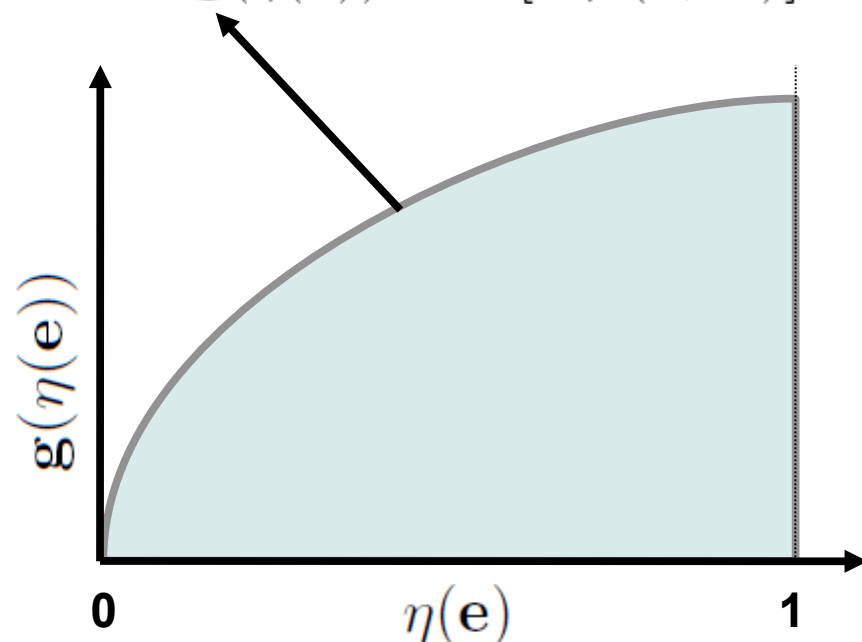
- DROP: consumes no energy, gains nothing
- TX: consumes 1 energy quantum, accrues  $V_k$

# Reward function $g(\eta)$

- If  $\eta(\mathbf{e}) = \text{Prob}\{\text{TX when energy is } \mathbf{e}\}$ , use a strictly convex+increasing  $g(\eta)$  as the **reward**
  - ▣ i.e., payoff by transmitting with probability  $\eta(\mathbf{e})$

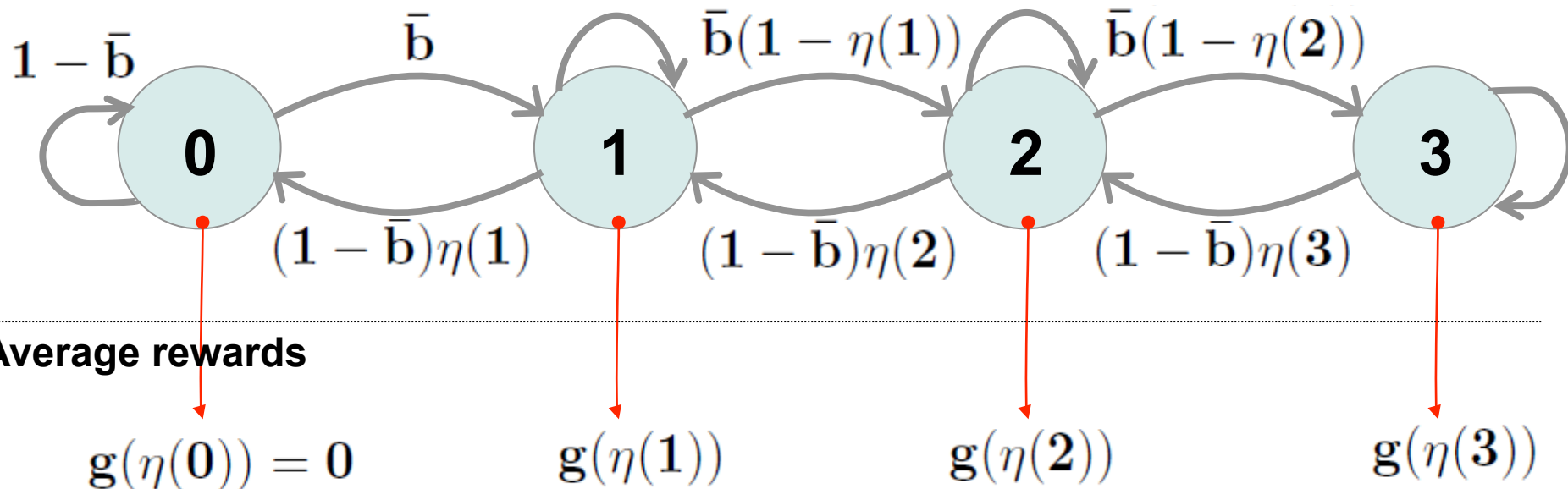
Average reward  $g(\eta(\mathbf{e})) = \mathbb{E} [V\mu(\mathbf{e}, \mathbf{V})]$

- E.g.: expectation of the importance of the packets transmitted



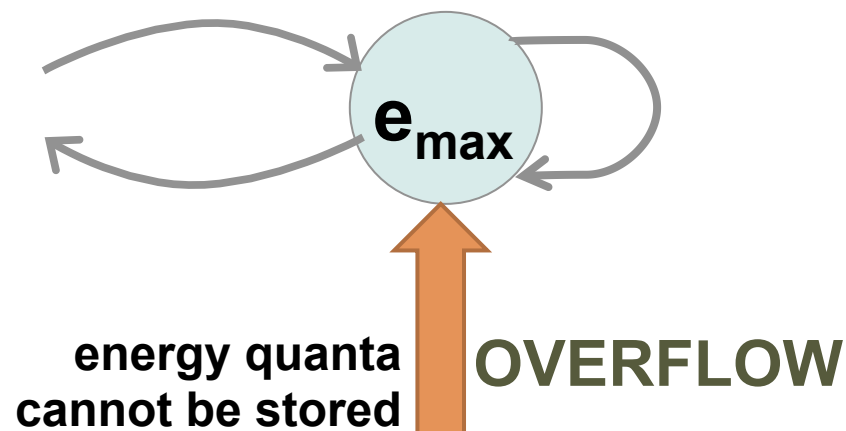
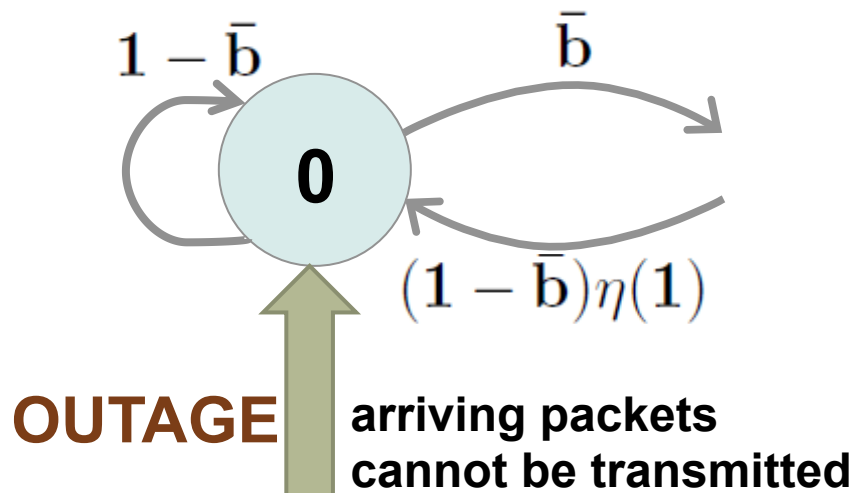
# Modeled as a Markov chain

- Energy state  $\mathbf{e}$  = discrete number of quanta
- State transitions depend on the TX prob.  $\eta(\mathbf{e})$  and the energy arrival probability



# Events to avoid

- **Outage:** a packet arriving when the energy is  $e = 0$  cannot be transmitted (reward is lost)
- **Overflow:** a quantum arriving when  $e = e_{\max}$ , it cannot be stored (must transmit a packet)





# Optimization problem

- maximize: average long-term importance (i.e. reward) accrued at RX

$$G(\mu; E_0, V_0) = \lim_{K \rightarrow \infty} \inf \frac{1}{K} \mathbb{E} \left[ \sum_{k=0}^{K-1} \mu(E_k, V_k) V_k \mid E_0, V_0 \right]$$

$$\mu^* = \arg \max_{\mu} G(\mu; E_0, V_0)$$

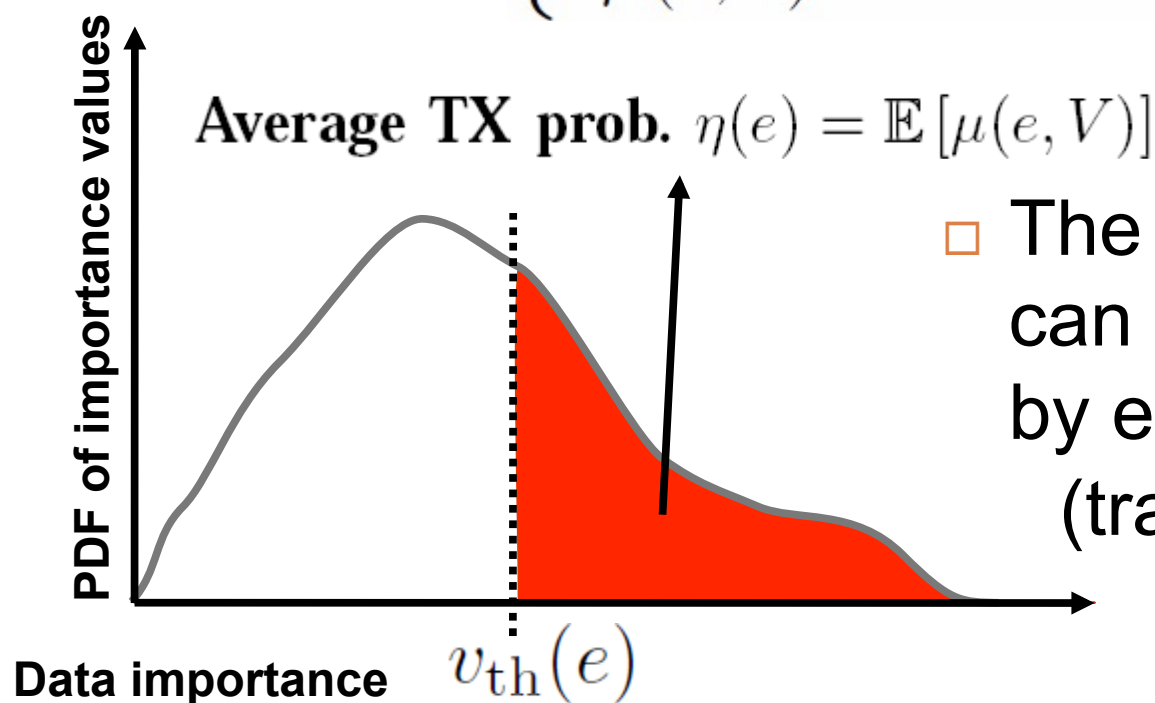


- find structural properties of the optimal policy
- low-complexity policy with good performance

# Lemma: there's a threshold

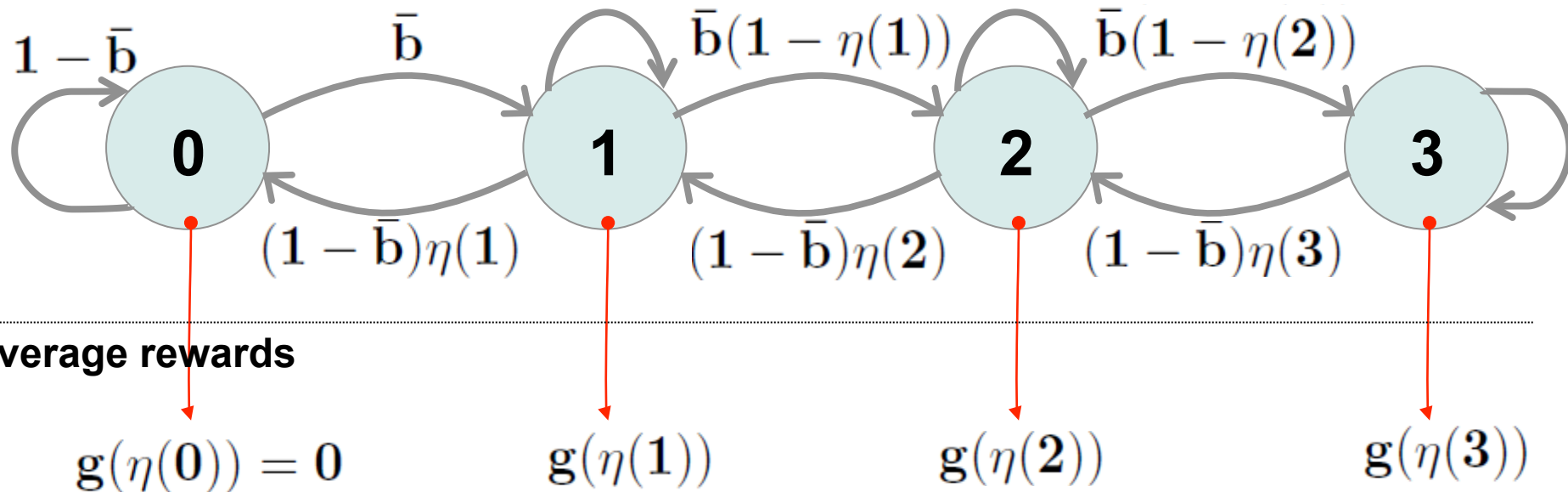
- The optimal policy  $\mu$  has a threshold behavior

$$\begin{cases} \mu(e, v) = 1 & v \geq v_{\text{th}}(e) \\ \mu(e, v) = 0 & v < v_{\text{th}}(e) \end{cases}$$



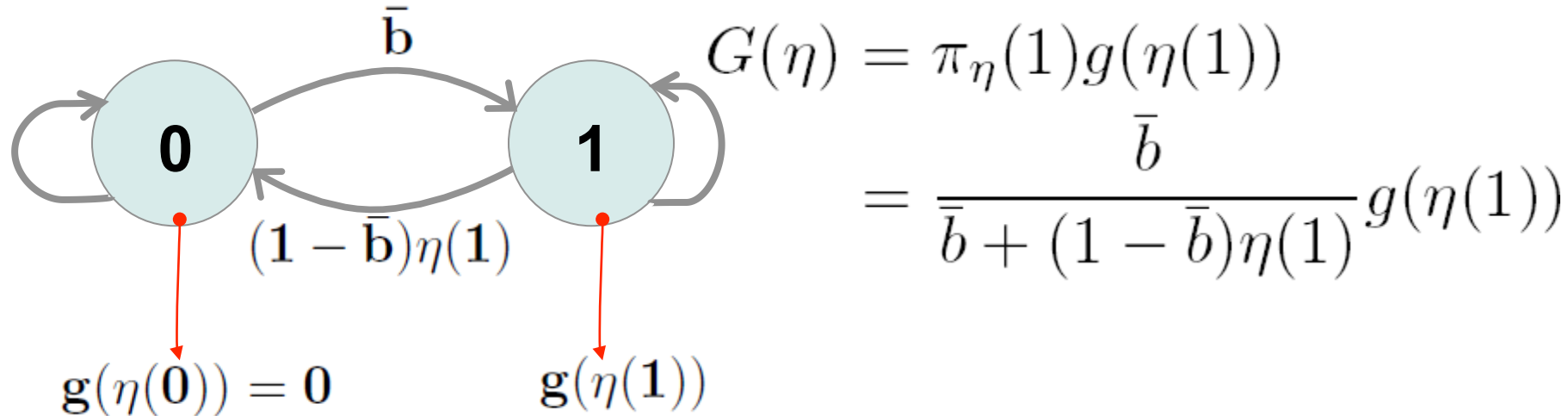
- The optimal threshold can be characterized by either  $v_{\text{th}}$  or  $\eta(\mathbf{e})$  (transmission prob.)

# Solving the optimization



- Average long term reward:  $G(\eta) = \sum_{e=1}^{e_{\max}} \pi_{\eta}(e) g(\eta(e))$
- To optimize:  $\eta^* = \arg \max_{\eta} G(\eta)$  (must be a threshold!)

# Example, $e_{\max} = 1$



- Just decide  $\eta(1)$  with an optimal trade-off:
  - ▣ small  $\eta(1)$  = low outage chances, low avg reward
  - ▣ large  $\eta(1)$  = higher avg reward, outage more likely

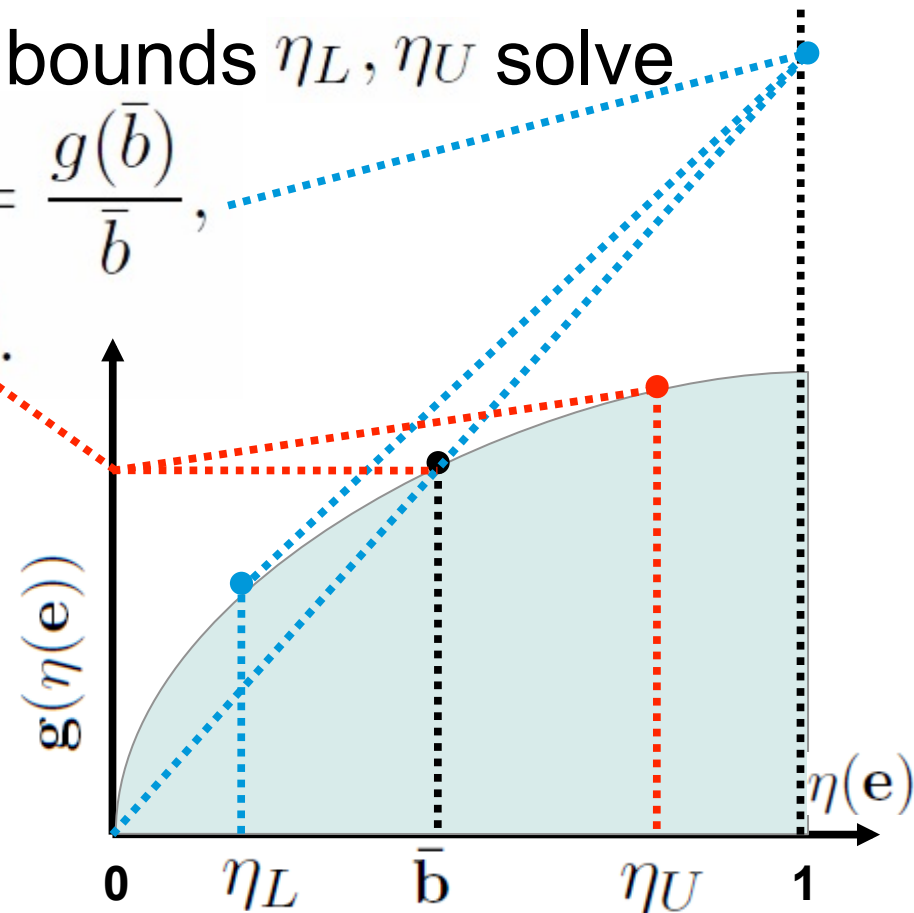
# Theorem

- Optimal policy  $\eta^*(e)$  is strictly increasing in  $e$
- $\eta^*(e) \in (\eta_L, \eta_U)$  where bounds  $\eta_L, \eta_U$  solve

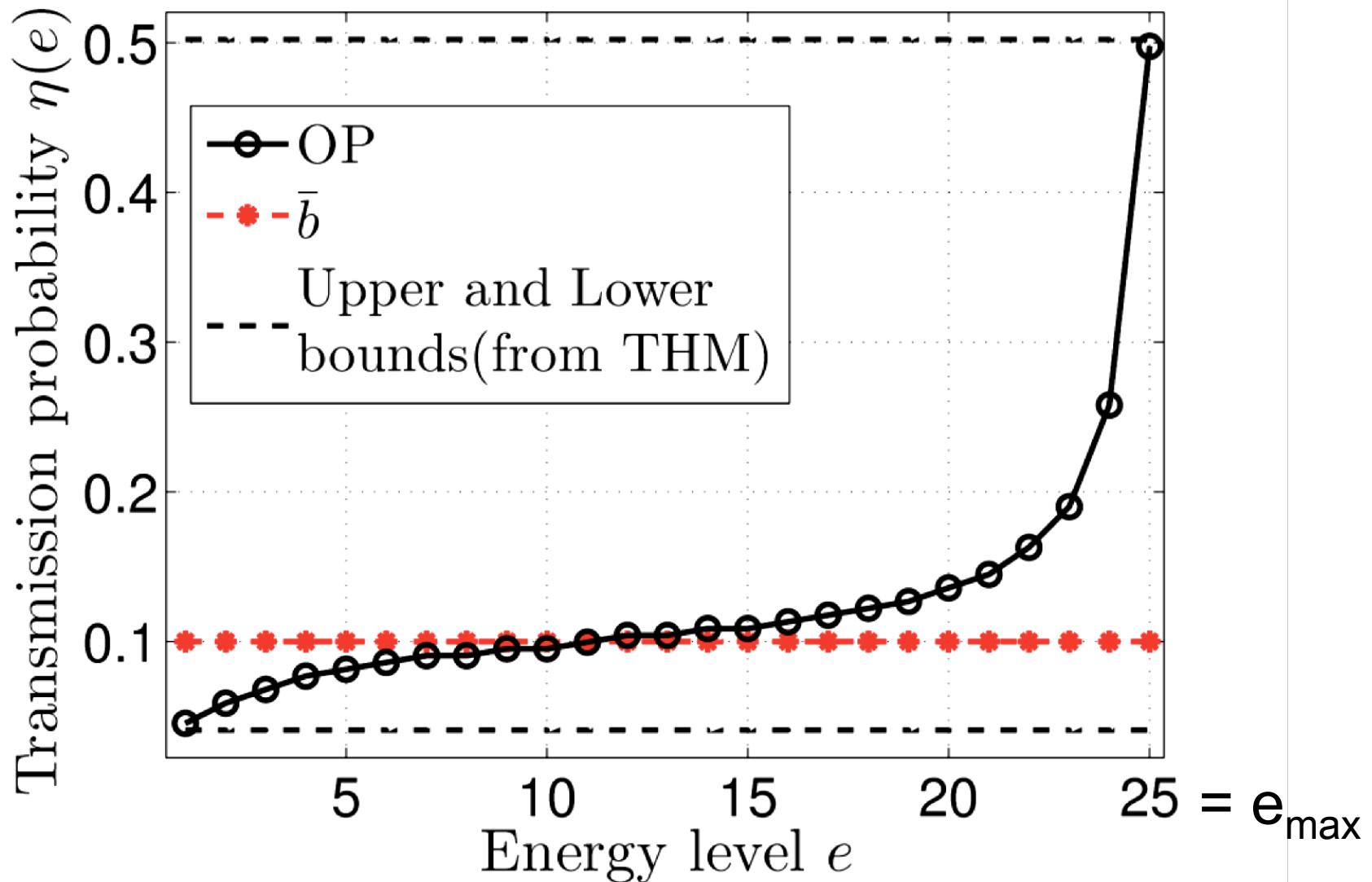
$$g(\eta_L) + (1 - \eta_L)g'(\eta_L) = \frac{g(\bar{b})}{\bar{b}},$$

$$g(\eta_U) - \eta_U g'(\eta_U) = g(\bar{b}).$$

geometric interpretation



# Exact result from ILP

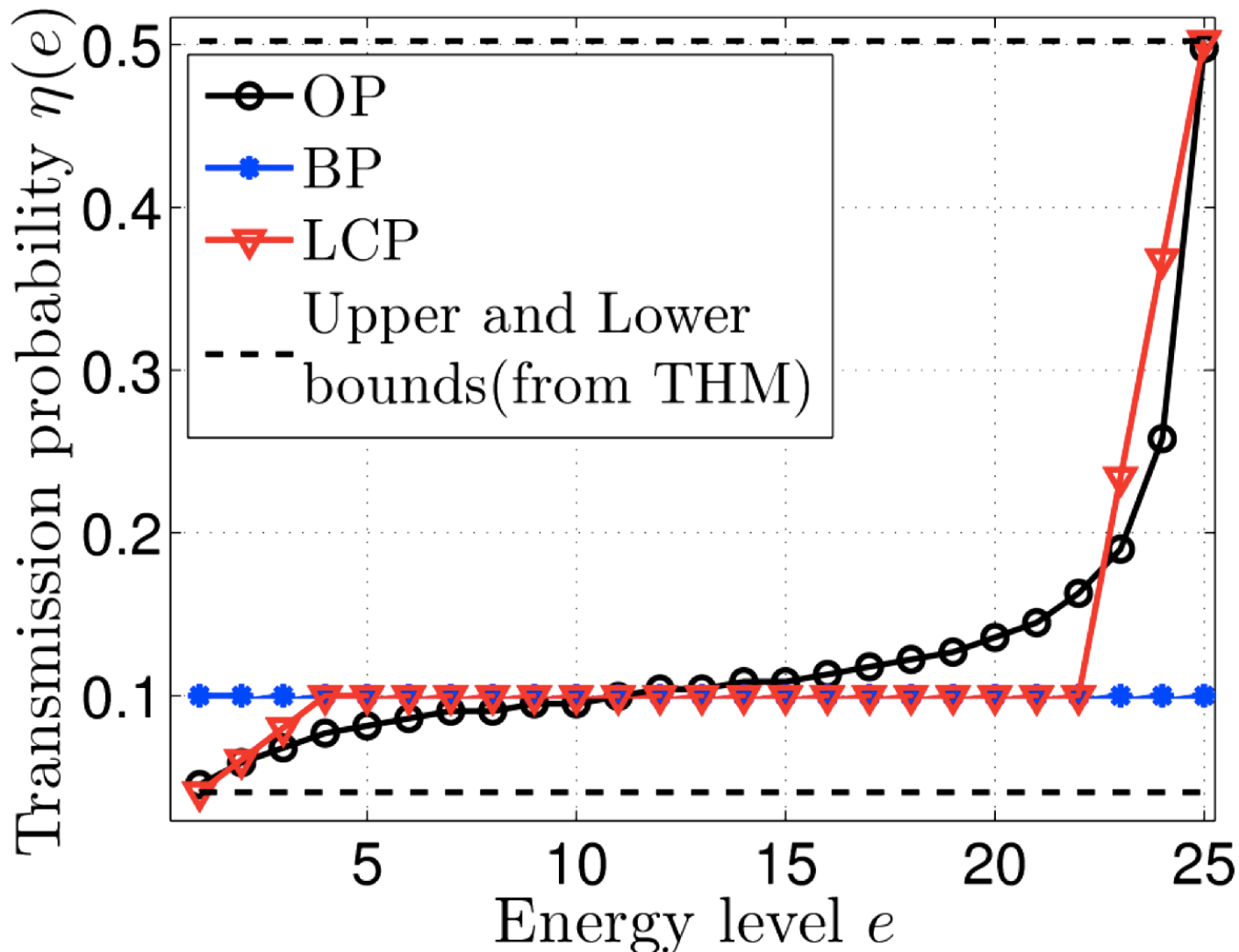


# So it is optimal to be...



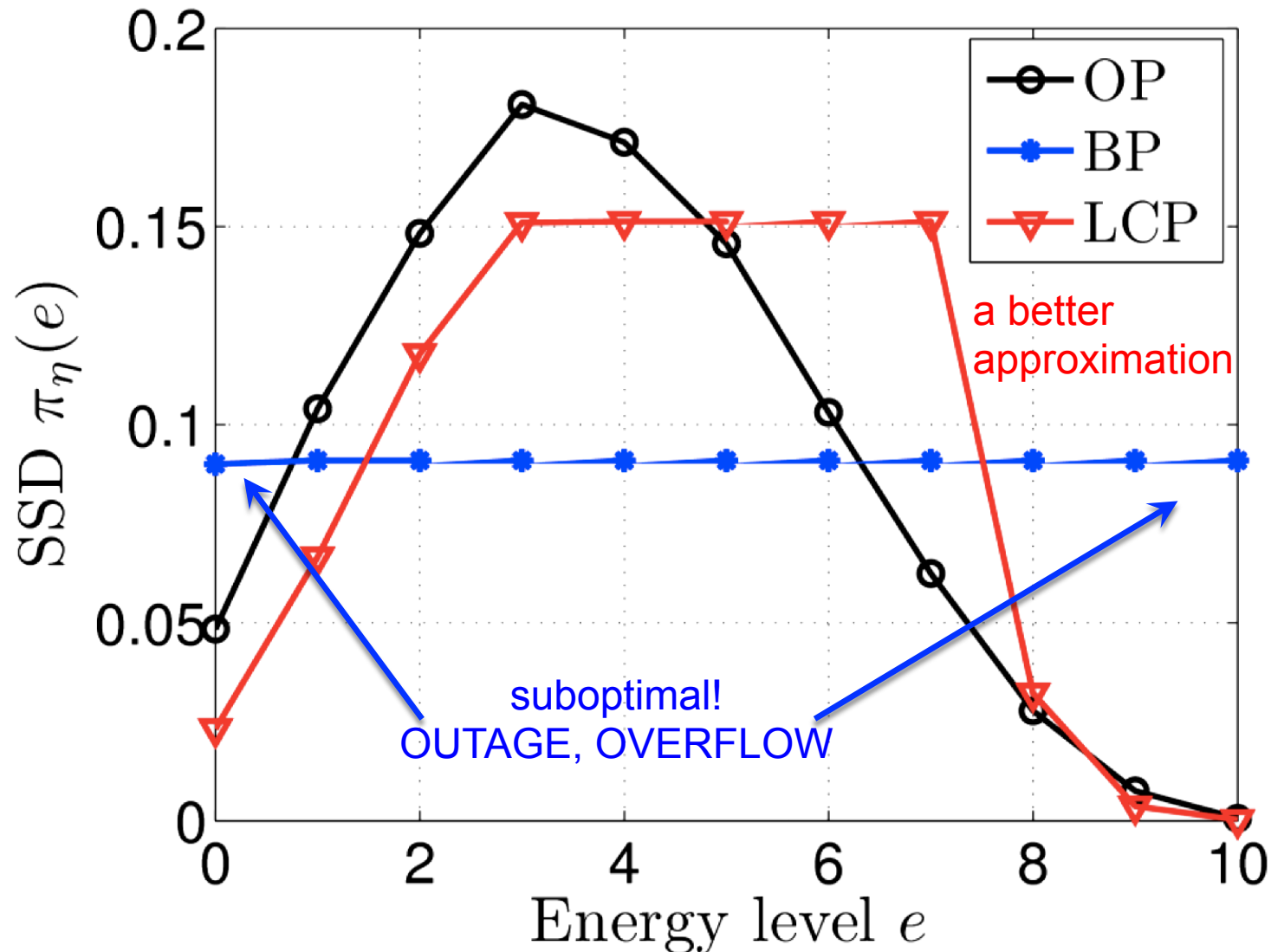
- aggressive when the energy is high
- conservative when the energy is low
- balanced when the energy is intermediate
  - ▣ i.e., on average, to use energy with rate  $\bar{b}$  (the same as it arrives)
- Being ALWAYS balanced is suboptimal. Idea:
  - ▣ at low energy, linear increase from  $\eta_L$  to  $\bar{b}$
  - ▣ at intermediate energy, constant =  $\bar{b}$
  - ▣ at high energy, linear increase from  $\bar{b}$  to  $\eta_U$

# Low complexity policy





# Steady state



# A practical example

- Objective: to maximize the network throughput
  - ▣ Rayleigh fading: channel gain  $H_k \sim \mathcal{E}(1)$
  - ▣ the importance of a packet is the achievable rate

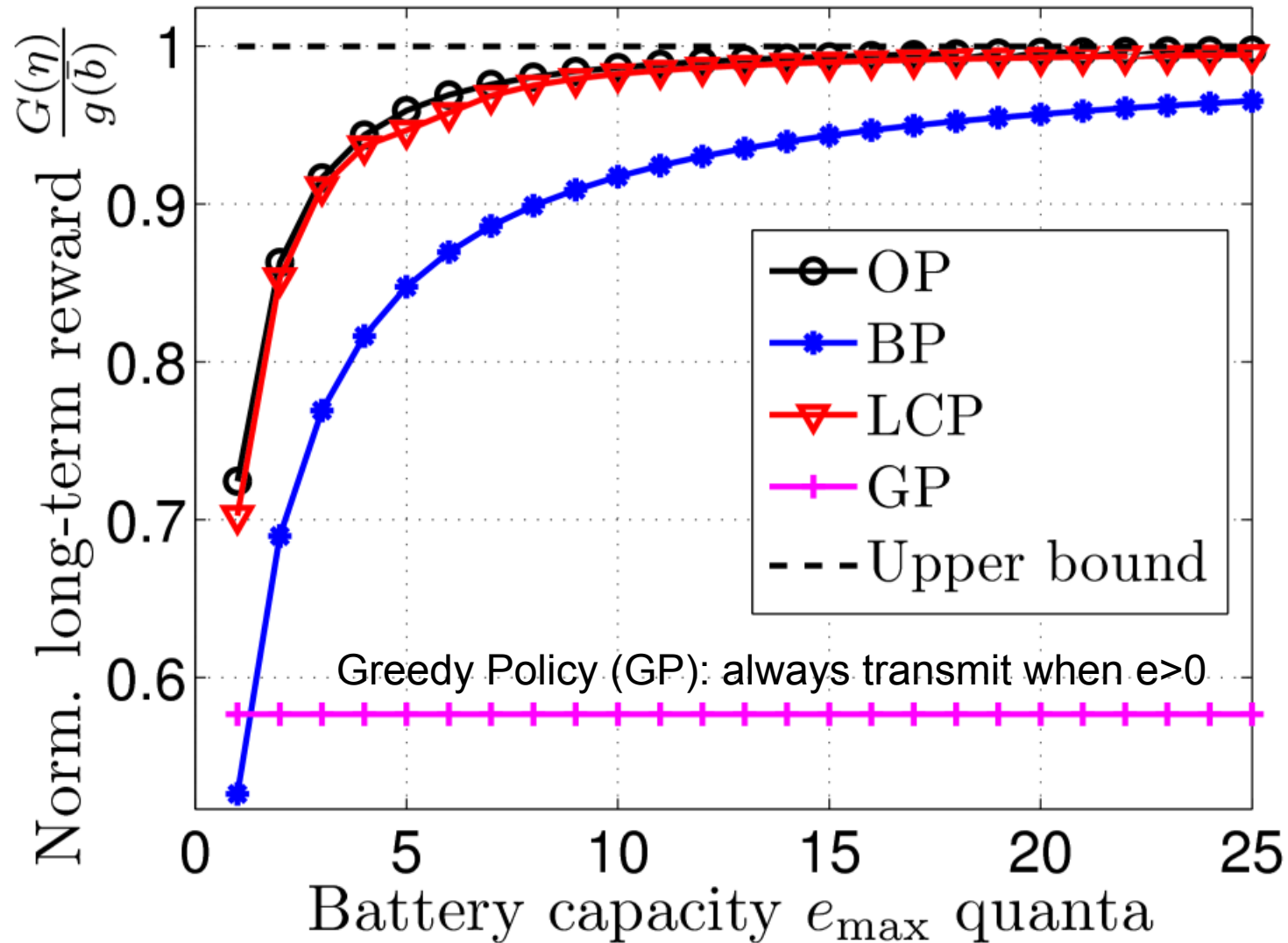
$$V_k = \log_2(1 + \text{SNR}H_k)$$

- ▣ A threshold  $h_{\text{th}}(e)$  can be set for the channel

$$\eta(e) = \int_{h_{\text{th}}(e)}^{+\infty} e^{-h} dh = e^{-h_{\text{th}}(e)}$$

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

# Results



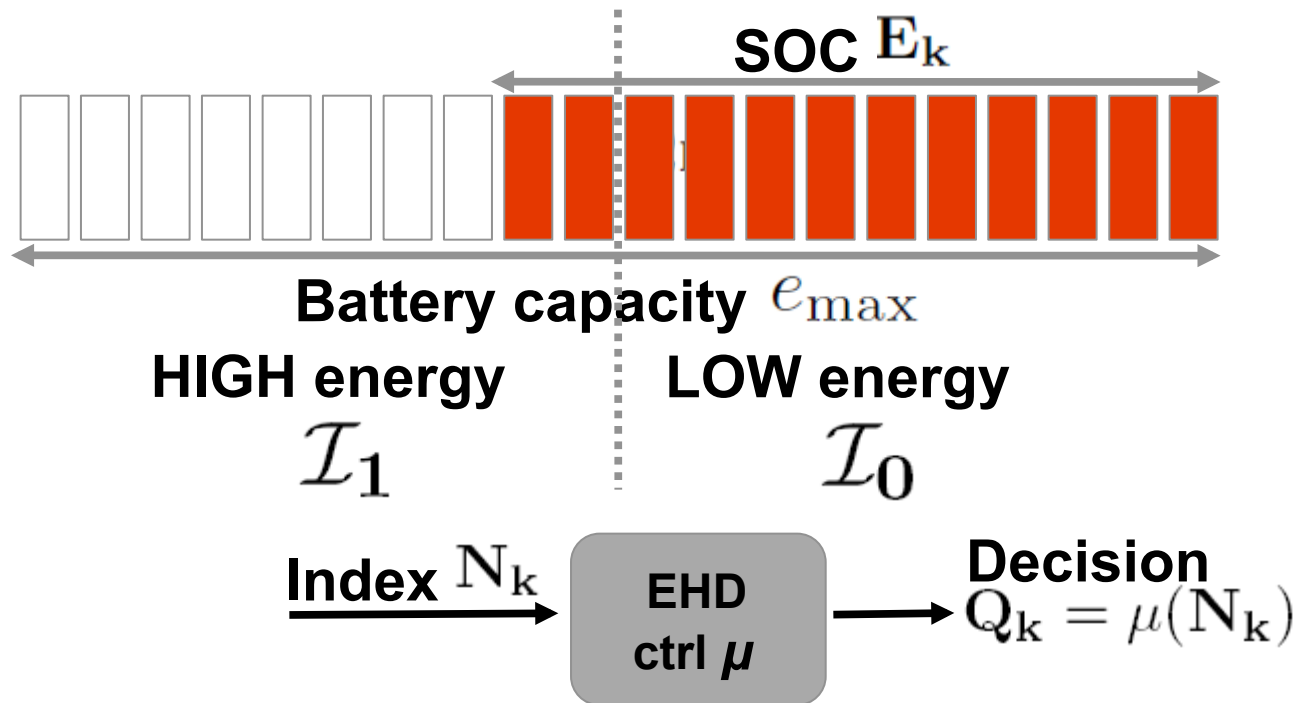
# State-of-charge knowledge



- These policies rely on a 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  $Q_k > 1$  (that is, we have tasks consuming a variable amount of energy)

# EHD with uncertain SOC

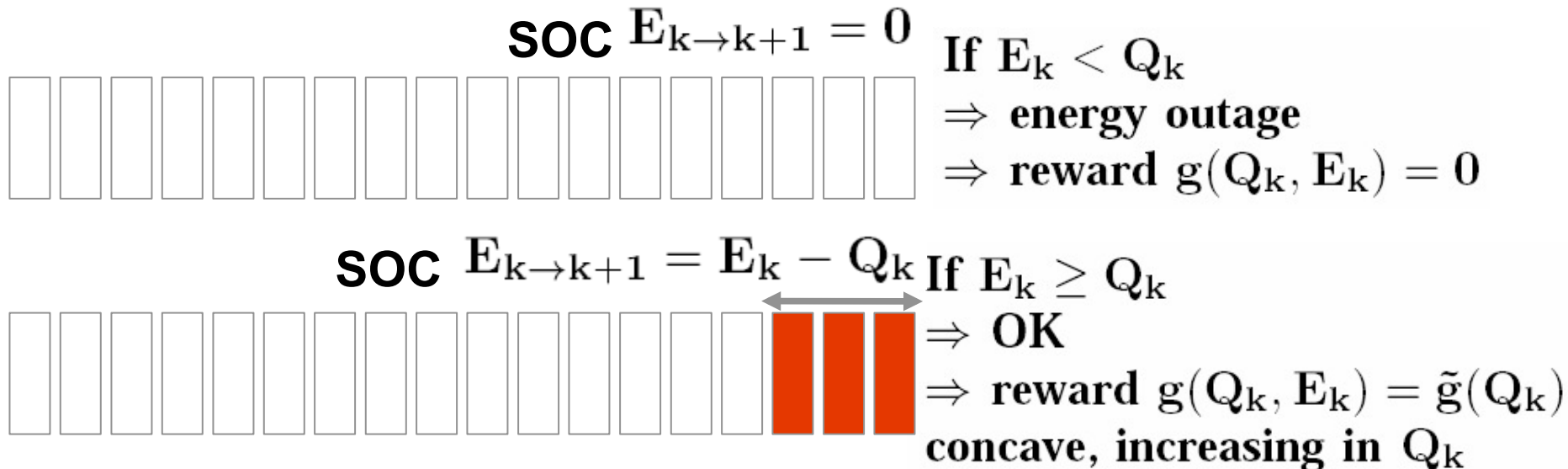
- Model of the EHD at time  $k$



- The controller may be informed on the past history (all past  $Q_k$ 's, intervals, outages)

# EHD with uncertain SOC

- Again, compute a reward:



- Same trade-off between:

- ▣ aggressive: avoids OVERFLOW, accrues reward
- ▣ conservative: avoids OUTAGE, and also exploits the concavity of the reward function

# Optimization problem

- Maximize long-term reward

$$G(\mu, \mathbf{e}_0) = \lim_{K \rightarrow \infty} \inf \frac{1}{K} \mathbb{E} \left[ \sum_{k=0}^{K-1} g(\mathbf{Q}_k, \mathbf{E}_k) \mid \mathbf{E}_0 = \mathbf{e}_0 \right]$$

$$\mu^* = \arg \max_{\mu} G(\mu, \mathbf{e}_0)$$

we only know the initial  
value of the energy!

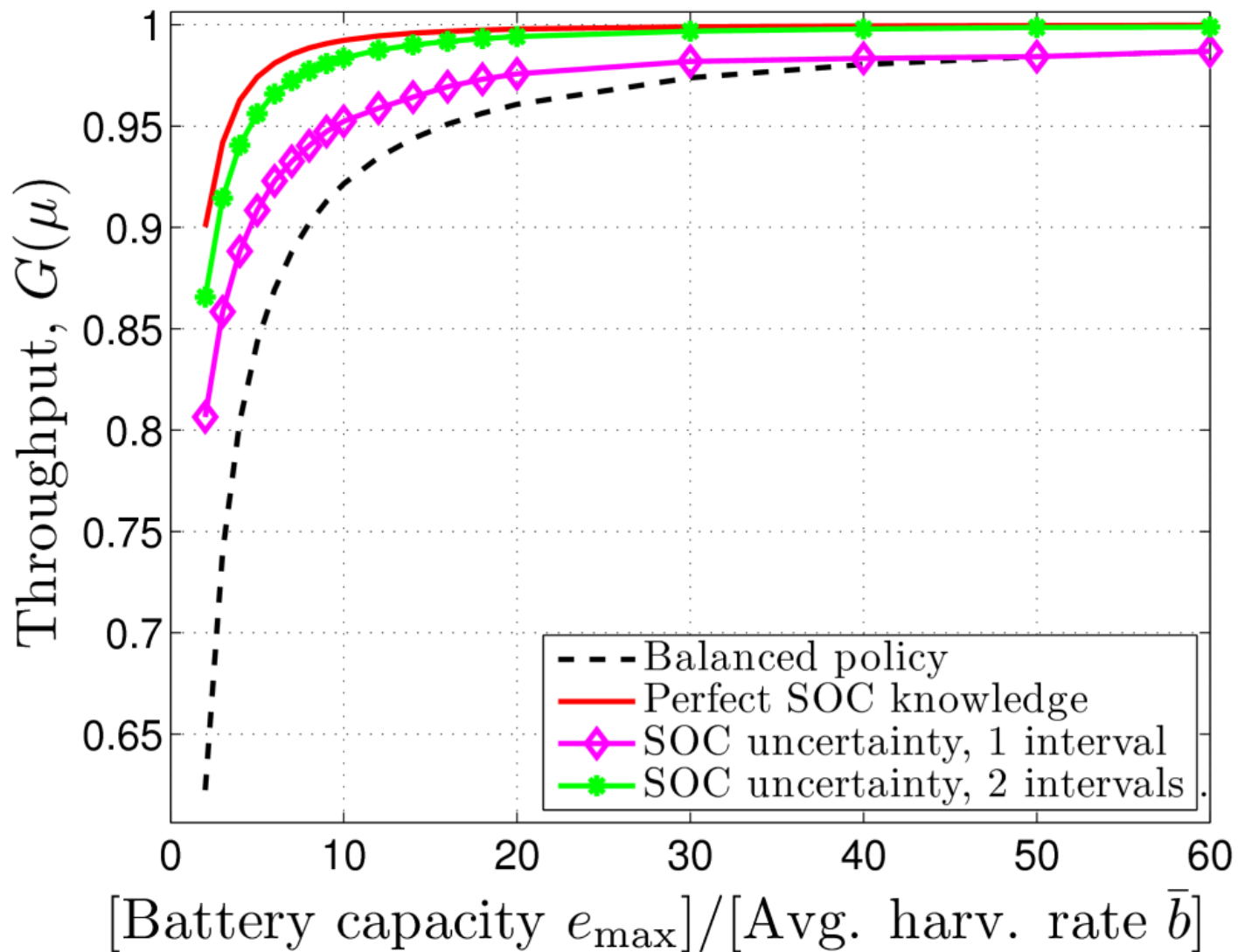
- Partially Observable Markov Decision Process
  - ▣ Optimal policy depends on the past history
  - ▣ Focus on policies using just current SOC interval
  - ▣ Solution by exhaustive search

# Example and results

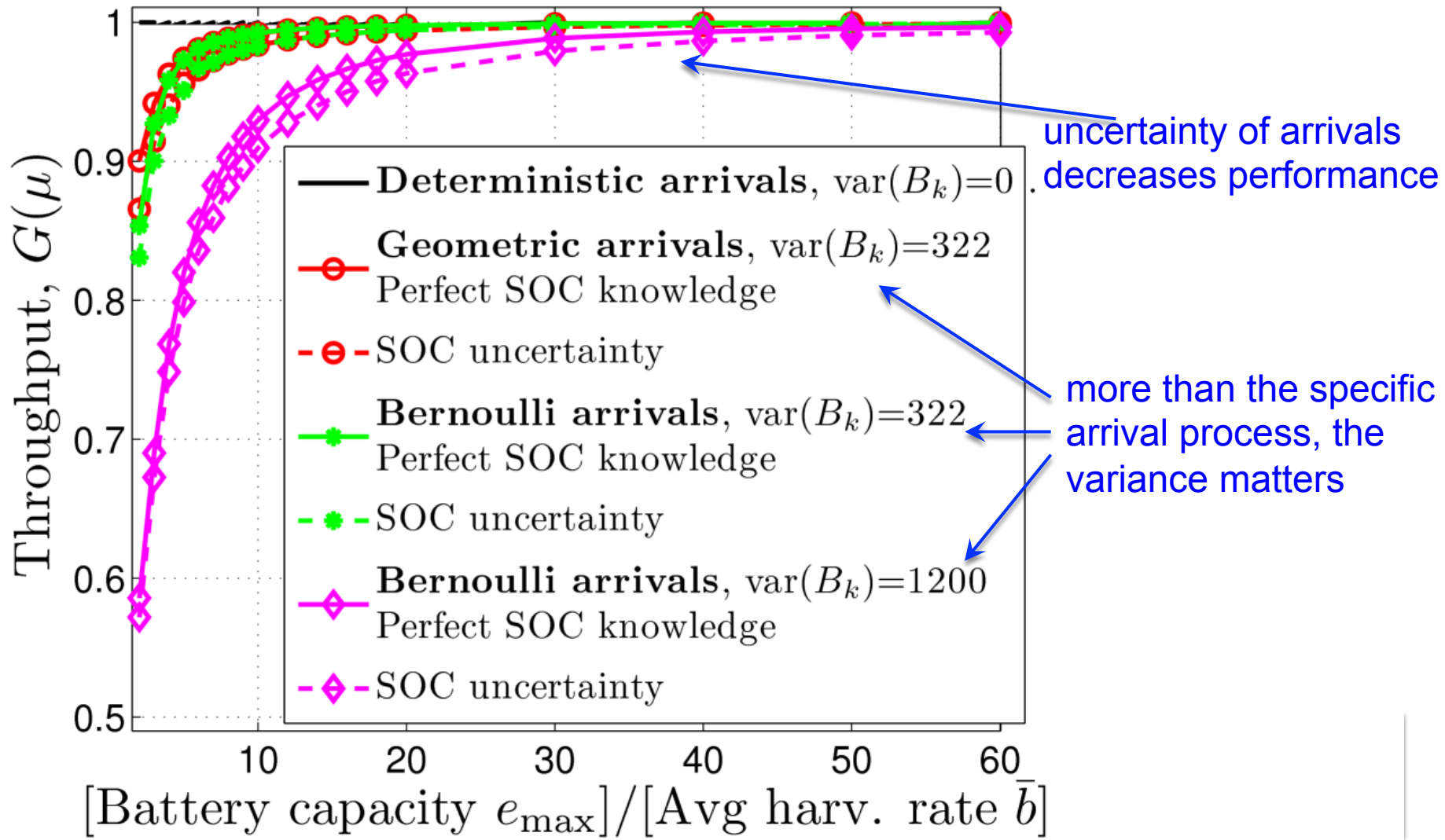
- Scenario: maximize throughput
  - ▣ Reward: achievable rate  $\tilde{g}(q) = \frac{\ln(1 + \alpha q)}{\ln(1 + \alpha \bar{b})}$
  - ▣ Static channel with  $\alpha = 1$
  - ▣ Geometric arrival rate,  $\bar{b} = 20$
  
- Policies compared:
  - ▣ balanced policy (BP):  $Q_k = \bar{b}$
  - ▣ optimal policy with perfect SOC knowledge
  - ▣ imperfect SOC knowledge, 2 intervals
  - ▣ imperfect SOC knowledge, 1 interval



# Numerical results

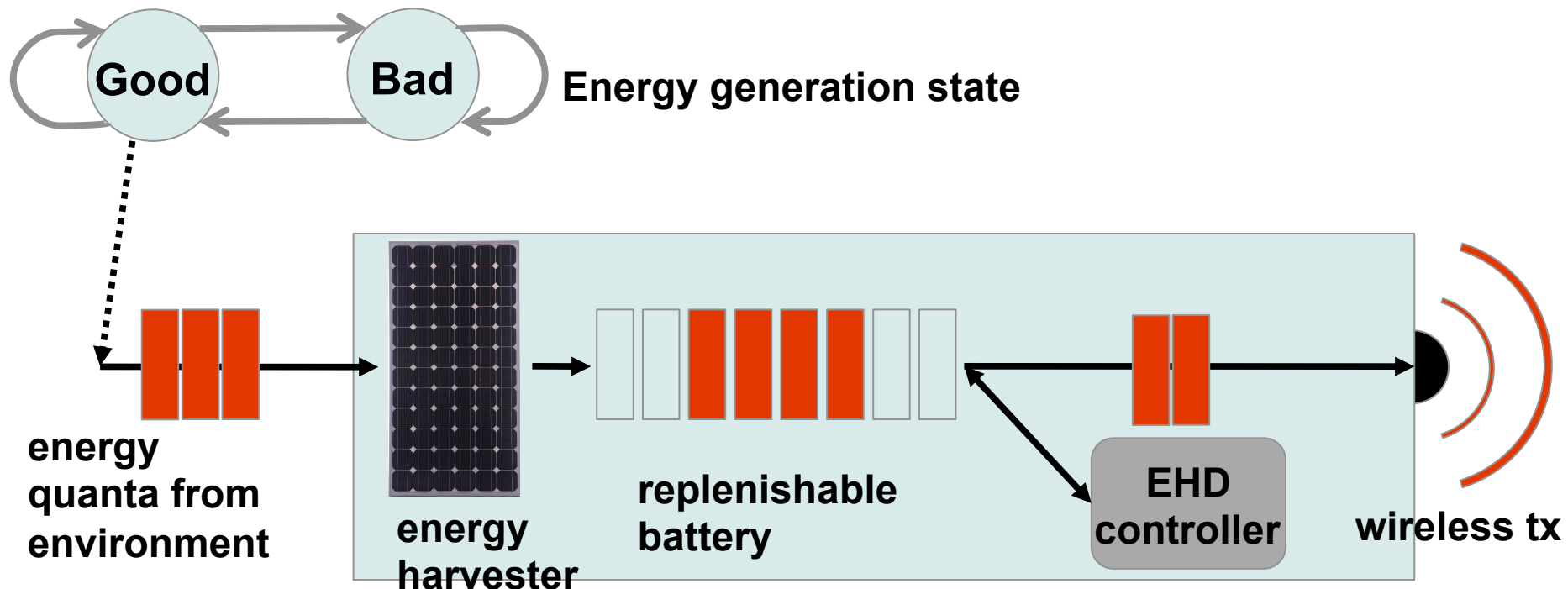


# Other arrival distributions



# Energy arrival process

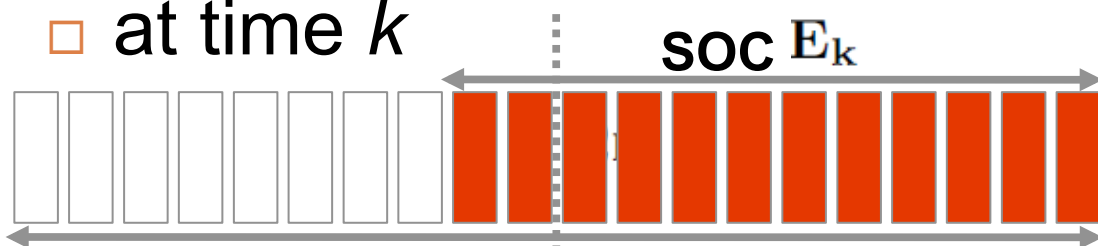
- Energy harvesting process is not really i.i.d.
  - ▣ Correlation is present (e.g., it can be Markov-like)



## Energy Harvesting Device (EHD)

# Combining all the elements

□ at time  $k$



Battery capacity  $e_{\max}$   
HIGH energy  $\mathcal{I}_1$   
LOW energy  $\mathcal{I}_0$

Index  $N_k$

EHD  
ctrl  $\mu$

Decision

$Q_k = \mu(N_k, S_{k-1})$



Energy generation state  $S_{k-1}$   
In previous timeslot  $k-1$ ,

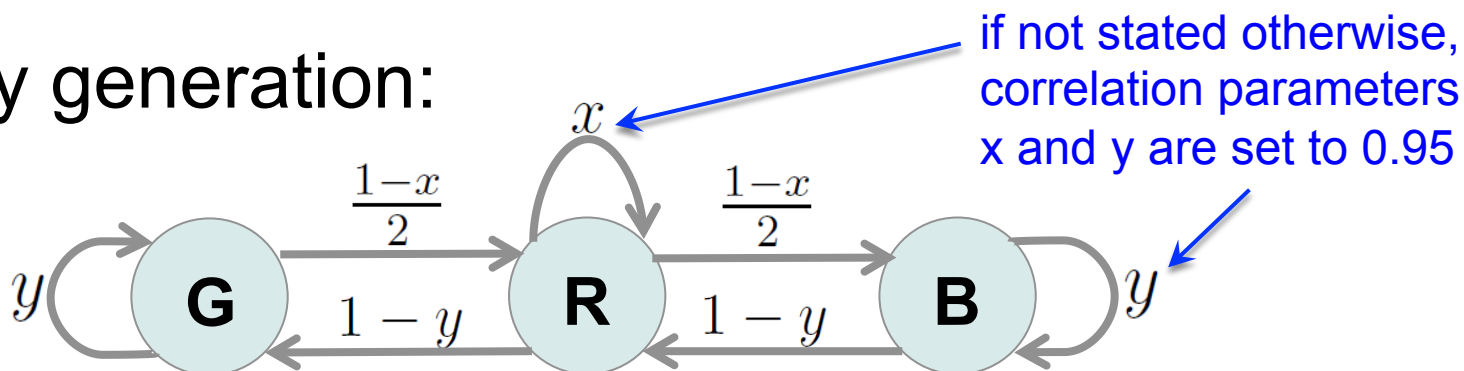
$$\Pr(S_{k-1} = s | B_0, \dots, B_{k-1}) = \frac{p_B(B_{k-1} | s) \sum_{\sigma \in \mathcal{S}} p_S(s | \sigma) \Pr(S_{k-2} = \sigma | B_0, \dots, B_{k-2})}{\sum_{\tilde{s} \in \mathcal{S}} p_B(B_{k-1} | \tilde{s}) \sum_{\sigma \in \mathcal{S}} p_S(\tilde{s} | \sigma) \Pr(S_{k-2} = \sigma | B_0, \dots, B_{k-2})}$$

# Example of scenario

## Throughput maximization

- Reward = achievable rate  $\tilde{g}(q) = \frac{\ln(1 + \alpha q)}{\ln(1 + \alpha \bar{b})}$   
with  $\alpha = 1$ ,  $\bar{b} = 20$

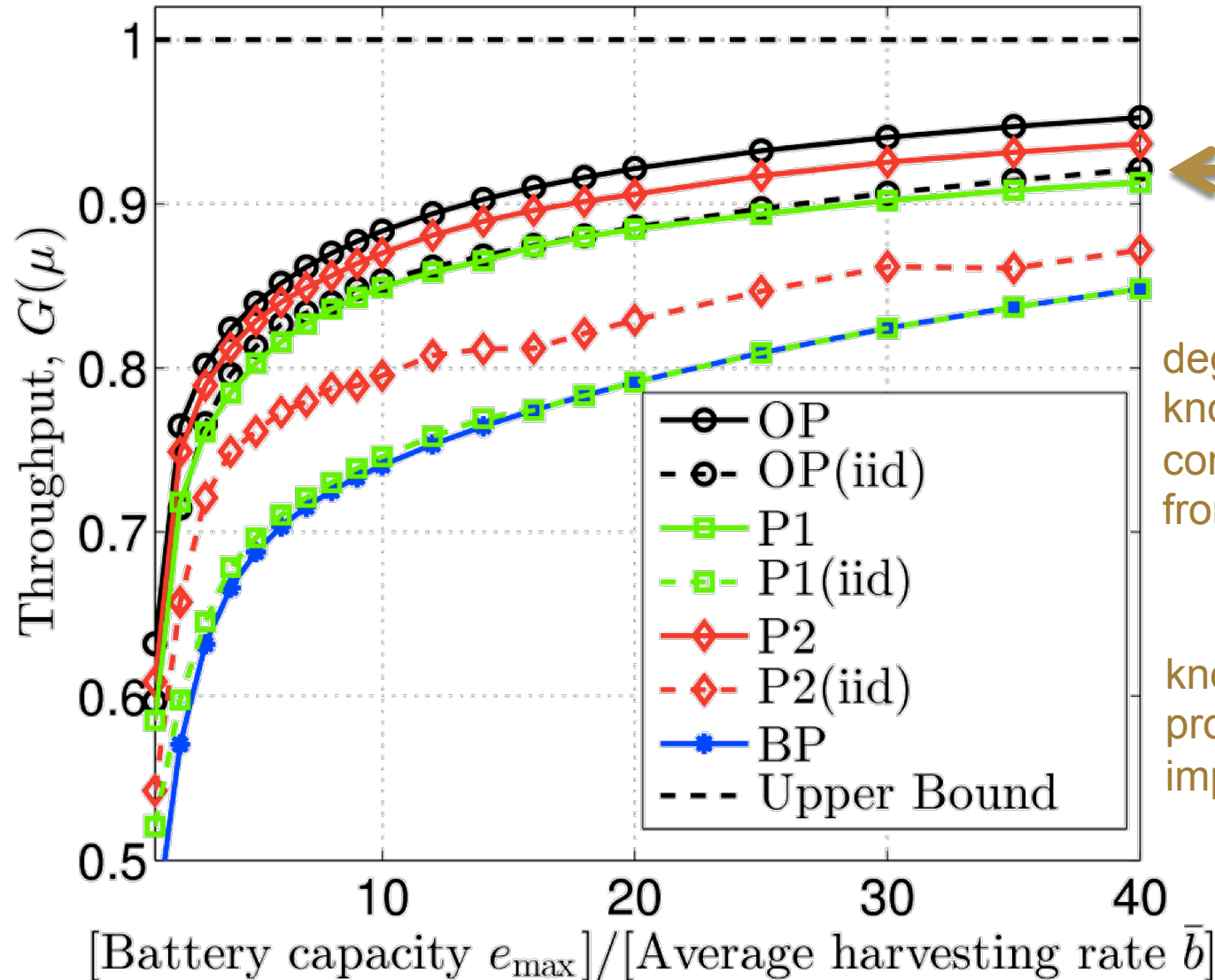
## Energy generation:



- G** (GOOD), deterministic  $B_k = 2\bar{b}$
- B** (BAD), deterministic,  $B_k = 0$
- R** (RANDOM), geometric, mean  $\mathbb{E}[B_k | S_k = \mathbf{R}] = \bar{b}$

- **OP**: optimal. Knows SOC  $E_k$ , generation state  $S_{k-1}$
- **P1**: 1-level uncertainty, knows  $S_{k-1}$ , SOC unknown
- **P2**: 2-level uncertainty, the EHD just knows whether the SOC is HIGH/LOW, and knows  $S_{k-1}$
- **BP**: Balanced Policy  $Q_k = \bar{b}, \forall k$ , asymptotically optimal for “large” batteries
- Policies labeled by **iid**: neglect correlation in energy generation process, assume iid process.

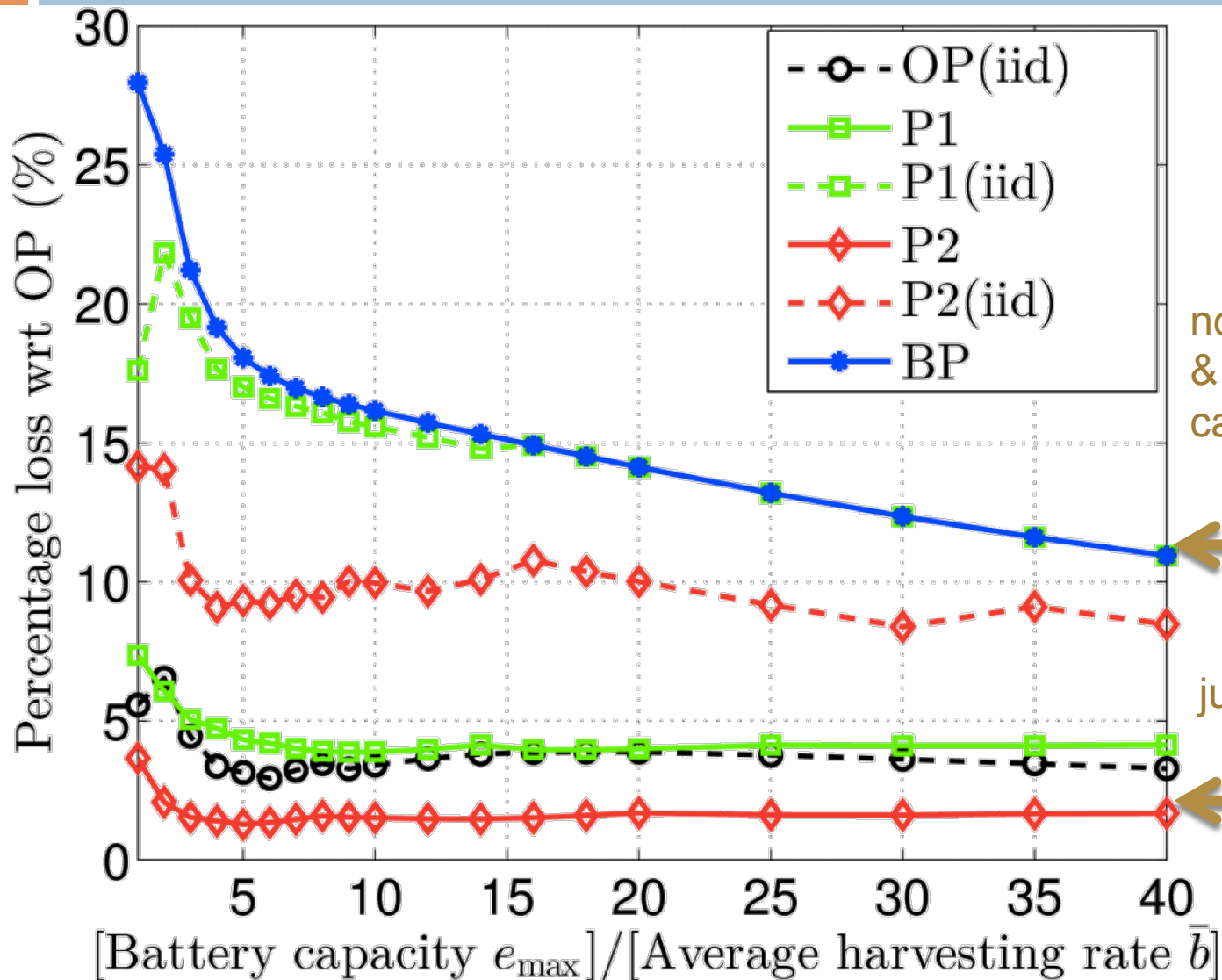
# Comparison



degradation from not knowing arrivals is comparable with that from not knowing SOC

knowing the arrival process is as much important as the SOC

# Loss from the optimum



not knowing the SOC  
& the arrival process  
can be very bad

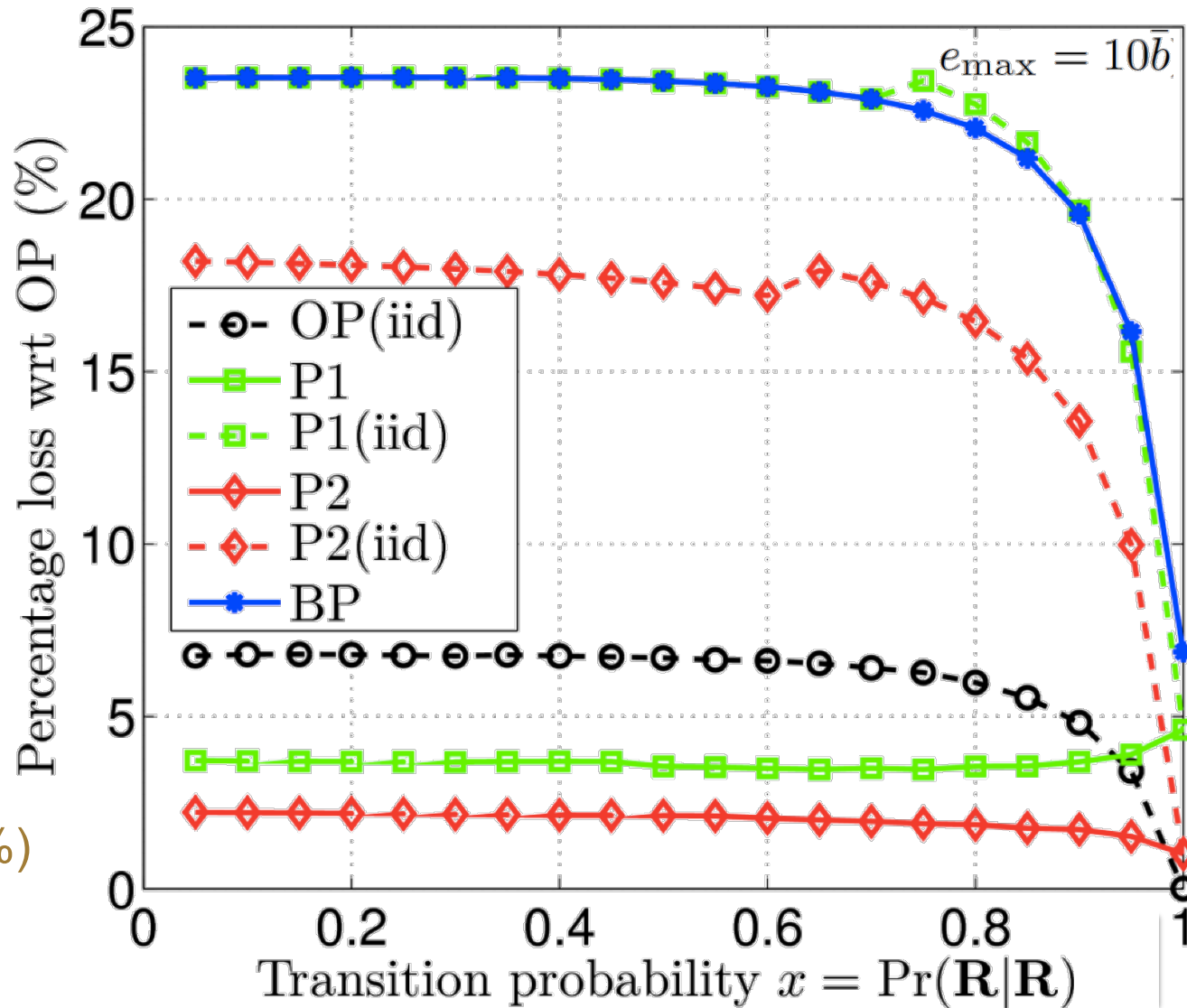
just some knowledge:  
not so bad!



# Energy arrival correlation



when the arrival process  $\rightarrow$  iid, policies assuming this are not so bad, but if  $x < 0.8$  they lose a lot (up to 20%)



# Conclusions



- Analysis of sensors energy harvesting as QS
  - ▣ Modeling aspects / optimization frameworks
- Lessons from increased realism
  - ▣ simplified policies (whose main goal is to avoid wasting energy or losing packets) work fine
  - ▣ not knowing the battery SOC at all is bad, but knowing even a rough quantization may be fine
  - ▣ knowledge of the arrival process is also important