The impact of battery degradation on Harvesting-based Wireless Sensor Devices

Ruggero Carli

DEPARTMENT OF INFORMATION ENGINEERING
UNIVERSITY OF PADOVA

Department of
Information Engineering,
University of Padova

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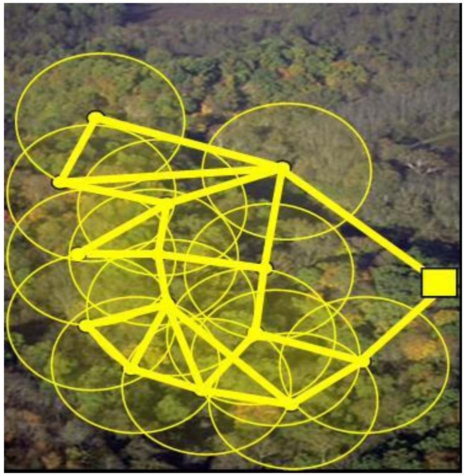
Collaborators: Nicolò Michelusi, Leonardo Badia, Luca Corradini, Michele Zorzi

Wireless sensor networks (WSNs)

- Wireless Sensor Networks
  - Environemental monitoring
  - Buildings surveillance
  - Faults detection
  - …

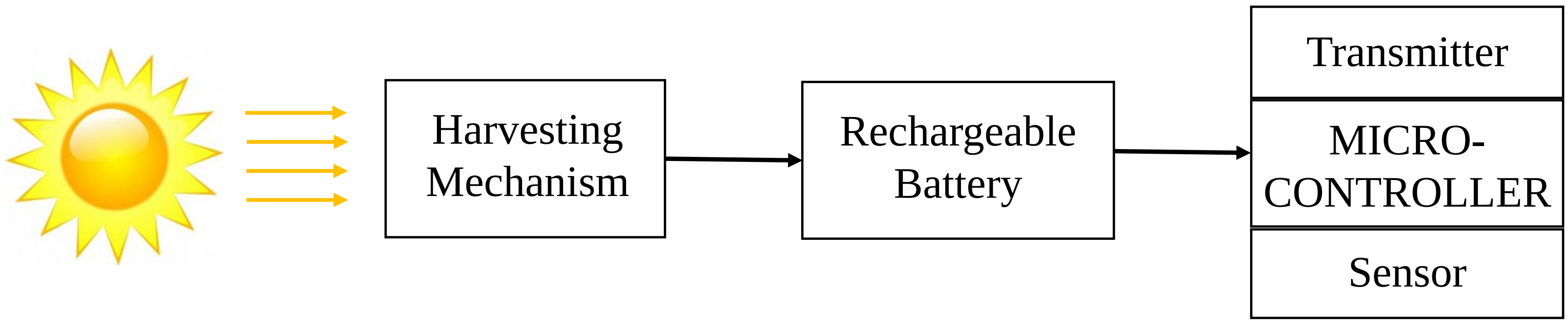


- Requirement : prolonged and unsupervised sensor operation over time

- Energy autonomy ?
- How to prolong the life of a sensor ?

WSNs + Harvesting

- Wireless Sensor Networks + **Harvesting**

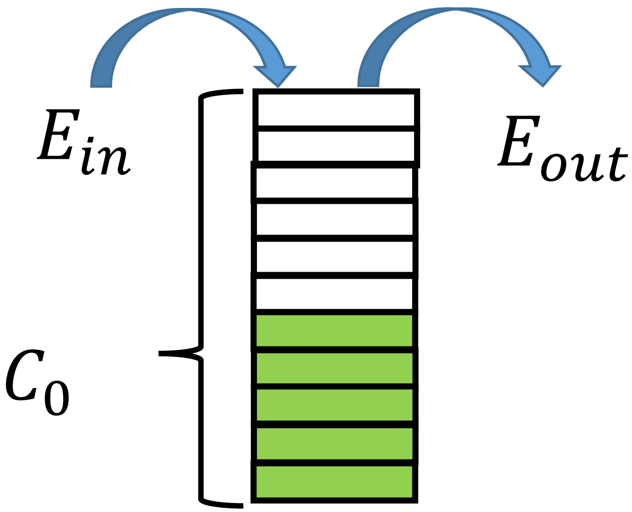


- Wireless Sensor Networks + Harvesting + **Energy Aware Policy**

Algorithms for the ***management*** of the energy buffer (no energy overflow, etc.) to provide a ***stable operation*** to guarantee some Quality of Service (QoS), e.g., throughput, network sum rate…

Battery as a buffer

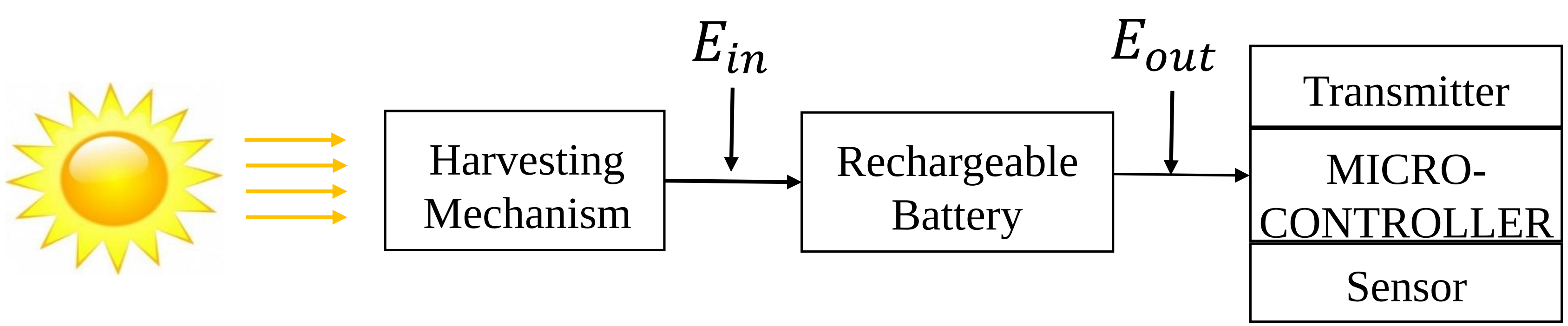
Rechargeable batteries are typically modeled by a ***buffer***



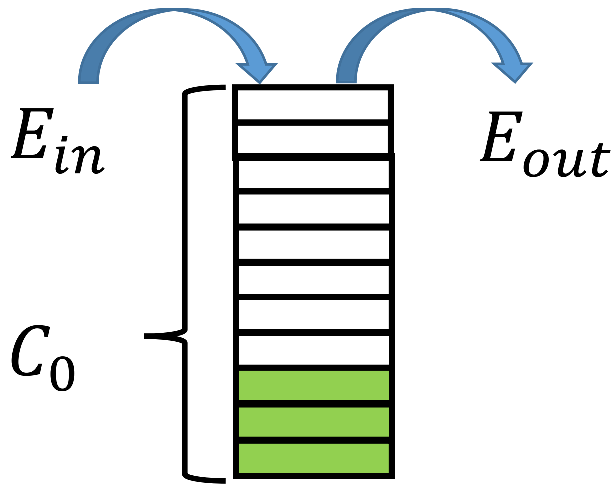
E_{in} : energy supplied by the harvesting process

E_{out} : energy required by the controller to perform communication, processing, sensing tasks

C_0 : nominal capacity of the battery



Battery as a buffer



Assumption

C_0 : is typically assumed ***constant*** over the time

⬇

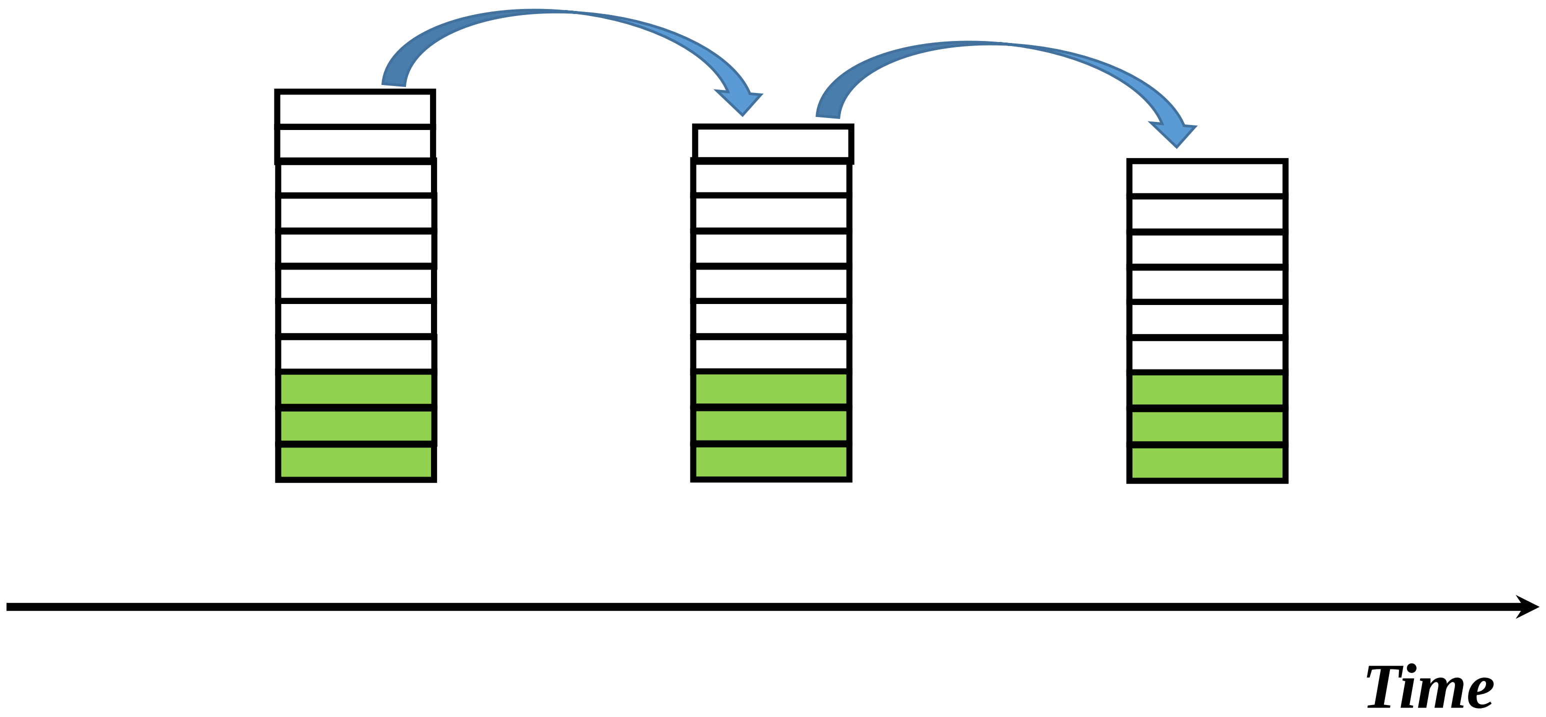
ideal and ***perpetual*** battery operation

*No consideration of battery **degradation issues** related to battery usage*

Degradation effects

Typical assumption : C_0 is constant over time

TODAY : degradation effects which cause C_0 to ***diminish*** over time



Degradation effects : how to use battery?

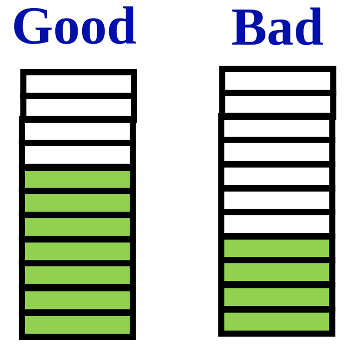
TODAY : degradation effects which cause C_0 to ***dimish*** over time

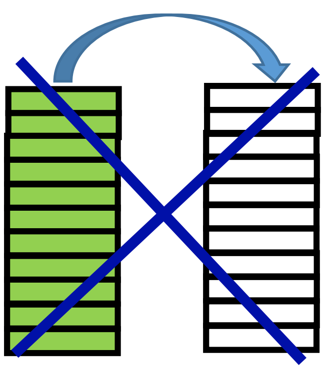
It depends on ***how the battery is used***

Main idea

The **deeper** the **discharge** of the battery

The **faster** the **degradation**



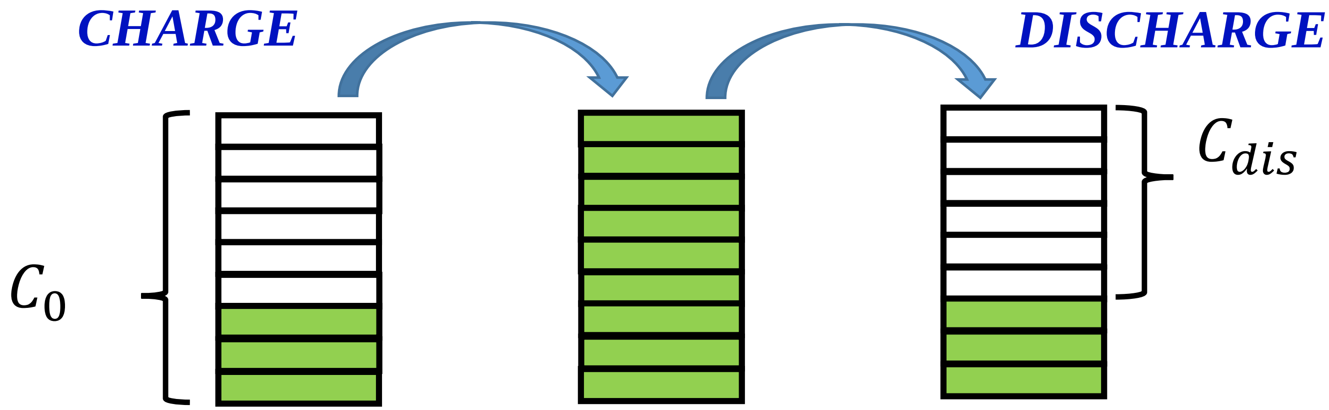


Rule of thumb

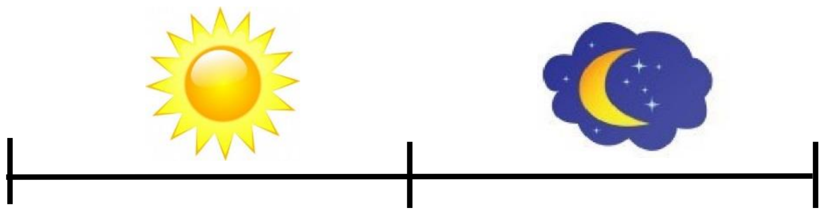
- Frequent and shallow discharge periods
- No exploitation of the battery charge with deep discharge cycles

Charge – discharge cycling

The charge/discharge process of the battery is called ***cycling***



Photovoltaic scavenger



$$D = \frac{C_{dis}}{C_0}$$ ***Depth of Discharge (DoD)***

Charge delivered by a battery

IDEAL SITUATION

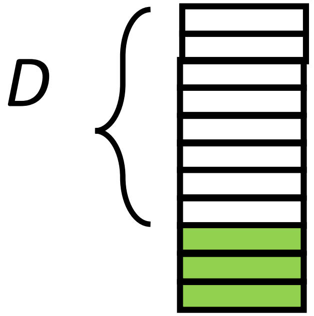
↓

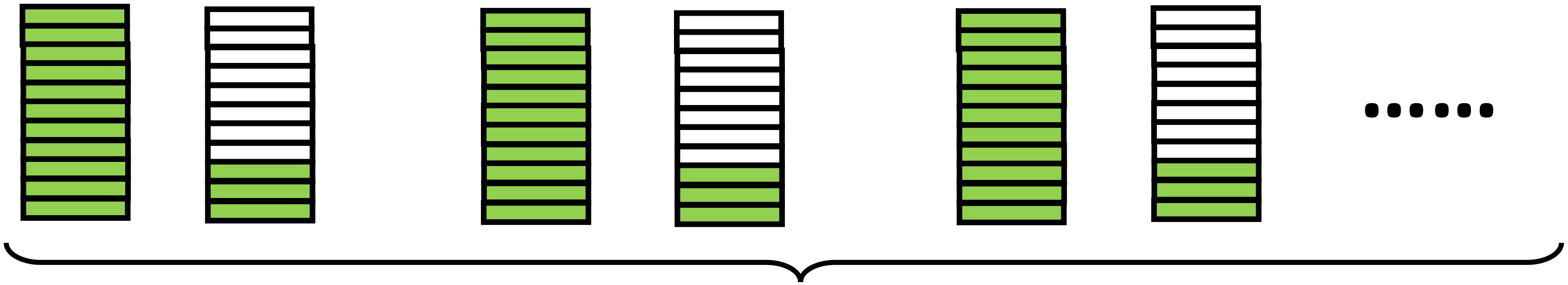
No degradation on C_0

↓

$$Q(N_{cyc}) = N_{cyc} C_0 D$$

$Q(N_{cyc})$: Total charge delivered by the battery, after N_{cyc} cycles at D





N_{cyc}

Battery cycle life

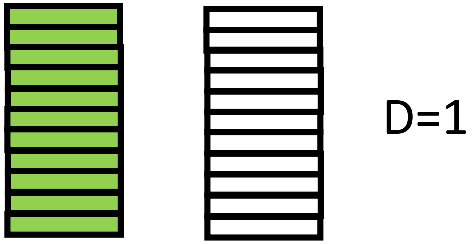
TWO FACTS complicate the ideal scenario

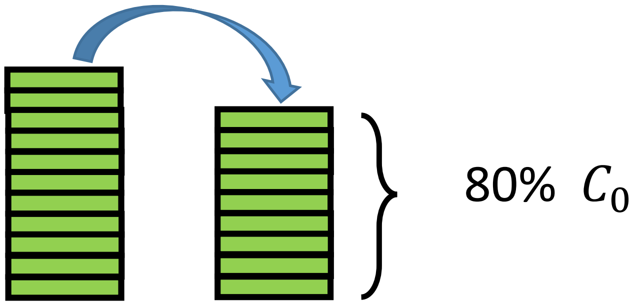
1) A rechargeable battery has a ***finite cycle life***

(degradation mechanisms reduce C_0 to unrecoverable levels)

Definition (battery cycle life)

Manufacturers typically define the battery cycle life N_{cyc} as the number of cycles a battery delivers at DoD D=1 before C_0 drops below a given threshold, e.g. 80% or 50% of the initial value.





Battery cycle life

TWO FACTS complicate the ideal scenario

2) The degradation process strongly depends on ***how the battery is cycled***

(shallow DoDs result in a slower degradation of C_0)

Example : a microbattery rated with $N_{cyc} = 100$ cycles at 100% DoD

may last up to $N_{cyc} = 1000$ cycles at 20% DoD

(data sheets of Li-Ion rechargeable batteries)

roughly twice the energy is extracted in this case

N_{cyc} versus D (DoD) dependance

Simple heuristic model for the N_{cyc} vs D dependance

Exponential model

$$N_{cyc}(D) = N_{cyc,0}\, e^{\alpha(1-D)}$$

- $N_{cyc,0}$: represents the cycle life at 100%
- α: characteristic constant of the battery

- Exponential models have been proved to be a good fit from data of a rather wide range of battery chemistries and sizes
- They may be taken also as rapresentative for microbatteries targeted for low-power equipment

Take home message

Take Home message

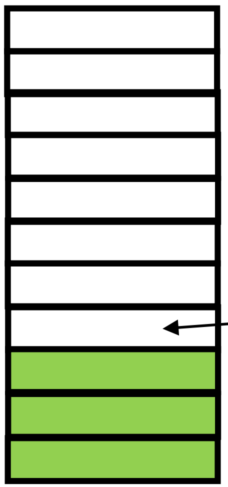
The **deeper** the **discharge** of the battery

↘ The **faster** the **degradation**

Exponential models opens up intriguing options for more advanced energy-aware policies

Stochastic Model ⟶ Markov Decision Process

Battery model



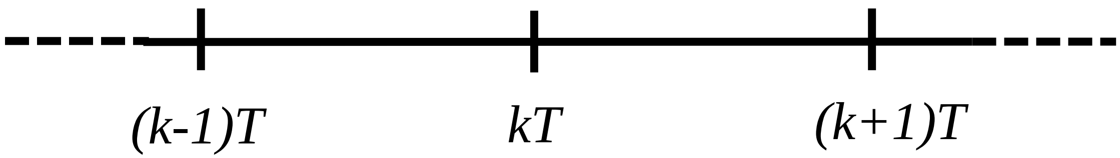
- C_0 : nominal capacity of the battery
- Battery is uniformly quantized to a number of charge levels

  $\Delta c \ll C_0$: quantization step
- $q_{max} = \left\lfloor \frac{C_0}{\Delta c} \right\rfloor$: number of charge levels

Set of possible charge levels $\{0, 1, \dots, q_{max}\}$

System model

We consider a slotted-time system

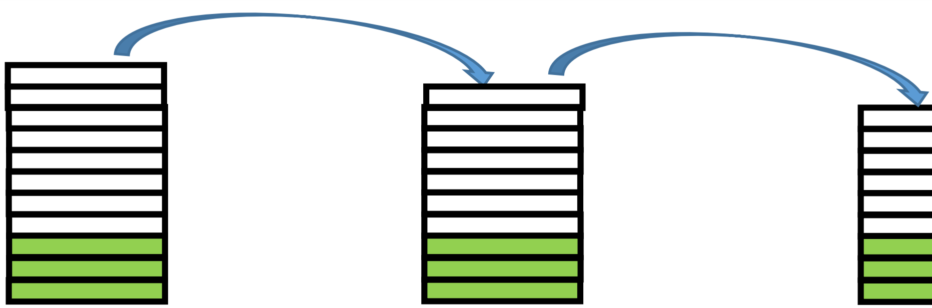


T : slot duration

C_0 : **decreases over time**

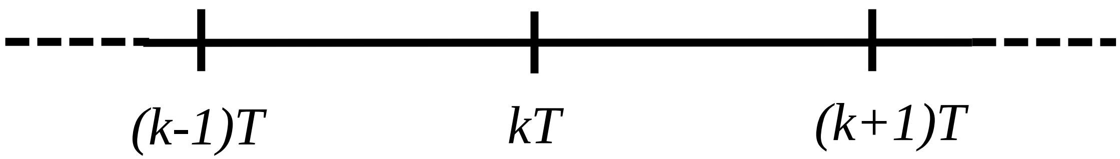
$Q_{max}(k)$: **battery capacity at time k**

$$Q_{max}(k) \leq Q_{max}(k-1) \qquad Q_{max}(0) = q_{max} = C_0$$



$Q_{max}(k-1)$ $\quad$ $Q_{max}(k)$ $\quad$ $Q_{max}(k+1)$

System model



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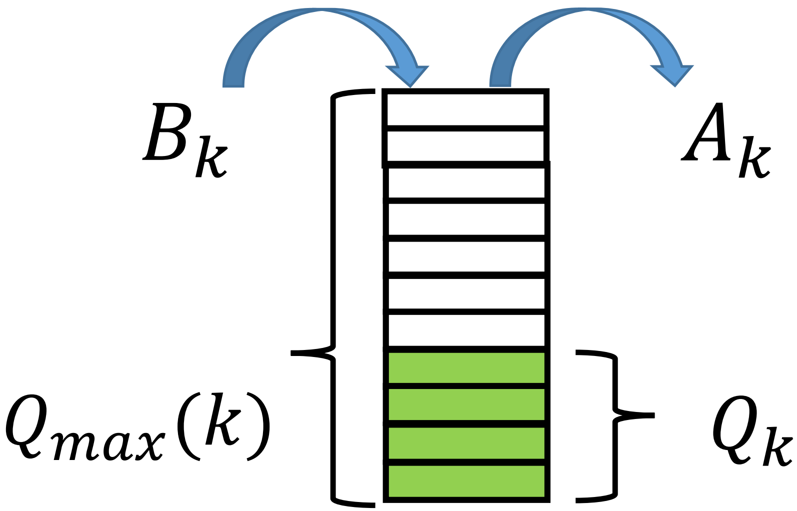


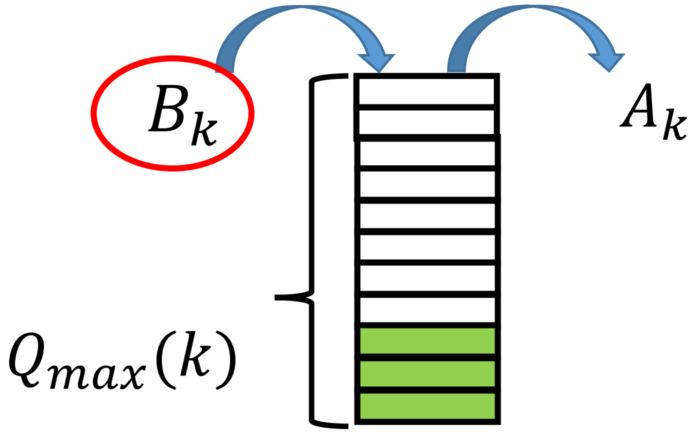
Q_k: charge level of the battery

B_k: energy from the harvesting process

A_k: energy used for the action process

$$Q_{k+1} = \min\{\ [Q_k - A_k]^+ + B_k,\quad Q_{max}(k)\ \}$$

System model



B_k: harvesting process

$B_k \in \{0,1,\dots,B\}$

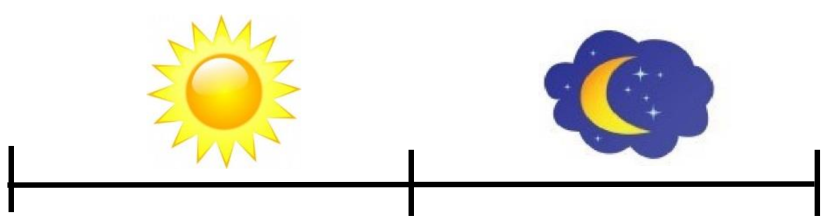
$B_k \rightarrow$ Markov process

We define an underlying energy harvesting process $\{S_k\}$

$\{S_k\}$: irreducible Markov Chain

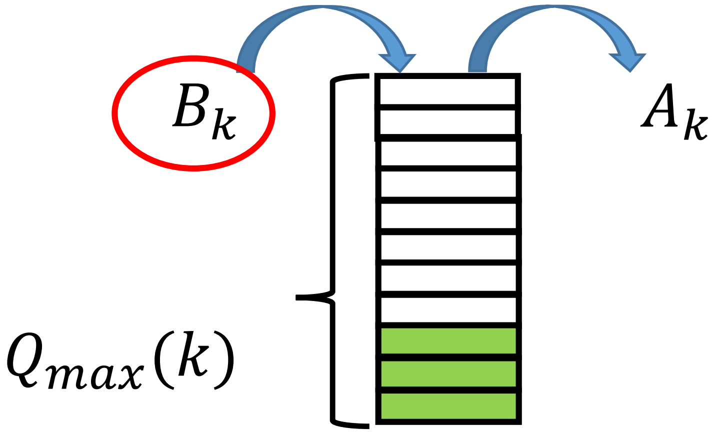
- $p_s(s_{k+1}|s_k) \triangleq \Pr(S_{k+1} = s_{k+1}|S_k = s_k)$
- $\pi_S(s)$ steady state distribution

Photovoltaic scavenger



$S_k = \{\text{day, night}\}$

System model



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$B_k \in \{0,1,\dots,B\}$

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We define an underlying energy harvesting process $\{S_k\}$

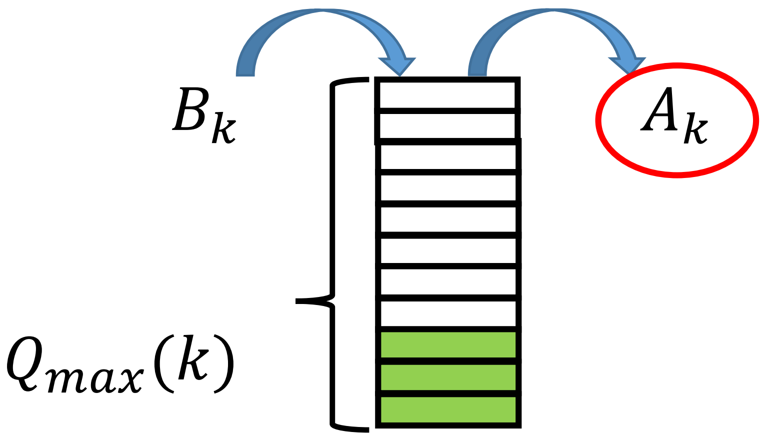
$\{S_k\}$: irreducible Markov Chain

- $p_s(s_{k+1}|s_k) \triangleq \Pr(S_{k+1} = s_{k+1}|S_k = s_k)$
- $\pi_S(s)$ steady state distribution

Given S_k, B_k is drawn according to the transition probabilities

$$p_B(b_k|s_k) \triangleq \Pr(B_k = b_k|S_k = s_k)$$

System model



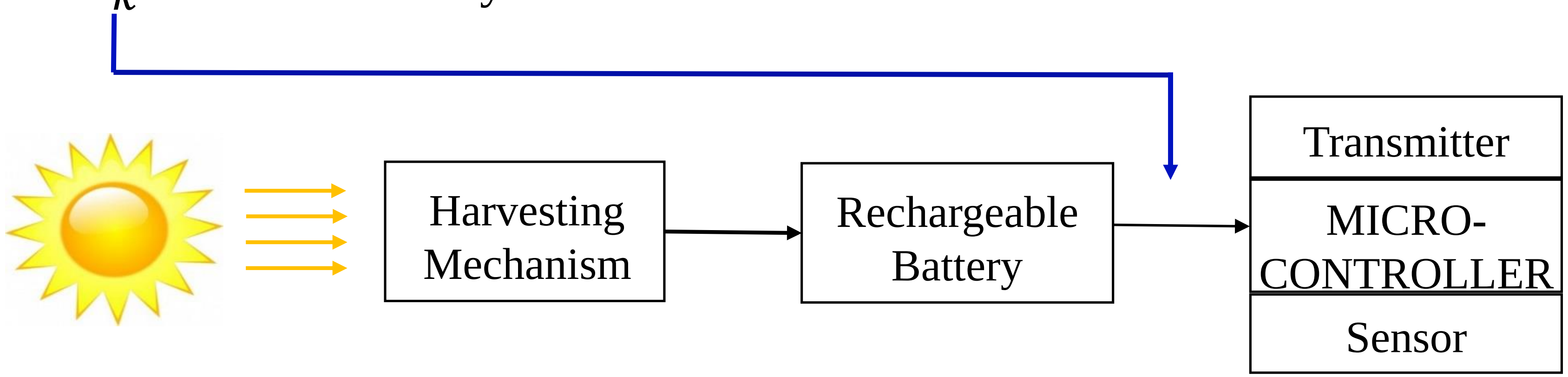
A_k: ***action process***

$A_k \in \{A_{min}, \dots, A_{max}\} \cup \{0\}$

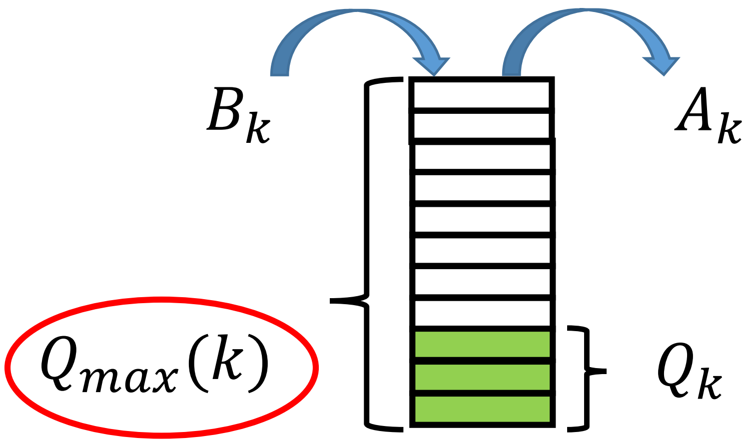
A_{min}, A_{max} : max, min loads requirements

$A_k = 0$ idle state

A_k is determined by the controller



System model



$Q_{max}(k)$: decreases over time

H_k: ***battery health state***

$H_k \in \{0,1,\dots,H_{max}\}$

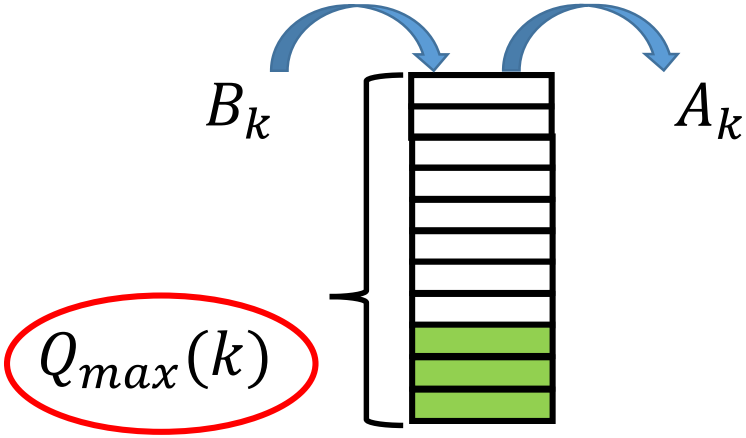
$H_k = H_{max}$: **good health**

$H_k = 0$: **bad health**

Given H_k ⟶ $Q_{max}(k) = \left\lfloor \frac{H_k}{H_{max}} q_{max} \right\rfloor$

$Q_k \in \{0,1,\dots,Q_{max}(k)\}$

System model



$Q_{max}(k)$: dimishes over time

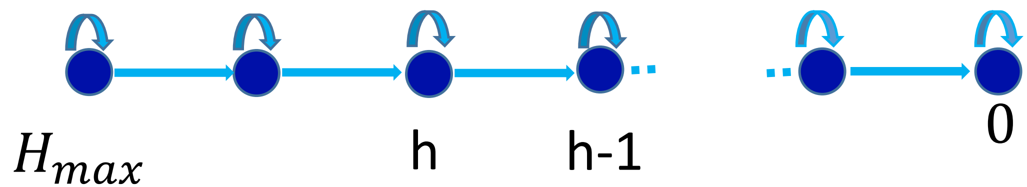
H_k: ***battery health state***

$H_k \in \{0,1,\ldots,H_{max}\}$

$H_k = H_{max}$: **good health**

$H_k = 0$: **bad health**

H_k **Markov chain (depending on q and h)**



Transition probabilities (from h to h-1)

$$p_H(h;q) \triangleq \Pr(H_{k+1} = h-1 \mid H_k = h, Q_k = q)$$

System model

Assumption

- $p_H(h;q) > 0, \qquad \forall\, h \text{ and } q \in Q(h)$
- $p_H(h;q) \ll 1, \qquad \forall\, h \text{ and } q \in Q(h)$
- $p_H(h_1;q_1) \geq p_H(h_2;q_2) \qquad \forall\, h_2 \geq h_1, q_2 \geq q_1$

- battery health state will reach $H_k = 0$
- degradation processes operate over time scales much longer than the cycling period and communication time-slot
- the more the discharged and degraded the battery

the faster the battery degradation process

System model

$\boldsymbol{Z_k} = (Q_k, H_k, S_{k-1})$: is the state

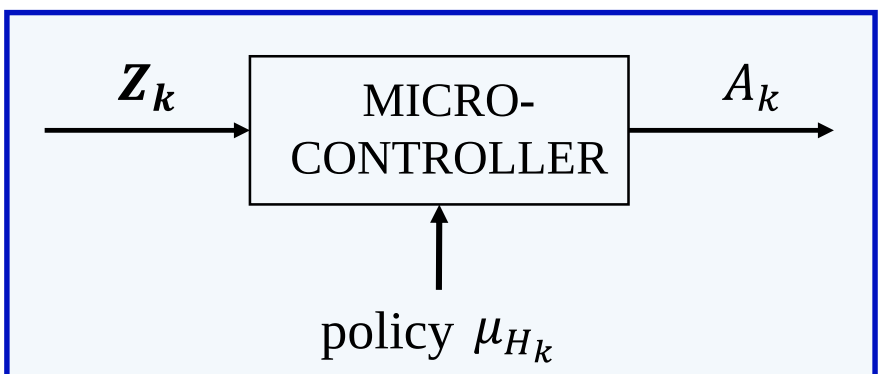
Q_k: charge level

H_k: health level

S_{k-1}: harvesting state

→ It is assumed to be **known!**

Given $\boldsymbol{Z_k} = (Q_k, H_k, S_{k-1})$ → the controller determines the action A_k according to a policy μ_{H_k}



System model

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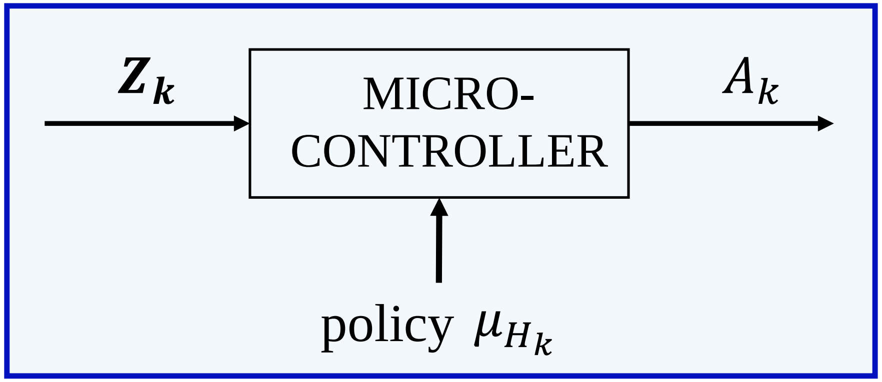


μ_{H_k} is a ***probability measure*** on the action space $\{A_{min}, \dots, A_{max}\} \cup \{0\}$

μ_{H_k} : is parametrized by the state (Q_k, S_{k-1})

$\mu_{H_k}(a;\ Q_k, S_{k-1})$ is the probability of requesting a charge quanta from the battery given (Q_k, S_{k-1})

Reward function

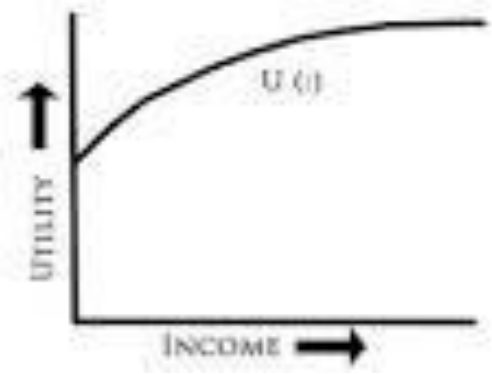
Reward in time slot k

It is a function of

- The state $\boldsymbol{Z_k} = (Q_k, H_k, S_{k-1})$
- The action $\boldsymbol{A_k}$

$$g(A_k, Q_k) = \begin{cases} 0 & A_k > Q_k \\ g^*(A_k) & A_k \leq Q_k \end{cases}$$

g^* is a concave function

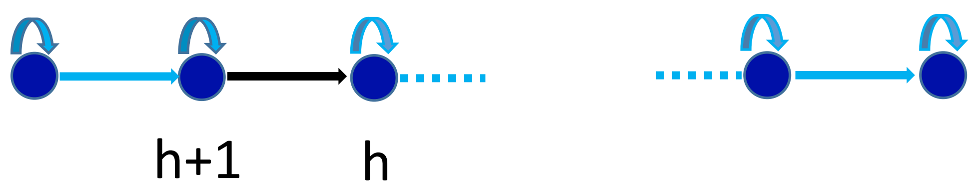


Hitting times of health state

Hitting times (Health state)

$$K_h = min\{\, k \geq 0 \colon H_k = h\}$$

Denotes the time in which the health state transitions from the state h+1 to the state h



K_h is a random variable which depends on the realization of $\{B_k, A_k, H_k\}$

Optimization functions

Total average reward at state h

$$G_{\mu}^{tot}(h, \boldsymbol{Z_0}) = \mathbf{E}\left[\sum_{k=K_h}^{K_{h-1}-1} g(A_k, Q_k) \middle| \boldsymbol{Z_0}\right]$$

The battery life at state h

$$T_{\mu}(h, \boldsymbol{Z_0}) = \mathbf{E}\left[K_{h-1} - K_h \middle| \boldsymbol{Z_0}\right]$$

Total average reward per time-slot

$$G_{\mu}(h, \boldsymbol{Z_0}) = \frac{G_{\mu}^{tot}(h, \boldsymbol{Z_0})}{T_{\mu}(h, \boldsymbol{Z_0})}$$

Battery Lifetime

Let $\boldsymbol{G}^*$ *be a minimum* ***Quality of Service requirement*** $(\boldsymbol{QoS})$

Constraint: $G_\mu(h, \boldsymbol{Z_0}) \geq \boldsymbol{G}^*$

Definition (Battery Lifetime)

$$T_\mu(\boldsymbol{G}^*, \boldsymbol{Z_0}) = \sum_{h \geq h_\mu^*} T_\mu(h, \boldsymbol{Z_0})$$

$$\text{where } h_\mu^* = \max\left\{ h : G_\mu(h, \boldsymbol{Z_0}) < \boldsymbol{G}^* \right\} + 1$$

the lowest health state in which the **Quality of service requirement** is met

Optimization problem

Let $\boldsymbol{G}^*$ *be a minimum* ***Quality of Service requirement*** $(\boldsymbol{QoS})$

Constraint: $G_\mu(h, \boldsymbol{Z_0}) \geq \boldsymbol{G}^*$

Optimization Problem

To determine the optimal μ^* *such that the battery lifetime is maximized, under a given constraint on the minimum QoS* $\boldsymbol{G}^*$

$$\mu^* = \arg\max_{\mu} T_\mu(\boldsymbol{G}^*, \boldsymbol{Z_0}) = \arg\max_{\mu} \sum_{h \geq h_\mu^*} T_\mu(h, \boldsymbol{Z_0})$$

Optimization problem : the solution

Recall the **Assumption** :

$$p_H(h;q) \ll 1, \qquad \forall\, h \text{ and } q \in Q(h)$$

Time scale separation between the communication time slot and the battery degradation process

The micro−controller achieves a steady−state operation in each health state

The optimization problem can be decoupled into independent **Linear Program** problems on each health state

Numerical results

We consider a battery with

$$q_{max} = 500$$

$$H_{max} = 50$$

The degradation probabilities can be extrapolated from manufacturer provided- data employing

$$N_{cyc}(D) = N_{cyc,0}\, e^{\alpha(1-D)}$$

Good match

$$p_H(q,h) = \gamma \exp\left\{\alpha\left(1 - \frac{q}{q_{max}}\right)\right\}$$

Numerical results

Energy harvesting process $S_k \in \{\mathrm{B}, G\}$

$S_k = \mathrm{B} \rightarrow B_k = 0$ $(No\ energy\ harvested)$

$S_k = \mathrm{G} \rightarrow B_k = 20$ $(Constant\ energy\ harvested)$

Average energy harvested $\rightarrow \bar{b} = 10$

Action space $A_k \in \{0, \dots, 20\}$

Reward function $g^*(A_k) = \log_2\left(1 + \sigma A_k / \bar{b}\right)$

Numerical results

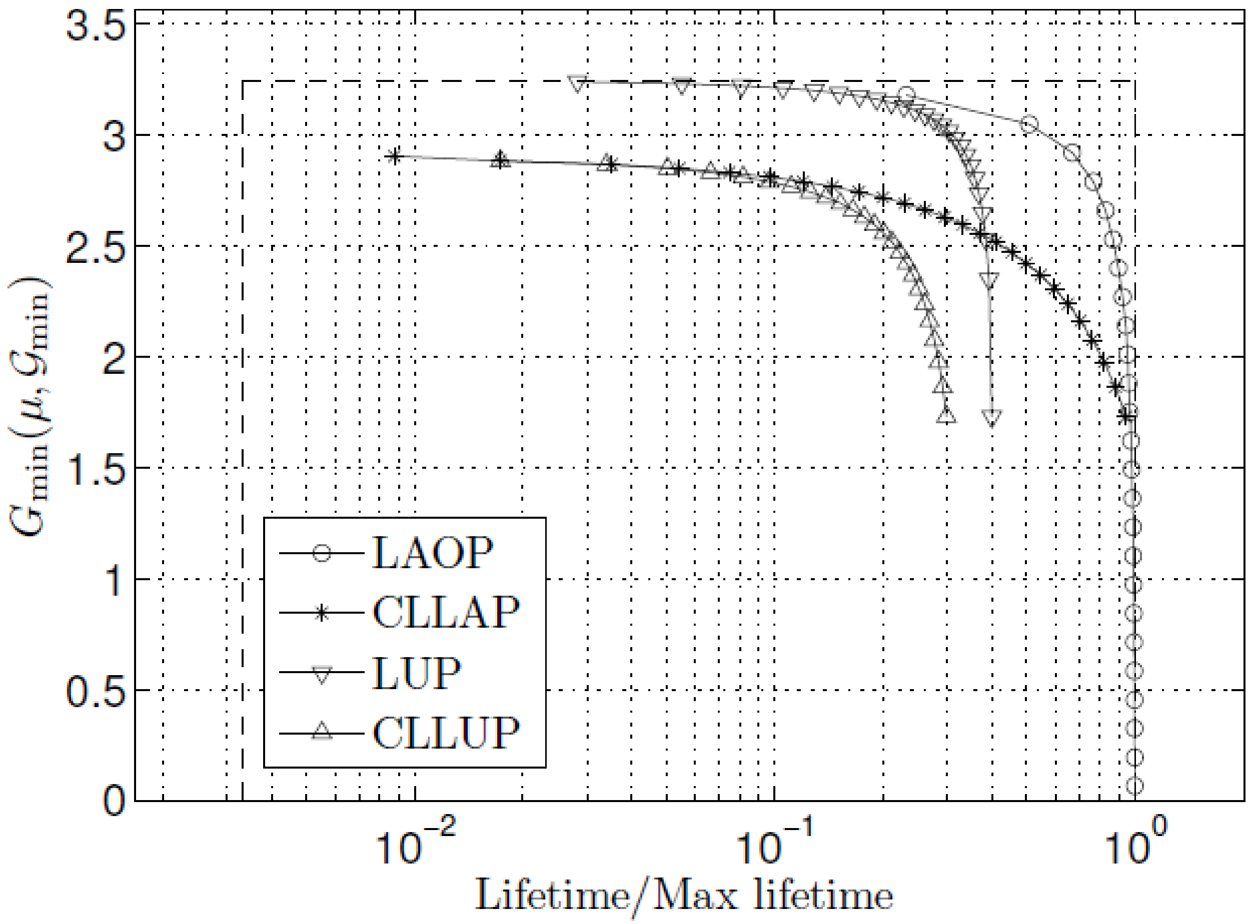
Constant load lifetime Unaware policy (CLLUP) : supports a constant load of $\bar{b}$ charge quanta.

Lifetime Unaware policy (LUP) : greedily maximizes the average long-term reward for the actual value of the battery capacity without taking into account the impact of the policy on the battery lifetime.

Lifetime Aware Optimal Policy (LAOP) : is the optimal policy solution

Constant load lifetime aware policy (CLLAP) : supports a constant load $\bar{b}$ when the battery charge level is above a given DoD, and remains idle otherwise

Numerical results



Minimum reward : *average reward per slot that is guaranteed over the entire battery lifetime*

Take home message

Degradation effects must be taken into account

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Stochastic Model ⟶ Markov Decision Process