



Self-sufficient Sensor Networks: from Energy Profiling to Optimal Sustainable Performance

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[Developing the
Science of Networks]

- Studied Electronics and Telecommunications at the University of Ferrara



Who am I

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- Joined the SIGNET group in 2006 and working on Wireless Sensor Networks

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INFORMATION
ENGINEERING

UNIVERSITY OF PADOVA



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Who am I

- Studied Electronics and Telecommunications at the University of Ferrara
- Joined the SIGNET group in 2006 and working on Wireless Sensor Networks
- CEO of Patavina Technologies between 2009 and 2013
- Now with IMDEA Networks Institute in Madrid

About this work

- Started during the SWAP project (2010-2014)
- Goal: design of self-sufficient networked sensor devices
- Partners: Patavina Technologies, Consorzio Ferrara Ricerche, Centre Tecnològic Telecomunicacions Catalunya, WorldSensing



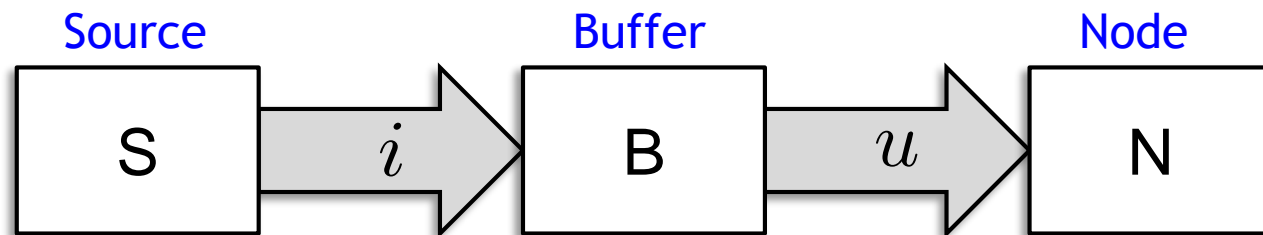
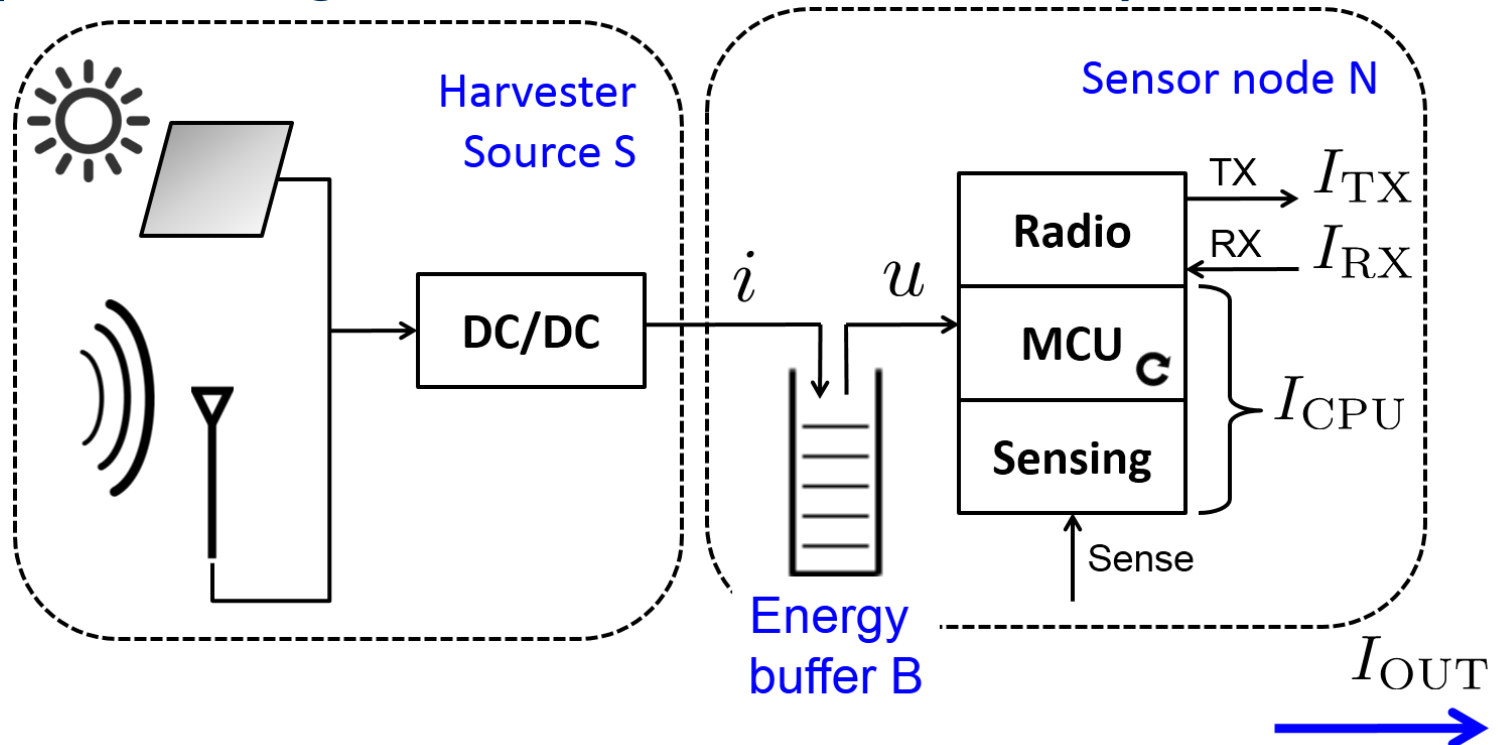
- Motivation
- Optimization Framework
- Energy Source Model
- Optimal Operational Point
- Self-Sufficient Energy Policies
- Results

Motivation

- The no-free-lunch theorem applies to Energy-Harvesting Wireless Sensor Networks
- Challenge:
 - Energy source is there but ...
 - ... it is **unreliable, erratic and intermittent**
- **Need for intelligent designs**
 - Adaptive energy mangement
 - Transmission vs Storage vs Scavenger Size

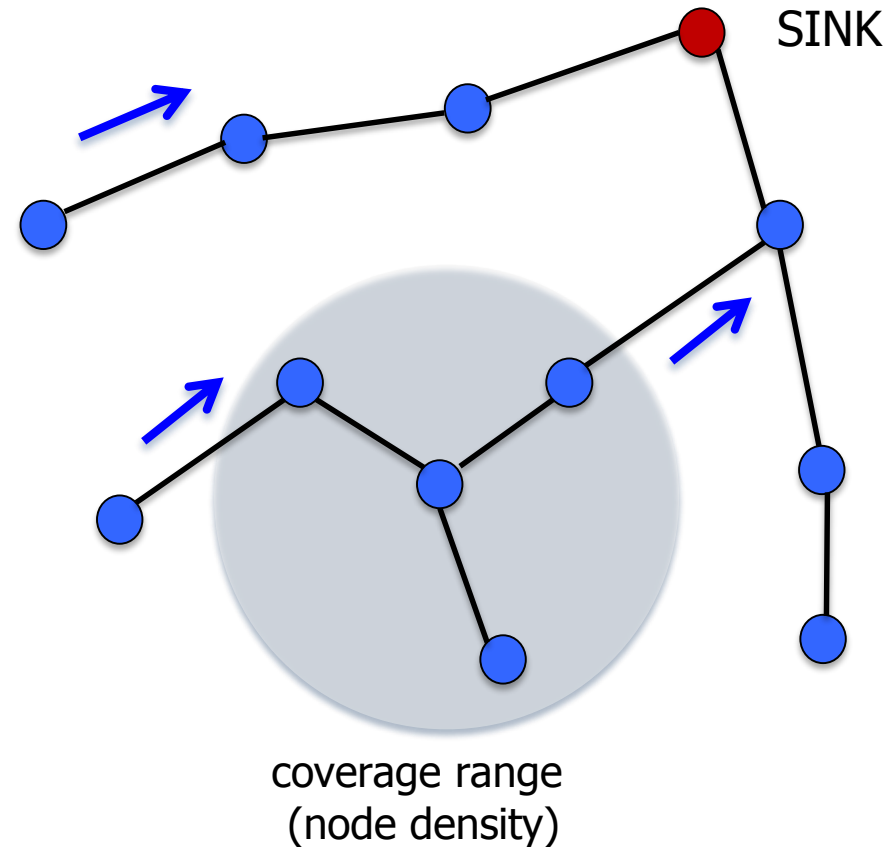
Scenario (1) - Sensor Model

- Sensor: wireless device with sensing, processing and communication capabilities

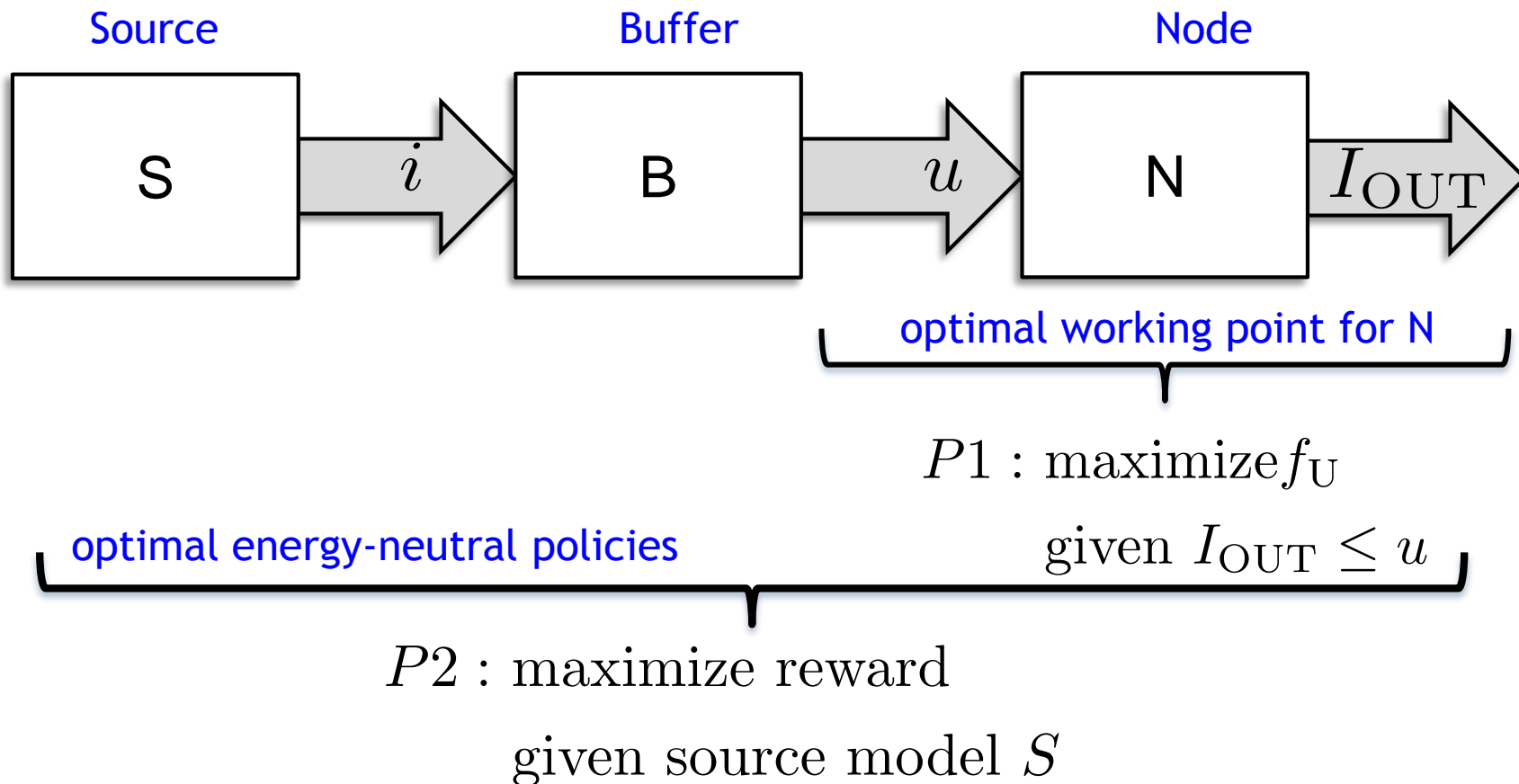


Scenario (2) - Network Model

- **Scenario**
 - Multi-hop routing
 - Data collection @ the sink
 - Energy harvesting nodes
- **Aspects to model**
 - MAC (channel access)
 - Routing
 - Energy consumption
 - Energy arrival



Optimization Framework



We optimize for the bottleneck node N → this assures network stability

1) Energy Source Model, S

- Input: harvester, energy availability
- Output: current statistics $f_c(i|x_s)$

2) Optimal Operational Point, P1

- Input: topology, MAC, hardware
- Output: duty-cycle, throughput (t_U^*, t_{dc}^*)

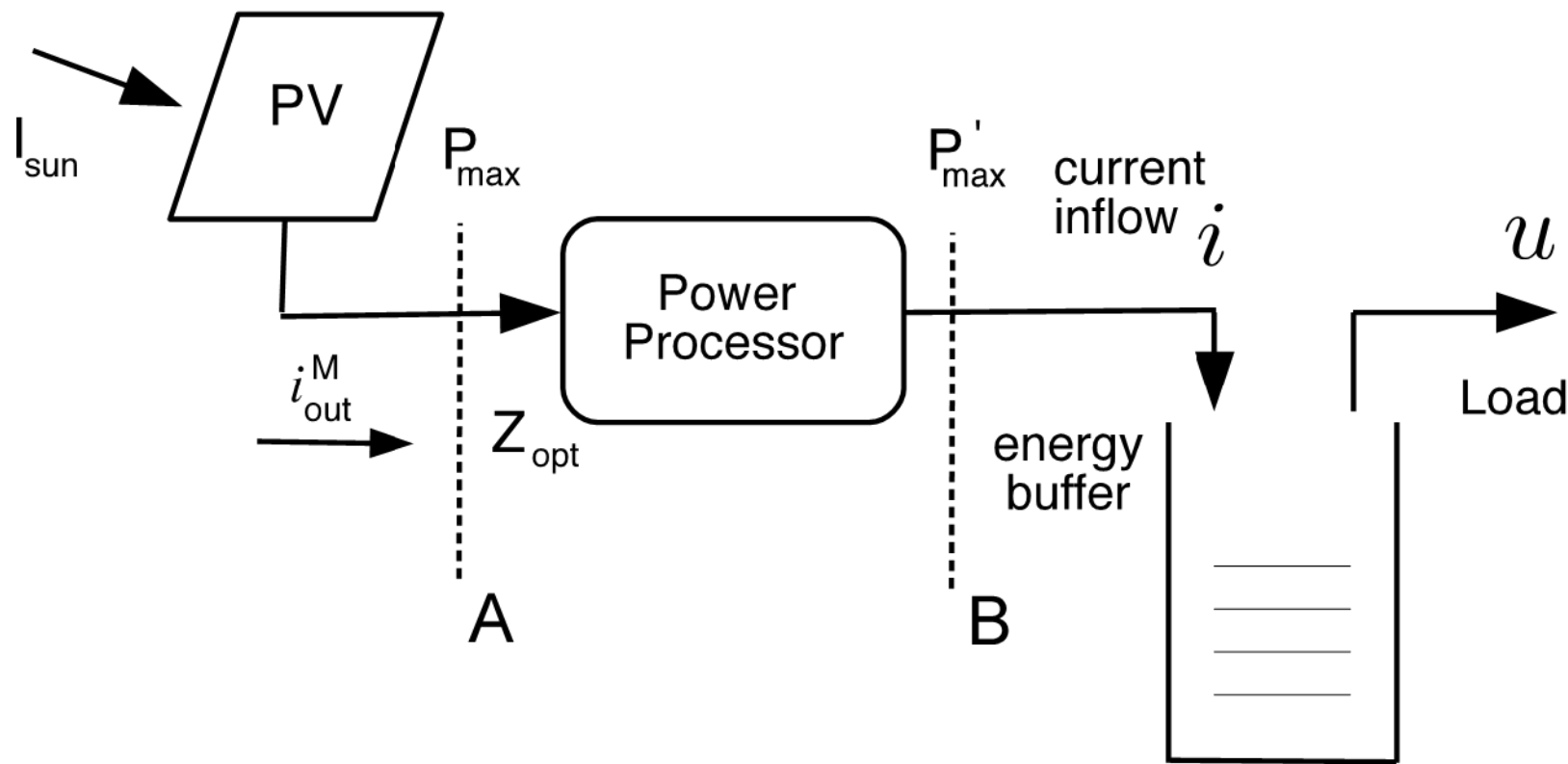
3) Energetically Self-Sufficient policies, P2

- Input: energy source/consumption models
- Output: energy management policies u

[illegible]

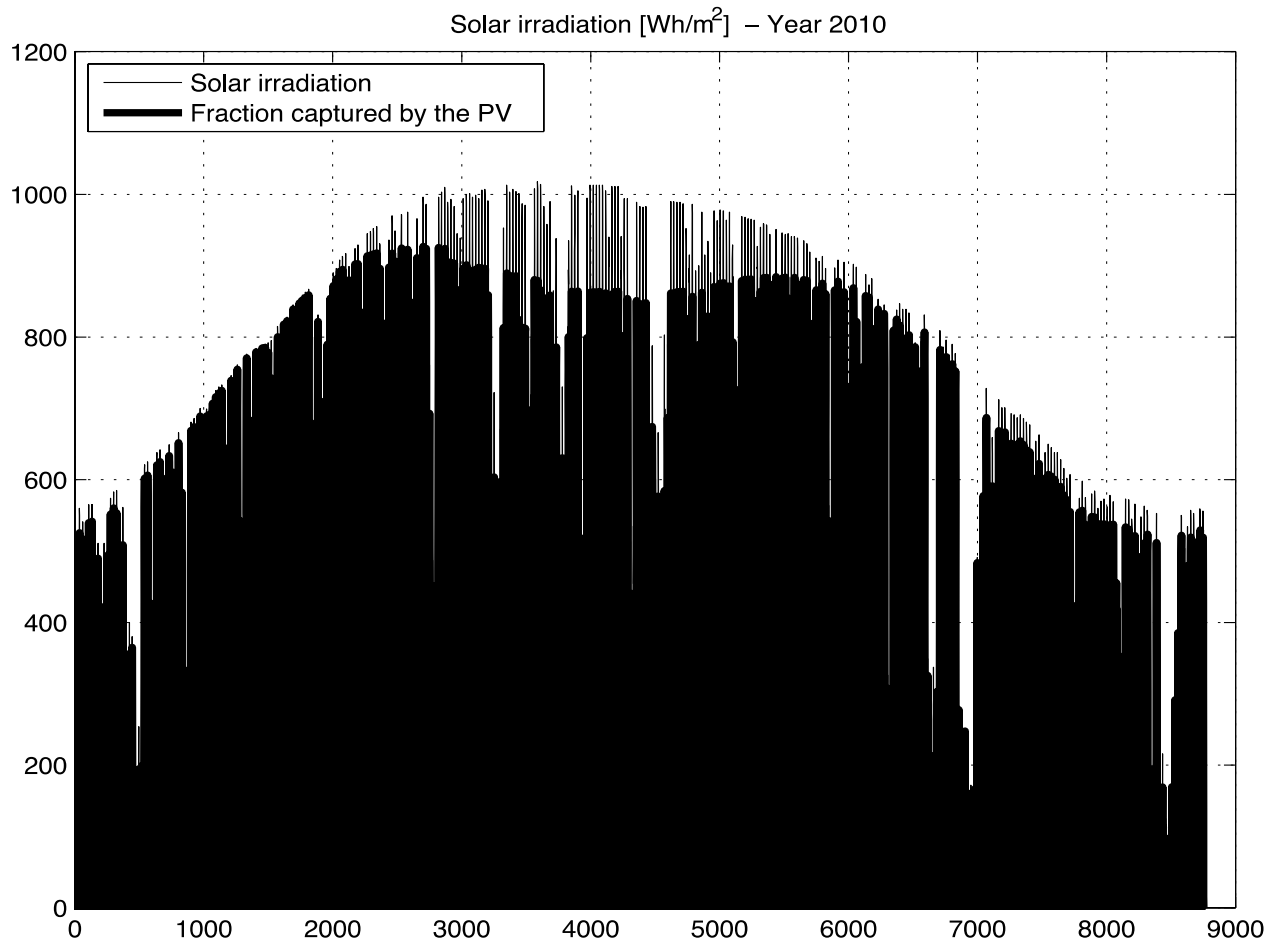
Energy Source Model

- Harvester: photovoltaic panel controlled by a processor to maximize the efficiency. The energy is stored in a battery.



Harvested Energy (1)

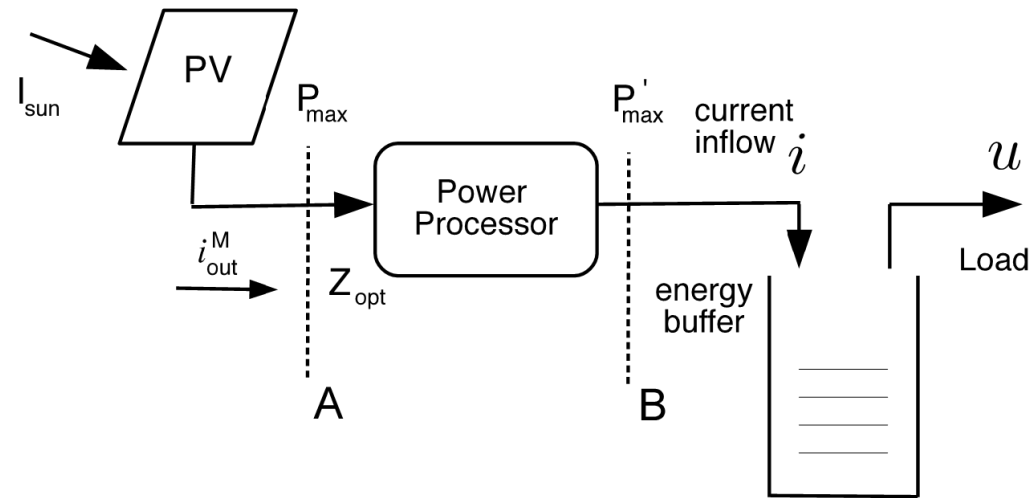
- Solar Irradiation for **Los Angeles** in 2010
from NREL: <http://www.nrel.gov/rredc/>



NREL, National Renewable Energy Laboratory, “Renewable Resource Data Center,” <http://www.nrel.gov/rredc/>

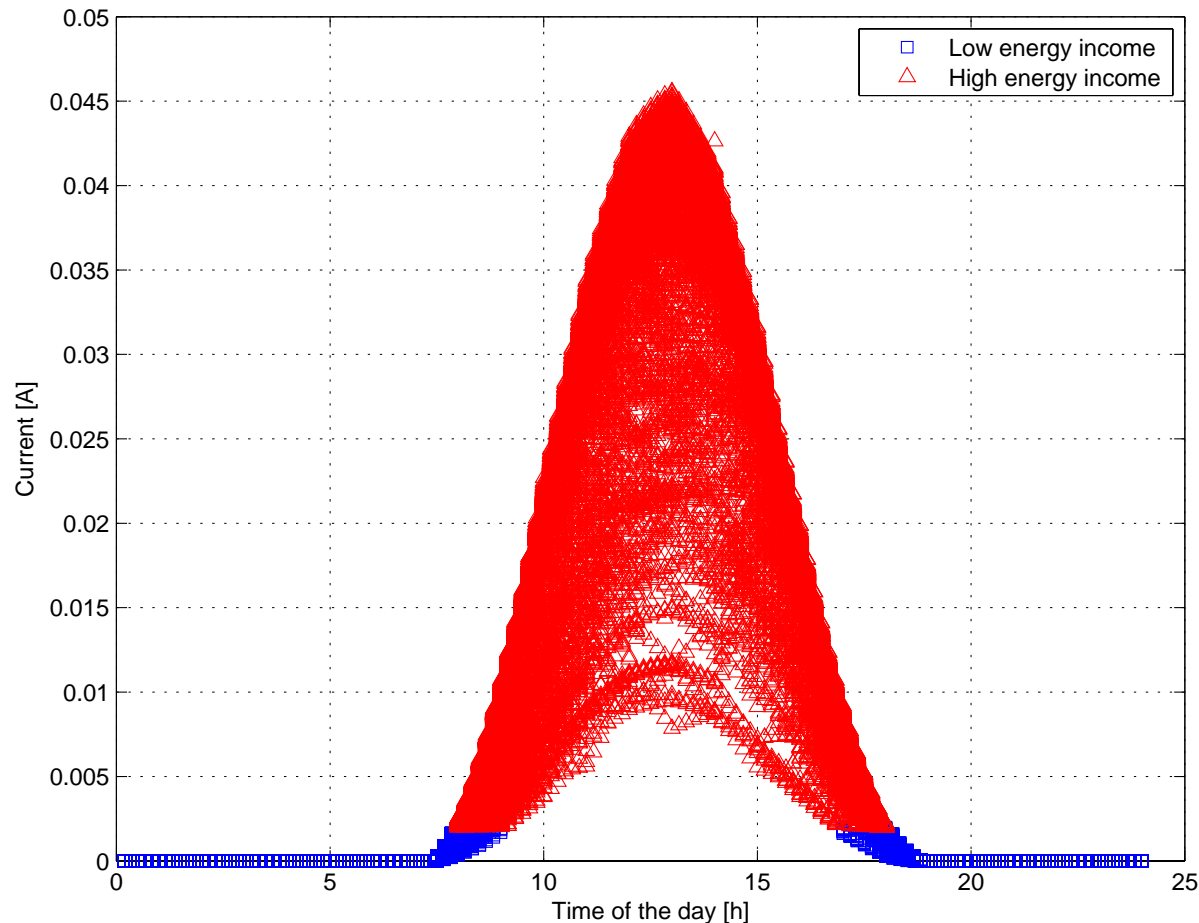
Harvested Energy (2)

- Solar radiation maps:
 - Latitude, longitude
 - Orientation of the panel
 - Day of year
 - Radiation maps
- PV technology:
 - Material
 - Efficiency
 - Panel size, tilt, azimuth
- DC/DC:
 - Efficiency
 - Optimal working point for the panel IV curve is assumed
- **Statistical characterization of DC/DC out current**
 - Current intensity [A]
 - Energy states (morning, afternoon, night, etc.)



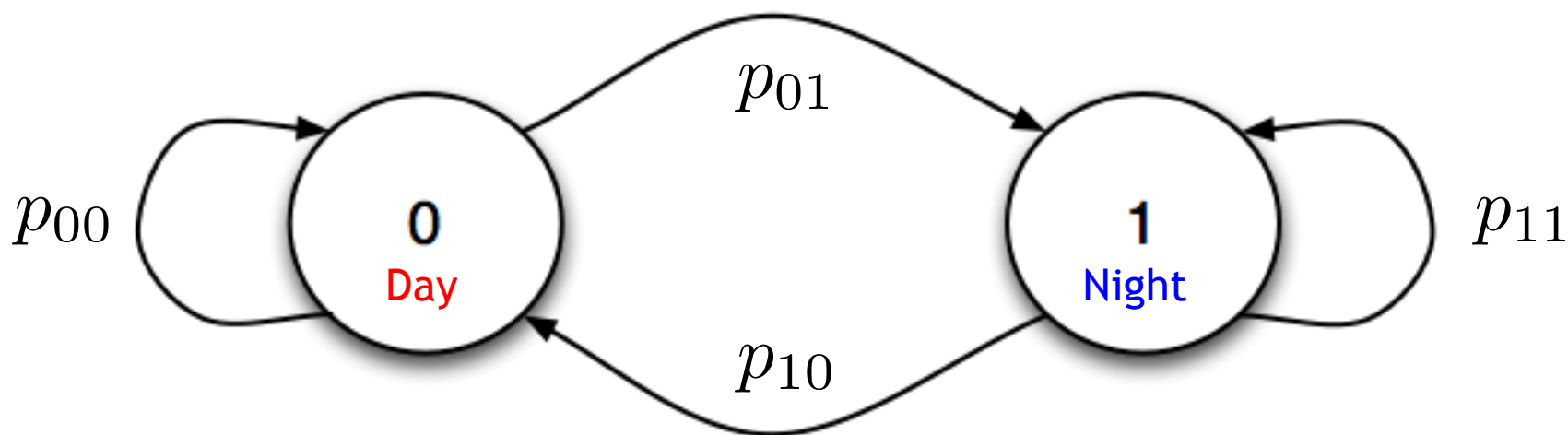
Example

- Statistics (pdf) of August (1999-2010)
 - Day/Night data clustering (duration and income)



Semi-Markov Model (SMM)

- Simplest 2-state model



Embedded chain probs

$$p_{10} = p_{01} = 1$$

$$p_{00} = p_{11} = 0$$

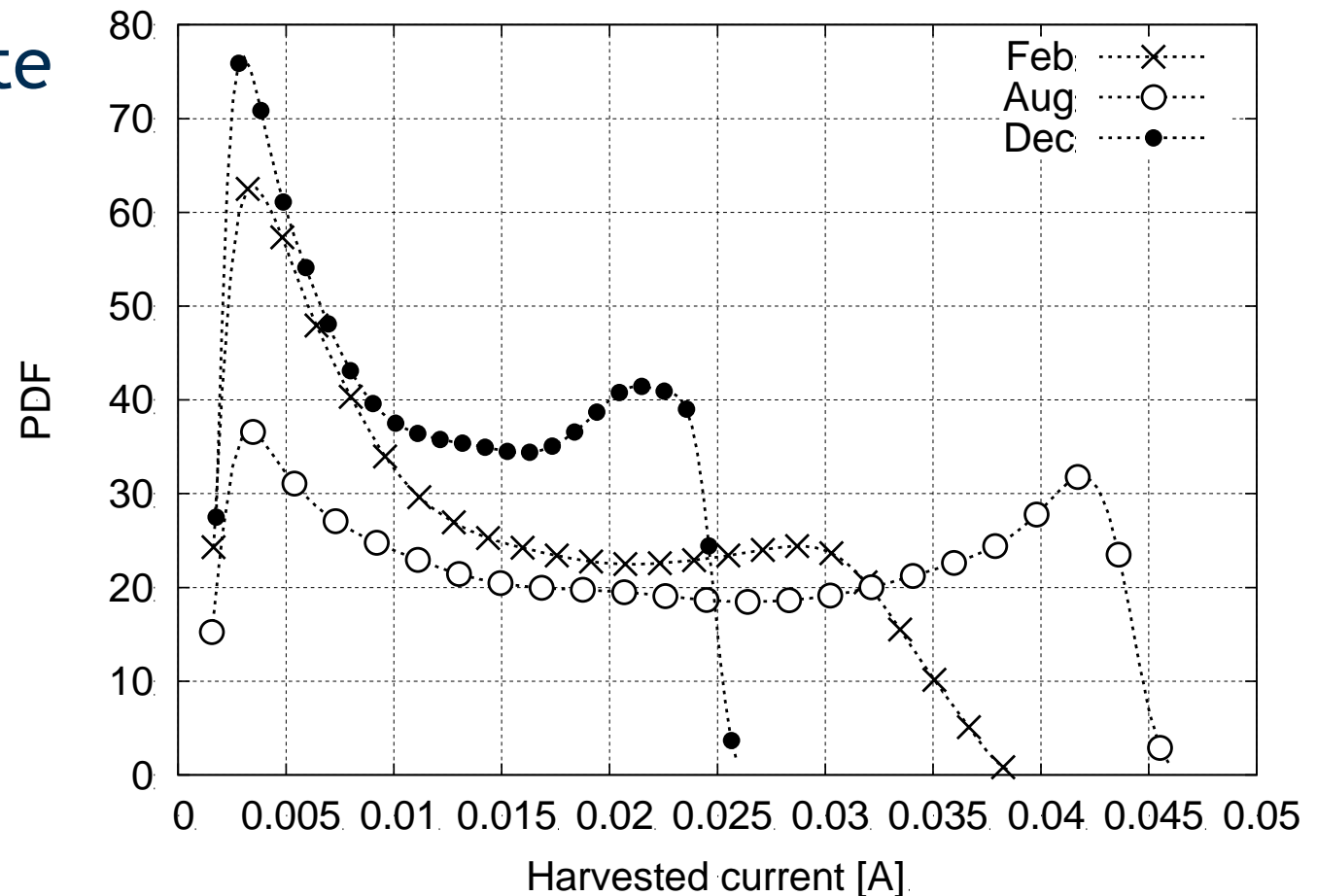
$$f_c(i|x_s) \text{ Harvested current}$$

$$f_d(\tau|x_s) \text{ Permanence time}$$

the approach has been generalized to any number of states

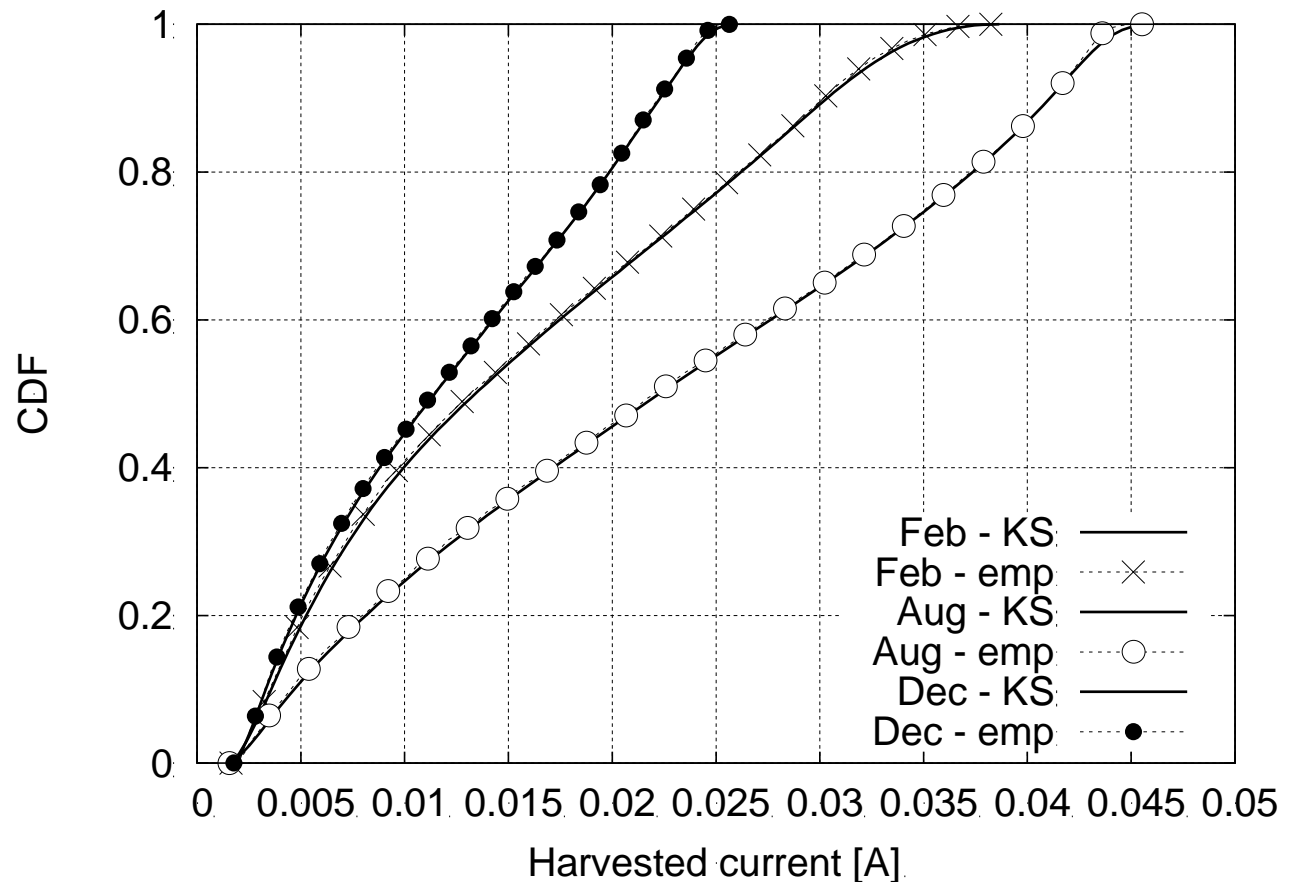
Statistics - Input Current $f_c(x|x_s)$

- Los Angeles data collected from 1999 to 2010
- Solar module: square 6x6 cm²
- Day state



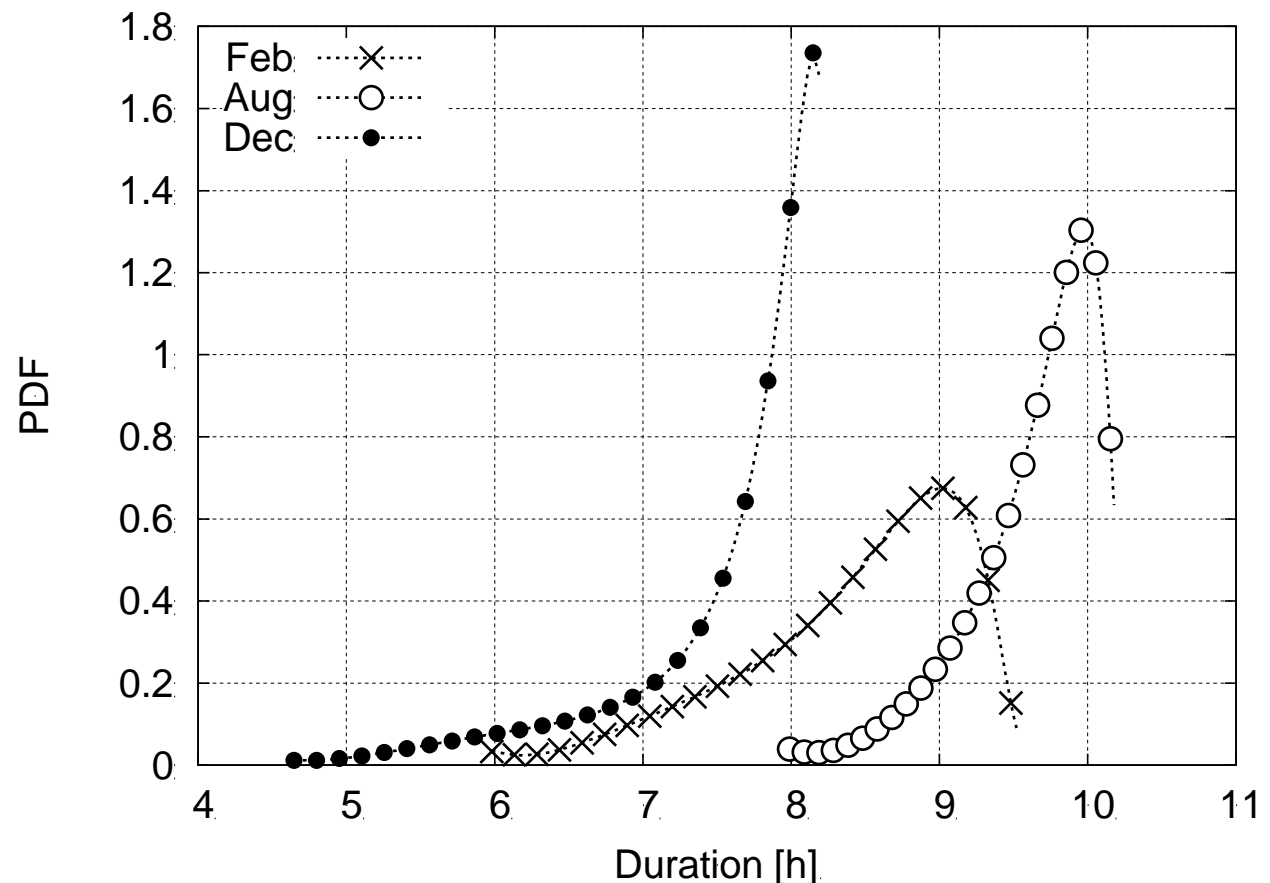
Statistics - Input Current CDF

- Los Angeles data collected from 1999 to 2010
- Solar module: square 6x6 cm²
- Day state



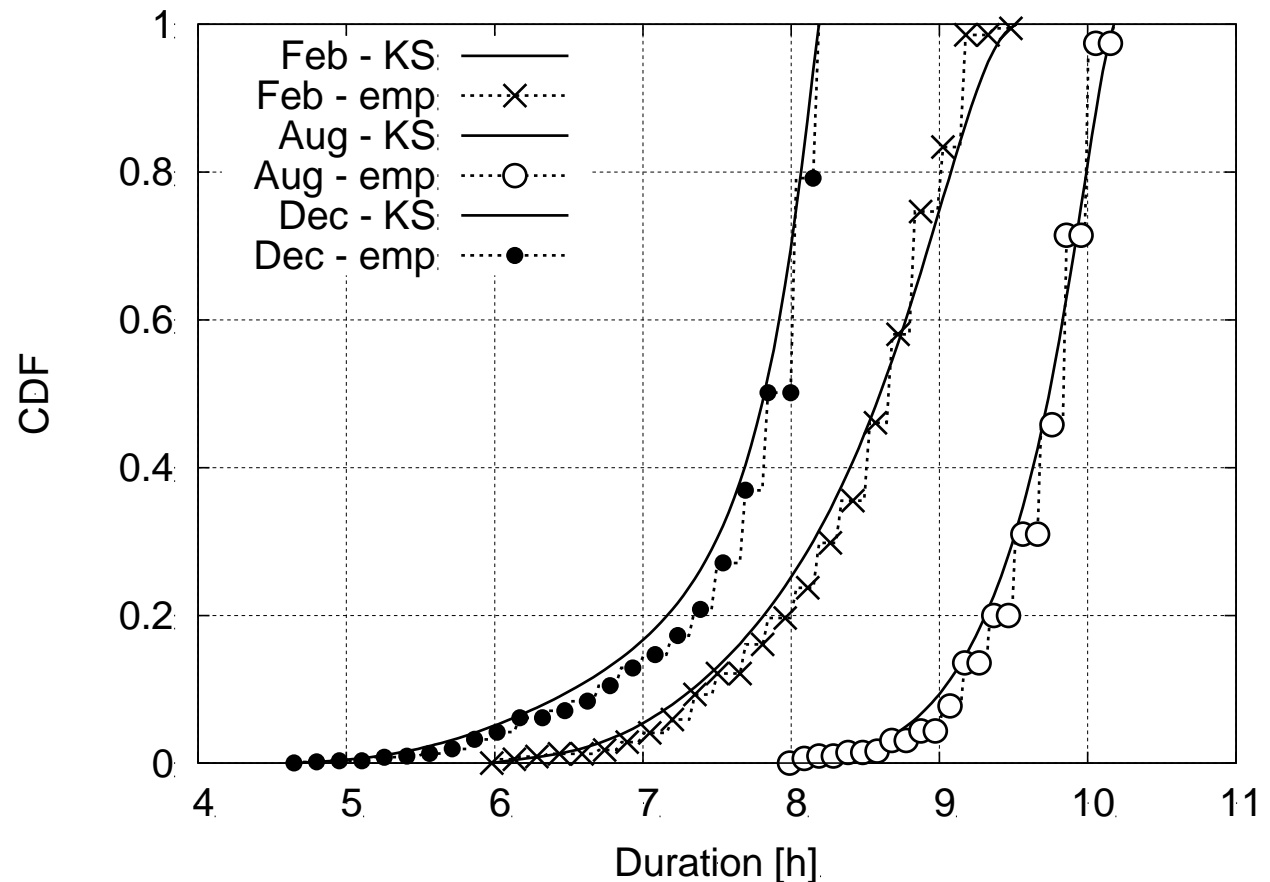
Statistics - State duration $f_d(x|x_s)$

- Los Angeles data collected from 1999 to 2010
- Solar module: square 6x6 cm²
- Day state

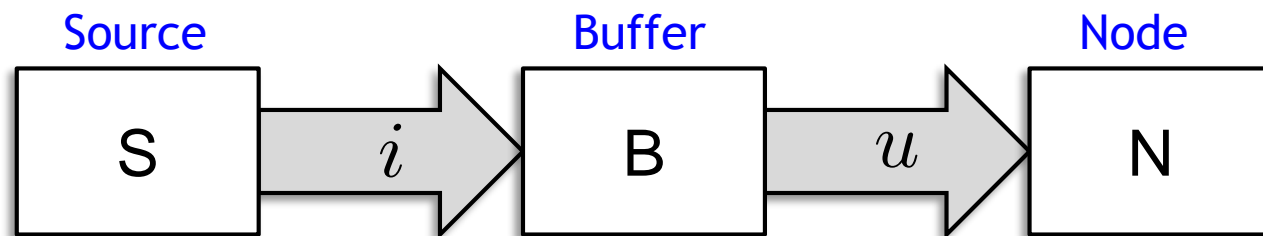


Statistics - State duration CDF

- Los Angeles data collected from 1999 to 2010
- Solar module: square 6x6 cm²
- Day state



- Stage
 - time t during which the SMM remains in one state
- Energy income
 - r.v. drawn @ beginning of stage from $f_c(i|x_s)$
- Duration
 - r.v. drawn @ beginning of stage from $f_d(\tau|x_s)$
- Decision
 - u : chosen @ beginning of stage



Δ -charge (q) in stage k

- Balance between

- Control u (current drained)
- Input current i (from panel)
- Stage duration τ

$$\left. \begin{array}{l} \text{– Control } u \text{ (current drained)} \\ \text{– Input current } i \text{ (from panel)} \\ \text{– Stage duration } \tau \end{array} \right\} q = (i - u)\tau$$

- The pdf of the variation of charge in a stage is:

$$h(q|x_s, u) = \int_{-\infty}^{+\infty} \frac{1}{|\tau|} f_d(\tau|x_s) f_c(q/\tau + u|x_s) d\tau$$

Discrete Time Markov Chain (DTMC)

- Instead of using the SMM directly, we define an equivalent DTMC with slotted time
- Slot time is fixed
- When moving between stages (slots):
 - $h(q|x_s, u)$ models the d-charge variation
 - u is the control for the current stage
 - x_s is the source state in the current stage
 - q is the variation of charge in the battery
 - The new status of the battery is given by:

$$x_b(k) = \max\{0, \min\{x_b(k-1) + q, Q_{\max}\}\}$$



SYSTEM MODEL: P1 - Optimal Operational Point

Energy Consumption Model

- MAC (channel access)
- Network topology
- Data gathering
- Networking
- Processing

$$I_X = i_X t_X f_X$$

Energy Consumption Model

- MAC (channel access)
- Network topology
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- Processing

current drawn
spent in state X

$$I_X = i_X t_X f_X$$


Energy Consumption Model

- MAC (channel access)
- Network topology
- Data gathering
- Networking
- Processing

current drawn

average time spent
in state X upon a
transition to that
state


$$I_X = i_X t_X f_X$$

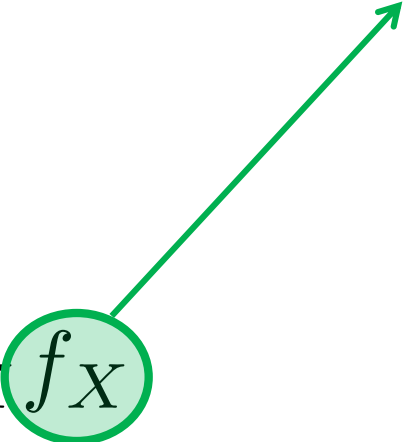
Energy Consumption Model

- MAC (channel access)
- Network topology
- Data gathering
- Networking
- Processing

current drawn

average time spent

visits per second to
state X (frequency)

$$I_X = i_X t_X f_X$$


Energy Consumption Model

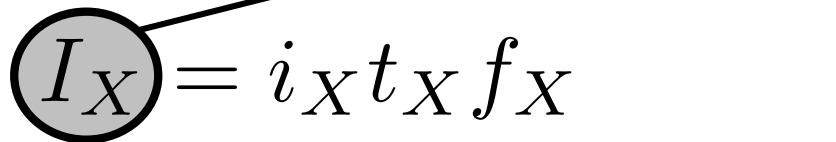
- MAC (channel access)
- Network topology
- Data gathering
- Networking
- Processing

current drawn

average time spent

visits per second

average current
drained


$$I_X = i_X t_X f_X$$

Energy Consumption Model

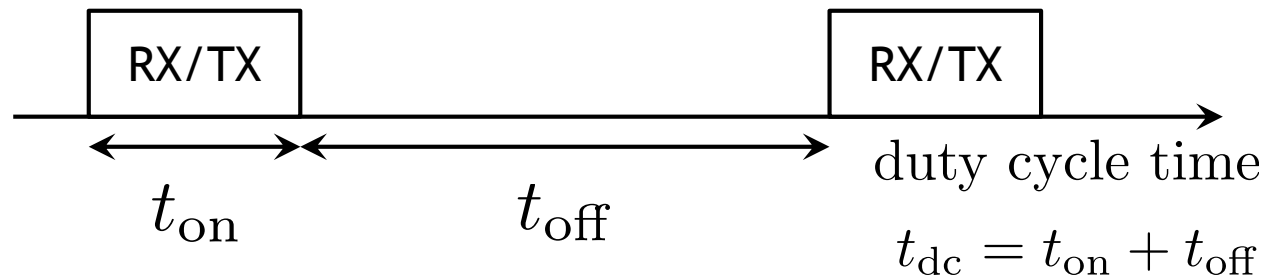
- Adding the contributions from all states

$$I_X = i_X t_X f_X \quad \text{Average current drained in state X}$$

$$r_X = t_X f_X \quad \text{Fraction of time spent in state X}$$

$$\begin{aligned} I_{\text{OUT}} &= \sum_{i \in \mathcal{X}} I_i \\ &= I_{\text{TX}} + I_{\text{RX}} + I_{\text{INT}} + I_{\text{CPU}} + I_{\text{IDLE-ON}} + I_{\text{IDLE-OFF}} \end{aligned}$$

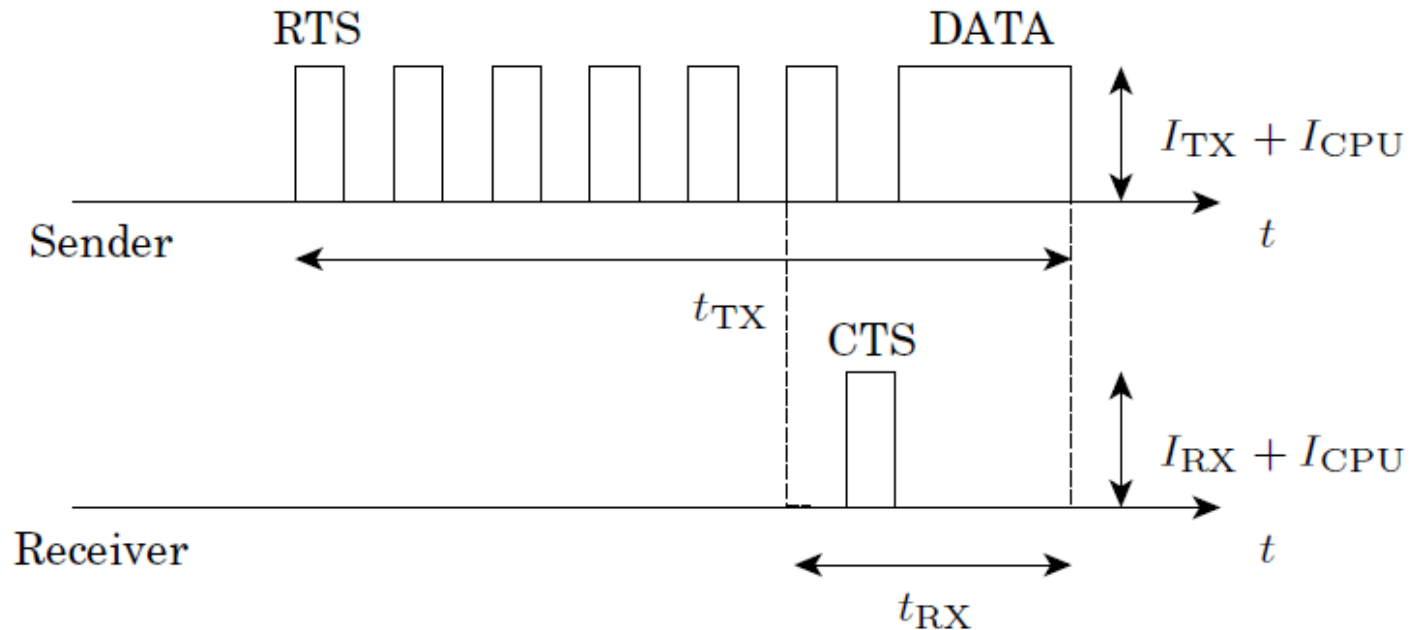
MAC: Duty-cycled WSN



- Energy consumption in TX, RX and IDLE is comparable
- Energy consumption is dominated by the PHY (radio)
- Commonly nodes are operated according to a duty-cycled approach
- **The duty cycle d [%] is defined as:**
$$d = \frac{t_{\text{on}}}{t_{\text{on}} + t_{\text{off}}}$$
- d usually ranges between $0.01 \square 0.1$ (nodes are awake 1 to 10% of the time)

MAC: Access Protocol

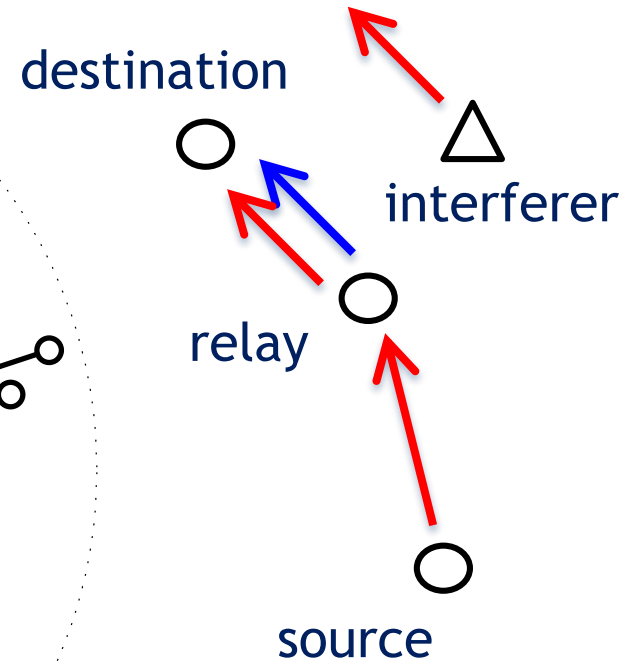
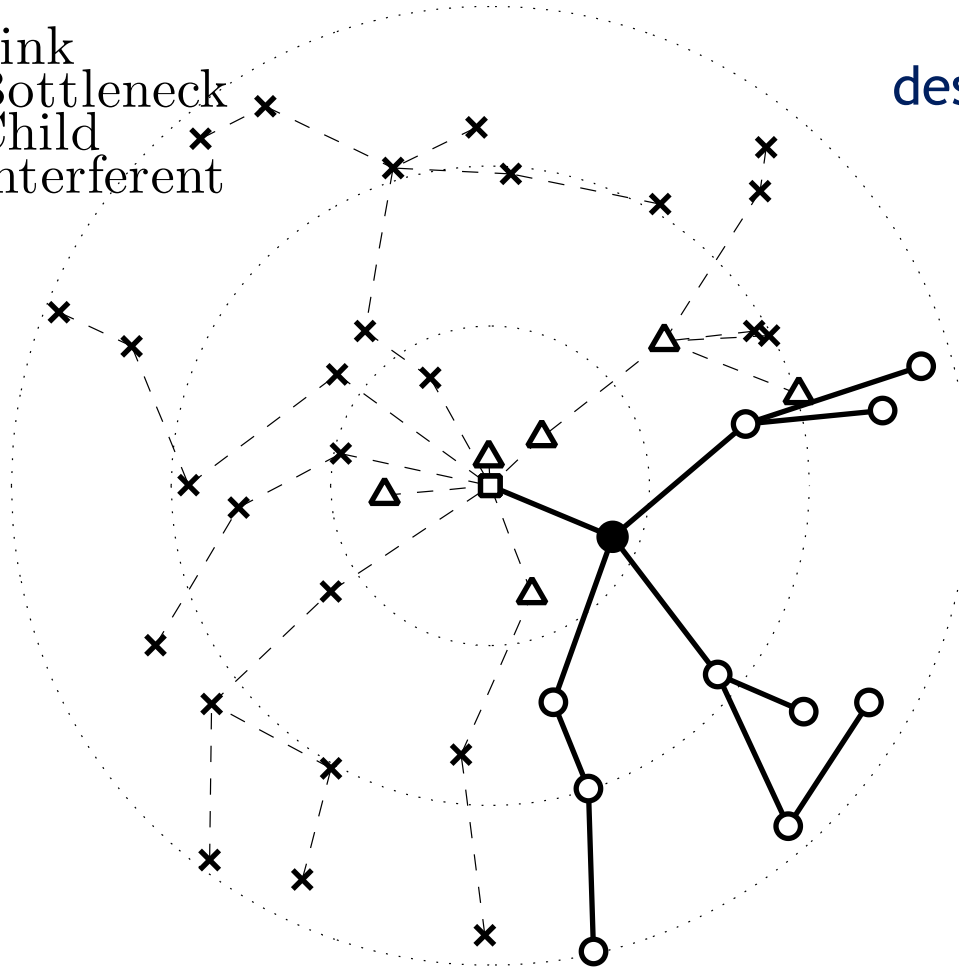
- **X-MAC** is used as the channel access technique
- allows asynchronous communication
- preamble-based, transmitter initiated



$$t_{TX} = t_{on} + t_{off}/2 + t_{data} + (f'_U/f_U - 1)t_{dc}$$

Topology, Routing & Bottleneck

- Sink
- Bottleneck
- Child
- △ Interferent



Topology, Routing & Bottleneck

Bottleneck node is the sensor that, due to its position in the network, is the fastest to deplete its battery

n_c **number of children nodes**, i.e., total number of nodes in the sub-tree rooted at the bottleneck

n_i **number of interfering nodes** (within the transmission range of the bottleneck)

n_{int} **accumulated number of interfering packets from interfering nodes**, accounting for endogenous (their own transmissions) and exogenous (transmissions of their children nodes) traffic

Data Gathering and Networking

- Data gathering requires all nodes to periodically send information to the sink
- Networking implies a bi-directional communication among all nodes

$$f_{\text{TX,DG}} = (1 + n_c)/t_U$$

$$f_{\text{RX,DG}} = n_c/t_U$$

$$f_{\text{TX,RPL}} = (2 + n_c)/t_{\text{rpl}}$$

$$f_{\text{RX,RPL}} = (1 + n_i + n_c)/t_{\text{rpl}}$$

Optimization Problem P1

$t_U \rightarrow$ average inter-packet transmission time

$t_{dc} \rightarrow$ duty cycle period ($t_{dc} = t_{on} + t_{off}$)

$I_{OUT} \rightarrow$ average current drained

$u \rightarrow$ maximum current drained

($u \rightarrow$ control action set by P2)

Optimization Problem P1

$$\underset{t_U, t_{dc}}{\text{maximize}} \quad f_U$$

$$\text{subject to: } I_{OUT} \leq u,$$

$$r_x \geq 0, \quad \forall x \in \chi_N,$$

$$t_U \geq 0, \quad t_{dc} \geq t_{on}.$$

- Constraints are polynomials
 - Convex optimization is possible
- Closed-form solution is available

Optimization Problem P1

- Problem setup:
 - Hardware defines consumption figures
 - MAC defines timings
 - Routing and topology define relays and bottleneck
- Result (t_U^*, t_{dc}^*)
 - Data gathering time and Duty-cycle
 - Achieving the maximum throughput
 - Subject to the given consumption \mathcal{U}

Example: Parameters

Timings

$$t_{\text{on}} = 6 \text{ ms}$$

$$t_{\text{off}} = 14 \text{ ms}$$

$$t_{\text{int}} = 10 \text{ ms}$$

$$t_{\text{CPU}} = 40 \text{ ms}$$

$$t_{\text{RPL}} = 6 \text{ h}$$

Energy

$$i_{\text{TX}} = 10 \text{ mA}$$

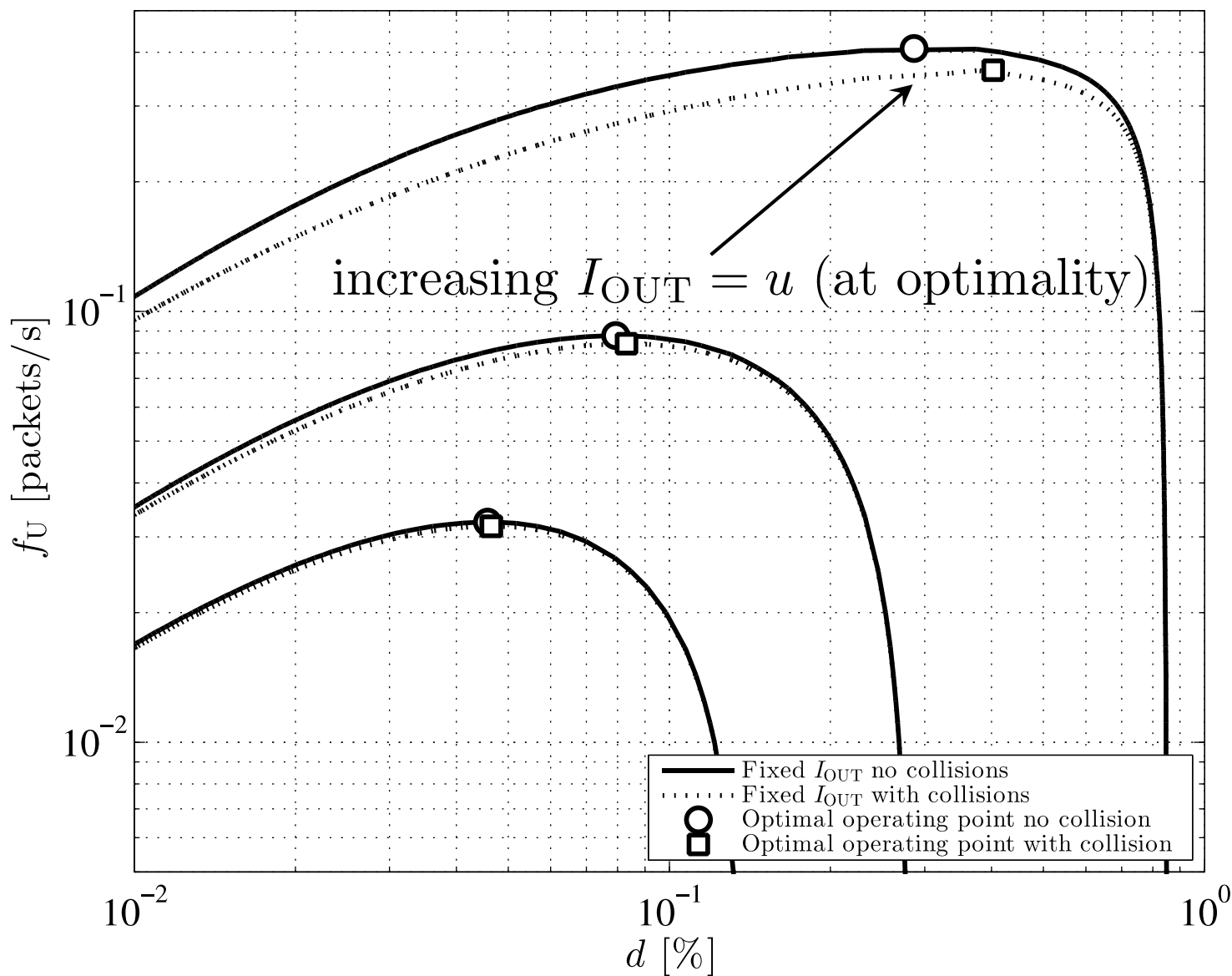
$$i_{\text{RX}} = 8.7 \text{ mA}$$

$$i_{\text{CPU}} = 26.6 \text{ mA}$$

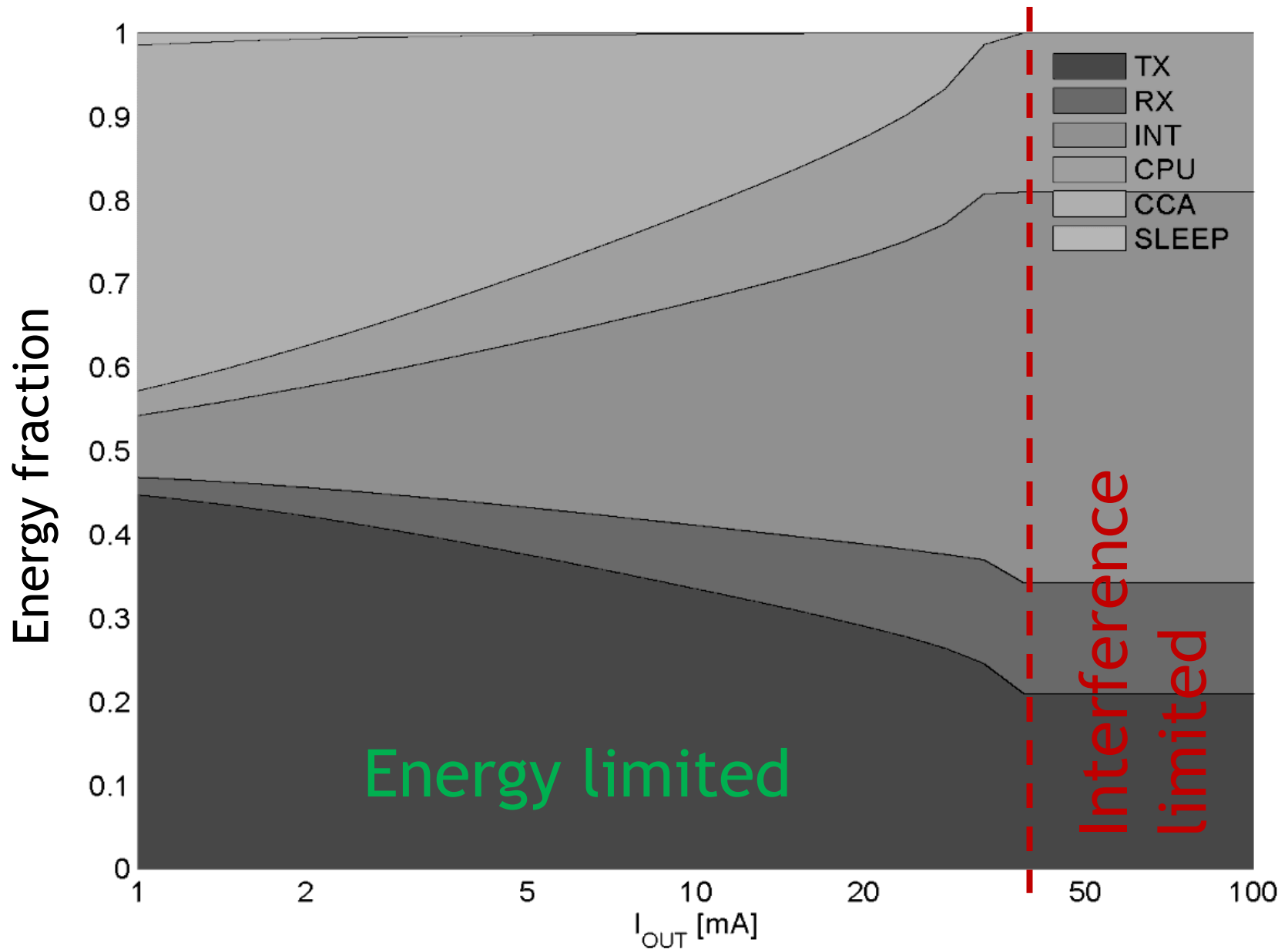
$$i_{\text{S}} = 0.015 \text{ mA}$$

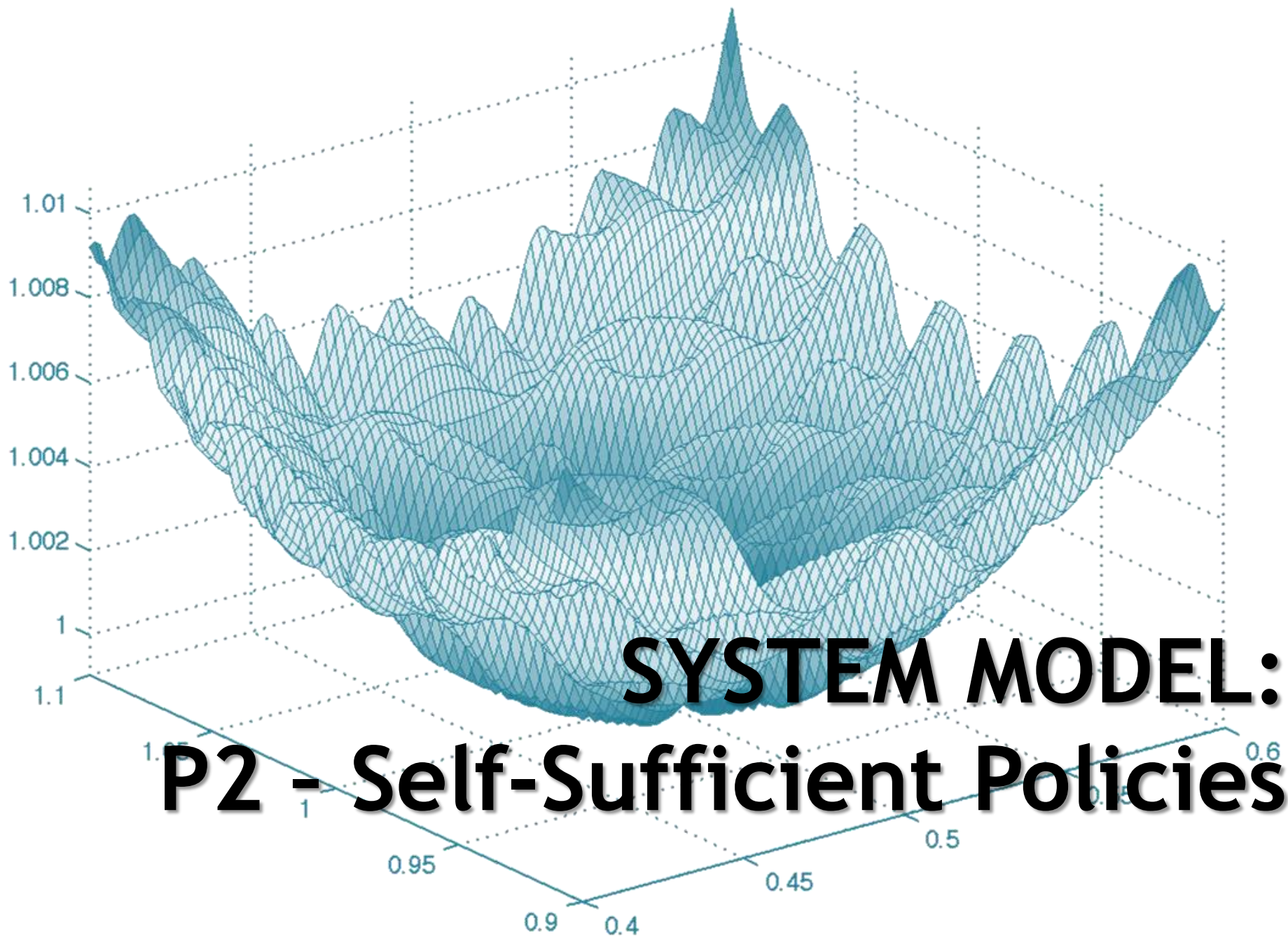
$$K_{\text{U}} = 10$$

Example: Solution



Example: Energy State Breakdown



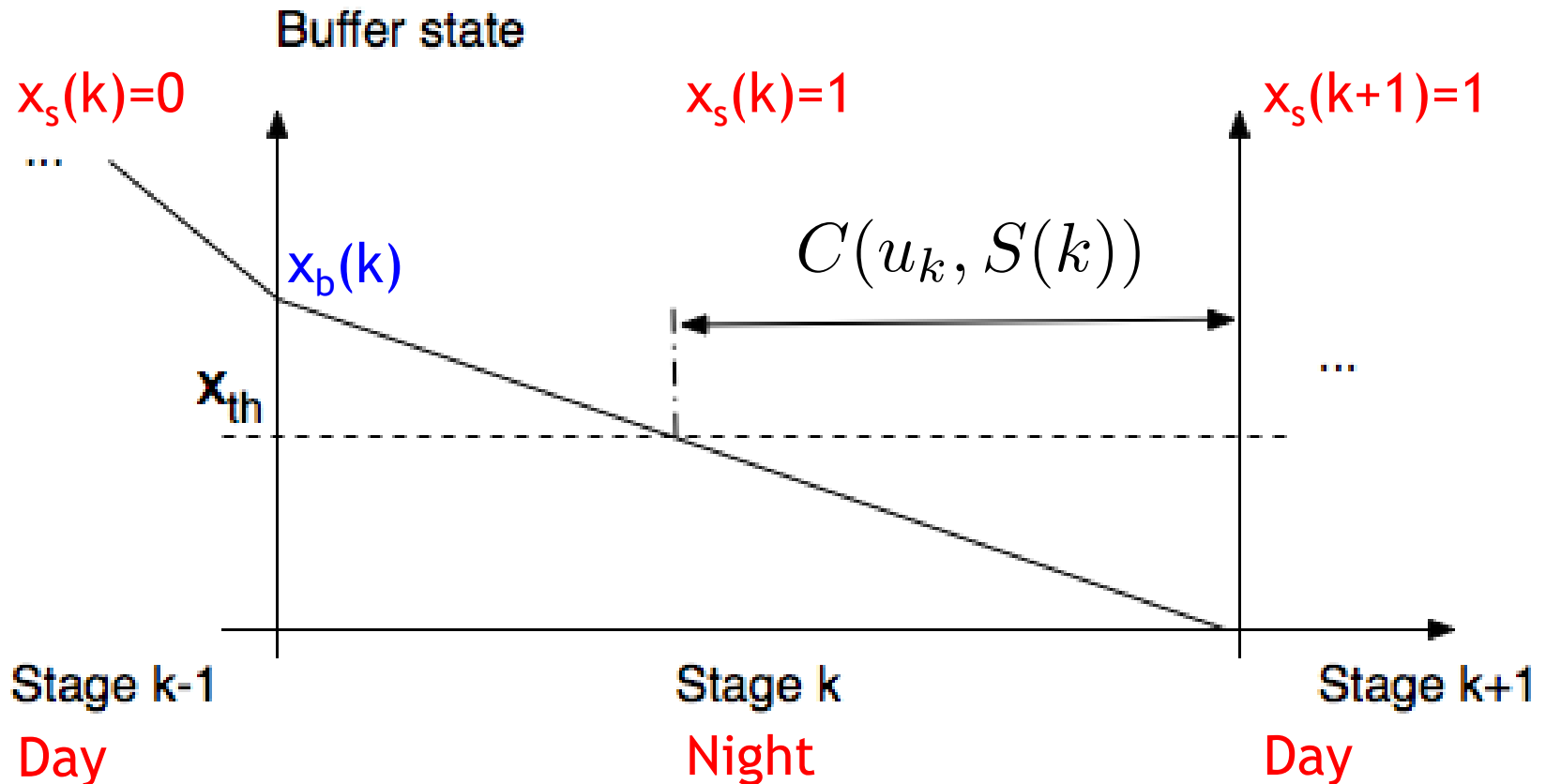


Problem Formulation

- **System state** $S(k)=(x_b(k),x_s(k))$
 - Energy buffer state $x_b(k)$ @ beginning of stage k
 - Energy source state $x_s(k)$ during stage k
- **Control** u_k
 - Current drained by the node (I_{out})
 - Immediate reward $R(u_k,S(k))$ (throughput [pkt/s])
- **Stage-Cost** $C(u_k,S(k))$
 - Average time spent with $x_b(k)<x_{th}(k)$ (outage threshold)
- **Stage-Reward** $R(u_k,S(k))$
 - Total reward: integral of $R(u_k,S(k))$ over the solution path

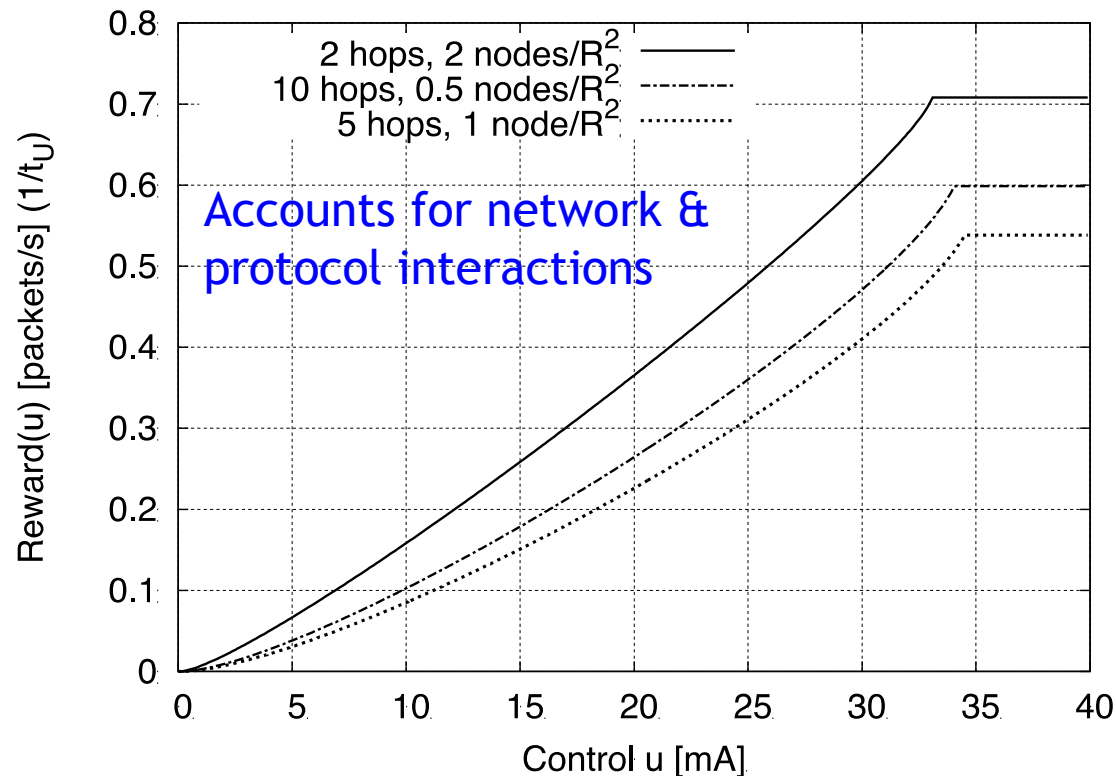
Single Stage Cost

- Average single-stage cost
 - Duration of time interval where $x_b(k) < x_{th}$



Single Stage Reward

- Average reward over a single stage k :
 - $R(u_k, S_k)$ multiplied by the time during which $x_b > 0$ (non-empty buffer)
 - $R(u_k, S_k)$ is obtained from problem P1



Optimal Policies

- Find the policy $\pi: (u_k(S(k)))$, that maximizes the expected long-term throughput (reward)
- Long-term expected cost below a threshold (fraction of time with low buffer state)
- Discount factor α : control the look-ahead capability of the optimal policy

$$\text{maximize}_{\pi} \left\{ \lim_{N \rightarrow +\infty} E \left[\sum_{k=0}^{N-1} \alpha^k R(u_k, S(k)) \middle| S(0) \right] \right\}$$

$$\text{subject to: } \lim_{N \rightarrow +\infty} E \left[\sum_{k=0}^{N-1} \alpha^k C(u_k, S(k)) \middle| S(0) \right] \leq C_{\text{th}}$$

Lagrangian Reward (1)

- A lagrangian λ is introduced to balance
 - Costs $C(u_k, S(k))$
 - Rewards $R(u_k, S(k))$
- The lagrangian is part of the solution
 - Choose λ
 - Solve optimal problem for this λ
 - Iterate over λ to find global optimum

$$R_{\mathcal{L}}(u_k, S(k)) = \underline{R(u_k, S(k))} - \lambda \underline{C(u_k, S(k))}$$

Lagrangian Reward (2)

- Large λ : cost prevails
 - Small reward, Small cost
 - cost constraint is satisfied whp
 - λ can be decreased
- Small λ : reward prevails
 - High reward (more aggressive policies), large cost
 - cost constraint is not satisfied
 - λ has to be increased
- Binary search over λ

$$R_{\mathcal{L}}(u_k, S(k)) = \underline{R(u_k, S(k))} - \lambda \underline{C(u_k, S(k))}$$

Lagrangian Bellman Equation

- Expected reward from stake k onwards

$$J(S(k)) = \max_{u_k \in U(S(k))} \left\{ E[R_{\mathcal{L}}(u_k, S(k))] + \alpha \int_{-\infty}^{+\infty} J(S'(k+1)) h(q|x_s(k), u_k) \right\}$$

- Single-stage expected Lagrangian reward
- Discounted future expected reward weighted by the distribution of the charge variation

- Next stage

$$\begin{aligned} S'(k+1) &= (x_s(k+1), x_b(k+1)) \\ &= (1 - x_s(k), \max\{\min\{q + x_b, Q\}, 0\}) \end{aligned}$$

Diffraction grating

$$d \sin \theta = m \lambda \quad (m=0,1,2) \text{ maxima lines}$$

lit separation

$$D = \frac{m}{d \cos \theta} \text{ dispersion}$$

$$f = \frac{\text{radius of curvature}}{2}$$

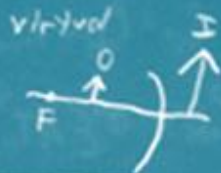
$$R = Nm^{\#} \text{ resolving power}$$

$$\frac{1}{p} + \frac{1}{i} = \frac{1}{f} \text{ spherical mirror}$$

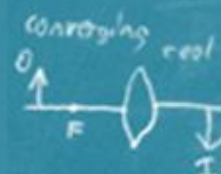
$$|m| = \frac{h'}{h} \quad m = -\frac{i}{p}$$

pos m = same orientation

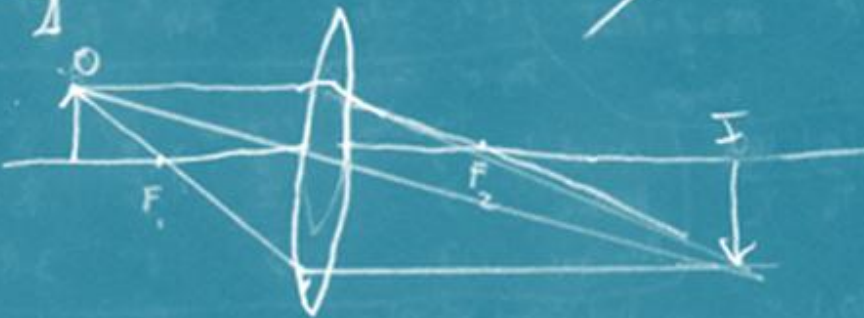
$$M = m_1 \cdot m_2$$



$$\frac{1}{f} = (n-1) \left(\frac{1}{r_1} - \frac{1}{r_2} \right) \quad r_1 \text{ is near object}$$



$$m_{\theta} = \frac{25 \text{ cm}}{f}$$



aperture diameter

$$\Delta \theta_{hw} = \frac{\lambda}{Nd \cos \theta} \text{ half width}$$

Plane mirrors

$$i = -p$$

Obj - S is pos if on same side as incoming light

Img - S' is pos if on same side of outgoing light

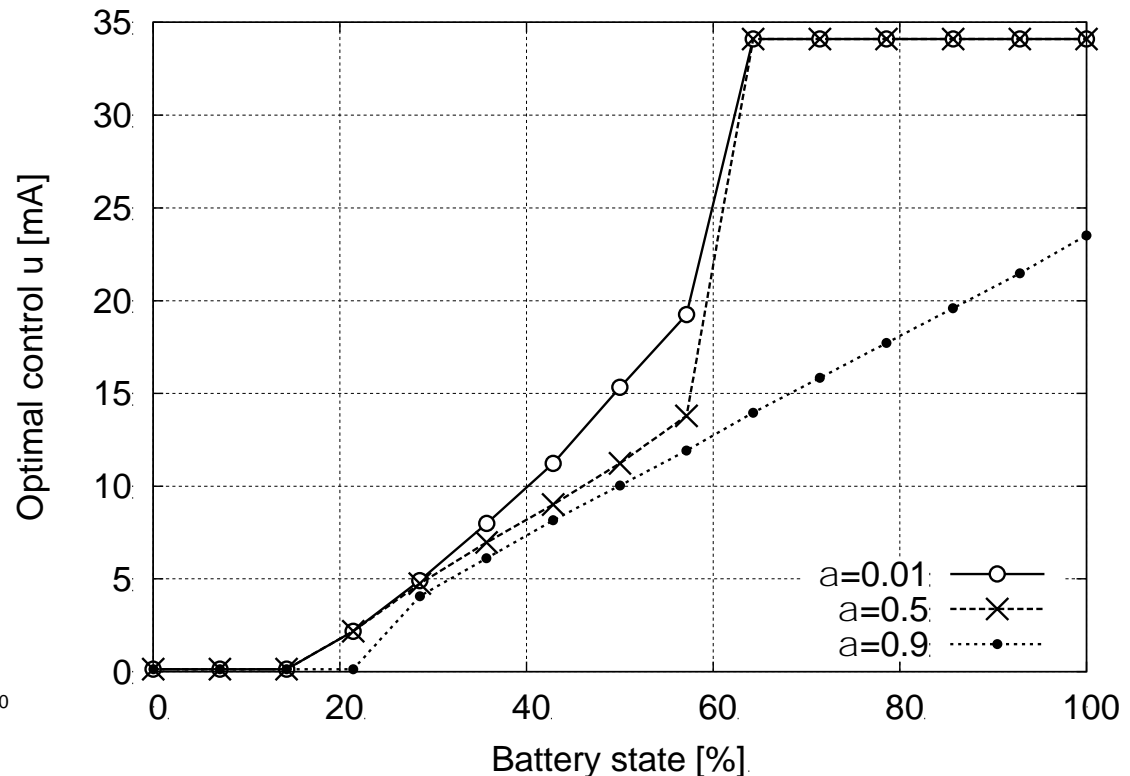
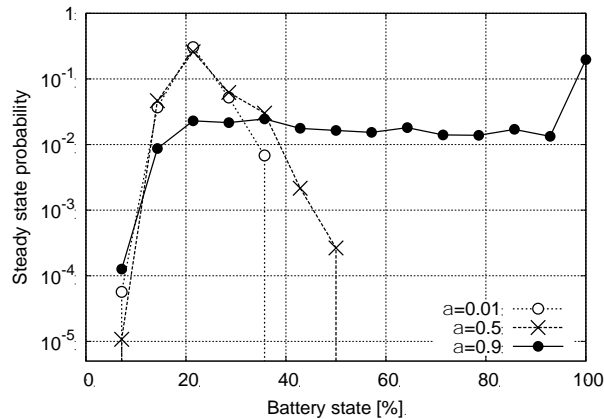
F - pos if on same side of outgoing light



RESULTS

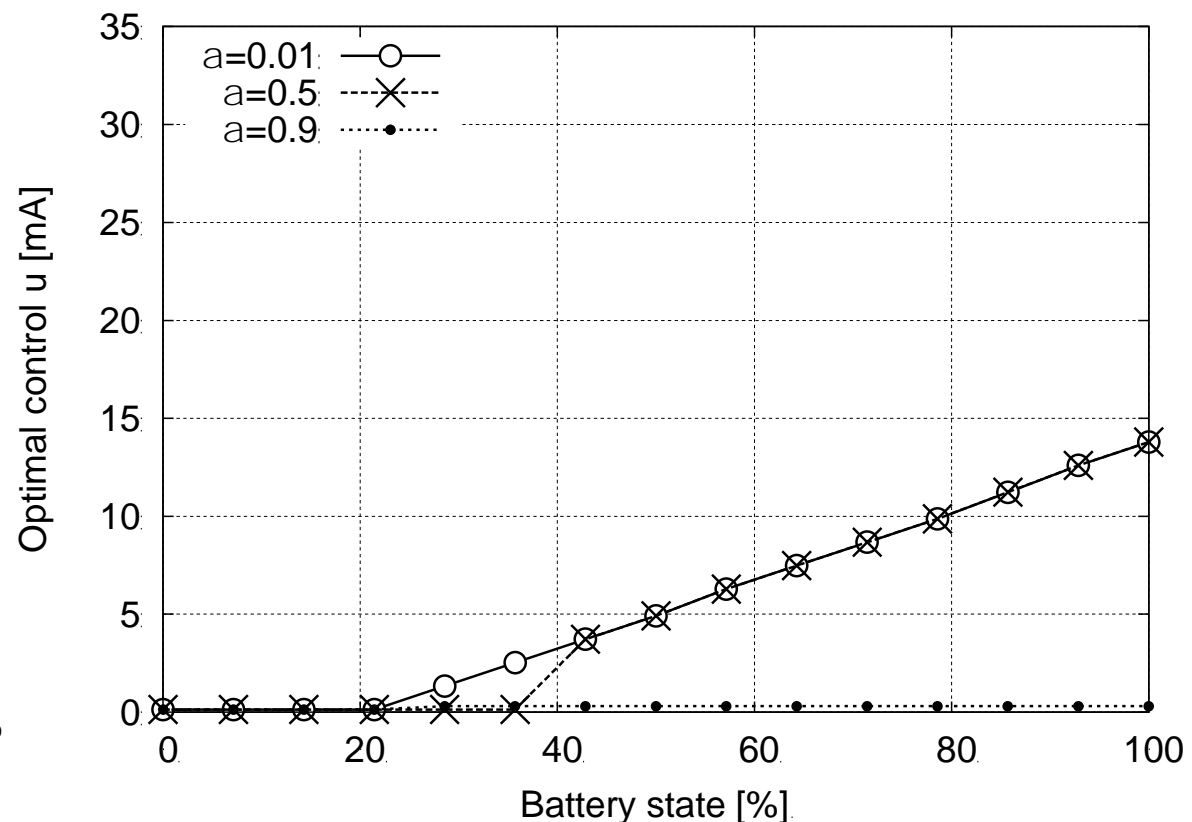
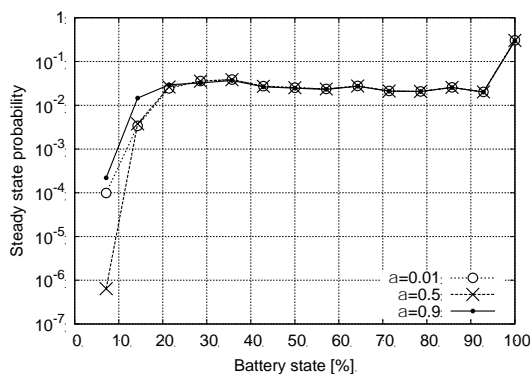
Discount Factor

- A larger discount factor increases the optimization horizon and makes the policies more conservative
- Day



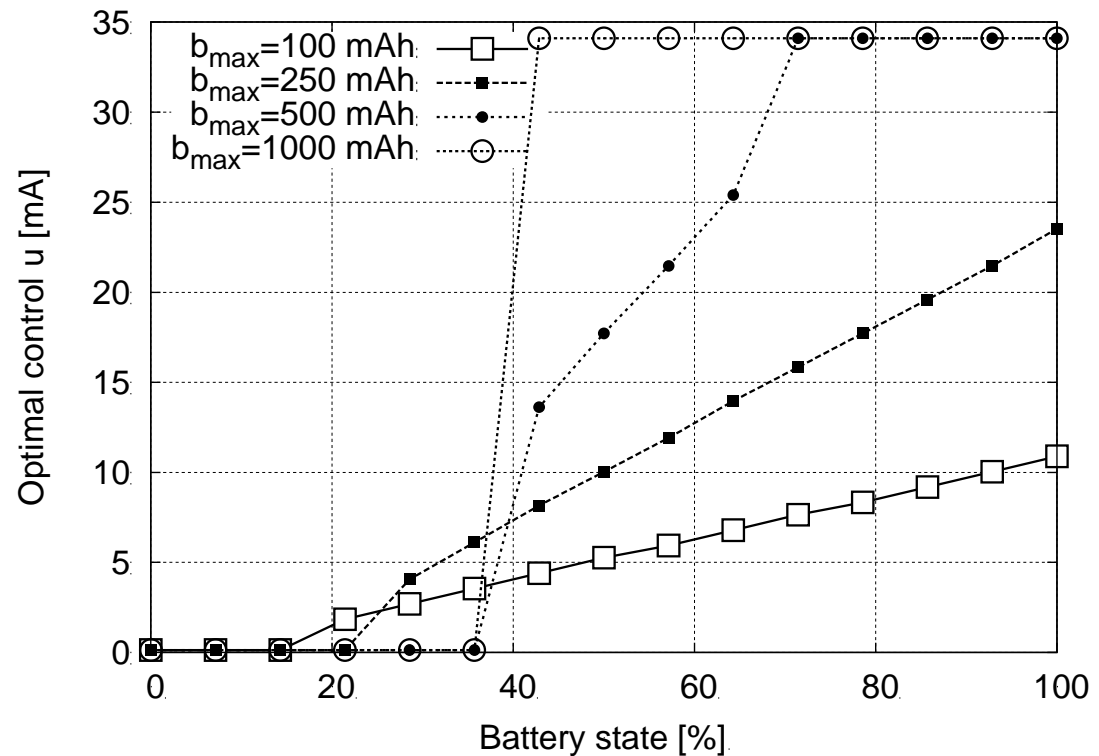
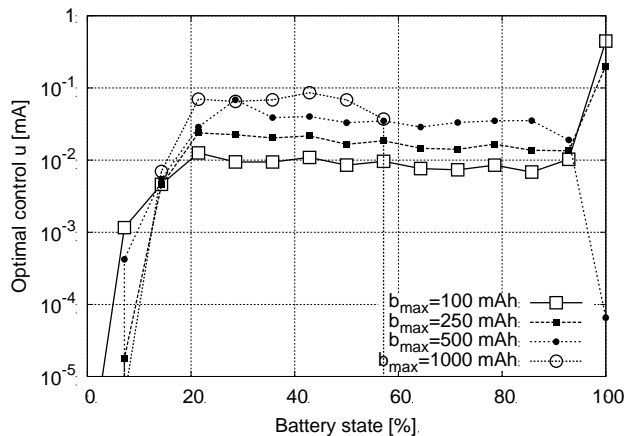
Discount Factor

- A larger discount factor increases the optimization horizon and makes the policies more conservative
- Night



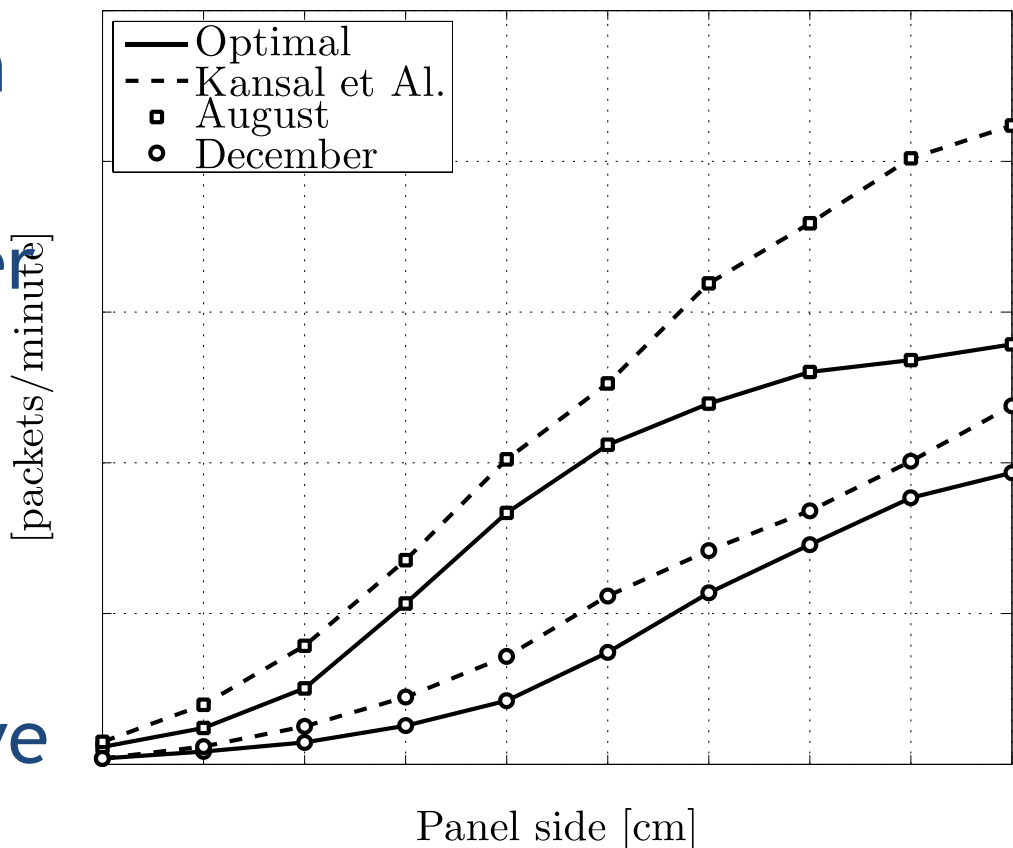
Battery Size

- Larger batteries allows for more aggressive policies with threshold behavior



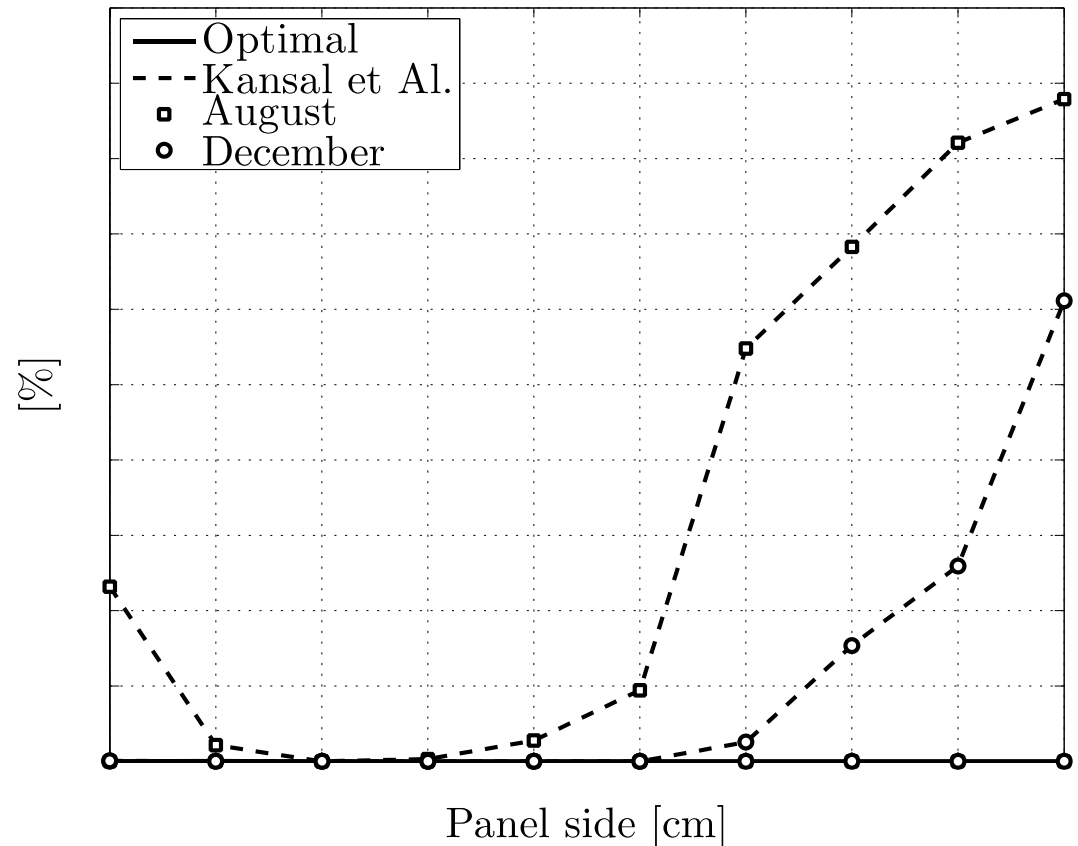
Throughput vs Panel Size

- Kansal et Al. propose a predictive approach that allows for higher throughput, but the aggressiveness is paid with higher outage rate
- Our optimization is bound not to violate the buffer condition
- More conservative



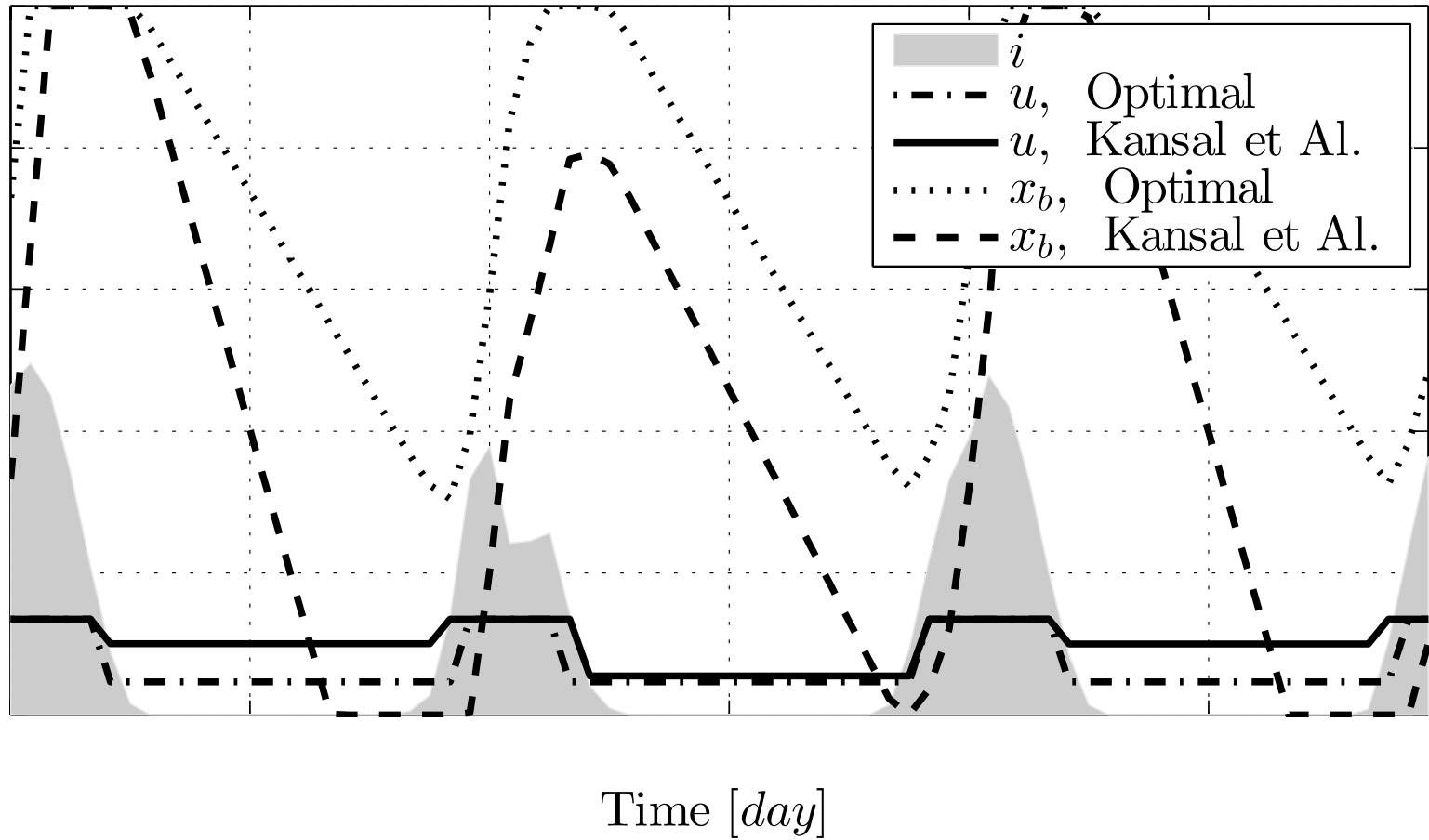
Outage vs Panel Size

- The more aggressive approach cannot prevent battery outage, which instead is avoided by our policies



Time variation

Current [mA] / Battery [mAh]



Bibliography

- [1] N. Bui and M. Rossi, “Staying Alive: System Design for Self-Sufficient Sensor Networks,” *ACM Transactions on Sensor Networks*, Vol.11, No 3, May 2015.
- [2] M. Miozzo, D. Zordan, P. Dini and M. Rossi, “SolarStat: Modeling Photovoltaic Sources through Stochastic Markov Sources,” *IEEE EnergyCon*, Dubvronik, Croatia, May 2014.
- [3] N. Bui and M. Rossi, “Dimensioning Self-Sufficient Networks of Energy Harvesting Embedded Devices,” *WifFex*, Kaliningrad, Russia, September 2013.
- [4] A. Kansal, J. Hsu, S. Zahedi and M. B. Srivastava, “Power management in energy harvesting sensor networks,” *ACM Transactions on Embedded Computing Systems (TECS)*, Vol. 6, No 4, 2007.

THANKS FOR THE ATTENTION

Self-sufficient Sensor Networks:
from Energy Profiling to Optimal
Sustainable Performance

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(a joint work with Michele Rossi, rossi@dei.unipd.it)

ANY QUESTION?

[Developing the
Science of Networks]



BACKUP SLIDES

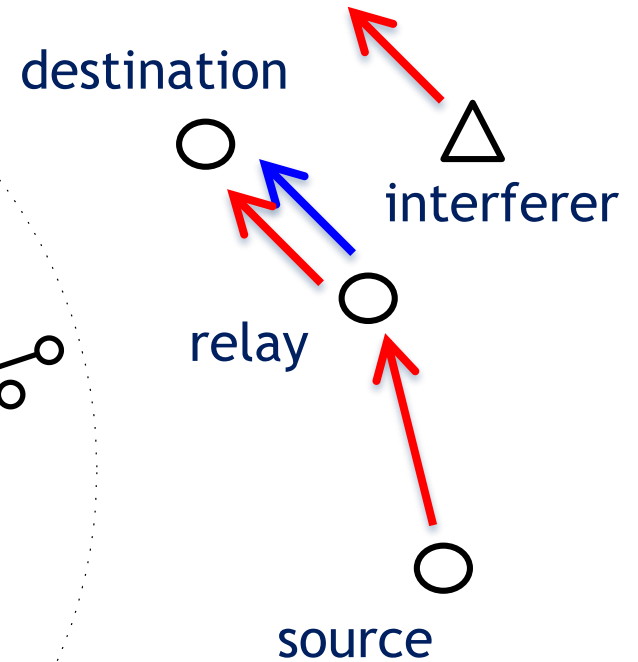
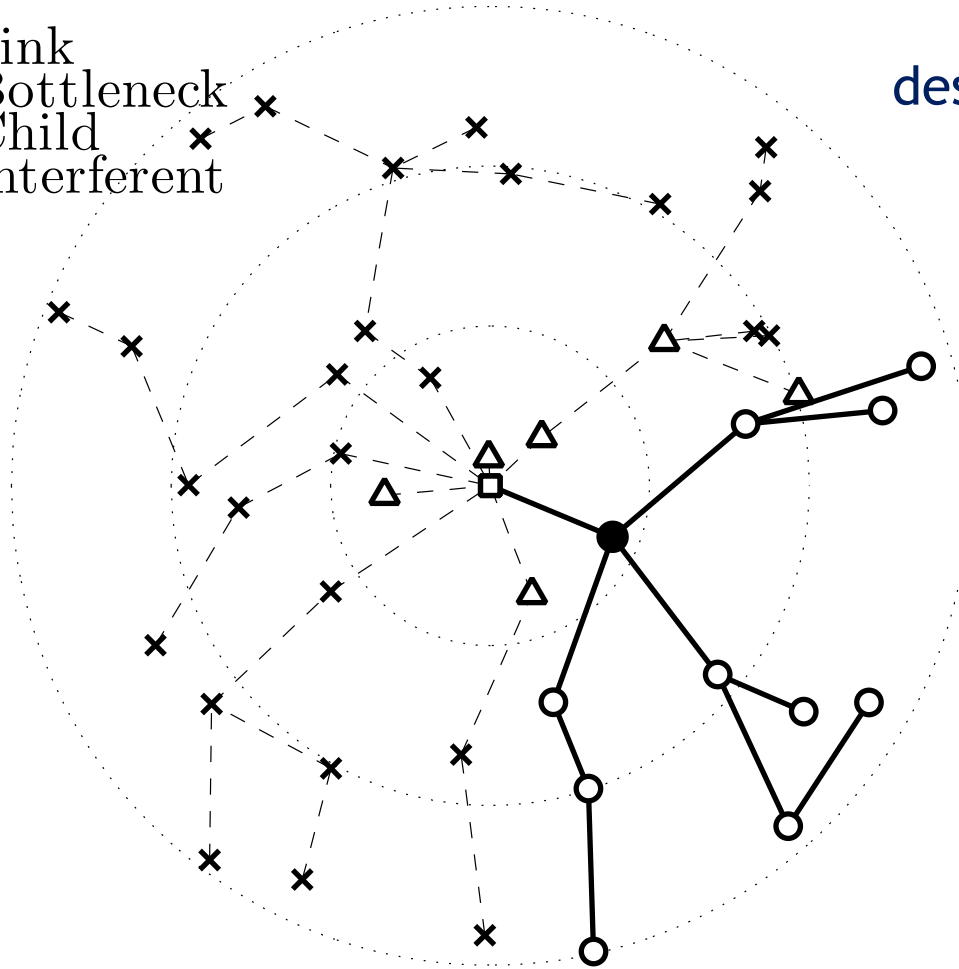
DISCUSSION

- LTE Discontinuous reception
 - Sleep time optimization against application latency
- D2D Communication
 - Terminals may relay traffic from other terminals to the base station

P1: DETAILS

Topology, Routing & Bottleneck

- Sink
- Bottleneck
- Child
- △ Interferent



Topology, Routing & Bottleneck

Bottleneck node is the sensor that, due to its position in the network, is the fastest to deplete its battery

n_c **number of children nodes**, i.e., total number of nodes in the sub-tree rooted at the bottleneck

n_i **number of interfering nodes** (within the transmission range of the bottleneck)

n_{int} **accumulated number of interfering packets from interfering nodes**, accounting for endogenous (their own transmissions) and exogenous (transmissions of their children nodes) traffic

Problem 1: DATA TX, RX

Transmitted and received packets per second due to Data Gathering (DG)

$$f_{\text{TX,DG}} = (1 + n_c)/t_U$$

$$f_{\text{RX,DG}} = n_c/t_U$$

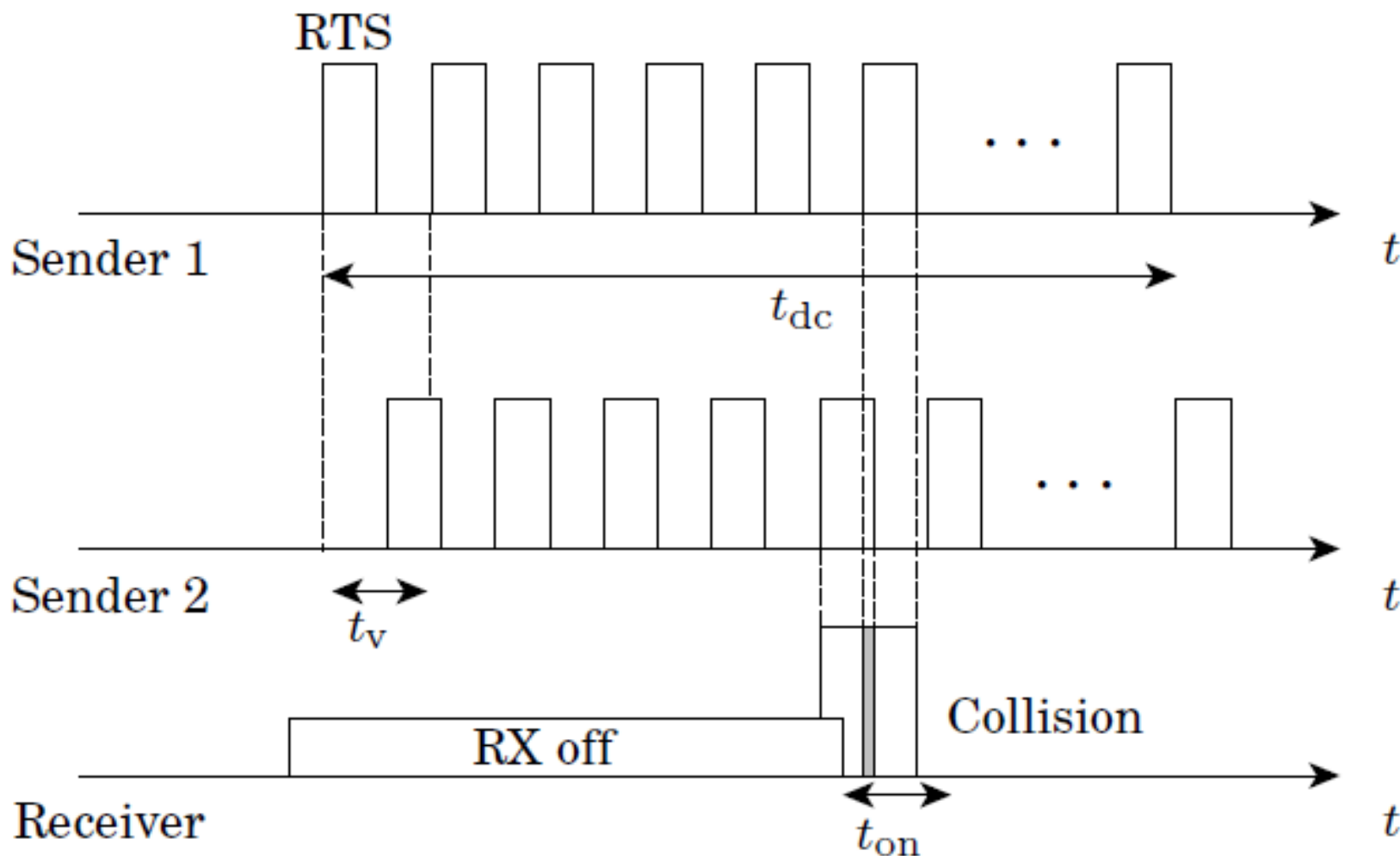
Packet transmission time (including collisions)

$$t_{\text{TX}} = t_{\text{on}} + t_{\text{off}}/2 + t_{\text{data}} + (f'_U/f_U - 1)t_{\text{dc}}$$

f'_U : TX frequency with collisions

f_U : TX frequency wo collisions

Problem 1: Collisions



Problem 1: RPL & DODAG

- Destination Oriented Directed Acyclic Graph (DODAG)
- RPL defines new ICMPv6 messages:
 - Dag Information Object (DIO): carries information that allows nodes to discover an DODAG instance, learn its config pars and select a parent node
 - Destination Advertisement Object (DAO): used to propagate destination information upwards the DODAG
 - Dag Information Solicitation (DIS): to solicitate the TX of a DODAG object from an RPL node (not used in the analysis)

Problem 1: DODAG upward routes

- Nodes periodically send **link-local** (broadcast) DIO messages
- Nodes listen for DIOs and use the information therein to construct a DODAG or maintain an existing one
- Based on the info on the DIOs a node chooses its parent so as to minimize the cost toward the DODAG root
- **Analysis:** DIOs are periodically sent by the nodes at a rate $1/t_{\text{rpl}}$

Problem 1: DODAG downward routes

- Nodes inform parents of their present and reachability to their descendants by sending a DAO message
- DAOs are aggregated at intermediate nodes while sent upstream
- DAOs propagate from the leaves to the DODAG root node
- **Analysis:** DAOs are sent by the leaf nodes at a rate $1/t_{\text{rpl}}$

Problem 1: RPL TX, RX

- 1 DIO and 1 DAO msg from bottleneck, n_c DAOs from its children nodes:

$$f_{\text{TX,RPL}} = (2 + n_c)/t_{\text{rpl}}$$

- 1 DIO from parent, n_c DAOs from children nodes, n_i DIOs from inter. nodes:

$$f_{\text{RX,RPL}} = (1 + n_i + n_c)/t_{\text{rpl}}$$

- DIOs are not treated as interference as they are broadcast (*ergo* they are received and treated as legitimate packets)

Problem 1: interference

- Rate of interfering packets:

$$f_{\text{INT}} = n_{\text{int}}(1/t_U + 1/t_{\text{rpl}})$$

- TX rate for data packets

$$1/t_U$$

- TX rate for RPL DODAG control packets

$$1/t_{\text{rpl}}$$

Problem 1: current consumption figures

TX time for a single pkt transmission

$$I_{TX} = (i_c + i_t) [t_{dc}/2 + t_{on}/2 + t_{data} + (f'_U/f_U - 1)t_{dc}] \times$$

$$\times [(1 + n_c)/t_U + (2 + n_c)/t_{rpl}] \text{ transmissions rate [pps]}$$

$$I_{RX} = (i_c + i_r)t_{data}[n_c/t_U + (1 + n_c + n_i)/t_{rpl}]$$

$$I_{INT} = (i_c + i_r)t_{int}n_{int}(1/t_U + 1/t_{rpl})$$

$$I_{CPU} = i_c t_{cpu} K_U / t_U$$

$$I_{CCA} = (i_c + i_r)d_c r_{IDLE}$$

$$I_{OFF} = i_s(1 - d_c)r_{IDLE}$$

Problem 1: current consumption figures

$$I_{TX} = (i_c + i_t)[t_{dc}/2 + t_{on}/2 + t_{data} + (f'_U/f_U - 1)t_{dc}] \times \\ \times [(1 + n_c)/t_U + (2 + n_c)/t_{rpl}]$$

$$I_{RX} = (i_c + i_r)t_{data}[n_c/t_U + (1 + n_c + n_i)/t_{rpl}]$$

$$I_{INT} = (i_c + i_r)t_{int}n_{int}(1/t_U + 1/t_{rpl})$$

$$I_{CPU} = i_c t_{cpu} K_U / t_U \Rightarrow \text{CPU time due to pkt generation}$$

$$I_{CCA} = (i_c + i_r)d_c r_{IDLE} \Rightarrow \text{CPU time due to IDLING - RADIO ON}$$

$$I_{OFF} = i_s(1 - d_c)r_{IDLE} \Rightarrow \text{CPU time due to IDLING - RADIO OFF}$$

$$r_{IDLE} = 1 - r_{TX} - r_{RX} - r_{INT} - r_{CPU}$$

Problem 1: closed-form solution

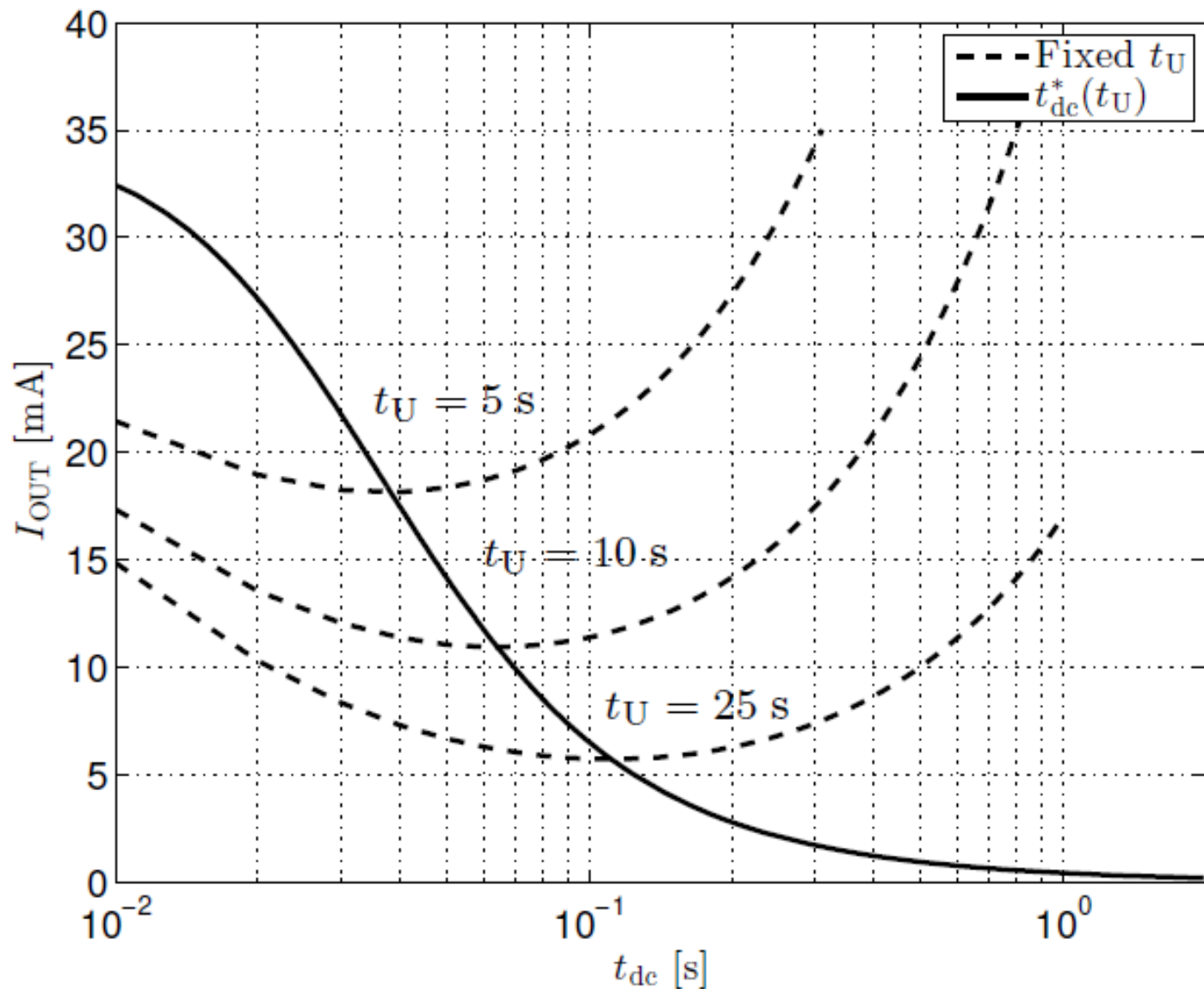
$$I_{\text{OUT}}(t_{\text{U}}, t_{\text{dc}}) = \sum_{i \in \mathcal{X}} I_i \quad \text{Total power consumption}$$

$$\frac{\partial I_{\text{OUT}}(t_{\text{U}}, t_{\text{dc}})}{\partial t_{\text{dc}}} = 0 \rightarrow t_{\text{dc}}^*(t_{\text{U}}) \quad \text{Optimal duty-cycle}$$

$$I_{\text{OUT}}(t_{\text{U}}, t_{\text{dc}}^*(t_{\text{U}})) - u = 0 \rightarrow t_{\text{U}}^*(u) \\ u \in [u_{\min}, u_{\max}]$$

$t_{\text{U}}^*(u)$ Min. inter-packet TX time for given u

Problem 1: optimal duty-cycle



TECHNICAL SOLUTIONS

Heuristic (1/2)

Heterogeneous buffer states

- DAOs are used to periodically report data (status of the nodes, etc.) to the DODAG root (i.e., the sink)
- We use these messages to periodically collect the energy buffer status of all nodes
- The sink decides which policy to adopt based on the minimum among all buffer states, $\min_i (B_i)$

Heuristic (2/2)

- The optimal policy is computed for the bottleneck node (worst case network parameters)
- This policy is used to decide the maximum energy consumption level for all nodes...
- ...based on the minimum among all buffer states, $\min_i (B_i)$

Outcome

- Policy will be suboptimal
- But will assure energy sustainability at all nodes

Heuristic - Results (1/2)

- **BN:** bottleneck node
- **SBN:** second-bottleneck node
 - Located in the sub-tree originating from the BN
 - With the second-highest energy consumption
- **Worst case assumption**
 - The SBN has the same parameters n_i , n_{int} as the BN
 - As just one node less as its number of children, i.e., $n_c - 1$

Heuristic - Results (2/2)

