Adaptive Power Management for Real-Time Event Streams

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Eidgenössische Technische Hochschule Zürich
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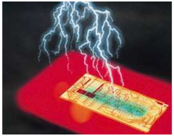
Problem Context

Power Dissipation

- Dynamic power consumption
- Static power consumption (leakage)



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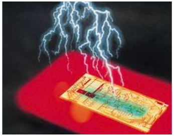

Energy Saving

- Dynamic Voltage Scaling
- Dynamic Power Management

Motivation

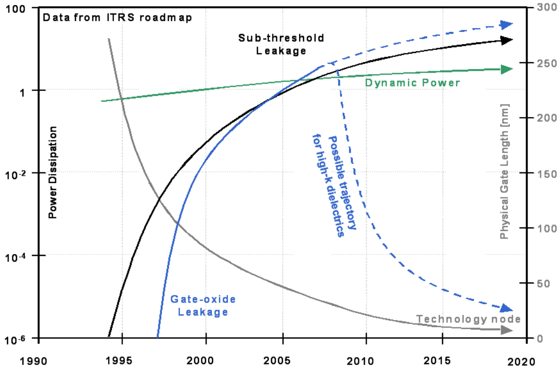

Figure1: ITRS Technology Roadmap: Power Trends.

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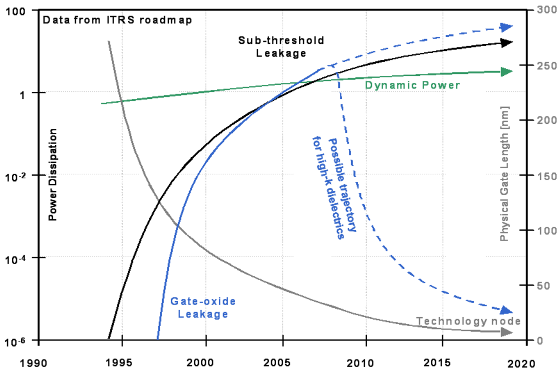


Figure1: ITRS Technology Roadmap: Power Trends.

The leakage power is comparable to or even more than the dynamic power dissipation

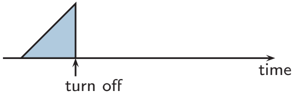
⇒ *Reducing the leakage power is crucial*

Challenges

- When to turn off
  - mode switch overhead

  $\Rightarrow$ Break Even Time

- When to turn off
  - mode switch overhead
  - ⇒ Break Even Time



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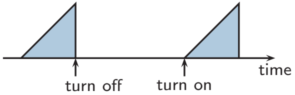

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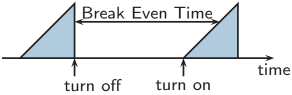

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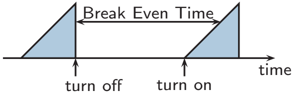

- When to turn on
  - as late as possible
  - cope with future burstiness

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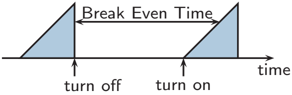

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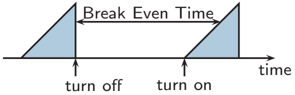

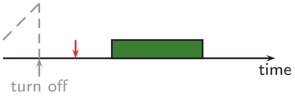

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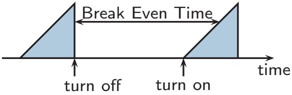

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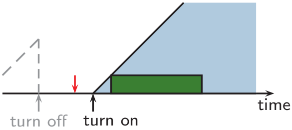

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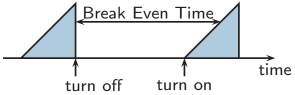

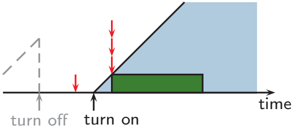

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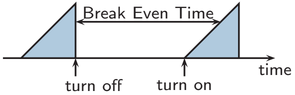

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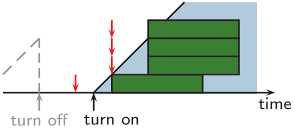

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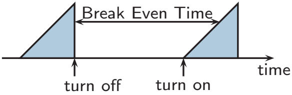

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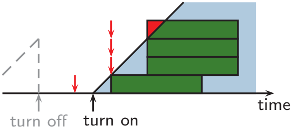

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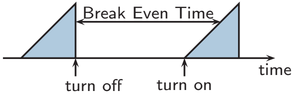
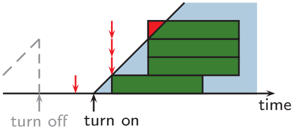
⇒ more complex for multiple streams





- Extend our online algorithms in RTSS'09 which adaptively control the power mode of a system (device) by
  - predicting the next moment for mode switch by considering both historical and future event arrivals
  - procrastinating the buffered and future events as late as possible without violating the timing and backlog constraints
- Propose method to cope with multiple streams with
  - preemptive fixed-priority scheduling
  - preemptive earliest-deadline-first scheduling
- Apply to streams with different characteristics to demonstrate the effectiveness

Outline

1. Introduction
2. Underlying Mathematical Model
3. Our Algorithms
4. Experimental Results

Model of Event Arrivals

- Traditionally
  - Periodic Real-Time Tasks
  - Sporadic Real-Time Tasks
  - ....

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- Traditionally
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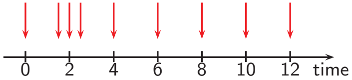
- Nowadays
  - Arrival curves
  - ⇒ Maximum/minimum arriving demand in *any interval* of length, e.g. 3 s



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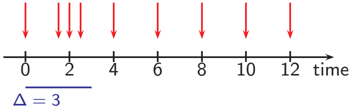

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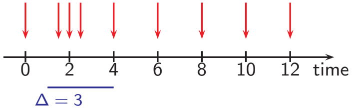

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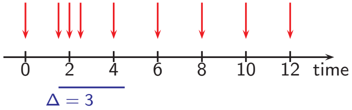

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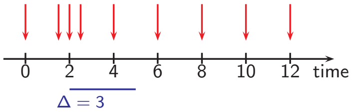

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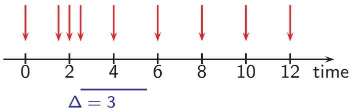

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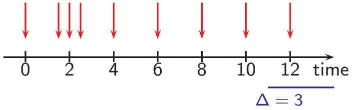

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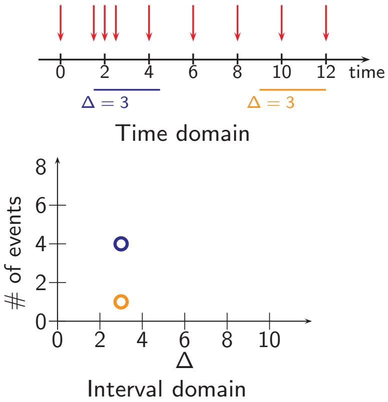

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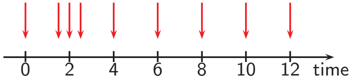

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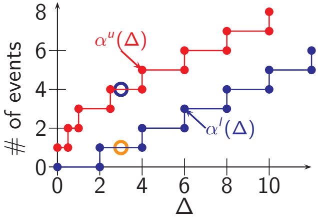

Interval domain

Model of Event Arrivals

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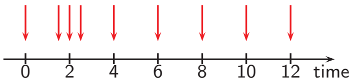
  - Arrival curves generalize traditional event models and are suitable to represent complex characteristics of event streams



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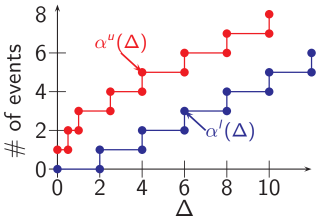

Interval domain

- Service curves
  - ⇒ Maximum/minimum available service in *any interval* of length Δ for the whole time span

Model of Resource Service

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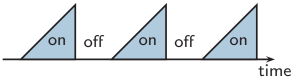

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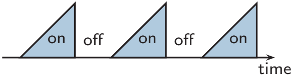

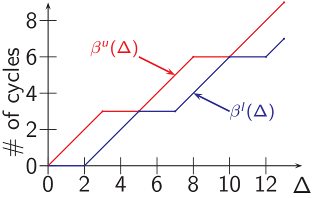

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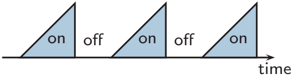

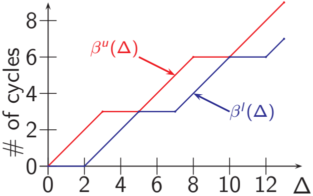

  - ▷ Service curves generalize different resource models

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  Given:

  - α is the stream arrival curve
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  $\Rightarrow$ maximum delay D

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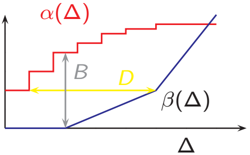

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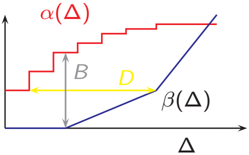

- Scheduling Analysis

  Suppose:
  - α is the stream arrival curve
  - D is the deadline of the stream
  - $\beta^A = \alpha(\Delta - D)$ is service demand of α
  - β^G is the service guarantee
  - $\Rightarrow$ the event stream is schedulable iff

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Analysis

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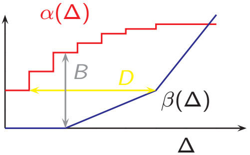

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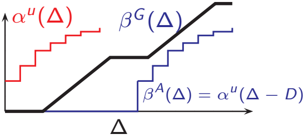

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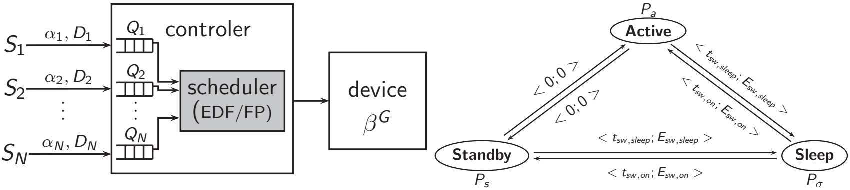
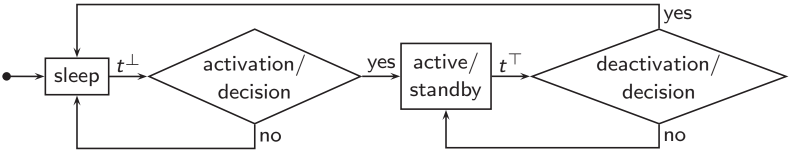


- System model
  - a device is managed by a controller
  - distributed backlogs to buffer events for each stream
  - events of different streams scheduled with EDF/FP policies
- Power model
  - *active* mode with power consumption P_a
  - *standby* mode with leakage power consumption P_s
  - *sleep* mode with power consumption P_δ
  - mode switch overhead: Break even time T_{BET}

The Control Flow of Our Approach

- Control flow



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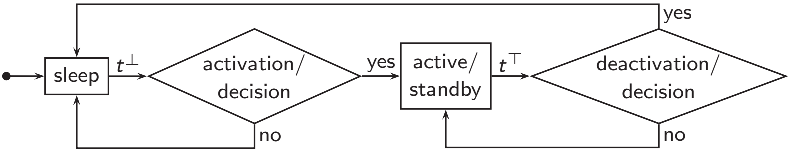

- Activation & Deactivation scheduling decisions
  - History Aware Deactivation (HAD) algorithm
  - Worst Case Greedy (WCG) activation algorithm
  - Event Driven Greedy (EDG) activation algorithm

Basic Routines

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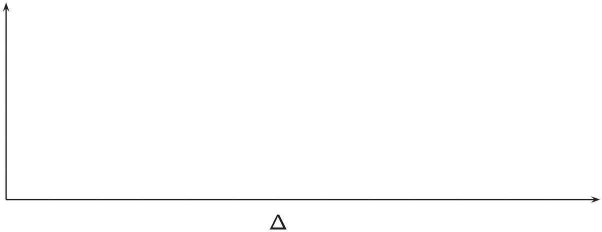

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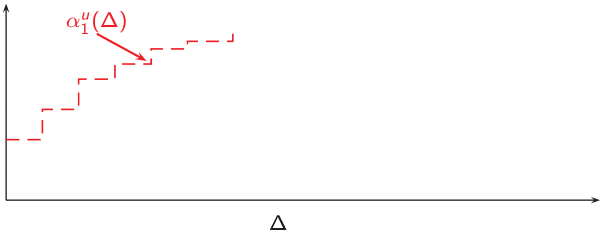

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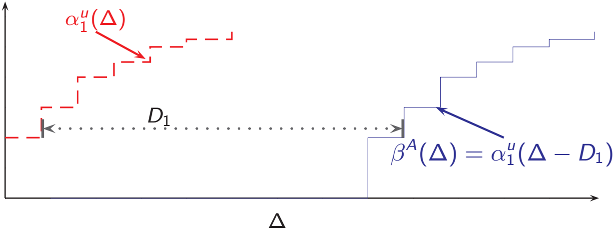

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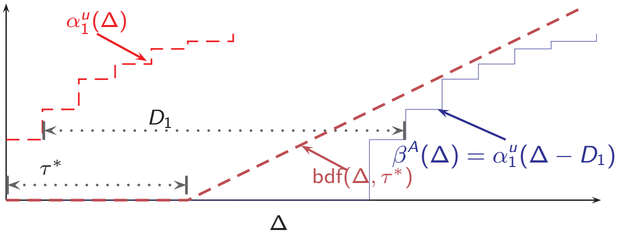

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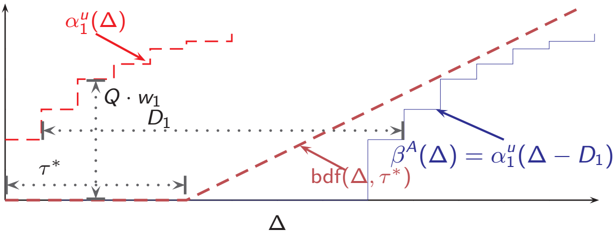

Basic Routines

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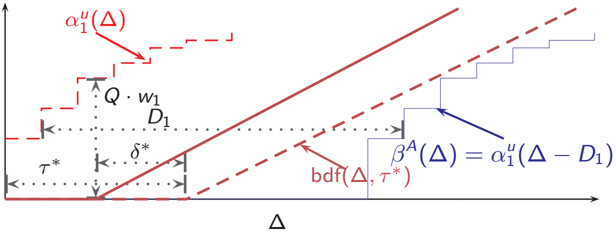

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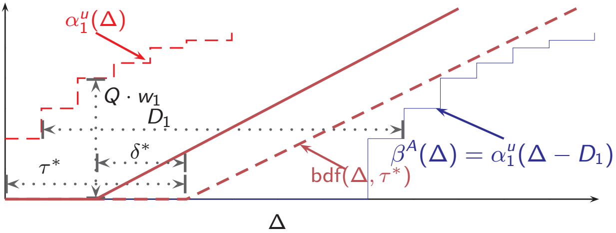
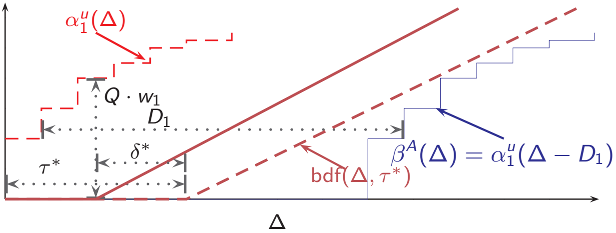
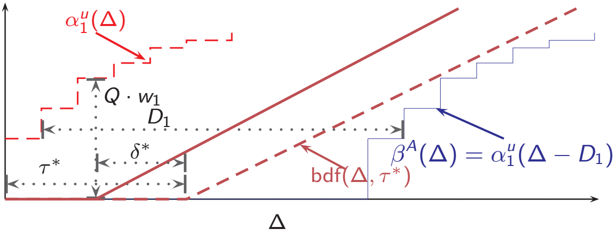


- Bounded delay function: **bdf**(Δ, τ)



- History aware arrival curve: $\alpha^u(\Delta, t)$

- Bounded delay function: $\mathbf{bdf}(\Delta, \tau)$



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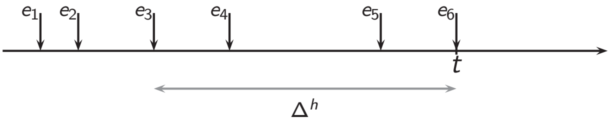

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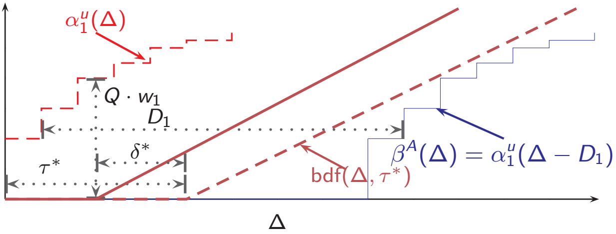

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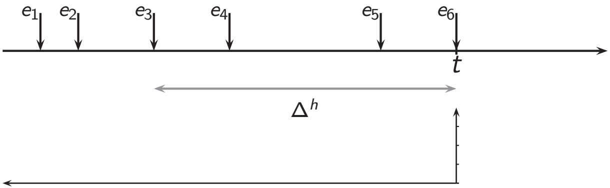

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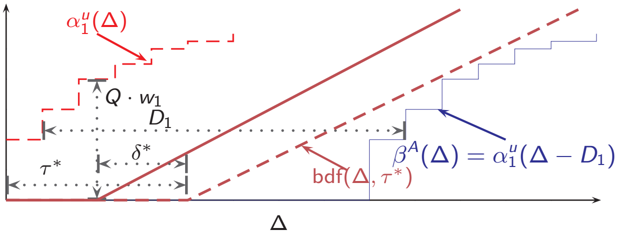

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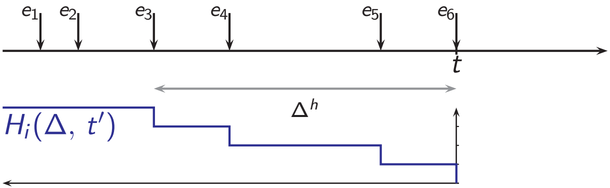

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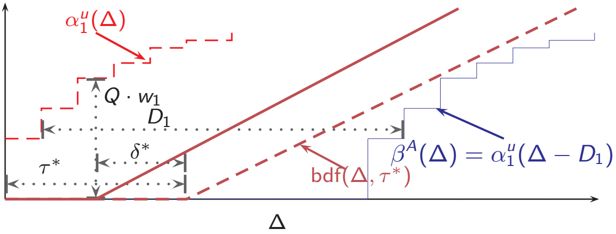

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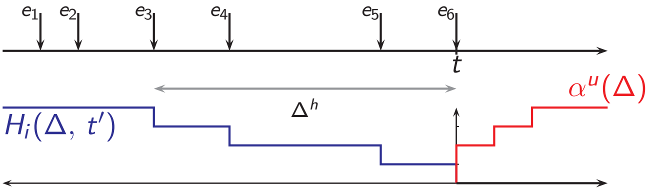

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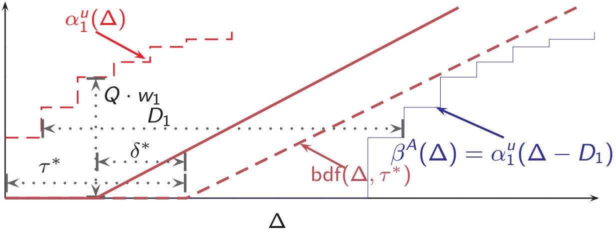

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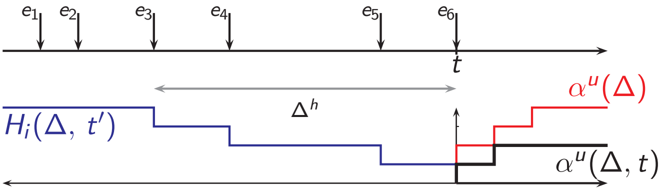

- Bounded delay function: $\mathbf{bdf}(\Delta, \tau)$

$$\mathbf{bdf}(\Delta, \tau) = \max\{0, (\Delta - \tau)\}, \forall \Delta \geq 0$$
$$\tau^* = \max\{\tau : \mathbf{bdf}(\Delta, \tau) \geq \beta^A(\Delta), \forall \Delta \geq 0\}$$
$$\delta^* = \max\left\{0, \min\{\delta : \alpha_i^u(\Delta) - \mathbf{bdf}(\Delta, \tau^* - \delta) \leq Q_i \cdot w_i, \forall \Delta\}\right\}$$

- History aware arrival curve: $\alpha^u(\Delta, t)$

$$H_i(\Delta, t') = \begin{cases} R_i(t') - R_i(t - \Delta), & \text{if } \Delta \leq \Delta^h; \\ R_i(t') - R_i(t' - \Delta^h), & \text{otherwise.} \end{cases}$$

$$\alpha_i^u(\Delta, t') \leq \inf_{\lambda \geq 0} \left\{\alpha_i^u(\Delta + \lambda) - H_i(\lambda, t')\right\}$$

Activation & Deactivation Algorithms

- History Aware Deactivation (HAD) algorithm
  - idea: turn off when the sleep interval can be larger than the break even time
- Worst Case Greedy (WCG) activation algorithm
  - idea: reevaluate when at the previous predication time
- Event Driven Greedy (EDG) activation algorithm
  - idea: reevaluate upon every event arrival
- Details refer to RTSS'09

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⇒ Key: How to compute a *valid but tight* service demand β^A

Computing Flow for Multiple-Stream Scenario

history-aware future arrival: α_i^u

↓

backlogged-aware and backlog-constrained demands: $\beta_i^\flat, \beta_i^\dagger$

↓

individual stream service demand β_i^*

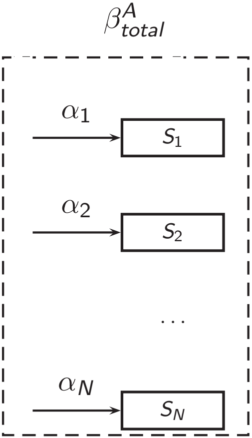
↓

total service demand β_{total}^A

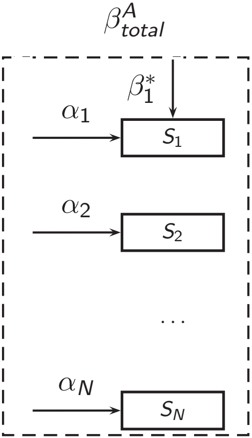
↓

bounded delay τ_{total} from β_{total}^A

Preemptive Fixed-Priority Scheduling



Preemptive Fixed-Priority Scheduling



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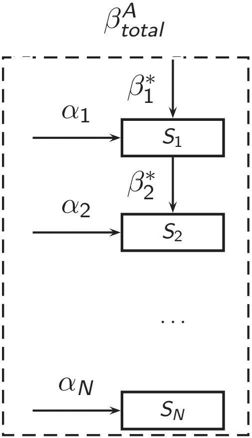

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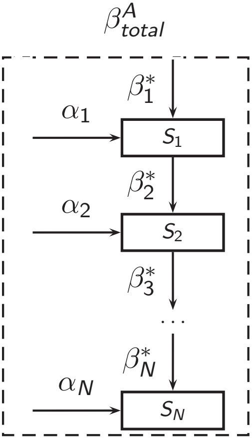

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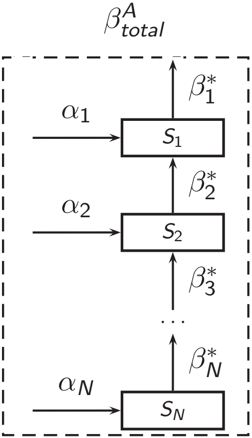

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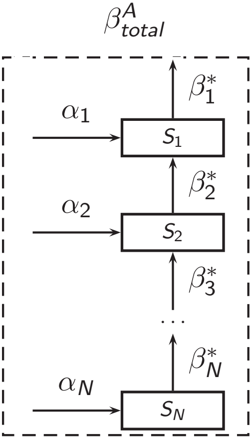
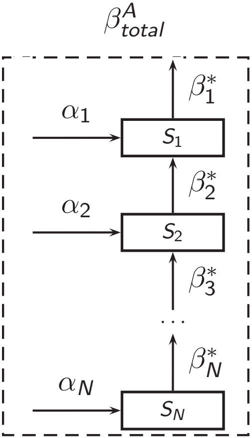


$$\beta^*_N(\Delta, t') = \max\{\beta^\flat_N(\Delta, t'), \beta^\dagger_N(\Delta, t')\}$$

Preemptive Fixed-Priority Scheduling



$$\beta^*_{k-1}(\Delta) = \max\left\{\beta^\sharp_{k-1}(\Delta),\, \beta^\flat_{k-1}(\Delta,\, t'),\, \beta^\dagger_{k-1}(\Delta,\, t')\right\}$$

$$\beta^\sharp_{k-1}(\Delta) \geq \inf\left\{\beta : \beta^*_k(\Delta,\, t') = \sup_{0\leq\lambda\leq\Delta}\left\{\beta(\lambda) - \alpha^u_{k-1}(\lambda,\, t')\right\}\right\}$$

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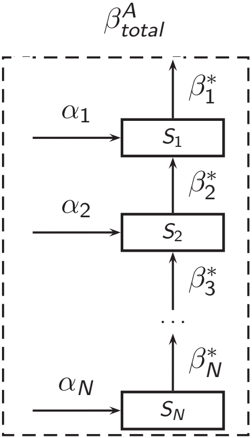
Preemptive Fixed-Priority Scheduling



$$\beta^A_{total}(\Delta) = \beta^*_1(\Delta)$$

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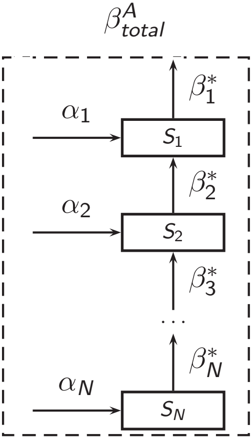

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$$\tau_{total} = \max\left\{\tau : \mathbf{bdf}(\Delta, \tau) \geq \beta^*_1(\Delta),\ \forall\Delta \geq 0\right\}$$

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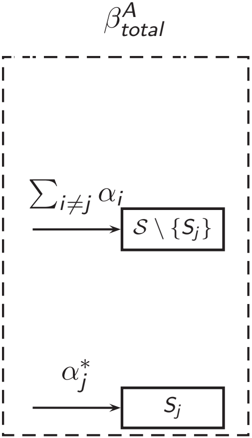
Preemptive Earliest-Deadline-First Scheduling



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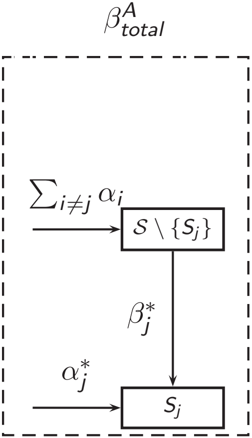

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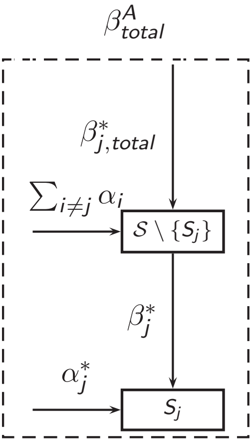
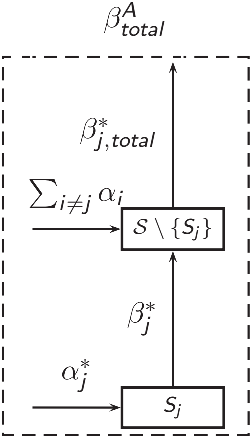
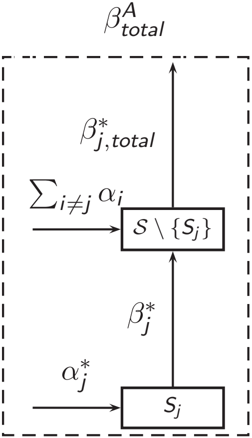



β_{total}^{A}
$\beta_{j,total}^{*}$
$\sum_{i \neq j} \alpha_i$
$\mathcal{S} \setminus \{S_j\}$
β_j^*
α_j^*
S_j

Preemptive Earliest-Deadline-First Scheduling



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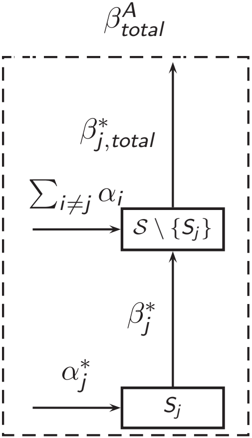

$$\beta^{*}_{j,total}(\Delta) = \max\left\{\beta^{\sharp}_{j}(\Delta), \sum_{i \neq j}^{N} \beta^{\flat}_{i}(\Delta, t')\right\}$$

$$\beta^{\sharp}_{j}(\Delta) \geq \inf\left\{\beta : \beta^{*}_{j}(\Delta, t') = \sup_{0 \leq \lambda \leq \Delta}\{\beta(\lambda) - \sum_{i \neq j}^{N} \alpha^{u}_{i}(\lambda, t')\}\right\}$$

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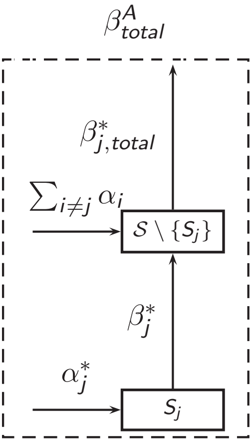

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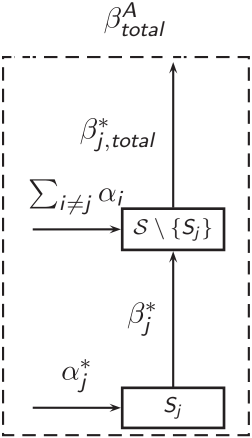

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Outline

1. Introduction
2. Underlying Mathematical Model
3. Our Algorithms
4. Experimental Results

Experiment Setup

- Event Stream Setting

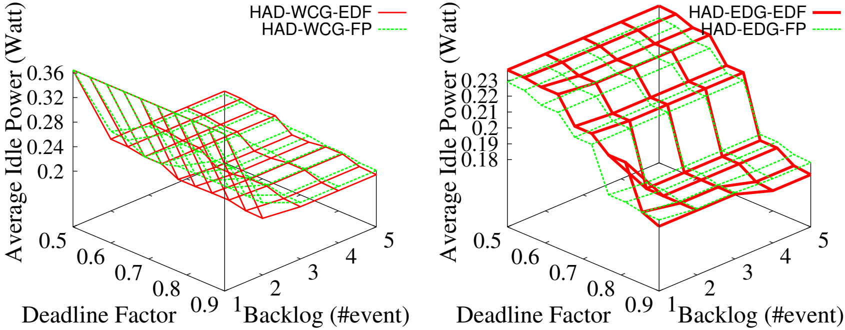
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
p (msec)	198	102	283	354	239	194	148	114	313	119
j (msec)	387	70	269	387	222	260	91	13	302	187
d (msec)	48	45	58	17	65	32	78	-	86	89
c (msec)	12	7	7	11	8	5	13	14	5	6

- Power Profiles for the Device

Device Name	P_a (Watt)	P_s (Watt)	P_σ (Watt)	t_{sw} (sec)	E_{sw} (mJ)
IBM Microdrive	1.3	0.5	0.1	0.012	9.6

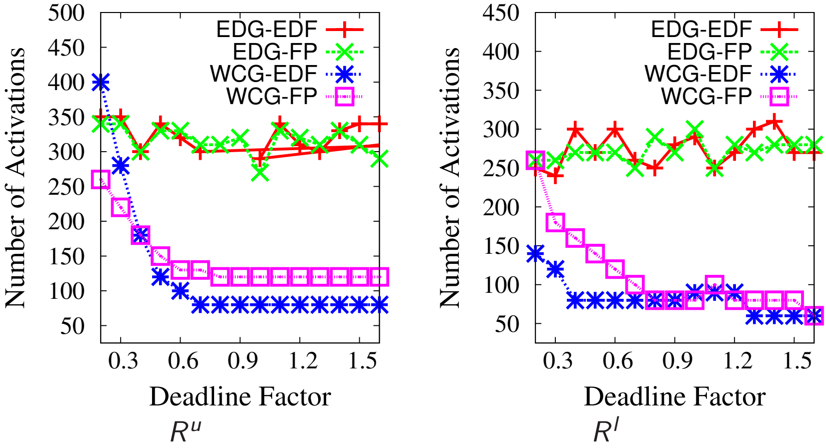
- Schemes to compare: HAD-EDG & HAD-WCG
- Bursting and sparse traces: R^u and R^l
- Implemented using RTC ToolBox
- Simulated on 1.7 GHz processor

Average Idle Power Consumption (Watt)



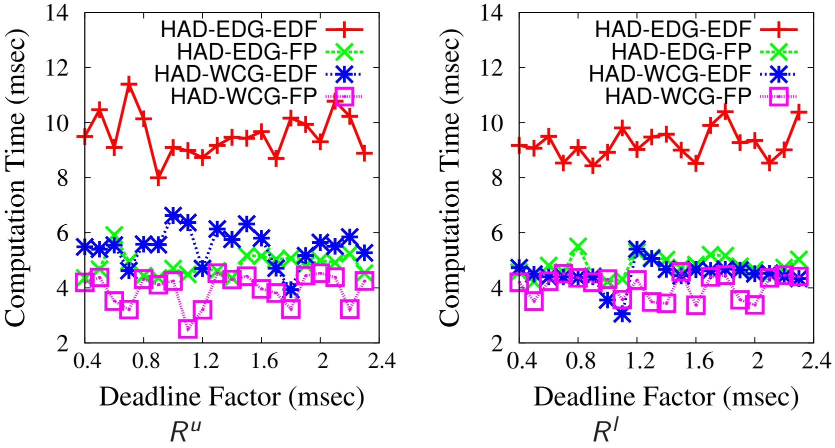
R^u R^l

- Idle power is reduced for both traces R^u and R^l



- EDG activation is varied according to the traces
- WCG activation is affected by the deadline

Computation Expense



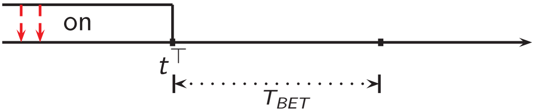
- Both schemes require a small computation time
- The increment for longer relative deadline is small

Conclusion

- Extend online algorithms which adaptively control the on/off of a device for multiple event streams with
  - preemptive fixed-priority scheduling
  - preemptive earliest-deadline-first scheduling
- Guarantee hard real-time requirements with respect to both timing and backlog constraints
- Experiments prove the effectiveness of the algorithms

Deactivation Algorithm (HAD)

The principle is to deactivate the device only when energy saving is possible.



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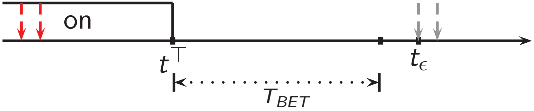

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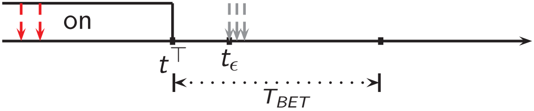

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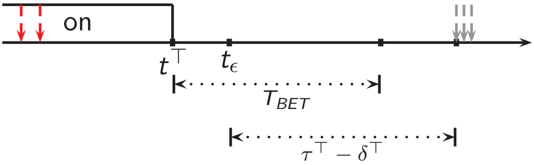

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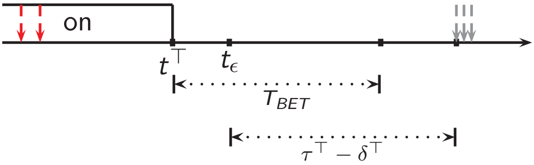
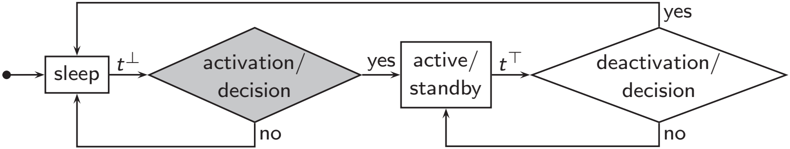


$$t_\epsilon \leftarrow \min_{t > t^\top} t \text{ such that } \bar{\alpha}_1^u(t - t^\top, t^\top) > 0$$

$$\tau^\top = \max\{\tau : \mathbf{bdf}(\Delta, \tau) \geq \alpha_1^u(\Delta - D_1, t_\epsilon)\}$$

$$\delta^\top = \max\left\{0, \min\{\delta : \alpha_1^u(\Delta, t_\epsilon) - \mathbf{bdf}(\Delta, \tau^\top - \delta) \leq Q \cdot w_1, \forall \Delta\}\right\}$$

Activation Algorithms



- Worst Case Greedy (WCG) Algorithm
  - Time triggered reevaluation
  - Suitable for bursty event arrival
- Event Driven Greedy (EDG) Algorithm
  - Event triggered reevaluation
  - Suitable for sparse event arrival

Worst Case Greedy Algorithm for Activation

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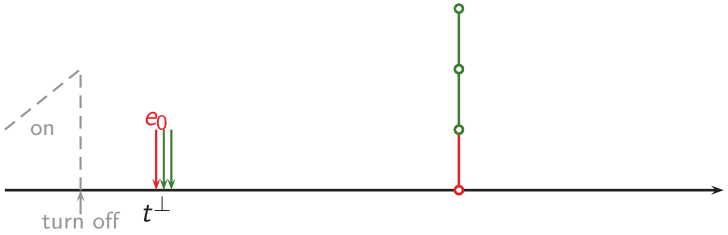
Worst Case Greedy Algorithm for Activation



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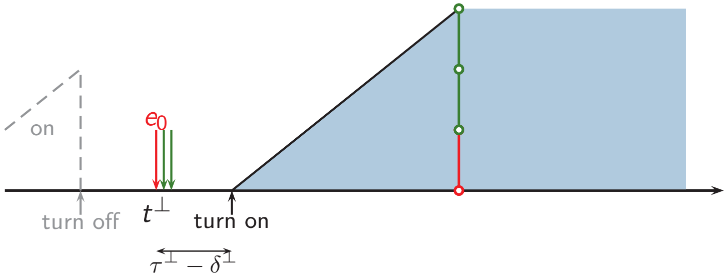
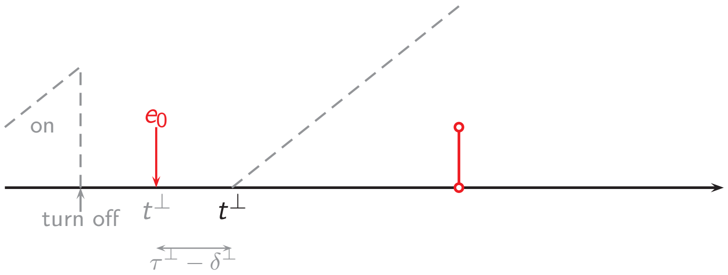
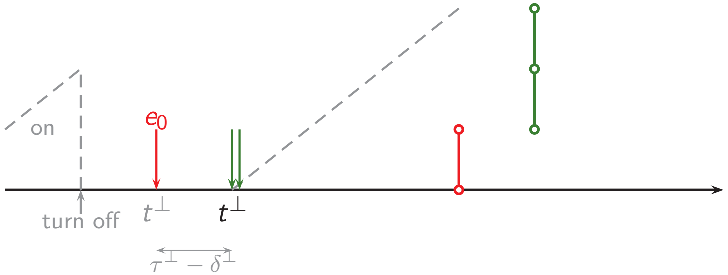



on
e_0
turn off
$t^\perp$
$t^\perp$
$\tau^\perp - \delta^\perp$

Worst Case Greedy Algorithm for Activation



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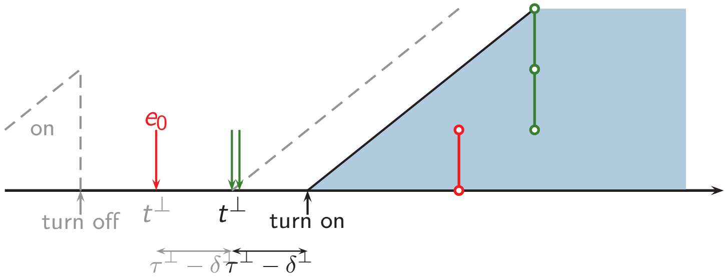

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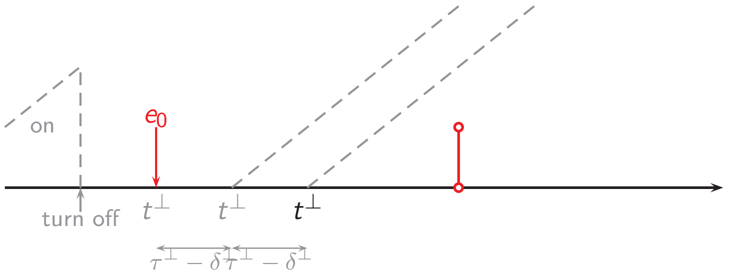
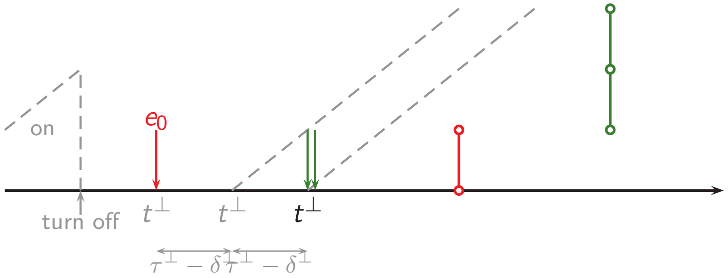
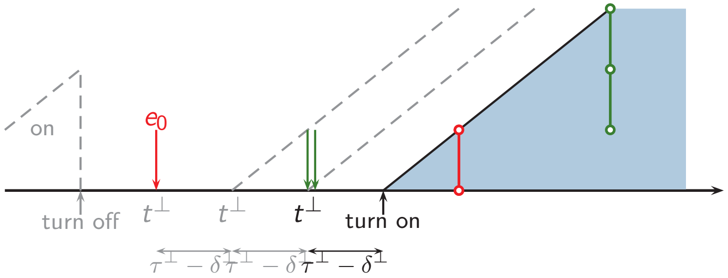
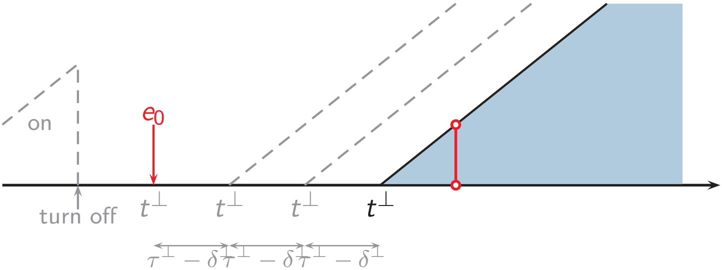


Worst Case Greedy Algorithm for Activation

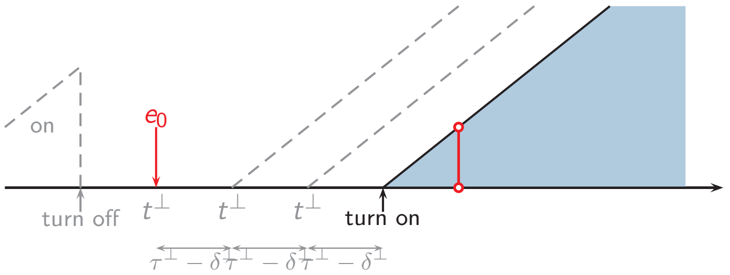


Worst Case Greedy Algorithm for Activation

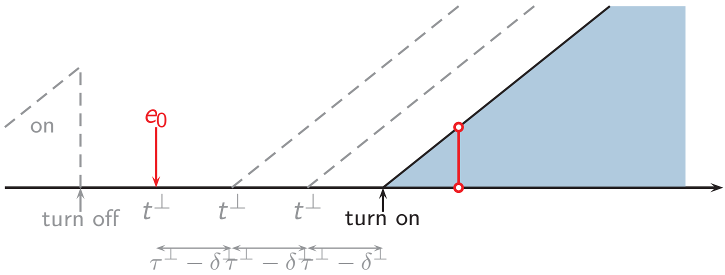



on
e_0
turn off
$t^{\perp}$
$t^{\perp}$
$t^{\perp}$
$t^{\perp}$
$\tau^{\perp} - \delta^{\perp}$
$\tau^{\perp} - \delta^{\perp}$
$\tau^{\perp} - \delta^{\perp}$

Worst Case Greedy Algorithm for Activation



Worst Case Greedy Algorithm for Activation

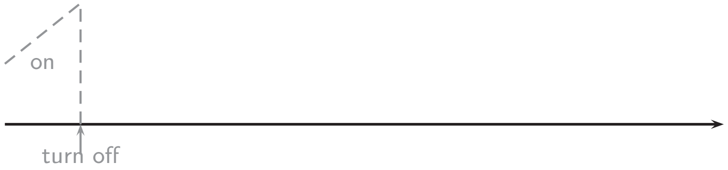


$$\beta^A(\Delta) = \alpha_1^u(\Delta - D_1,\ t^\perp) + w_1 \cdot B_1(\Delta,\ t^\perp)$$

$$\tau^\perp = \max\{\tau : \mathbf{bdf}(\Delta, \tau) \geq \beta^A(\Delta)\}$$

$$\delta^\perp = \max\left\{0,\ \min\{\delta : \alpha_1^u(\Delta, t^\perp) - \mathbf{bdf}(\Delta, \tau^\perp - \delta) \leq \left(Q - |\mathbf{E}(t^\perp)|\right) \cdot w_1,\ \forall\Delta\}\right\}$$

Event Driven Greedy Algorithm for Activation



Event Driven Greedy Algorithm for Activation

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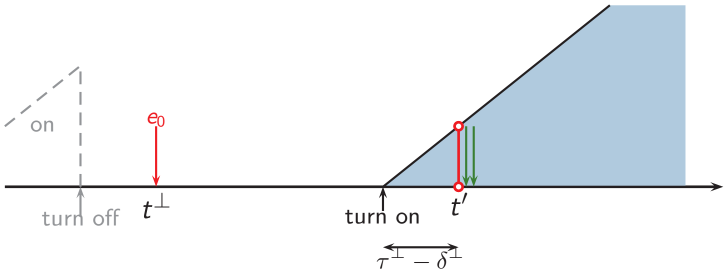
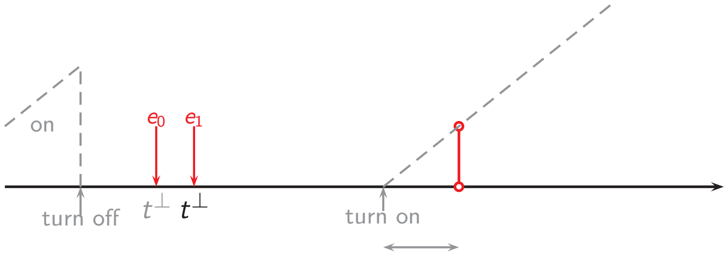
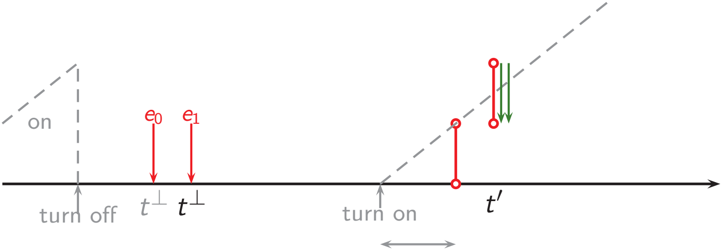


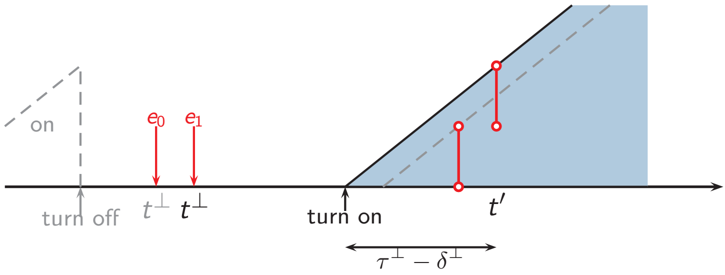
Event Driven Greedy Algorithm for Activation



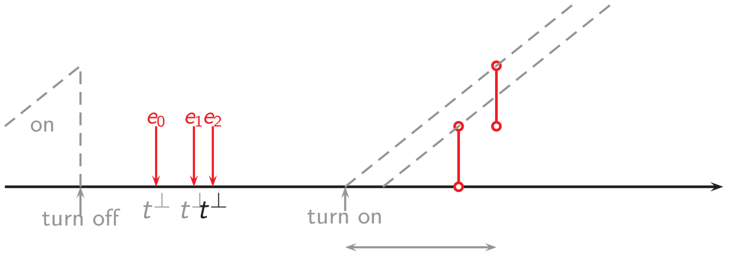
Event Driven Greedy Algorithm for Activation



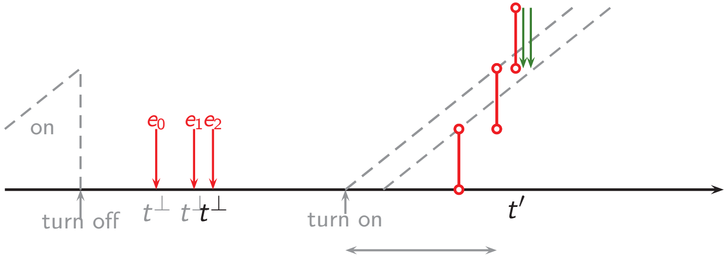
Event Driven Greedy Algorithm for Activation



Event Driven Greedy Algorithm for Activation



Event Driven Greedy Algorithm for Activation



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Scuola Superiore Sant'Anna
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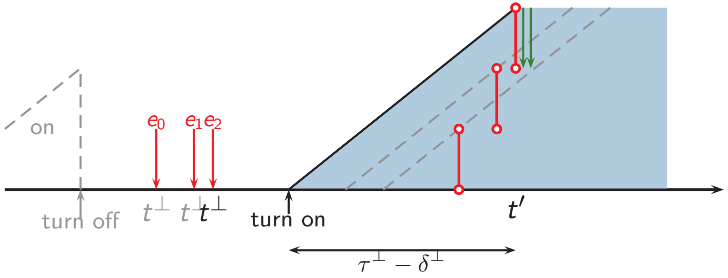

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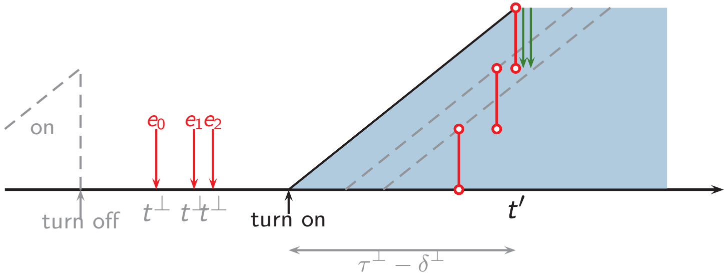
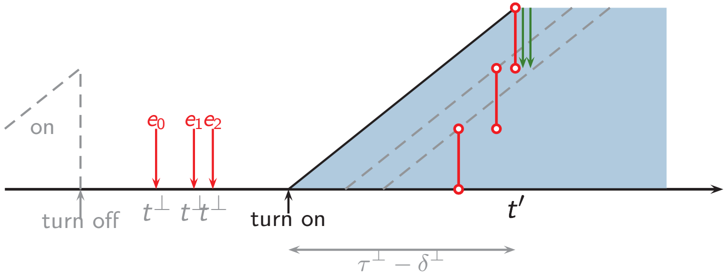


Event Driven Greedy Algorithm for Activation



$$\beta^A(\Delta) = \alpha_1^u(\Delta - D_1,\ t') + w_1 \cdot B_1'(\Delta,\ t')$$

$$\tau^\perp = \max\{\tau : \mathbf{bdf}(\Delta, \tau) \geq \beta^A(\Delta)\}$$

$$\delta^\perp = \max\Big\{0,\ \min\{\delta : \alpha_1^u(\Delta, t') - \mathbf{bdf}(\Delta, \tau^\perp - \delta) \leq \left(Q - |\mathbf{E}(t^\perp)| - \bar{\alpha}_1^l(\epsilon)\right) \cdot w_1,\ \forall\Delta\}\Big\}$$