

EC535 Introduction to Embedded Systems

I/O-oriented programming in Linux

- I/O service is not always available
 - Bandwidth limitation
 - Data not yet ready when one wants to read
 - Old data not yet transmitted when one wants to write again
 - Asynchronous nature of I/O
 - Data arrival time is unpredictable



Rules about sleeping



- Never sleep while running in atomic context.
 - What can go wrong?
 - Process holds a spinlock, other locks
 - Process disabled interrupts
- When process wakes up, it will not know what happened on the CPU while it was sleeping.
 - Make no assumptions based on earlier CPU states, check again.
- Make sure to verify who is going to wake the process up under what condition before implementing sleep.

Quick Poll

<https://shorturl.at/uxSyA>

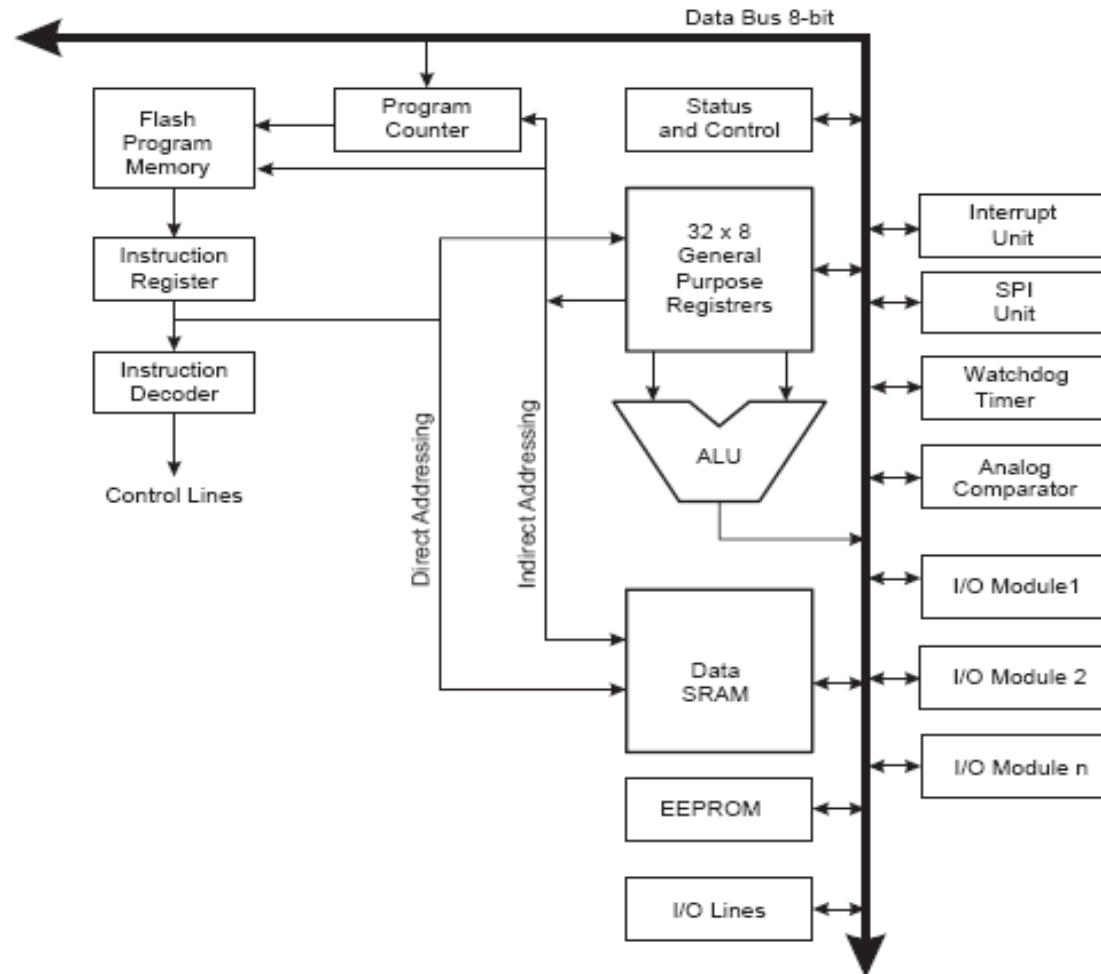
Team: Pairs for
Assignments, HW, Labs

Energy Efficiency

- Energy-efficient computing is needed by:
 - portable systems
 - increase battery lifetime
 - optimize thermal design -> form factor
 - non-portable systems
 - minimize cost
 - environmental concerns
- Electronic system design
 - Hardware: processing, storage, communication
 - Software: operating systems, applications
- Electronic system utilization
 - Runtime control and management
 - e.g., Dynamic Power Management (sleep states) & Dynamic Voltage Scaling (lower CPU frequency/voltage)

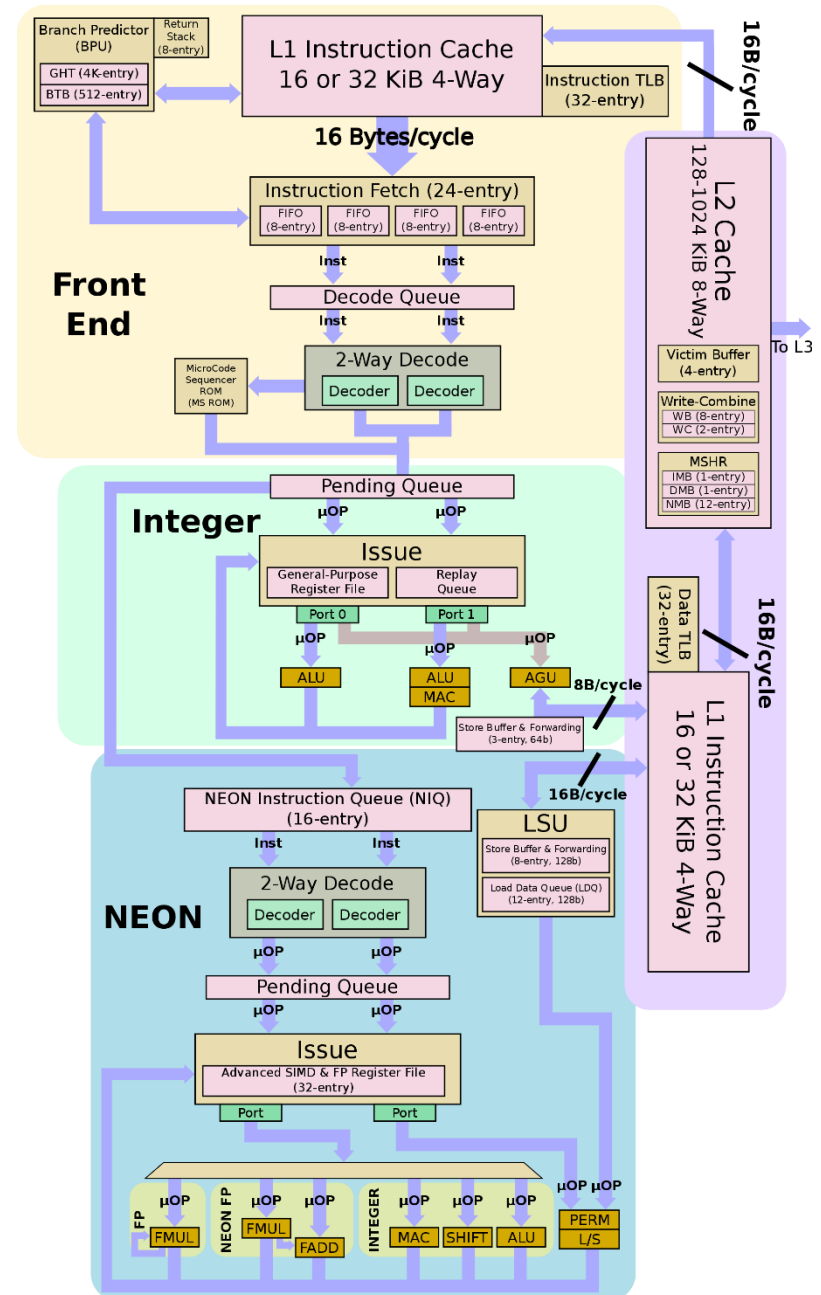
ATmega128L

- 4 or 8 MHz
- 8 bit
- 128KB Flash
- 4KB EEPROM
- 4KB SRAM
- 133 instructions
 - most single cycle
- 32 gen. regs
- 2 cycle multiplier
- 8 channel, 10 bit ADC; 1 kSamps/s max resolution

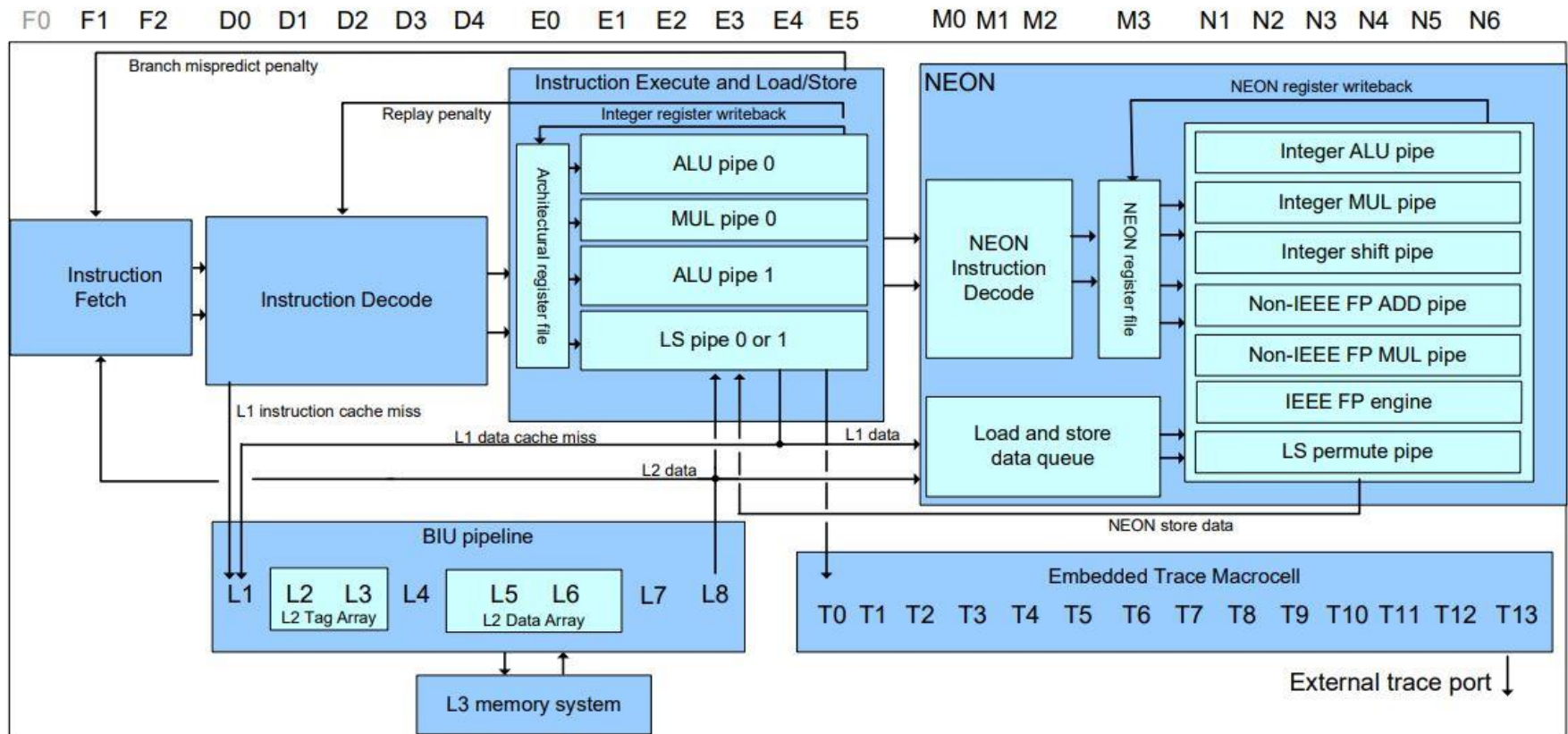


ARM Cortex-A8 Processor

- Pipeline: 13 stages
- 32-bit, ARMv7
- 16/32 KiB L1 I/D-Cache
- Support for various peripherals
- CPU freq: 600MHz-1.1GHz
- NEON SIMD instruction set extension
- Superscalar dual issue
- SoCs with Cortex-A8: Apple A4, Samsung Exynos 3110, TI OMAP3, many others



Cortex-A8 Pipeline



Comparing Power & Performance

- Cortex-A8
 - 0.43mW/MHz (e.g., <300mW for 600MHz)
- ATmega
 - Active: 4 MHz => 17 mW
 - Idle: 4 MHz => 12mW
 - Sleep: 45 uW

Portable Computers

- Lots of energy consumed in: display, hard disks, WLAN

Hard Disk

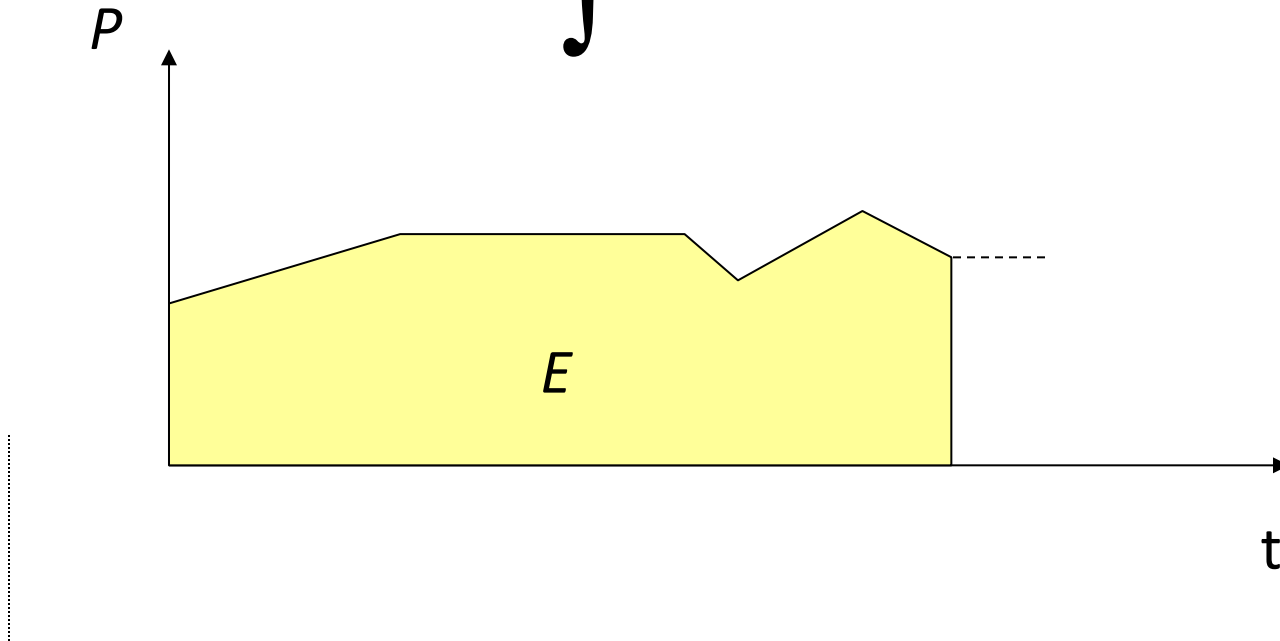
- Active power: 0.95 -2.5 W
- Idle power: 0.95 W
- Sleep: 0.13 W
- Sleep time: 0.67 s
- Wake-up time: 1.6 s

WLAN

- Transmission: 1.65 W
- Receiving: 1.4 W
- Doze: 0.045 W
- Down time: 62ms
- Wake-up time: 34 ms

Power (P) and Energy Relationship

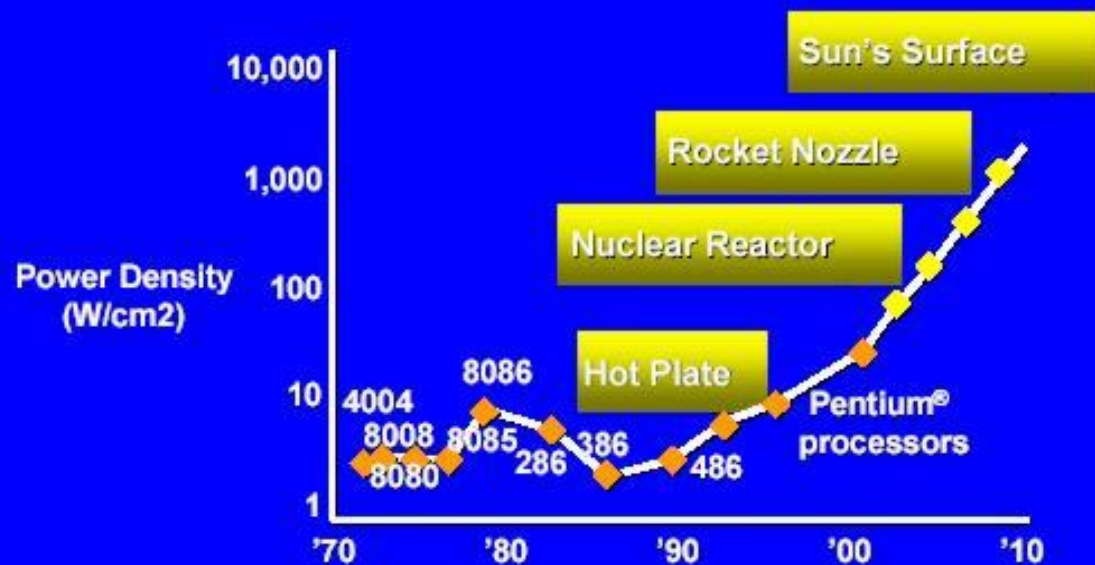
$$E = \int P dt$$



Low Power vs. Low Energy

- Minimizing the **power consumption** is important for
 - the design of the power supply
 - the design of voltage regulators
 - short term cooling
- Minimizing the **energy consumption** is important due to
 - restricted availability of energy (mobile systems)
 - limited battery capacities (only slowly improving)
 - high costs of energy
 - cooling
 - high costs
 - limited space
 - long lifetimes, low temperatures

Power Density Extrapolation

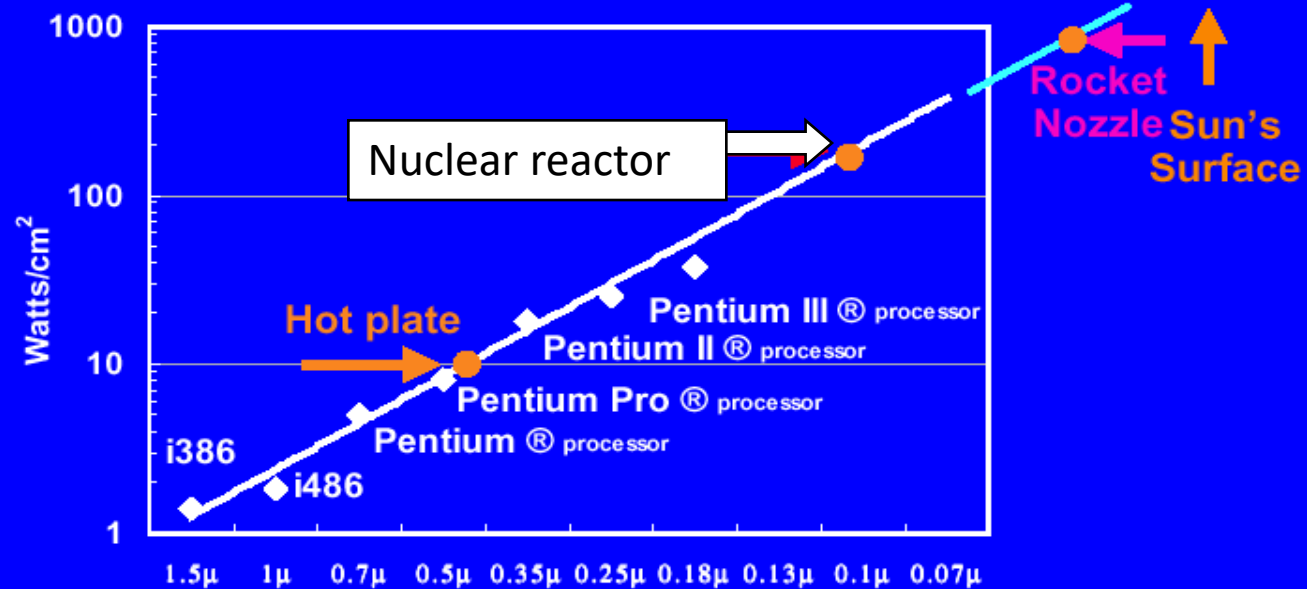


Gelsinger's Slide from ISSCC 2001

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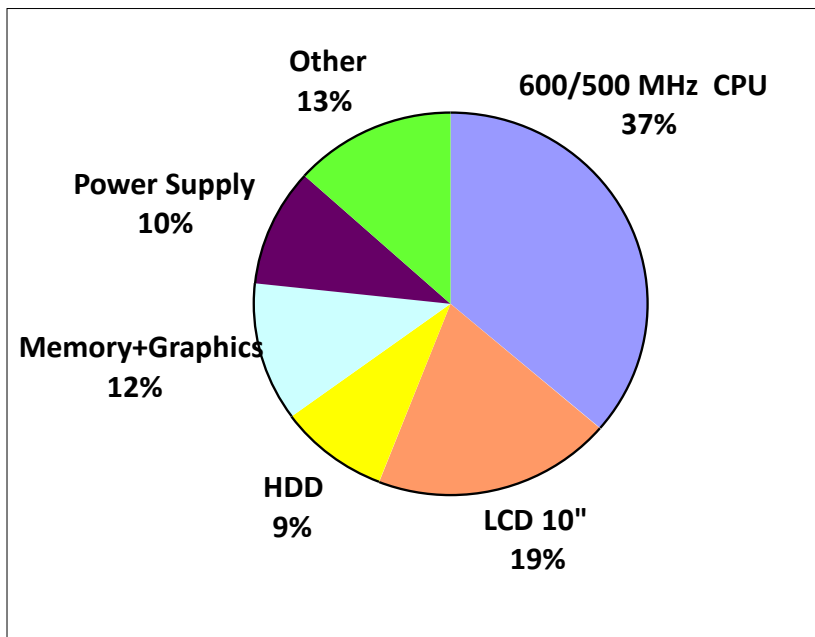
Power density continues to get worse



Surpassed hot-plate power density in 0.5μ
Not too long to reach nuclear reactor

Consider CPU & System Power

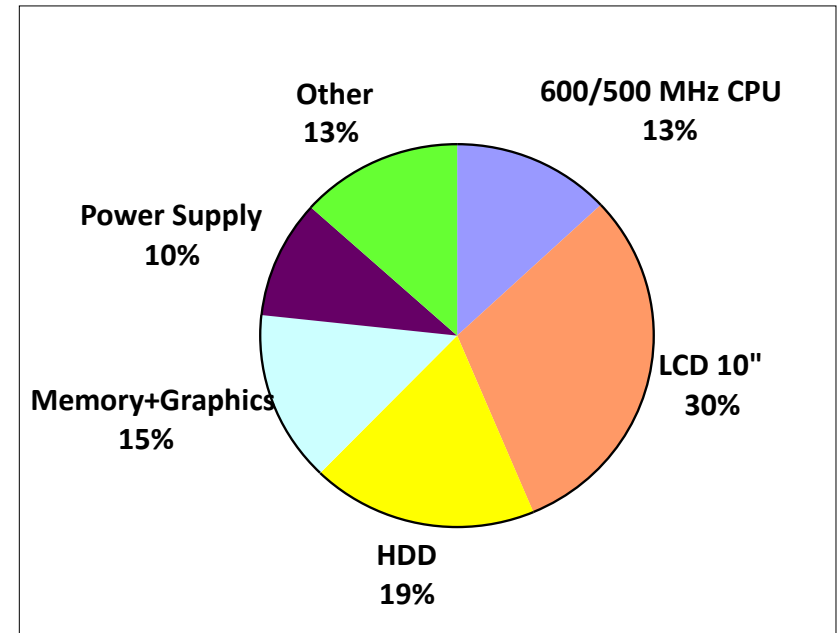
Mobile PC Thermal Design (TDP) System Power



Note: Based on Actual Measurements

***CPU Dominates Thermal
Design Power***

Mobile PC Average System Power



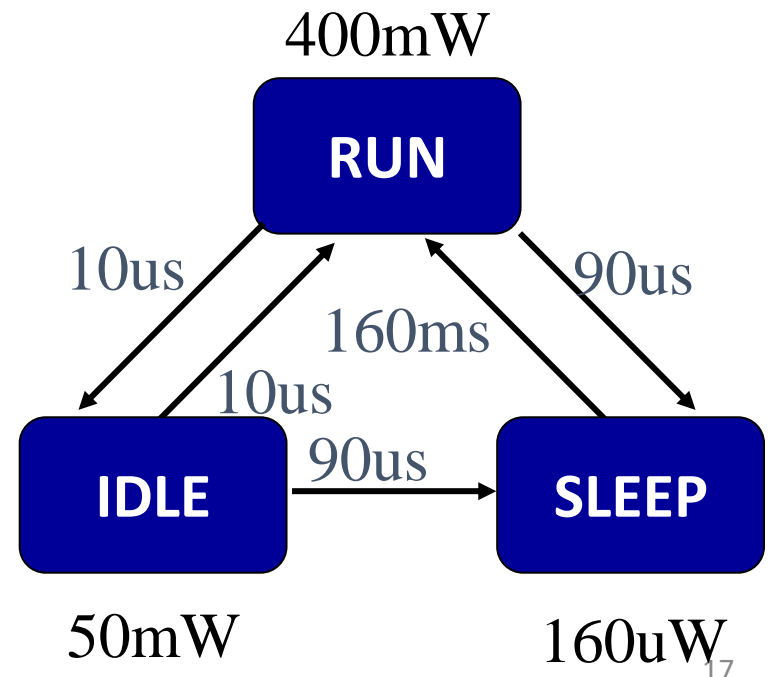
***Multiple Platform
Components Comprise
Average Power***

Power Manageable Components

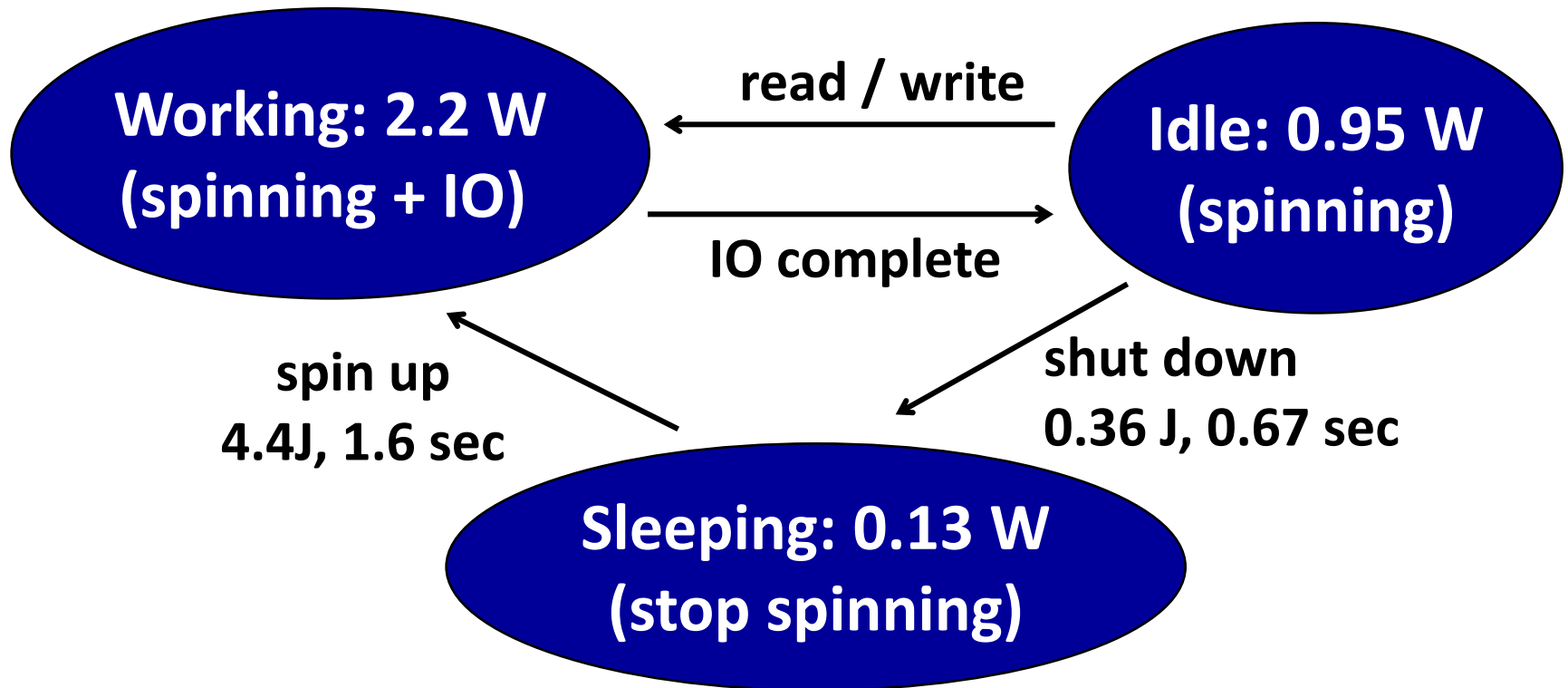
- Components with several internal states
 - Corresponding to power and service levels
- Abstracted as **power state machines**
 - State diagram with:
 - Power and service annotation on states
 - Power and delay annotation on edges

Example: SA-1100

- ◆ **RUN:** Operational
- ◆ **IDLE:** A SW routine may stop the CPU when not in use, while monitoring interrupts
- ◆ **SLEEP:** Shutdown of on-chip activity

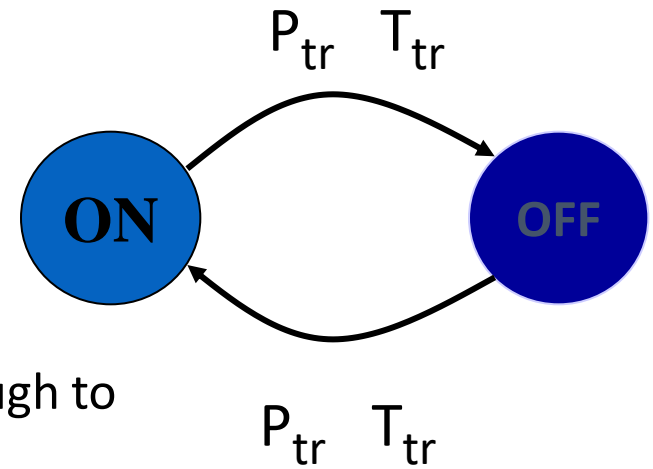


Example: Hard Disk Drive

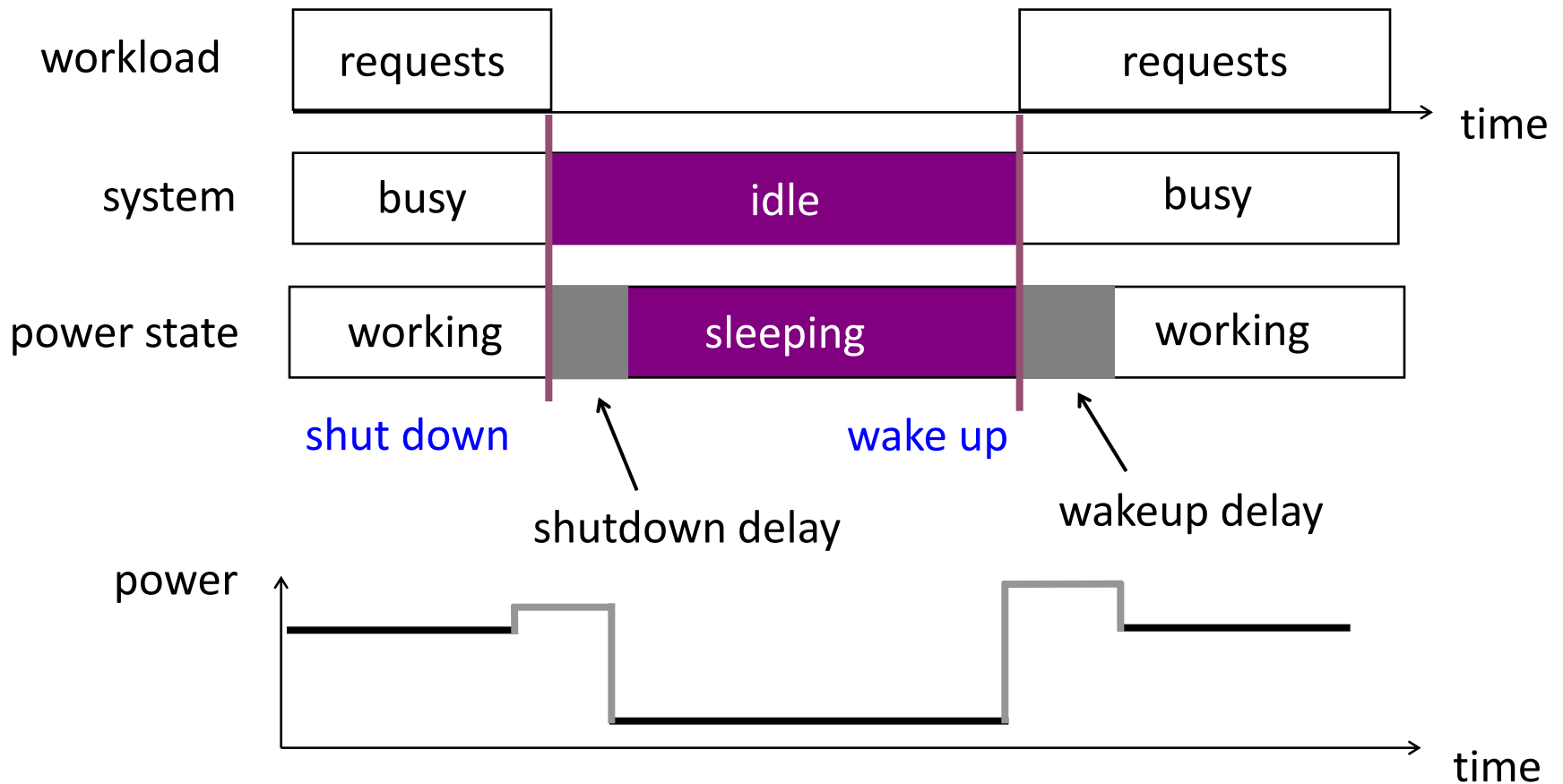


Dynamic Power Management

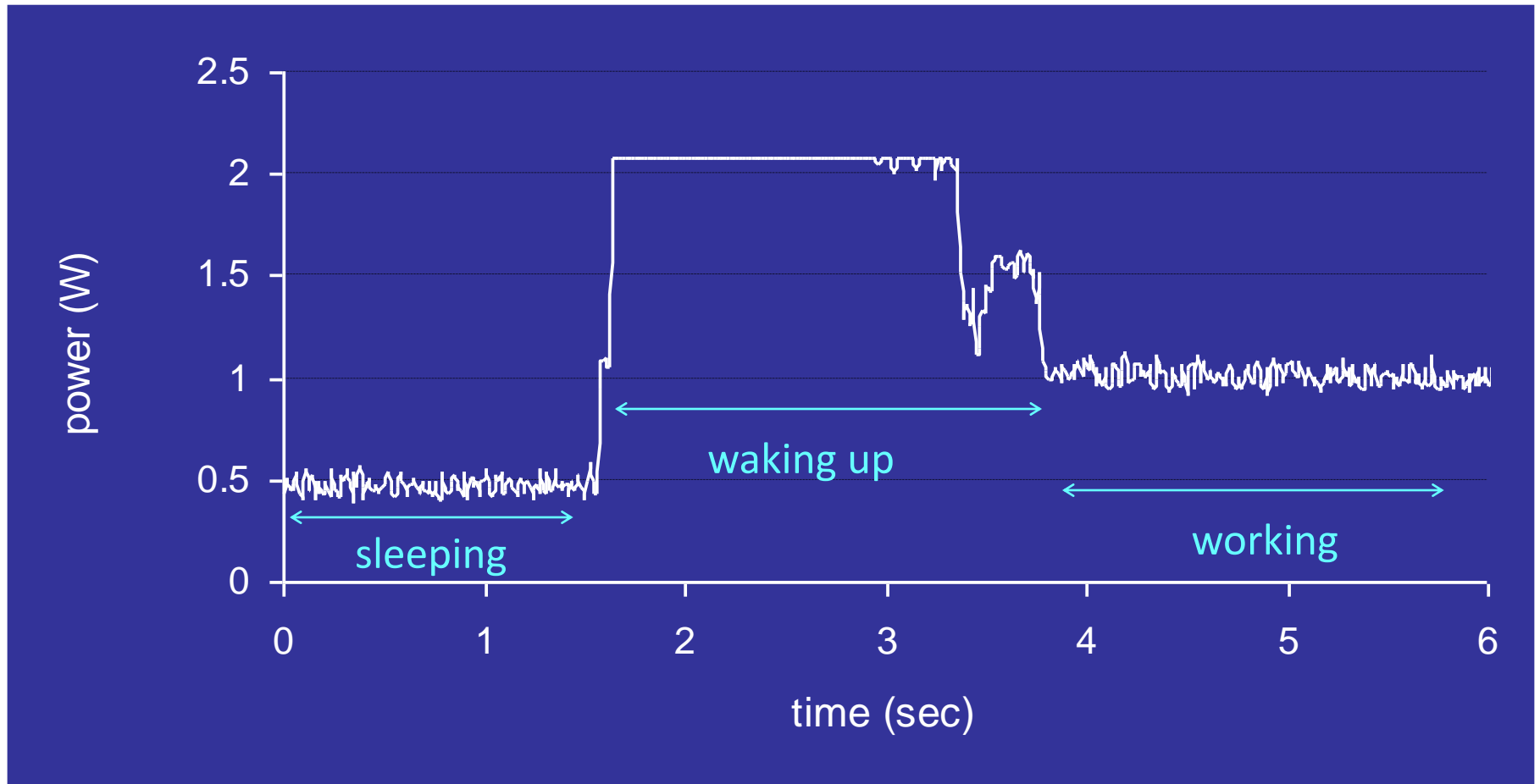
- State transition power (P_{tr}) and delay (T_{tr})
- If $T_{tr} = 0$, $P_{tr} = 0$ the policy is trivial
 - Stop a component when it is not needed
- If $T_{tr} \neq 0$ or $P_{tr} \neq 0$ (always...)
 - E.g., XScale 27x
 - 0.5 ms to sleep state
 - Shutdown only when idleness is long enough to neglect the cost
 - What if T and P fluctuate?



Workload and System Representation



Waking Up Hard Disk



Measurements done on a Fujitsu hard disk

Car Example

Imagine a car engine:

- If you turn it **off** for **5 seconds** but it takes **5 seconds' worth of fuel to restart**, you've **wasted** energy instead of saving any.
- If you leave it **off** for longer than 5 seconds, **then you start seeing energy savings**.

The system needs to be OFF long enough to **recover the transition energy loss**.

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-> System Break-Even Time

System Break-Even Time: T_{BE}

Minimum idle time for amortizing
the cost of component shutdown

$$T_{BE} = T_{tr} + T_{tr} \frac{P_{tr} - P_{on}}{P_{on} - P_{off}}$$



Transition delay (T_{tr})



Transition power (P_{tr})

Sleep power (P_{off})

Decision-Making

If $T_{\text{idle}} < T_{\text{BE}}$

Staying On is better

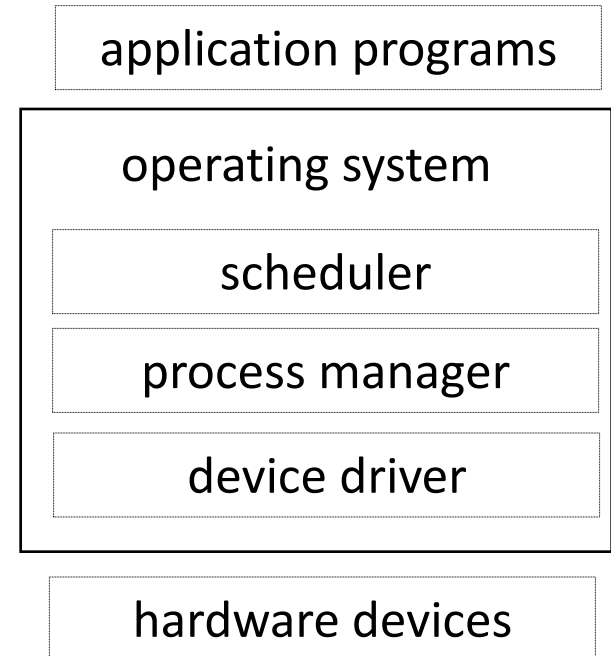
- frequent switching is inefficient

If $T_{\text{idle}} > T_{\text{BE}}$

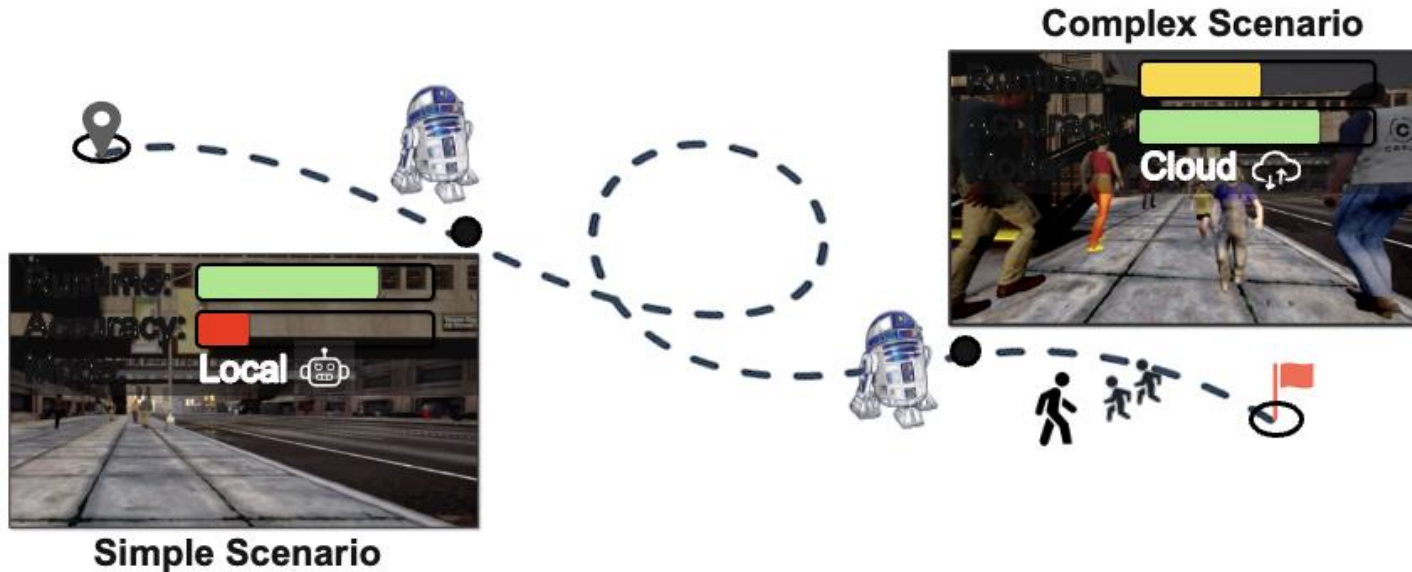
- system remains idle long enough to make up for the transition energy loss

DPM and Operating Systems

- ◆ Application
 - ❖ should not directly control hardware power
 - ❖ no power management in legacy programs
- ◆ Scheduler
 - ❖ selects processes and affects idle periods
- ◆ Process manager
 - ❖ knows multiple requesters
 - ❖ can estimate idle periods more accurately
- ◆ Driver
 - ❖ detects busy and idle periods
- ◆ Device
 - ❖ consumes power
 - ❖ should provide mechanism, not policy

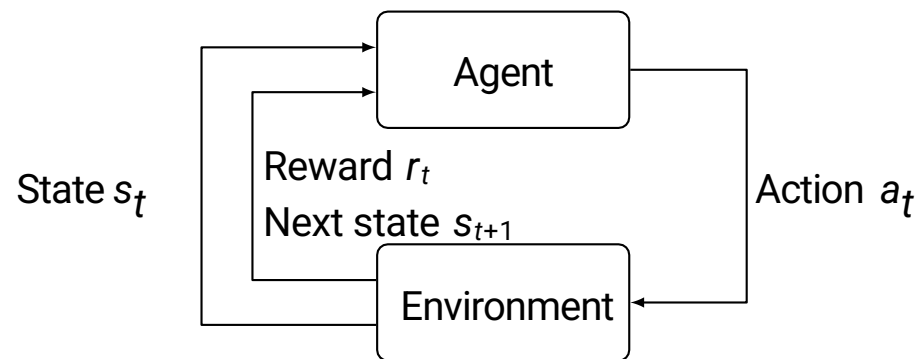


Schedule Should Depend on the Situation!



We present **UniLCD**, a novel local-cloud hybrid framework that dynamically routes computation between low-power local models and powerful cloud resources via reinforcement learning based on scenario complexity.

Sequential Decision Process



Agent observes environment state s_t at time t

Agent sends action a_t at time t to the environment

Environment returns the reward r_t and its new state s_{t+1} to the agent

Decision Process

Components:

- ▶ State: $s \in \mathcal{S}$ may be partially observed (e.g., game screen)
- ▶ Action: $a \in \mathcal{A}$ may be discrete or continuous (e.g., turn angle, speed)
- ▶ Policy: $\pi_\theta : \mathcal{S} \rightarrow \mathcal{A}$ we want to learn the policy parameters θ
- ▶ Optimal action: $a^* \in \mathcal{A}$ provided by expert demonstrator
- ▶ Optimal policy: $\pi^* : \mathcal{S} \rightarrow \mathcal{A}$ provided by expert demonstrator
- ▶ State dynamics: $P(s_{i+1}|s_i, a_i)$ simulator, typically not known to policy
Often deterministic: $s_{i+1} = T(s_i, a_i)$ deterministic mapping
- ▶ Rollout: Given s_0 , sequentially execute $a_i = \pi_\theta(s_i)$ & sample $s_{i+1} \sim P(s_{i+1}|s_i, a_i)$
yields trajectory $\tau = (s_0, a_0, s_1, a_1, \dots)$
- ▶ Loss function: $\mathcal{L}(a^*, a)$ loss of action a given optimal action a^*

Decision Process

Decision Process (MDP) defined by tuple:

$$(S, A, R, P, \gamma)$$

- ▶ S : set of possible states
- ▶ A : set of possible actions
- ▶ R : distribution of reward given (state,action) pair
- ▶ P :distribution over next state given (state,action) pair
- ▶ γ : discount factor

Many reinforcement learning problems can be formalized as MDPs

Markov Decision Process

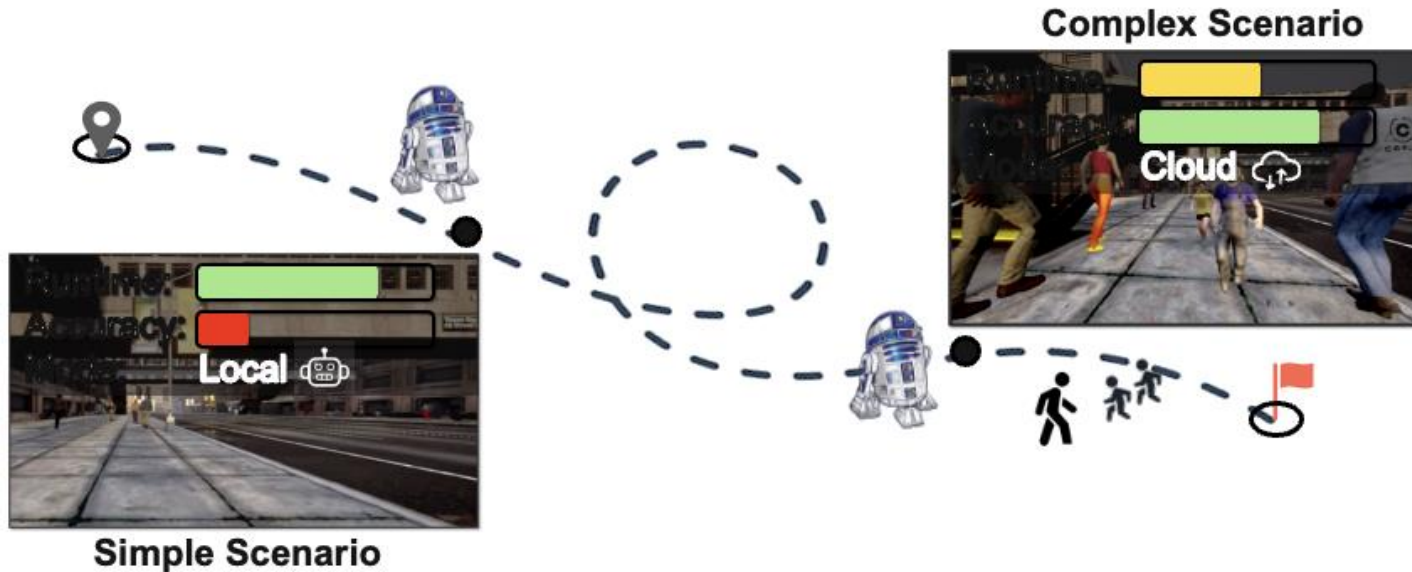
Markov property: Current state completely characterizes state of the world

- ▶ A state s_t is *Markov* if and only if

$$P(s_{t+1} | s_t) = P(s_{t+1} | s_1, \dots, s_t)$$

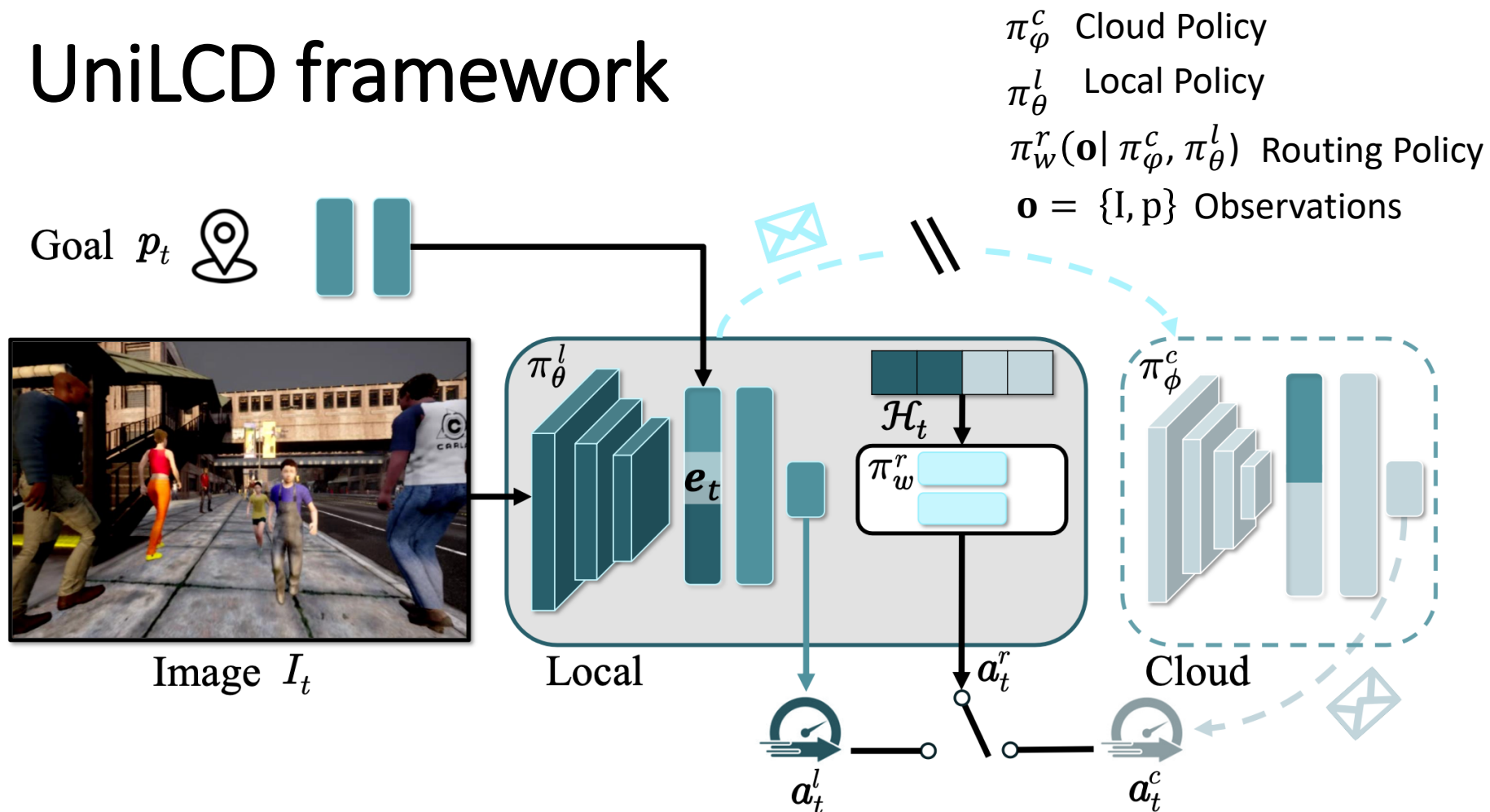
- ▶ "The future is independent of the past given the present"
- ▶ The state captures all relevant information from the history
- ▶ Once the state is known, the history may be thrown away
- ▶ i.e. the state is a sufficient statistic of the future

Schedule Should Depend on the Situation!



We present **UniLCD**, a novel local-cloud hybrid framework that dynamically routes computation between low-power local models and powerful cloud resources via reinforcement learning based on scenario complexity.

UniLCD framework



Multi-objective Reward Function

Task Reward: $r = (r_{geo} \cdot r_{speed} \cdot r_{energy} \cdot r_{action})^\alpha - r_{collision}$

Geodesic Reward: $r_{geo} = (1 - \tanh(d_{geo}))$

Speed Reward: $r_{speed} = \frac{v}{m_v}$

Energy Disadvantage: $r_{energy} = 1 - \frac{e}{m_e}$

Extreme Action Clip: $r_{action} = \mathbb{I}(|r_{speed}| < \varepsilon) \cdot \mathbb{I}\left(\left|\frac{d}{d_m}\right| < \varepsilon\right)$

d_{geo} : Geodesic distance

m_v : Maximum speed

m_e : Maximum energy

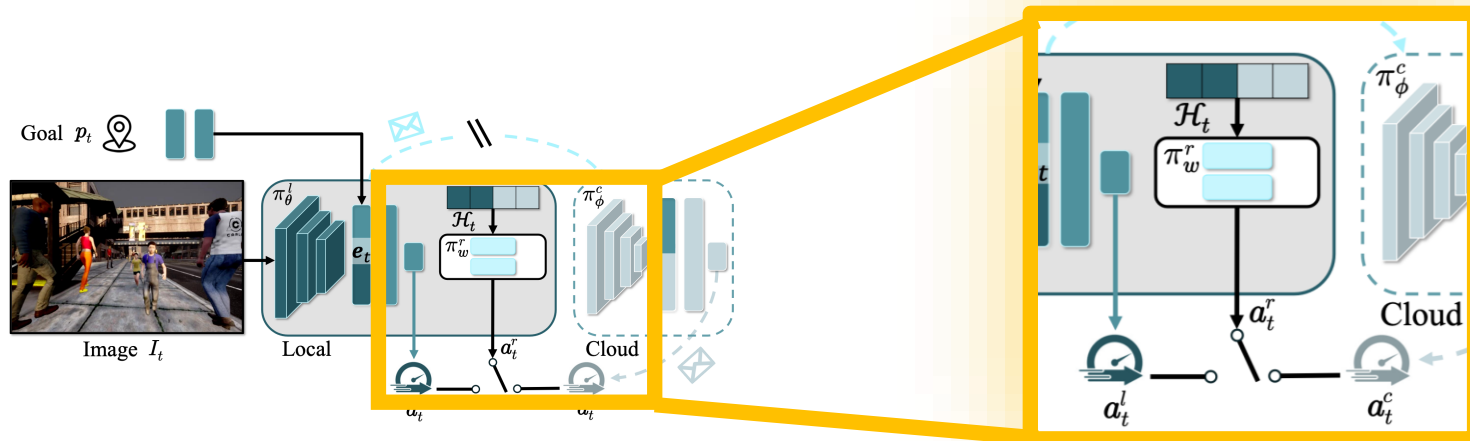
d_m : Maximum possible rotation

ε : 0.97 (Threshold for clipping action)

$r_{collision}$ is a substantially high negative penalty to our robot every time it collides with a pedestrian.

Routing Policy via Reinforcement Learning

- 1: **Input:** Image \mathbf{I} , next waypoint \mathbf{p} , local policy π_{θ}^l , cloud policy π_{ϕ}^c
- 2: **Initialize:** Number of iterations T , history \mathcal{H} , routing policy π_{ω}^r , reply buffer \mathcal{S}
- 3: Collect on policy samples:
- 4: **for** $t = 1$ **to** T **do**
- 5: Obtain local action \mathbf{a}_t^l and embeddings \mathbf{e}_t using local policy $\pi_{\theta}^l(\mathbf{I}_t, \mathbf{p}_t)$
- 6: Append $(\mathbf{a}_t^l, 0)$ to history \mathcal{H}_t
- 7: **if** $\pi_{\omega_t}^r(\mathcal{H}_t, \mathbf{e}_t) = 0$ **then** $\mathbf{a}_t = \mathbf{a}_t^l$
- 8: **else**
- 9: Send \mathbf{e}_t to cloud, $\mathbf{a}_t = \pi_{\phi}^c(\mathbf{I}_t, \mathbf{p}_t)$
- 10: Update last value of \mathcal{H}_t to $(\mathbf{a}_t, 1)$
- 11: **end if**
- 12: Compute instant reward using Eq. (2)
- 13: **if** Arrived destination **then** break
- 14: **end if**
- 15: Update replay buffer $\mathcal{S} = \mathcal{S} \cup \{\mathbf{I}_t, \mathbf{p}_t, \mathcal{H}_t, r_t\}$
- 16: Update routing policy parameters with PPO
- 17: **end for**

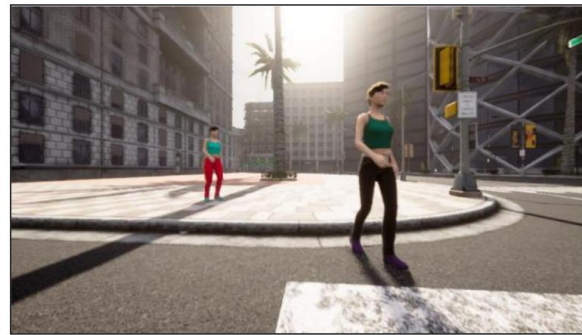


Simulation Environment

Low



Medium



High



Crowd



How to Evaluate Performance?

Navigation Score

$$\text{Navigation Score(NS)} = RC \cdot P_I^{IC} \cdot P_{RD}$$

Infraction Penalty(P_I) = 0.5

Route Deviation Penalty (P_{RD}) = $\begin{cases} 0.8, & \text{if } RD > \varepsilon_{RD} \\ 1.0, & \text{otherwise} \end{cases}$

Collision Count Per Meter IC

How to Evaluate Performance?

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$$\text{Navigation Score(NS)} = RC \cdot P_I^{IC} \cdot P_{RD}$$

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$$\text{Collision Count Per Meter } IC$$

Ecological Navigation Score

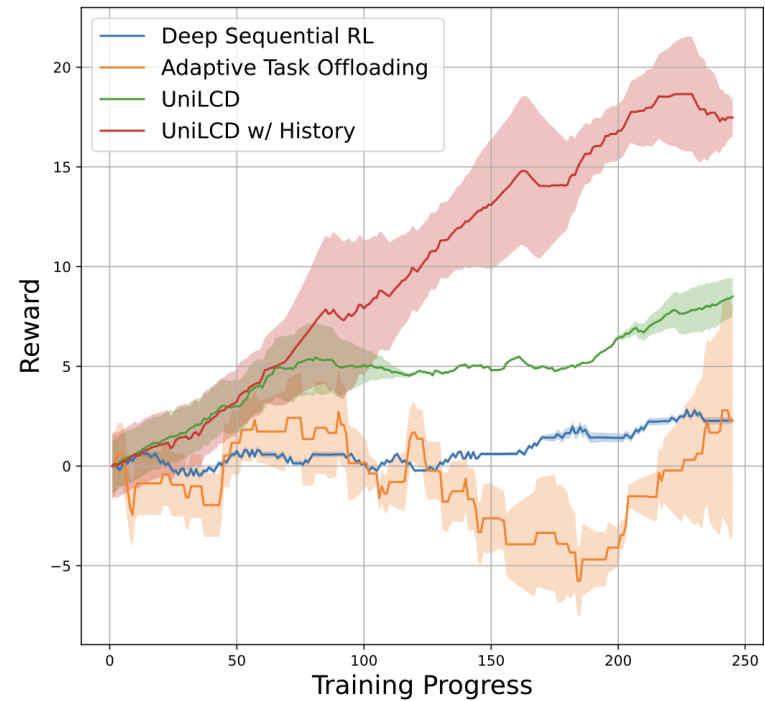
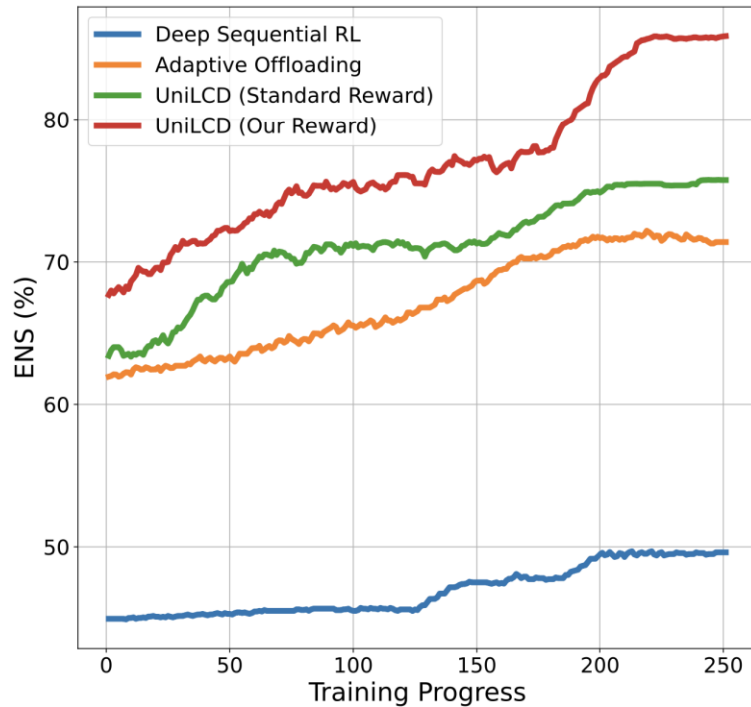
$$\text{Ecological Navigation Score(ENS)} = P_E \cdot \text{NS}$$

$$\text{Penalty term}(P_E) = 1 - \frac{\text{Energy}}{N_E}$$

$$\text{Normalization Factor}(N_E) = (E_{local} + E_{cloud}) \cdot (N_{local} + N_{cloud})$$

$$\text{Total energy consumption (Energy)} = E_{local} \cdot N_{local} + E_{cloud} \cdot N_{cloud}$$

Performance over training progression



Comparing UniLCD with other baselines

Method	ENS \uparrow	NS \uparrow	SR \uparrow	RC \uparrow	Infract. \downarrow	Energy \downarrow	FPS \uparrow
† Cloud-Only [84]	0.00	96.47	93.33	98.50	0.03	36.49	7.11
Local-Only [82]	63.43	67.33	0.00	75.23	0.16	4.33	65.40
<i>Baseline Methods:</i>							
Compressive Offloading [108]	13.98	80.16	0.00	80.16	0.00	90.66	1.82
† Selective Query [39]	24.14	61.28	0.00	82.68	0.11	45.35	18.14
† Adaptive Offloading [95]	37.42	40.37	70.00	94.05	1.22	4.80	30.14
Neurosurgeon [40]	39.85	63.10	0.00	80.54	0.03	28.31	12.53
SPINN [52]	36.31	72.75	60.00	92.73	0.35	18.94	20.37
Deep Sequential RL [97]	58.84	61.83	0.00	79.36	0.36	3.77	77.94
<i>UniLCD Module Ablations:</i>							
† Standard Reward	48.35	54.99	0.00	75.23	0.13	3.57	50.20
† Standard Reward w/ History	50.04	57.21	10.00	77.71	0.12	8.38	49.07
† Our Reward (Eq. (2))	48.30	79.90	56.66	91.15	0.19	21.72	16.05
† Our Reward w/ History	71.70	87.71	83.33	94.66	0.11	7.83	33.98
Our Reward (Eq. (2))	57.20	87.39	60.00	91.10	0.06	6.60	12.49
Our Reward w/ History	85.97	94.58	93.33	95.90	0.02	2.90	26.49

Local policy backbone ablations

Local Model Size	Params	ENS \uparrow	NS \uparrow	SR \uparrow	RC \uparrow	Infract. \downarrow	Energy \downarrow	FPS \uparrow
<i>UniLCD:</i>								
† Tiny	1.37	12.80	93.29	90.00	97.93	0.07	34.01	7.35
† Small	2.54	48.30	79.90	56.66	91.15	0.19	21.72	16.05
† Medium	3.50	50.92	87.87	80.00	95.50	0.12	21.19	15.10
<i>UniLCD w/ History:</i>								
† Tiny	1.37	0.00	91.27	93.33	98.50	0.11	36.52	6.42
† Small	2.54	71.70	87.71	83.33	94.66	0.11	7.83	33.98
† Medium	3.50	73.46	83.86	90.00	96.22	0.15	5.22	11.53
<i>UniLCD:</i>								
Stage 1	0.53	57.20	87.39	60.00	91.10	0.06	6.60	12.49
Stage 2	0.95	74.12	81.54	93.33	91.10	0.16	1.80	65.40
<i>UniLCD w/ History:</i>								
Stage 1	0.53	85.97	94.58	93.33	95.99	0.02	2.90	26.49
Stage 2	0.95	86.78	95.47	93.33	98.15	0.04	1.77	36.50

Reward component ablations

Reward	ENS\uparrow	NS\uparrow	SR\uparrow	RC\uparrow	Infract.\downarrow	Energy\downarrow	FPS\uparrow
All Terms	85.97	94.58	93.33	95.90	0.02	2.90	26.49
w/o r_{geo}	67.04	74.65	0.00	76.22	0.03	7.42	58.82
w/o r_{speed}	66.05	72.66	0.00	77.34	0.09	6.61	65.40
w/o r_{energy}	0.00	93.53	90.00	95.50	0.03	43.75	6.42

Qualitative Results

System Break-Even Time: T_{BE}

Minimum idle time for amortizing
the cost of component shutdown

$$T_{BE} = T_{tr} + T_{tr} \frac{P_{tr} - P_{on}}{P_{on} - P_{off}}$$



Transition delay (T_{tr})



Transition power (P_{tr})

Sleep power (P_{off})

Example:

Calculate Break-even Time

- Processor consumes:
 - 10mW when idle,
 - 1mW while sleeping,
 - 100mW while transitioning into/out of sleep state.
- Transition time:
 - 100ms into and out of sleep state (total)
 - No transition time into/out of idle state
- What is the “breakeven” time?