Global Scheduling Not Required:

Simple, Near-Optimal Multiprocessor Real-Time Scheduling with Semi-Partitioned Reservations

November 30, 2016
RTSS 2016

Björn B. Brandenburg and Mahircan Gül

Max Planck Institute for Software Systems

Artifact * Consistent * Well Documented * Easy to Reuse * Evaluated * AEC * RTSS

LITMUS^RT

Linux Testbed for Multiprocessor Scheduling in Real-Time Systems

http://www.litmus-rt.org

for **static** sets of **independent** **implicit-deadline** sporadic tasks

Global Scheduling Not Required:

Simple, Near-Optimal Multiprocessor Real-Time Scheduling with Semi-Partitioned Reservations

November 30, 2016
RTSS 2016

Björn B. Brandenburg and Mahircan Gül

Max Planck Institute for Software Systems

Artifact * Consistent * Well Documented * AEC * Evaluated * Easy to Reuse * RTSS

LITMUS^RT
Linux Testbed for Multiprocessor Scheduling in Real-Time Systems
http://www.litmus-rt.org

for ***static*** sets of ***independent*** ***implicit-deadline*** *sporadic tasks*

Global Scheduling Not Required:

Simple, Near-Optimal Multiprocessor Real-Time Scheduling with Semi-Partitioned Reservations

empirically

November 30, 2016
RTSS 2016

Björn B. Brandenburg and Mahircan Gül

Max Planck Institute for Software Systems

Artifact Consistent * Well Documented * Easy to Reuse * Evaluated RTSS AEC

LITMUS^RT
Linux Testbed for Multiprocessor Scheduling in Real-Time Systems
http://www.litmus-rt.org

Main Observation and Conclusions

Main Observation and Conclusions

Empirically, **near-optimal hard real-time schedulability**
— usually ≥**99% schedulable utilization** —
can be achieved with **simple**, **well-known and well-understood**, **low-overhead** techniques (+ a few tweaks).

Main Observation and Conclusions

Empirically, **near-optimal hard real-time schedulability**
— usually ≥**99% schedulable utilization** —
can be achieved with **simple**, **well-known and well-understood**, **low-overhead** techniques (+ a few tweaks).

➔ ***Global, optimal scheduling not required***
(for the considered type of workloads!)

Pragmatically speaking, *little reason to favor complex algorithms that are (more) difficult to understand, to implement, and to extend if* ***a simple approach will do***.

Main Observation and Conclusions

Empirically, **near-optimal hard real-time schedulability**
— usually ≥**99% schedulable utilization** —
can be achieved with **simple**, **well-known and well-understood**, **low-overhead** techniques (+ a few tweaks).

→ ***Global, optimal scheduling not required***
(for the considered type of workloads!)

Pragmatically speaking*, little reason to favor complex algorithms that are (more) difficult to understand, to implement, and to extend if* ***a simple approach will do****.*

→ ***Future work should focus on more demanding workloads***
(on preemptive multiprocessor real-time scheduling)

Static, independent, implicit-deadline tasks are by now very well supported.

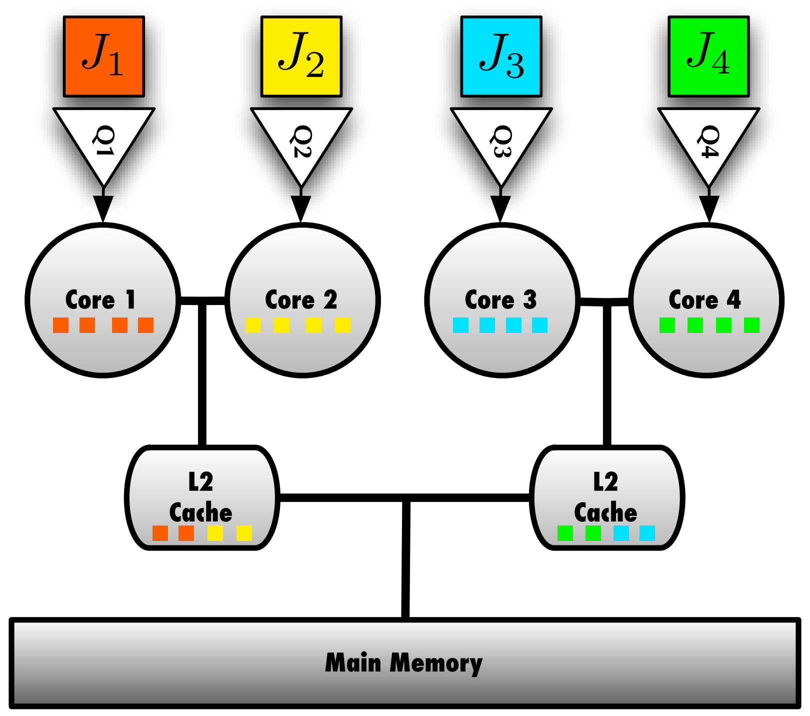
Motivation

Multiprocessor Real-Time Scheduling

Multiprocessor Real-Time Scheduling

Partitioning

1. **Assign** tasks to cores (offline).
2. Schedule each core **independently** (like a uniprocessor).

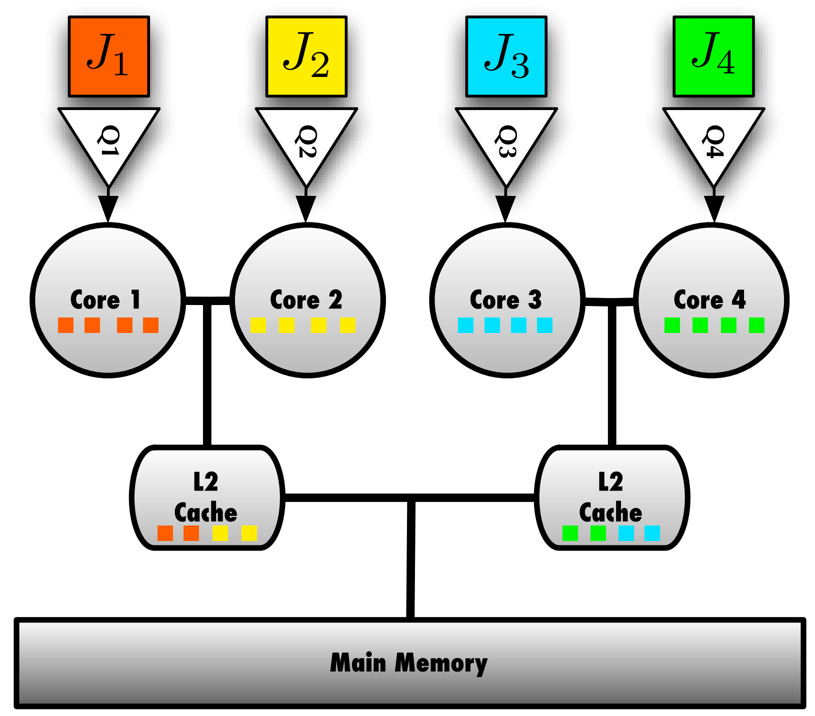


Multiprocessor Real-Time Scheduling

```
Partitioning

1. Assign tasks to
   cores (offline).

2. Schedule each core
   independently (like
   a uniprocessor).
```



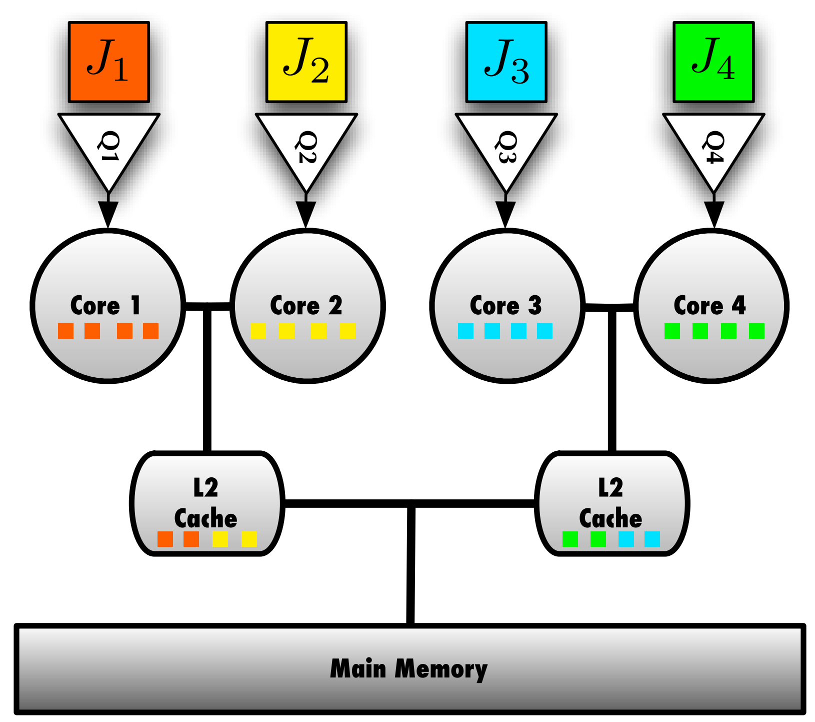
Partitioned Scheduling

➡ simple to implement
➡ simple to understand
➡ simple to extend
➡ KISS-compatible

Multiprocessor Real-Time Scheduling

<u>Partitioning</u>

1. **Assign** tasks to cores (offline).
2. Schedule each core **independently** (like a uniprocessor).



Partitioned Scheduling

- ➡ simple to implement
- ➡ simple to understand
- ➡ simple to extend
- ➡ KISS-compatible

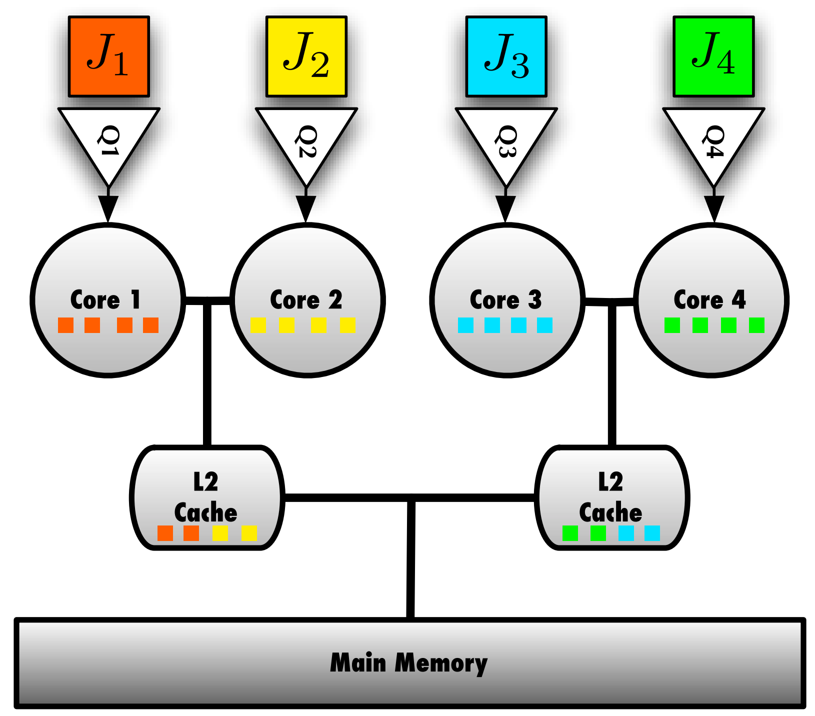
But: non-optimal

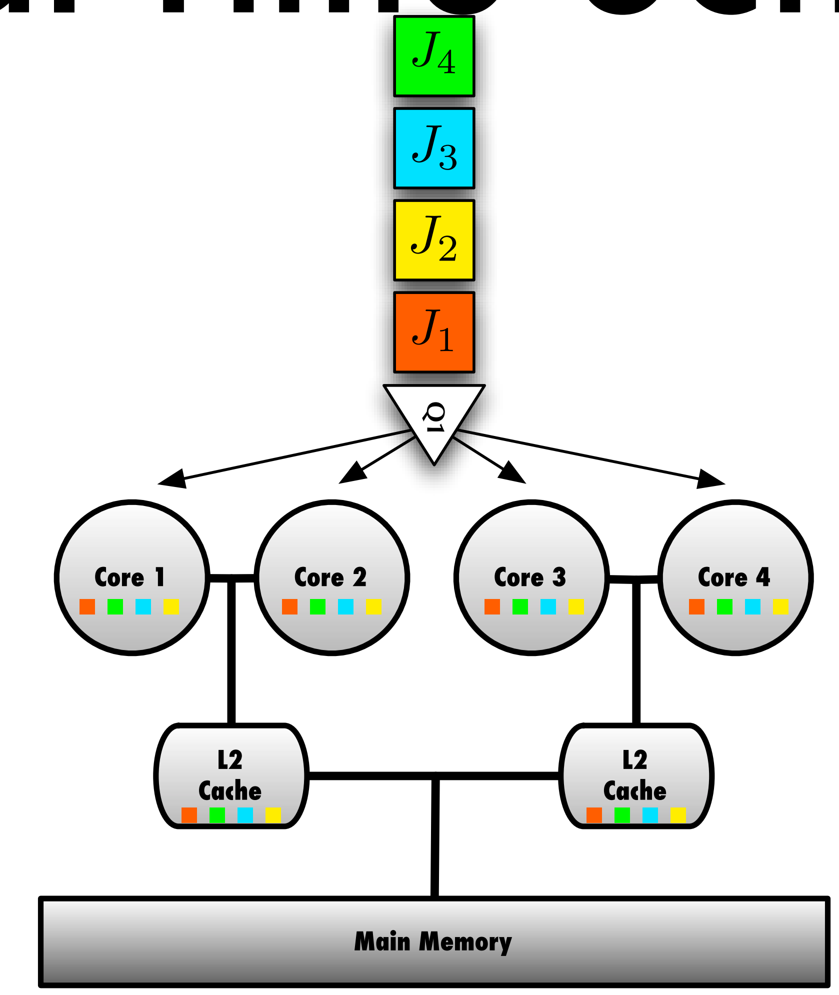
- ➡ need to place tasks (bin packing)
- ➡ mapping may be difficult to find
- ➡ mapping may not exist
- ➡ worst-case utilization bound ~50%

Multiprocessor Real-Time Scheduling

Partitioning

1. **Assign** tasks to cores (offline).
2. Schedule each core **independently** (like a uniprocessor).





Global/Optimal Scheduling

1. Keep **all cores busy** with sequential tasks.
2. Globally **coordinate** to reschedule and migrate tasks as needed.

Partitioned Scheduling

- ➡ simple to implement
- ➡ simple to understand
- ➡ simple to extend
- ➡ KISS-compatible

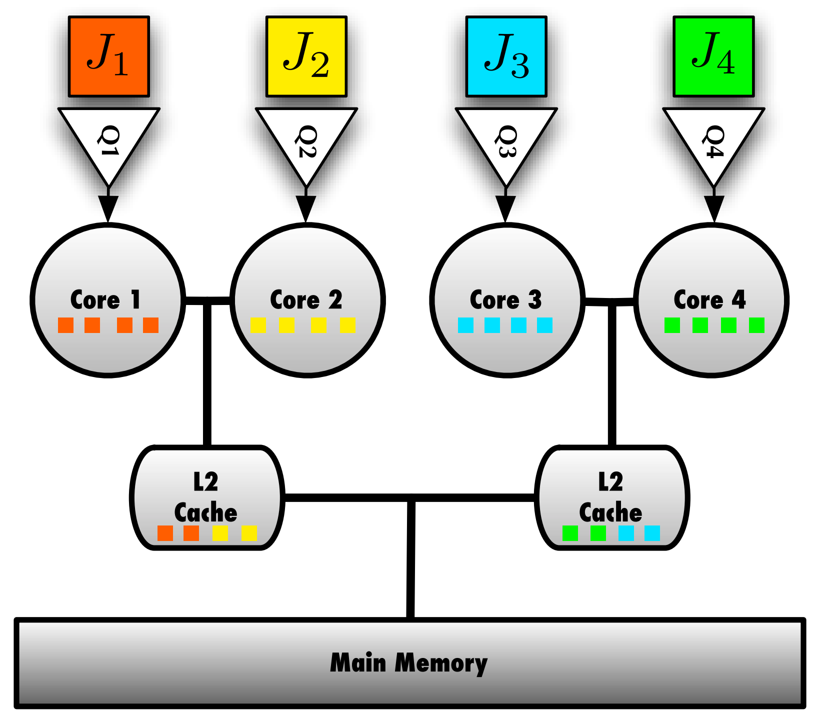
But: non-optimal

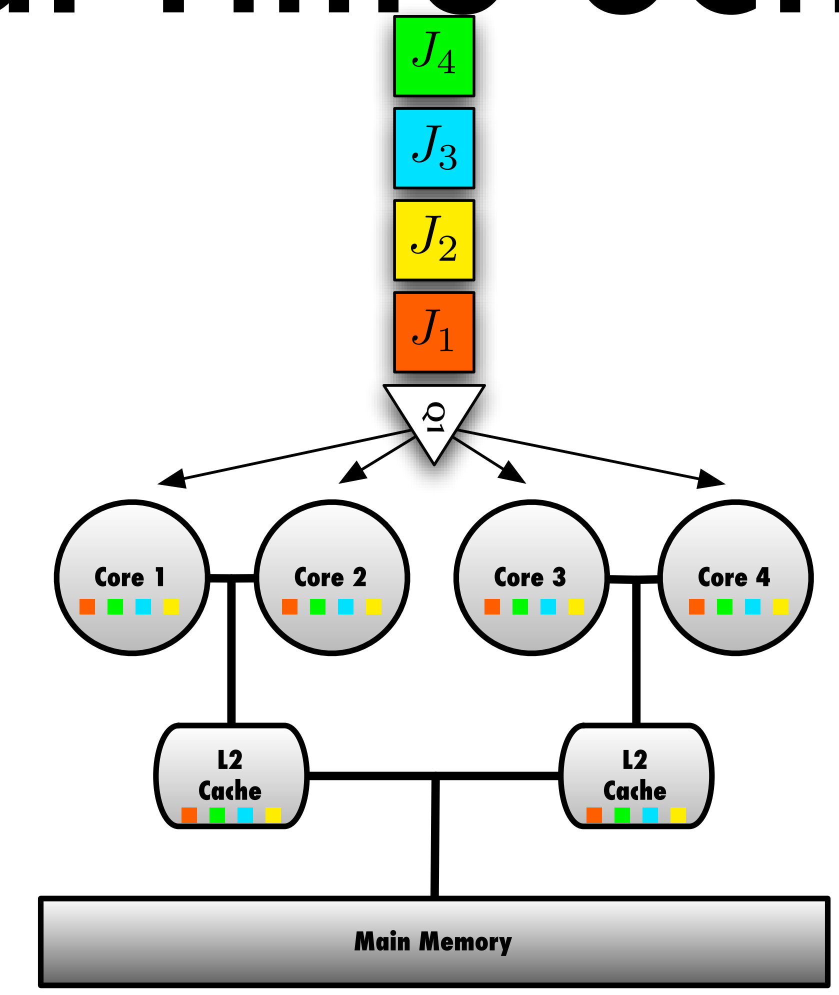
- ➡ need to place tasks (bin packing)
- ➡ mapping may be difficult to find
- ➡ mapping may not exist
- ➡ worst-case utilization bound ~50%

Multiprocessor Real-Time Scheduling

Partitioning

1. **Assign** tasks to cores (offline).
2. Schedule each core **independently** (like a uniprocessor).





Global/Optimal Scheduling

1. Keep **all cores busy** with sequential tasks.
2. Globally **coordinate** to reschedule and migrate tasks as needed.

Partitioned Scheduling

- ➡ simple to implement
- ➡ simple to understand
- ➡ simple to extend
- ➡ KISS-compatible

But: non-optimal

- ➡ need to place tasks (bin packing)
- ➡ mapping may be difficult to find
- ➡ mapping may not exist
- ➡ worst-case utilization bound ~50%

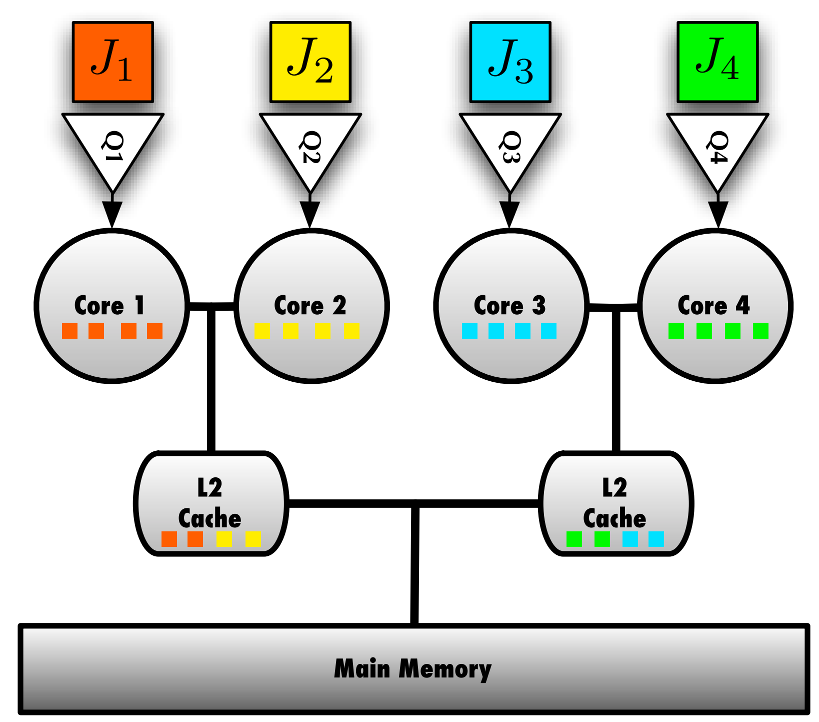
Global Scheduling

- ➡ optimality possible: 100% utilization
  - *under restrictive assumptions*
- ➡ many elegant algorithms: PD^2, BF, LLRef, EKG, U-EDF, RUN, QPS, …

Multiprocessor Real-Time Scheduling

Partitioning

1. **Assign** tasks to cores (offline).
2. Schedule each core **independently** (like a uniprocessor).

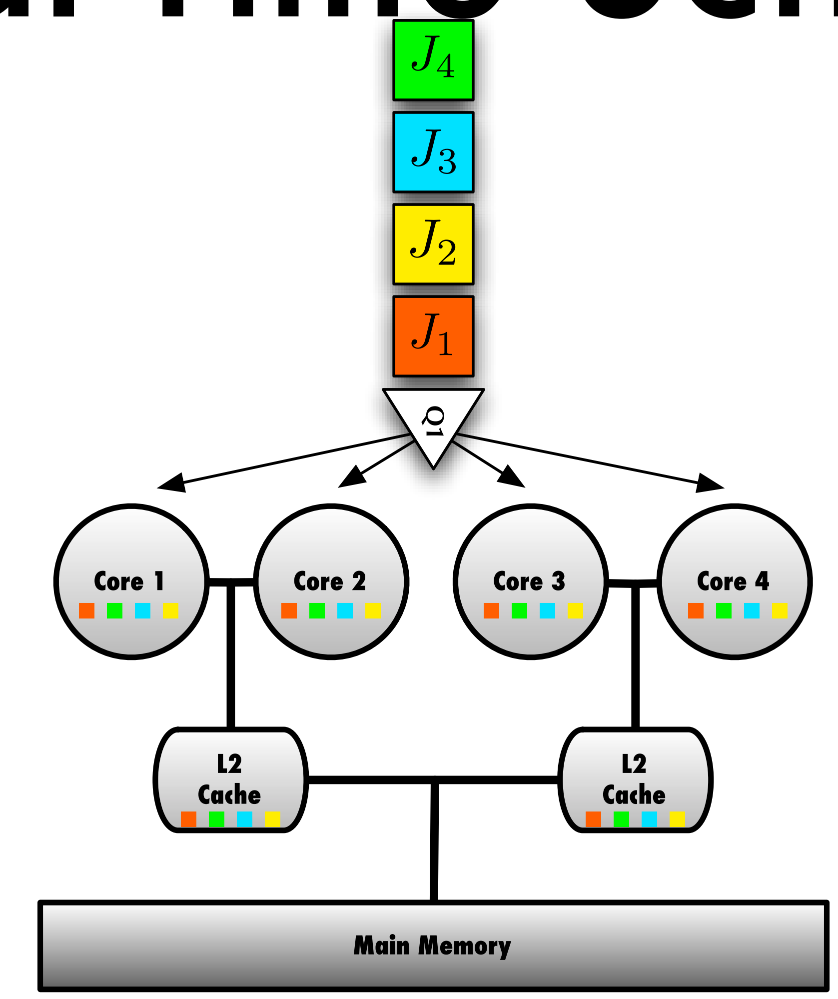


Partitioned Scheduling

- ➡ simple to implement
- ➡ simple to understand
- ➡ simple to extend
- ➡ KISS-compatible

But: non-optimal

- ➡ need to place tasks (bin packing)
- ➡ mapping may be difficult to find
- ➡ mapping may not exist
- ➡ worst-case utilization bound ~50%



Global/Optimal Scheduling

1. Keep **all cores busy** with sequential tasks.
2. Globally **coordinate** to reschedule and migrate tasks as needed.

Global Scheduling

- ➡ optimality possible: 100% utilization
  - *under restrictive assumptions*
- ➡ many elegant algorithms: PD^2, BF, LLRef, EKG, U-EDF, RUN, QPS, …

But: high conceptual complexity

- ➡ difficult to understand
- ➡ difficult to implement (efficiently)
- ➡ difficult to extend
- ➡ difficult to test/validate/certify

The Question

(How) can we make global scheduling work in practice?

Much work in the last 10 years, both theory and systems…

The Question

~~(How) can we make global scheduling work in practice?~~

Do we actually need global, optimal scheduling!?

The Real Question

The "claim to fame" of global, optimal multiprocessor scheduling is 100% schedulable utilization…

The Real Question

The "claim to fame" of global, optimal multiprocessor scheduling is 100% schedulable utilization…

*How to get **close to 100%** without giving up on **simplicity**?*

The Real Question

The "claim to fame" of global, optimal multiprocessor scheduling is 100% schedulable utilization…

*How to get **close to 100%** without giving up on **simplicity**?*

…and how close can we get?

The Real Question

The "claim to fame" of global, optimal multiprocessor scheduling is 100% schedulable utilization…

How to get ***close to 100%*** *without giving up on* ***simplicity****?*

…and how close can we get?

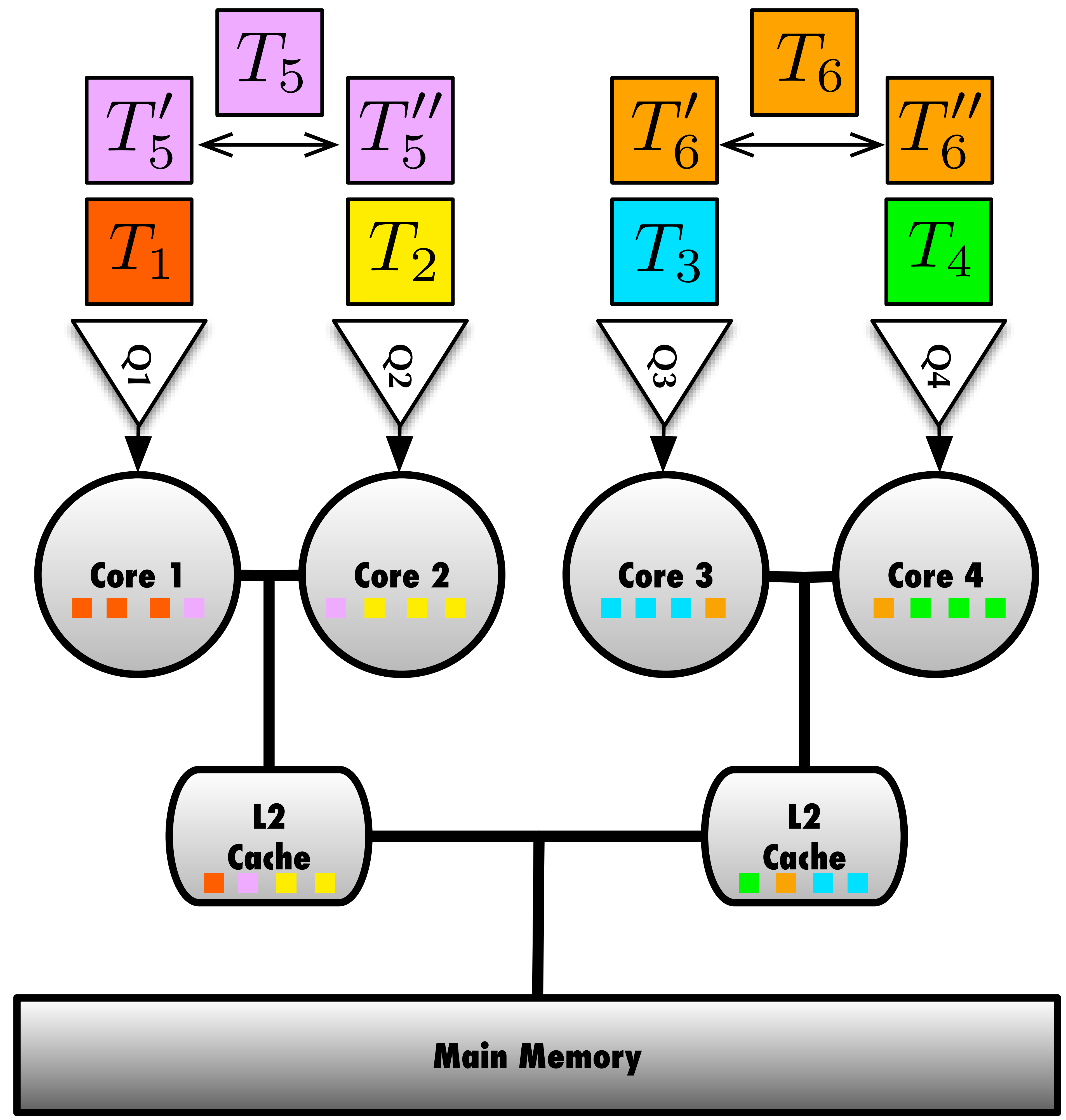
Assumptions in Optimality Proofs:

- static set of tasks w/ static parameters
- independent tasks
- periodic or sporadic tasks
- implicit deadlines
- no jitter, no overheads, etc.

Essential Background

Hybrid: Semi-Partitioned Scheduling

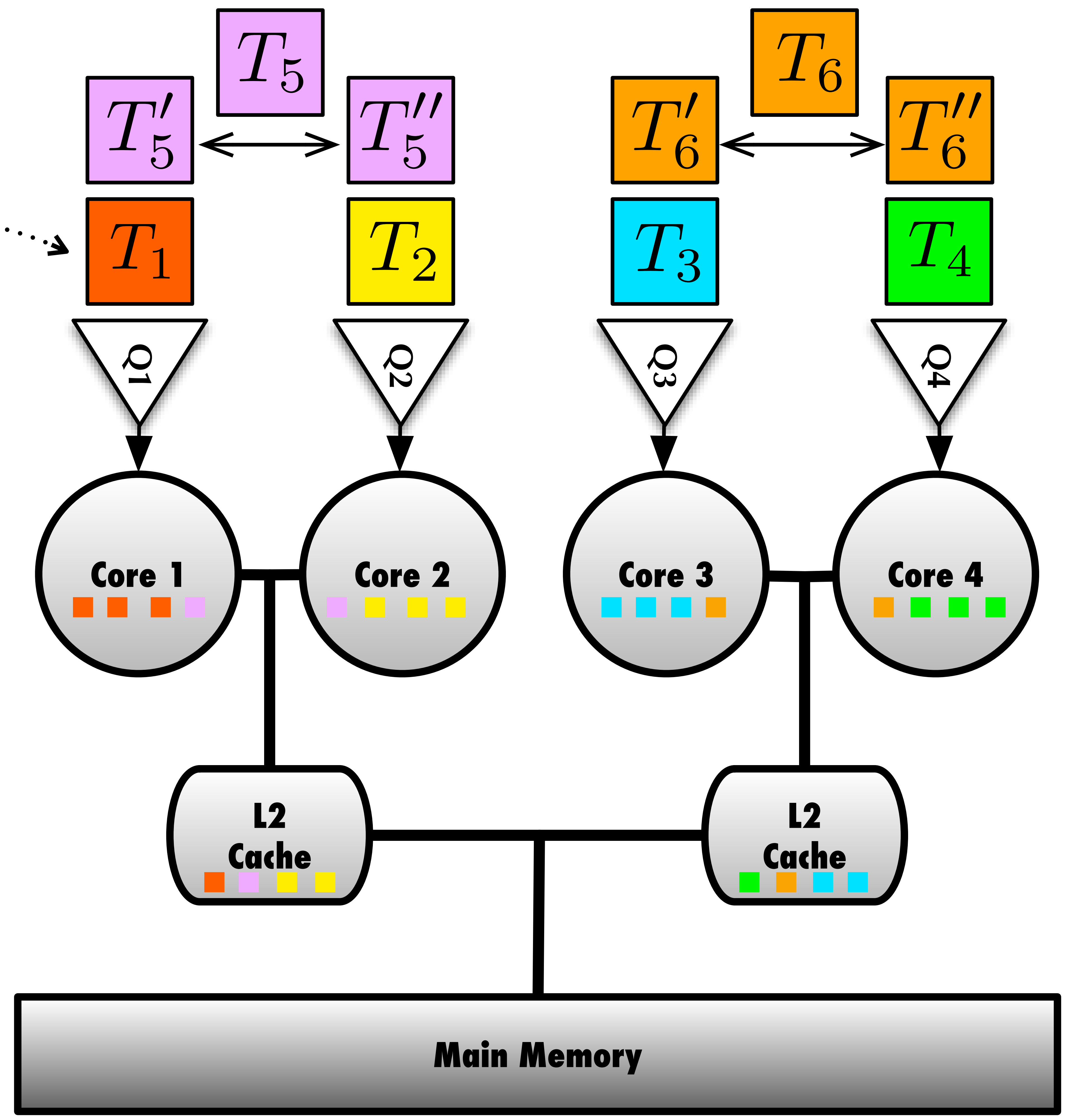
(Anderson et al., 2005)



Hybrid: Semi-Partitioned Scheduling

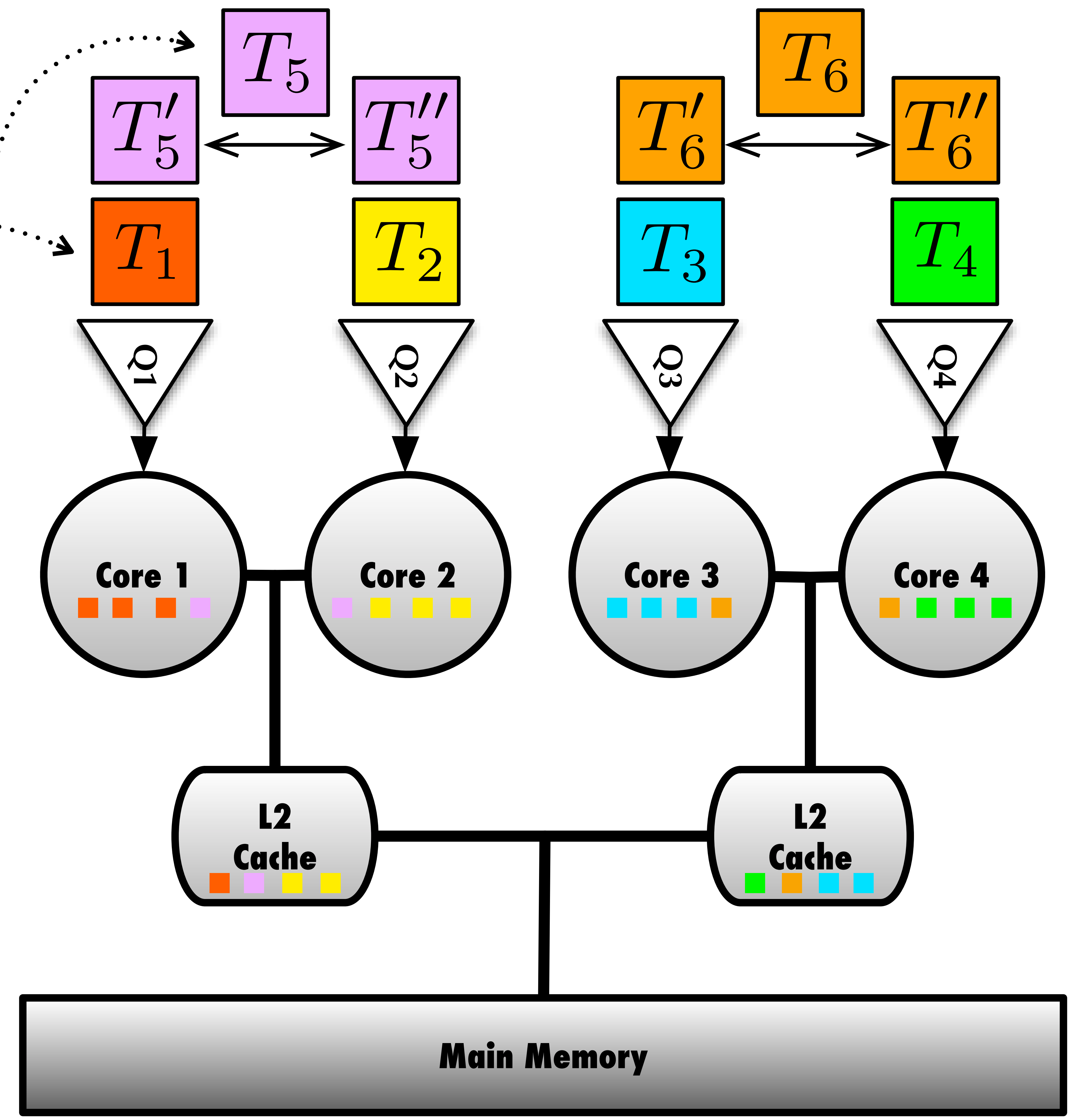
(Anderson et al., 2005)

- Statically assign **most** tasks



Hybrid: Semi-Partitioned Scheduling
(Anderson et al., 2005)

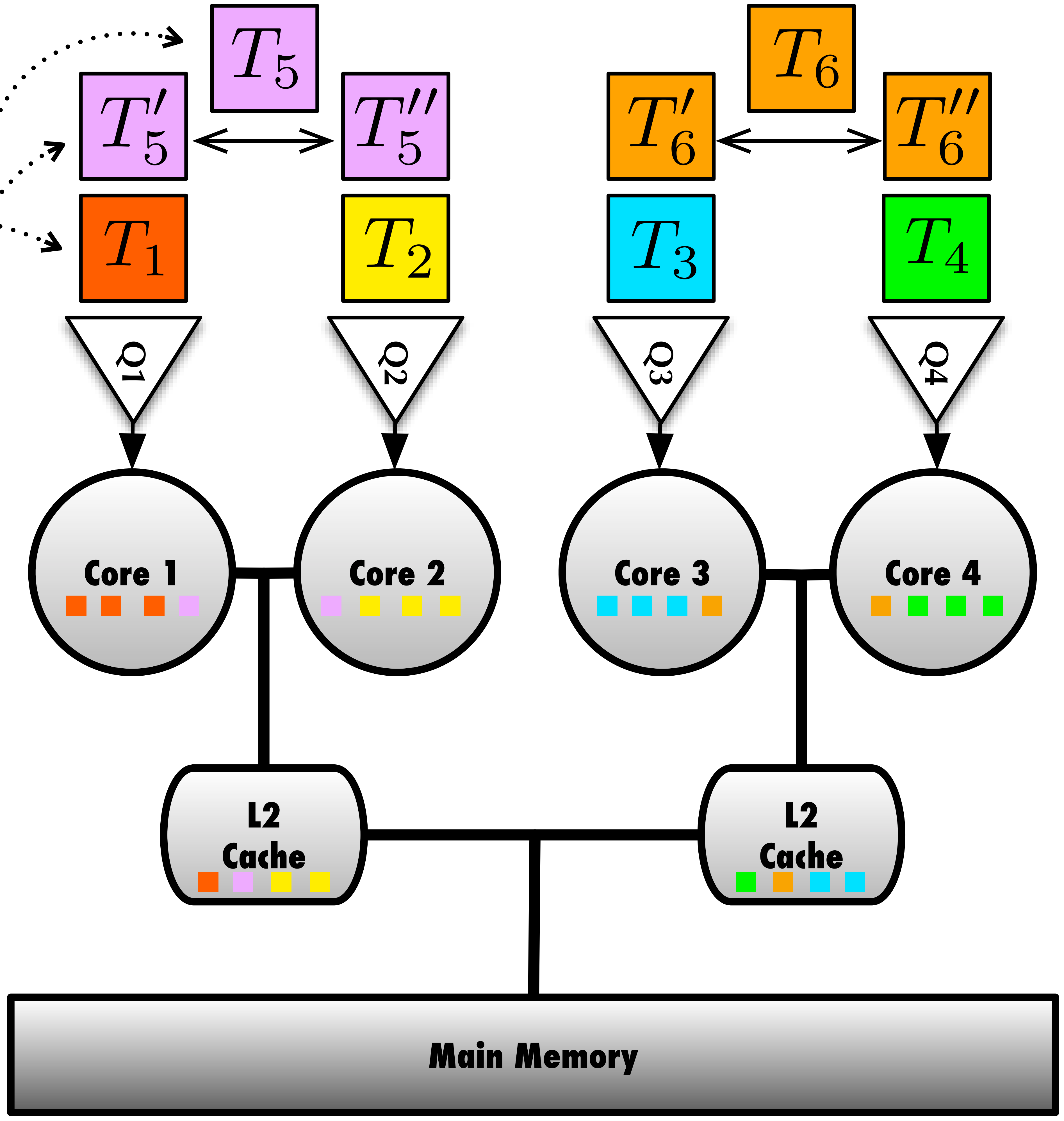
- Statically assign **most** tasks
- Tasks **that don't fit** are **split into subtasks** with **precedence constraints**



Hybrid: Semi-Partitioned Scheduling

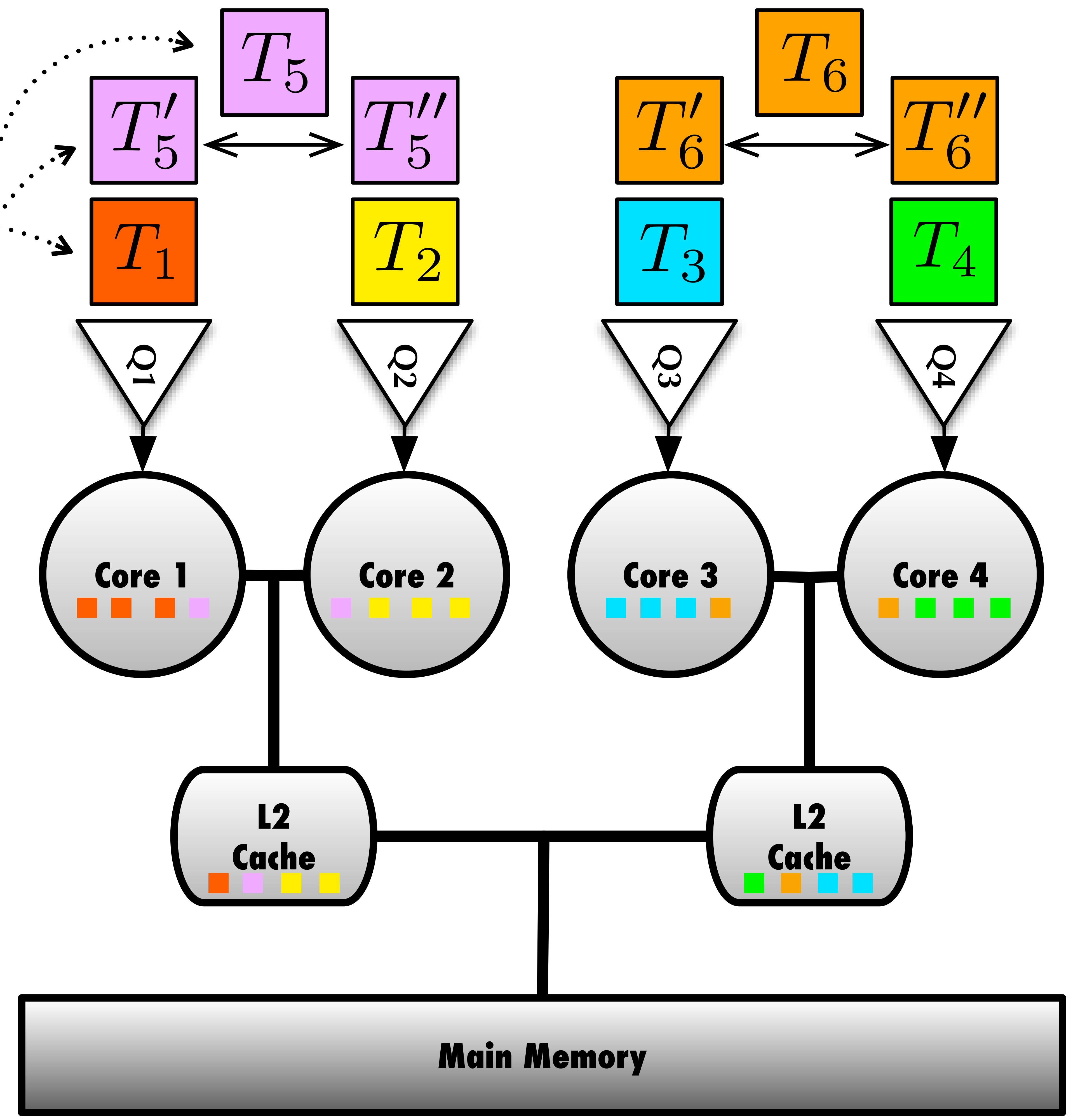
(Anderson et al., 2005)

- Statically assign **most** tasks
- Tasks **that don't fit** are **split into subtasks** with **precedence constraints**
- Assign subtasks to cores → some original tasks **migrate**



Hybrid: Semi-Partitioned Scheduling
(Anderson et al., 2005)

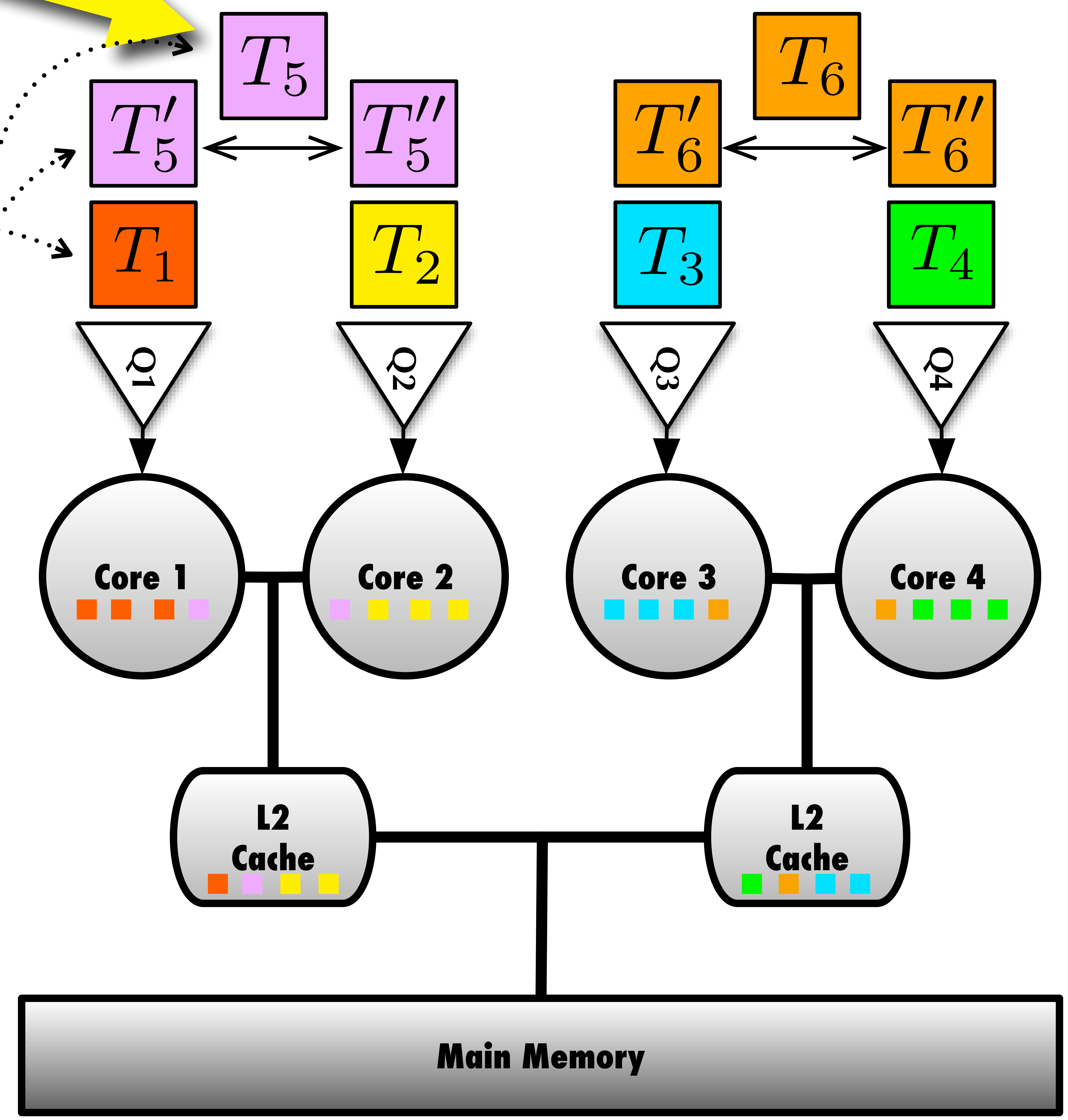
- Statically assign **most** tasks
- Tasks **that don't fit** are **split into subtasks** with **precedence constraints**
- Assign subtasks to cores → some original tasks **migrate**
- this is a **process migration** → no code changes in the task



Task T_5 split into two logical subtasks (= two budgets)

At runtime, T_5 migrates between cores 1 and 2.

- Statically assign **most** tasks
- Tasks **that don't fit** are **split into subtasks** with **precedence constraints**
- Assign subtasks to cores
  → some original tasks **migrate**
- this is a **process migration**
  → no code changes in the task



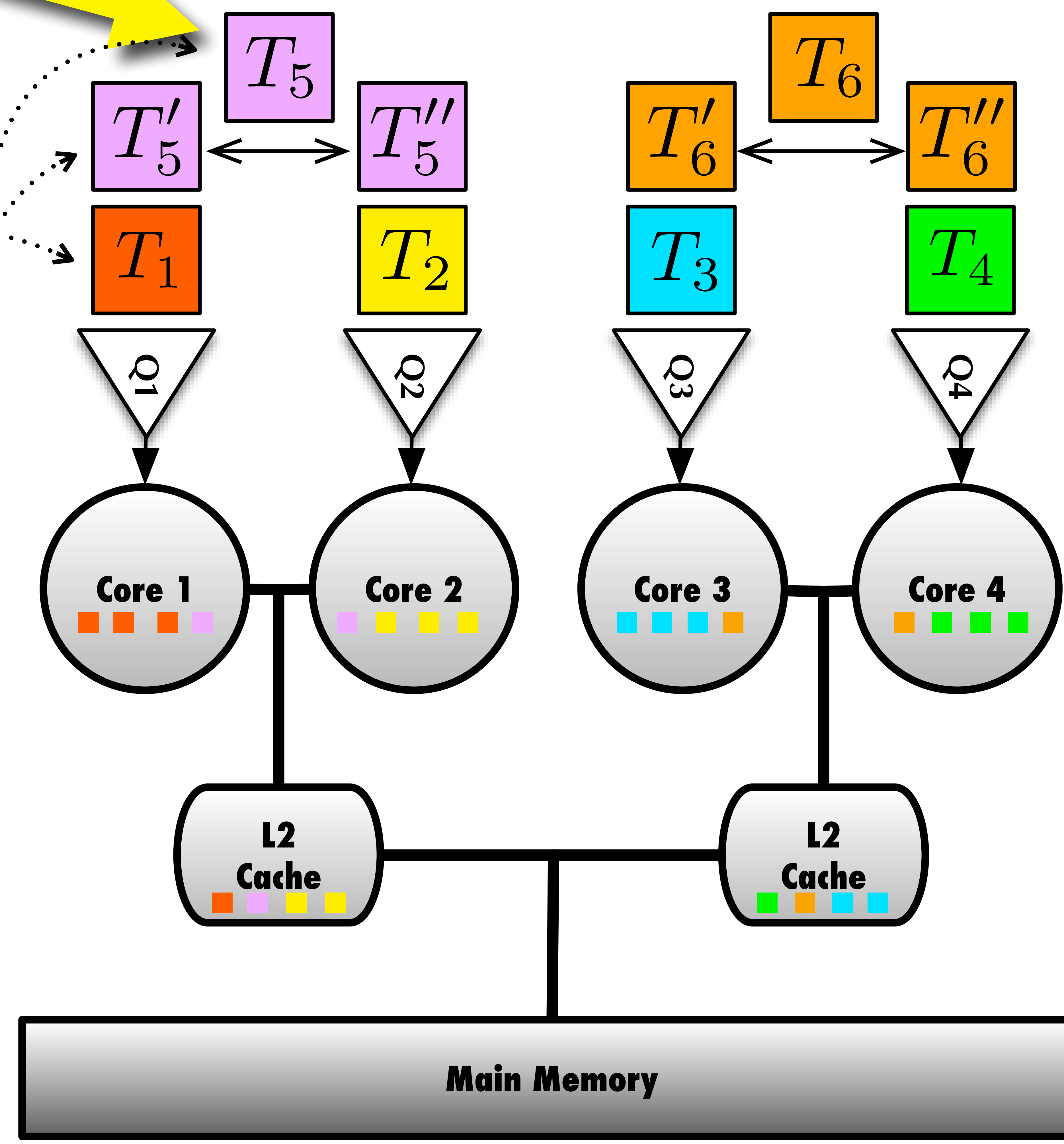
Task T_5 split into two logical subtasks (= two budgets)

At runtime, T_5 migrates between cores 1 and 2.

… ing

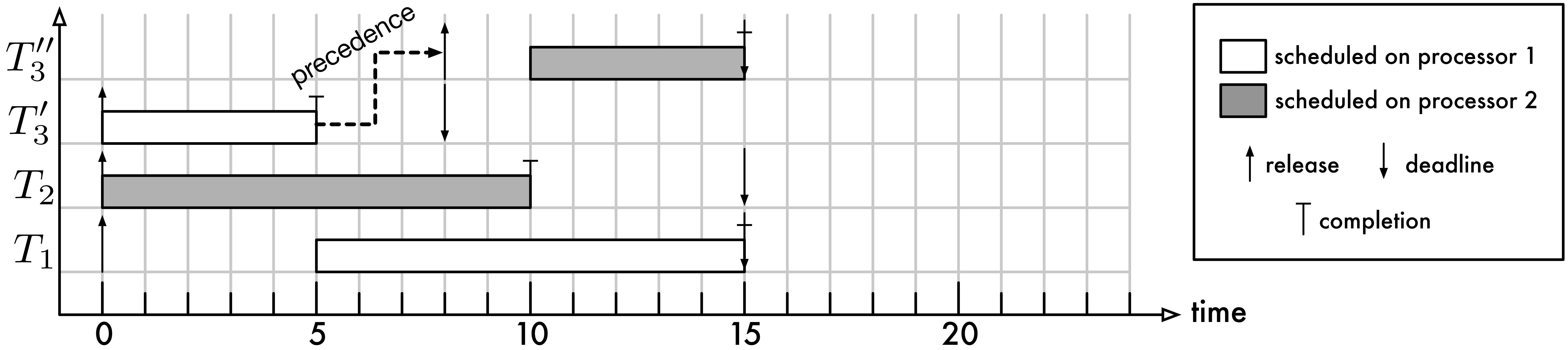
(Anderson … al., 2005)

- Statically assign **most** tasks
- Tasks **that don't fit** are **split into subtasks** with **precedence constraints**
- Assign subtasks to cores
  → some original tasks **migrate**
- this is a **process migration**
  → no code changes in the task



*Many **heuristics** for how to split, when to migrate, and where to assign subtasks…*

Hybrid: Semi-Partitioned Scheduling



Simple Example

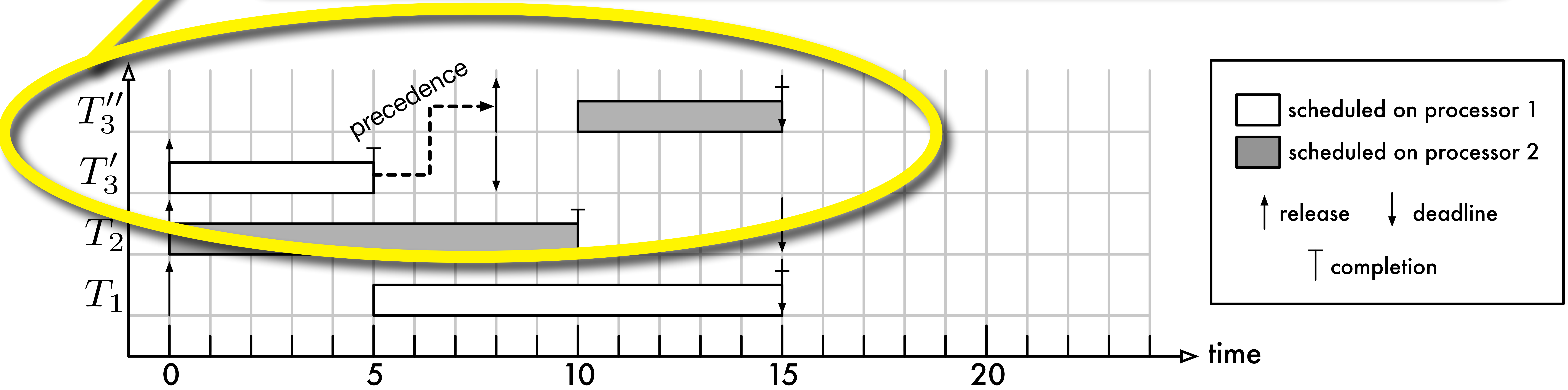
- Three identical tasks
  - period **P** = 15
  - WCET **C** = 10

One approach: split T_3

- into two subtasks T'_3, T''_3
  - C’ = C” = 5
  - P’ = P” = 15
  - D’ = 8, D” = 7

Semi-Partitioning

Still **core-local decisions**, one **cross-core activation**.



Simple Example

- Three identical tasks
  - period **P** = 15
  - WCET **C** = 10

One approach: split T_3

- into two subtasks T'_3, T''_3
  - C' = C'' = 5
  - P' = P'' = 15
  - D' = 8, D'' = 7

The C=D Splitting Strategy

(Burns et al., 2012)

The C=D Splitting Strategy

(Burns et al., 2012)

Assumption

➡ Earliest-Deadline First (**EDF**) policy is in use on each core

The C=D Splitting Strategy

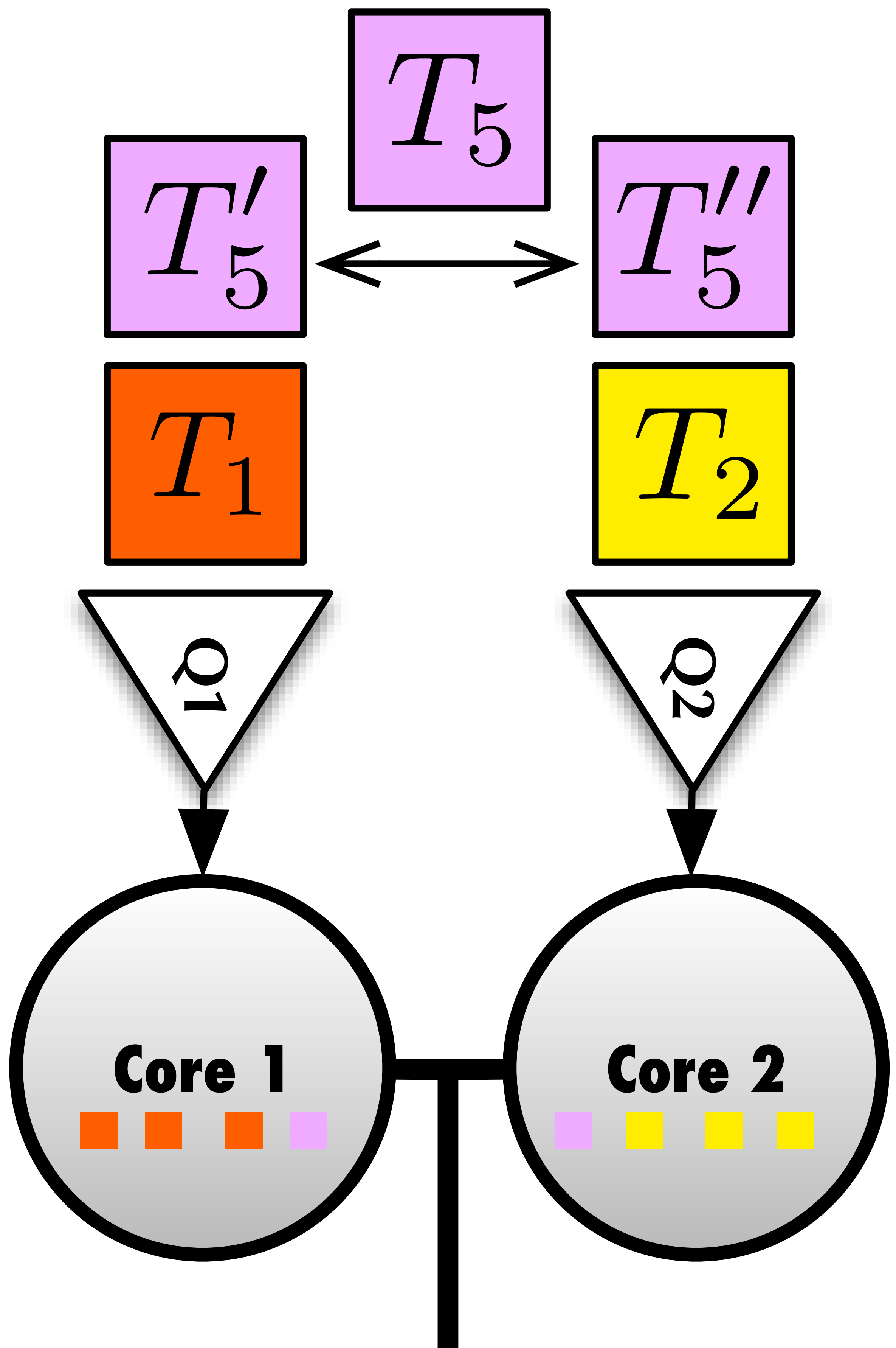
(Burns et al., 2012)

Assumption

➡ Earliest-Deadline First (**EDF**) policy is in use on each core

Suppose T_5 does not fit (in its entirety) onto Core 1

➡ How to allocate **some part** of T_5 on Core 1?



The C=D Splitting Strategy

(Burns et al., 2012)

Assumption

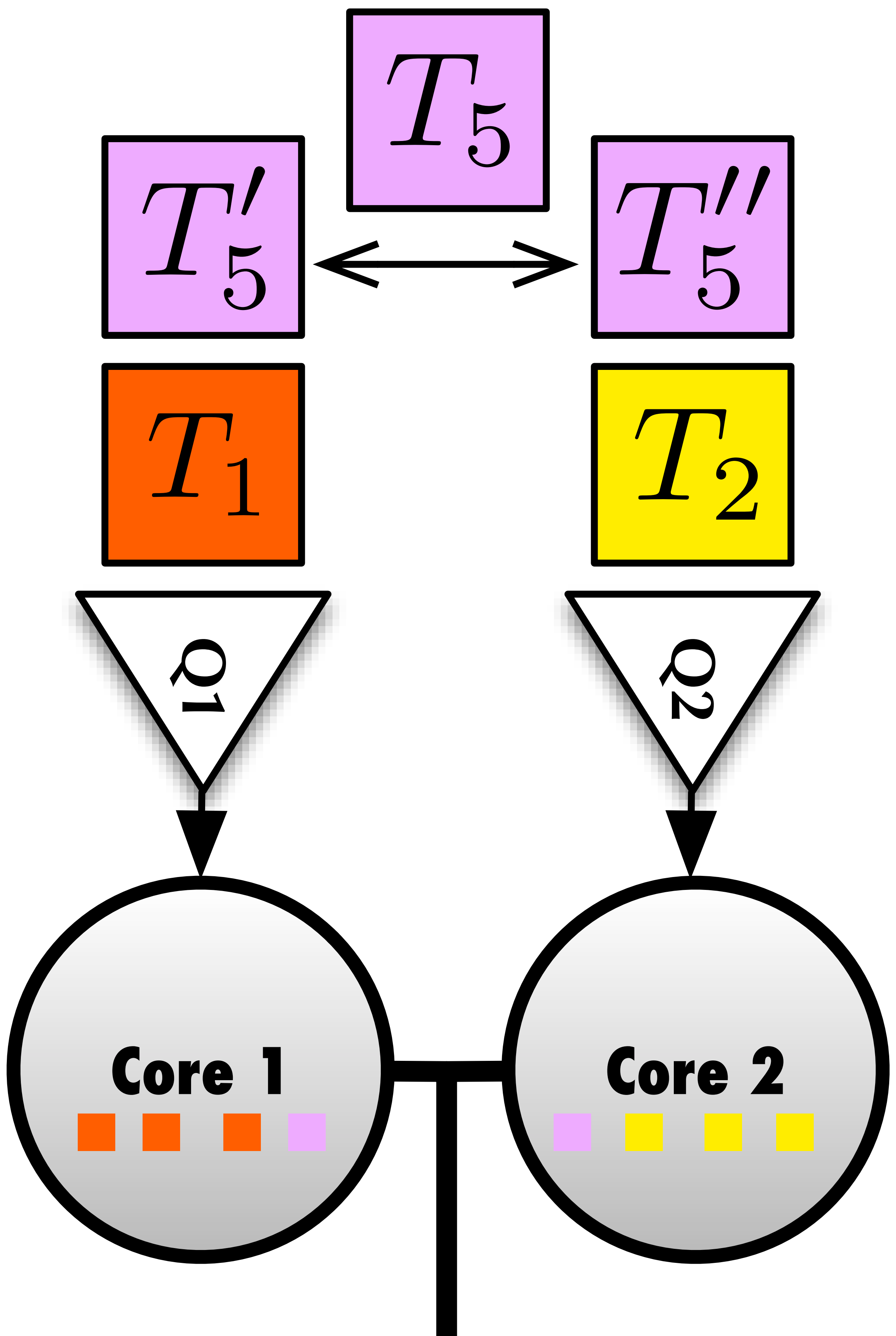
- ➡ Earliest-Deadline First (**EDF**) policy is in use on each core

Suppose T_5 does not fit (in its entirety) onto Core 1

- ➡ How to allocate **some part** of T_5 on Core 1?

C=D Approach

- ➡ Given parameters (*C*, *D*, *P*)…
  …identify **largest** **C'** and matching **C''** such that
  - *C' + C'' = C* // split execution cost
  - *D' = C'* // **zero-laxity subtask**
  - *D'' = D - D'* // **remaining laxity subtask**
  - *P' = P'' = P* // period remains unchanged
  - *and first subtask is schedulable on Core 1*



zero laxity ↔ forced to be scheduled immediately

laxity = relative deadline - execution cost

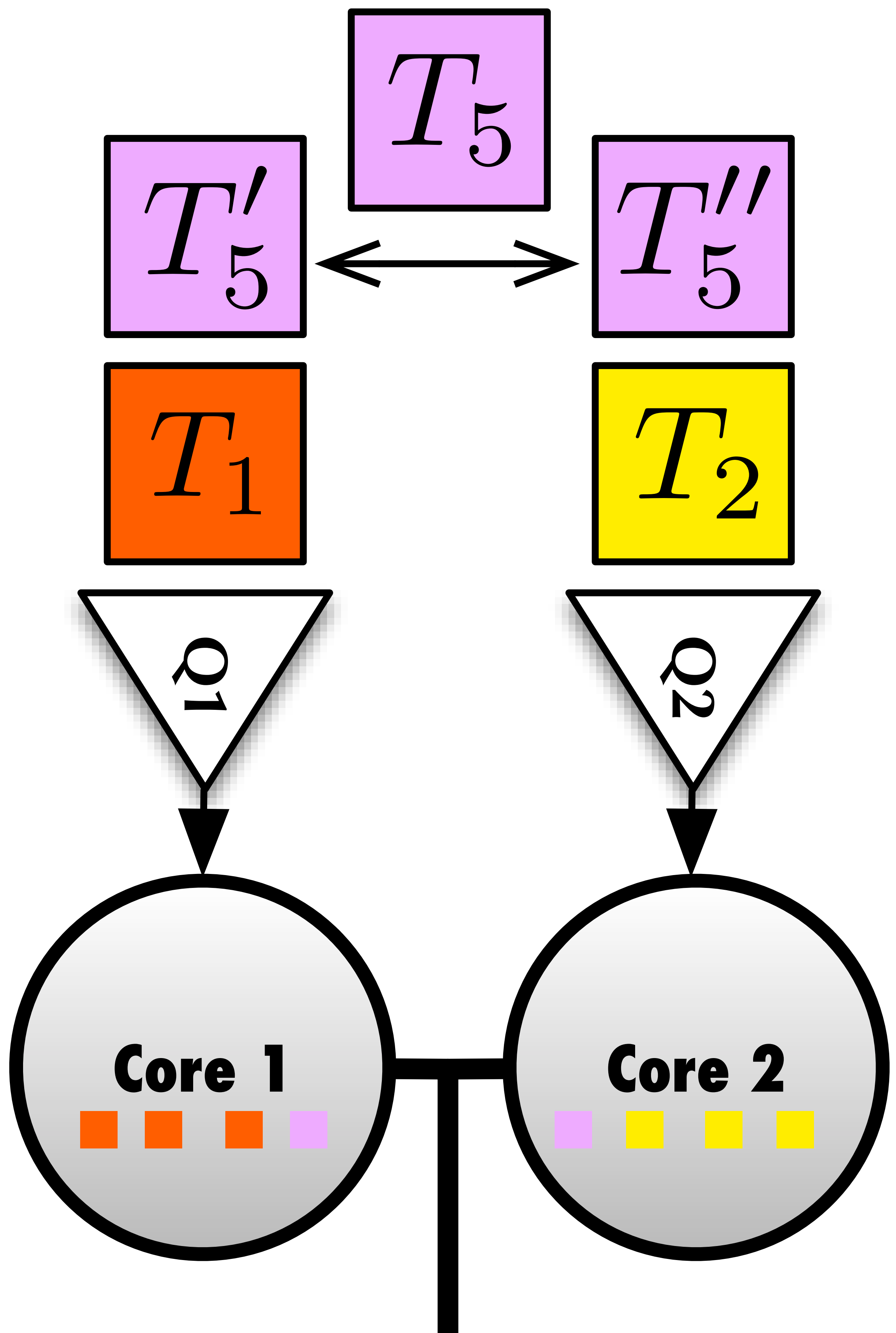
Suppose T_5 does not fit (in its entirety) onto Core 1

➡ How to allocate **some part** of T_5 on Core 1?

C=D Approach

➡ Given parameters (*C*, *D*, *P*) …
…identify **largest C'** and matching **C''** such that

- *C' + C'' = C* // split execution cost
- *D' = C'* // **zero-laxity subtask**
- *D'' = D - D'* // **remaining laxity subtask**
- *P' = P'' = P* // period remains unchanged
- *and first subtask is schedulable on Core 1*



Reservation-Based Scheduling

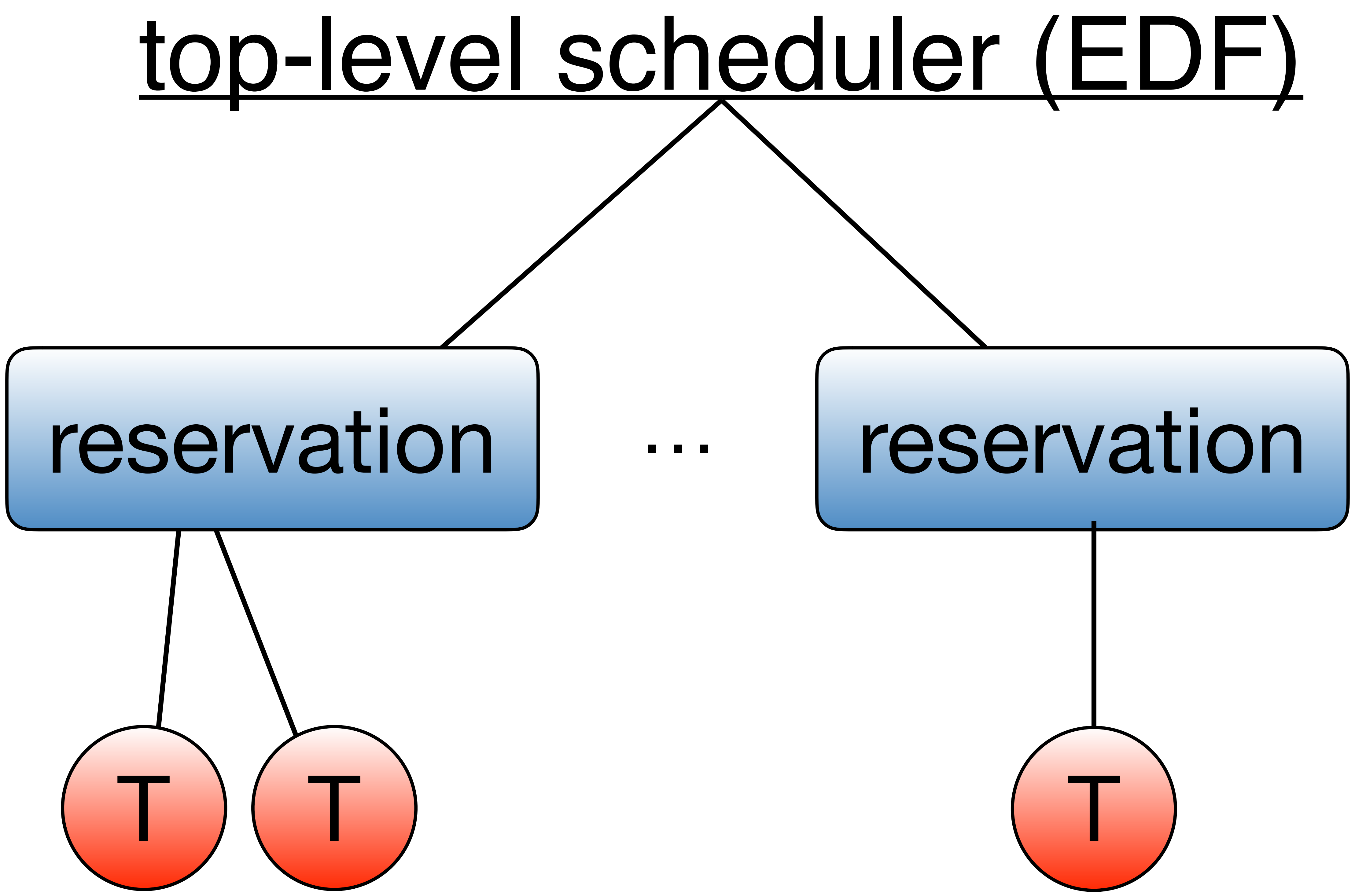
(Mercer et al., 1993)

Reservation-Based Scheduling

(Mercer et al., 1993)

Two-Level Scheduling

- ➡ threads / tasks encapsulated in reservations
- ➡ to schedule:
  - first pick **reservation**
  - then pick **thread**



Reservation-Based Scheduling

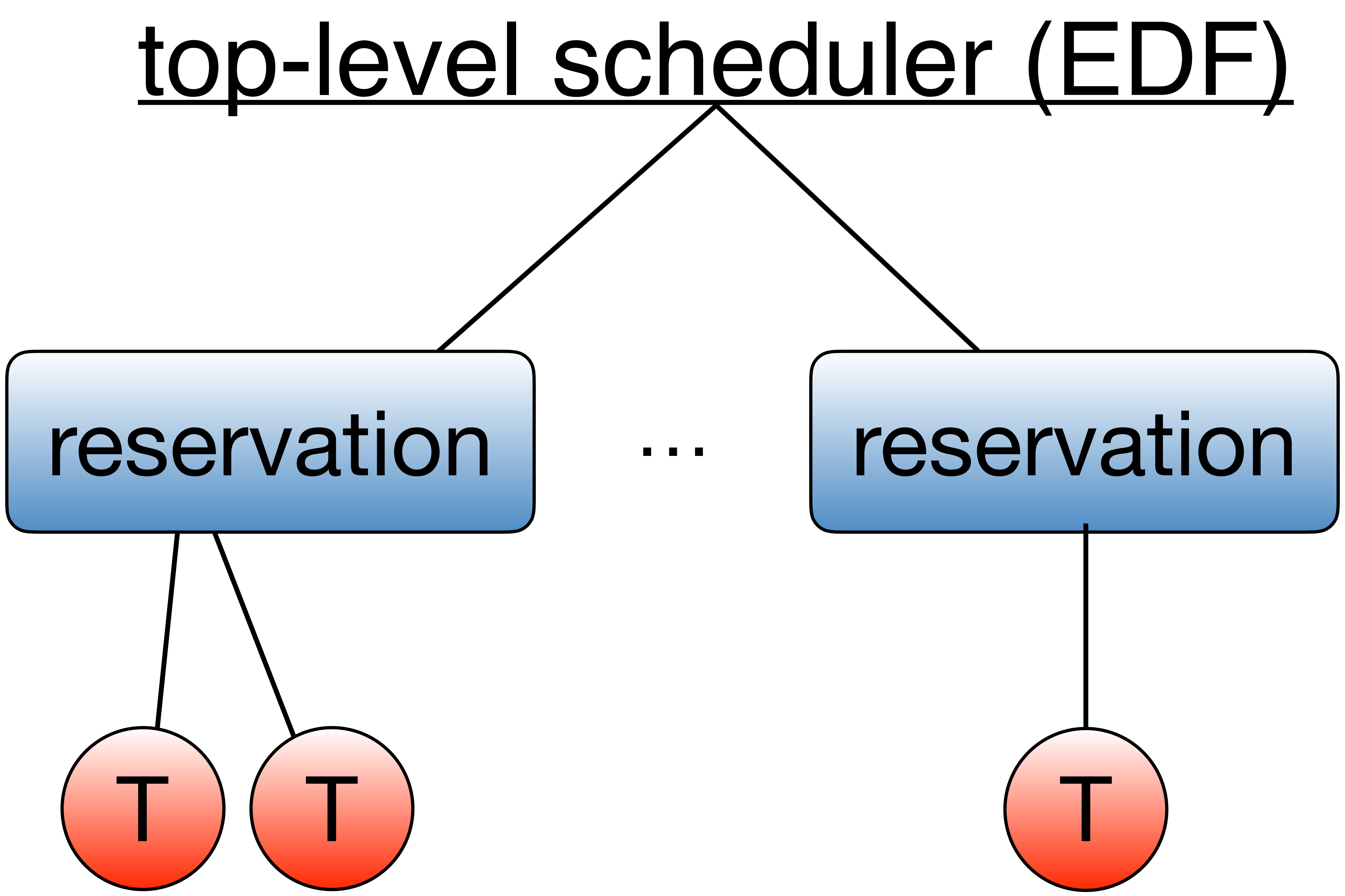
(Mercer et al., 1993)

Two-Level Scheduling

- threads / tasks encapsulated in reservations
- to schedule:
  - first pick **reservation**
  - then pick **thread**

Reservations (or Servers)

- *many* algorithms available in the literature
- Most simple one:
  - **sporadic polling server**
    = sporadic task
      + budget enforcement

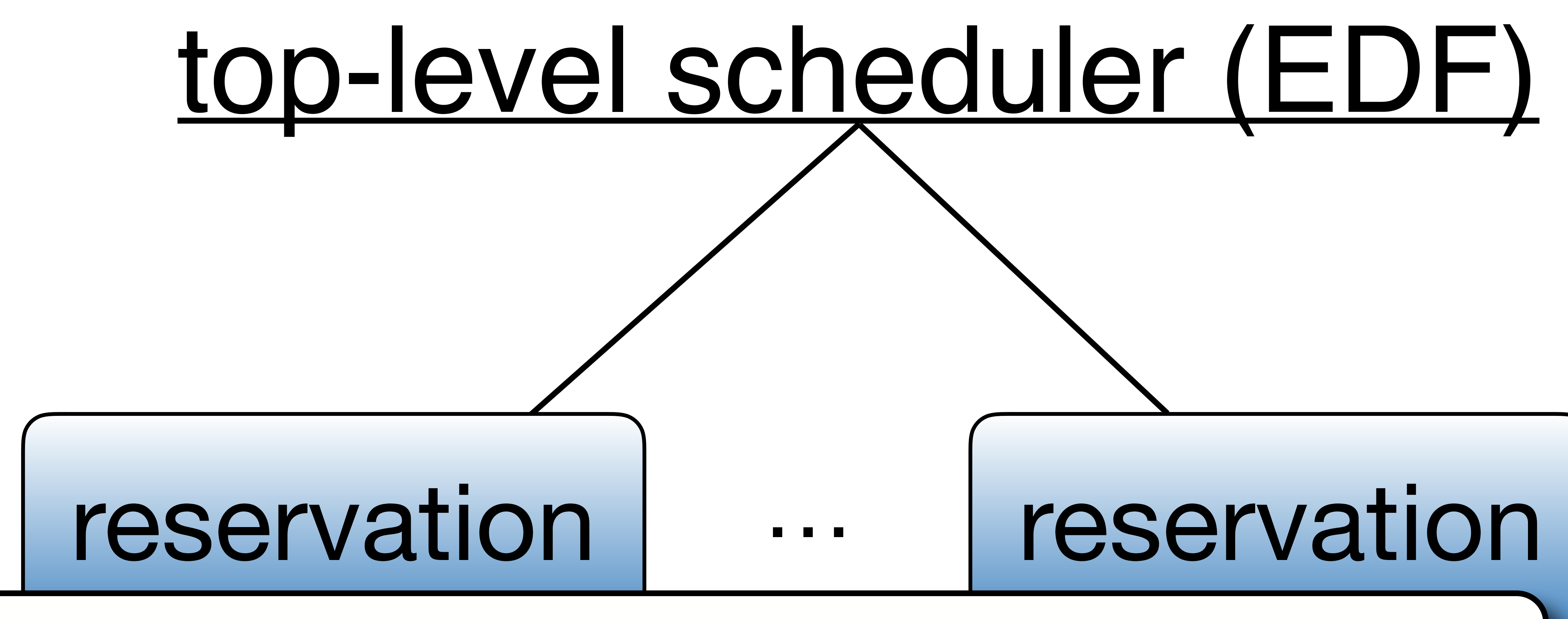


Reservation-Based Scheduling

(Mercer et al., 1993)

Two-Level Scheduling

- threads / tasks encapsulated in reservations
- to schedule:
  - first pick **reservation**
  - then pick **thread**



Reservations (or Servers)

- *many* algorithms available in the literature
- Most simple one:
  - **sporadic polling server**
    = sporadic task
    + budget enforcement

Hard vs. Soft Reservations

(Rajkumar et al., 1998)

When running out of budget:

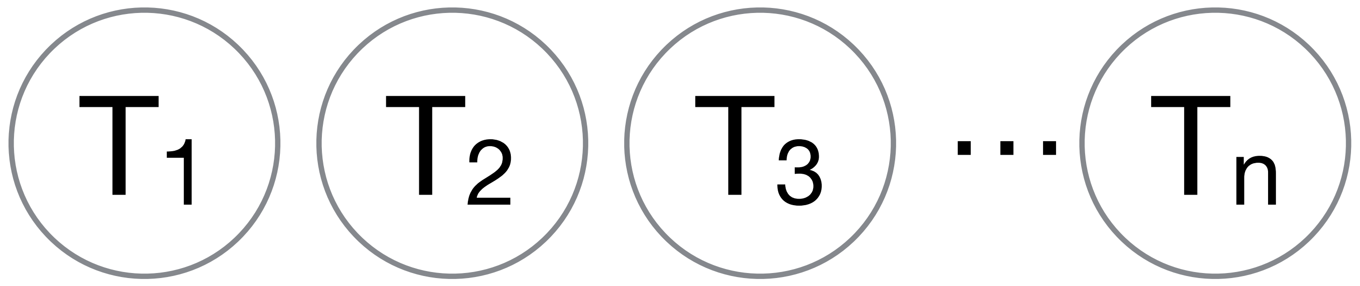
hard = cut off from service
soft = may consume **idle time** with background priority

A Simple Semi-Partitioned Reservations Approach

Approach in a Nutshell

T_1 T_2 T_3 $\cdots$ T_n

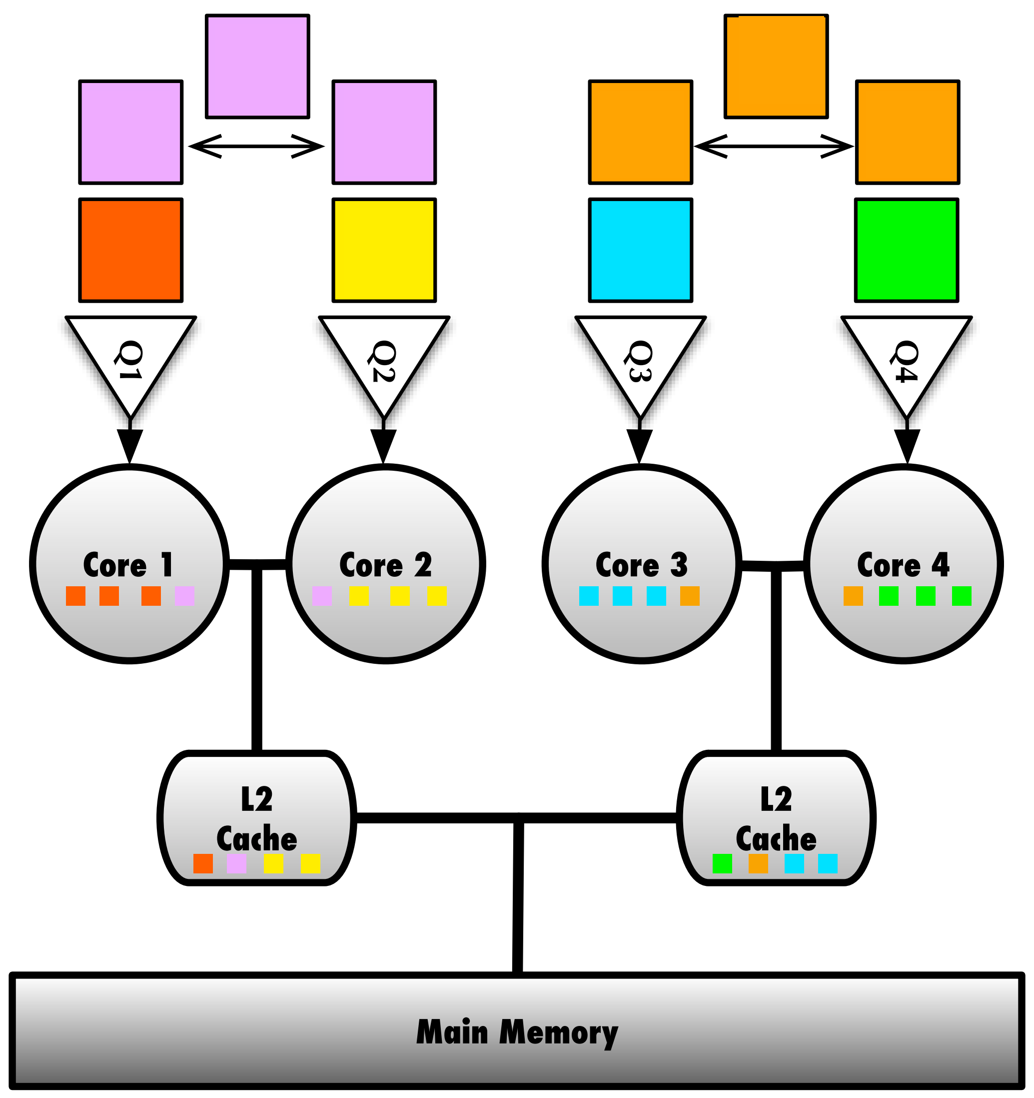
Approach in a Nutshell



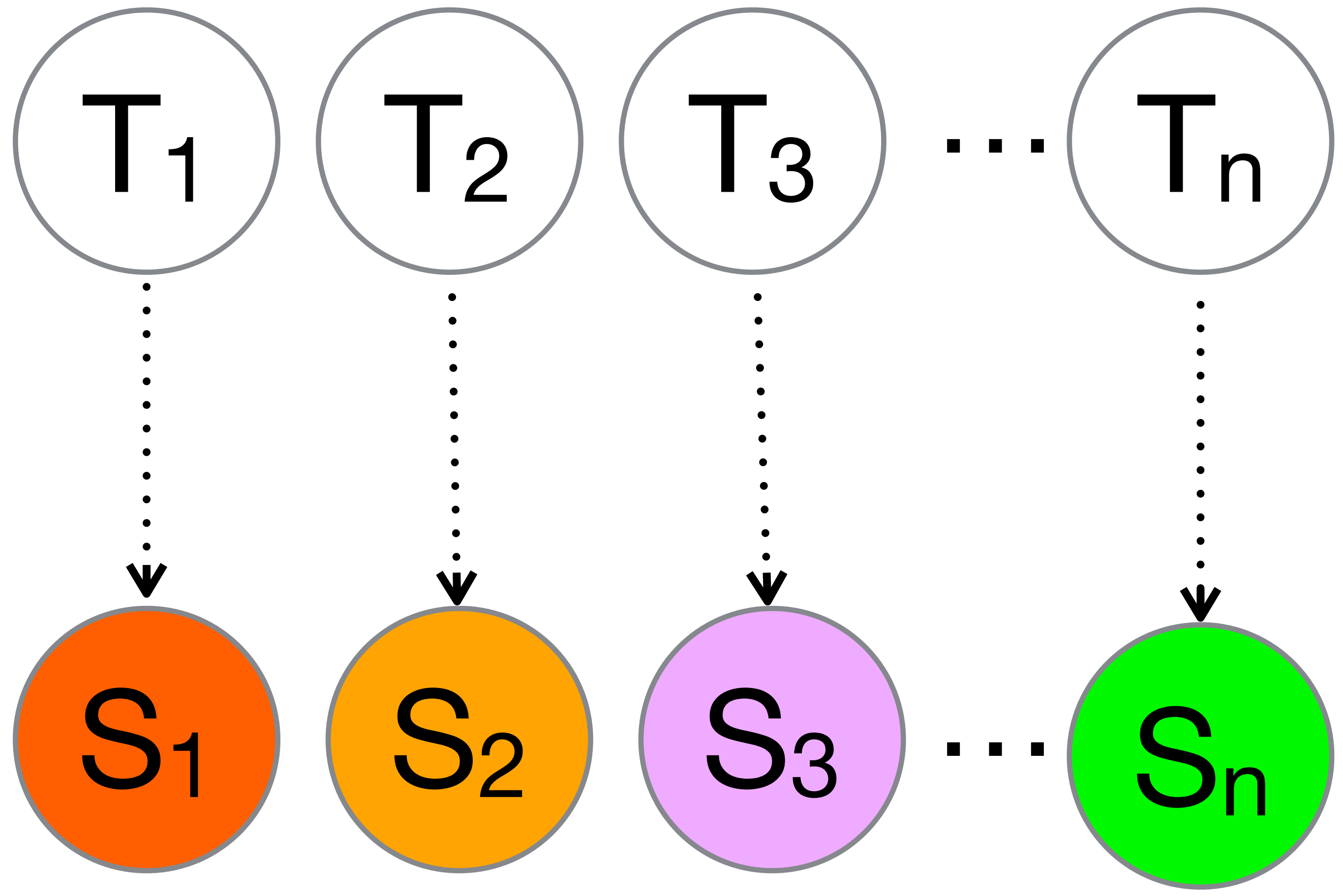
1) Partitioned Reservation Scheduler

➡ EDF-based, completely local

➡ simple to implement efficiently



Approach in a Nutshell



1) Partitioned Reservation Scheduler

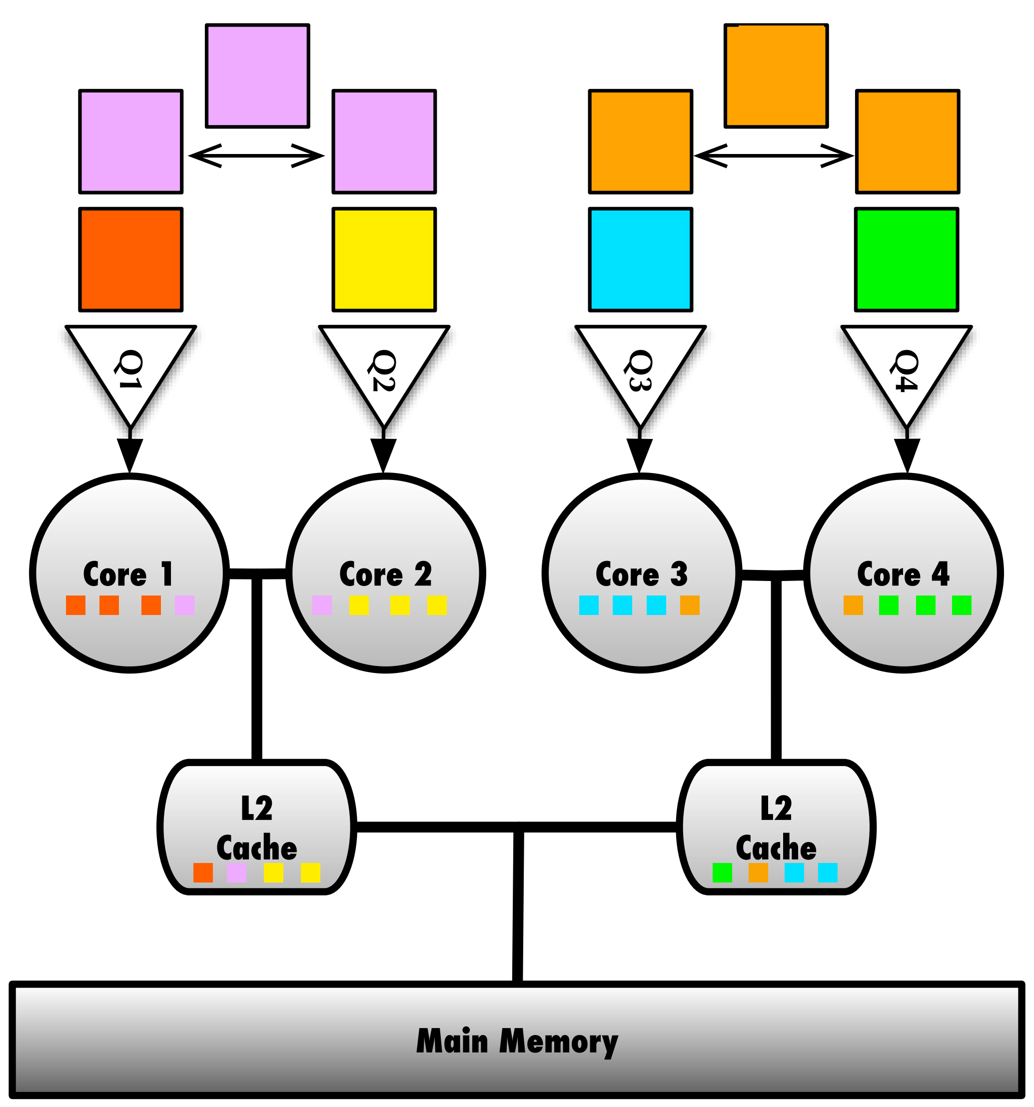
➡ EDF-based, completely local

➡ simple to implement efficiently

2) One Task ↔ One Reservation

➡ initially, reservation parameters = task parameters

➡ soft **sporadic polling reservations** (or CBS or…)

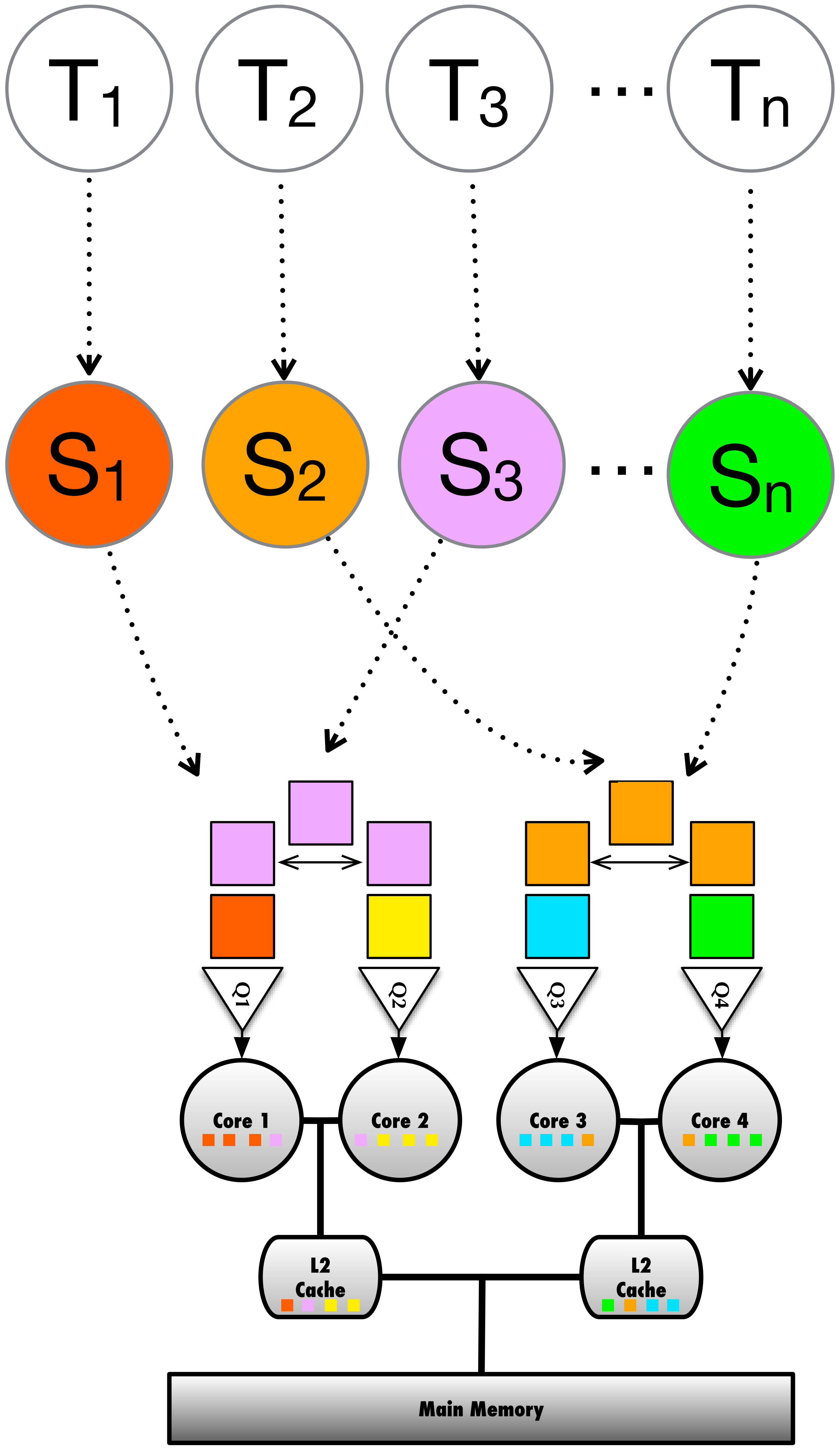


Approach in a Nutshell

1) Partitioned Reservation Scheduler
- ➡ EDF-based, completely local
- ➡ simple to implement efficiently

2) One Task ↔ One Reservation
- ➡ initially, reservation parameters = task parameters
- ➡ soft **sporadic polling reservations** (or CBS or…)

3) Use C=D + Some Tweaks…
- ➡ place all reservations, **splitting** some if necessary
- ➡ potentially **tweak reservation parameters**
- ➡ try to **avoid migrations** whenever possible



Approach in a Nutshell

1) Partitioned Reservation Scheduler

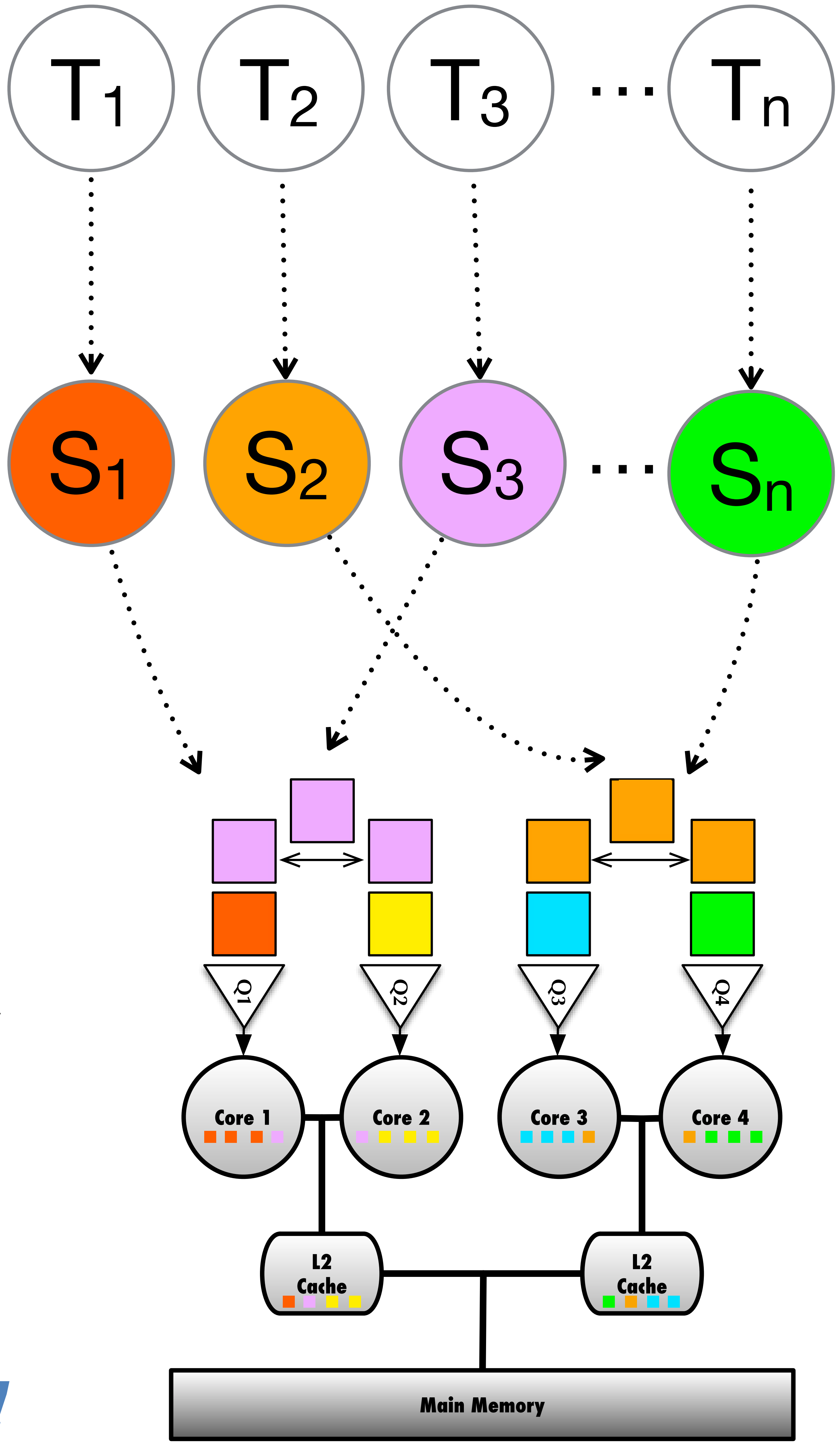
- ➡ EDF-based, completely local
- ➡ simple to implement efficiently

2) One Task ↔ One Reservation

- ➡ initially, reservation parameters = task parameters
- ➡ soft **sporadic polling reservations** (or CBS or…)

3) Use C=D + Some Tweaks…

- ➡ place all reservations, **splitting** some if necessary
- ➡ potentially **tweak reservation parameters**
- ➡ try to **avoid migrations** whenever possible



…and that's it!

Tweak 1: Try Many Heuristics

Tweak 1: Try Many Heuristics

Most heuristics are cheap…

➡ …so don't choose, run them "all."

Tweak 1: Try Many Heuristics

Most heuristics are cheap…

➡ …so don't choose, run them "all."

Observation: It pays to play with details

➡ **When** to split, **how much** to split off, **where** to place subtasks…

➡ Minor differences add up.

Tweak 1: Try Many Heuristics

Most heuristics are cheap…

- ➡ …so don't choose, run them "all."

Observation: It pays to play with details

- ➡ **When** to split, **how much** to split off, **where** to place subtasks…
- ➡ Minor differences add up.

Observation: C=D works also well with worst-fit decreasing (WFD)

- ➡ Trivial…
- ➡ …but prior evaluations of C=D have focused primarily on **first-fit decreasing** (**FFD**) and thus not exploited its full potential.

Tweak 2: Pre-Assign Failures (PAF) Meta-Heuristic

Tweak 2: Pre-Assign Failures (PAF) Meta-Heuristic

Idea: Use Heuristic Failure as a Signal in a Feedback Loop

➡ *The tasks that couldn't be placed must be difficult somehow…*

…so try to place them first!

Tweak 2: Pre-Assign Failures (PAF) Meta-Heuristic

Idea: Use Heuristic Failure as a Signal in a Feedback Loop

➡ *The tasks that couldn't be placed must be difficult somehow…*

…so try to place them first!

```
Procedure PAF(h1, h2, taskset)

Initialize:

    • rest = taskset

    • failures = ∅

While no solution is found:

    1. Assign all tasks in failures with h1
       → give up if this fails

    2. Assign all tasks in rest with h2 while respecting
       pre-assignment by h1
       → success if complete solution is found
       → otherwise move any unplaced tasks to failures
```

Tweak 2: Pre-Assign Failures (PAF) Meta-Heuristic

Idea: Use Heuristic Failure as a Signal in a Feedback Loop

➡ *The tasks that couldn't be placed must be difficult somehow…*

…so try to place them first!

```
Procedure PAF(h1, h2, taskset)

Initialize:
    • rest = taskset
    • failures = ∅

While no solution is found:
    1. Assign all tasks in failures with h1
       → give up if this fails
    2. Assign all tasks in rest with h2 while respecting
       pre-assignment by h1
       → success if complete solution is found
       → otherwise move any unplaced tasks to failures
```

regular task-placement heuristics (e.g., WFD, FFD + C=D)

Tweak 3: Reduce Periods (RP) Meta-Heuristic

Tweak 3: Reduce Periods (RP) Meta-Heuristic

Observation: the C=D splitting heuristic is not "scale invariant"

- splitting off a subtask with ***C'=D'=1*** from a ***(C=2, P=10)*** task
  vs.
  splitting off a subtask with ***C'=D'=100*** from a ***(C=200, P=1000)*** task
- Both subtasks have 10% utilization and 100% density…
  …but ***C'=D'=1*** is ***much* easier to accommodate**.

Tweak 3: Reduce Periods (RP) Meta-Heuristic

Observation: the C=D splitting heuristic is not "scale invariant"

- splitting off a subtask with ***C'=D'=1*** from a ***(C=2, P=10)*** task
  vs.
  splitting off a subtask with ***C'=D'=100*** from a ***(C=200, P=1000)*** task
- Both subtasks have 10% utilization and 100% density…
  …but ***C'=D'=1*** is ***much* easier to accommodate**.

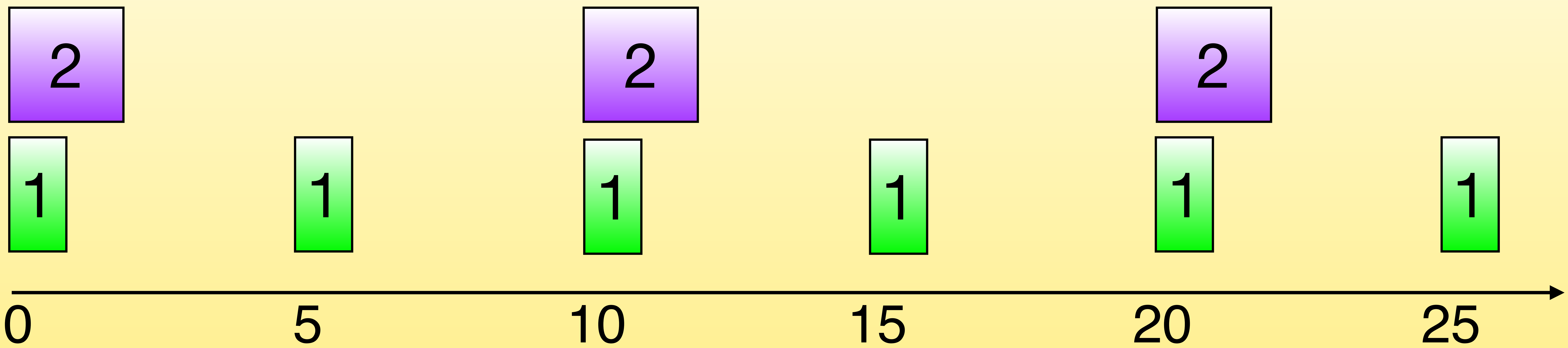
Idea: transform period prior to semi-partitioning

- apply **period transformation** to spread out the load of "difficult" tasks
- very effective at reducing the "**chunk size**" that C=D must deal with

Example

If a task requires **2 ms** every **10 ms**,

we can instead also schedule it for **1 ms** every **5 ms**:



Idea: transform period prior to semi-partitioning

- ➡ apply **period transformation** to spread out the load of "difficult" tasks
- ➡ very effective at reducing the "**chunk size**" that C=D must deal with

Tweak 3: Reduce Periods (RP) Meta-Heuristic

Observation: the C=D splitting heuristic is not "scale invariant"

- splitting off a subtask with ***C'=D'=1*** from a ***(C=2, P=10)*** task
  vs.
  splitting off a subtask with ***C'=D'=100*** from a ***(C=200, P=1000)*** task
- Both subtasks have 10% utilization and 100% density…
  …but ***C'=D'=1*** is ***much* easier to accommodate**.

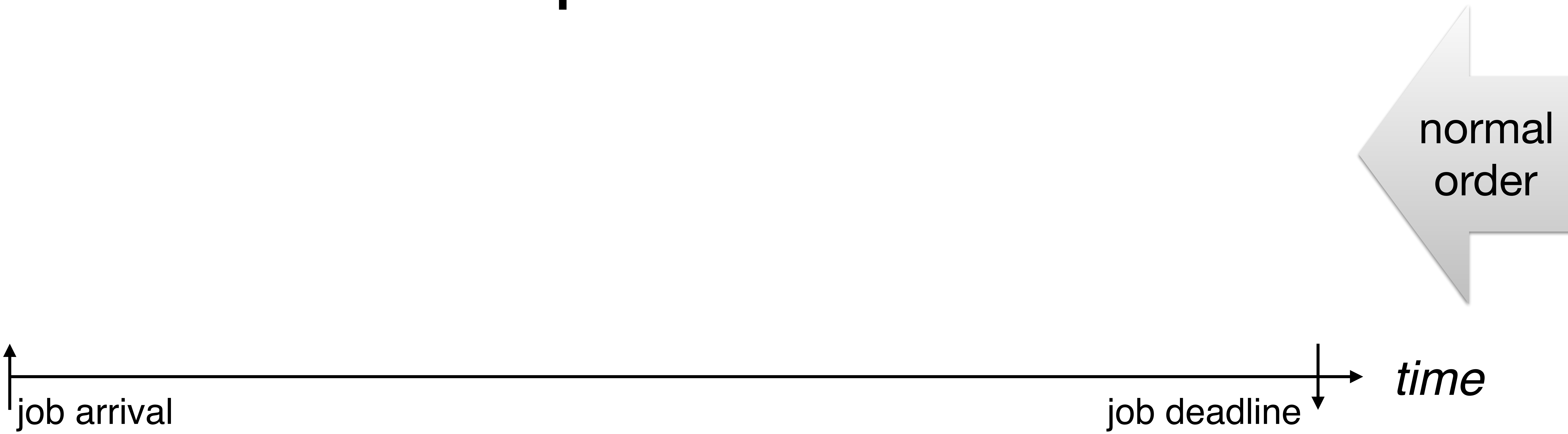
Idea: transform period prior to semi-partitioning

- apply **period transformation** to spread out the load of "difficult" tasks
- very effective at reducing the "**chunk size**" that C=D must deal with

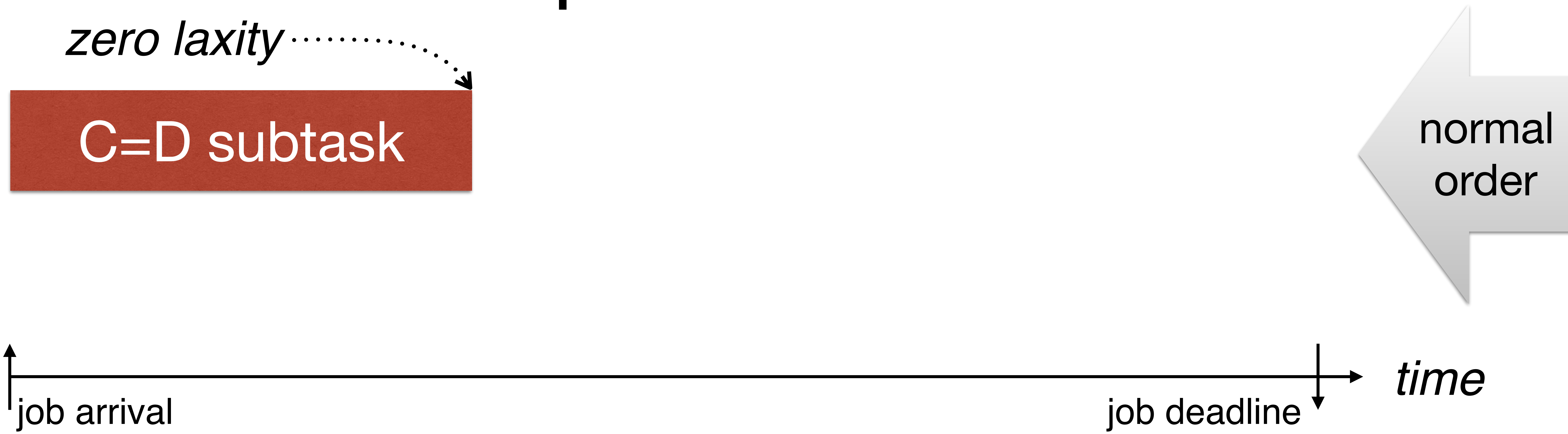
Practical Considerations

- trivial to support: **no code changes**, just tweak reservation parameters
- tradeoff: increased **preemption / migration frequency**

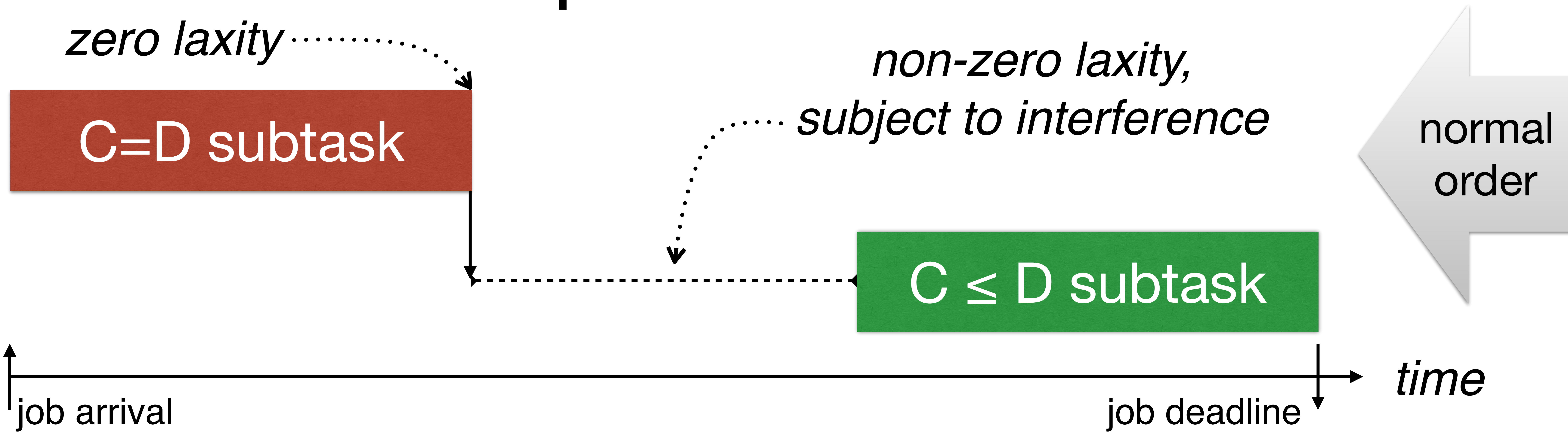
Tweak 4: Flip the C=D Subtask Order



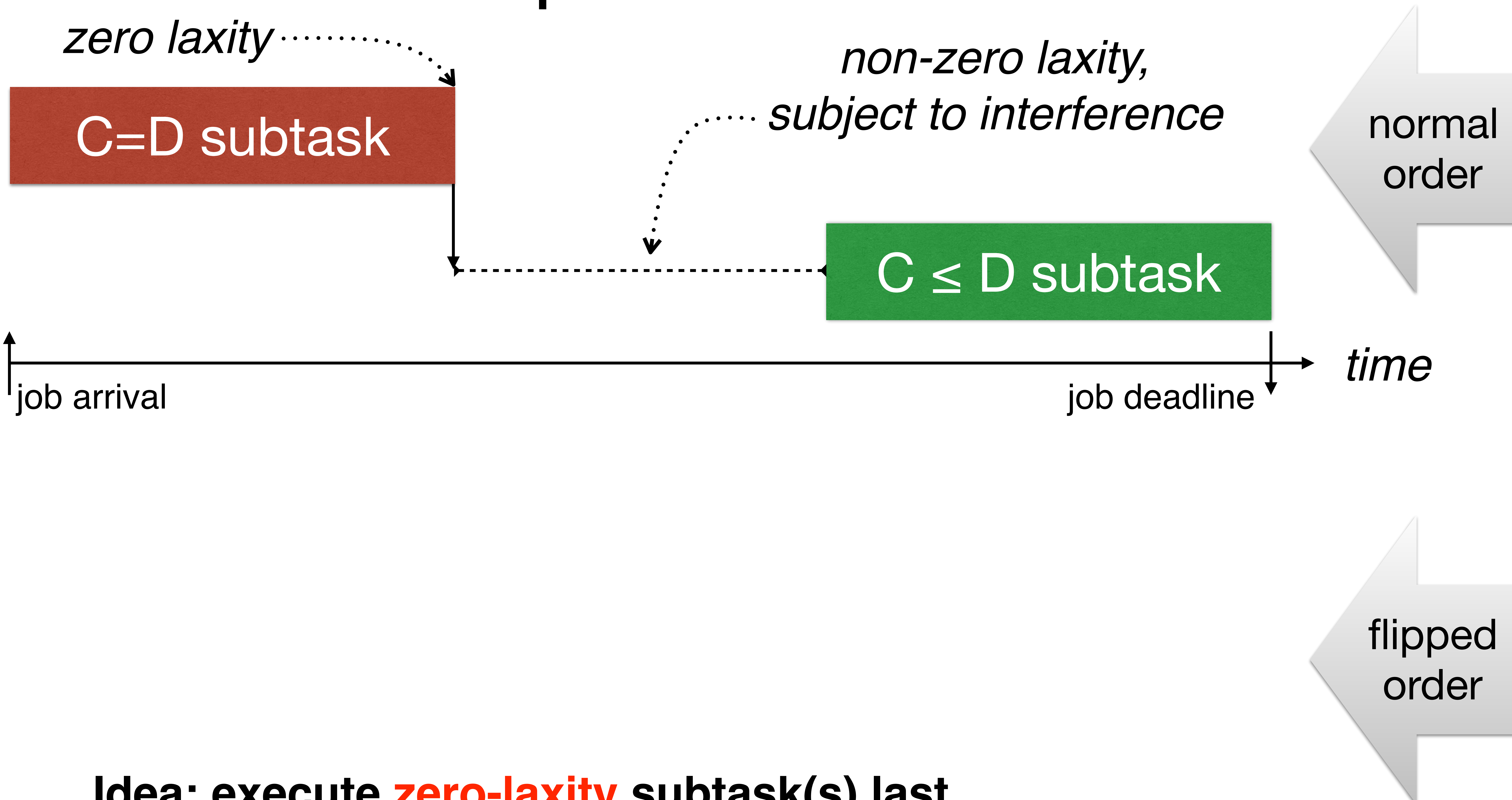
Tweak 4: Flip the C=D Subtask Order



Tweak 4: Flip the C=D Subtask Order



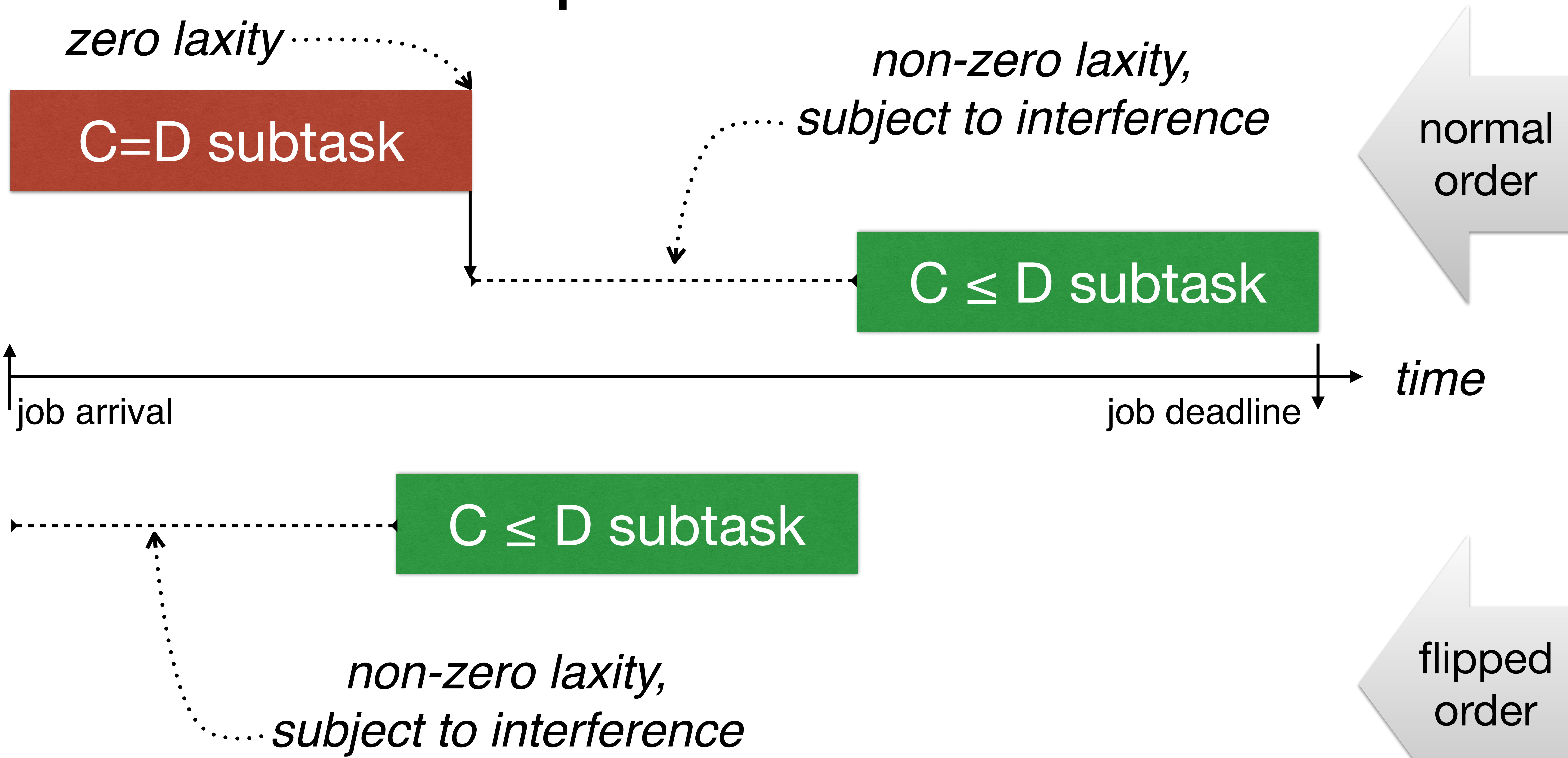
Tweak 4: Flip the C=D Subtask Order



Idea: execute zero-laxity subtask(s) last

- ➡ Irrelevant from theory point of view: order is arbitrary.
- ➡ Quite useful from systems point of view…

Tweak 4: Flip the C=D Subtask Order

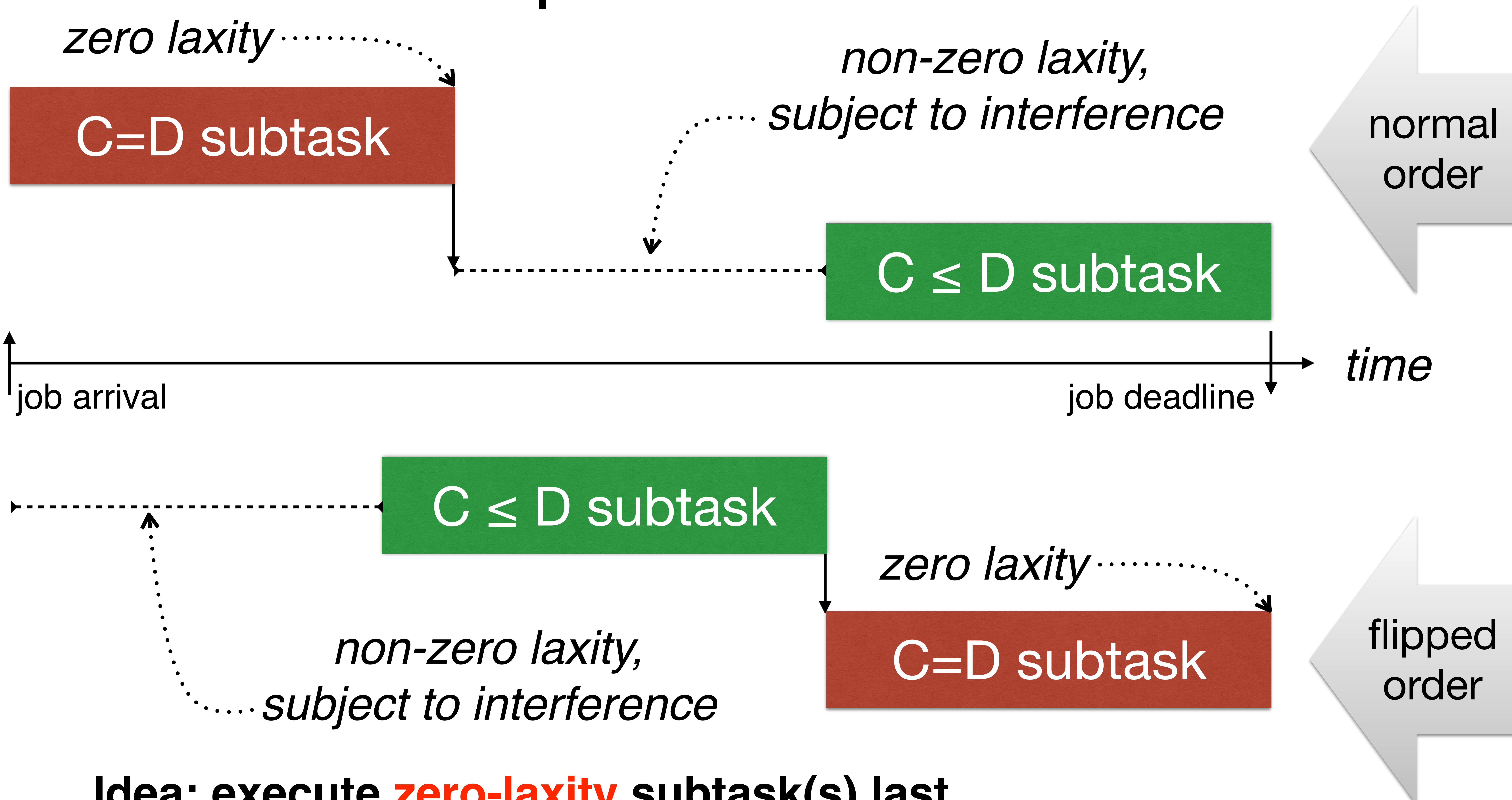


Idea: execute zero-laxity subtask(s) last

➡ Irrelevant from theory point of view: order is arbitrary.

➡ Quite useful from systems point of view…

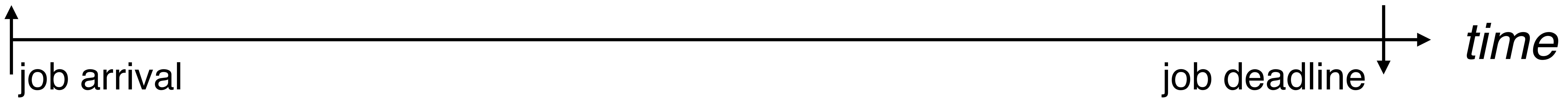
Tweak 4: Flip the C=D Subtask Order



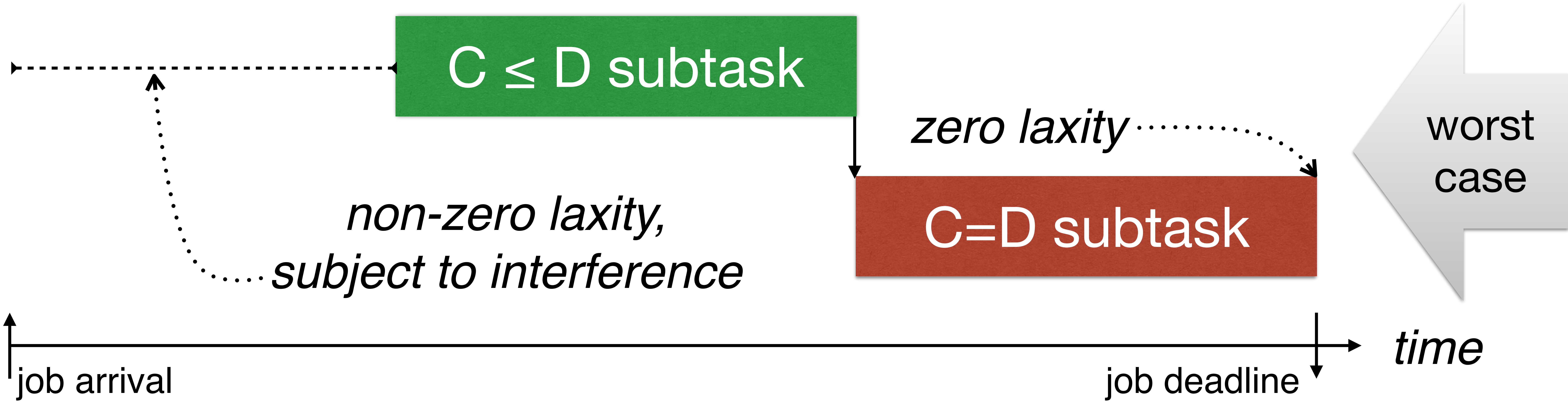
Idea: execute zero-laxity subtask(s) last

- ➡ Irrelevant from theory point of view: order is arbitrary.
- ➡ Quite useful from systems point of view…

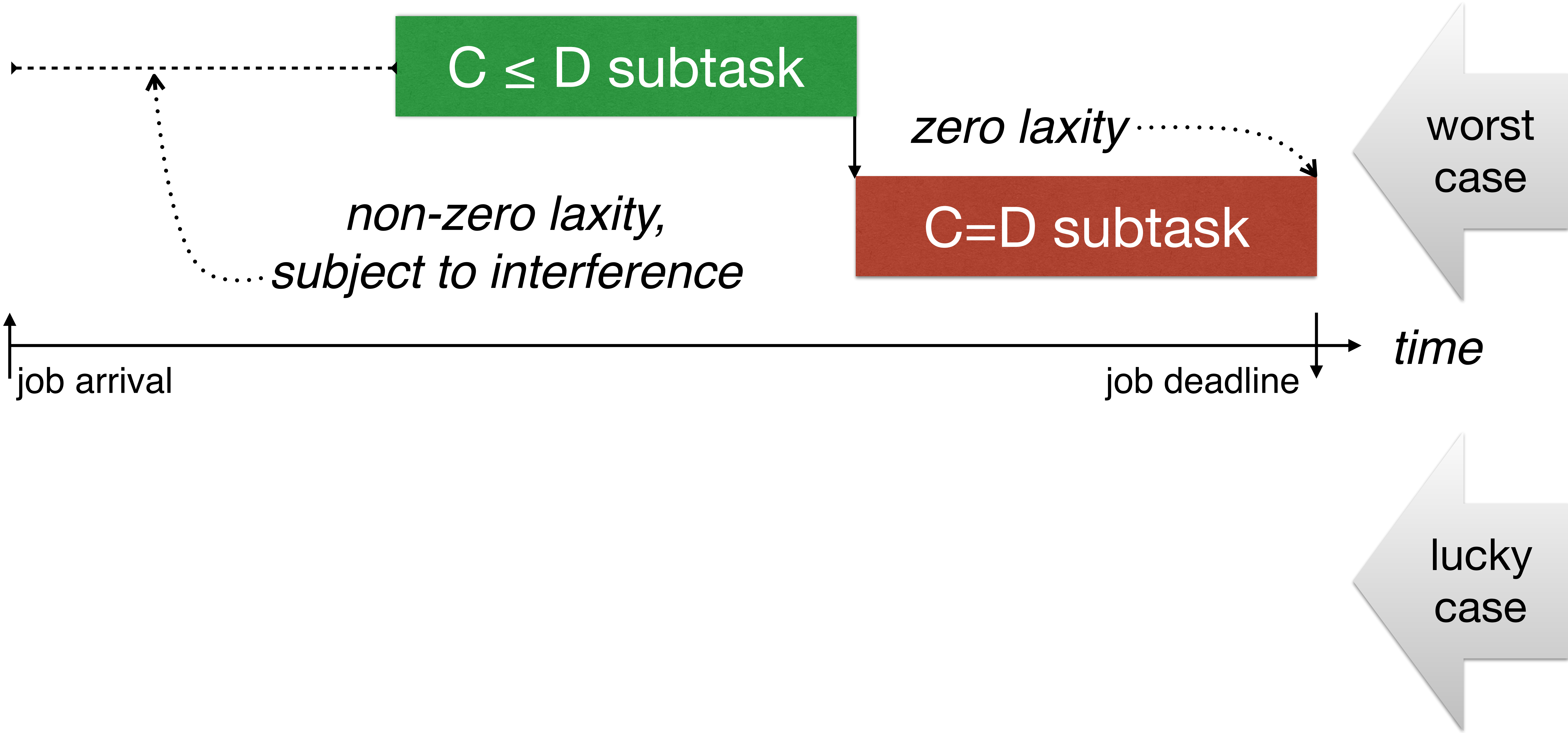
Tweak 5: Use Slack to Avoid Migrations



Tweak 5: Use Slack to Avoid Migrations



Tweak 5: Use Slack to Avoid Migrations

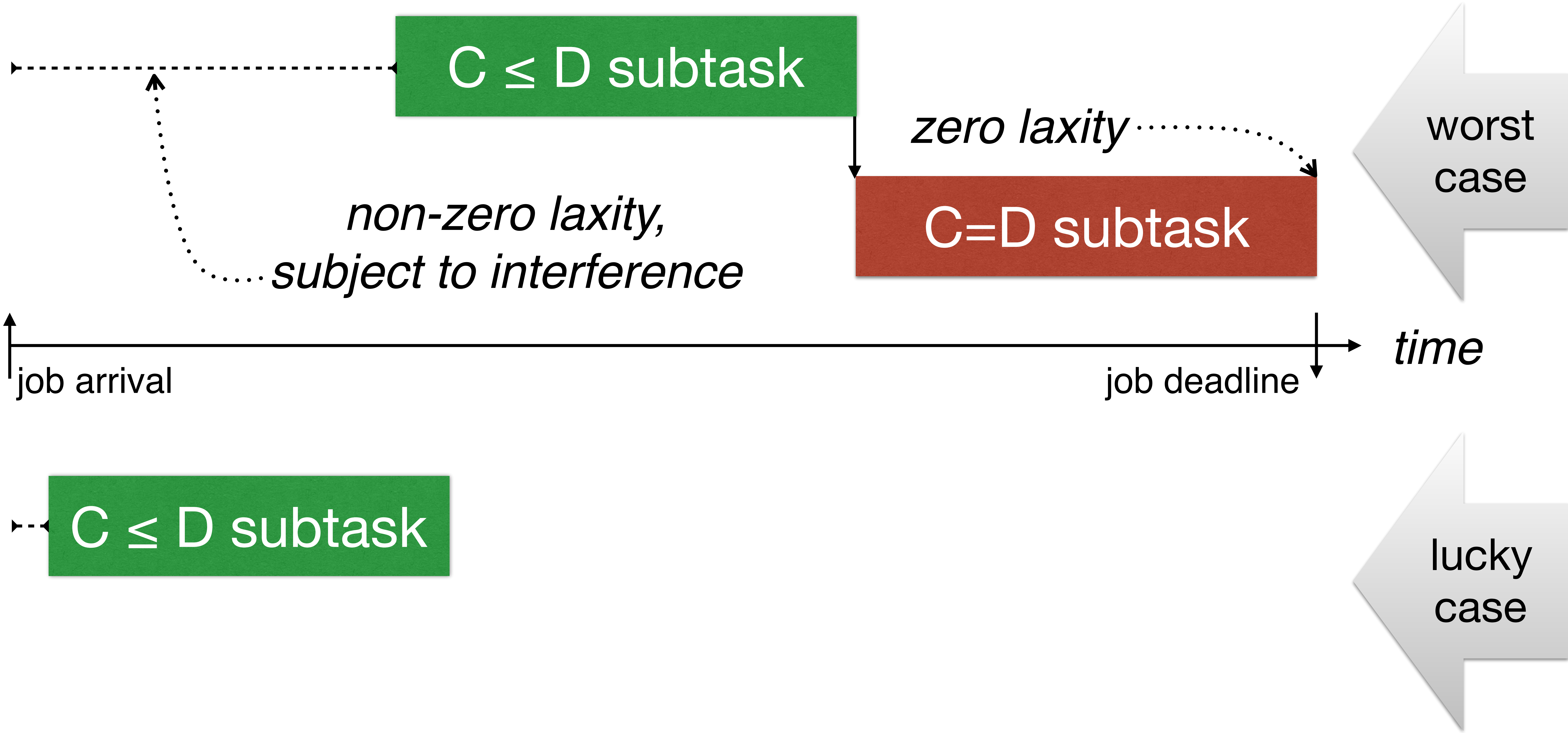


Idea: use a *simple* slack reclamation scheme

➡ finish job before it must migrate (➔ thanks to *flipped* subtask order)

➡ our implementation uses CASH (Caccamo et al., 2000)

Tweak 5: Use Slack to Avoid Migrations

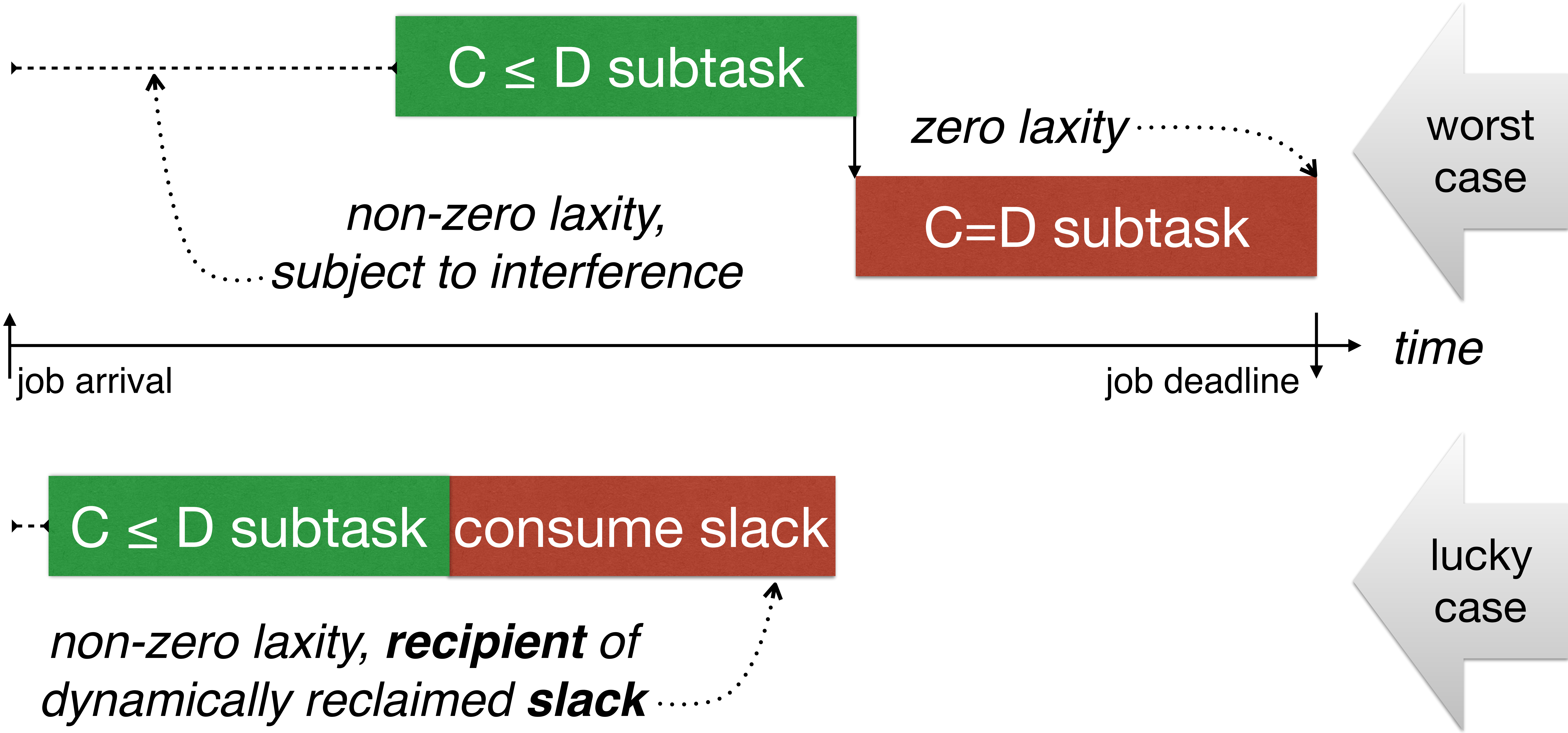


Idea: use a *simple* slack reclamation scheme

➡ finish job before it must migrate (➔ thanks to *flipped* subtask order)

➡ our implementation uses CASH (Caccamo et al., 2000)

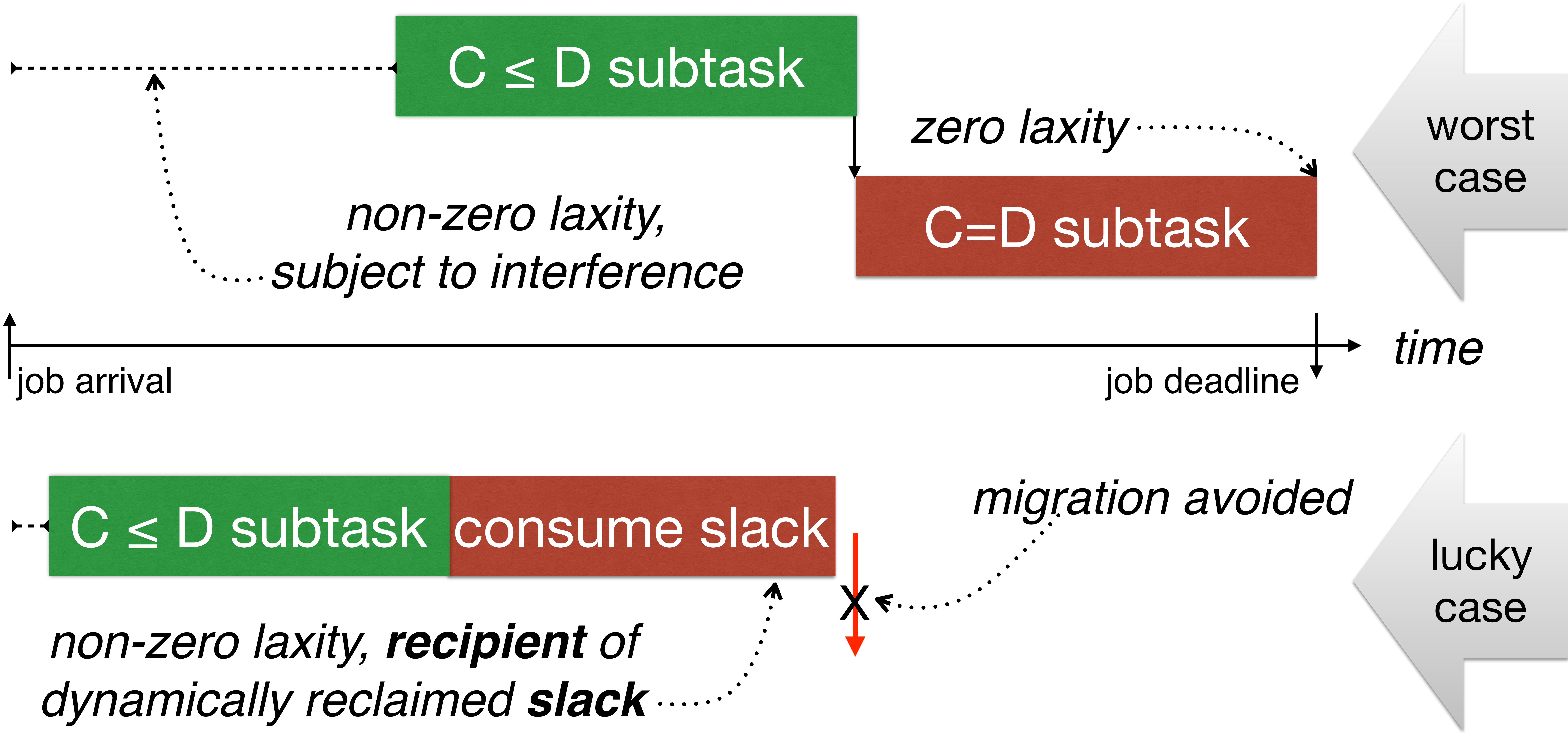
Tweak 5: Use Slack to Avoid Migrations



Idea: use a *simple* slack reclamation scheme

- ➡ finish job before it must migrate (➔ thanks to *flipped* subtask order)
- ➡ our implementation uses CASH (Caccamo et al., 2000)

Tweak 5: Use Slack to Avoid Migrations



Idea: use a *simple* slack reclamation scheme

➡ finish job before it must migrate (➔ thanks to *flipped* subtask order)

➡ our implementation uses CASH (Caccamo et al., 2000)

Does it work in theory?

— schedulability experiments —

Schedulability Experiments — Setup

Schedulability Experiments — Setup

Metric

- schedulability $= \dfrac{number\ of\ schedulable\ task\ sets}{total\ number\ of\ tested\ task\ sets}$
- optimal ↔ schedulability = 1

Schedulability Experiments — Setup

Metric

- ➡ schedulability $= \dfrac{number\ of\ schedulable\ task\ sets}{total\ number\ of\ tested\ task\ sets}$
- ➡ optimal ↔ schedulability = 1

Number of Processors *m*

- ➡ considered range: 2, 4, 8, 16, 24, 32, 64 processors

Schedulability Experiments — Setup

Metric

➡ schedulability $= \dfrac{number\ \ of\ \ schedulable\ \ task\ \ sets}{total\ \ number\ \ of\ \ tested\ \ task\ \ sets}$

➡ optimal ↔ schedulability = 1

Number of Processors *m*

➡ considered range: 2, 4, 8, 16, 24, 32, 64 processors

Number of Tasks *n*

➡ considered range: *m* + 1, …, 3*m*

Schedulability Experiments — Setup

Metric

- schedulability $= \dfrac{number\ of\ schedulable\ task\ sets}{total\ number\ of\ tested\ task\ sets}$
- optimal ↔ schedulability = 1

Number of Processors *m*

- considered range: 2, 4, 8, 16, 24, 32, 64 processors

Number of Tasks *n*

- considered range: *m* + 1, …, 3*m*

Task Periods

- chosen from {1, 2, 4, 5, 8, 10, 20, 25, 40, 50, 100, 125, 200, 250, 500, 1000} uniformly at random (in milliseonds)
- range commonly found in automotive systems

Schedulability Experiments — Setup

Metric

- ➡ schedulability $= \dfrac{number\ of\ schedulable\ task\ sets}{total\ number\ of\ tested\ task\ sets}$
- ➡ optimal ↔ schedulability = 1

Number of Processors *m*

- ➡ considered range: 2, 4, 8, 16, 24, 32, 64 processors

Number of Tasks *n*

- ➡ considered range: *m* + 1, …, 3*m*

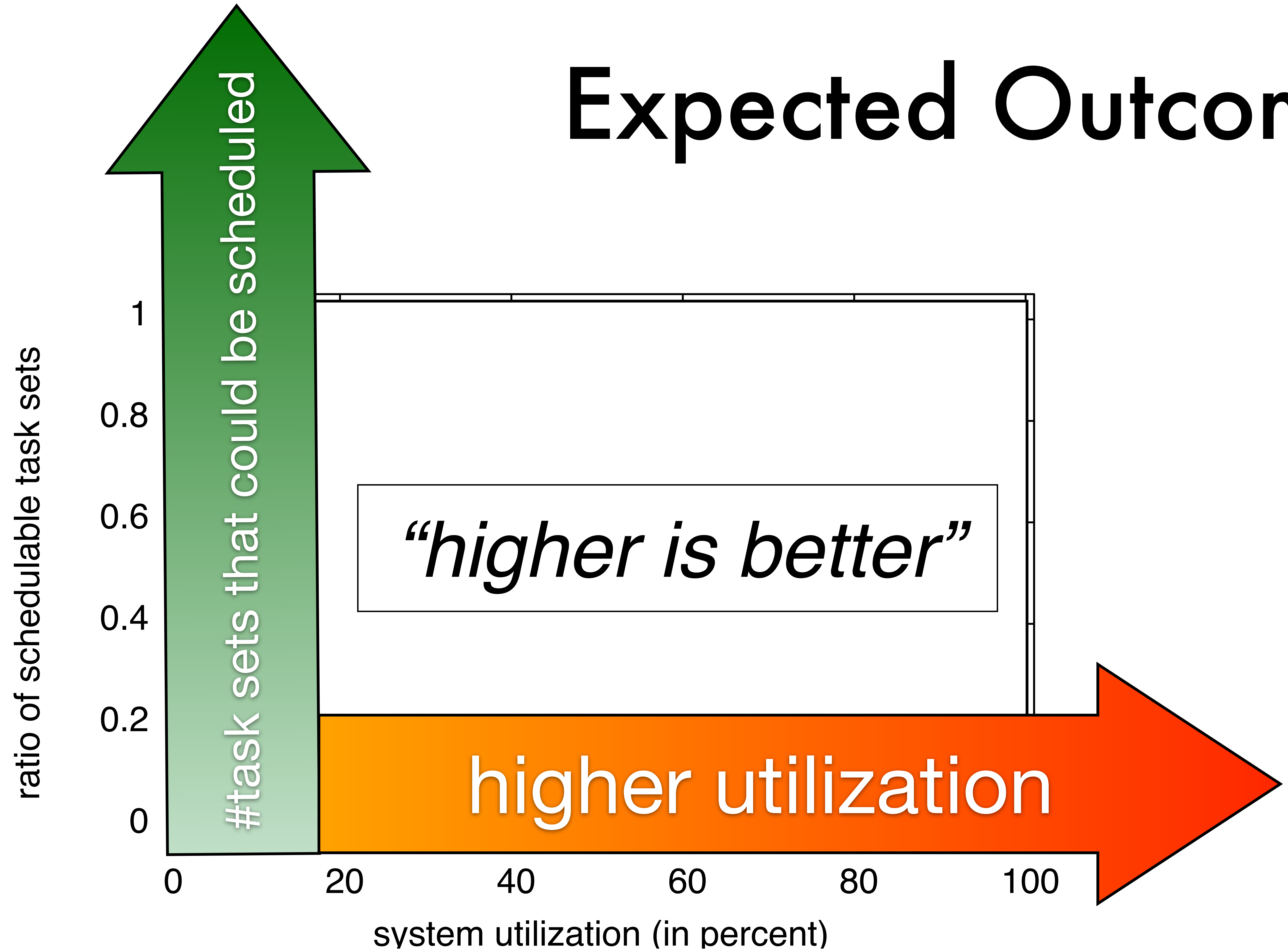
Task Periods

- ➡ chosen from {1, 2, 4, 5, 8, 10, 20, 25, 40, 50, 100, 125, 200, 250, 500, 1000} uniformly at random (in milliseonds)
- ➡ range commonly found in automotive systems

Task Utilization

- ➡ Emberson et al. (2010) task-set generator (designed to be unbiased)
- ➡ "UNC style" task-set generator (used in prior LITMUS^{RT} studies)

Expected Outcome



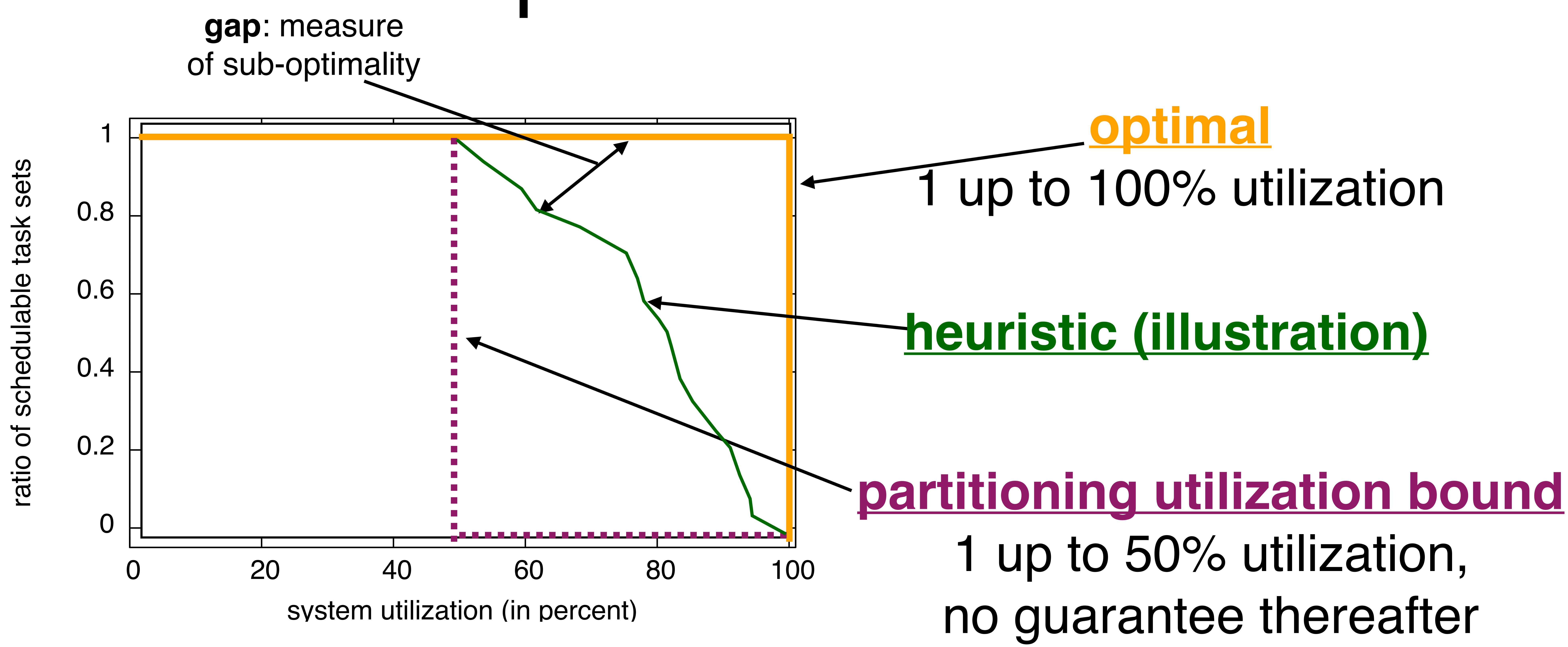
Smaller n = more difficult bin-packing instance

➡ fewer, larger items = harder problem

Higher utilization = more difficult bin-backing instance

➡ less spare capacity = harder problem

Expected Outcome



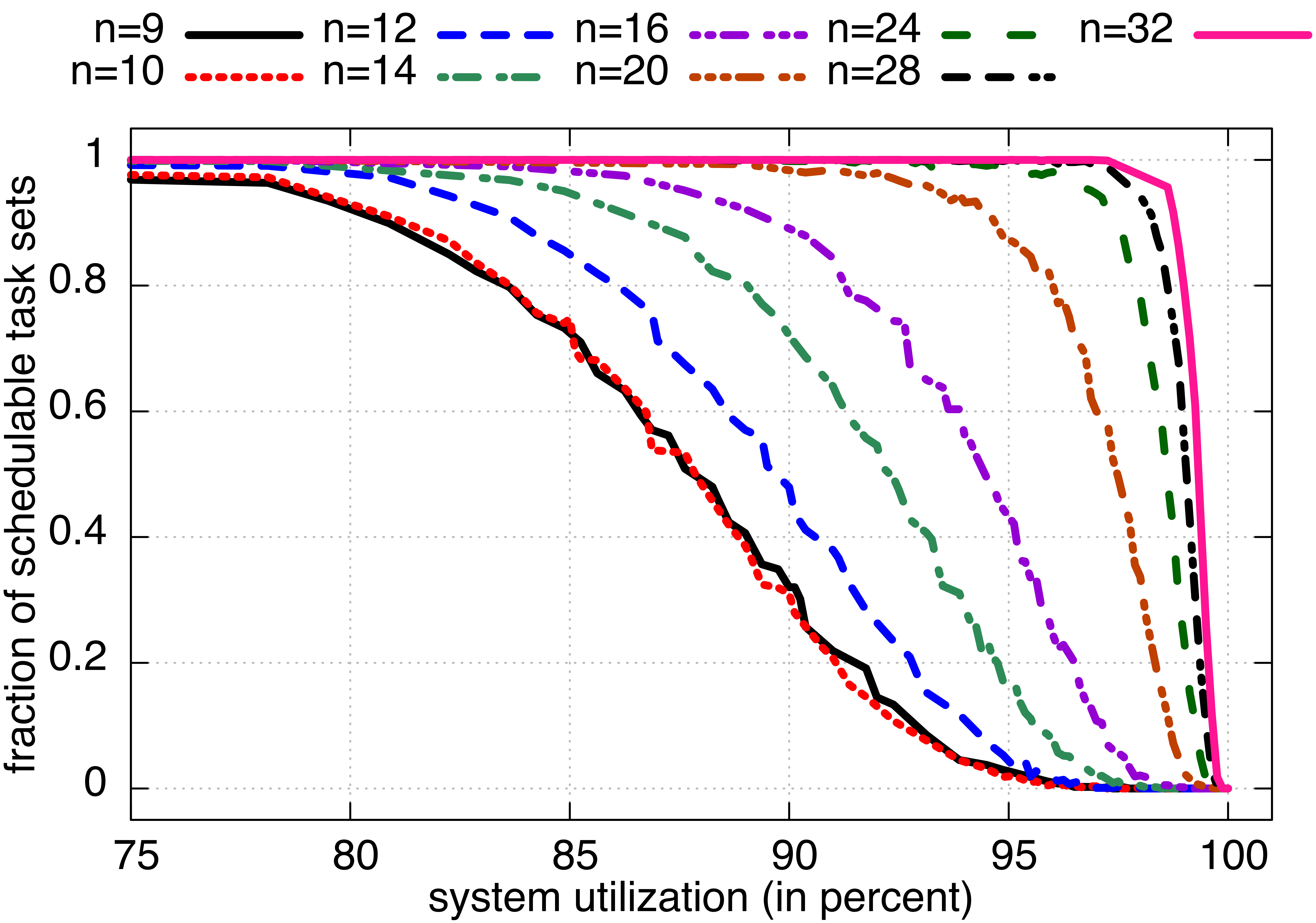
Smaller n = more difficult bin-packing instance

➡ fewer, larger items = harder problem

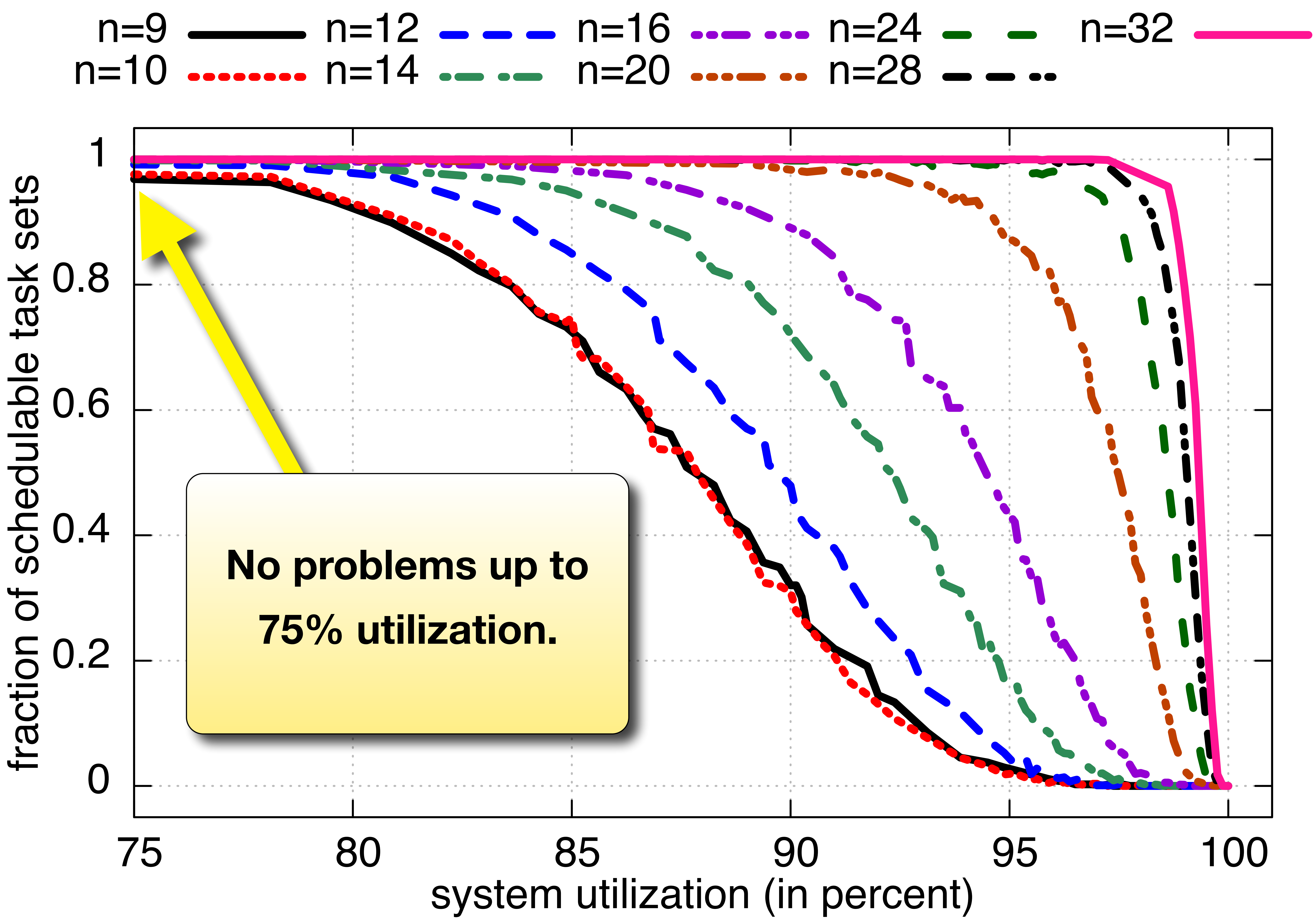
Higher utilization = more difficult bin-backing instance

➡ less spare capacity = harder problem

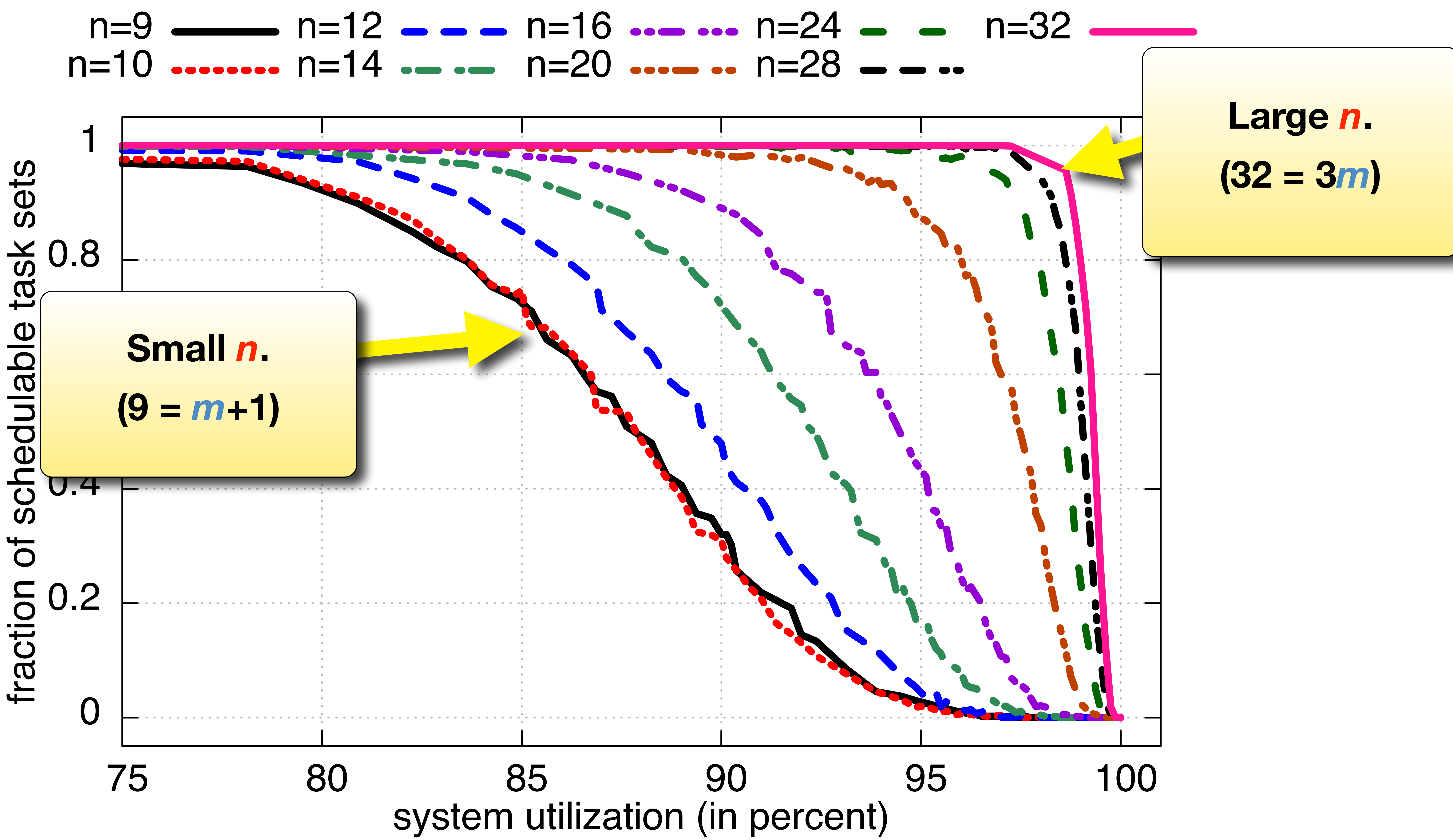
Performance of Partitioned Scheduling (8 Cores)



Performance of Partitioned Scheduling (8 Cores)



Performance of Partitioned Scheduling (8 Cores)

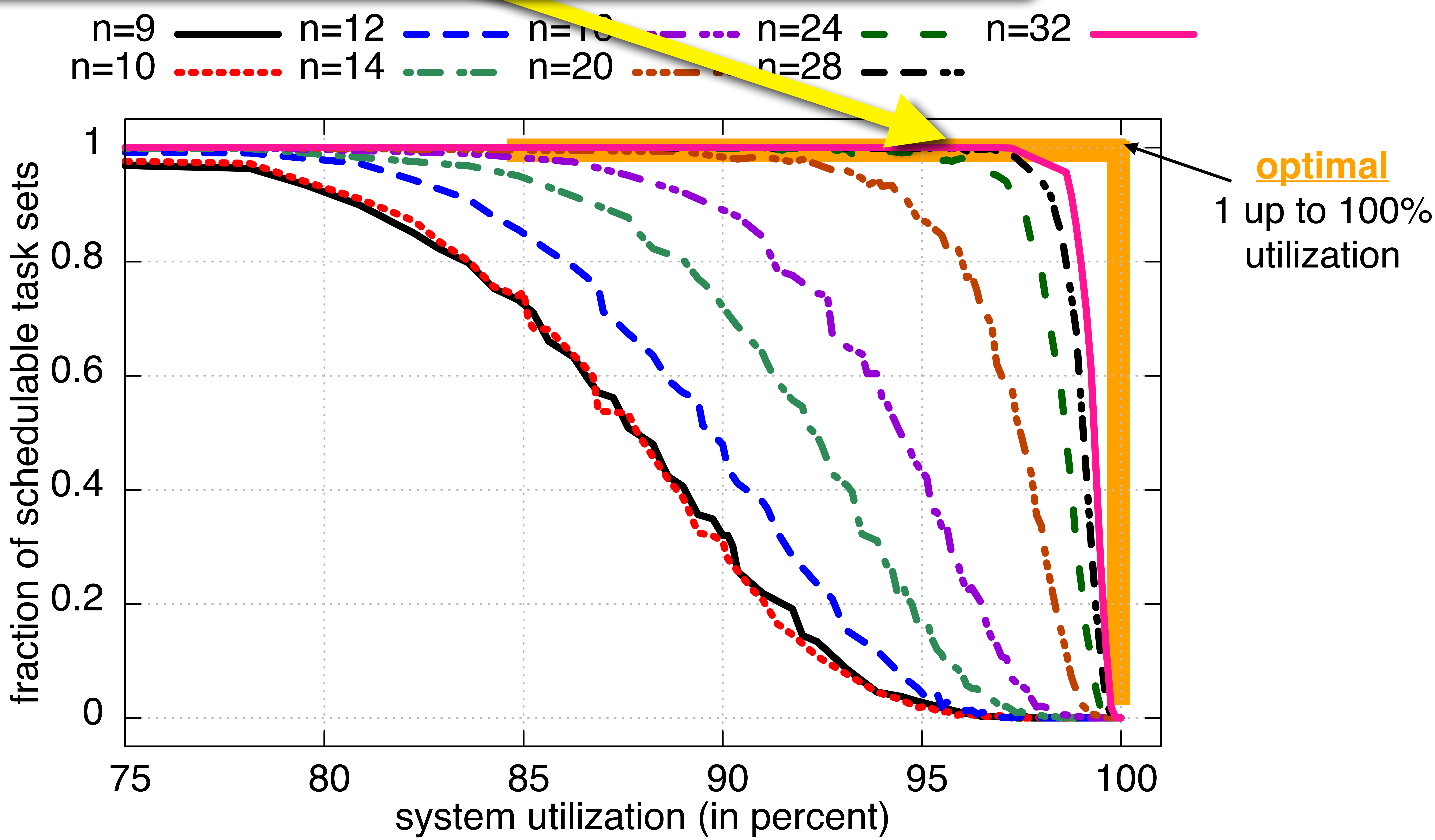


g (8 Cores)

Close to optimal (>95% schedulable utilization) for n = 3m = 24

→ *scheduling with implicit deadlines is difficult*

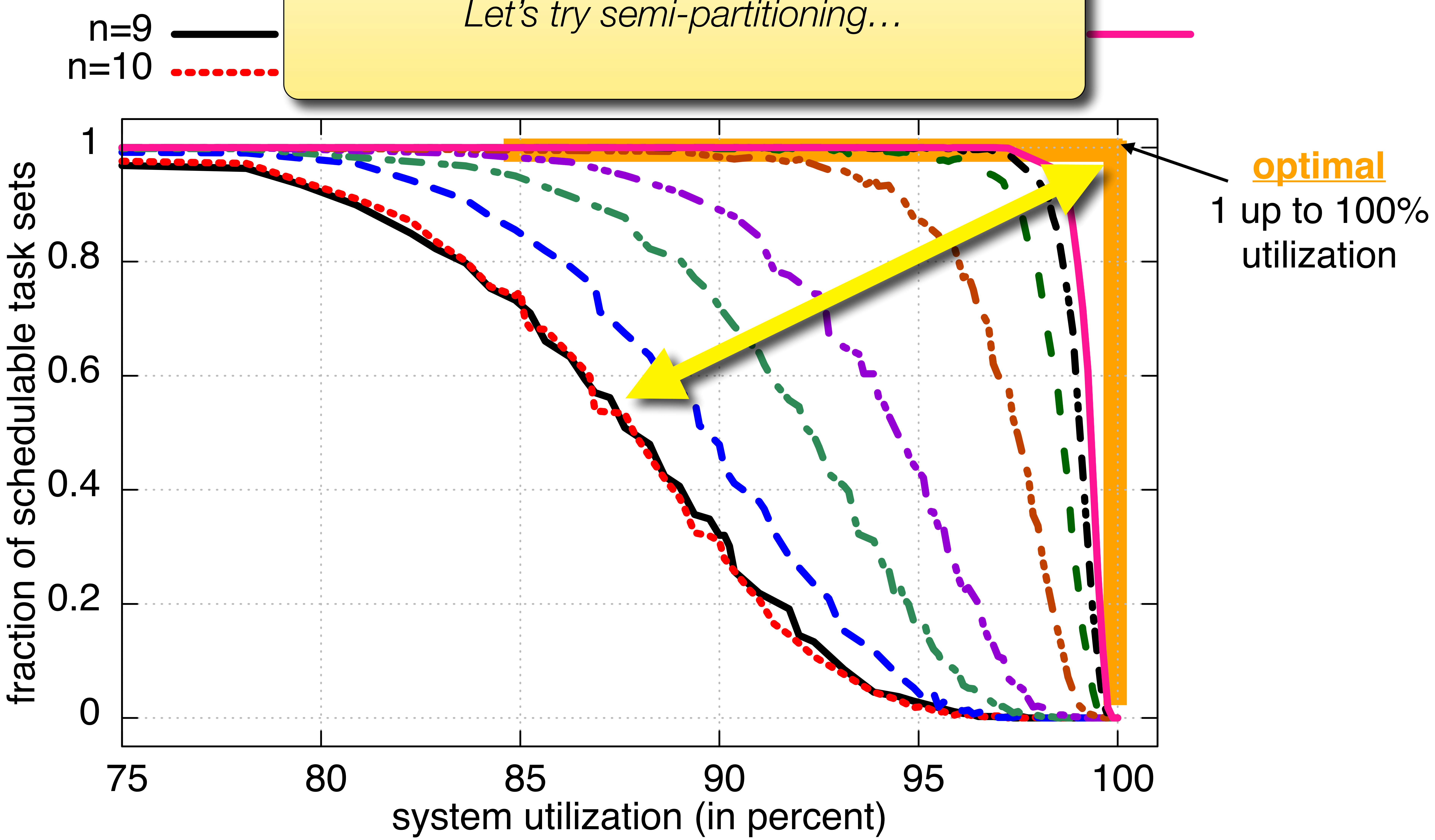
only for small n, high-utilization task sets



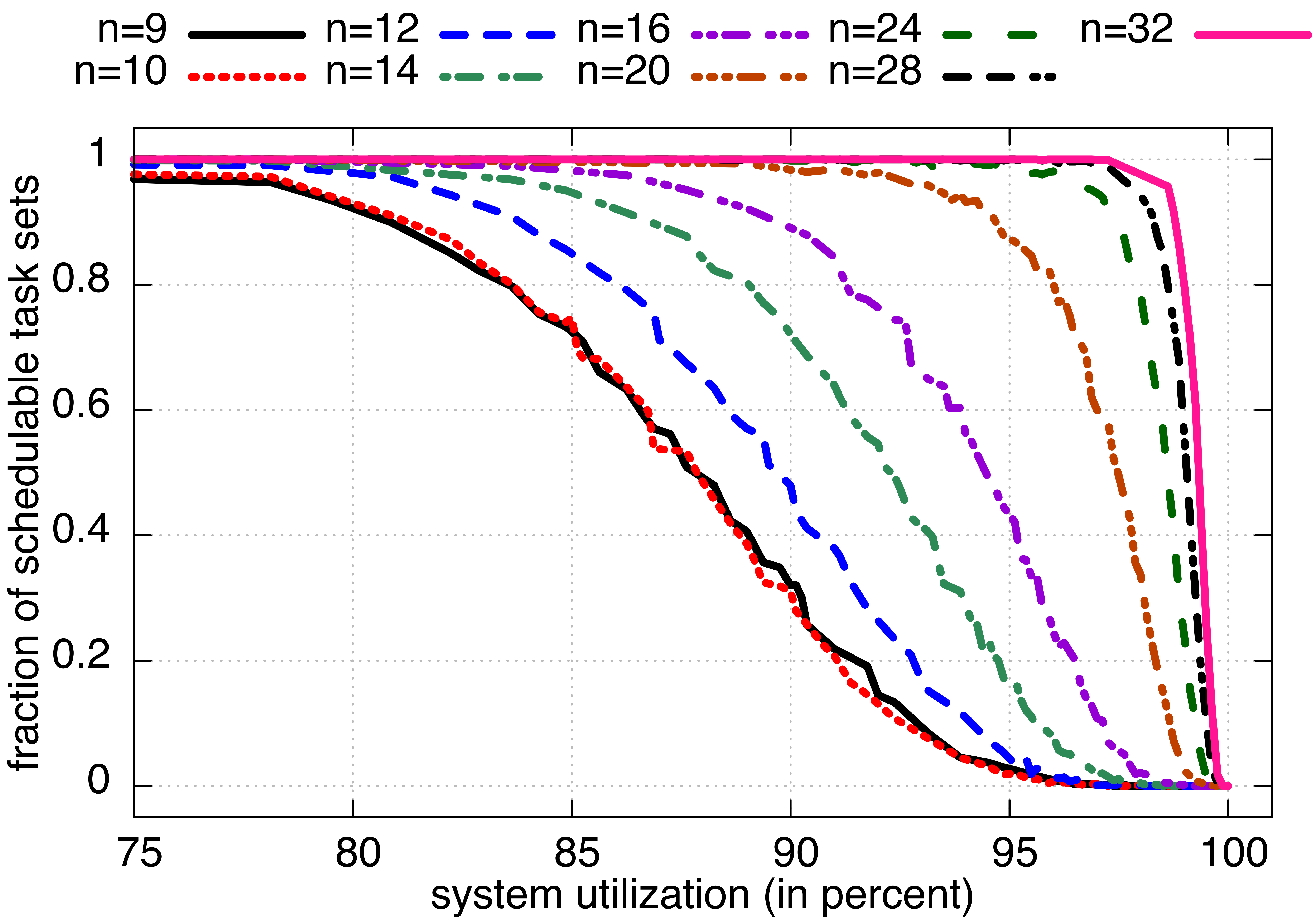
Performanc… (8 Cores)

Not a big gap for optimal algorithms to exploit: much complexity for little gain!

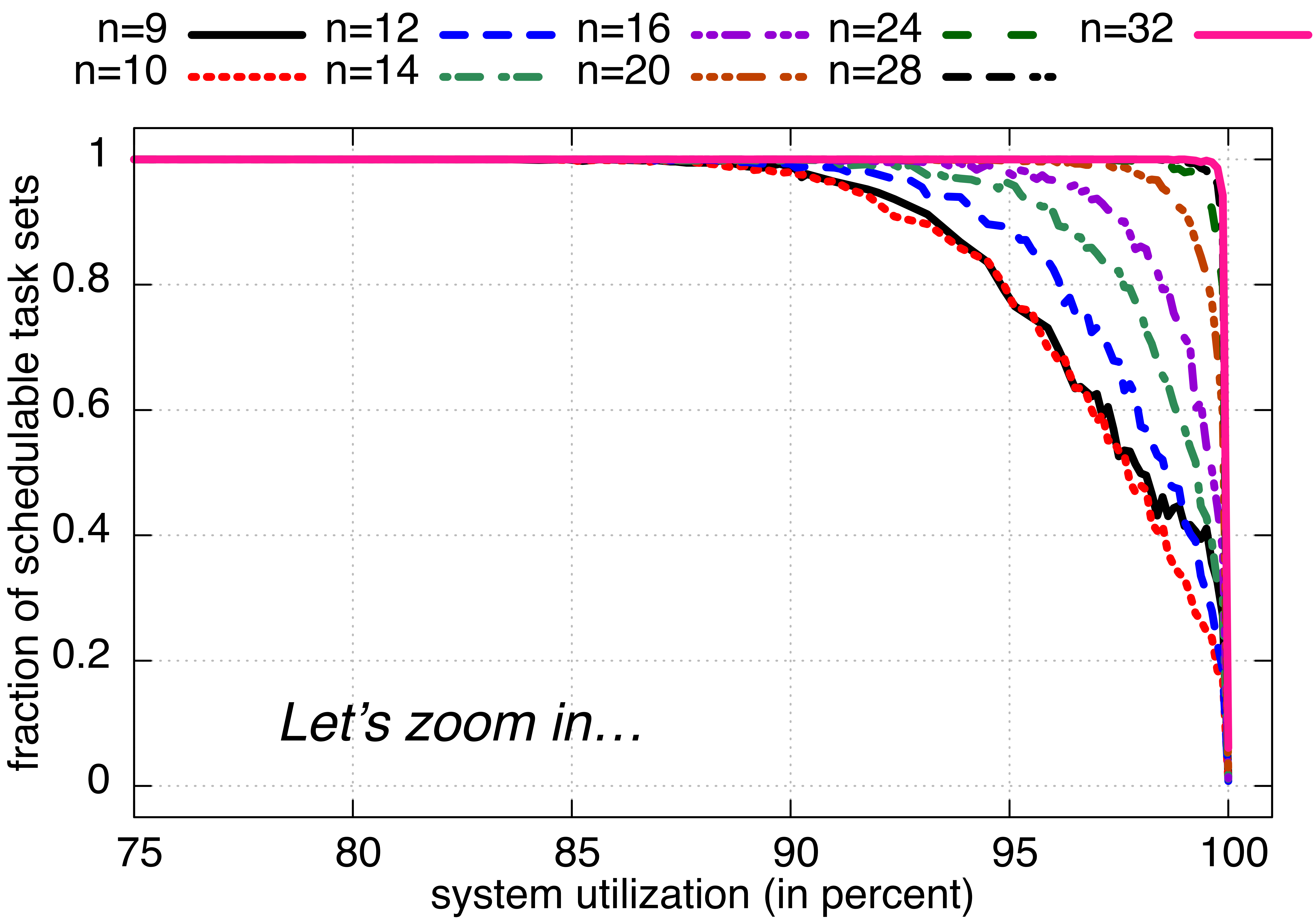
Let's try semi-partitioning…



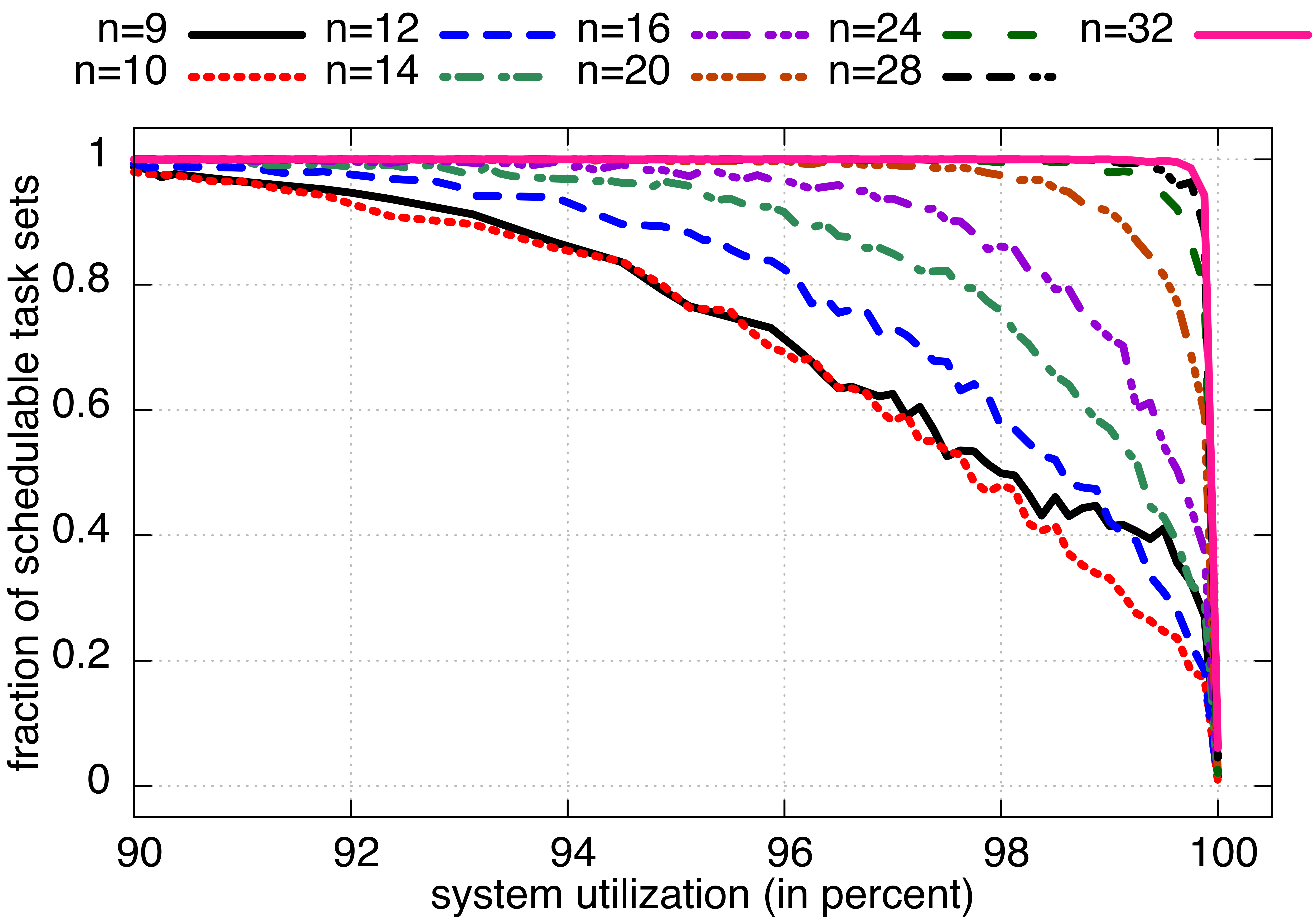
Before: Partitioning Only



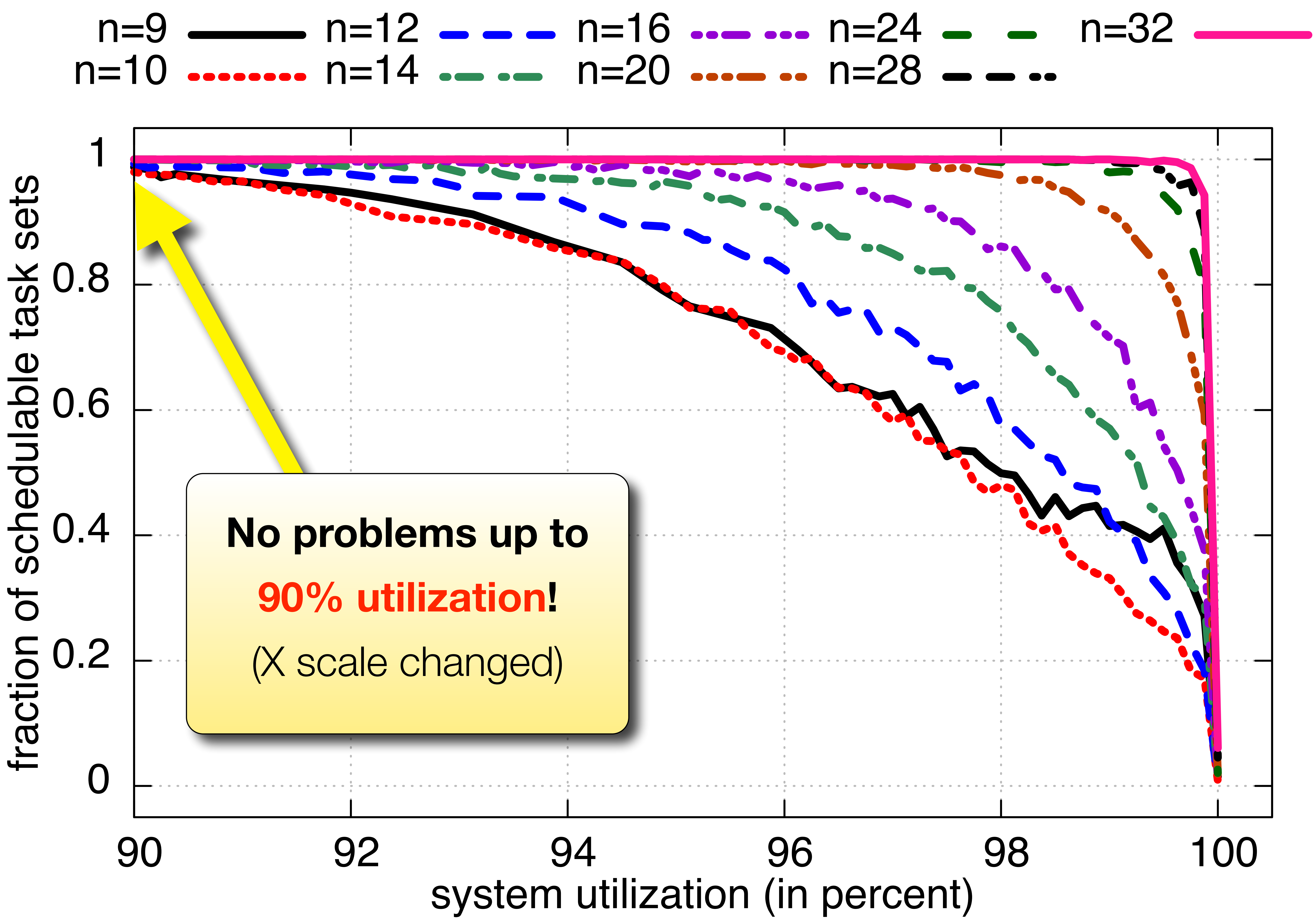
With Basic Semi-Partitioning



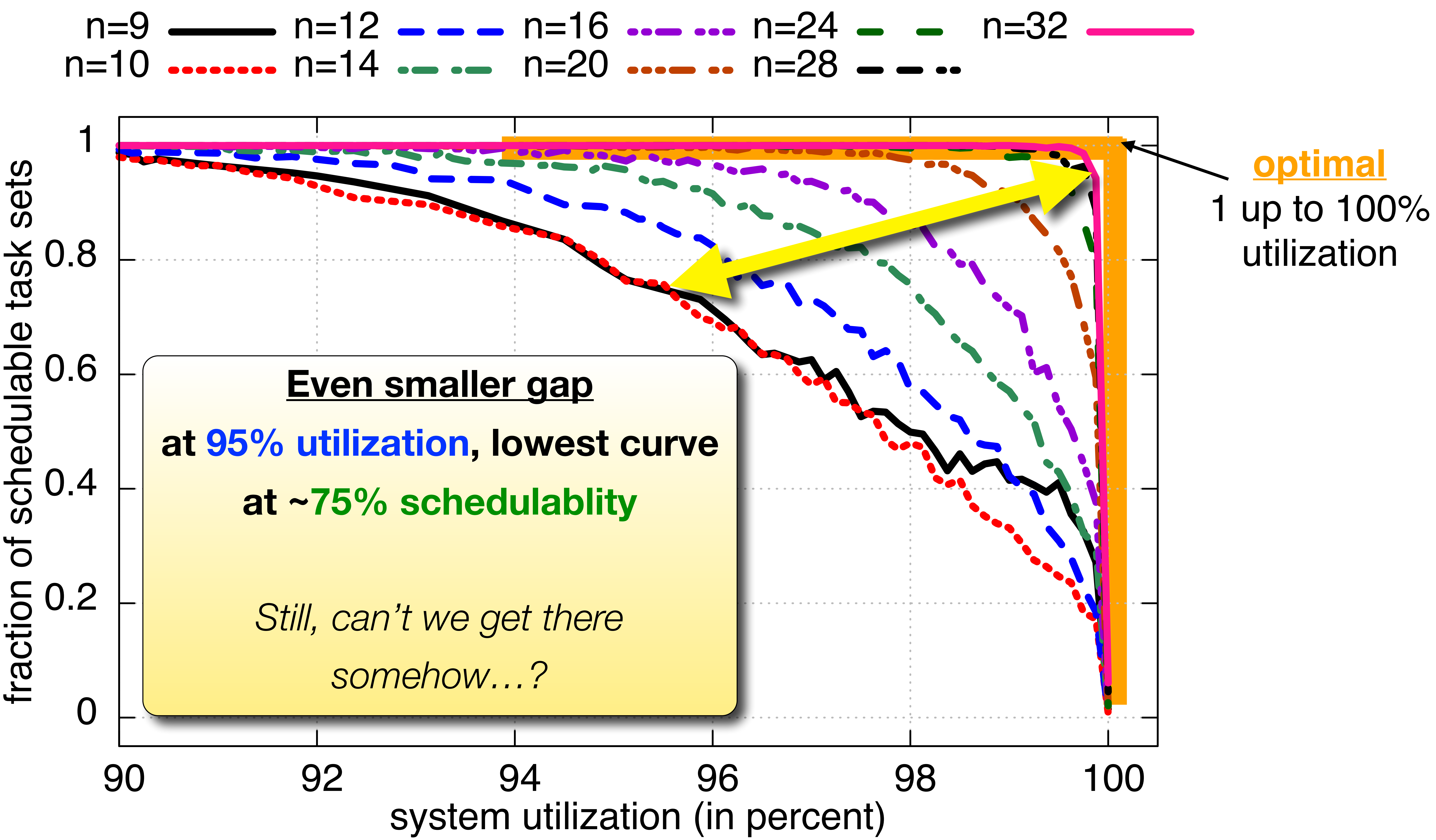
With Basic Semi-Partitioning [Zoomed In]



With Basic Semi-Partitioning [Zoomed In]



With Basic Semi-Partitioning [Zoomed In]

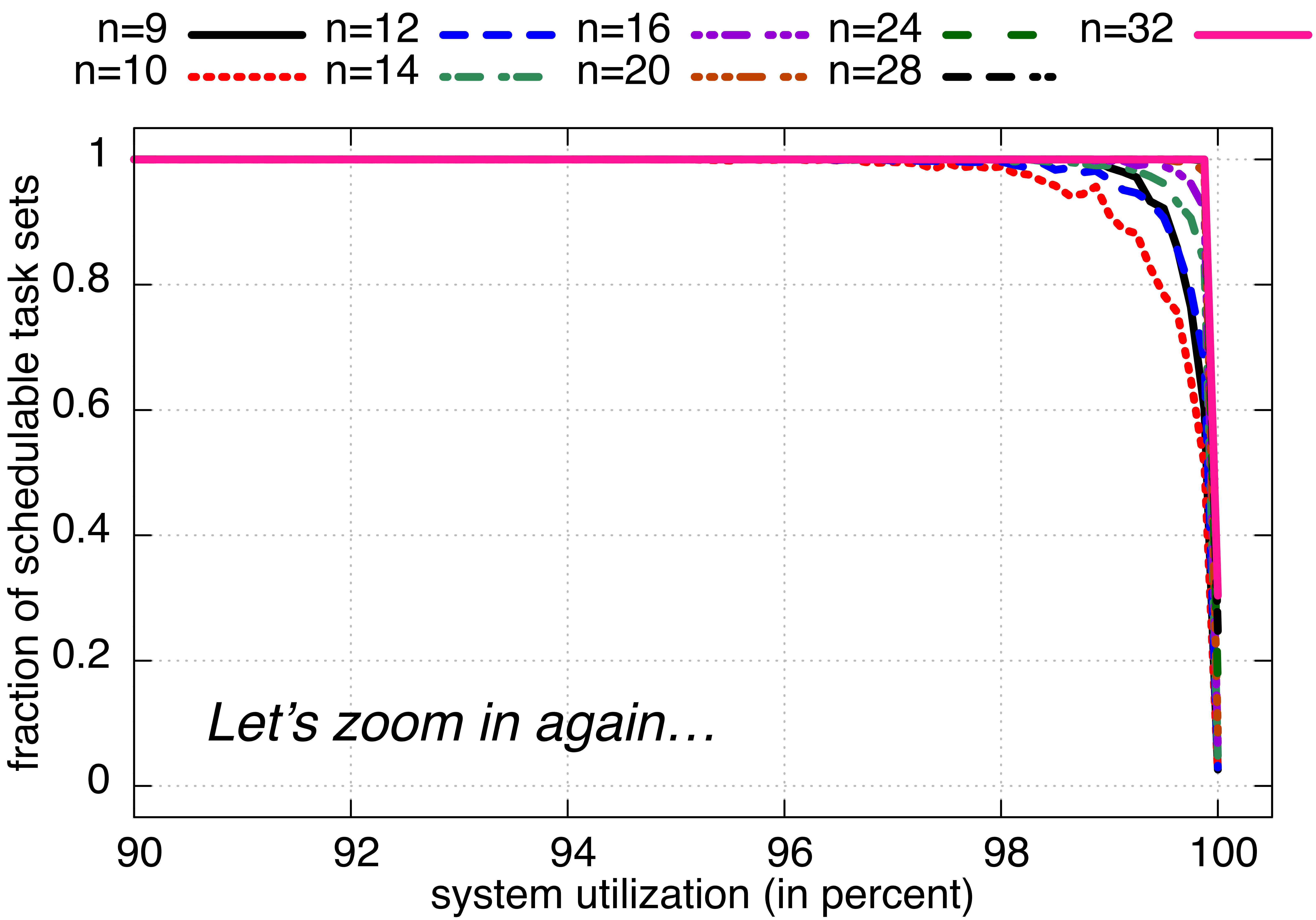


Even smaller gap

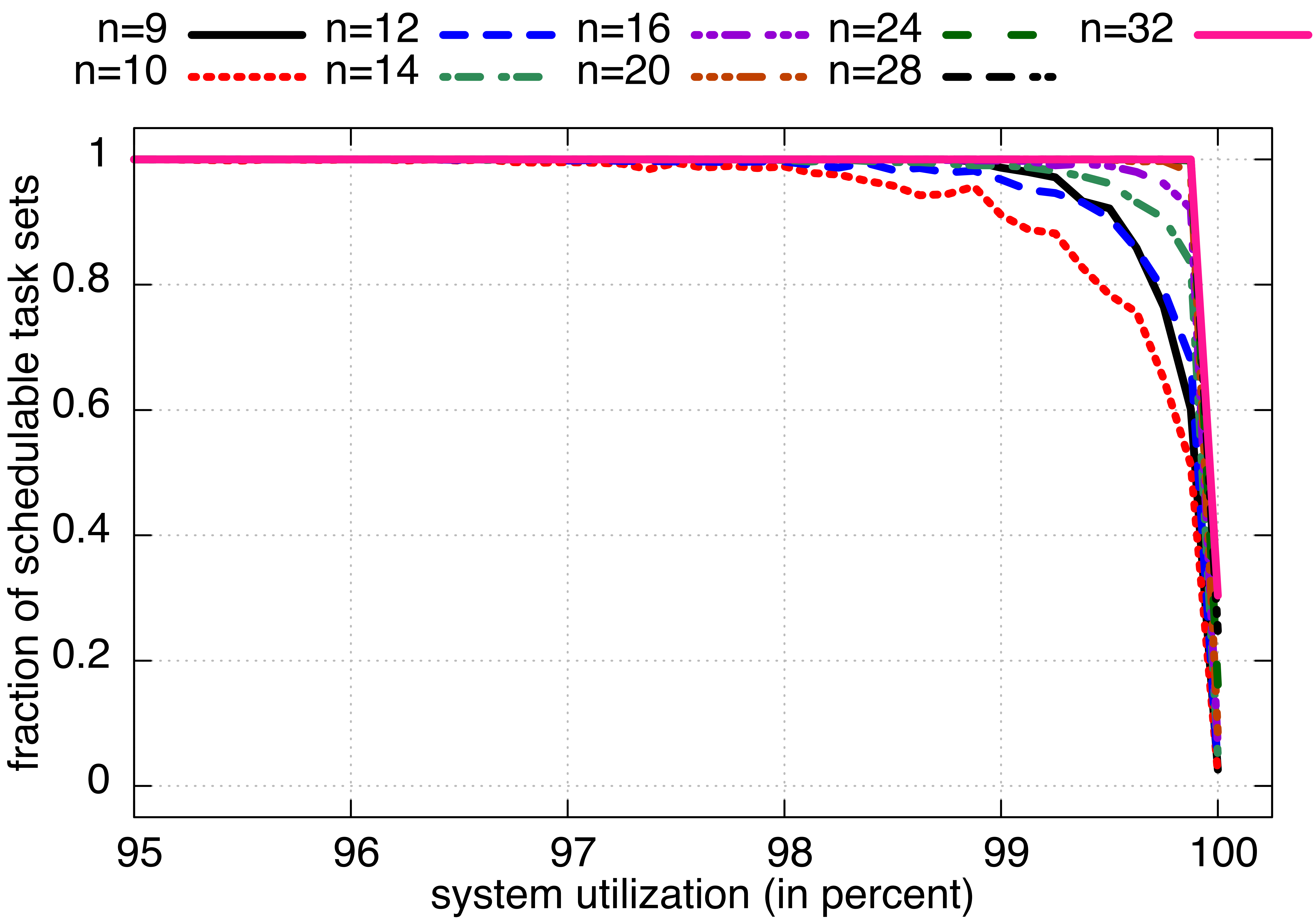
at 95% utilization, lowest curve at ~75% schedulablity

Still, can't we get there somehow…?

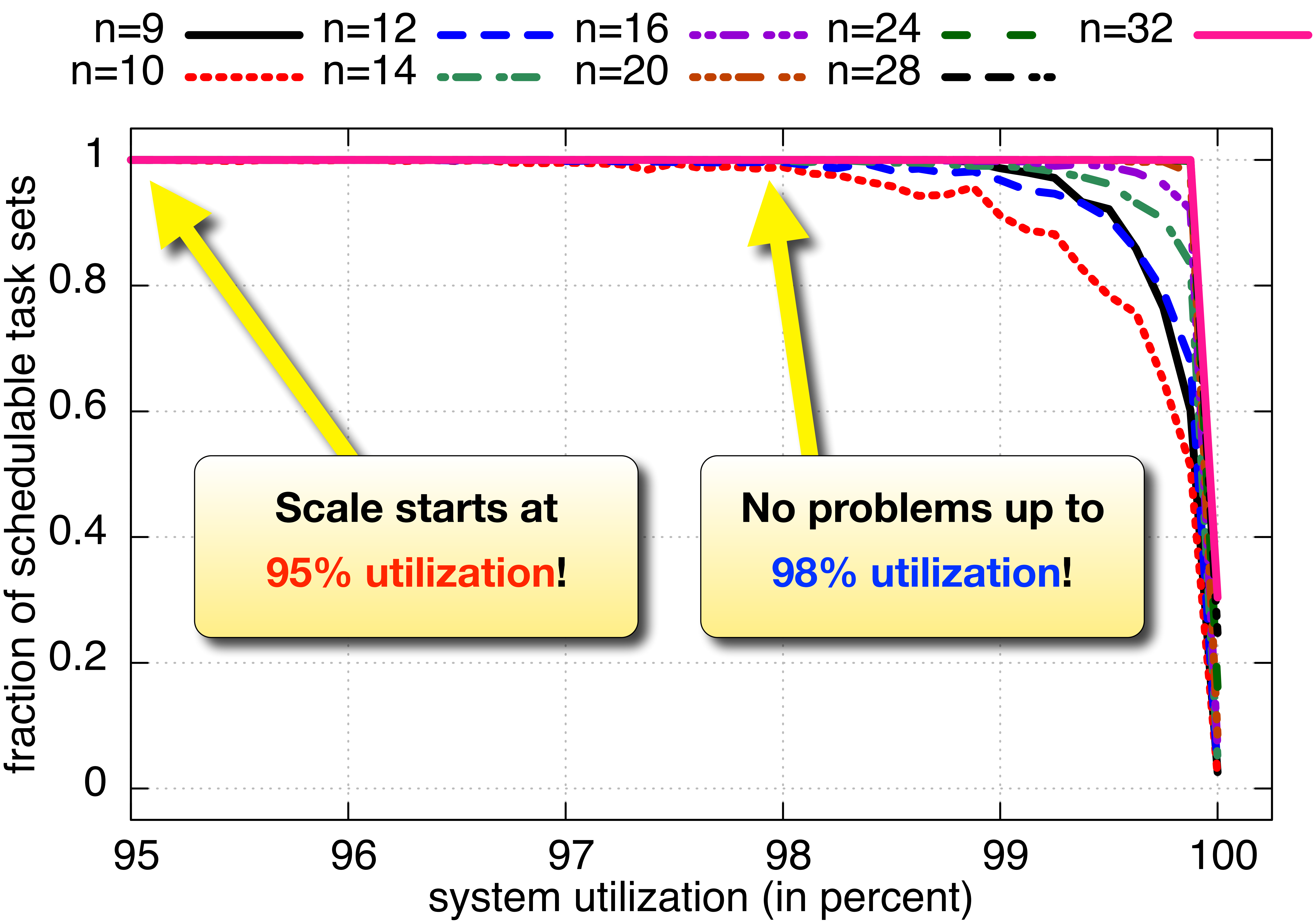
With Pre-Assign Failures Heuristic (PAF)



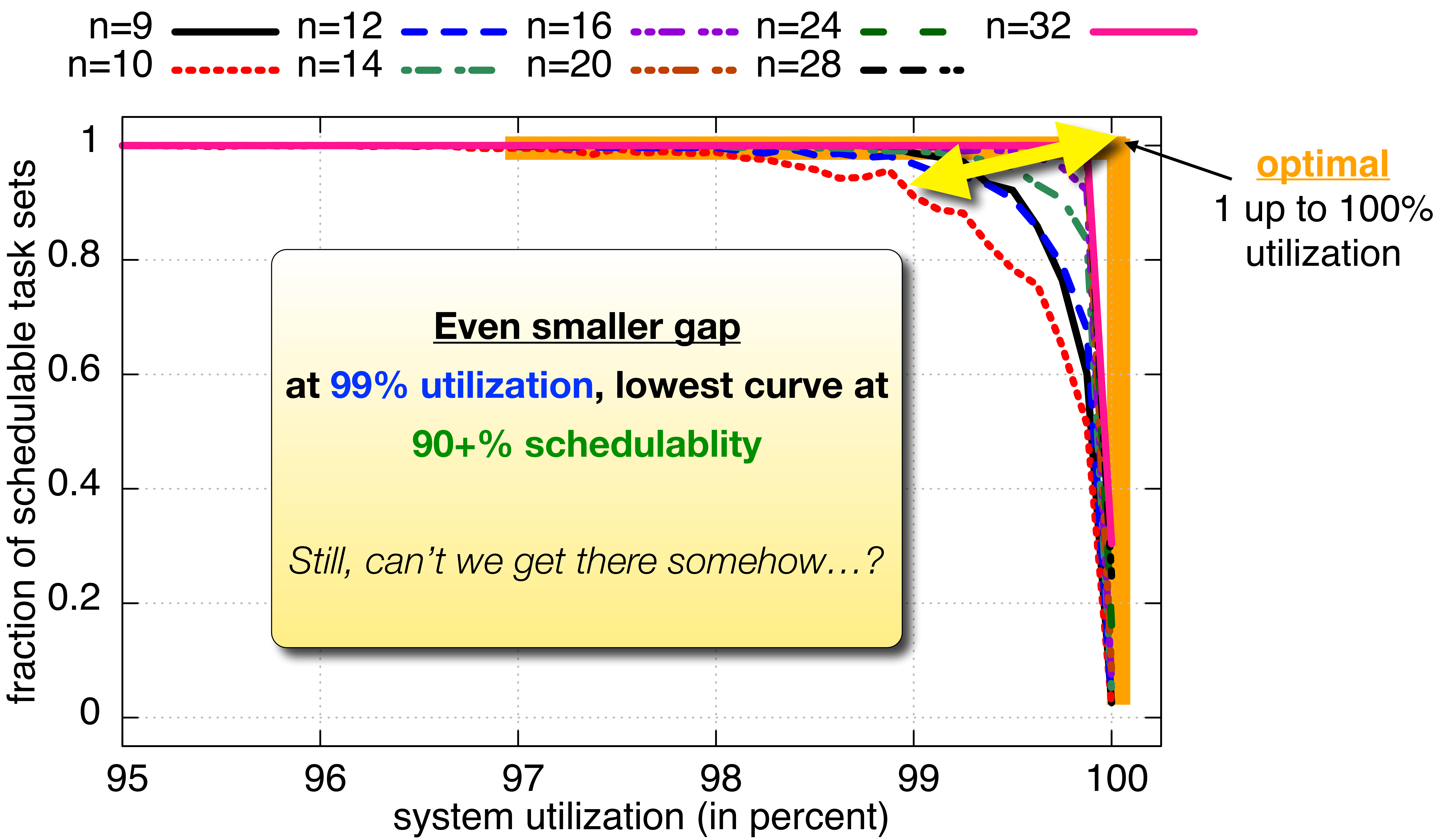
With Pre-Assign Failures Heuristic (PAF) [2X Zoomed In]



With Pre-Assign Failures Heuristic (PAF) [2X Zoomed In]



With Pre-Assign Failures Heuristic (PAF) [2X Zoomed In]

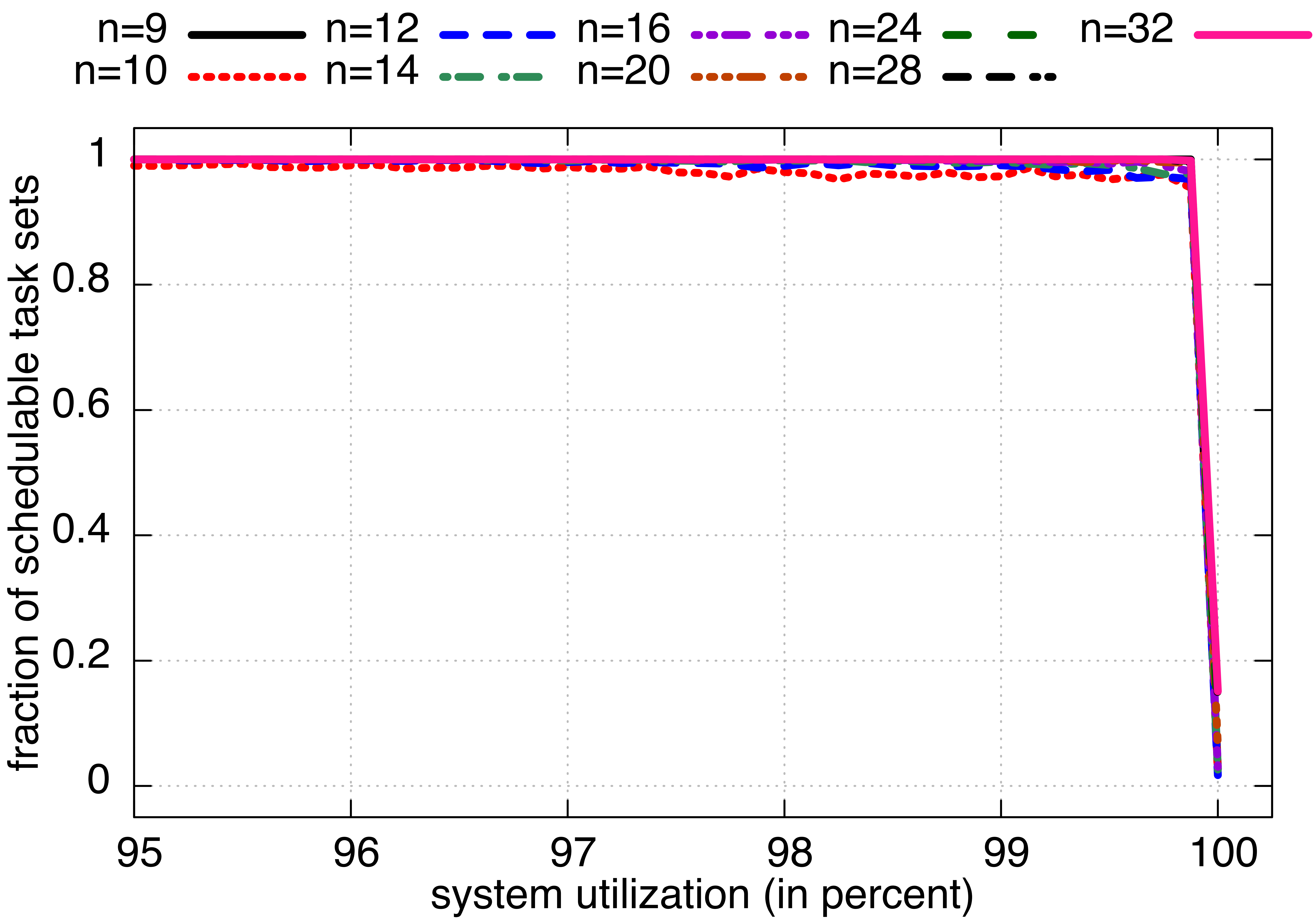


Even smaller gap

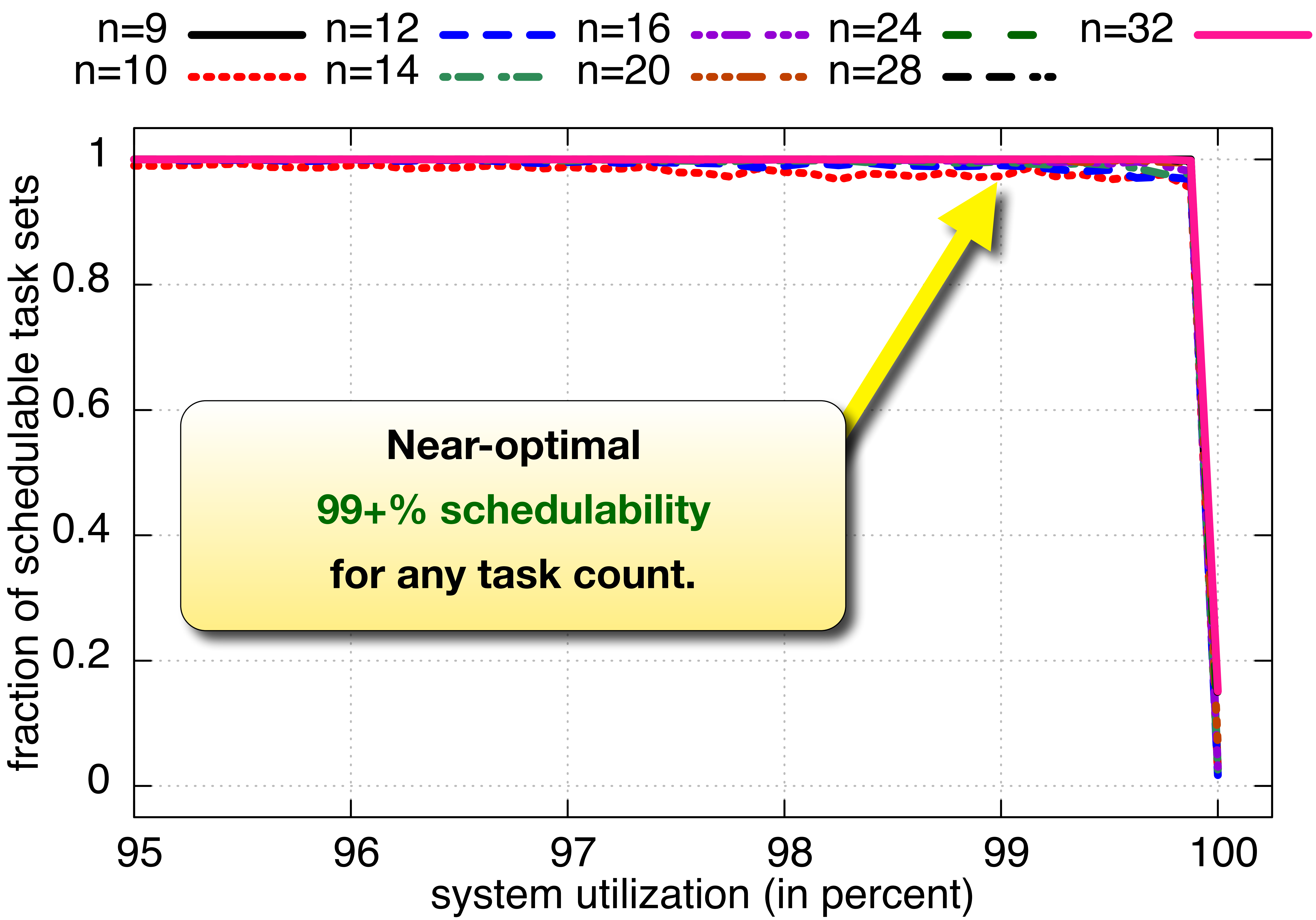
at 99% utilization, lowest curve at 90+% schedulablity

Still, can't we get there somehow…?

Semi-Partitioning with PAF + Period Transformation

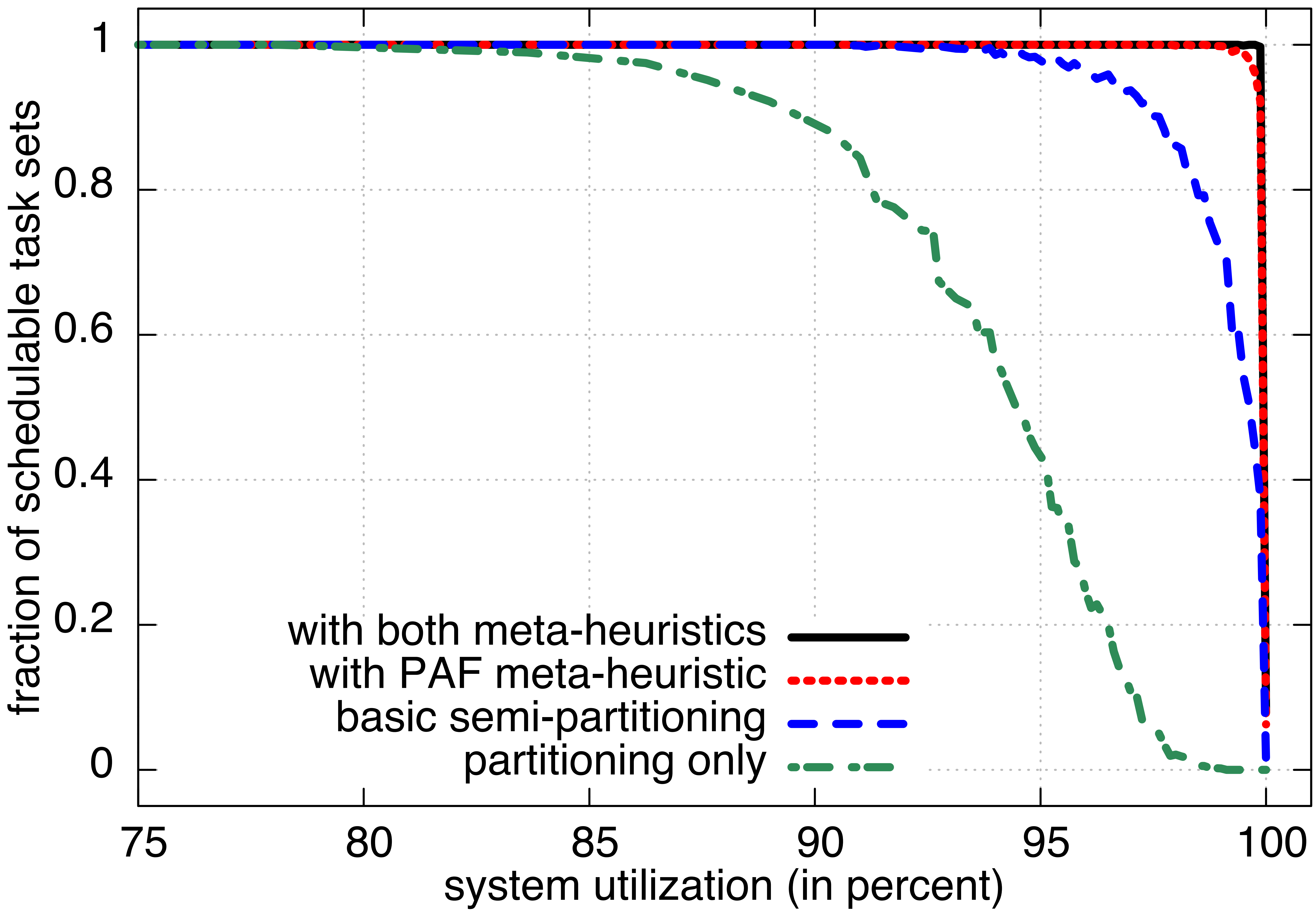


Semi-Partitioning with PAF + Period Transformation



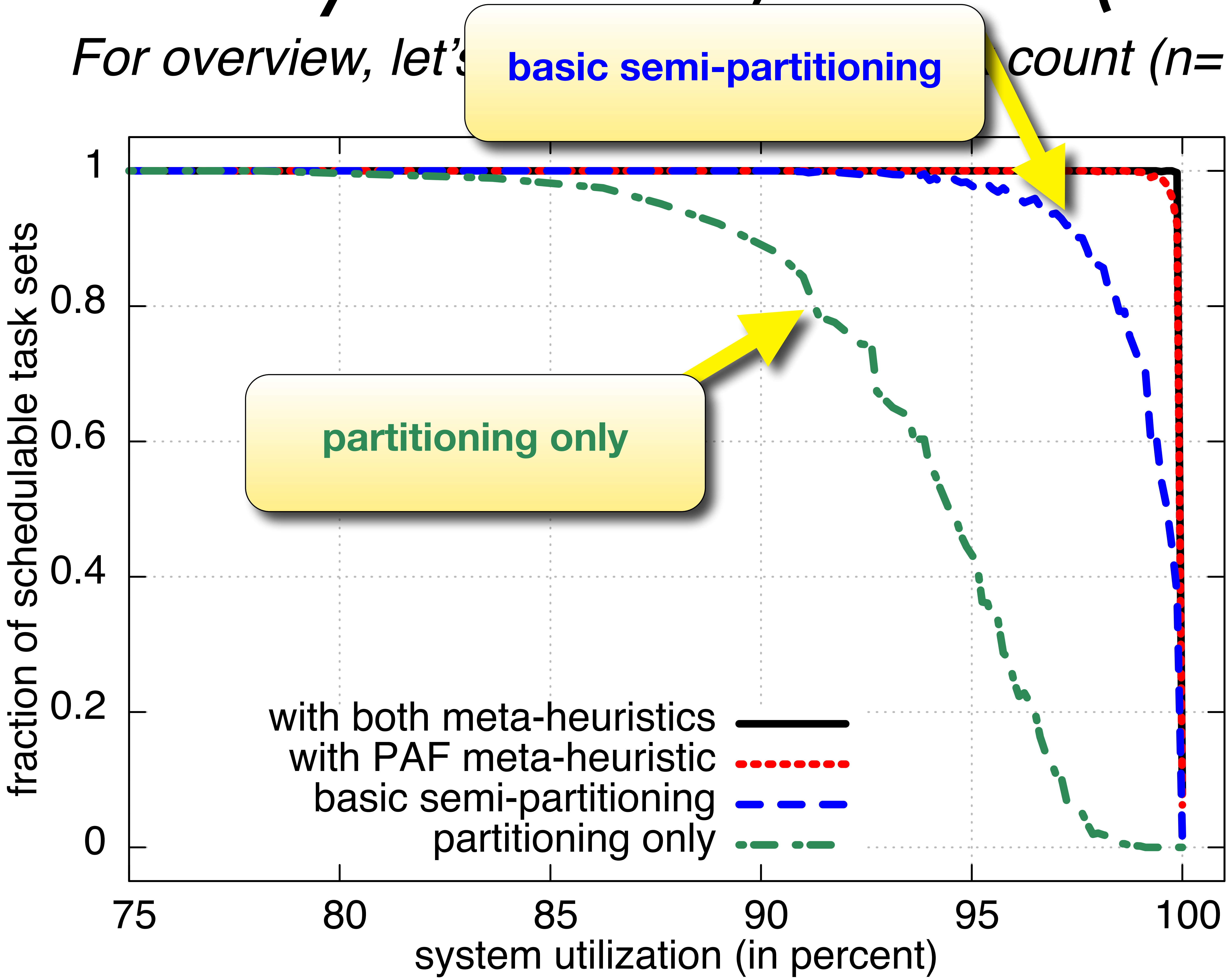
Summary for 8 Cores, 16 Tasks (n=2m)

For overview, let's consider just one task count (n=16).



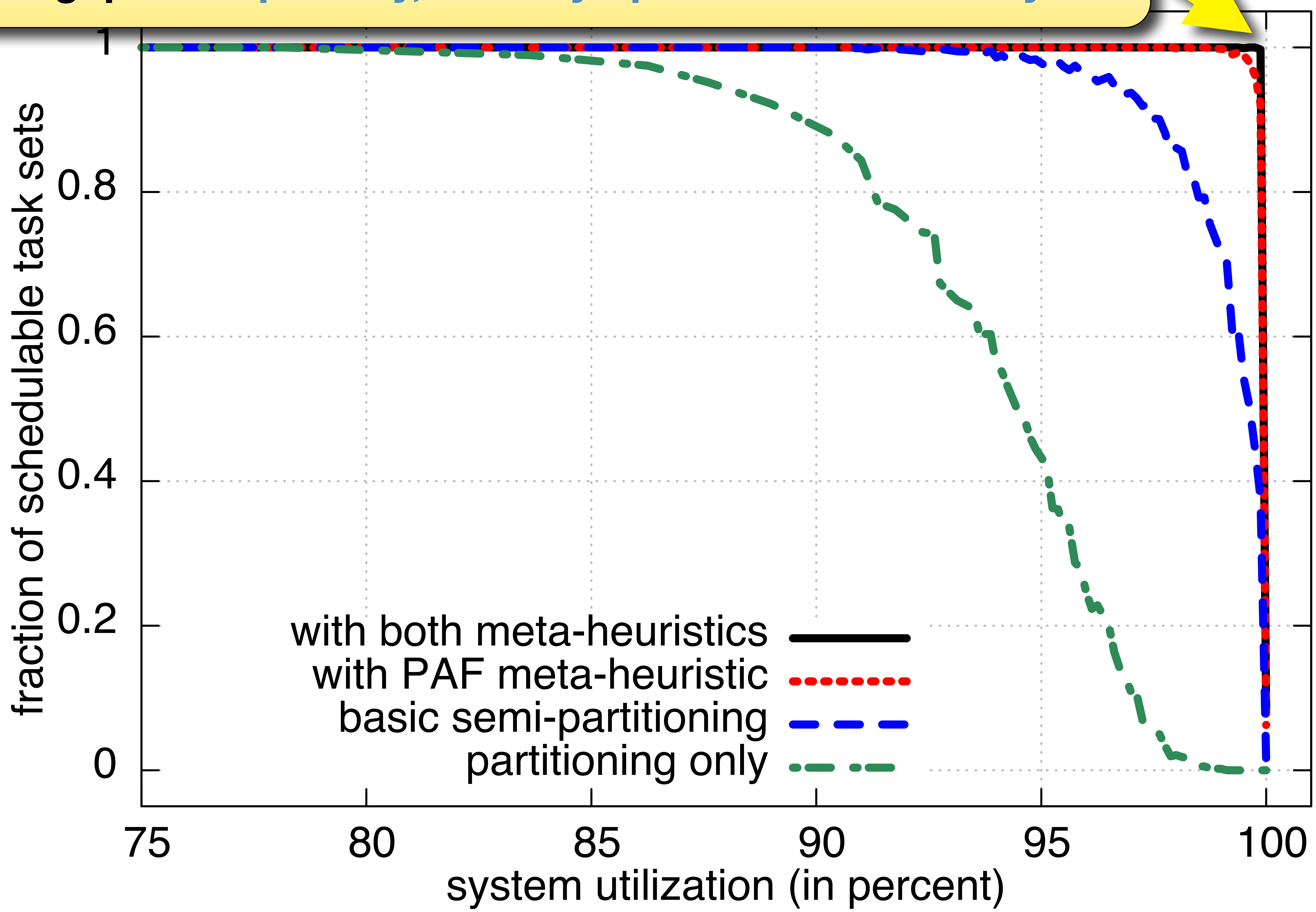
Summary for 8 Cores, 16 Tasks (n=2m)

For overview, let's ... count (n=16).



Summary for 8 Cores, 16 Tasks (n=2m)

PAF surprisingly effective & period transformation closes the last gap — empirically, virtually optimal schedulability

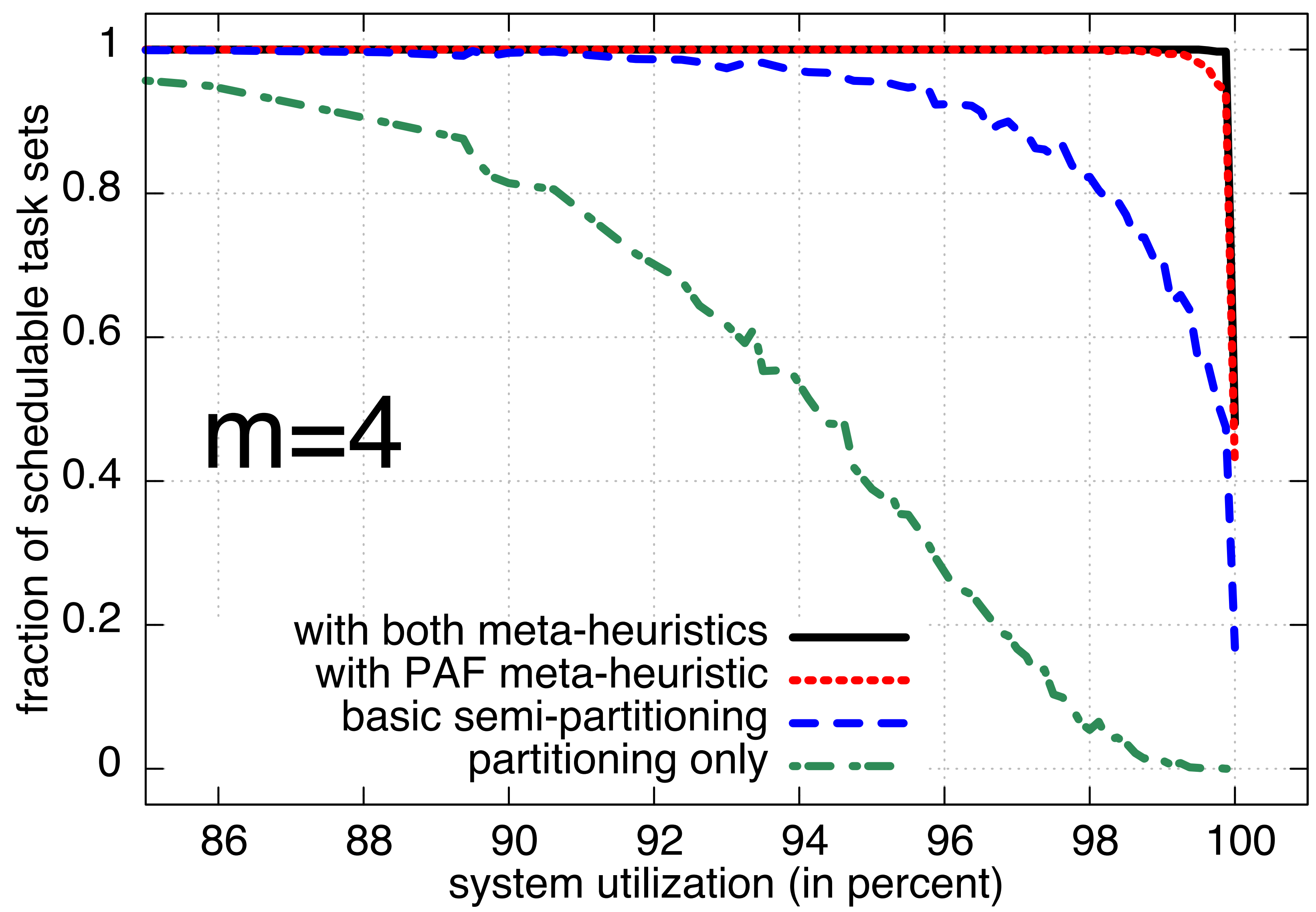


What about other core counts? (n=2m)

→ *trends largely independent of m*

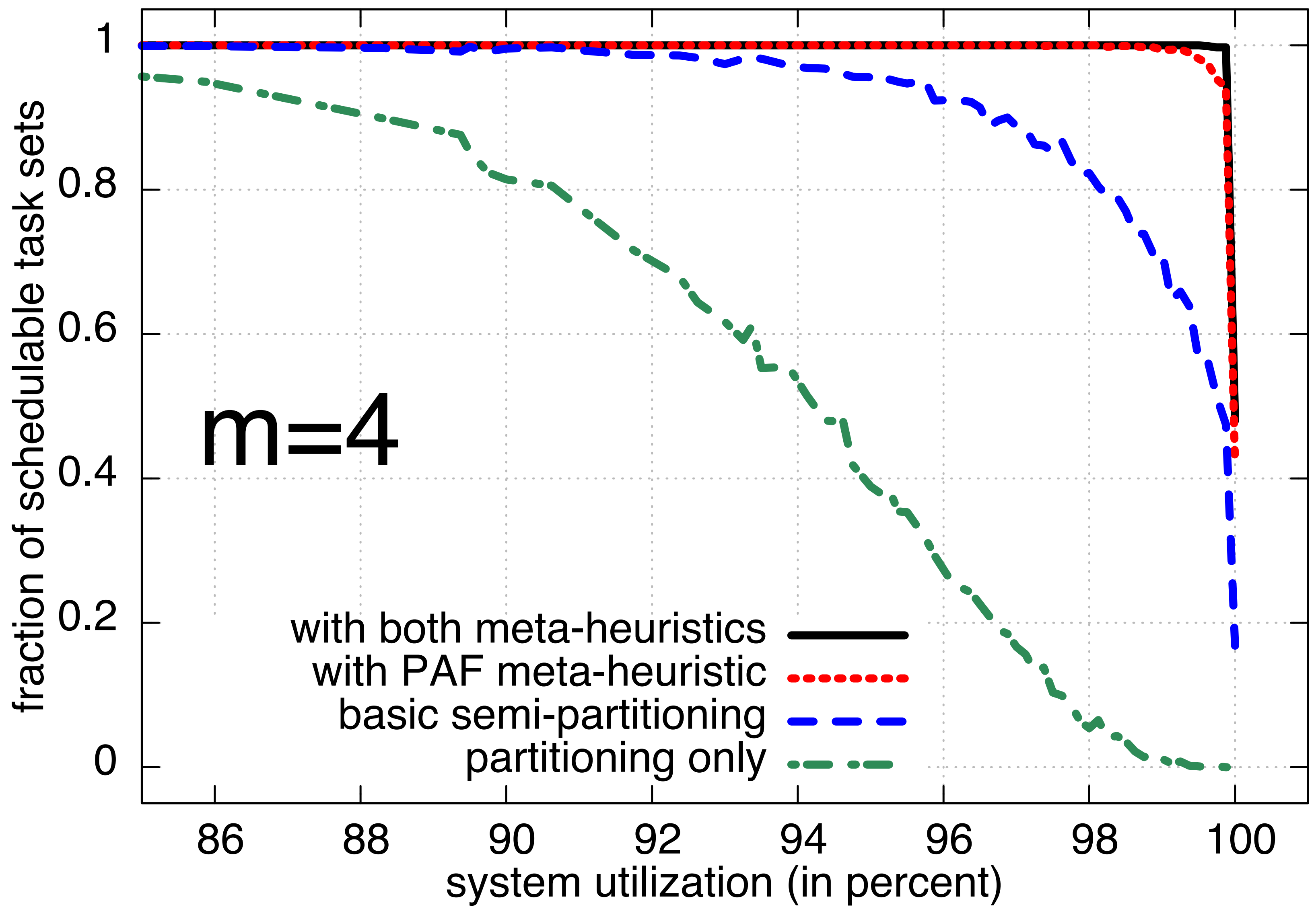
What about other core counts? (n=2m)

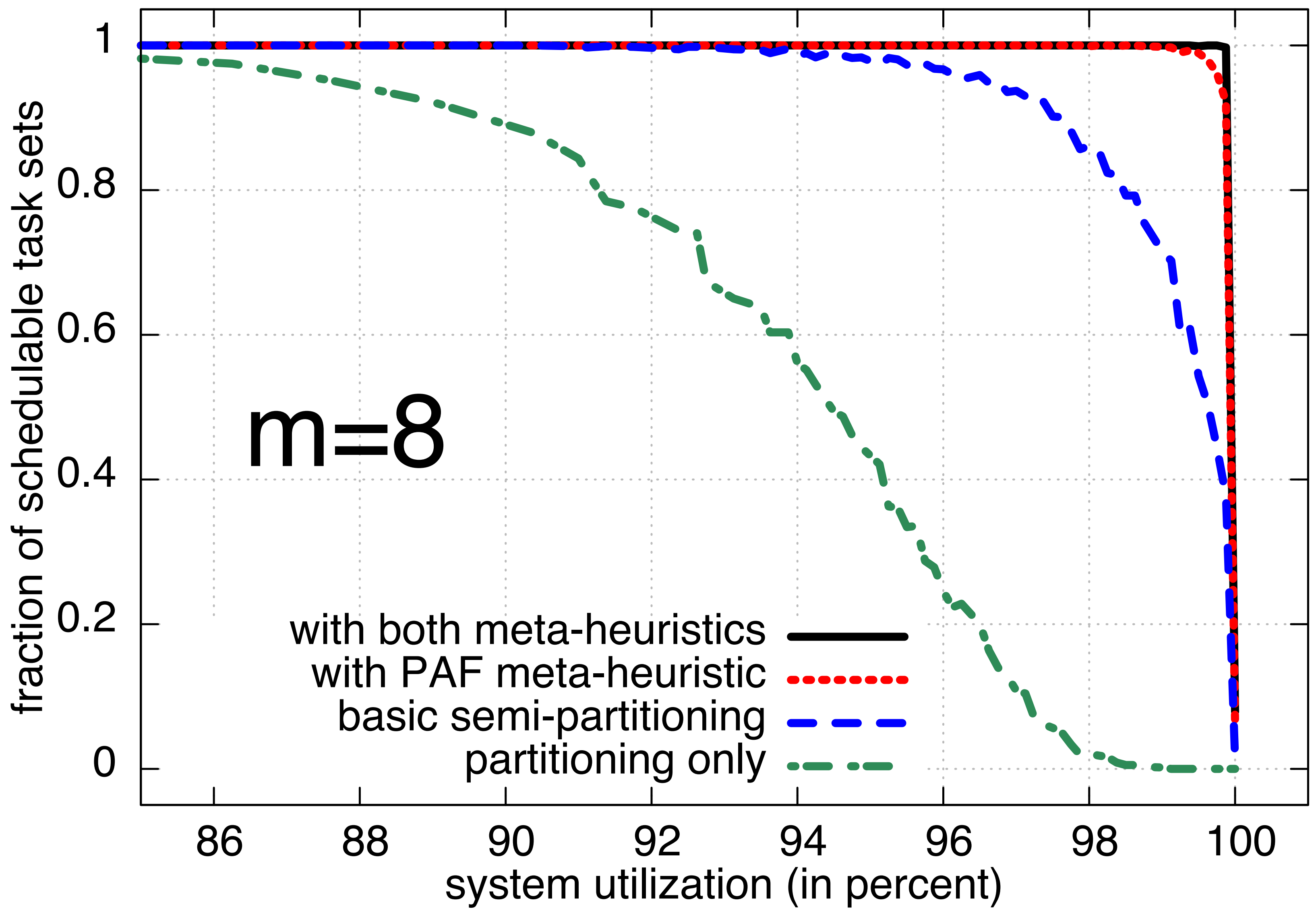
→ *trends largely independent of m*



What about other core counts? (n=2m)

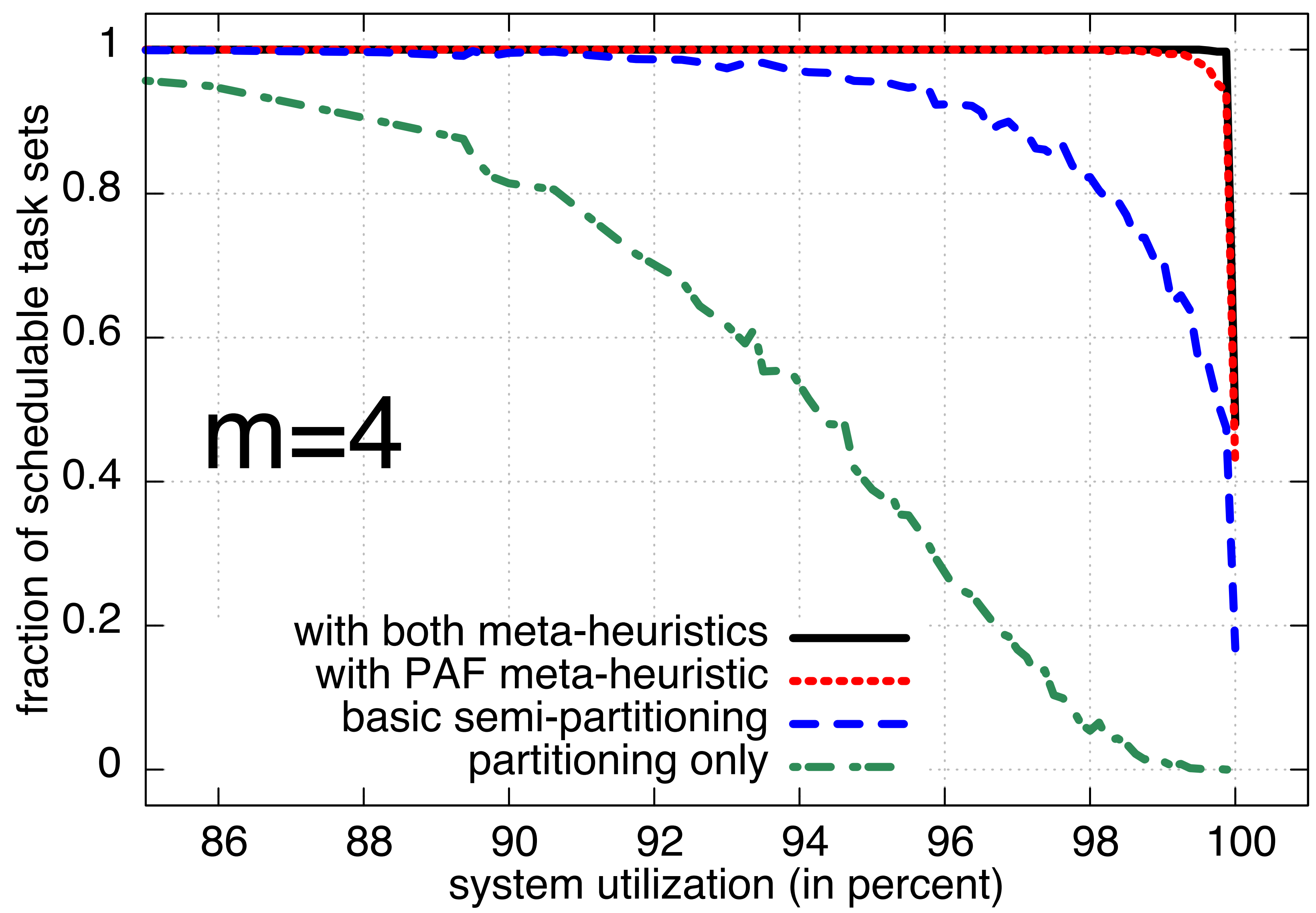
→ *trends largely independent of m*

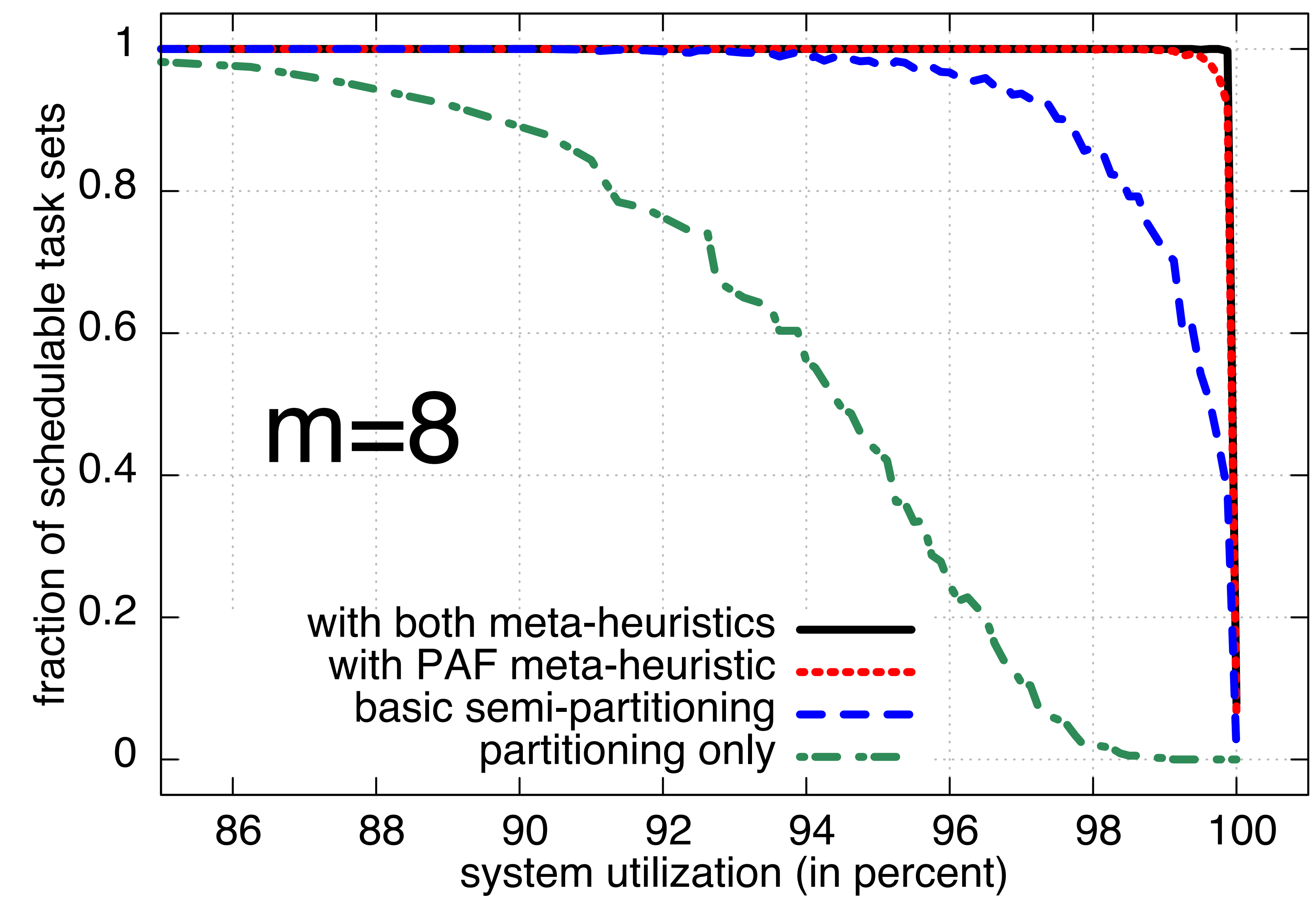


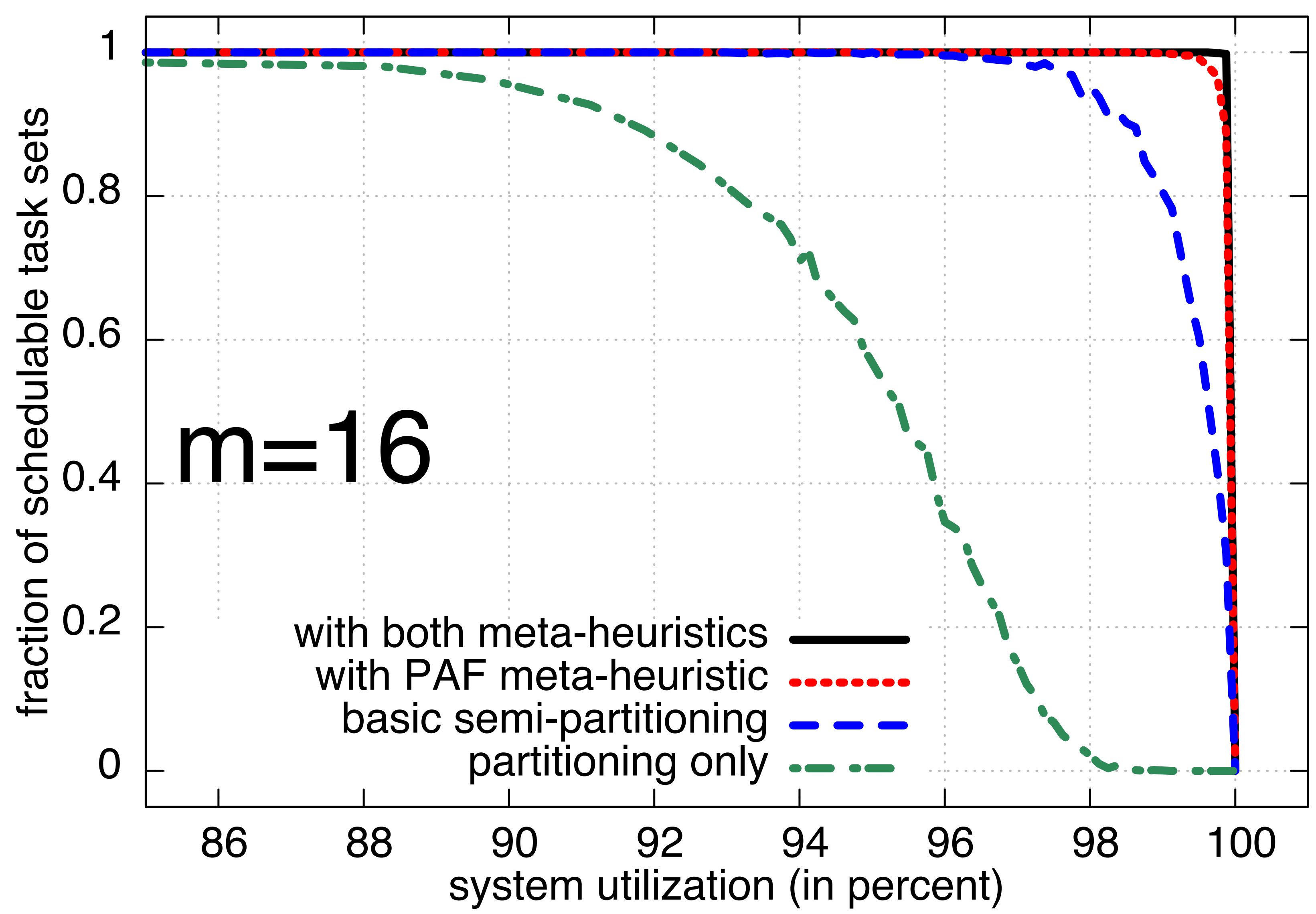


What about other core counts? (n=2m)

→ trends largely independent of m

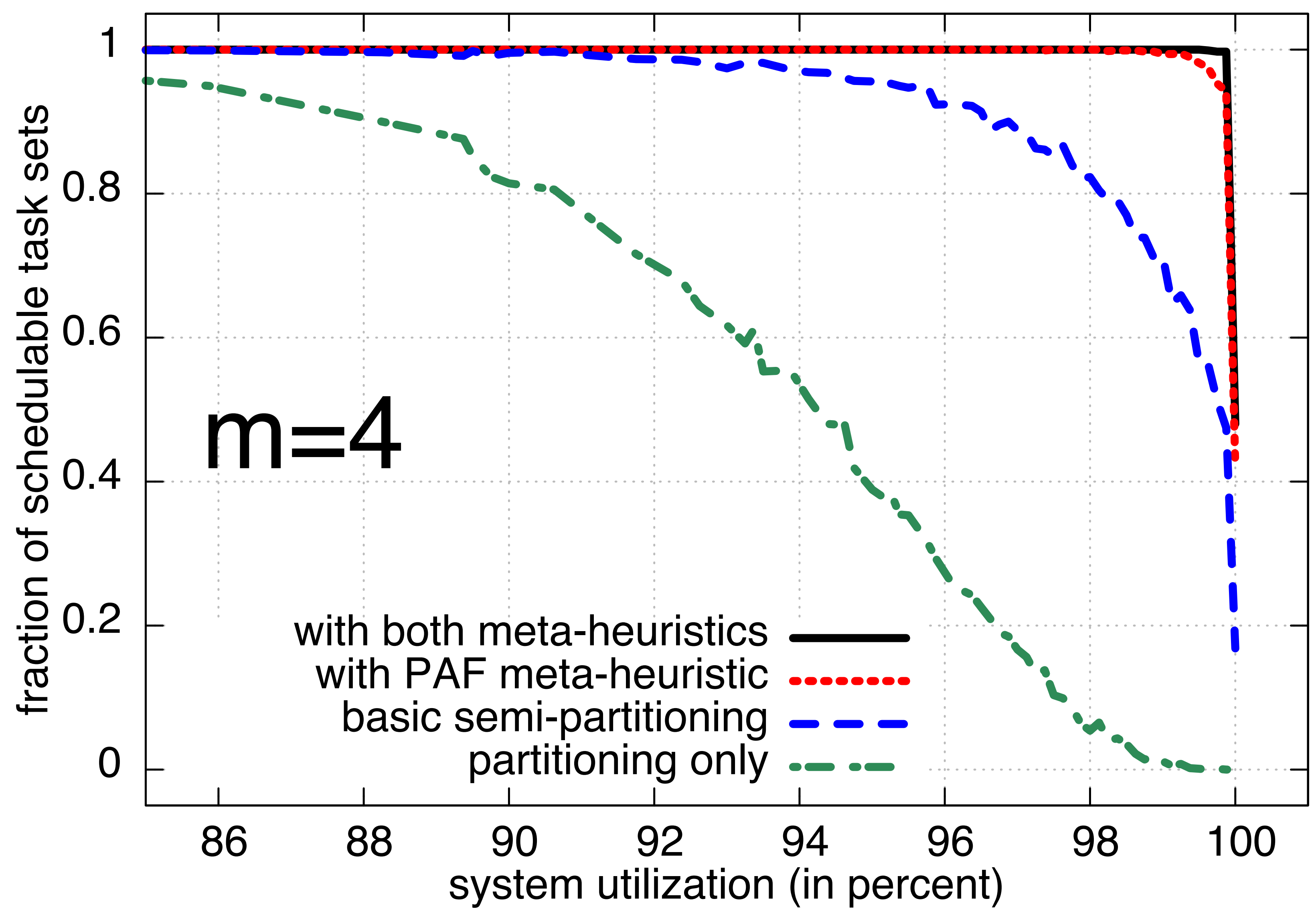


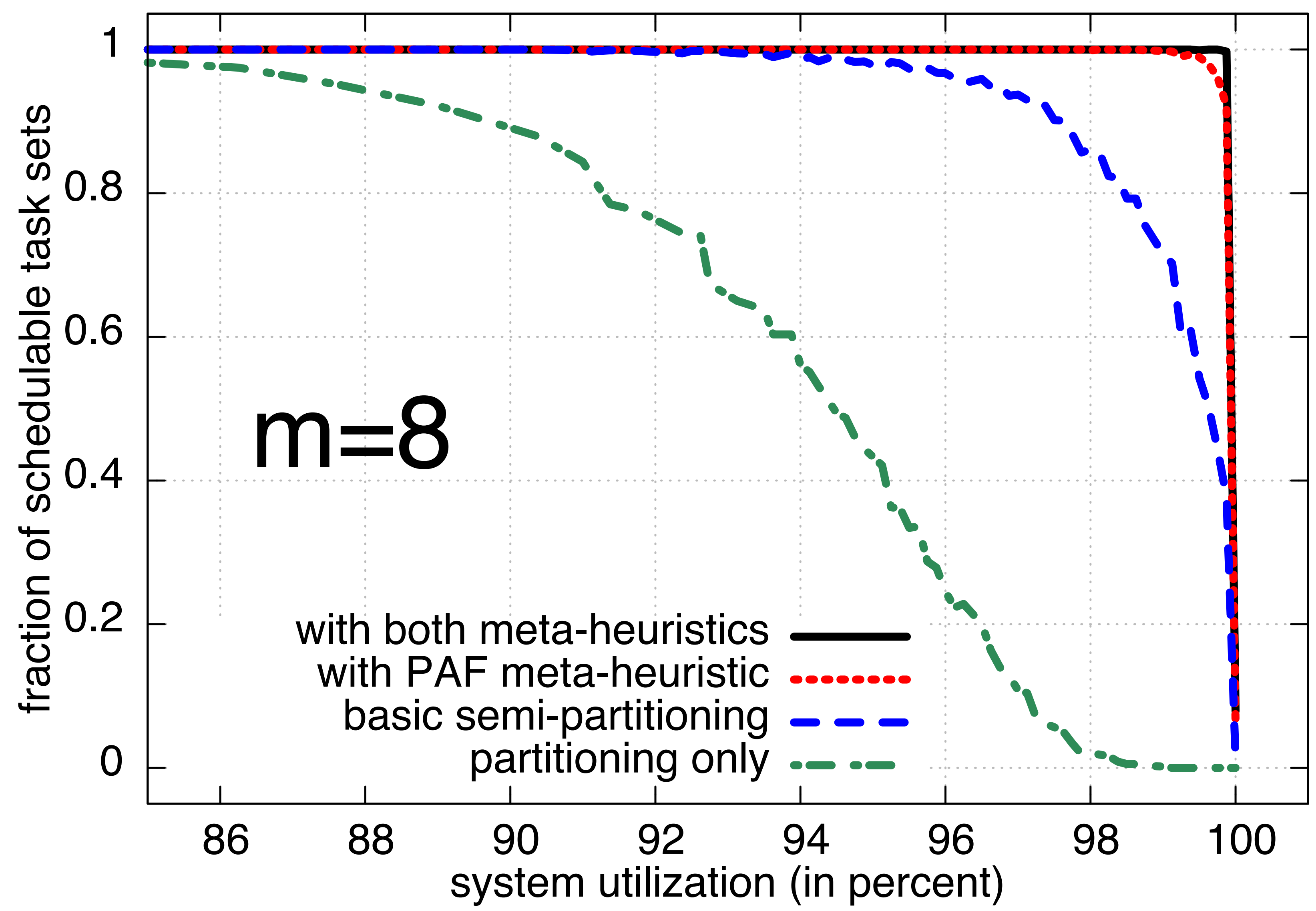


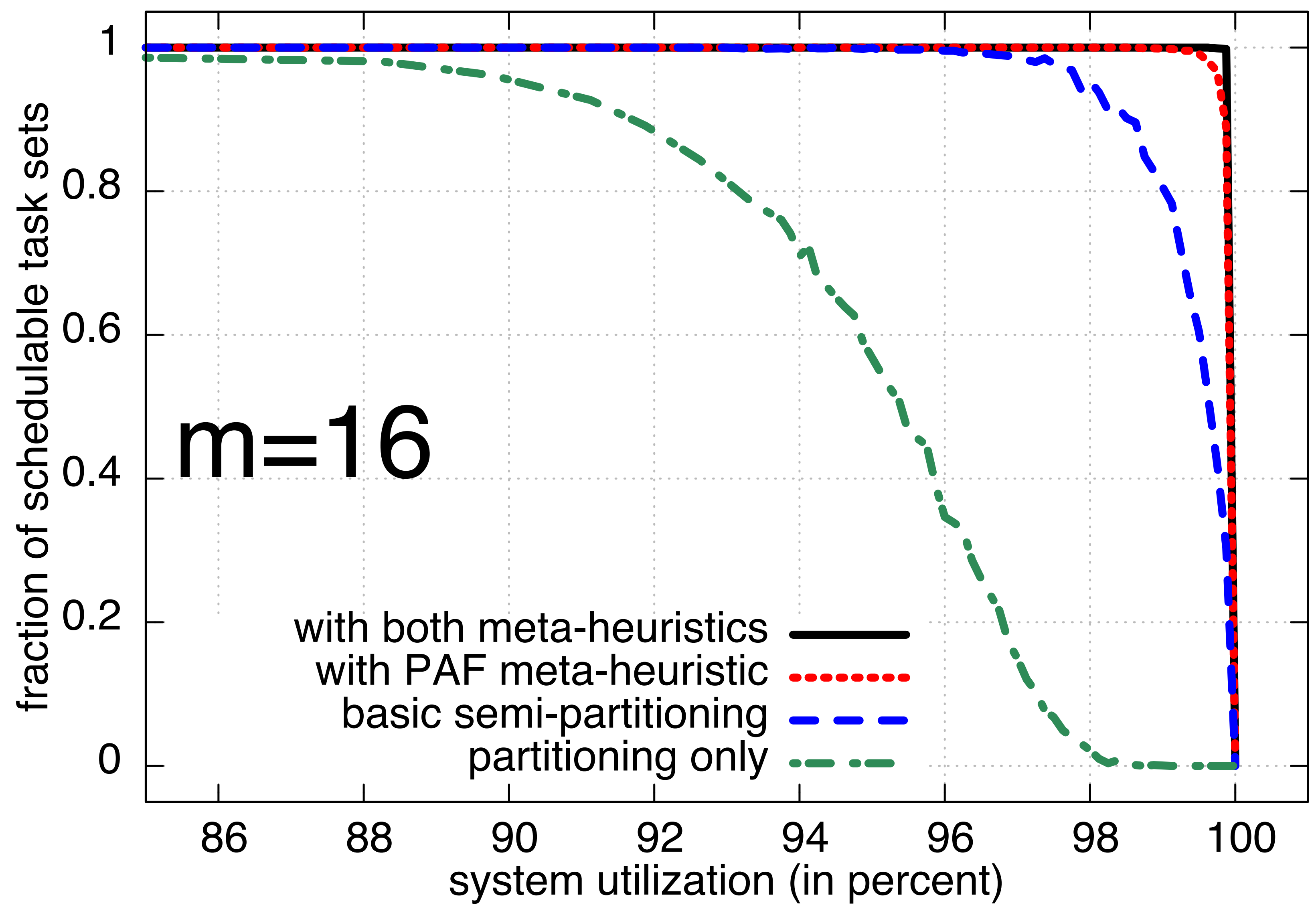


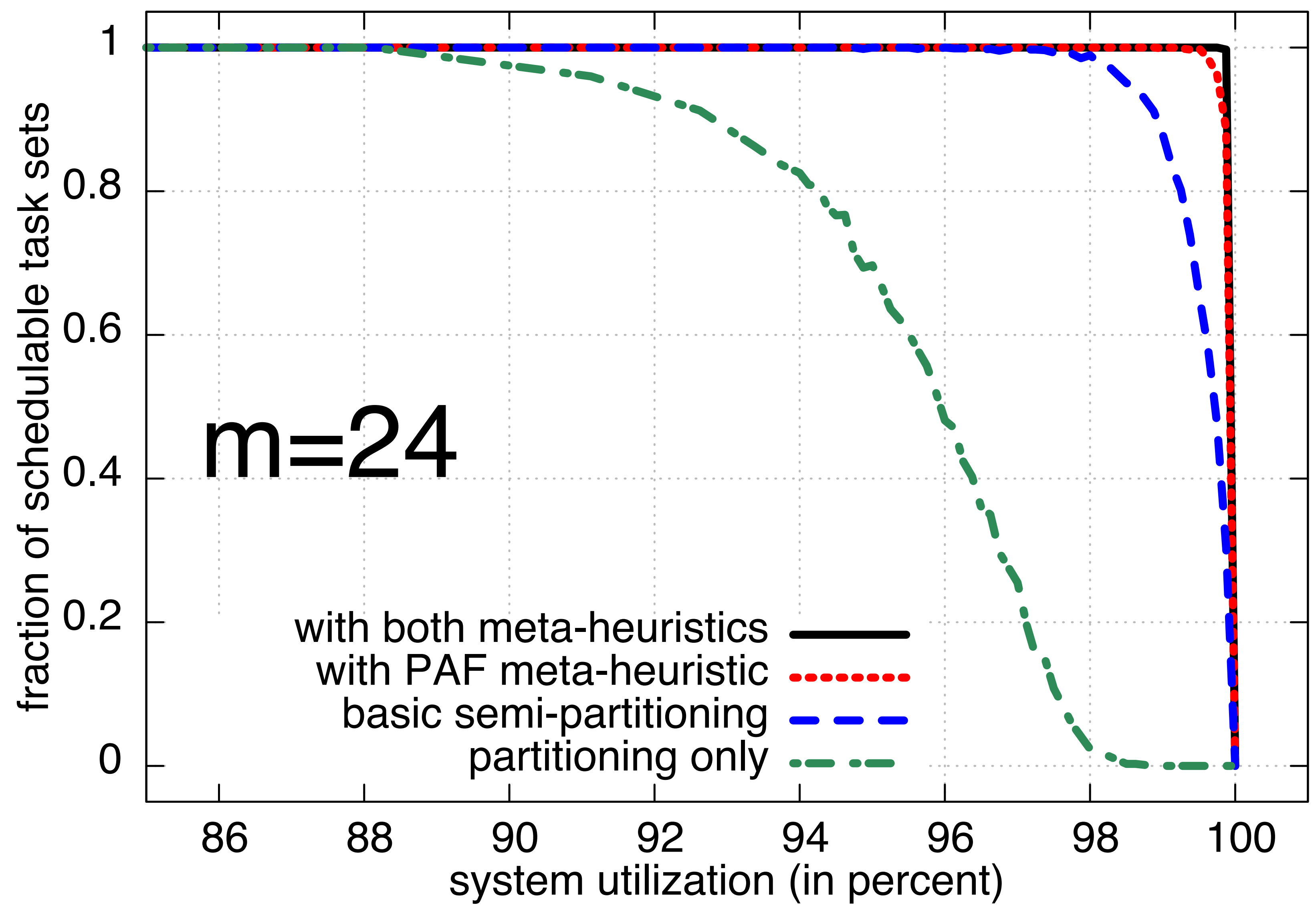
What about other core counts? (n=2m)

→ *trends largely independent of m*







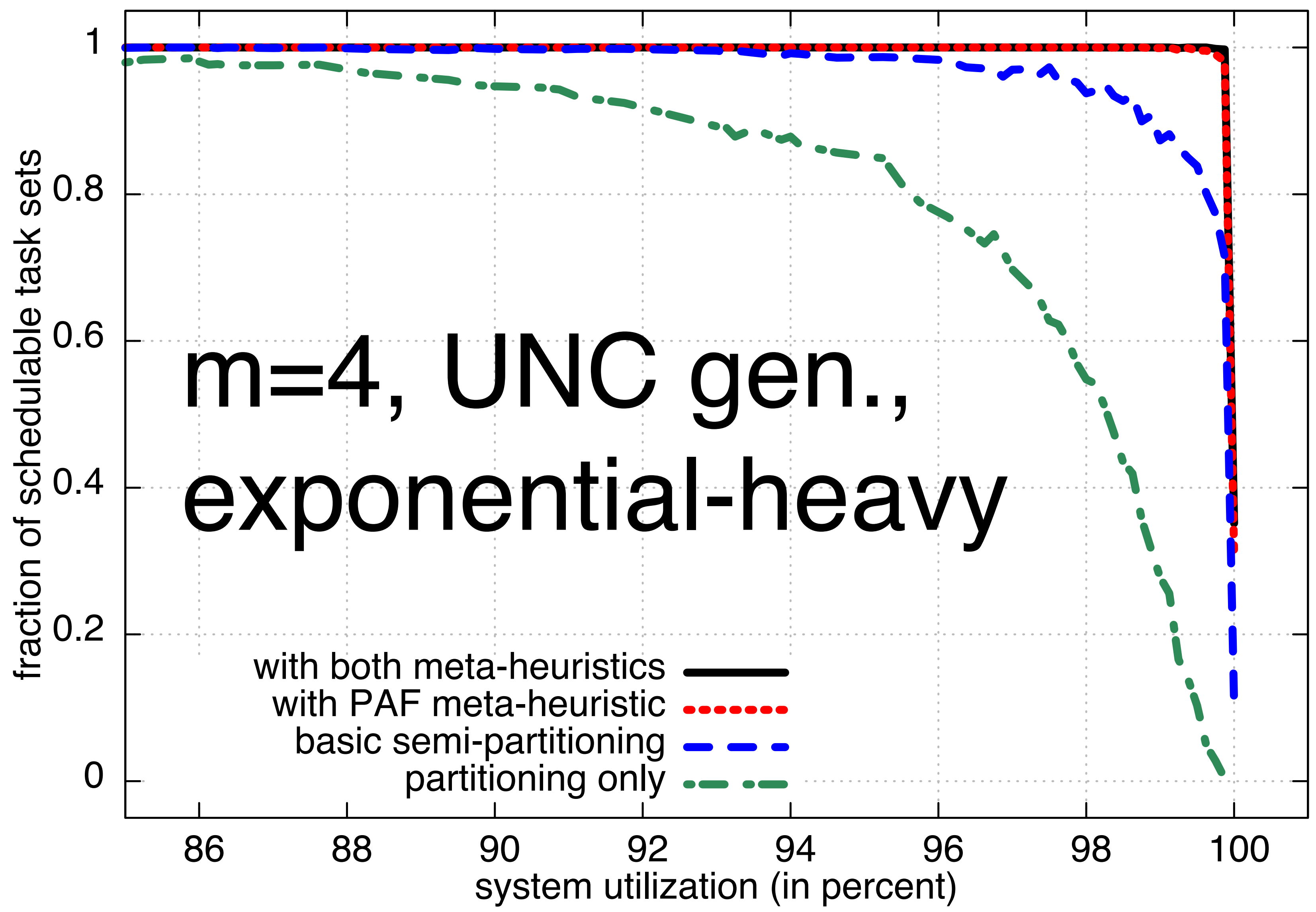


What about the task-set generator? (n=2m)

→ *very similar for completely different task-set generator*

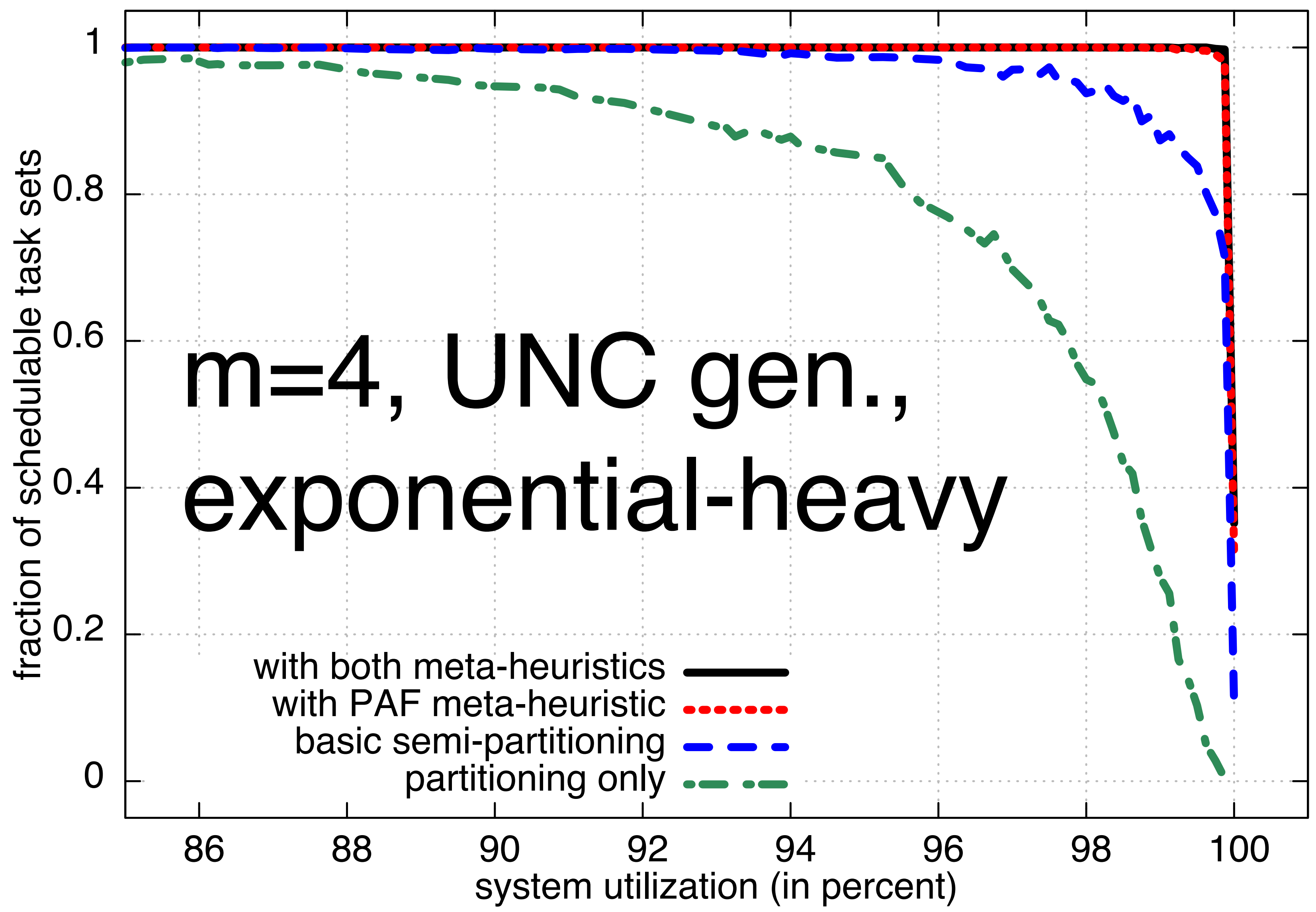
What about the task-set generator? (n=2m)

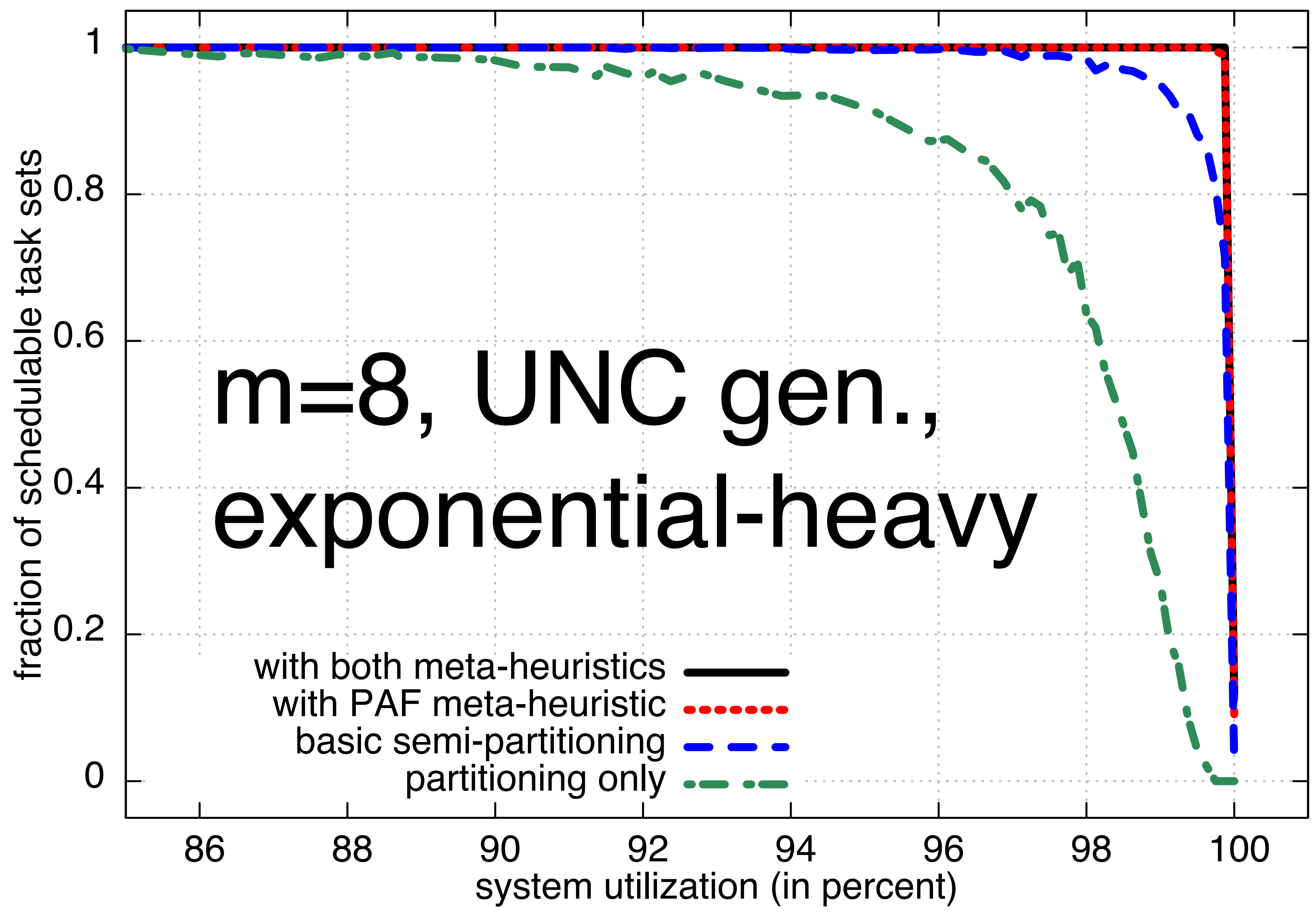
→ *very similar for completely different task-set generator*



What about the task-set generator? (n=2m)

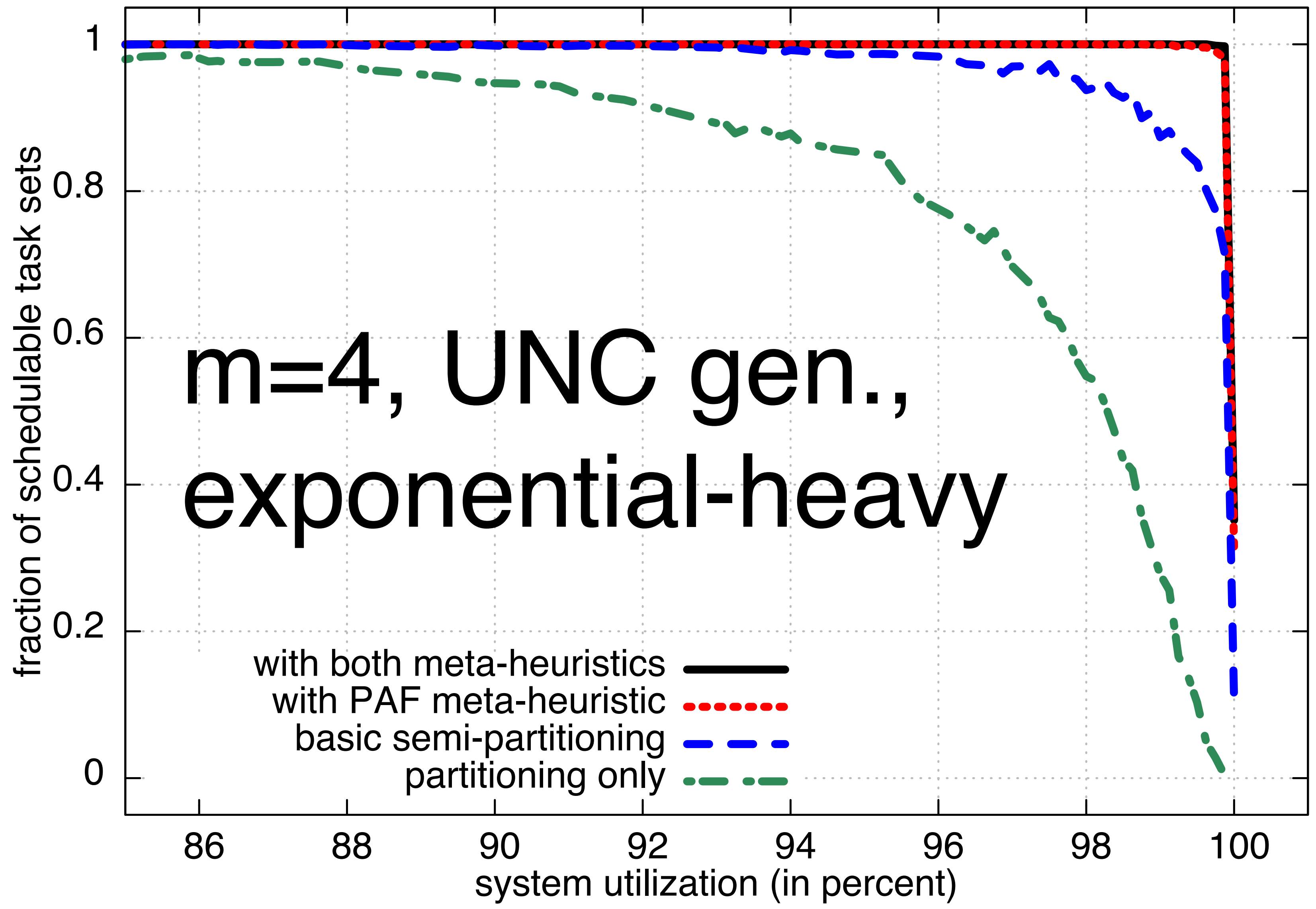
→ *very similar for completely different task-set generator*

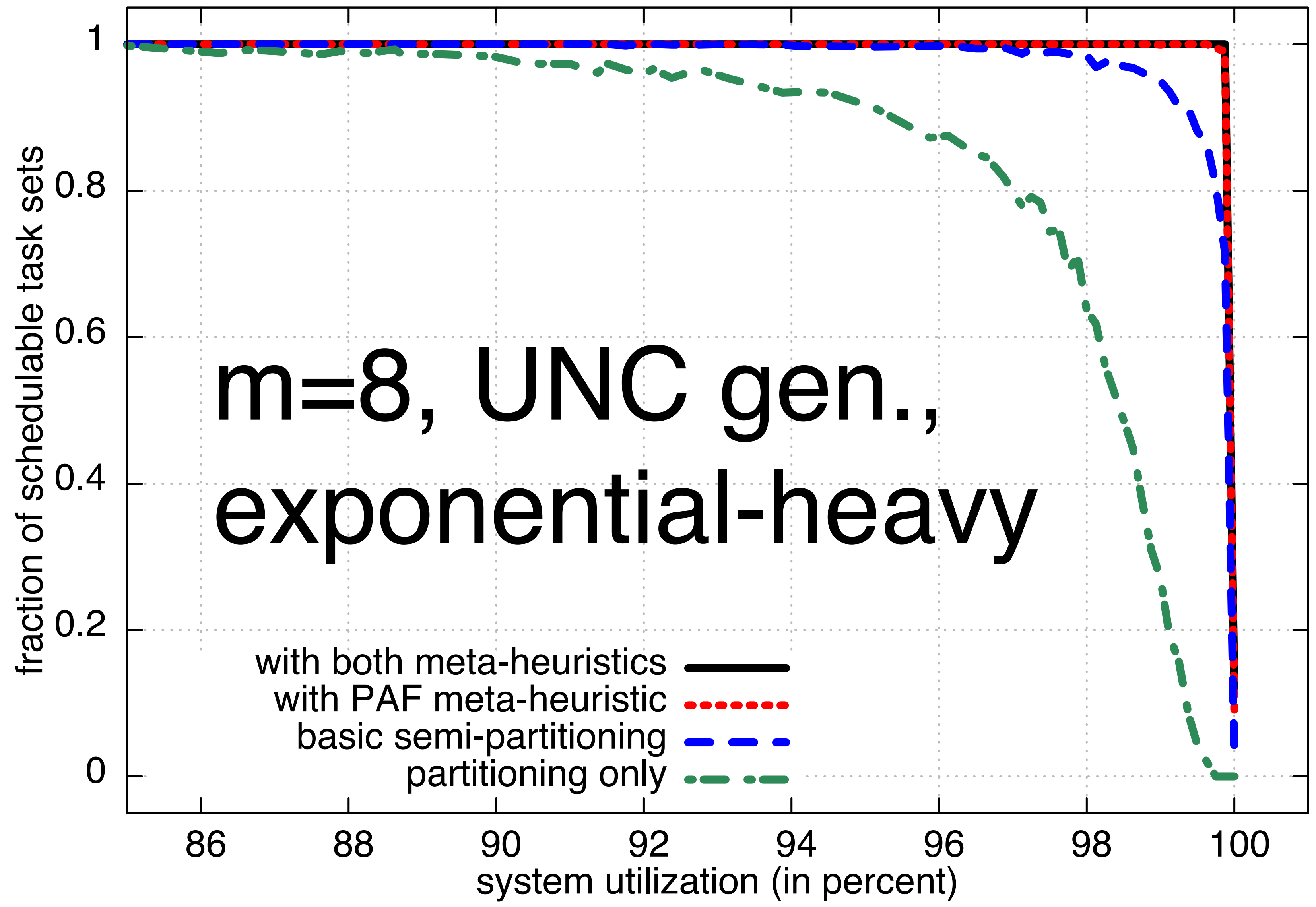


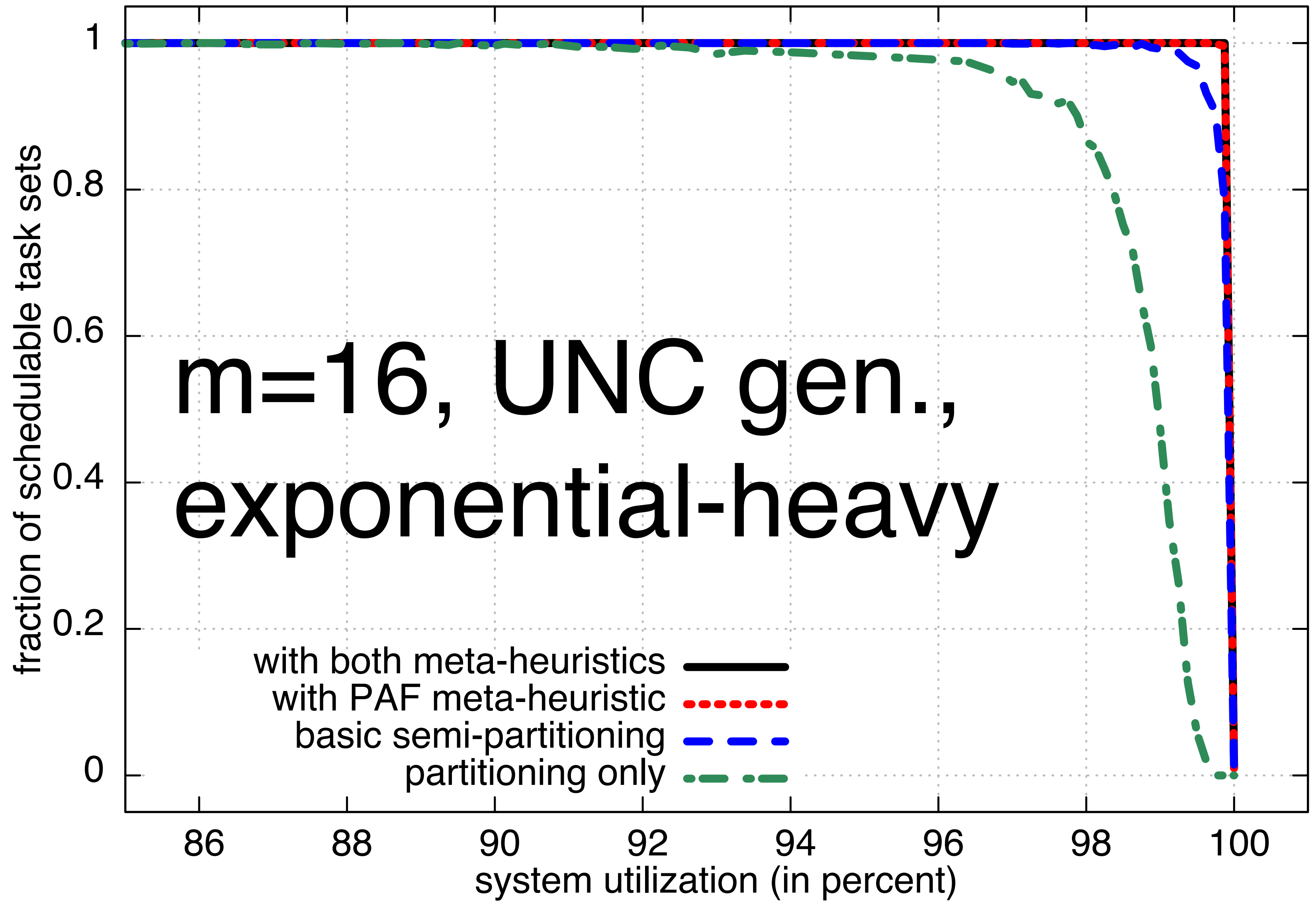


What about the task-set generator? (n=2m)

→ *very similar for completely different task-set generator*

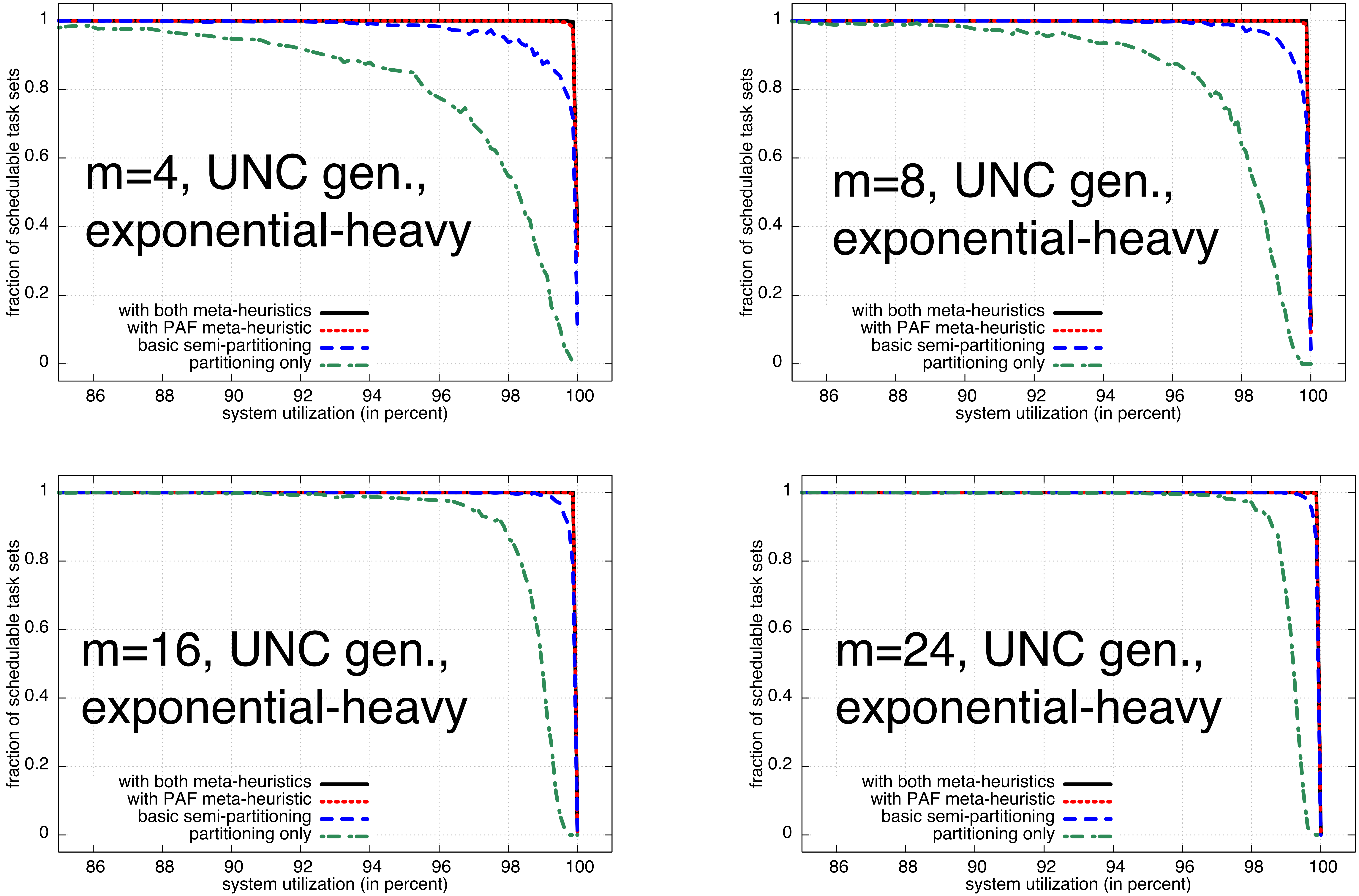




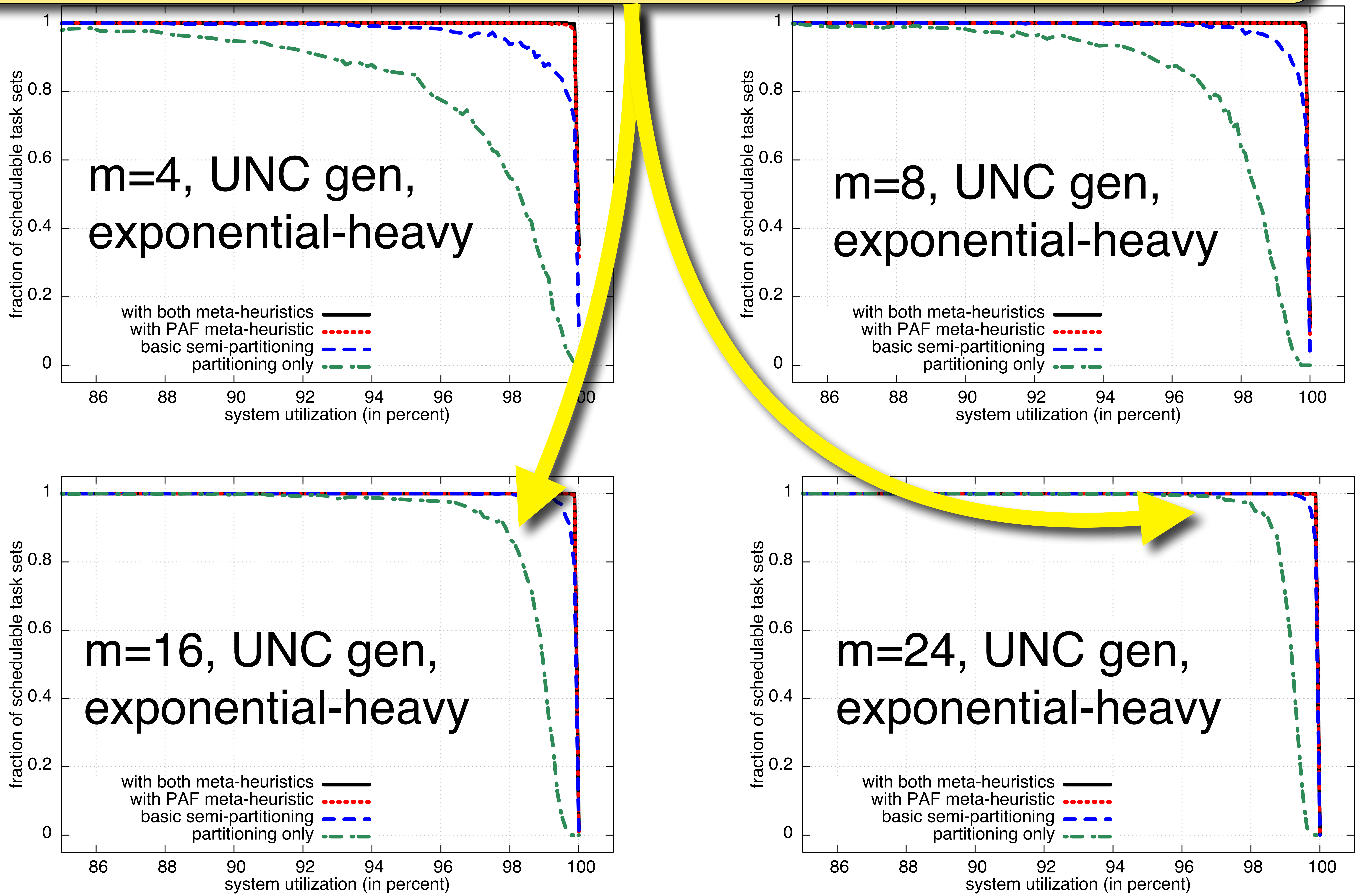


What about the task-set generator? (n=2m)

→ *very similar for completely different task-set generator*



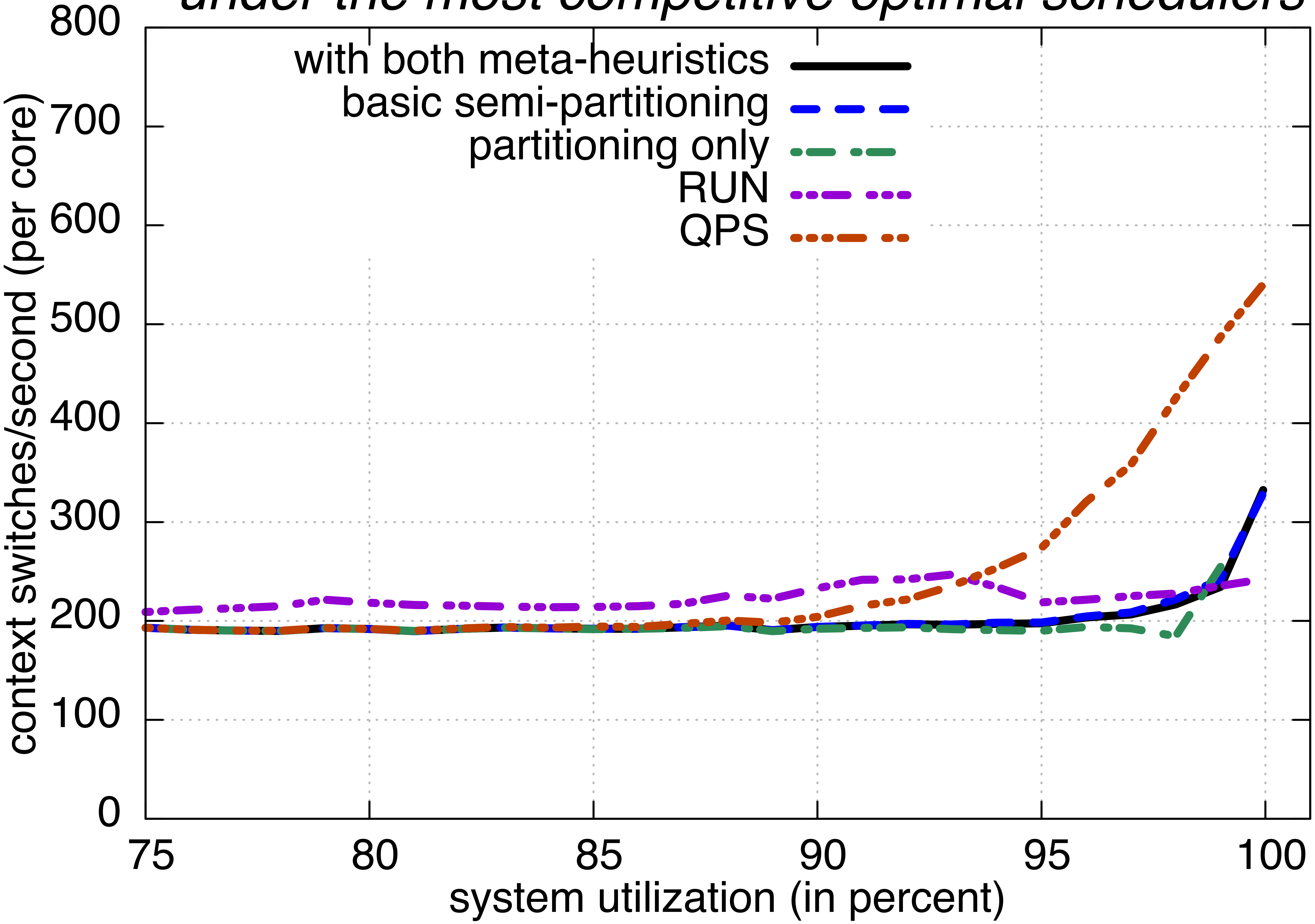
Schedulability increases for larger *m* since task count is not controlled with this task-set generator (→ *more cores = more tasks/core = easier problem*).



What about context-switch rates? (m=8, n=2m)

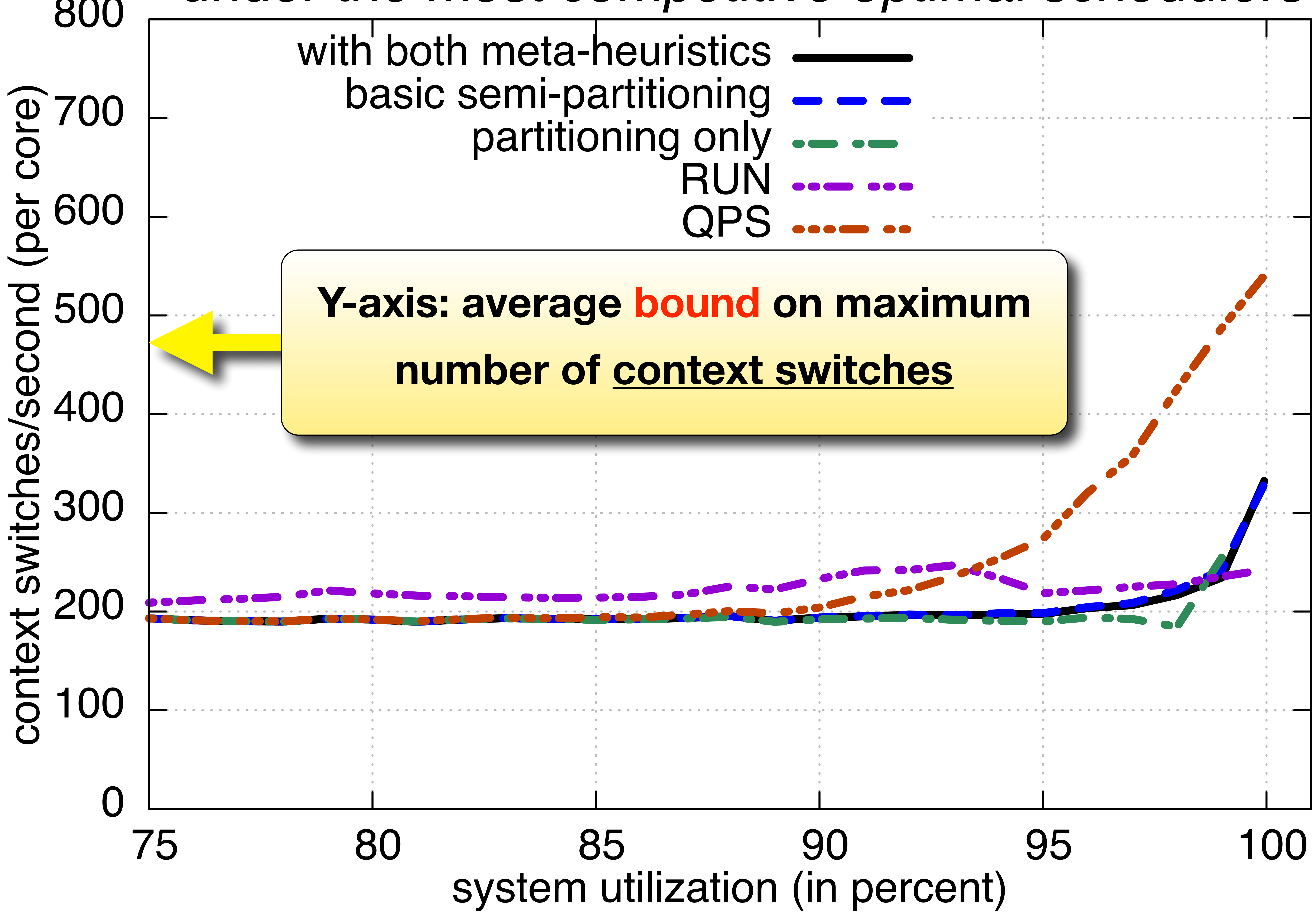
What about context-switch rates? (m=8, n=2m)

→ *while there is an uptick in context switches, it is usually lower than under the most competitive optimal schedulers*



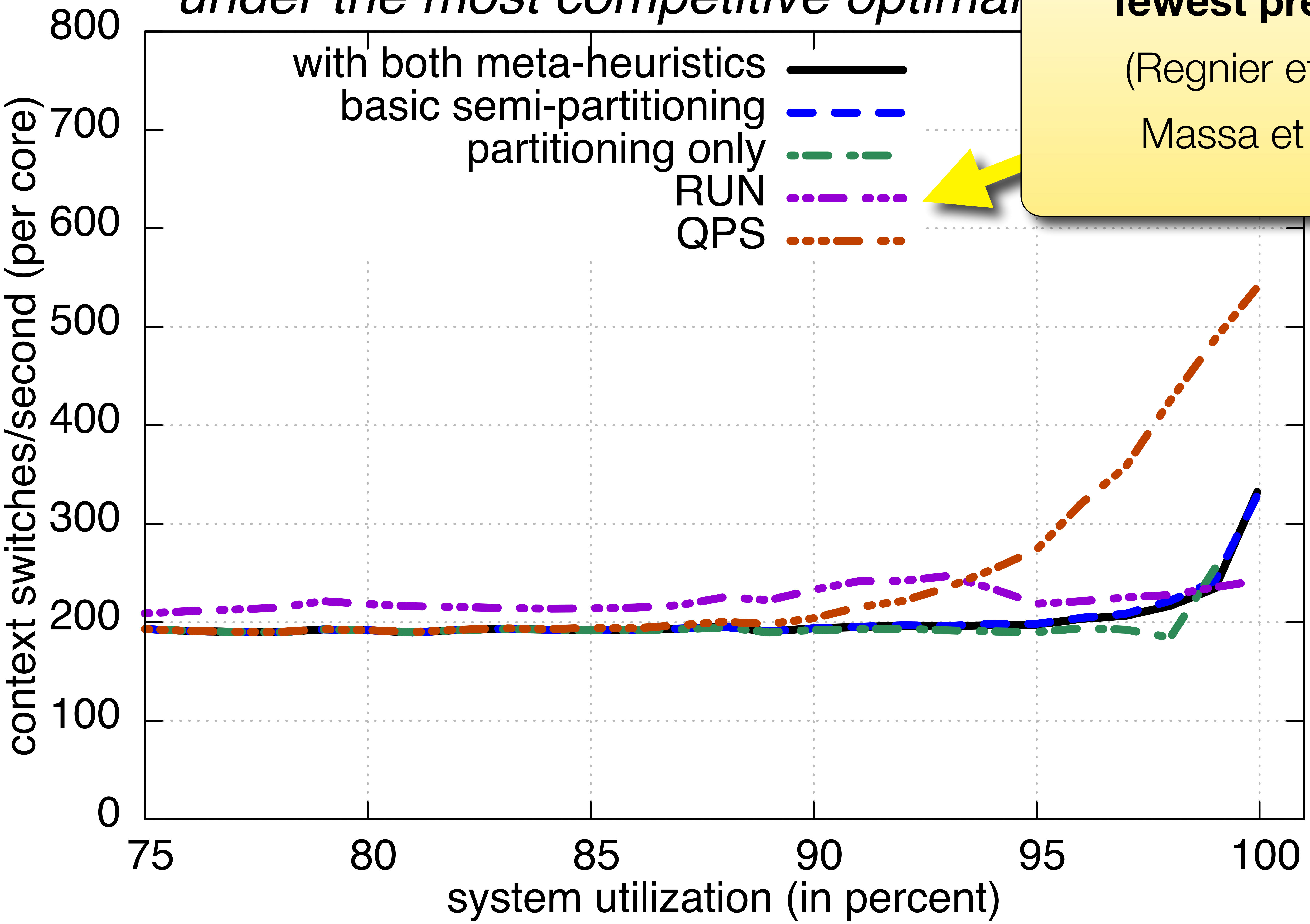
What about context-switch rates? (m=8, n=2m)

→ *while there is an uptick in context switches, it is usually lower than under the most competitive optimal schedulers*



What about context-switch rates

→ *while there is an uptick in context switches, under the most competitive optimal*



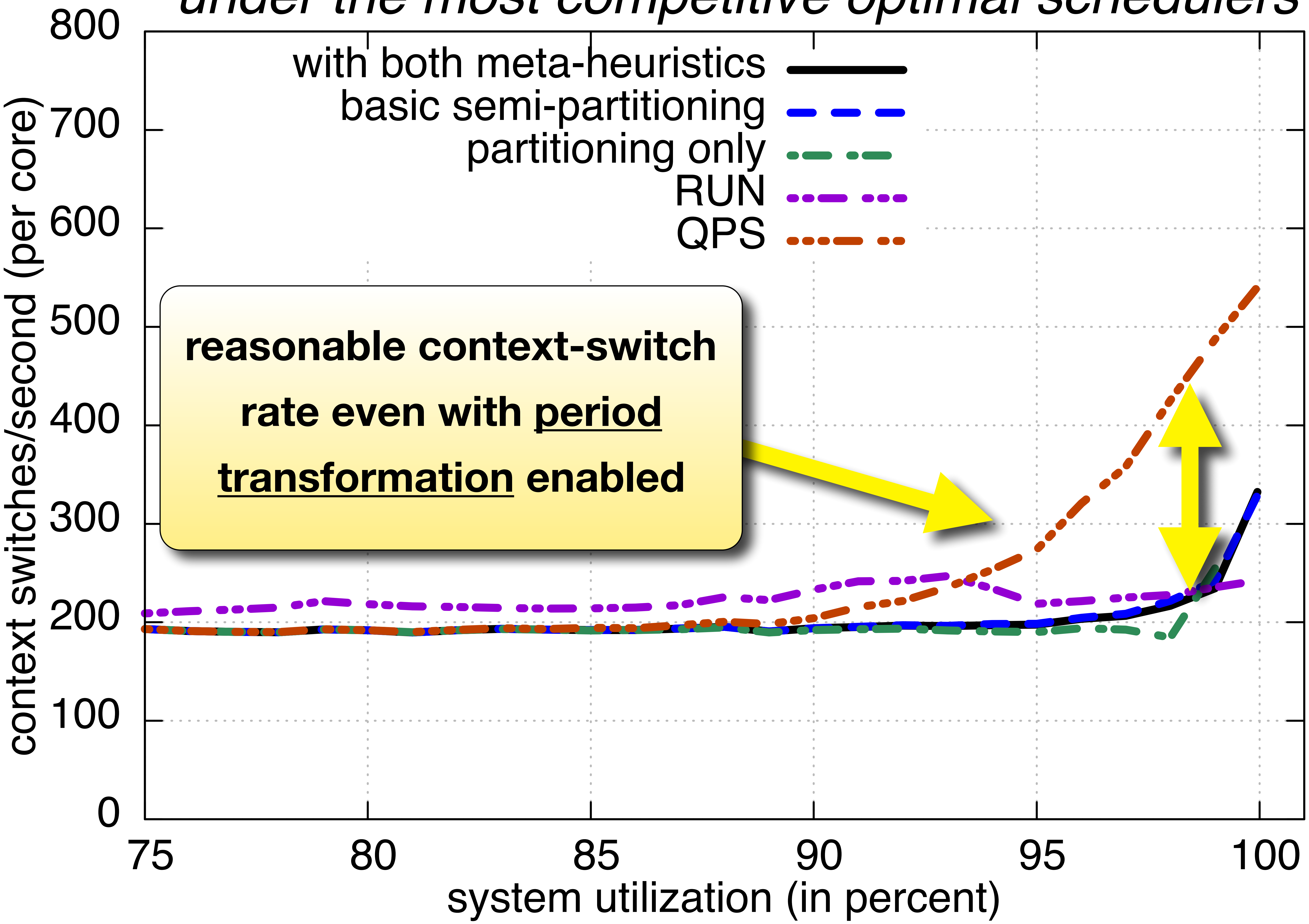
RUN & QPS

optimal schedulers with fewest preemptions

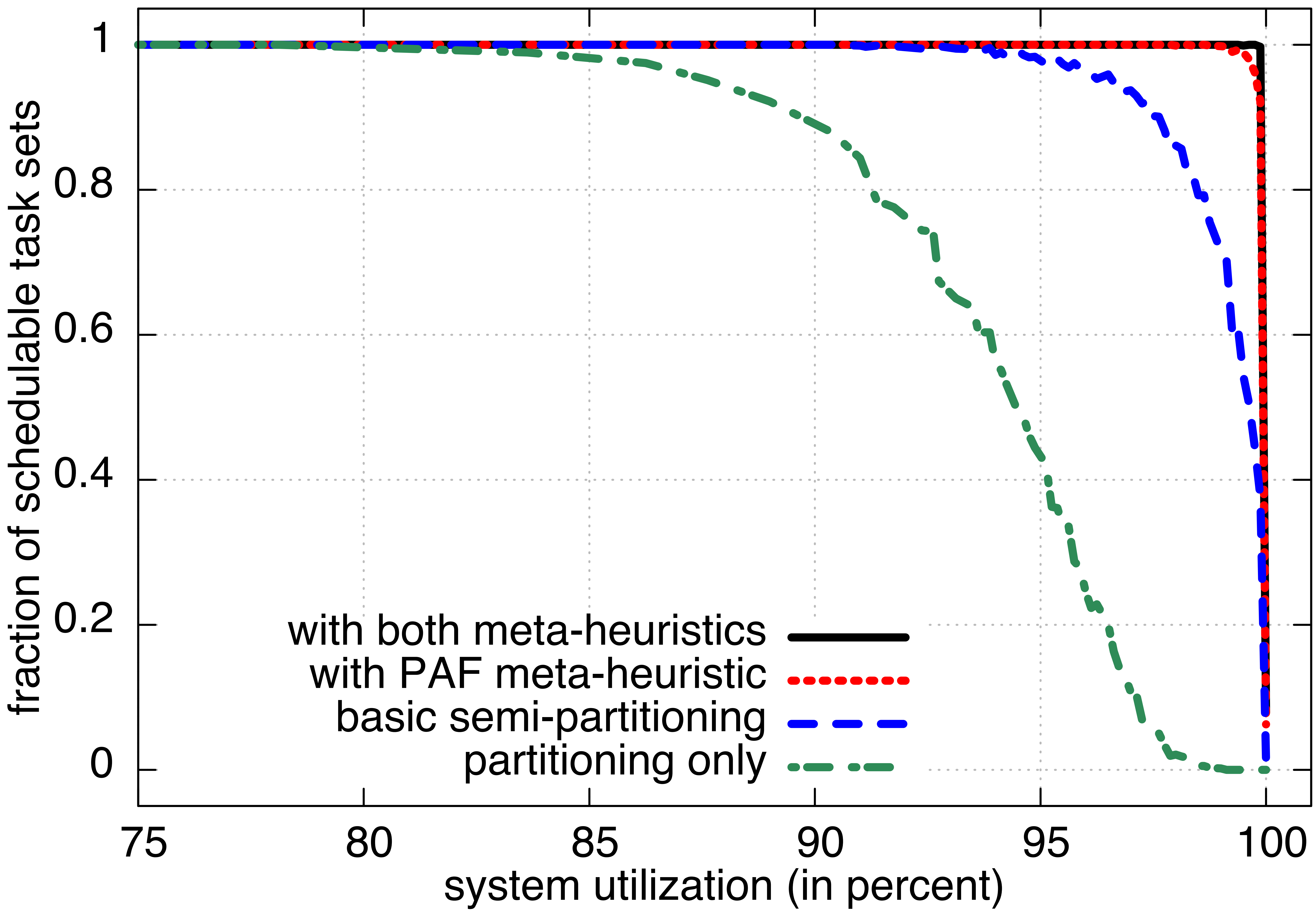
(Regnier et al., 2013; Massa et al., 2016)

What about context-switch rates? (m=8, n=2m)

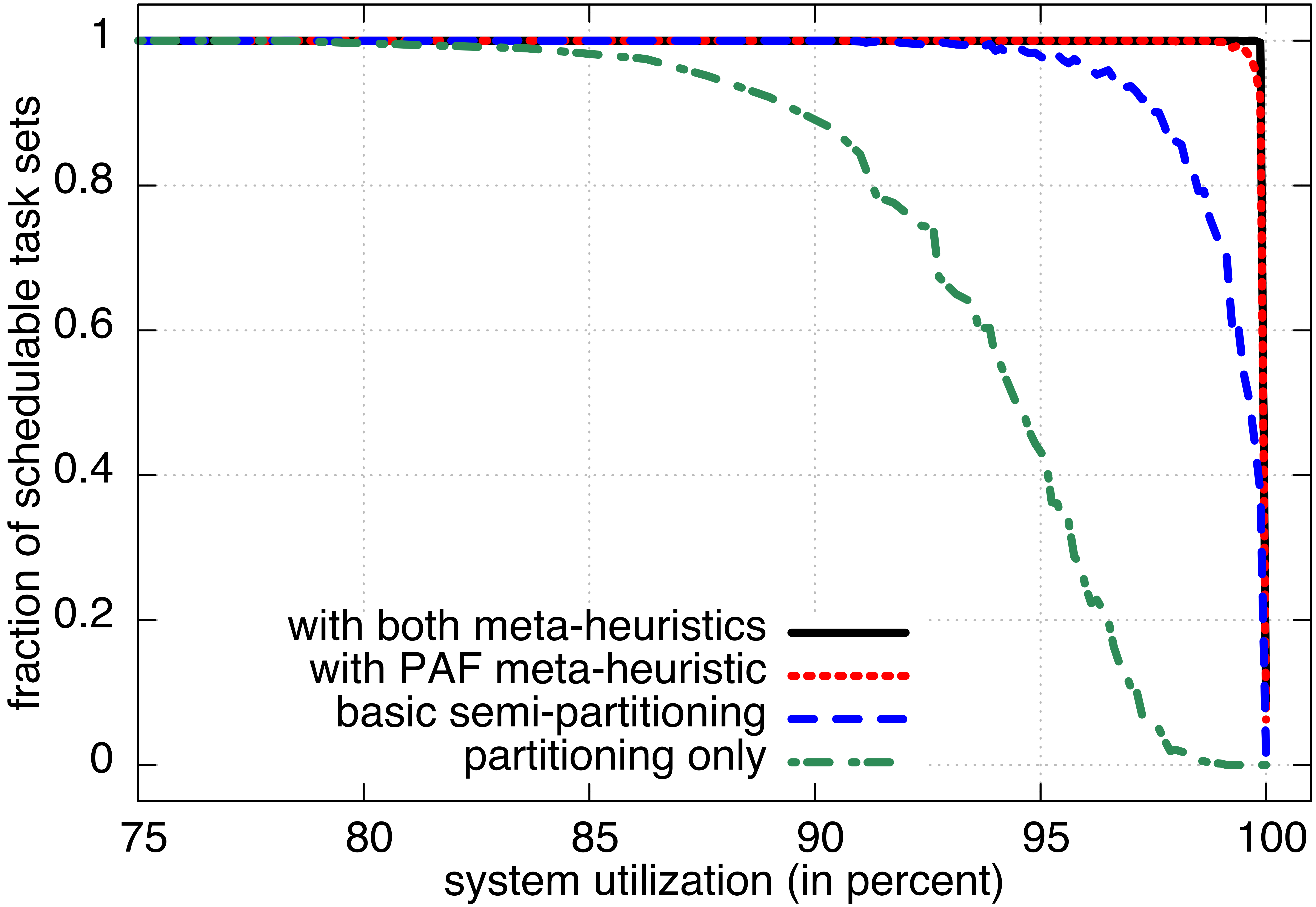
→ *while there is an uptick in context switches, it is usually lower than under the most competitive optimal schedulers*



Schedulability Experiments — Summary



Empirically, **near-optimal hard real-time schedulability**
— usually ≥**99% schedulable utilization** —
can be achieved with **simple**, **well-known and well-understood**,
low-overhead techniques (+ a few tweaks).



Does it work in practice?

— Implementation in LITMUS^{RT} —

LITMUS^{RT}

Linux Testbed for Multiprocessor Scheduling in Real-Time Systems

www.litmus-rt.org

LITMUS^{RT}

Linux Testbed for Multiprocessor Scheduling in Real-Time Systems

Linux-based **Multiprocessor** Research RTOS.

THE UNIVERSITY *of* NORTH CAROLINA *at* CHAPEL HILL

[2006–2011]

Actively maintained since 2006
17 public releases,
spanning **40** Linux kernel versions
Latest release: **2016.1**

Max Planck Institute for Software Systems

[2011–]

www.litmus-rt.org

Experiments with the Real System

Experiments with the Real System

Experiment 1: Comparison with stock LITMUS^{RT} schedulers

➡ **Partitioned** Fixed-Priority (**P-FP**)

➡ **Partitioned** Earliest-Deadline First (**P-EDF**)

➡ **Global** Earliest-Deadline First (**G-EDF**)

Experiments with the Real System

Experiment 1: Comparison with stock LITMUS^{RT} schedulers

- **Partitioned** Fixed-Priority (**P-FP**)
- **Partitioned** Earliest-Deadline First (**P-EDF**)
- **Global** Earliest-Deadline First (**G-EDF**)

Experiment 2: Comparison with RUN and QPS

- latest and greatest **optimal** multiprocessor schedulers
- implementations kindly provided by Compagnin et al. (2014, 2015)

Experiments with the Real System

Experiment 1: Comparison with stock LITMUS^{RT} schedulers

- **Partitioned** Fixed-Priority (**P-FP**)
- **Partitioned** Earliest-Deadline First (**P-EDF**)
- **Global** Earliest-Deadline First (**G-EDF**)

Experiment 2: Comparison with RUN and QPS

- latest and greatest **optimal** multiprocessor schedulers
- implementations kindly provided by Compagnin et al. (2014, 2015)

Experiment 3: Effect of Slack on Frequency of Migrations

- How effective is “**flipped C=D** + slack reclamation”?

Experiments with the Real System

Experiment 1: Comparison with stock LITMUS^{RT} schedulers

- ➡ **Partitioned** Fixed-Priority (**P-FP**)
- ➡ **Partitioned** Earliest-Deadline First (**P-EDF**)
- ➡ **Global** Earliest-Deadline First (**G-EDF**)

Experiment 2: Comparison with RUN and QPS

- ➡ latest and greatest **optimal** multiprocessor schedulers
- ➡ implementations kindly provided by Compagnin et al. (2014, 2015)

Experiment 3: Effect of Slack on Frequency of Migrations

- ➡ How effective is "**flipped C=D** + slack reclamation"?

Platform: Stress Scalability

- ➡ 44 cores: 2 × 22-core Xeon E5-2699 v4 @ 2.2 GHz
- ➡ 256 KiB private L2, 55 MiB shared L3

LITMUS^{RT}

Linux Testbed for Multiprocessor Scheduling in Real-Time Systems

Experiments with the Real System

Experiment 1: Comparison with stock LITMUS^{RT} schedulers

- **Partitioned** Fixed-Priority (**P-FP**)
- **Partitioned** Earliest-Deadline First (**P-EDF**)
- **Global** Earliest-Deadline First (**G-EDF**)

Experiment 2: Comparison with RUN and QPS

- latest and greatest **optimal** multiprocessor schedulers
- implementations kindly provided by Compagnin et al. (2014, 2015)

Experiment 3: Effect of Slack on Frequency of Migrations

- How effective is "**flipped C=D** + slack reclamation"?

Platform: Stress Scalability

- 44 cores: 2 × 22-core Xeon E5-2699 v4 @ 2.2 GHz
- 256 KiB private L2, 55 MiB shared L3

LITMUS^{RT}
Linux Testbed for Multiprocessor Scheduling in Real-Time Systems

Data

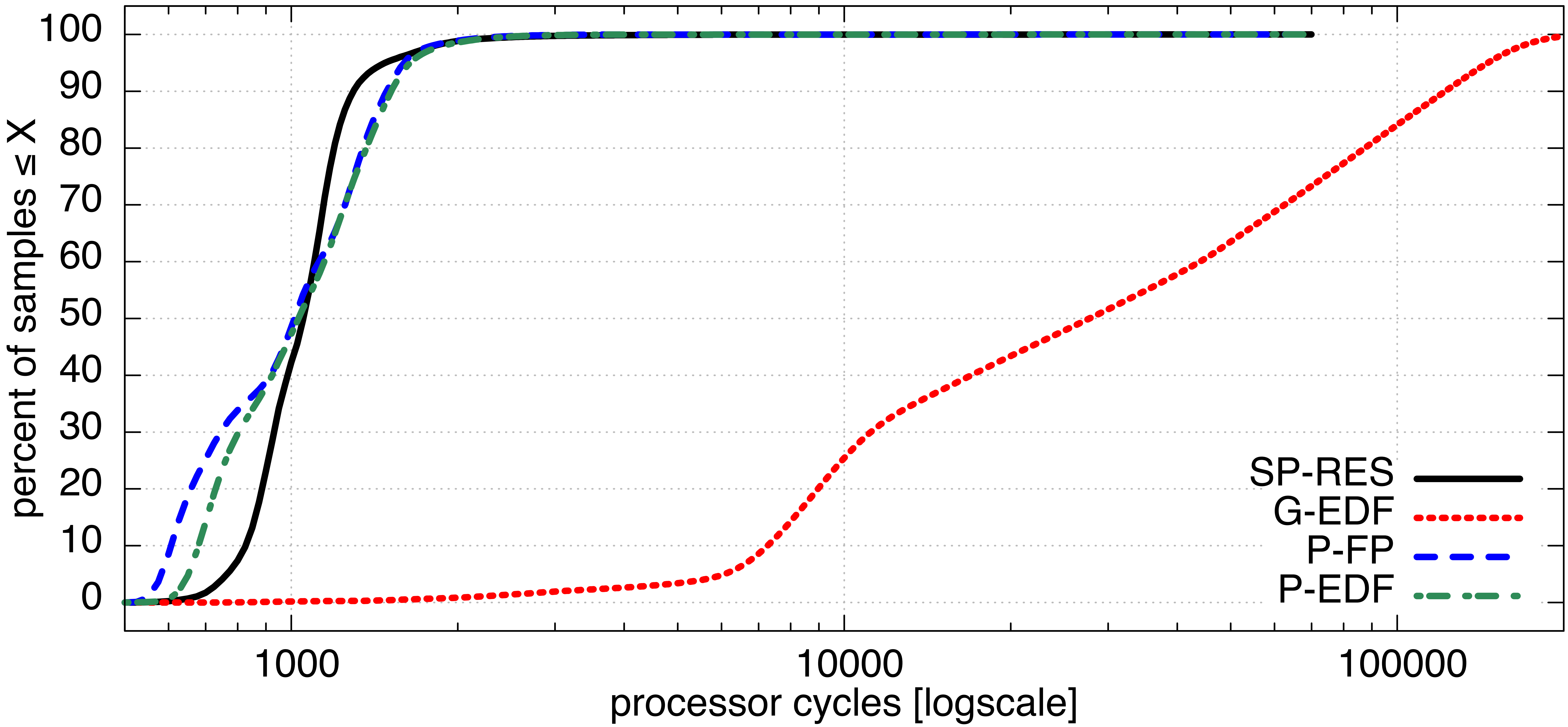
- traced overhead with *Feather-Trace*, schedule with *sched-trace*
- over six billion samples collected over 12+ hours of execution
- here: **scheduling overhead** — *picking the next process to run*

Experiment 1: Comparison with Stock Schedulers

***scheduling** overhead measured on a 44-core Intel Xeon platform*

Experiment 1: Comparison with Stock Schedulers

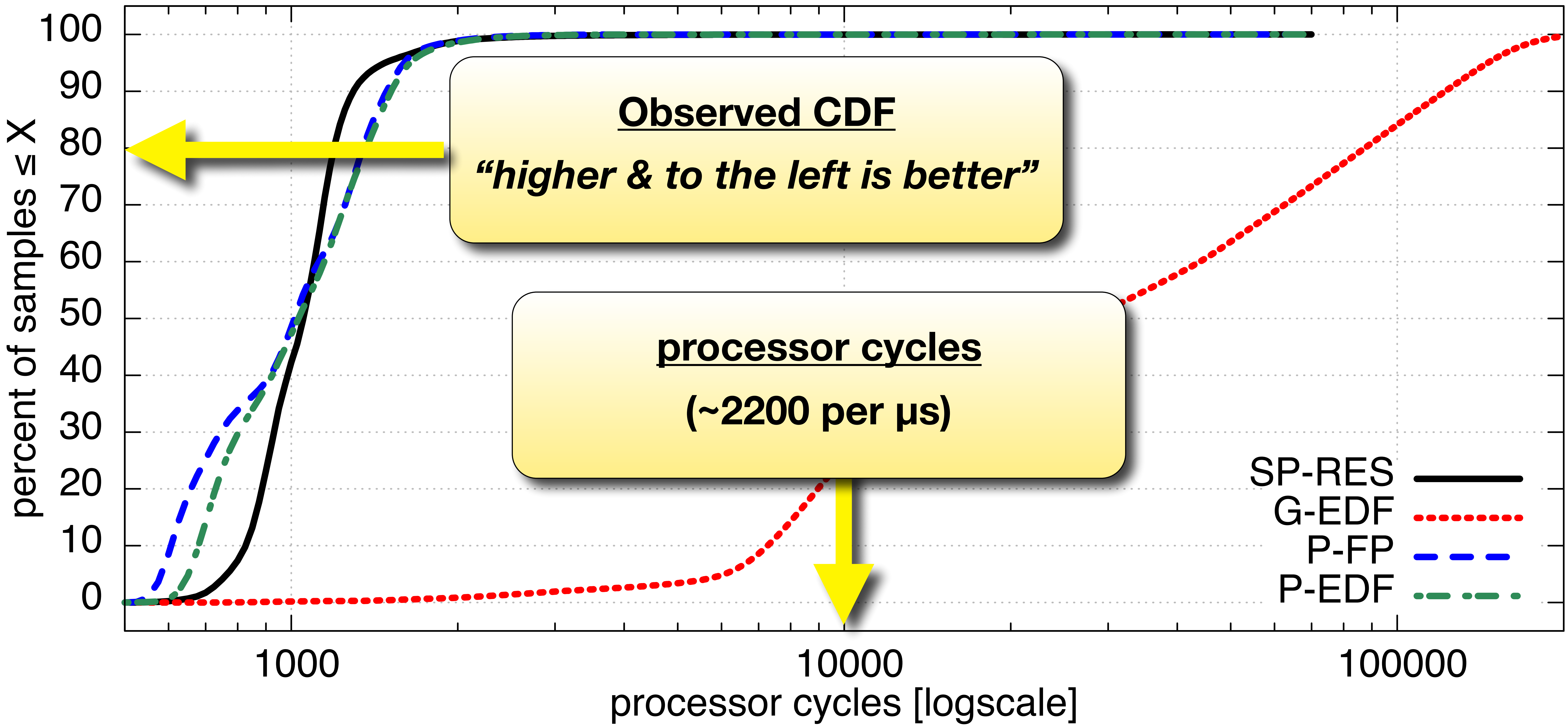
scheduling *overhead measured on a 44-core Intel Xeon platform*



➔ semi-partitioned (SP-RES) largely similar to partitioned schedulers (P-FP, P-EDF), not similar to (non-optimal) global EDF (G-EDF)

Experiment 1: Comparison with Stock Schedulers

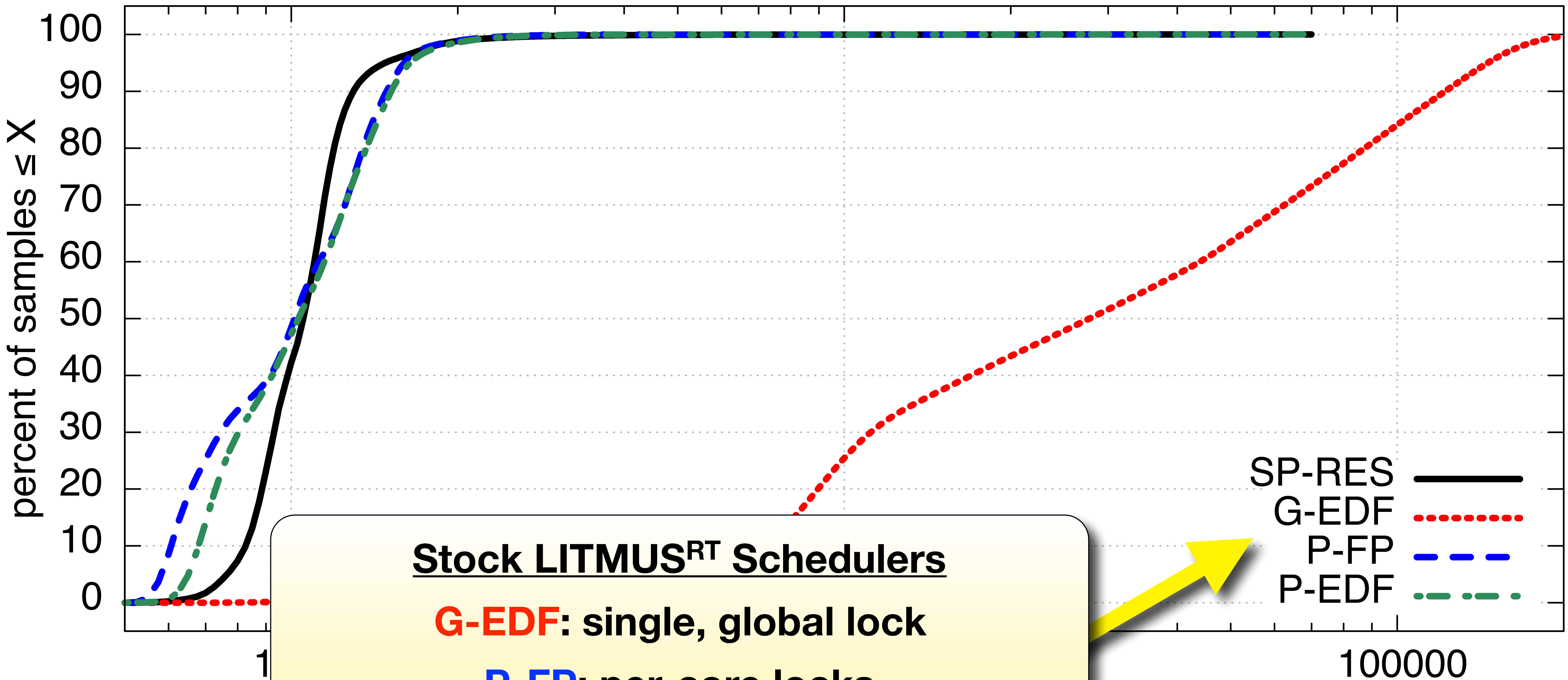
scheduling *overhead measured on a 44-core Intel Xeon platform*



➔ semi-partitioned (SP-RES) largely similar to partitioned schedulers (P-FP, P-EDF), not similar to (non-optimal) global EDF (G-EDF)

Experiment 1: Comparison with Stock Schedulers

***scheduling** overhead measured on a 44-core Intel Xeon platform*



Stock LITMUS^{RT} Schedulers

G-EDF: single, global lock

P-FP: per-core locks

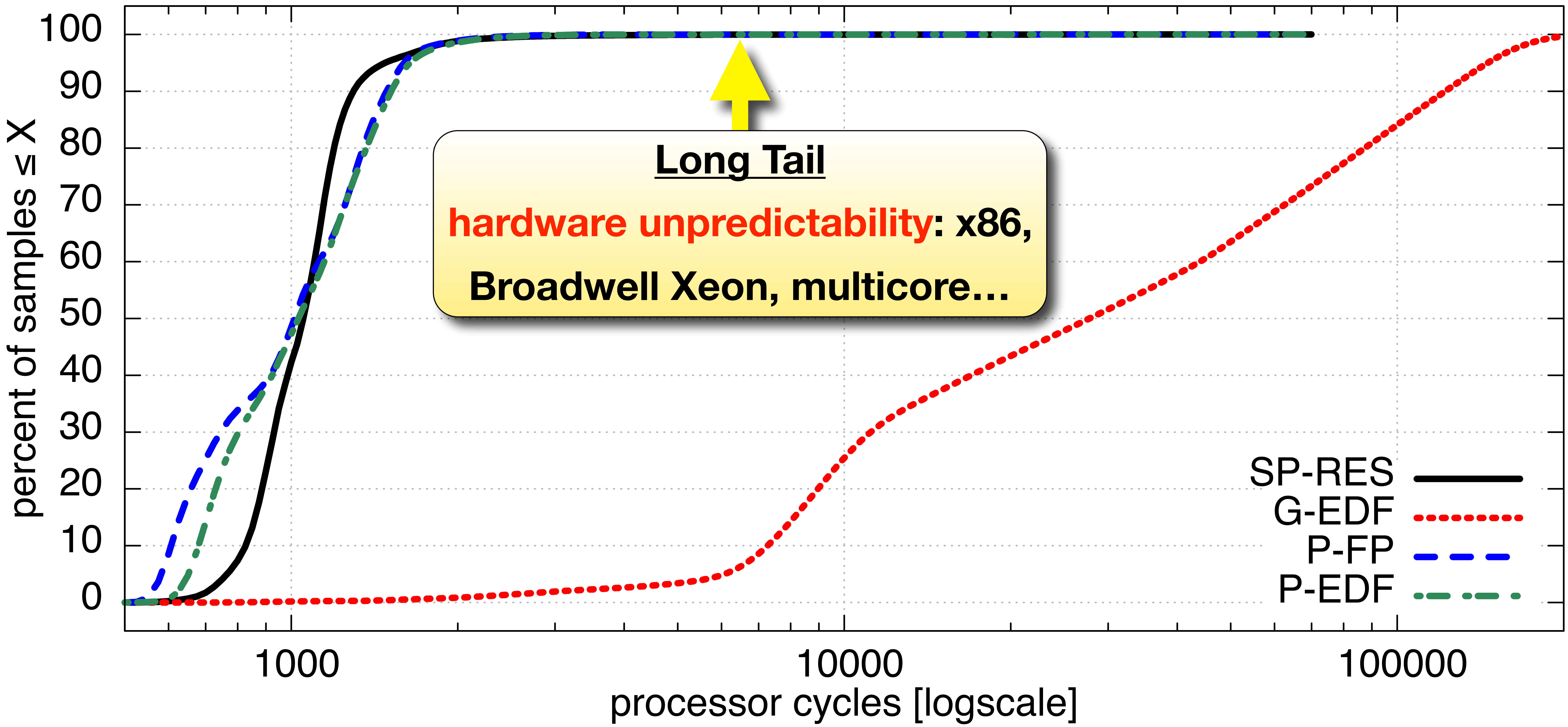
P-EDF: per-core locks

SP-RES: per-core locks

➔ semi-part … partitioned schedulers (P-FP, P- … obal EDF (G-EDF)

Experiment 1: Comparison with Stock Schedulers

***scheduling** overhead measured on a 44-core Intel Xeon platform*



➔ semi-partitioned (SP-RES) largely similar to partitioned schedulers (P-FP, P-EDF), not similar to (non-optimal) global EDF (G-EDF)

99th percentile overhead

SP-RES: 2,092 cycles (~1µs)

P-EDF: 2,150 cycles (~1µs)

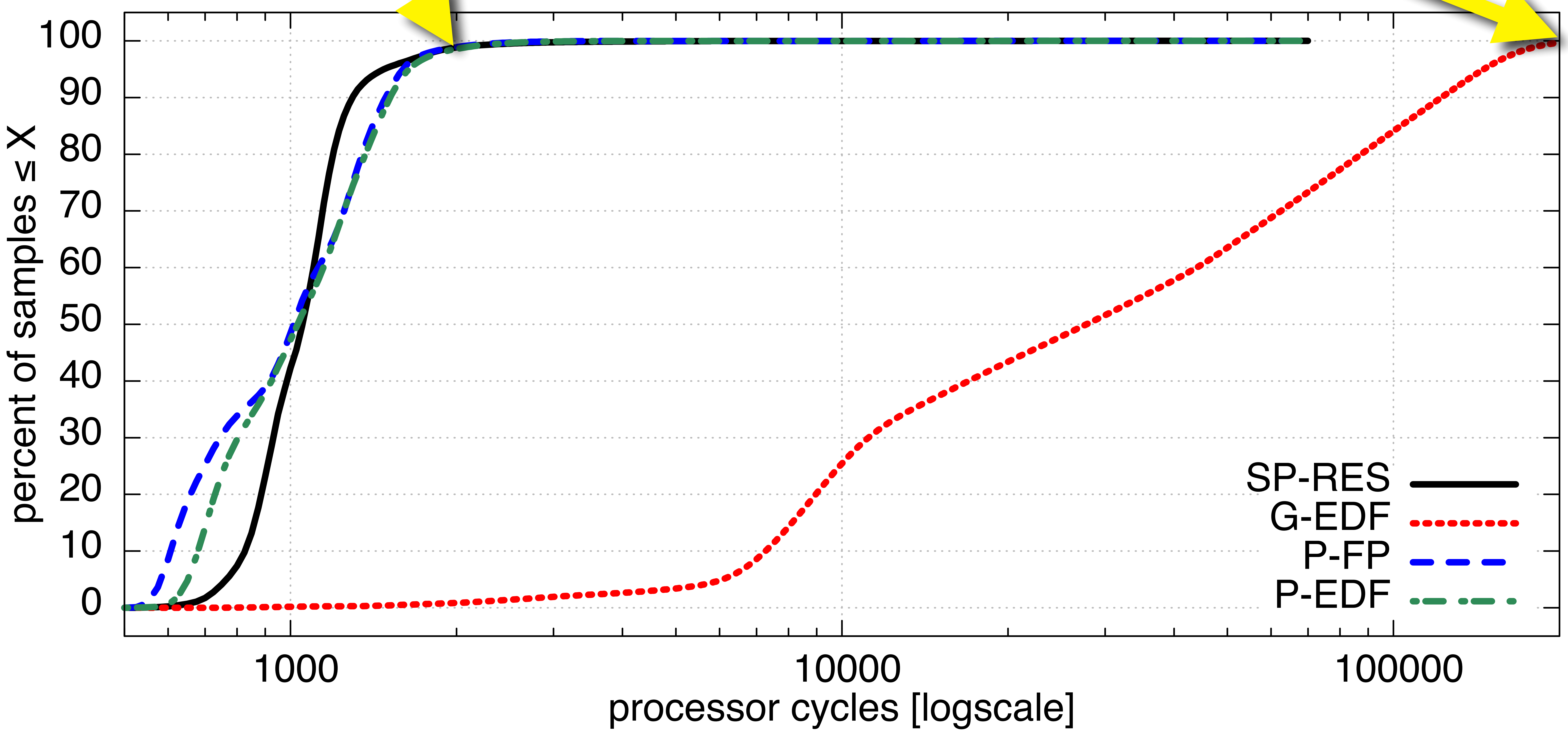
P-FP: 2,059 cycles (~1µs)

mparison ... rs

easured o... rm

99th percentile overhead

G-EDF: 181,934 cycles (~82µs)



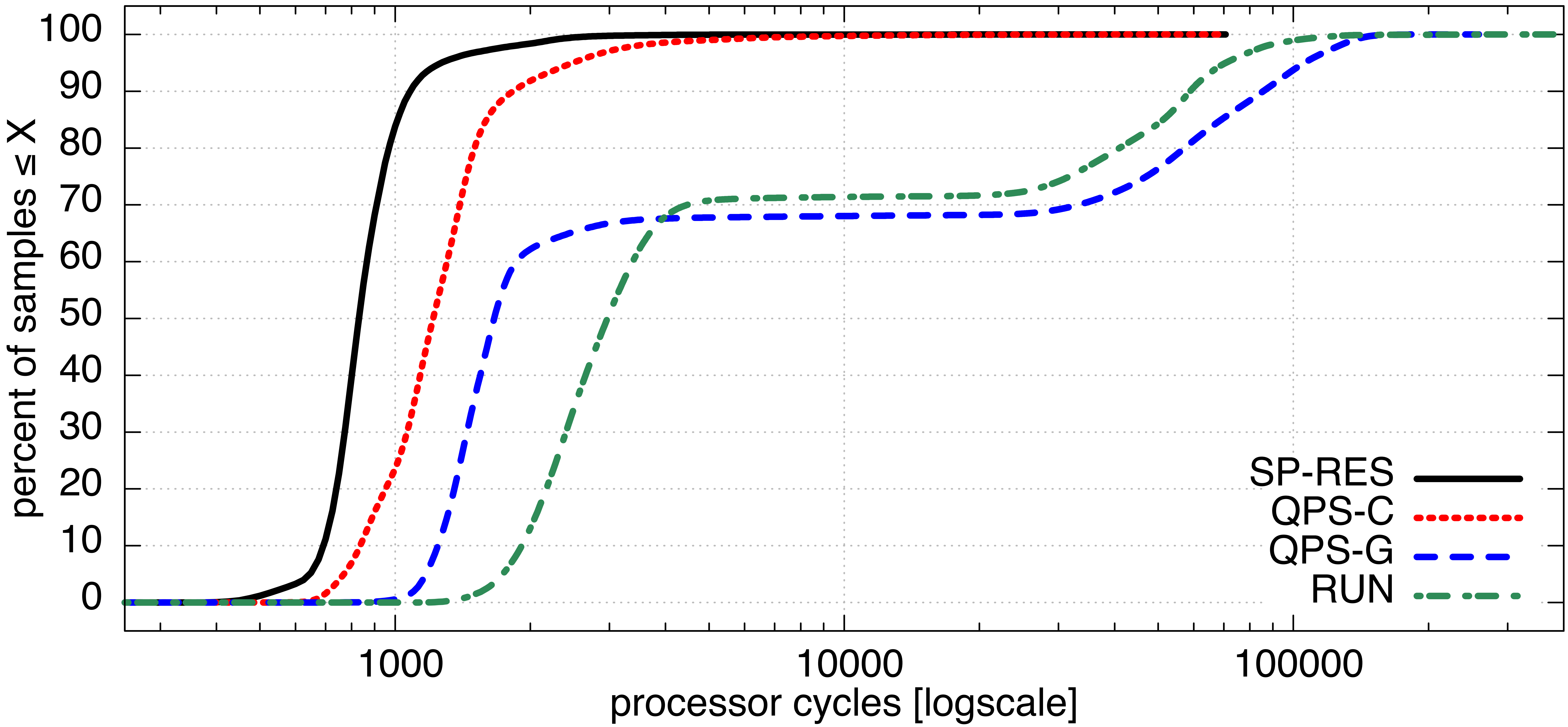
➔ semi-partitioned (SP-RES) largely similar to partitioned schedulers (P-FP, P-EDF), not similar to (non-optimal) global EDF (G-EDF)

Experiment 2: Comparison with RUN and QPS

scheduling *overhead measured on a 44-core Intel Xeon platform*

Experiment 2: Comparison with RUN and QPS

scheduling *overhead measured on a 44-core Intel Xeon platform*

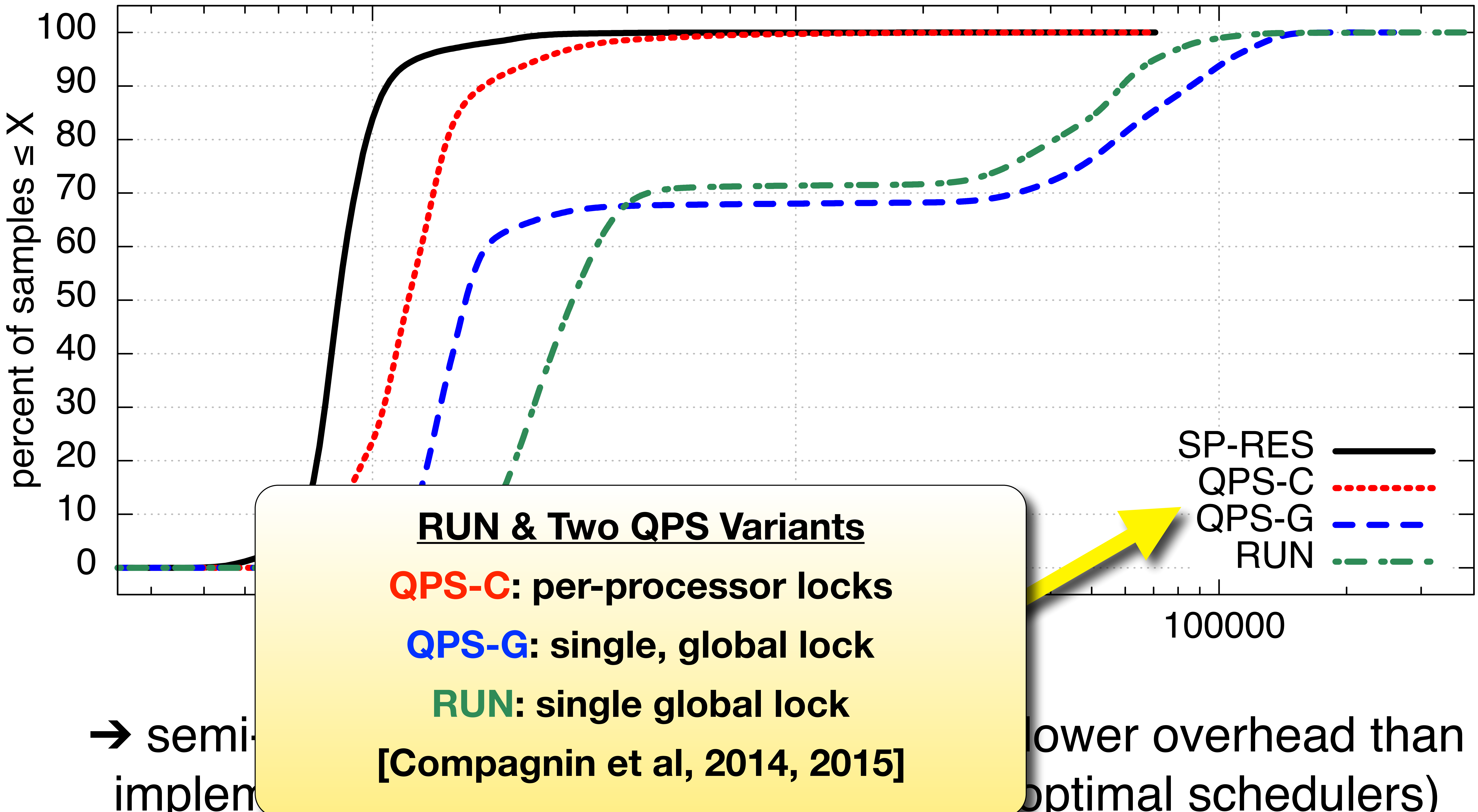


➔ semi-partitioned (SP-RES) shows much lower overhead than implementations of RUN and QPS (latest optimal schedulers)

(RUN and QPS implementations kindly provided by Compagnin et al.)

Experiment 2: Comparison with RUN and QPS

***scheduling** overhead measured on a 44-core Intel Xeon platform*



➔ semi- … lower overhead than implem… optimal schedulers)

(RUN and QPS implementations kindly provided by Compagnin et al.)

99th percentile overhead

SP-RES: 2,255 cycles (~1µs)

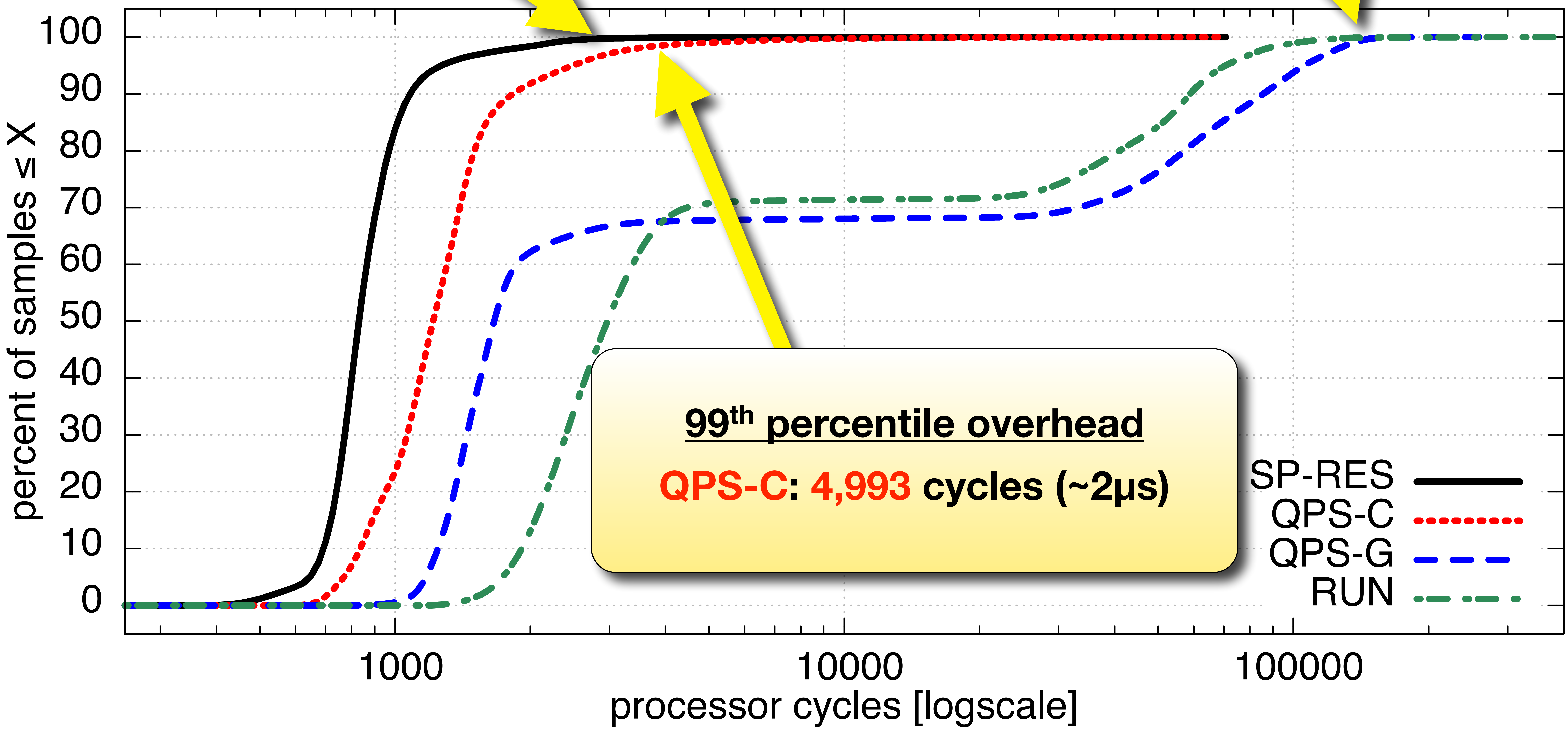
mparis

easured o

99th percentile overhead

RUN: 101,294 cycles (~46µs)

QPS-G: 135,994 cycles (~61µs)



99th percentile overhead

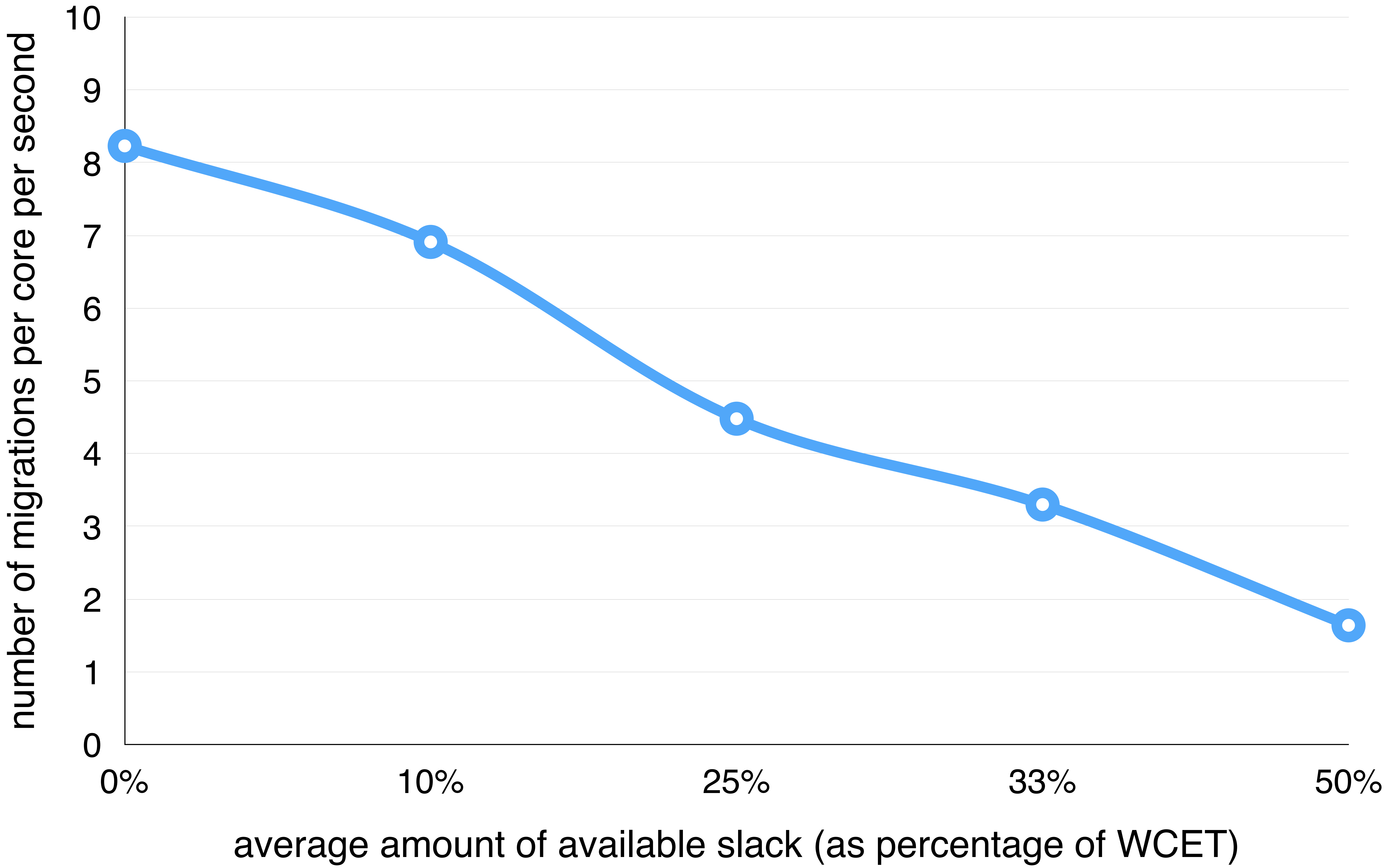
QPS-C: 4,993 cycles (~2µs)

➔ semi-partitioned (SP-RES) shows much lower overhead than implementations of RUN and QPS (latest optimal schedulers)

(RUN and QPS implementations kindly provided by Compagnin et al.)

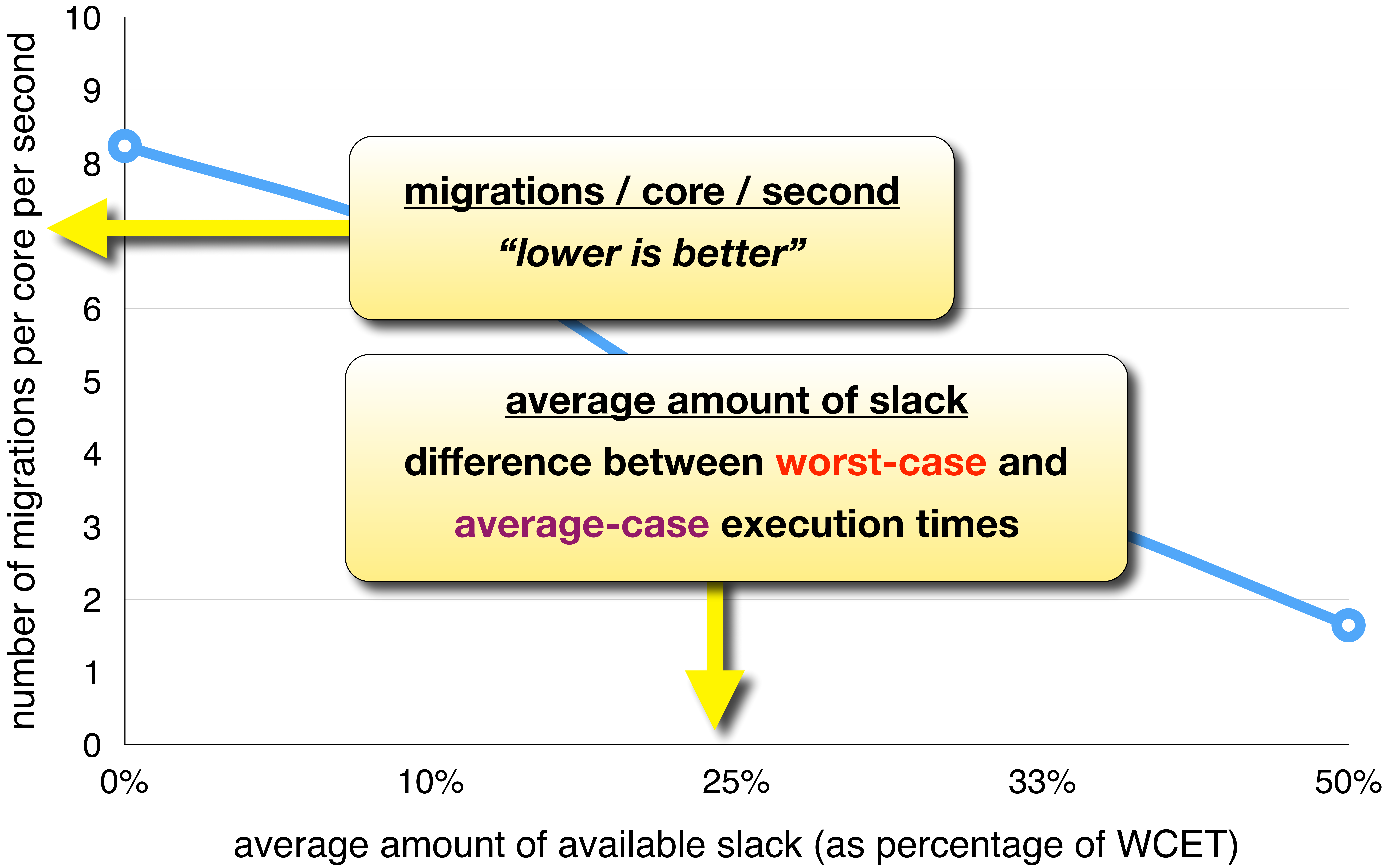
Experiment 3: Impact of Slack Reclamation

Experiment 3: Impact of Slack Reclamation



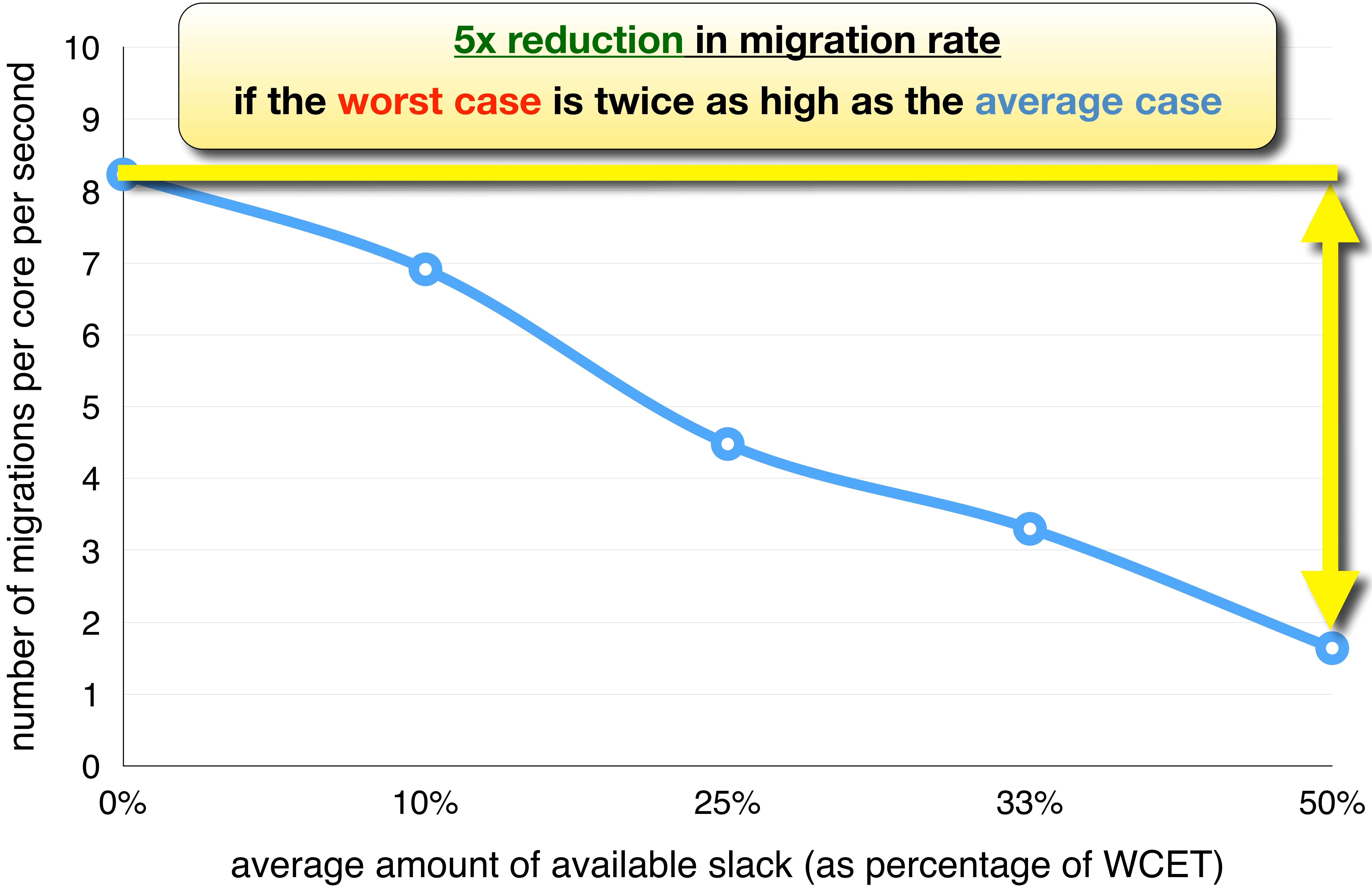
➔ slack reclamation is effective: more slack = fewer migrations

Experiment 3: Impact of Slack Reclamation



➔ slack reclamation is effective: more slack = fewer migrations

Experiment 3: Impact of Slack Reclamation



➔ slack reclamation is effective: more slack = fewer migrations

Discussion & Conclusion

Study Limitations

Study Limitations

Software Malleability

- This schedulability study is **biased against** partitioned / semi-partitioned scheduling (as are many before it).
- *If no mapping is found, engineers may be able to* ***refactor*** *"large" tasks and* ***redistribute*** *or* ***pipeline*** *some functionality.*
- Example: remapping *runnables* in AUTOSAR.

Study Limitations

Software Malleability

- This schedulability study is **biased against** partitioned / semi-partitioned scheduling (as are many before it).
- *If no mapping is found, engineers may be able to **refactor** "large" tasks and **redistribute** or **pipeline** some functionality.*
- Example: remapping *runnables* in AUTOSAR.

Task Set Generation

- Randomly generated task sets, based on standard methods.
- Is there a ***practically relevant*** class of independent, implicit-deadline workloads for which all semi-partitioning heuristics consistently fail?

(*I don't think so.*)

Practical Extensions

Practical Extensions

What about **constrained/arbitrary** deadlines?

Practical Extensions

What about **constrained/arbitrary** deadlines?

*…everything but the RP meta-heuristic **still works**.*

…no optimal online schedulers exist (Fisher et al., 2010).

Practical Extensions

What about **constrained/arbitrary** deadlines?

*…everything but the RP meta-heuristic **still works**.*

…no optimal online schedulers exist (Fisher et al., 2010).

What about **precedence** constraints?

Practical Extensions

What about **constrained/arbitrary** deadlines?

*…everything but the RP meta-heuristic **still works**.*

…no optimal online schedulers exist (Fisher et al., 2010).

What about **precedence** constraints?

*…can **reuse uniprocessor techniques** (jitter).*

…can introduce additional heuristics.

Practical Extensions

What about **constrained/arbitrary** deadlines?

*…everything but the RP meta-heuristic **still works**.*

…no optimal online schedulers exist (Fisher et al., 2010).

What about **precedence** constraints?

*…can **reuse uniprocessor techniques** (jitter).*

…can introduce additional heuristics.

What about **self-suspensions**?

Practical Extensions

What about **constrained/arbitrary** deadlines?

*…everything but the RP meta-heuristic **still works**.*

…no optimal online schedulers exist (Fisher et al., 2010).

What about **precedence** constraints?

*…can **reuse uniprocessor techniques** (jitter).*

…can introduce additional heuristics.

What about **self-suspensions**?

*…already supported (**slack**).*

…implementation already supports deferrable servers.

*…**semi-partitioned deferrable servers**?*

Practical Extensions

What about **constrained/arbitrary** deadlines?

*…everything but the RP meta-heuristic **still works**.*
…no optimal online schedulers exist (Fisher et al., 2010).

What about **precedence** constraints?

*…can **reuse uniprocessor techniques** (jitter).*
…can introduce additional heuristics.

What about **self-suspensions**?

*…already supported (**slack**).*
…implementation already supports deferrable servers.
*…**semi-partitioned deferrable servers**?*

What about **locking**?

Practical Extensions

What about **constrained/arbitrary** deadlines?

*…everything but the RP meta-heuristic **still works**.*

…no optimal online schedulers exist (Fisher et al., 2010).

What about **precedence** constraints?

*…can **reuse uniprocessor techniques** (jitter).*

…can introduce additional heuristics.

What about **self-suspensions**?

*…already supported (**slack**).*

…implementation already supports deferrable servers.

*…**semi-partitioned deferrable servers**?*

What about **locking**?

…multiprocessor bandwidth inheritance (MBWI).

…spin locks (Biondi et al., 2015).

…future work (MC-IPC, MrsP, ???).

Further Overheads and Challenges

Further Overheads and Challenges

What about **migration** overheads?

Further Overheads and Challenges

What about **migration** overheads?

…lower than under global scheduling.

*…can **control** precisely **which tasks** migrate (➔ PAF).*

Further Overheads and Challenges

What about **migration** overheads?

…lower than under global scheduling.

*…can **control** precisely **which tasks** migrate (➔ PAF).*

What about **cache/bus/memory interference**?

Further Overheads and Challenges

What about **migration** overheads?

…lower than under global scheduling.

*…can **control** precisely **which tasks** migrate (➔ PAF).*

What about **cache/bus/memory interference**?

…orthogonal concern (known techniques apply).

*…**no worse** than under global scheduling.*

Further Overheads and Challenges

What about **migration** overheads?

…lower than under global scheduling.

*…can **control** precisely **which tasks** migrate (➔ PAF).*

What about **cache/bus/memory interference**?

…orthogonal concern (known techniques apply).

*…**no worse** than under global scheduling.*

What about **energy/power/thermal** constraints?

Further Overheads and Challenges

What about **migration** overheads?

…lower than under global scheduling.

*…can **control** precisely **which tasks** migrate (➔ PAF).*

What about **cache/bus/memory interference**?

…orthogonal concern (known techniques apply).

*…**no worse** than under global scheduling.*

What about **energy/power/thermal** constraints?

…much prior work available (uni + partitioned).

*…but **race-to-idle** might favor global scheduling.*

Further Overheads and Challenges

What about **migration** overheads?

…lower than under global scheduling.

*…can **control** precisely **which tasks** migrate (➔ PAF).*

What about **cache/bus/memory interference**?

…orthogonal concern (known techniques apply).

*…**no worse** than under global scheduling.*

What about **energy/power/thermal** constraints?

…much prior work available (uni + partitioned).

*…but **race-to-idle** might favor global scheduling.*

What about **adaptive, dynamic,** or **open systems**?

Further Overheads and Challenges

What about **migration** overheads?

…lower than under global scheduling.

*…can **control** precisely **which tasks** migrate (➔ PAF).*

What about **cache/bus/memory interference**?

…orthogonal concern (known techniques apply).

*…**no worse** than under global scheduling.*

What about **energy/power/thermal** constraints?

…much prior work available (uni + partitioned).

*…but **race-to-idle** might favor global scheduling.*

What about **adaptive, dynamic,** or **open systems**?

*…**this is were global scheduling really shines**.*

…future work on on-the-fly repartitioning and load-balancing.

Summary

Summary

Simple Approach

➡ semi-partitioned scheduling + reservations + try many heuristics

➡ effective: pre-assign failures (PAF), period transformation (RP)

Summary

Simple Approach

- ➡ semi-partitioned scheduling + reservations + try many heuristics
- ➡ effective: pre-assign failures (PAF), period transformation (RP)

Theoretical performance: Schedulability

- ➡ near optimal: empirically, ~99% schedulable utilization
- ➡ under same conditions as assumed in proofs of optimality

Summary

Simple Approach

- ➡ semi-partitioned scheduling + reservations + try many heuristics
- ➡ effective: pre-assign failures (PAF), period transformation (RP)

Theoretical performance: Schedulability

- ➡ near optimal: empirically, ~99% schedulable utilization
- ➡ under same conditions as assumed in proofs of optimality

Practical performance: Overheads

- ➡ similar to a plain partitioned scheduler (→ quite low)
- ➡ migration frequency can be reduced with slack reclamation

Summary

Simple Approach

- semi-partitioned scheduling + reservations + try many heuristics
- effective: pre-assign failures (PAF), period transformation (RP)

Theoretical performance: Schedulability

- near optimal: empirically, ~99% schedulable utilization
- under same conditions as assumed in proofs of optimality

Practical performance: Overheads

- similar to a plain partitioned scheduler (→ quite low)
- migration frequency can be reduced with slack reclamation

Subjective Complexity

- *Much* simpler to understand and explain than optimal schedulers
- *Much* simpler to build and maintain than optimal schedulers
- **Future work**: hopefully much simpler to extend, too.

Companion Web Page

https://mpi-sws.org/~bbb/papers/details/rtss16

Code

- ➡ illustrative pseudo code (not in paper)
- ➡ LITMUS^{RT} scheduler plugin + libraries
- ➡ schedulability experiments (SchedCAT)

Artifact Evaluation Instructions

- ➡ how to run our experiments (quite detailed)
- ➡ also a good LITMUS^{RT} tutorial / recipe

All Data & Graphs

- ➡ including comparisons of all individual heuristics (not in paper)
- ➡ including all "UNC style experiments " (not in paper)
- ➡ including all overhead CDFs and plots

Thanks! Questions?

Companion page

https://mpi-sws.org/~bbb/papers/details/rtss16

LITMUS^RT

Linux Testbed for Multiprocessor Scheduling in Real-Time Systems

http://www.litmus-rt.org

Max
Planck
Institute
for
Software Systems

Björn B. Brandenburg
bbb@mpi-sws.org
http://www.mpi-sws.org/~bbb

EMBEDDED SYSTEMS WEEK

EMSOFT 2017

Call for Papers

International Conference on Embedded Software

October 15-20, 2017 Seoul, South Korea

The ACM SIGBED International Conference on Embedded Software (EMSOFT) brings together researchers and developers from academia, industry, and government to advance the science, engineering, and technology of embedded software development. Since 2001, EMSOFT has been the premier venue for cutting-edge research in the design and analysis of software that interacts with physical processes, with a long-standing tradition for results on cyber-physical systems, which compose computation, networking, and physical dynamics.

Abstract Submission:
March 31, 2017

Full Paper Submission:
April 7, 2017 (firm deadline)

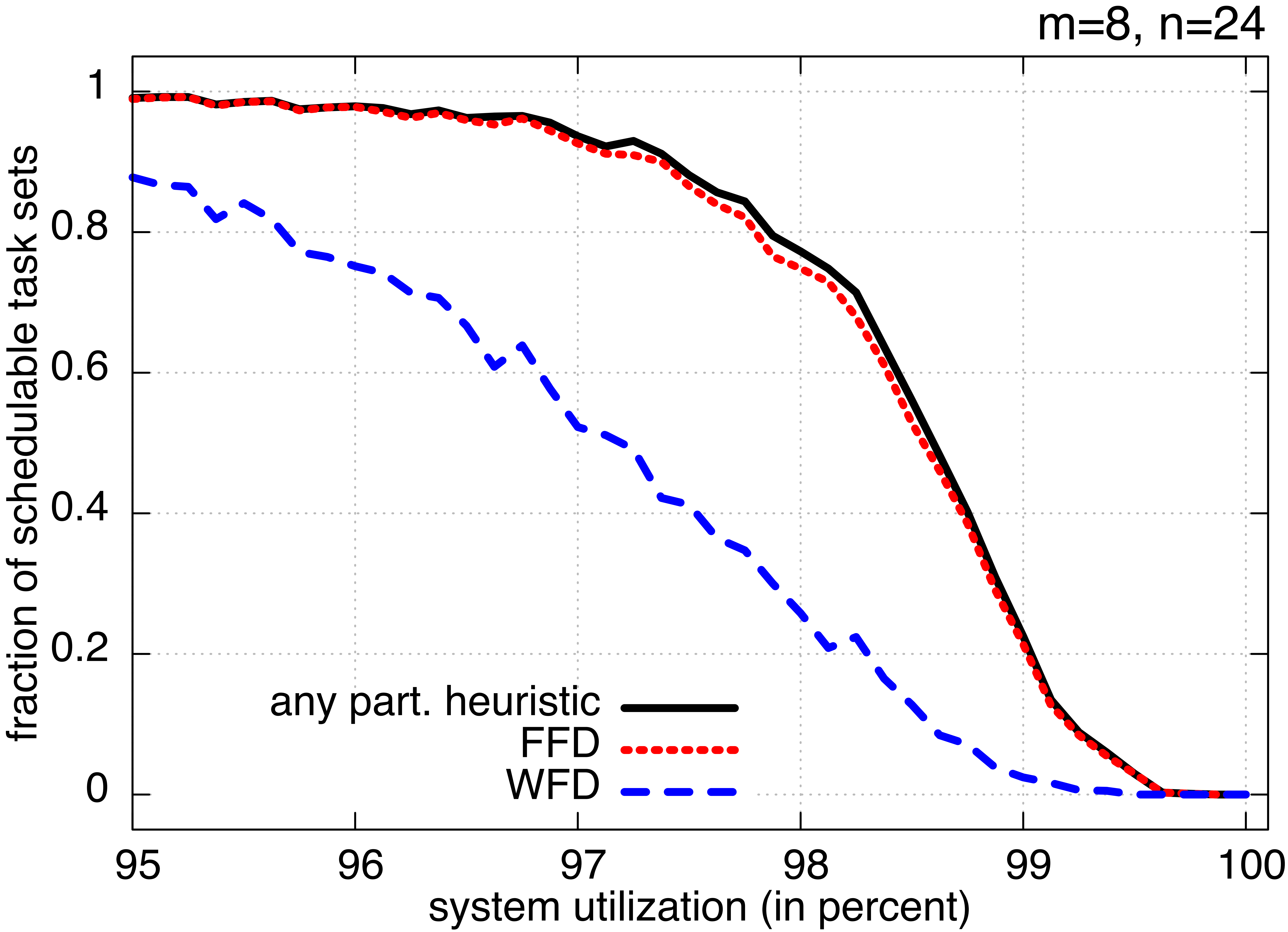
Conference:
October 15-20, 2017

Venue:
Lotte Hotel, Seoul, South Korea

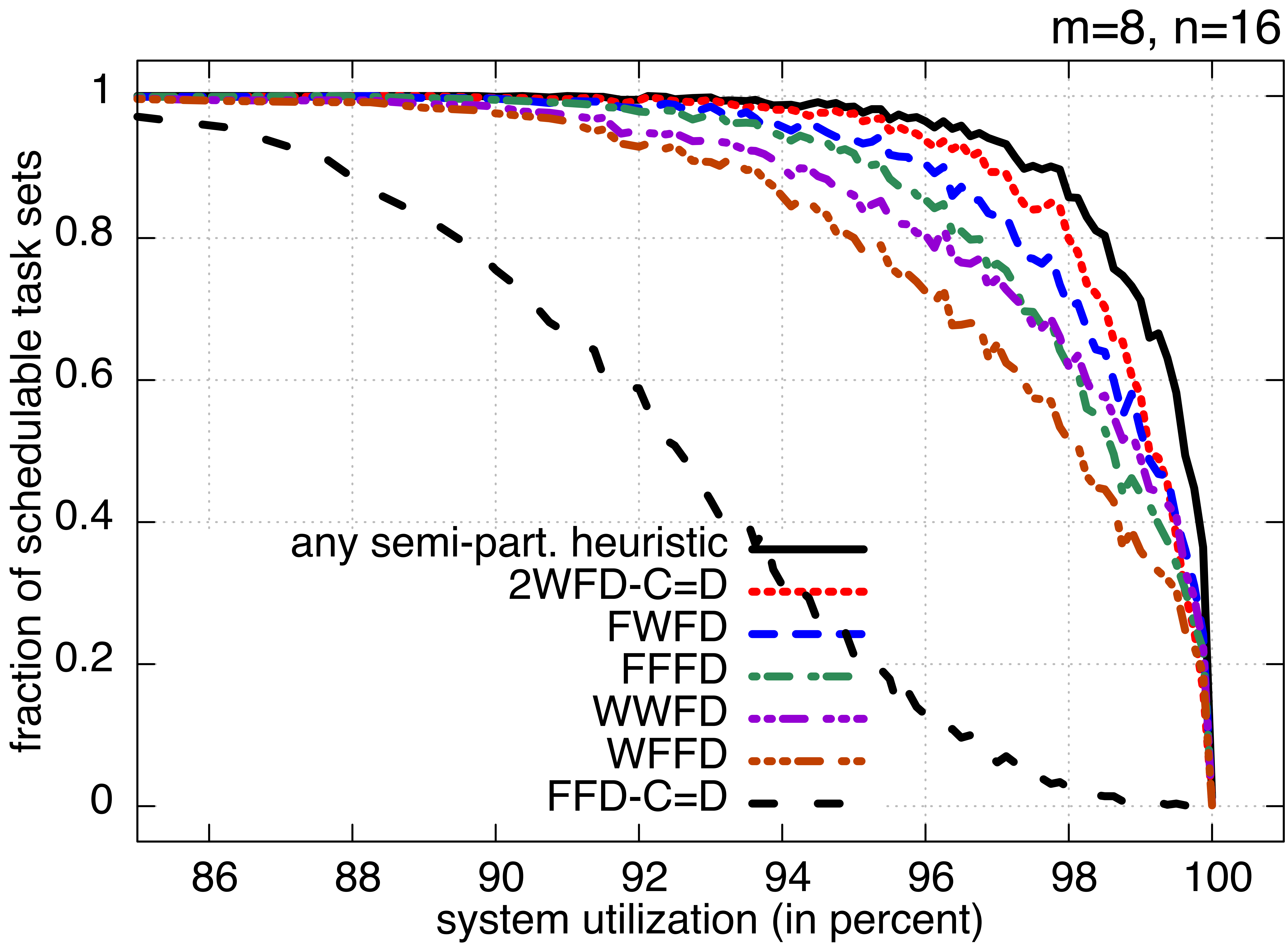
real-time systems — **embedded software** — CPS — IoT
control — testing and validation — verification
operating and runtime systems — compilers & analysis tools
security — reliability — dependability — energy — …

Appendix

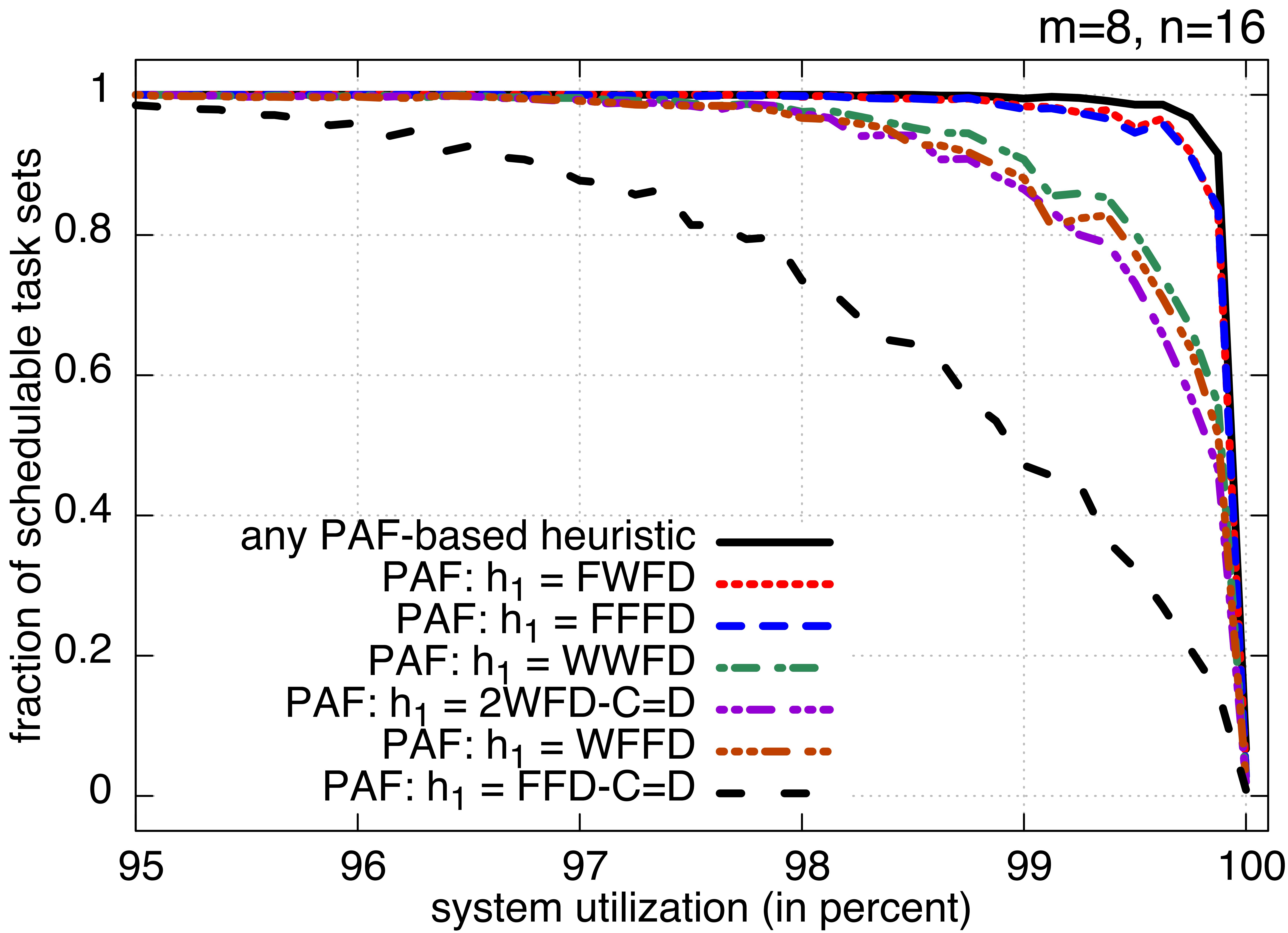
Individual Heuristics – Partitioning Only



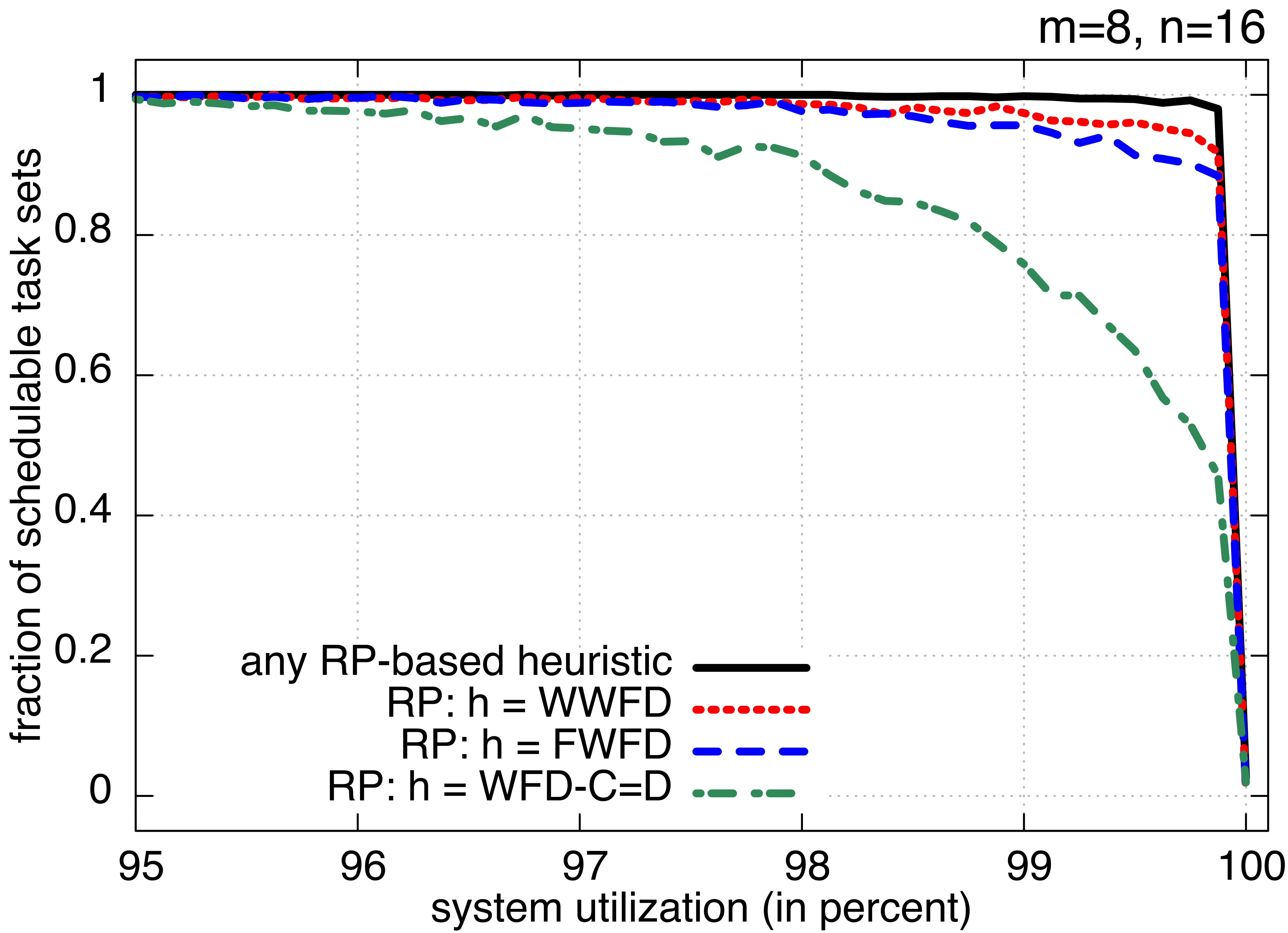
Individual Heuristics — Basic Semi-Partitioning



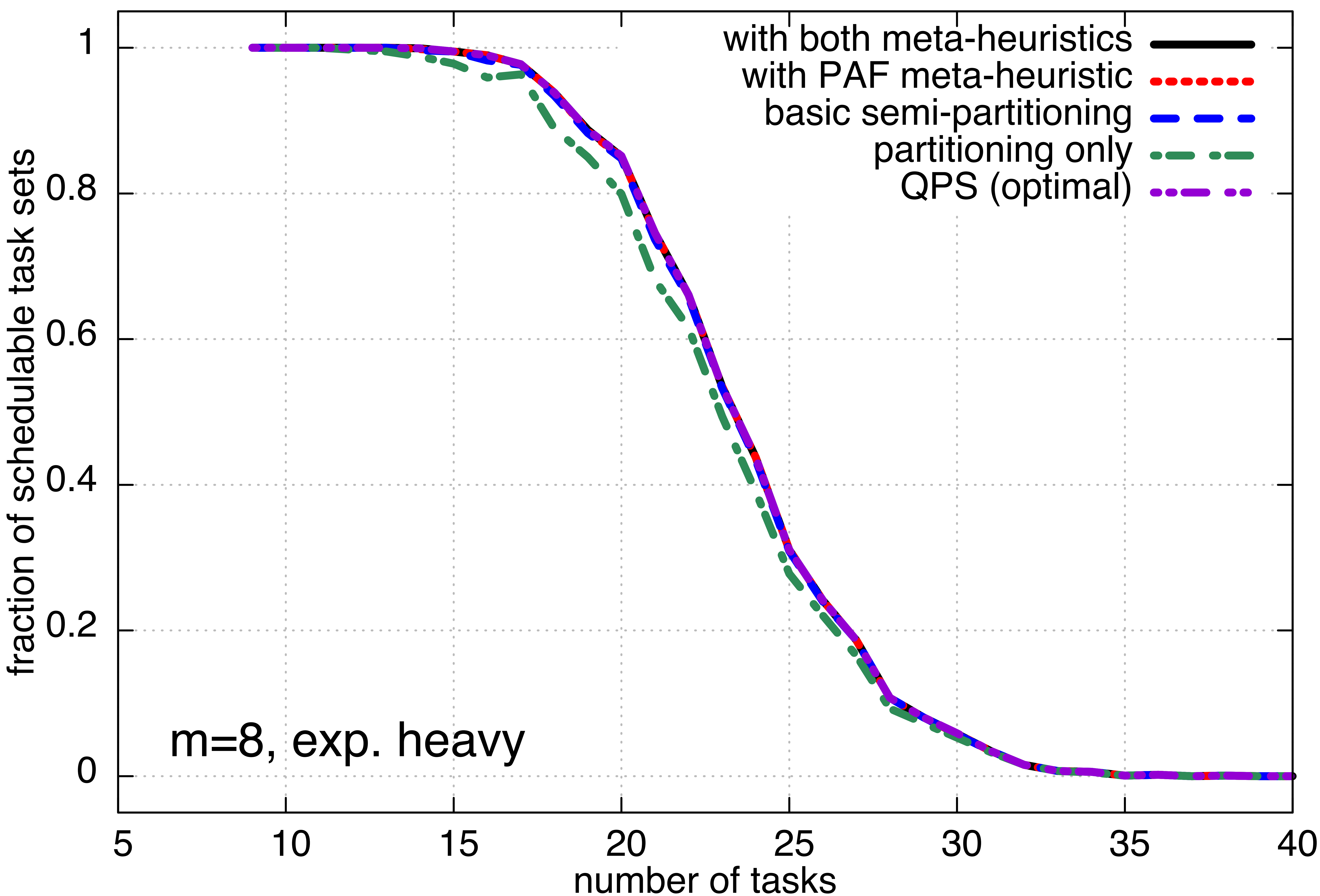
Individual Heuristics — Semi-Partitioning + PAF



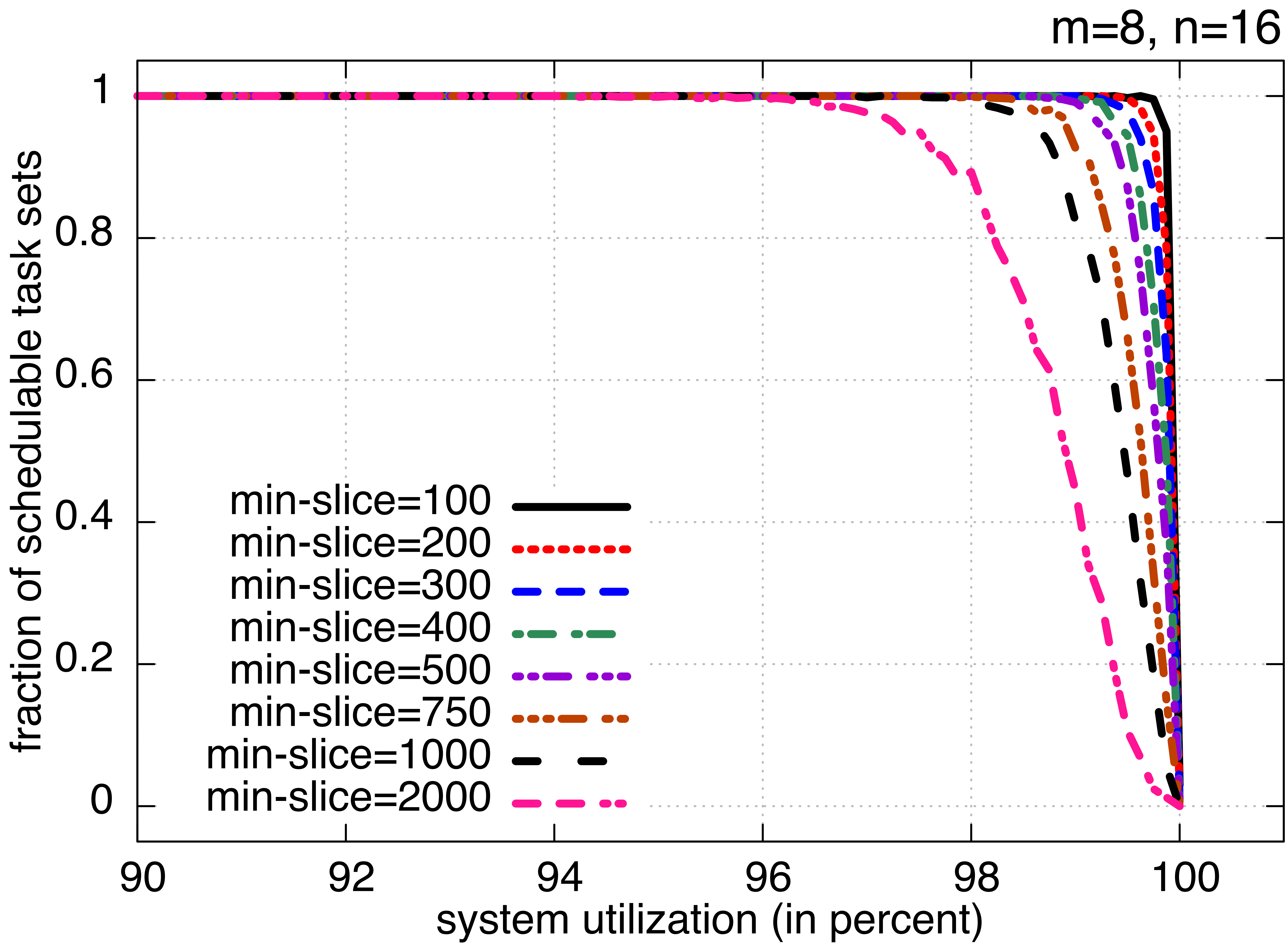
Individual Heuristics – Semi-Partitioning + RP



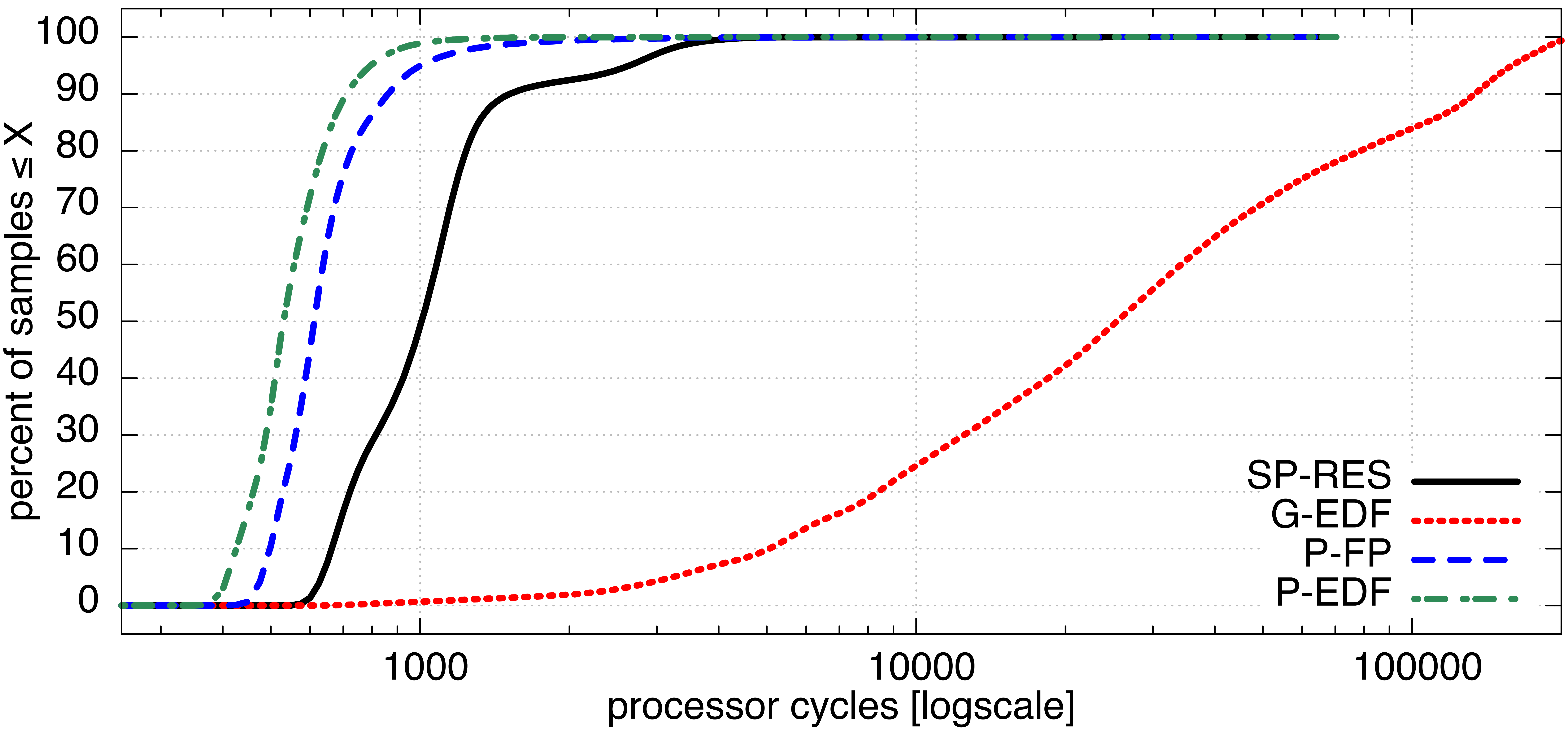
UNC Style Experiments, Varying Task Count



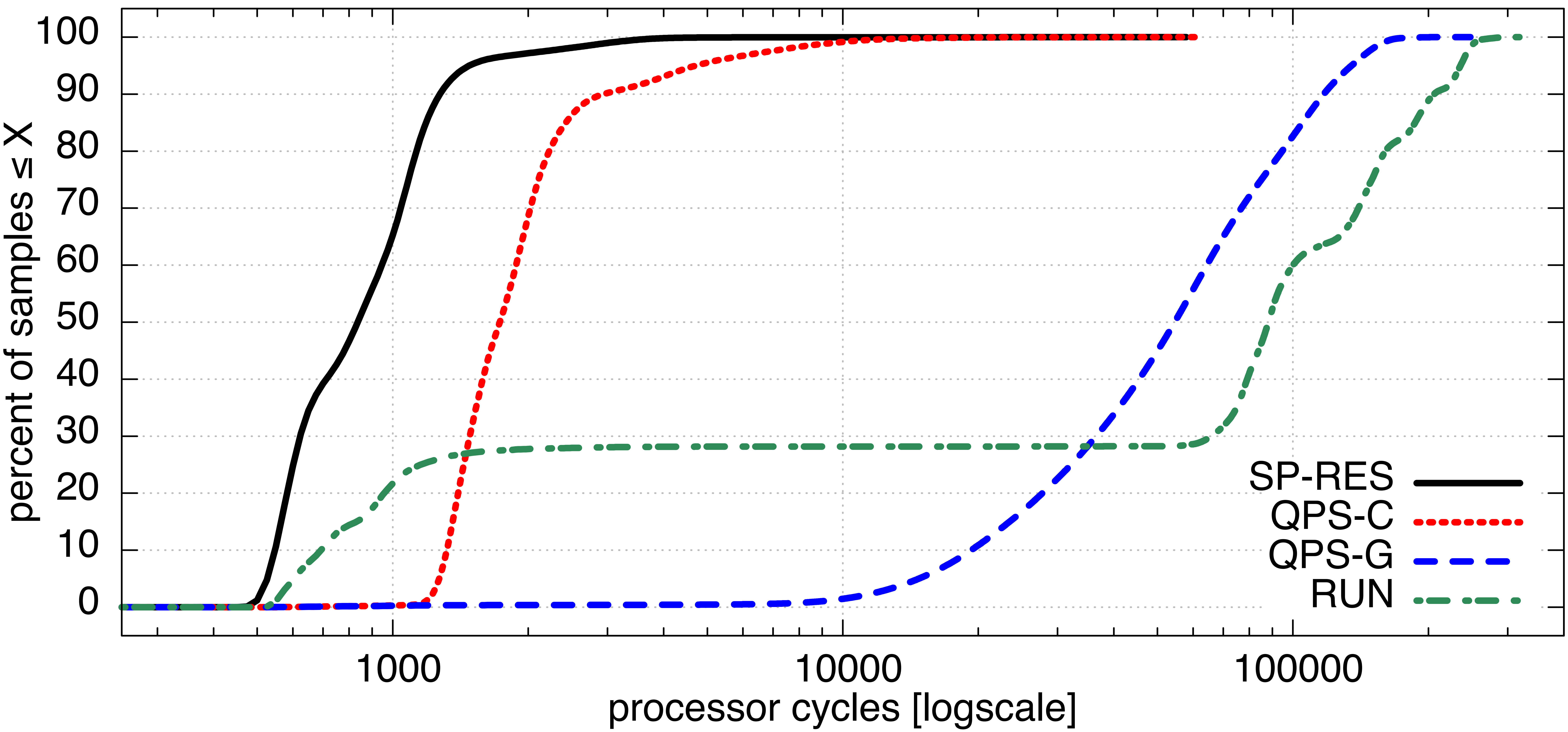
Minimum-Split Size Experiments



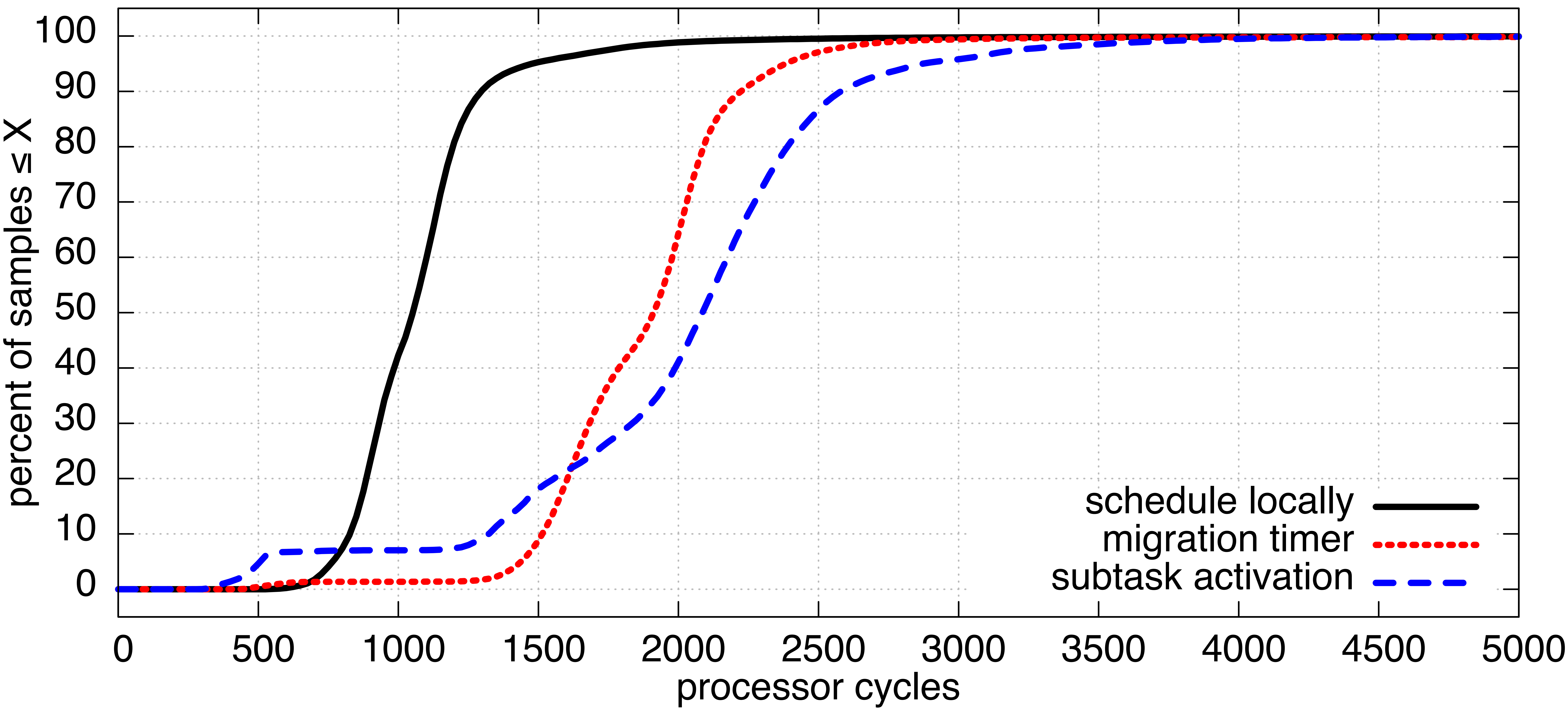
Release Overhead (1/2)



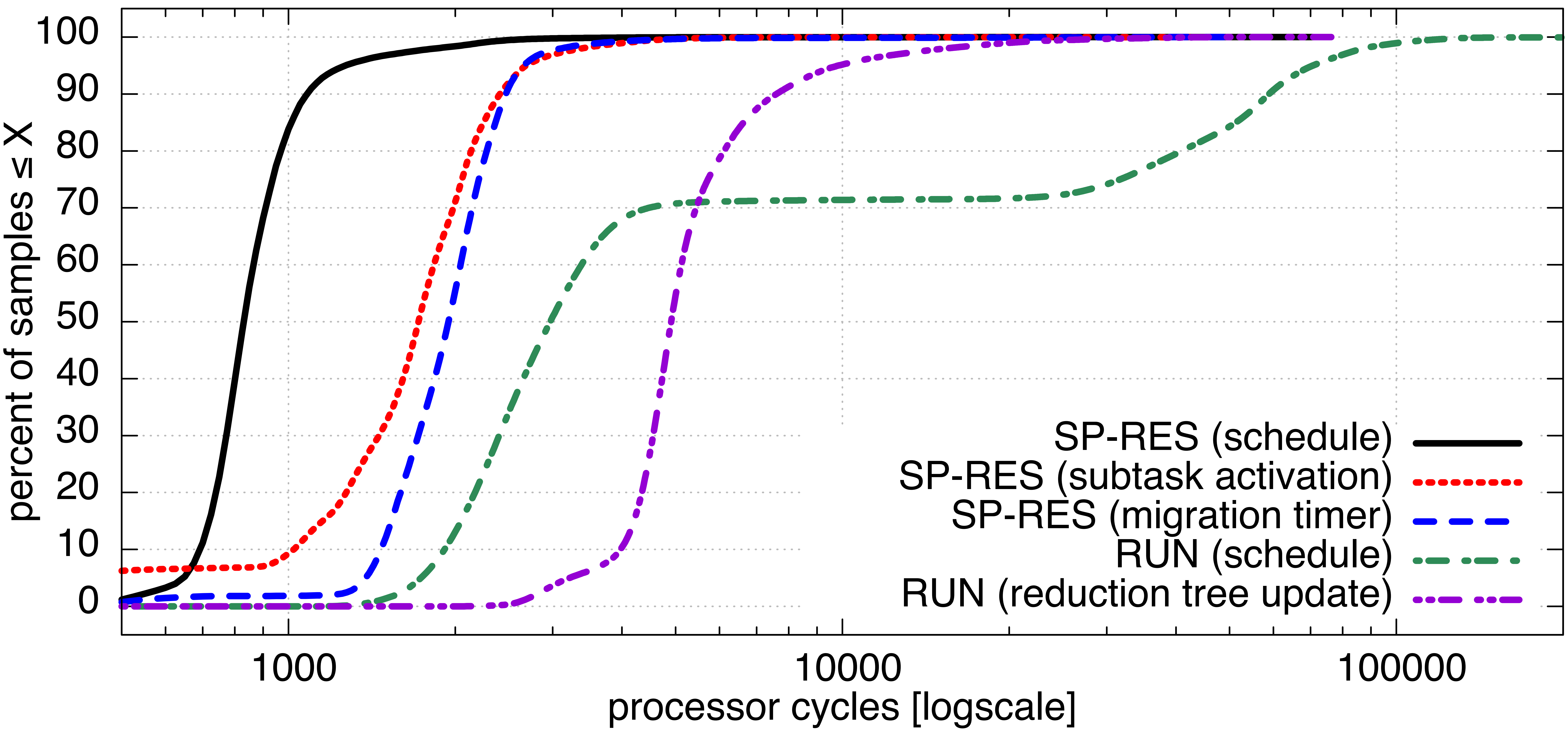
Release Overhead (2/2)



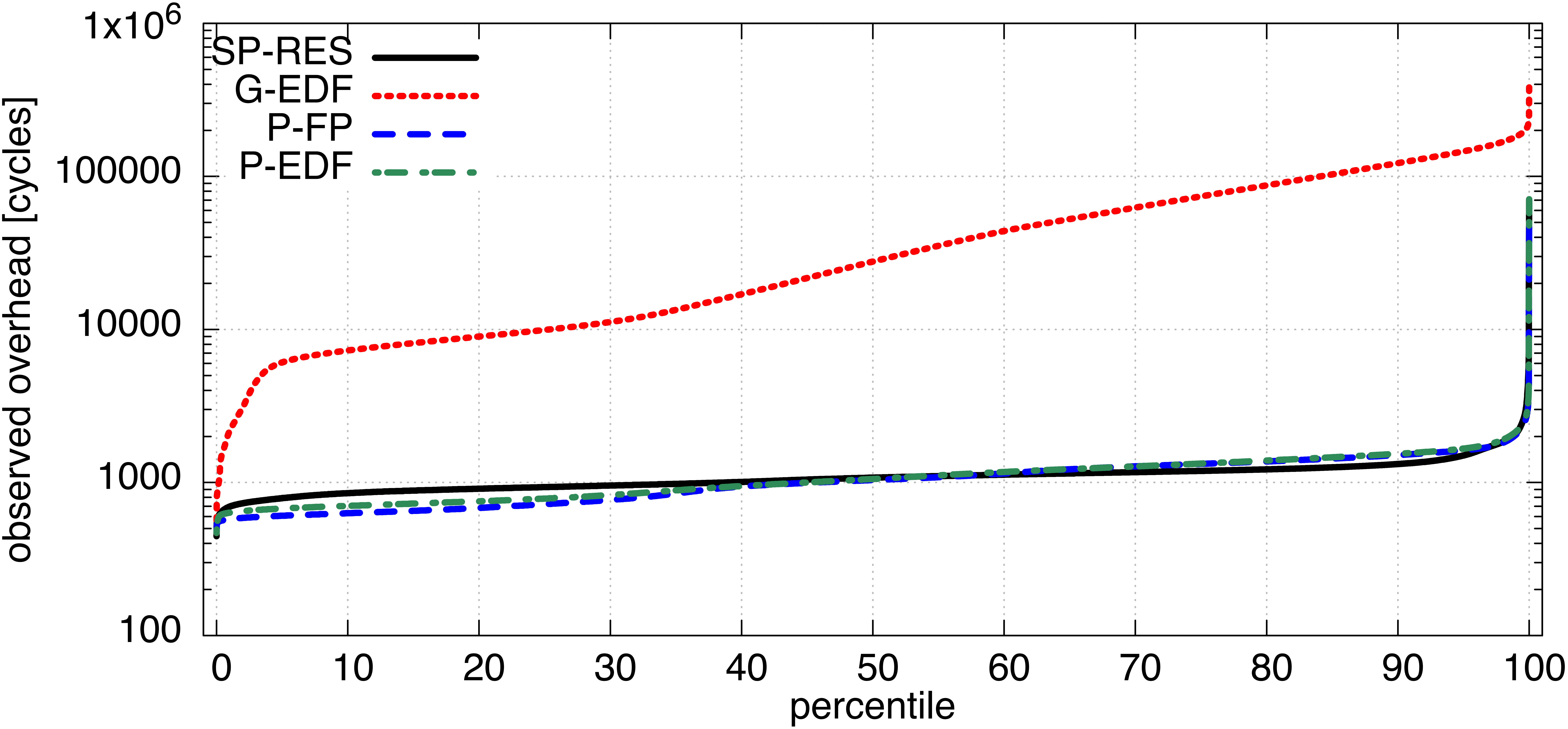
Extra Overheads (1/2)



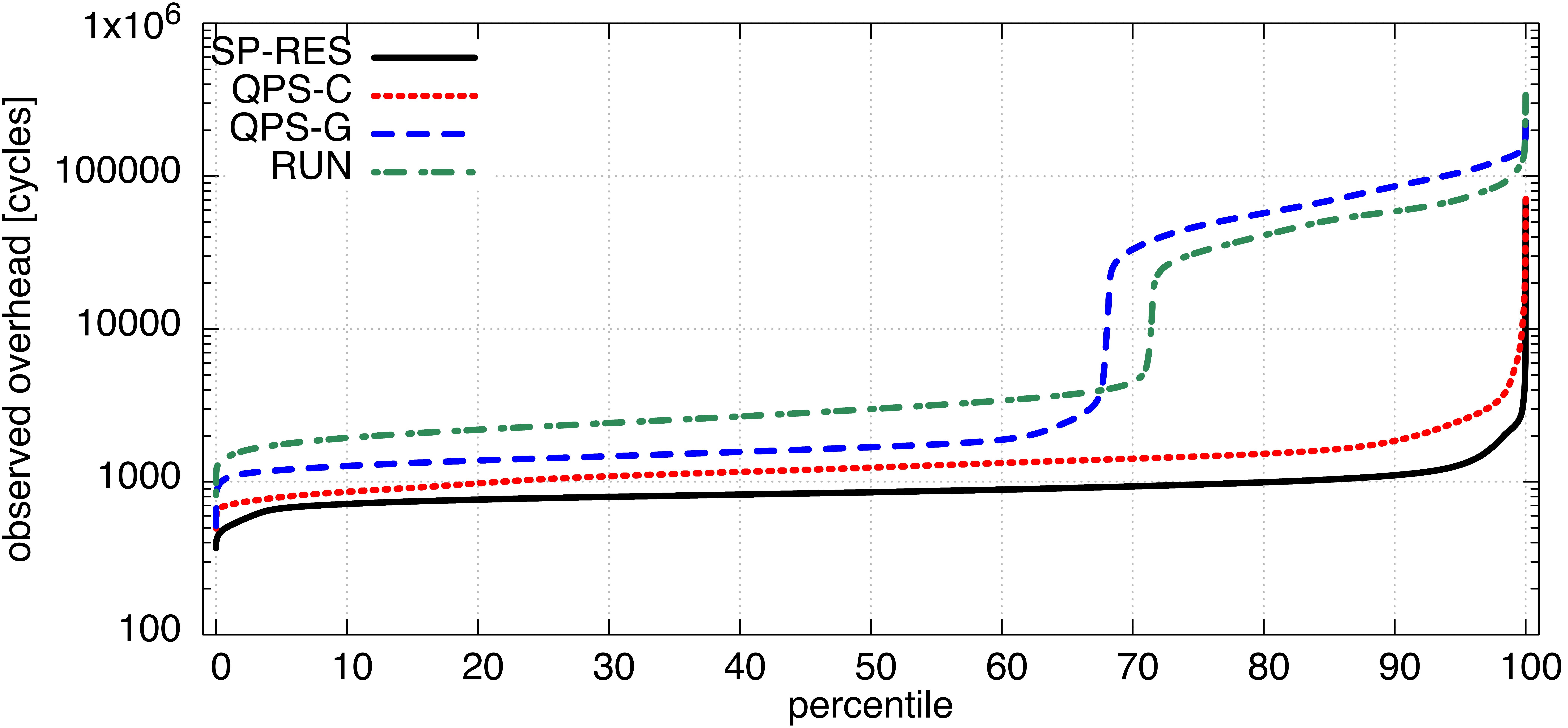
Extra Overheads (2/2)



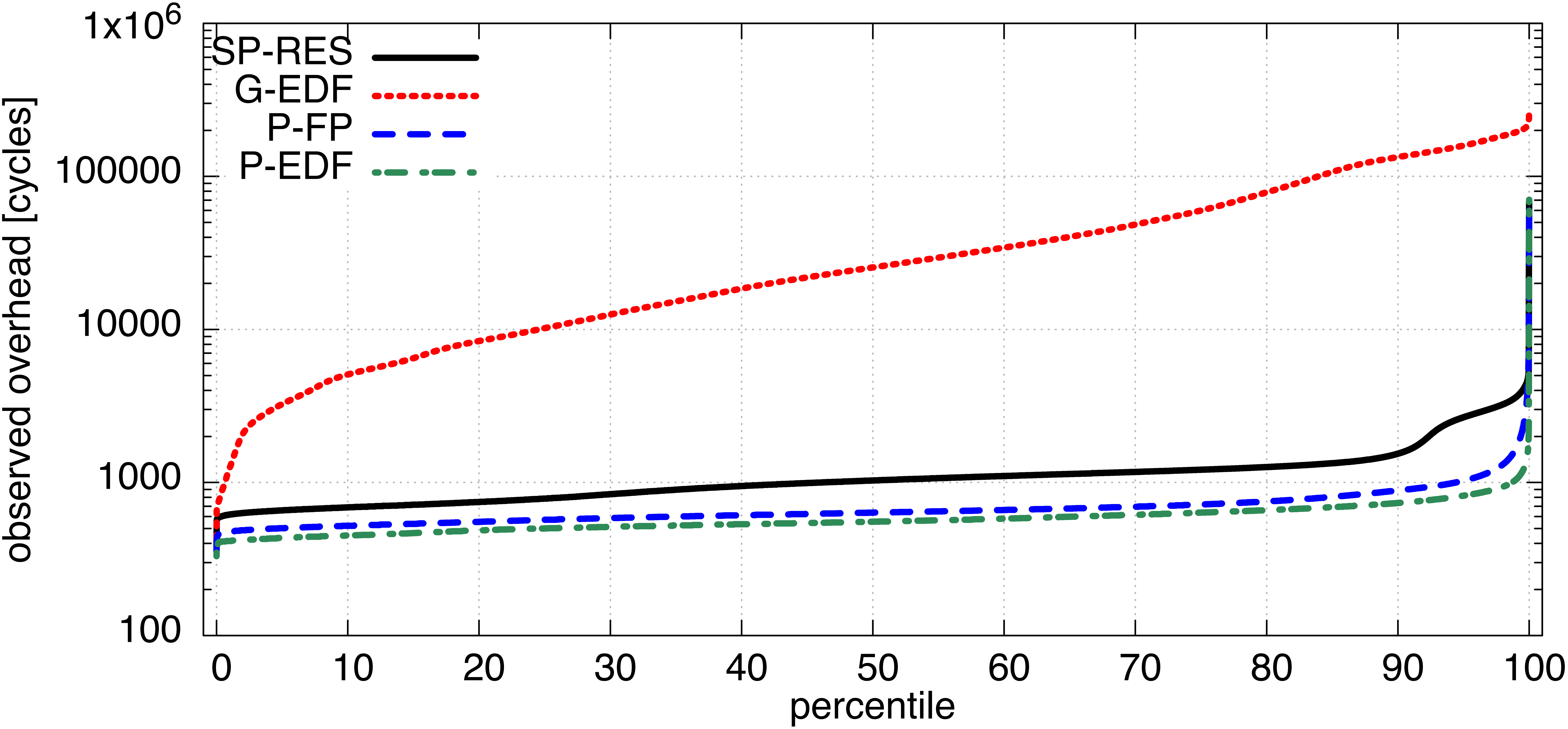
Percentile Plots – Schedule Overhead (1/2)



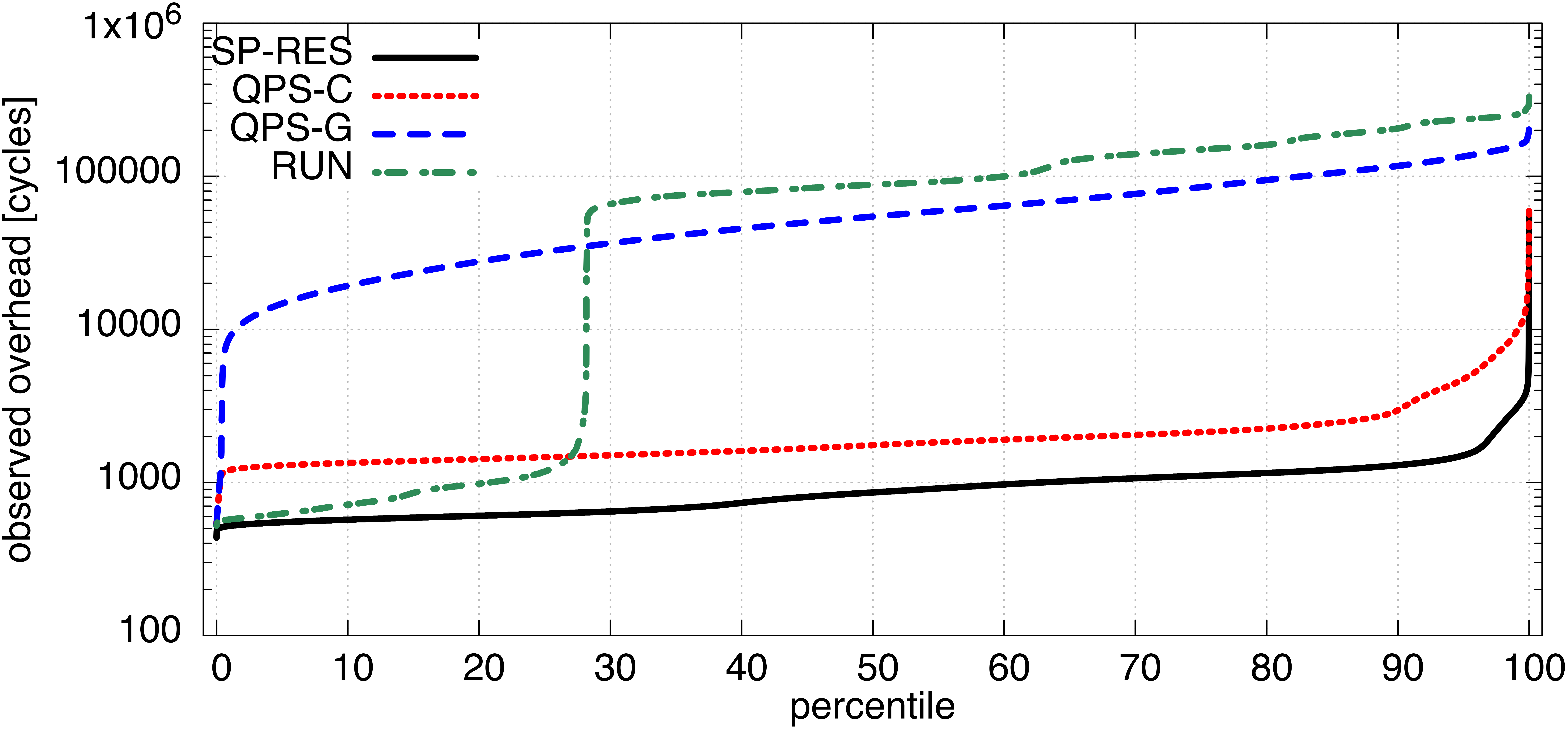
Percentile Plots — Schedule Overhead (2/2)



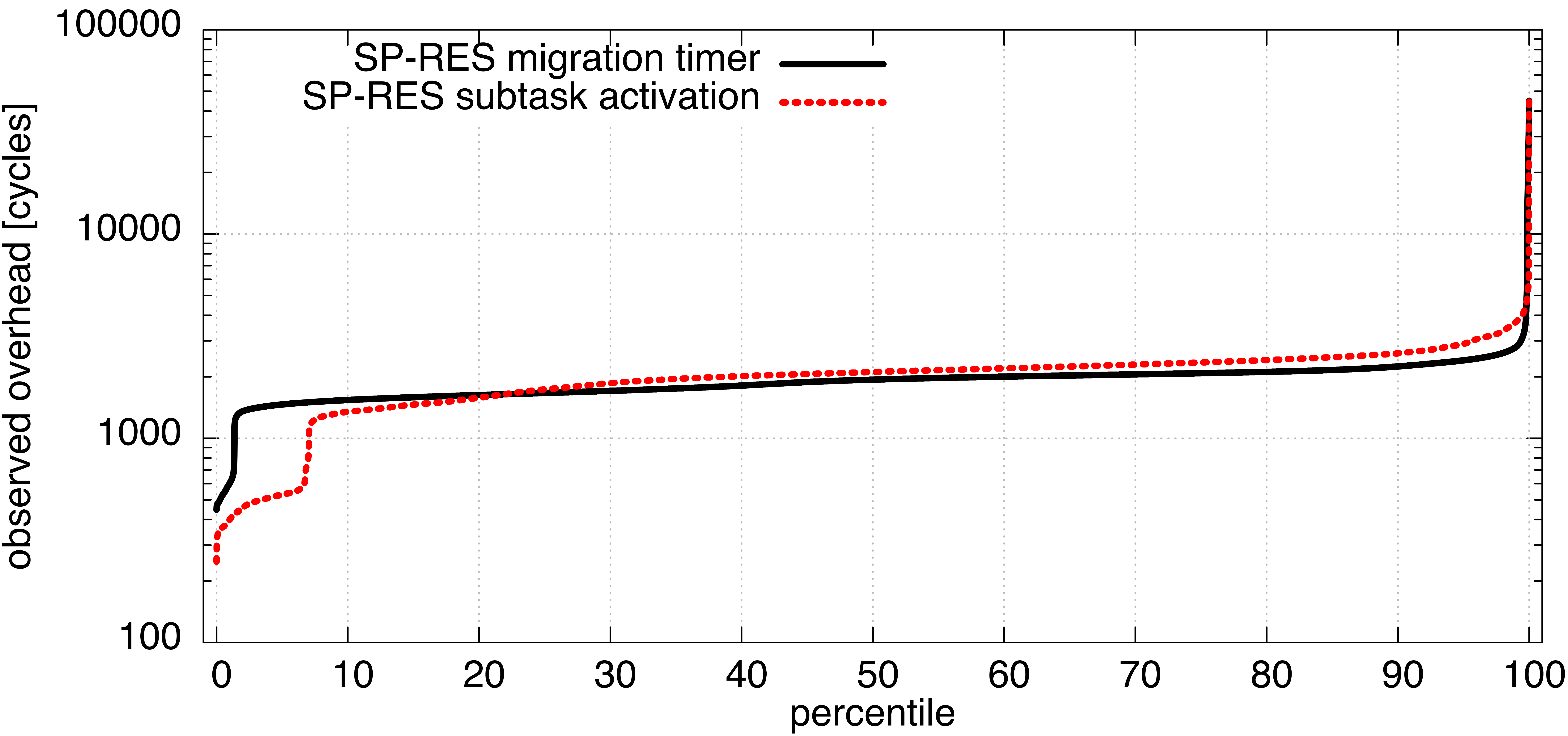
Percentile Plots — Release Overhead (1/2)



Percentile Plots — Release Overhead (2/2)



Percentile Plots — Release Overhead (1/2)



Percentile Plots — Release Overhead (2/2)