Energy-Aware Robust Resource Management for Parallel Computing Systems

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Outline

- stochastic model for resource allocation
- static resource allocation with energy minimization
- dynamic resource allocation with energy constraint
- conclusions

Heterogeneous Parallel Computing System

- interconnected set of different types of machines with varied computational capabilities
- workload of tasks with different computational requirements
- each task may perform differently on each machine
  - furthermore: machine A can be better than machine B for task 1 but not for task 2

Resource Management

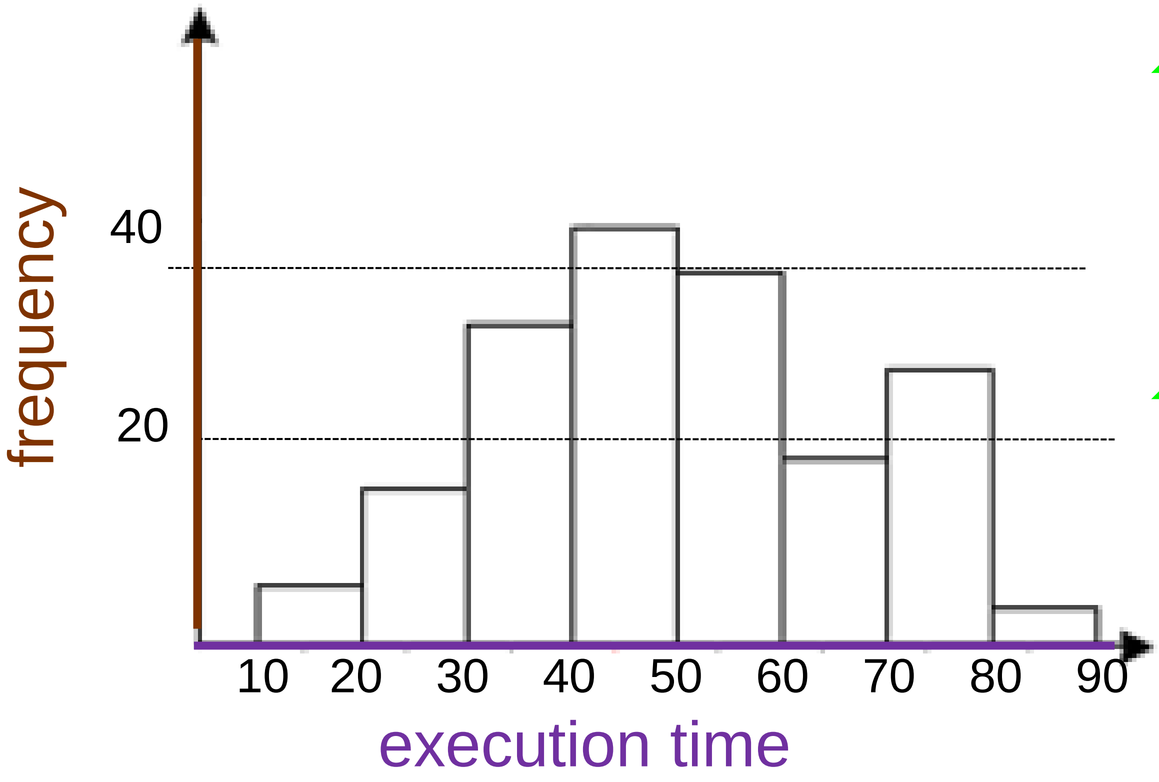
- assign tasks to machines
  - optimize some performance measure
  - possibly meet system constraint
- in general, known **NP-complete** problem
  - cannot find optimal solution in reasonable time
  - ex.: 5 machines and 30 tasks
    $\rightarrow$ 5^{30} possible assignments
  - if it only took 1 nanosecond to evaluate each assignment
    - 5^{30} nanoseconds > 1,000 years!
  - use **heuristics** to find near-optimal solutions

Stochastic Model for Robustness

- reference
  - “Stochastic Robustness Metric and its Use for Static Resource Allocations”
  - by Shestak, Smith, Maciejewski, and Siegel
  - *Journal of Parallel and Distributed Computing*
  - August 2008, Vol. 68, No. 8, pp. 1157-1173

Modeling Uncertain Task Execution Times

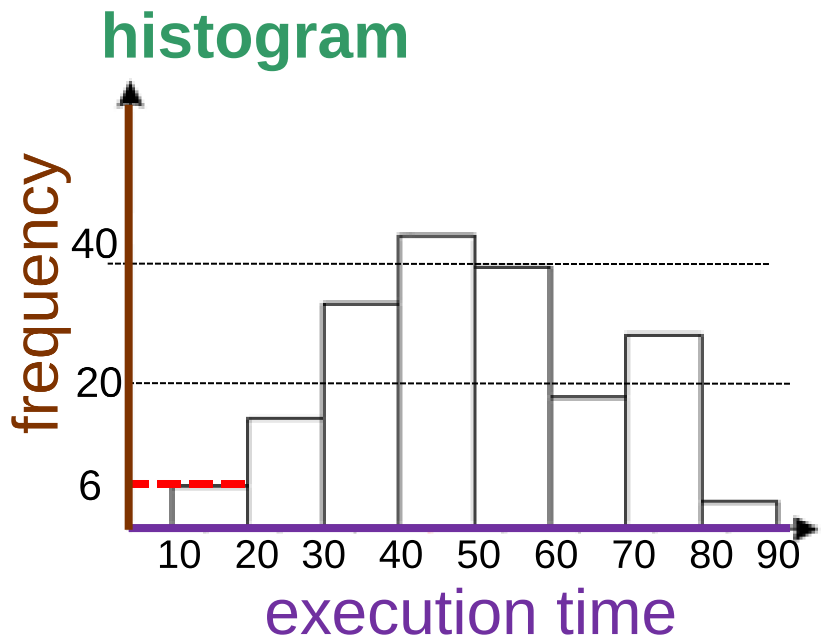
- execution of a given task on a given machine is data dependent
- collect in a **histogram** a history samples of
  - execution time of a given task on a given machine
  - over different representative data sets

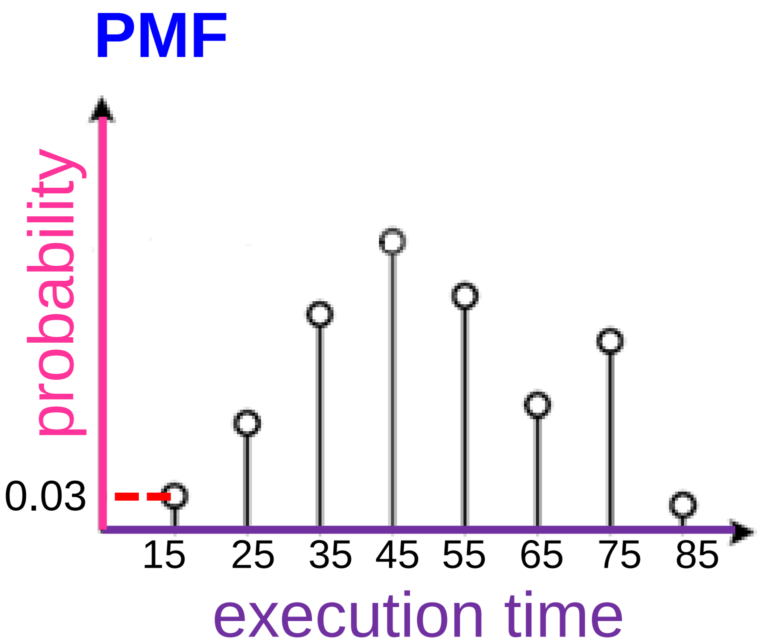


- x-axis: execution time within 10 second interval bins
- y-axis: frequency = height of bar for a given interval

Generating a PMF from a Histogram

- a probability mass function (PMF) can be generated using a histogram
- convert the frequency to a probability to create PMF
  - probability = frequency/total # samples
- example: probability of value from 10 to 19 = 6/200 = 3%

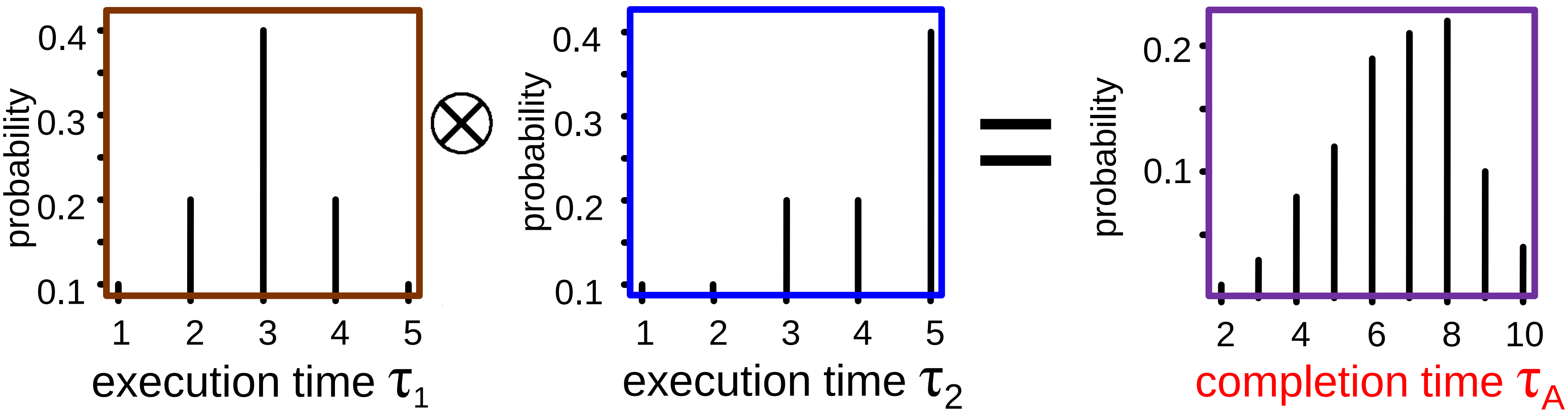




PMF for Completion Time of Machine

- assume task 1 and task 2 only tasks assigned to machine A
  - can find completion time PMF for machine A to do both tasks
  - if tasks independent, it is the "discrete convolution" (combination) of the execution time PMFs for the two tasks

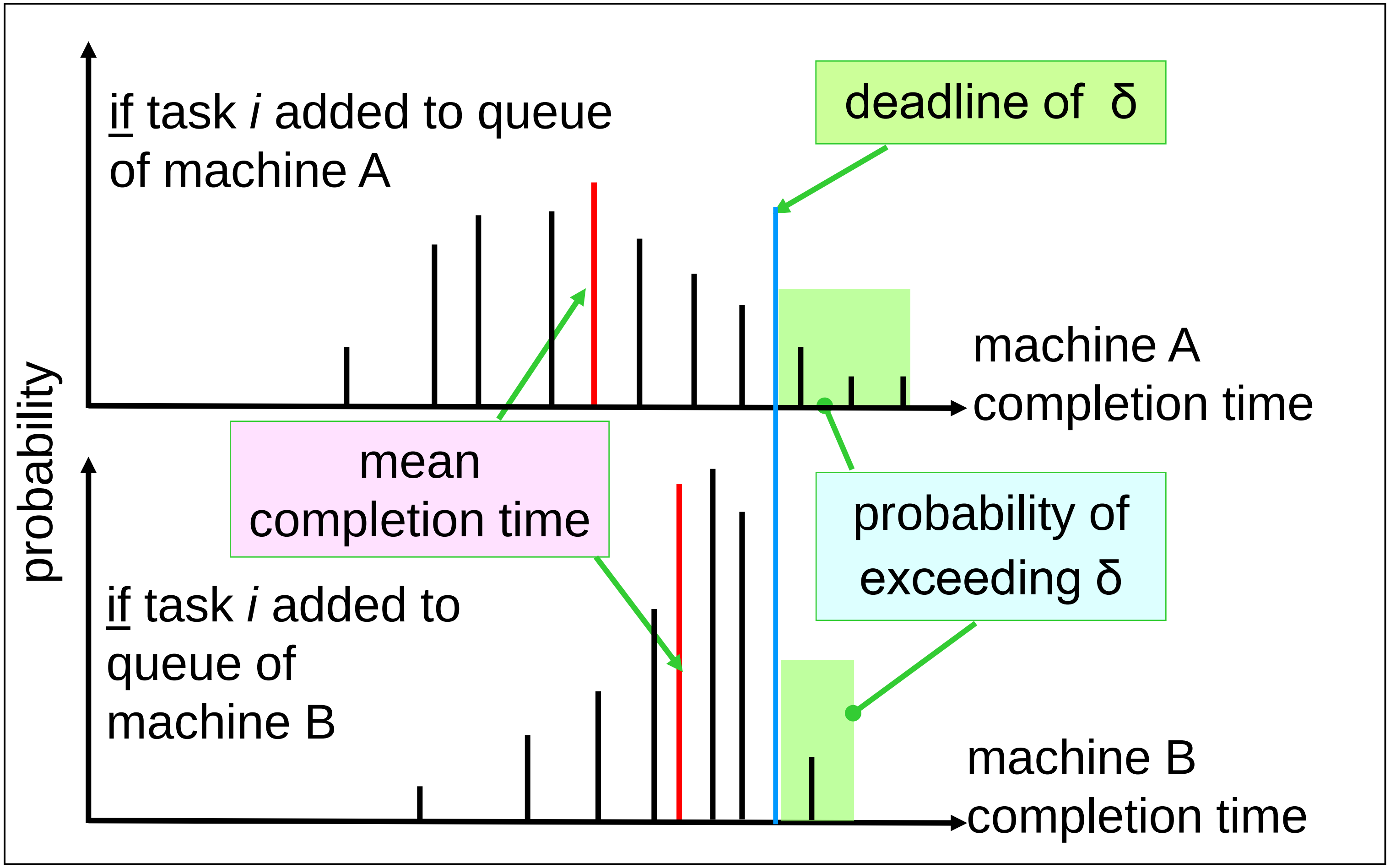
PMF for t_1 on machine A | PMF for t_2 on machine A | PMF for completion time of machine A



- $p(\tau_A = k) = \sum_{\tau_1 + \tau_2 = k} (p(\tau_1) \cdot p(\tau_2))$

Example of Use of Stochastic Model in Allocation

- PMFs for machine completion time based on
  - (1) PMFs for tasks already assigned to that machine, and
  - (2) PMF for task *i* – which <u>may</u> be assigned to that machine



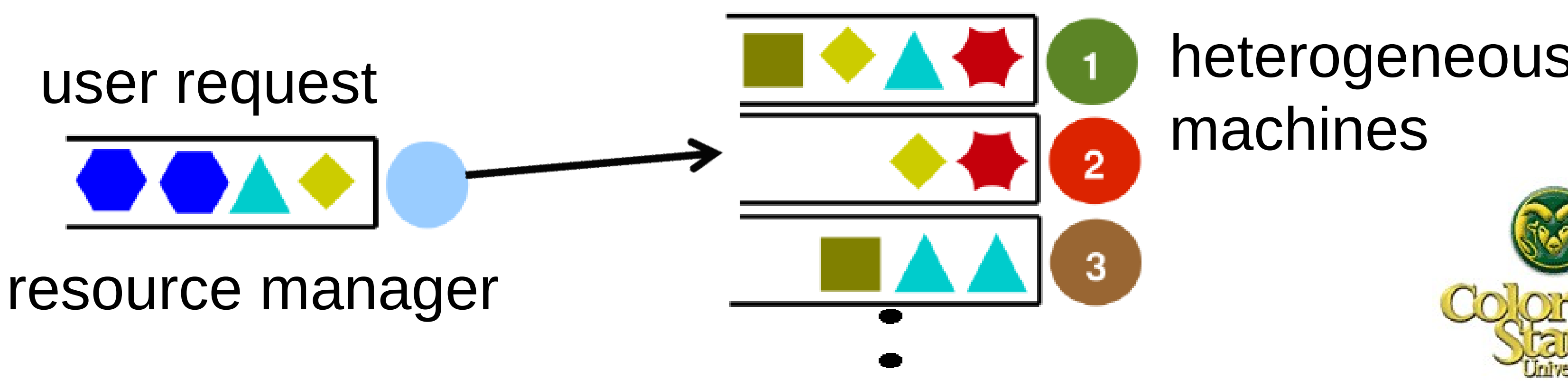
- assign task *i* to machine A or B?
- mean → A
- sum of heights of pulses > deadline → B

Static Resource Allocation

- determine allocation of set of tasks to machines off-line
- know in advance which tasks are to be executed during a given interval of time (e.g., the next day)
- "bag-of-tasks"
- uses
  - planning future work in production environment
    - e.g., resource manager plans when and where tasks will execute the next day
  - predictive "what-if" studies
    - e.g., system administrator wants to quantify the benefit of adding more machines to the network
  - post-mortem analysis of a dynamic heuristic
    - e.g., static allocation based on trace to compare performance to dynamic results

Dynamic Resource Allocation

- tasks assigned to machines as they arrive (on-line)
- tasks are from a known set (e.g., Digital Globe, NCAR, ORNL)
- do <u>not</u> know in advance
  - which tasks (from the known set) will need to be executed
  - when tasks will arrive
  - what data sets will be processed
- set of machines in the computing system can change
- can use feedback about status of machines
- because done as tasks arrive,
  must execute faster than static heuristics



Outline

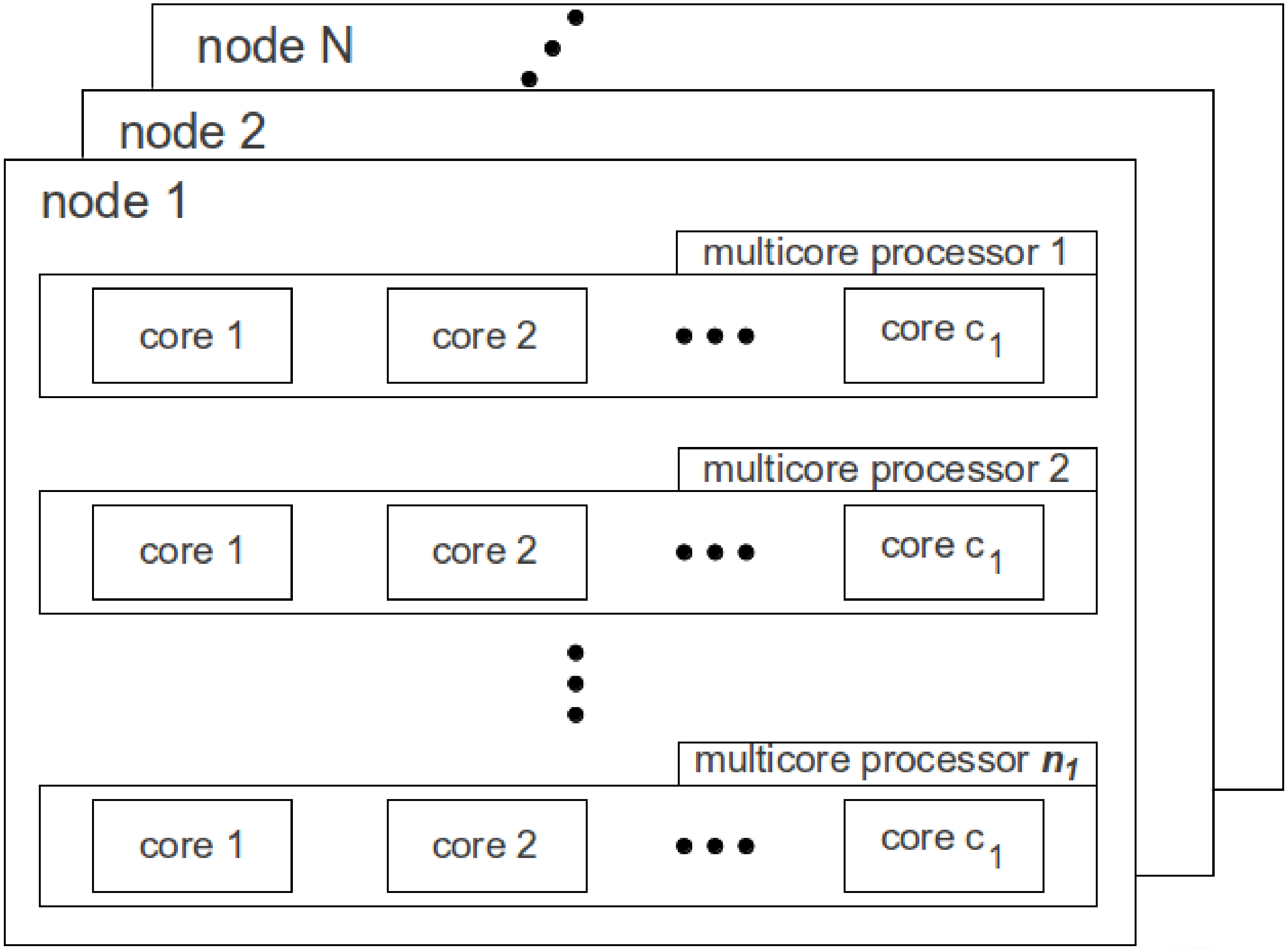
- stochastic model for resource allocation
- static resource allocation with energy minimization
- dynamic resource allocation with energy constraint
- conclusions

Static Heuristics with Energy Minimization

- reference
  - "Stochastically Robust Static Resource Allocation for Energy Minimization with a Makespan Constraint in a Heterogeneous Computing Environment"
  - by Apodaca, Young, Briceño, Smith, Pasricha, Maciejewski, Siegel, Bahirat, Khemka, Ramirez, and Zou
  - *9th ACS/IEEE International Conference on Computer Systems and Applications (AICCSA '11)*
  - December 2011

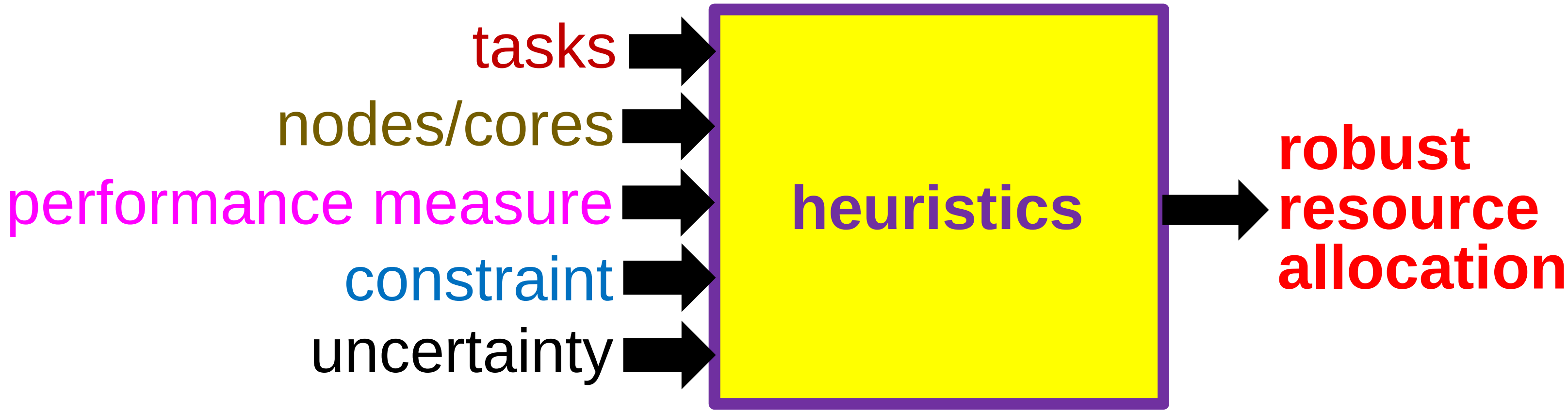
Architecture Model

- N heterogeneous compute nodes
- each compute node i has n_i homogeneous multicore processors, $1 \le n_i \le 4$
- each multicore processor j in compute node i has c_i homogeneous cores, $1 \le c_i \le 4$



Problem Statement for Static Study

- known collection of independent tasks
- common deadline δ to complete all tasks
- uncertainty in execution time of given task on given core type due to data dependencies is represented as PMF
- energy used is concern because of costs
- goal: design robust resource management techniques that
  - minimize expected energy used (performance measure)
  - constraint on probability of finishing by deadline (robustness)



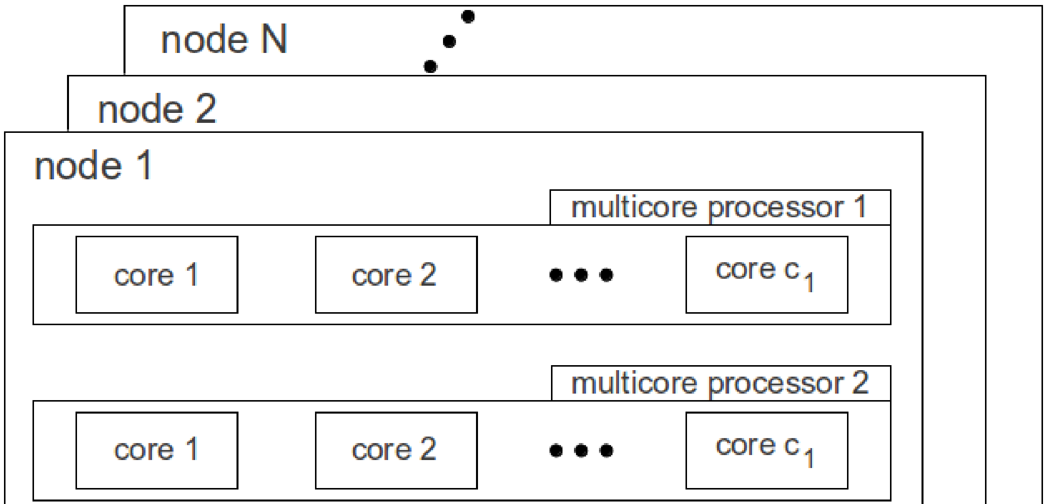
Robustness Definition

- term "robustness" usually used without explicit definition

- THE THREE ROBUSTNESS QUESTIONS
  1. what behavior makes the system robust?
     - finishing all tasks by the common deadline δ
  2. what uncertainty is the system robust against?
     - each task's execution times may vary substantially based on input data
  3. how do we quantify robustness?
     - the probability that a given resource allocation will complete all tasks by the common deadline δ

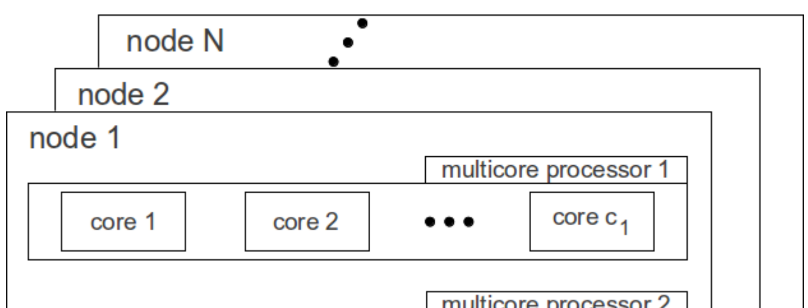
Energy Model – Hierarchy

- nodes shut off when all internal multicore processors are idle
  - when one or more internal multicore processors are on, however, a node incurs power overhead (e.g., for disks, fans)
- multicore processors shut off when all internal cores are idle
  - when one or more internal cores are on, however, a multicore processor incurs power overhead (e.g., for L3 cache)
- each core executes continuous sequence of tasks
  - shut down core/processor/node ASAP



Energy Model – DVFS

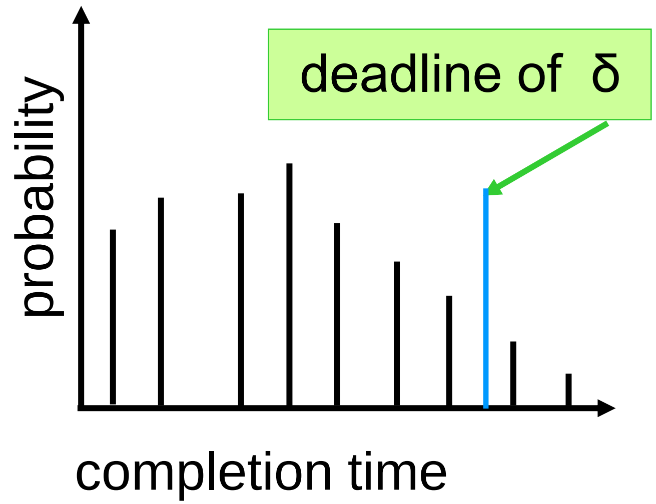
- each core uses Dynamic Voltage and Frequency Scaling (DVFS)
- five P-states (performance states)
  - P0 highest power to P4 lowest power
  - higher power consumption → faster execution
  - typically – lower power P-state → less energy but more time
    - depends on ratio of overhead energy to CPU energy
    - type of task: memory-intensive, CPU-intensive
- execution time PMF for each task - each core type - each P-state
- for each P-state for each core type, average scalar value for power consumption (energy per second)
- cores can switch states independently - negligible overhead



Formal Definition of Robustness for Static Study

- given a resource allocation (including P-state assignments)
  - let D_{ijk} be the finishing time distribution PMF for all tasks assigned to core k in multicore processor j in compute node i
  - let $p(D_{ijk}, \delta)$ be probability of finishing before δ given D_{ijk}
    - sum of pulses < δ in PMF
- overall system robustness ψ
  - probability of all tasks finishing by δ

$$\psi = \prod_{1 \le i \le N} \prod_{1 \le j \le n_i} \prod_{1 \le k \le c_i} p\left(D_{ijk}, \delta\right)$$



Heuristics for Static Study

- recall - goal: design robust resource management techniques
  - minimize expected energy used (performance measure)
  - constraint on probability of finishing by deadline (robustness)
- the robustness constraint is ***R***%
  - this could be specified by the system administrator
  - simulation study: we use robustness constraint to be 90%
- heuristics from the paper
  - Min-Min
  - Genetic Algorithm (GA)
  - Tree Search
  - Tabu

Genetic Algorithm (GA) – Chromosome

- chromosome structure – represents possible solution (allocation)
  - number of genes (length) = number of tasks to be mapped
  - t^{th} entry is a four-tuple (i, j, k, π)
  - denotes mapping **task *t*** to **node *i***, **multicore processor *j***, **core *k***, in **P-state *π***
  - order of task execution within a core does not matter

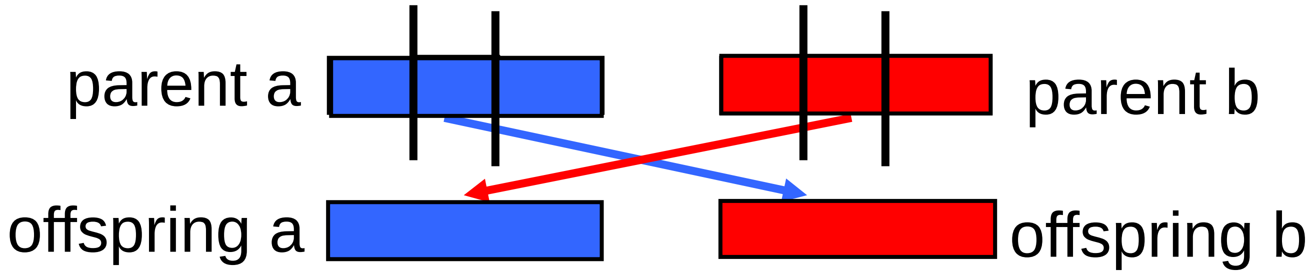
task	1	2	3	4	...
node	2	1	2	3	...
processor	4	2	1	1	...
core	2	2	3	1	...
P-state	0	4	2	1	...

Genetic Algorithm (GA) - Population

- fixed size population of chromosomes – collection of solutions
- Genitor-style GA (steady-state GA)
- population ordered by fitness value as follows:
  - chromosomes that meet robustness constraint in increasing order of expected energy (lower better)
  - rest in decreasing order of robustness (higher better)
- initial population generation
  - five seeds based on Min-Min
    - greedy heuristic
    - run for a fixed P-state
    - done 5 times, 1 per P-state
  - rest simple greedy heuristic that meets constraint

GA – Crossover Operation

- randomly select a pair of "parents" for crossover with a probability p_c
- choose two points x & y such that $x < y \leq$ number of tasks
- swap genes in range [x, y] between chromosomes
- generates two offspring



GA – Task-Assignment Mutation Operation

- each chromosome has probability p_{tm} of being mutated
- each gene within selected chromosome has probability p_{tmg} of being mutated
- change assignment to random core, in random P-state

task	1	2	3	4	…
node	2	1	2	3	…
processor	4	2	1	1	…
core	2	2	3	1	…
P-state	0	4	2	1	…

4
3
1
0

GA – P-State Mutation Operation

- each chromosome has probability p_{pm} of being mutated
- each gene within selected chromosome has probability p_{pmg} of being mutated
- change P-state of random task to random P-state

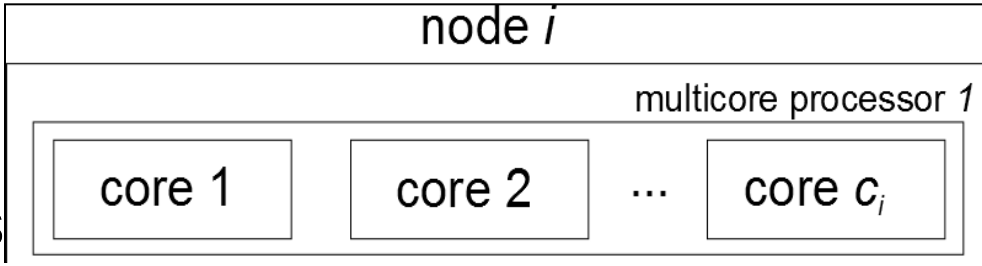
task	1	2	3	4	…
node	2	1	2	3	…
processor	4	2	1	1	…
core	2	2	3	1	…
P-state	0	4	2	1	…

0

GA – Procedure Overview

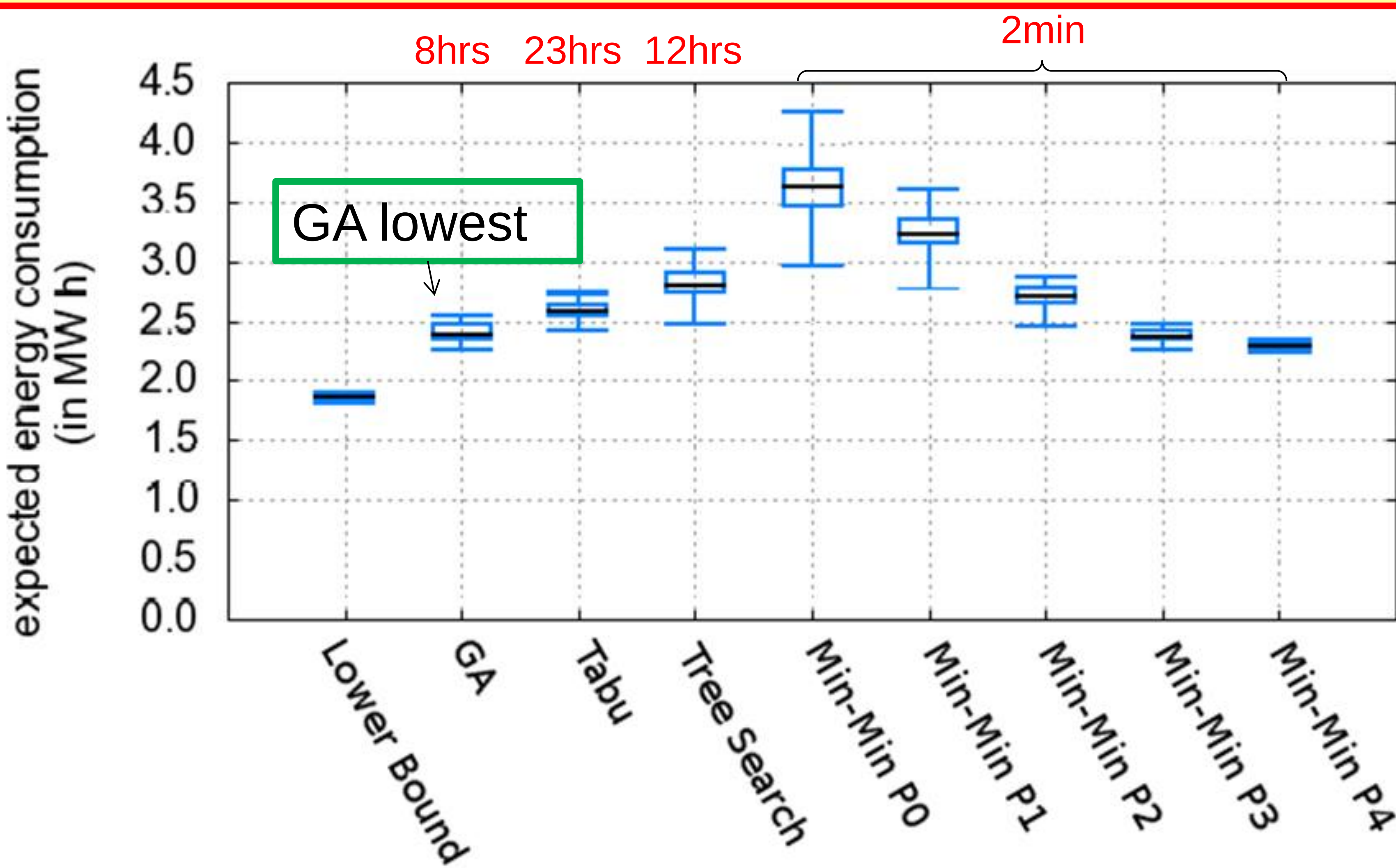
- generate initial population (size denoted *S*)
- repeat for a given number of iterations
  - do *S* times: choose two random chromosomes, and with probability p_c produce two offspring via crossover
    - insert offspring in ordered population and trim to size *S*
  - for each chromosome in population, make offspring via task-assignment mutation with probability p_{tm}
    - insert offspring in ordered population and trim to size *S*
  - for each chromosome in population, make offspring via P-state mutation with probability p_{pm}
    - insert offspring in ordered population and trim to size *S*
- return best chromosome encountered

Simulation Setup for Static Study



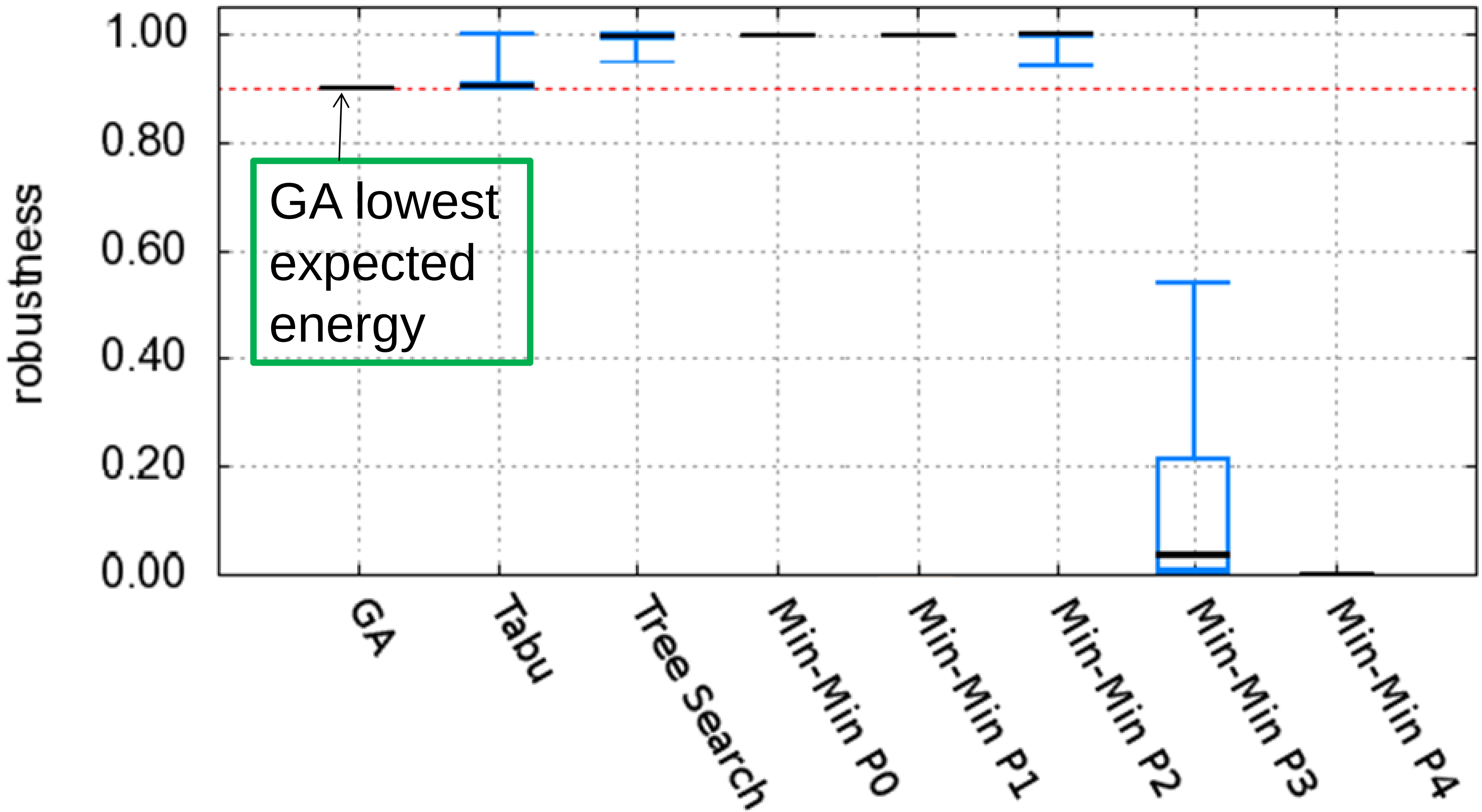
- 4000 tasks
- total of 25 compute nodes
- total of 63 multicore processors (randomly varied 1 to 4 per node)
- total of 178 cores (randomly varied 1 to 4 per processor)
- average overhead ~50% of total energy (varied across nodes)
- 90% probability constraint on finishing by deadline (robustness)
- GA parameters, determined by experimentation:
  - $p_c = 0.005$, $p_{tm} = 0.25$, $p_{tmg} = 0.001$, $p_{pm} = 0.025$, $p_{pmg} = 0.0005$
  - population size: 100
- 50 different simulation trials were run for each heuristic
  - different PMFs for task execution times

Results Static Study – Expected Energy



- box and whiskers: min, 1st quartile, median, 3rd quartile, max
- Min-Min in P-states 3 and 4 did not meet robustness constraint
- red: heuristic execution times

Results Static Study – Robustness



- robustness constraint (90%) shown as red dashed line
- no need to have robustness over 90%

Results Static Study – Discussion

- recall goal: design robust resource management techniques that
  - minimize expected energy used (performance measure)
  - constraint on probability of finishing by deadline (robustness)
- in general, lower performance P-states result in lower total expected energy (good) BUT lower robustness (bad)
  - use combination
- GA had lowest expected energy consumption and exactly met robustness constraint
- GA execution time per trial was 8 hours
  - not a problem because done off-line for static production environment

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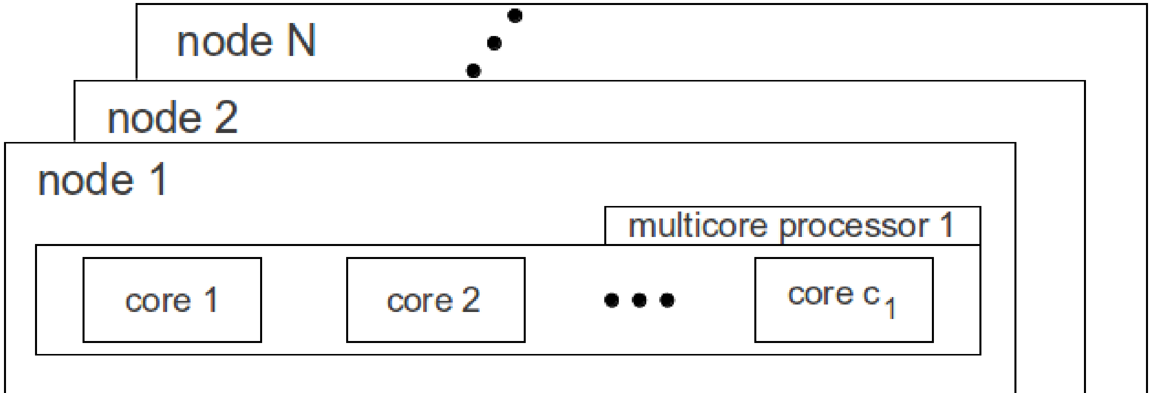
Colorado State University

Dynamic Heuristics with Energy Minimization

- reference
  - “Deadline and Energy Constrained Dynamic Resource Allocation in a Heterogeneous Computing Environment”
  - by Young, Apodaca, Briceño, Smith, Pasricha, Maciejewski, Siegel, Khemka, Bahirat, Ramirez, and Zou
  - *Journal of Supercomputing*
  - February 2013, Vol. 63, No. 2, pp. 326-347

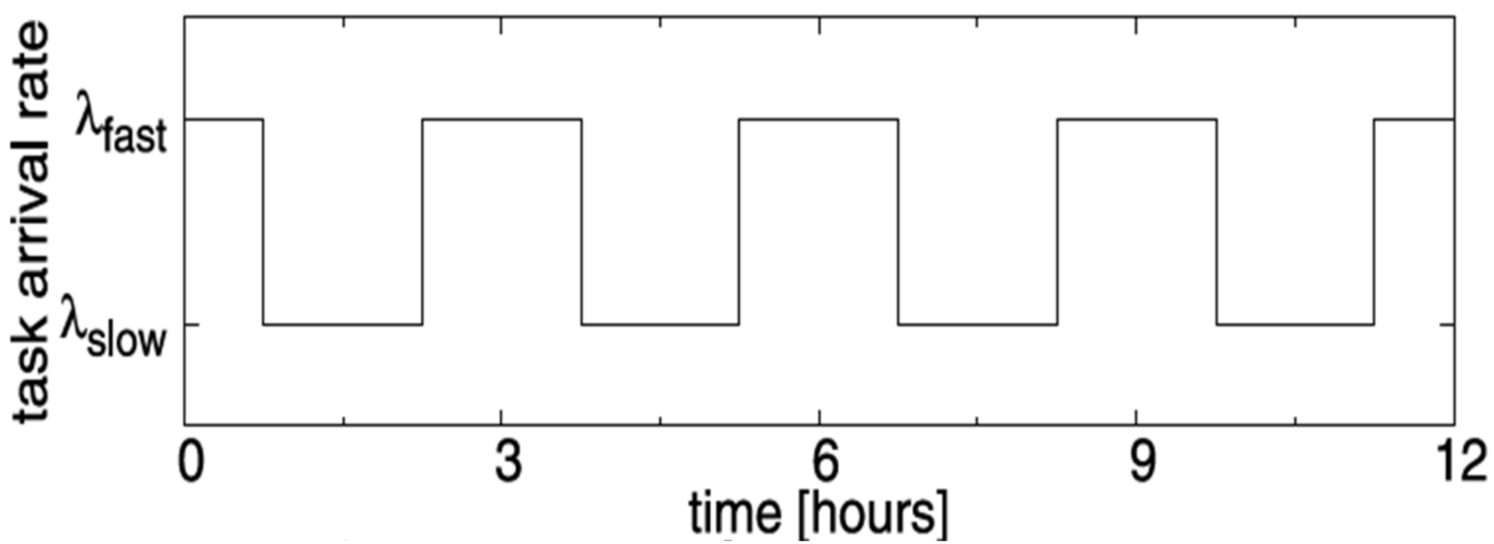
Problem Statement for Dynamic Study

- multi-core architecture similar to static study
  - cores always on
    - idle: P4
    - overhead power constant therefore not considered
- dynamic resource allocation
- goal: given a set of independent tasks with individual deadlines, design robust resource management techniques that
  - complete as many tasks as possible by their individual deadlines (performance measure)
  - subject to a constraint on total energy consumption



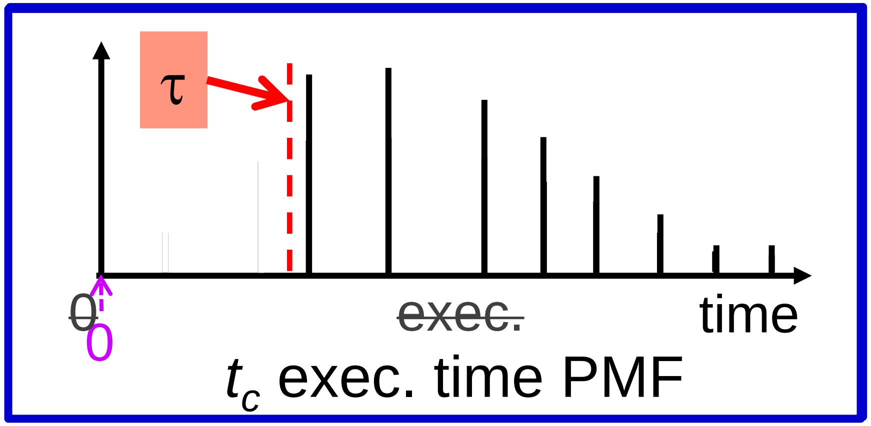
System Model for Dynamic Study

- dynamic, immediate-mode scheduler
  - each task scheduled when it arrives
- collection of known task types
- task type execution time per type of core represented by a PMF
  - can be found from historical data, experiments
- task arrivals modeled as two-phase Poisson process
  - oversubscribed: tasks arrive at a faster rate (**λ_{fast}**)
  - undersubscribed: tasks arrive at a slower rate (**λ_{slow}**)



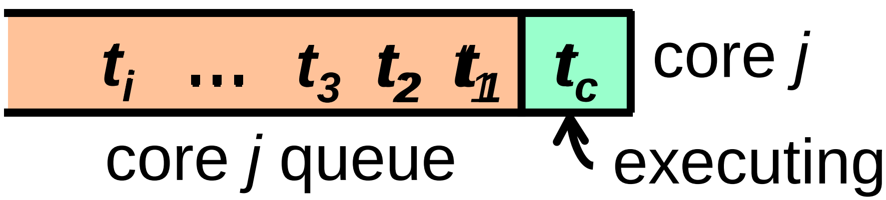
Completion Time PMF for Currently Executing Task

- assume currently executing task t_c is assigned to core j
- for task t_c
  - start with execution time PMF for that task on core j
  - shift PMF to begin at core j ready time
  - drop pulses less than current time τ
  - renormalize PMF



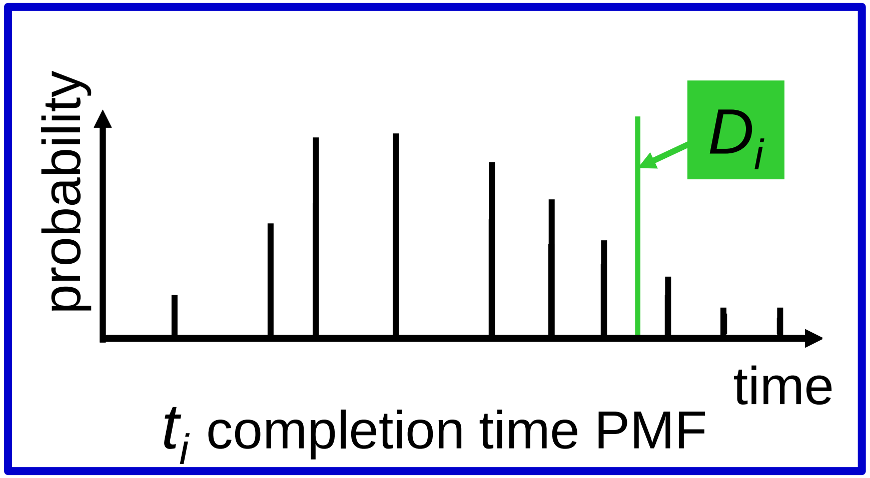
Completion Time PMF for a Task t_i

- to get task t_i completion time PMF ***convolve***
  - resulting completion time PMF for currently executing task t_c
  - execution time PMFs for all tasks queued ahead of task t_i on core j
  - execution time PMF for task t_i on core j



Expected Number of On-time Completions

- in resulting task t_i completion time PMF
  - sum pulses ≤ task t_i individual deadline D_i
  - this is probability task t_i will complete by its deadline



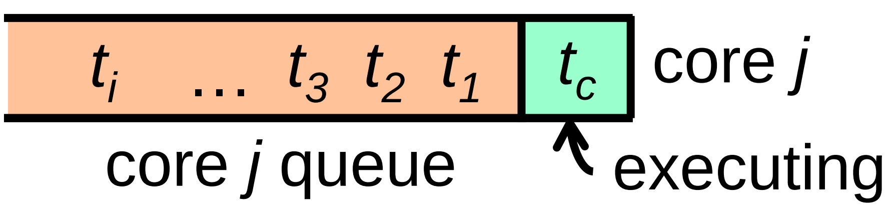
- sum "probability task will complete by its deadline" over all tasks – currently executing or queued
  - "expected number of on-time completions"
  - this is the measure of robustness

Robustness Definition for Dynamic Study

- **The Three Robustness Questions**
  1. what makes the system robust?
     - complete all tasks by their individual deadlines
  2. what uncertainties are the system robust against?
     - each task's execution times may vary substantially based on input data
  3. how is robustness quantified?
     - number of "expected on-time completions"

Start-Time Cancellation

- if start-time cancellation is used:
  - ready-to-execute task is cancelled if it has a probability of completing by its deadline below a **threshold**
    - tunable parameter by experimentation
    - 30% in this simulation study
  - to calculate t_i completion time PMF
    - omit any task queued ahead of task t_i whose probability of meeting its deadline < threshold
    - just prediction that it will be cancelled



- a task cannot be stopped once execution started

Heuristics for Dynamic Study

- recall goal: set of independent tasks with <u>individual</u> deadlines
  - complete as many tasks as possible by their <u>individual</u> deadlines (performance measure)
  - subject to a constraint on total energy consumption
- assign each task to a node, multi-core processor, core, and P-state when it arrives (immediate mode)
- can use filters to add energy and/or robustness awareness
- may leave tasks unassigned or cancel a task
- heuristics from the paper
  - Lightest Load
  - Minimum Expected Completion Time
  - Shortest Queue
  - Random (for comparison)

Heuristic: Lightest Load

- attempt to balance energy and robustness by minimizing a "load" *L*
- for a given task, consider its *L* value for each core and P-state
- En_{ex}: expected energy consumed for the assignment
  - product of the expected execution time and the power consumption
- *p*: probability of the task completing by its deadline for the assignment
- $L = (100 - p) \times En_{ex}$
  - smaller is better
  - when $p = 100$ then En_{ex} is effectively ignored
    - frequently occurs during end of undersubscribed periods
- assign incoming task to the core/P-state combination with the smallest *L* value

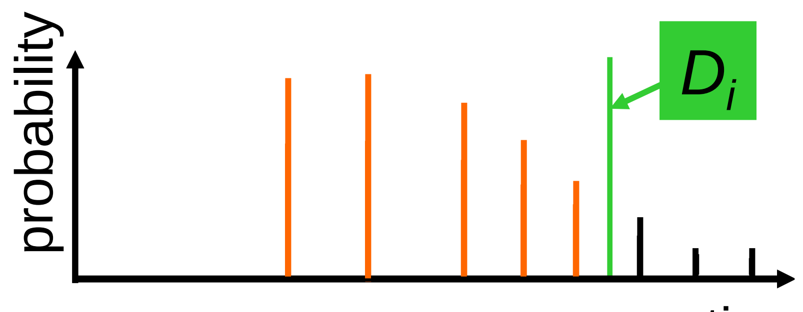
Energy Filter Based on Estimated Remaining

- restrict potential core/P-state assignments to those $\leq$ energy threshold $En_{thresh}(t)$ at time step t
  - discard task if no assignment meets threshold
- $En_{mul}(t)$:
  - three fixed values: for different levels of average queue depth
  - found empirically using a subset of simulation trials
- $t_{rem}(t)$: time remaining in the 12−hour simulation trial
- $En_{rem}(t)$: estimated energy remaining in 12-hour interval
  - energy constraint minus (expected for queued plus “simulated actual” for completed)
- c_{tot}: total number of cores in the system
- t_{avg}: average task execution time

- $$En_{thresh}(t) = En_{mul}(t) \times \overbrace{En_{rem}(\mathrm{t})/\underbrace{[\overbrace{(t_{rem}(t)/t_{avg})}^{\text{\# tasks/core}} \times c_{tot}]}_{\text{total \# tasks}}}^{\text{fair share per task}}$$

Robustness Filter

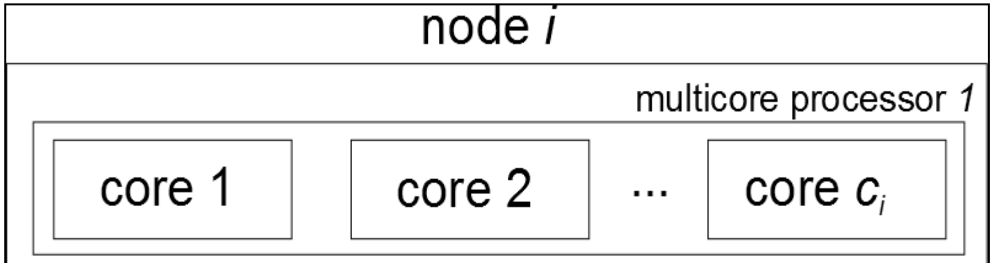
- based on the task's contribution to the total robustness measure
- restrict potential assignments using a robustness threshold p_{thresh} on the probability of the task completing by its individual deadline
  - limits assignments to those that will increase the expected number of on-time completions (robustness) by at least the threshold
  - threshold found empirically (simulation study: $p_{\text{thresh}} = 30\%$)
  - discard task if no assignment meets threshold



t_i completion time PMF

Simulation Setup for Dynamic Study

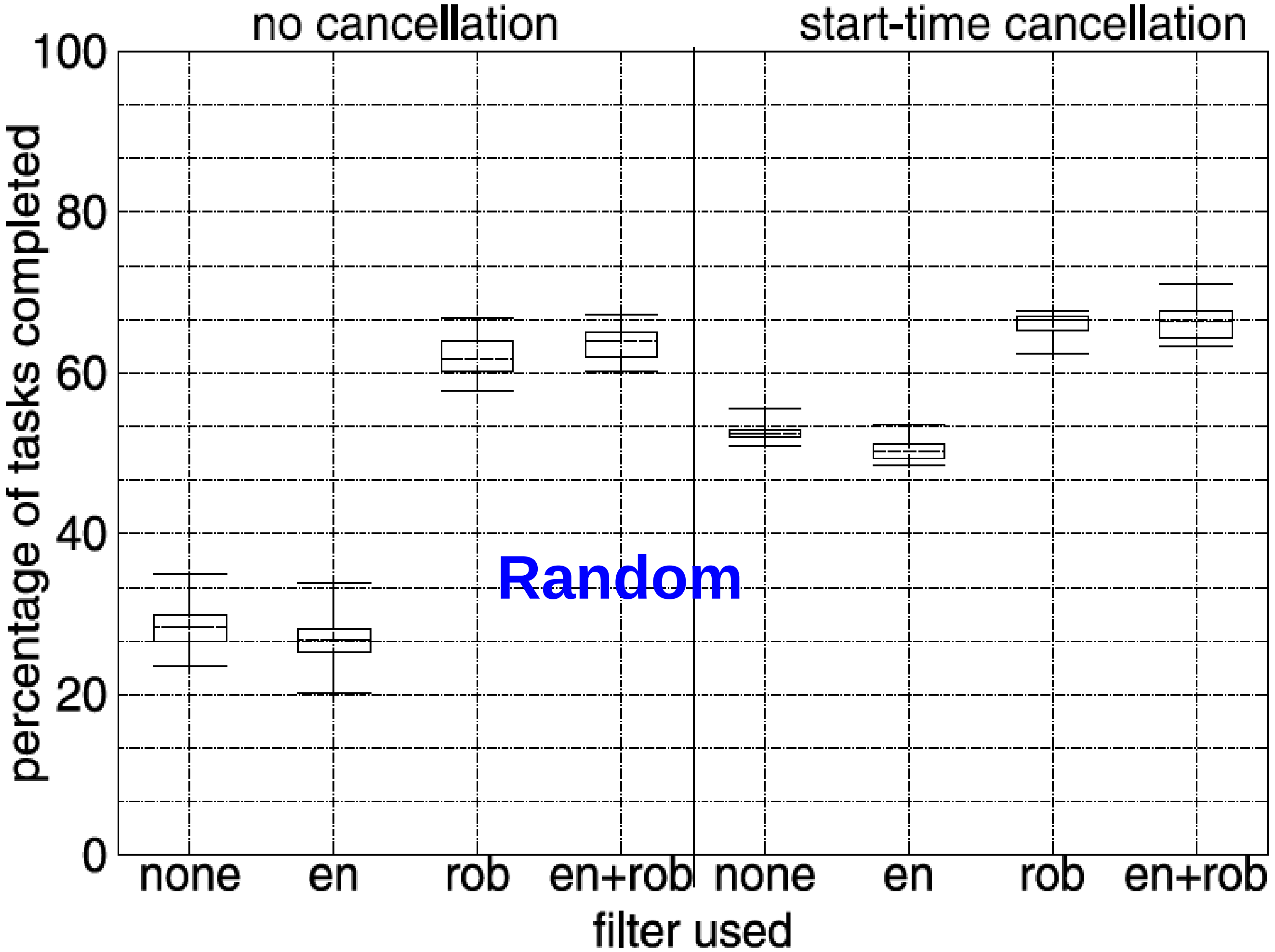
- 12-hour trial window, ~1,650 tasks, 100 task types
- total of 25 compute nodes
- total of 63 multicore processors (varied 1 to 4 per node)
- total of 178 cores (varied 1 to 4 per processor)



- variations among 50 simulation trials:
  - task-type mix
  - task arrival times
  - task "simulated actual" execution times (sample PMFs)
- individual deadline = arrival time + average execution time of its task type over all machines & P-states + average over all tasks
  - tight deadlines

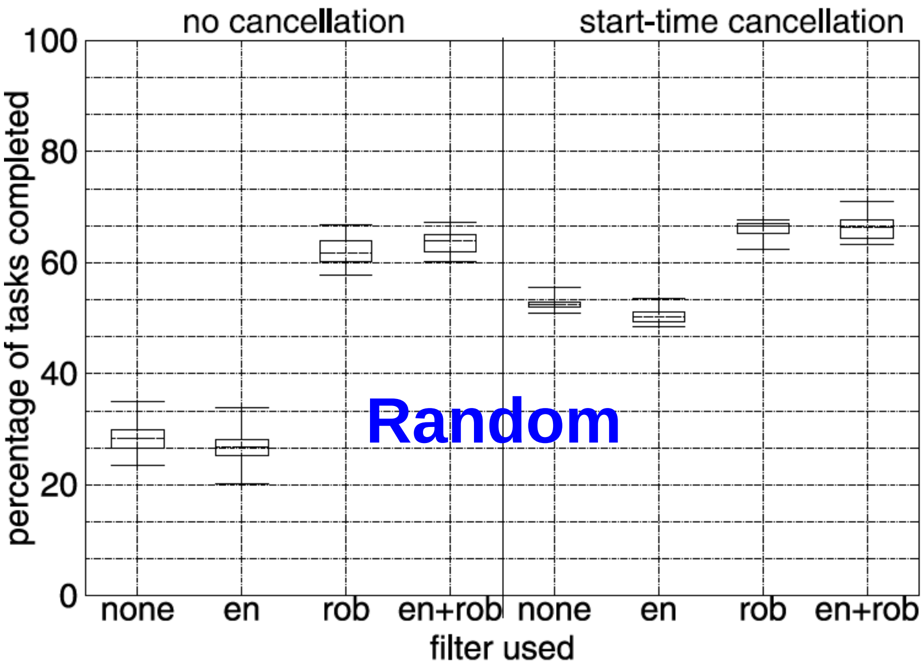
Results: Impact of Filters and Cancellation

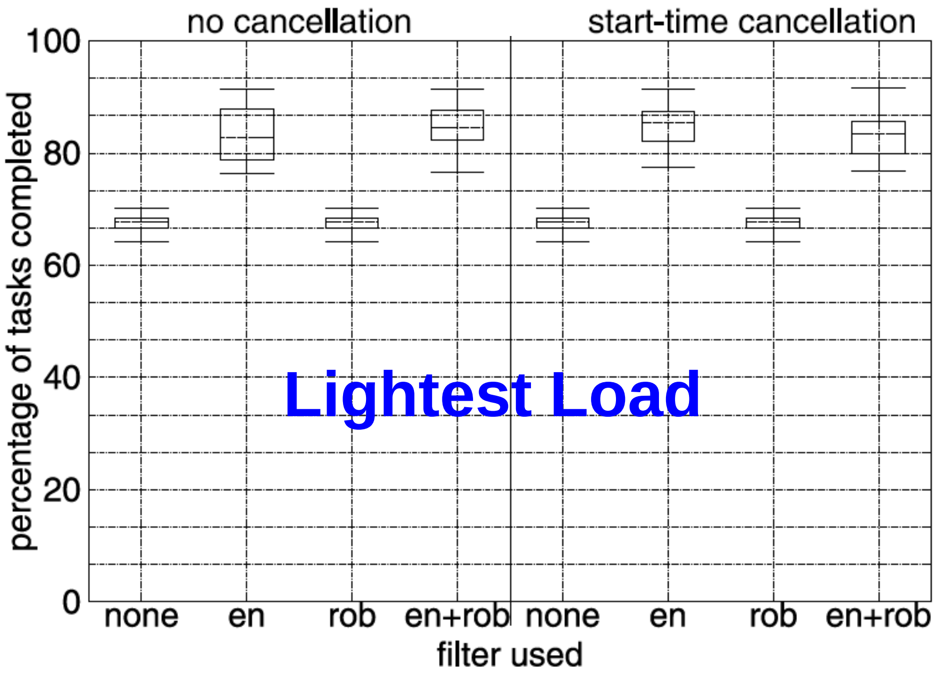
- randomly assign incoming task to a random core and P-state
- “robustness filter” and “energy + robustness filter” and “start time cancellation” improve over random assignment



Results: Random versus Heuristic

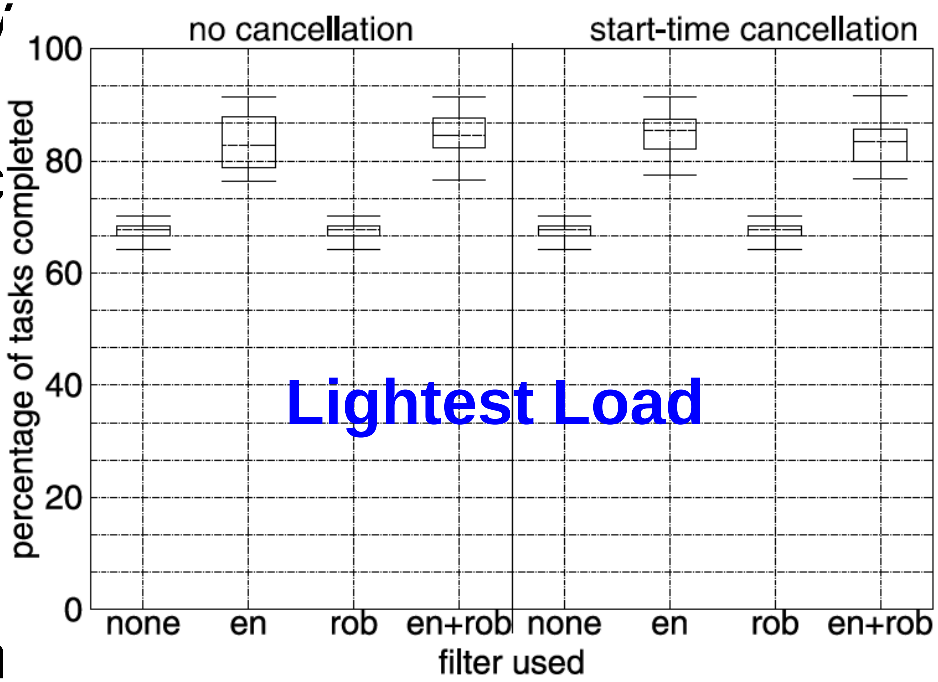
- heuristics better than Random





Results: Dynamic Study Discussion

- heuristics performed comparably
- filters together better than none
- filters more impact than heuristic choice or cancellation
- "robustness filter" little impact
  - probability task meeting its individual deadline
  - eliminating mappings that would not have been chosen



- "energy filter" ensures energy left for tasks that arrive later
- start-time cancellation has limited impact
  - heuristic already considers task execution times
  - difficult for start-time cancellation to predict perfectly

Outline

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Current and Future Research

- explore **stochastic robustness** allocation **heuristics** for different
  - static and dynamic
  - performance measure, constraints
  - workload and platform characteristics
- use **energy** or **power** as performance metric or constraint
- consider that **cost of power** may **vary** during day
- impact of DVFS for **memory vs. compute intensive** tasks
- study interaction of energy and **time-dependent utility** functions
- combine **multiple** uncertainties in single robustness measure
- combining PMFs/probabilities when **not independent** (ex**. DAG**)
- how to be robust with respect to **inaccuracies** in the PMFs
- model conflicts due to **resource sharing** in multi-core systems
- **thermal-aware** resource management
- **multi-objective optimization** of energy/power and QoS

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Concluding Remarks

- **The Three Robustness Questions**
  1. what behavior of the system makes it robust?
  2. what uncertainties is the system robust against?
  3. how is robustness of the system quantified?
- presented a stochastic model for robust resource allocation
- used stochastic robustness in energy-aware resource allocation
- listed areas for future research
- for more information and references to other relevant research
  www.engr.colostate.edu/~hj/Robust_Papers.pdf