Energy-efficient scheduling

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Energy: a crucial issue

- Data centers
  - $330, 000, 000, 000$ Watts hour in 2007: more than France
  - $533, 000, 000$ tons of CO_2: in the top ten countries
- Exascale computers (10^{18} floating operations per second)
  - Need effort for feasibility
  - 1% of power saved $\rightsquigarrow$ 1 million dollar per year
- Lambda user
  - 1 billion personal computers
  - $500, 000, 000, 000, 000$ Watts hour per year
- $\rightsquigarrow$ crucial for both environmental and economical reasons

Energy: a crucial issue

- Data centers
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Power dissipation of a processor

- $P = P_{\text{leak}} + P_{\text{dyn}}$
  - P_{leak}: constant
  - $P_{\text{dyn}} = B \times V^2 \times f$

constant

supply voltage

frequency

- Standard approximation: $P = P_{\text{leak}} + f^{\alpha}$ $\quad (2 \leq \alpha \leq 3)$
- Energy $E = P \times \mathit{time}$
- **D**ynamic **V**oltage and **F**requency **S**caling
  - Real life: discrete speeds
  - Continuous speeds can be emulated

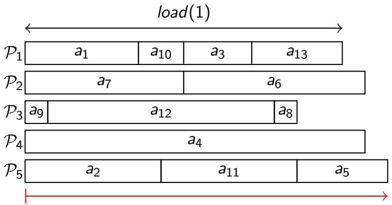
Outline

Framework

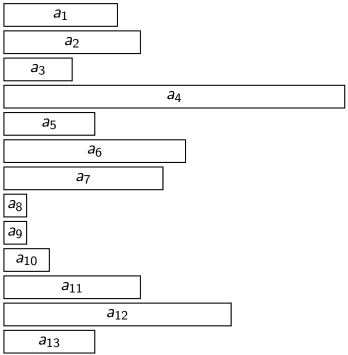
- Scheduling independent jobs
- GREEDY algorithm: assign next job to least-loaded processor
- Two variants:
  ONLINE-GREEDY: assign jobs on the fly
  OFFLINE-GREEDY: sort jobs before execution

Classical problem

- n independent jobs $\{J_i\}_{1 \leq i \leq n}$, a_i = size of J_i
- p processors $\{\mathcal{P}_q\}_{1 \leq q \leq p}$
- allocation function $alloc : \{J_i\} \to \{\mathcal{P}_q\}$
- load of $\mathcal{P}_q$ = $load(q) = \sum_{\{i \mid alloc(J_i)=\mathcal{P}_q\}} a_i$



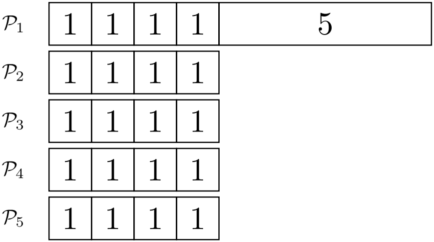
Execution time:
$\max_{1 \leq q \leq p} \quad load(q)$



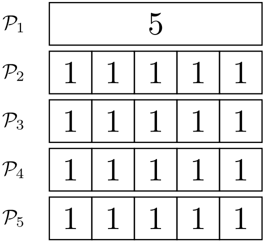
OnLine-Greedy

Theorem

OnLine-Greedy *is a* $2 - \frac{1}{p}$ *approximation (tight bound)*



OnLine-Greedy



Optimal solution

OffLine-Greedy

Theorem

OffLine-Greedy *is a* $\frac{4}{3} - \frac{1}{3p}$ *approximation (tight bound)*

$\mathcal{P}_1$	9	5	5
$\mathcal{P}_2$	9	5	
$\mathcal{P}_3$	8	6	
$\mathcal{P}_4$	8	6	
$\mathcal{P}_5$	7	7	

OffLine-Greedy

$\mathcal{P}_1$	5	5	5
$\mathcal{P}_2$	9	6	
$\mathcal{P}_3$	9	6	
$\mathcal{P}_4$	8	7	
$\mathcal{P}_5$	8	7	

Optimal solution

Bi-criteria problem

- Minimizing (dynamic) power consumption:
  $\Rightarrow$ use slowest possible speed $P_{dyn} = f^{\alpha} = f^3$

- Bi-criteria problem:
  Given bound $M = 1$ on execution time,
  minimize power consumption while meeting the bound

Bi-criteria problem statement

- n independent jobs $\{J_i\}_{1 \leq i \leq n}$, a_i = size of J_i
- p processors $\{\mathcal{P}_q\}_{1 \leq q \leq p}$
- allocation function $alloc : \{J_i\} \to \{\mathcal{P}_q\}$
- load of $\mathcal{P}_q = load(q) = \sum_{\{i \mid alloc(J_i)=\mathcal{P}_q\}} a_i$

$(load(q))^3$ power dissipated by $\mathcal{P}_q$

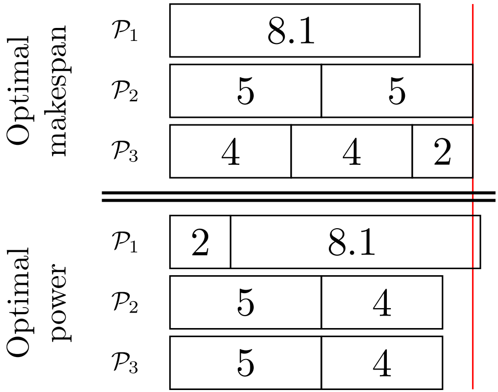
$\sum_{q=1}^{p} (load(q))^3$
Power

$\max_{1 \leq q \leq p} load(q)$
Execution time

Same GREEDY algorithm . . .

- Strategy: assign next job to least-loaded processor
- Natural for execution-time
  - smallest increment of maximum load
  - minimize objective value for currently processed jobs
- Natural for power too
  - smallest increment of total power (convexity)
  - minimize objective value for currently processed jobs

. . . but different optimal solution!



- Makespan 10, power 2531.441
- Makespan 10.1, power 2488.301

GREEDY and L_r norms

$$N_r = \left(\sum_{q=1}^{p} (load(q))^r \right)^{\frac{1}{r}}$$

- Execution time $N_\infty = \lim_{r \to \infty} N_r = \max_{1 \le q \le p} load(q)$
- Power $(N_3)^3$

Known results

N_2, OffLine-Greedy

- Chandra and Wong 1975: upper and lower bounds
- Leung and Wei 1995: tight approximation factor

N_3, OffLine-Greedy

- Chandra and Wong 1975: upper and lower bounds

N_r

- Alon et al. 1997: PTAS for offline problem
- Avidor et al. 1998: upper bound $2 - \Theta(\frac{\ln r}{r})$ for OnLine-Greedy

Contribution

N_3

- Tight approximation factor for ONLINE-GREEDY
- Tight approximation factor for OFFLINE-GREEDY

- Greedy for power fully solved!

Approximation for OnLine-Greedy

$$\frac{P_{\text{online}}}{P_{\text{opt}}} \leq \underbrace{\frac{\frac{1}{p^3}\left(\left(1+(p-1)\beta\right)^3+(p-1)\left(1-\beta\right)^3\right)}{\beta^3+\frac{(1-\beta)^3}{(p-1)^2}}}_{f_p^{(\text{on})}(\beta)}$$

Theorem

- *$f_p^{(\text{on})}$ has a single maximum in $\beta_p^{(\text{on})} \in [\frac{1}{p}, 1]$*
- OnLine-Greedy *is a $f_p^{(\text{on})}(\beta_p^{(\text{on})})$ approximation*
- *This approximation factor is tight*

Approximation for OffLine-Greedy

$$\frac{P_{\text{offline}}}{P_{\text{opt}}} \le \underbrace{\frac{\frac{1}{p^3}\left(\left(1+\frac{(p-1)\beta}{3}\right)^3 + (p-1)\left(1-\frac{\beta}{3}\right)^3\right)}{\beta^3 + \frac{(1-\beta)^3}{(p-1)^2}}}_{f_p^{(\text{off})}(\beta)}$$

Theorem

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- *This approximation factor is tight*

Numerical values of approximation ratios

p	OnLine-Greedy	OffLine-Greedy
2	1.866	1.086
3	2.008	1.081
4	2.021	1.070
5	2.001	1.061
6	1.973	1.054
7	1.943	1.048
8	1.915	1.043
64	1.461	1.006
512	1.217	1.00083
2048	1.104	1.00010
2^{24}	1.006	1.000000025

Large values of p

Asymptotic approximation factors

OnLine-Greedy	$\frac{4}{3}$	1
OffLine-Greedy	2	1

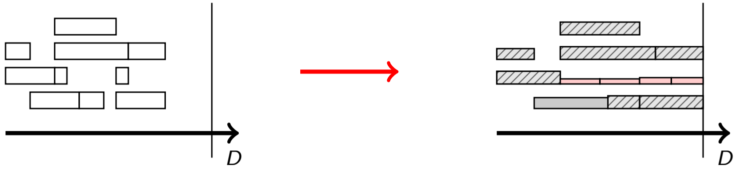
$\uparrow$ *optimal*

Outline

Motivation

- Mapping of tasks is given (ordered list for each processor and dependencies between tasks)
- If deadline not tight, why not take our time?
- Slack: unused time slots

Goal: efficiently use speed scaling (DVFS)



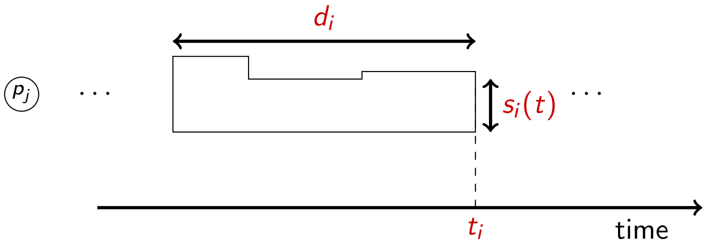
Speed models

		Change speed	
		Anytime	**Beginning of tasks**
Type of speeds	$[s_{\min}, s_{\max}]$	CONTINUOUS	-
	$\{s_1, ..., s_m\}$	VDD-HOPPING	DISCRETE, INCREMENTAL

- CONTINUOUS: great for theory
- Other "discrete" models more realistic
- VDD-HOPPING simulates CONTINUOUS
- INCREMENTAL is a special case of DISCRETE with equally-spaced speeds: for all $1 \leq q < m$, $s_{q+1} - s_q = \delta$

Tasks

- DAG: $\mathcal{G} = (V, E)$
- $n = |V|$ tasks T_i of weight $w_i = \int_{t_i - d_i}^{t_i} s_i(t)dt$
- d_i: task duration; t_i: time of end of execution of T_i



Parameters for T_i scheduled on processor p_j

Makespan

Assume T_i is executed at constant speed s_i

$$d_i = \mathcal{E}xe(w_i, s_i) = \frac{w_i}{s_i}$$

$$t_j + d_i \leq t_i \text{ for each } (T_j, T_i) \in E$$

Constraint on makespan:
$t_i \leq D$ for each $T_i \in V$

Energy

Energy to execute task T_i once at speed s_i:

$$E_i(s_i) = d_i s_i^3 = w_i s_i^2$$

$\rightarrow$ Dynamic part of classical energy models

Bi-criteria problem

- Constraint on deadline: $t_i \leq D$ for each $T_i \in V$
- Minimize energy consumption: $\sum_{i=1}^{n} w_i \times s_i^2$

Complexity results

Minimizing energy with fixed mapping on p processors:

- CONTINUOUS: Polynomial for some special graphs, geometric optimization in the general case
- DISCRETE: NP-complete (reduction from 2-partition); approximation algorithm
- INCREMENTAL: NP-complete (reduction from 2-partition); approximation algorithm
- VDD-HOPPING: Polynomial (linear programming)

Summary

- Results for CONTINUOUS, but not very practical

- In real life, DISCRETE model (DVFS)

- VDD-HOPPING: good alternative, mixing two consecutive modes, smoothes out the discrete nature of modes

- INCREMENTAL: alternate (and simpler in practice) solution, with one unique speed during task execution; can be made arbitrarily efficient

Outline

Framework

- DAG: $\mathcal{G} = (V, E)$
- $n = |V|$ tasks T_i of weight w_i

- p identical processors fully connected
- DVFS: interval of available continuous speeds $[s_{\min}, s_{\max}]$
- One speed per task

- (I will not discuss results for the VDD-HOPPING model)

Makespan

Execution time of T_i at speed s_i:

$$d_i = \frac{w_i}{s_i}$$

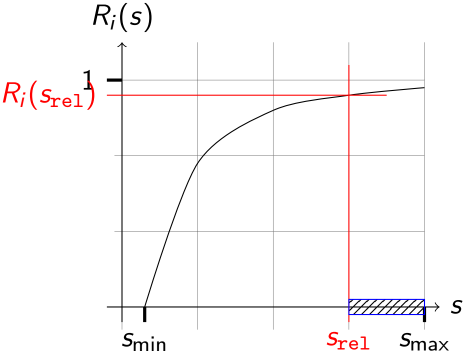
If T_i is executed twice on the same processor at speeds s_i and s'_i:

$$d_i = \frac{w_i}{s_i} + \frac{w_i}{s'_i}$$

Constraint on makespan:
end of execution before deadline D

Reliability

- *Transient fault*: local, no impact on the rest of the system
- Reliability R_i of task T_i as a function of speed s
- Threshold reliability (and hence speed $s_{\texttt{rel}}$)



Re-execution: a task is re-executed *on the same processor, just after its first execution*

With two executions, reliability R_i of task T_i is:

$$R_i = 1 - (1 - R_i(s_i))(1 - R_i(s_i'))$$

Constraint on reliability:
RELIABILITY: $R_i \geq R_i(s_{\texttt{rel}})$, and at most one re-execution

Energy

- Energy to execute task T_i once at speed s_i:

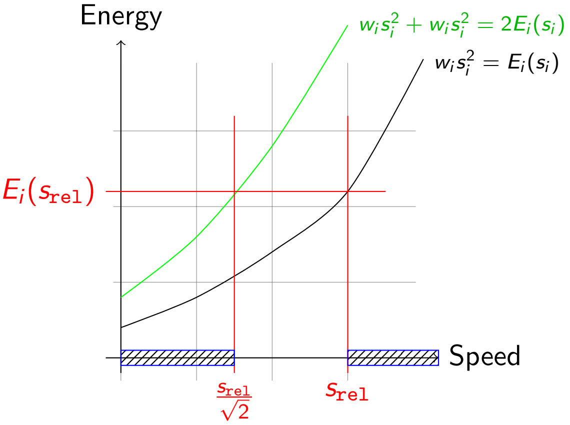
$$E_i(s_i) = w_i s_i^2$$

$\rightarrow$ Dynamic part of classical energy models

- With re-executions, it is natural to take the worst-case scenario:

$$\textsc{Energy} : E_i = w_i \left(s_i^2 + s_i'^2\right)$$

Energy and reliability: set of possible speeds



Tri-Crit-Cont

Given $\mathcal{G} = (V, E)$
Find

- A schedule of the tasks
- A set of tasks $I = \{i \mid T_i \text{ is executed twice}\}$
- Execution speed s_i for each task T_i
- Re-execution speed s'_i for each task in I

such that

$$\sum_{i \in I} w_i (s_i^2 + s_i'^2) + \sum_{i \notin I} w_i s_i^2$$

is minimized, while meeting reliability and deadline constraints

Complexity results

- One speed per task
- Re-execution at same speed as first execution, i.e., $s_i = s'_i$

- TRI-CRIT-CONT is NP-hard even for a linear chain, but not known to be in NP (because of CONTINUOUS model)
- Polynomial-time solution for a fork

Energy-reducing heuristics

Two steps:

- Mapping (NP-hard) → List scheduling
- Speed scaling + re-execution (NP-hard) → Energy reducing

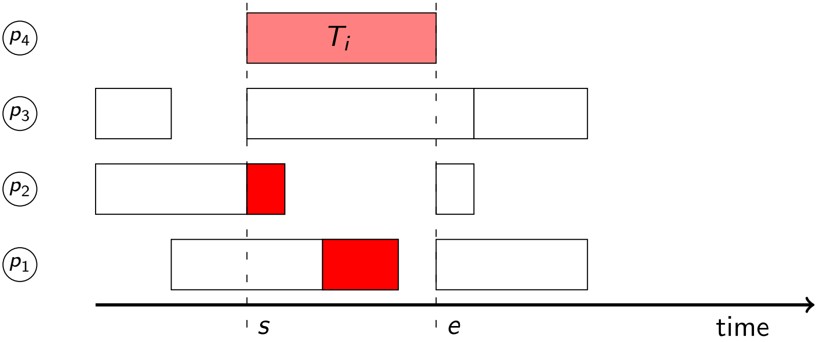
- The list-scheduling heuristic maps tasks onto processors at speed $s_{\max}$, and we keep this mapping in step two
- Step two = slack reclamation! Use of deceleration and re-execution

Deceleration and re-execution

- Deceleration: select a set of tasks that we execute at speed $\max(s_{\texttt{rel}}, s_{\max}\frac{\max_{i=1..n} t_i}{D})$: slowest possible speed meeting both reliability and deadline constraints
- Re-execution: greedily select tasks for re-execution

Super-weight (SW) of a task

- SW: sum of the weights of the tasks (including T_i) whose execution interval is included into T_i's execution interval
- SW of task slowed down = estimation of the total amount of work that can be slowed down together with that task



Selected heuristics

- **A.SUS-Crit**: efficient on DAGs with low degree of parallelism
  - Set the speed of every task to $\max(s_{\texttt{rel}}, s_{\max} \frac{\max_{i=1..n} t_i}{D})$
  - Sort the tasks of every *critical path* according to their **SW** and try to re-execute them
  - Sort all the tasks according to their **weight** and try to re-execute them

- **B.SUS-Crit-Slow**: good for highly parallel tasks: re-execute, then decelerate
  - Sort the tasks of every *critical path* according to their **SW** and try to re-execute them. If not possible, then try to slow them down
  - Sort all tasks according to their **weight** and try to re-execute them. If not possible, then try to slow them down

Results

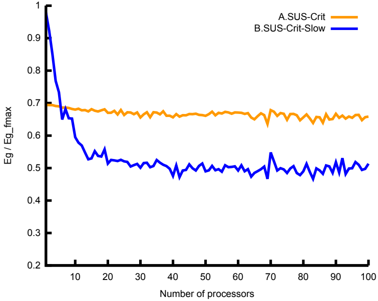
We compare the impact of:

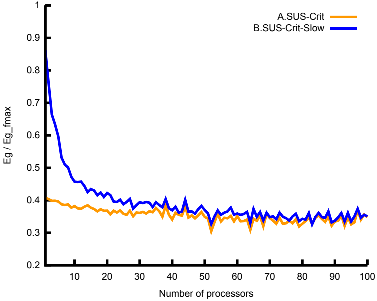
- the number of processors p
- the ratio D of the deadline over the minimum deadline D_{min} (given by the list-scheduling heuristic at speed s_{max})

on the output of each heuristic

Results normalized by heuristic running each task at speed s_{max}; the lower the better

Results





With increasing p, $D = 1.2$ (left), $D = 2.4$ (right)

- A better when number of processors is small
- B better when number of processors is large
- Superiority of B for tight deadlines: decelerates critical tasks that cannot be re-executed

Summary

- Tri-criteria energy/makespan/reliability optimization problem
- Various theoretical results
- Two-step approach for polynomial-time heuristics:
  - List-scheduling heuristic
  - Energy-reducing heuristics
- Two complementary energy-reducing heuristics for TRI-CRIT-CONT

Outline

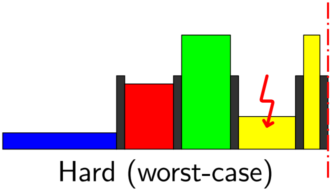
Framework

- Execution of a divisible task (W operations)
- Failures may occur
  - Transient faults
  - Resilience through checkpointing
- Objective: minimize expected energy consumption $\mathbb{E}(E)$, given a deadline bound D

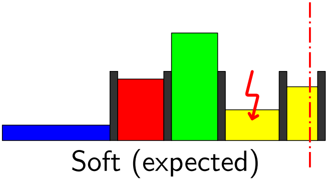
- Probabilistic nature of failure hits: expectation of energy consumption is natural (average cost over many executions)
- Deadline bound: two relevant scenarios (soft or hard deadline)

Soft vs hard deadline

- Soft deadline: met in expectation, i.e., $\mathbb{E}(T) \leq D$ (average response time)
- Hard deadline: met in the worst case, i.e., $T_{wc} \leq D$



VS



Execution time, one single chunk

One single chunk of size W

- Checkpoint overhead: execution time T_C
- Instantaneous failure rate: λ

- First execution at speed s: $T_{\text{exec}} = \frac{W}{s} + T_C$
- Failure probability: $P_{\text{fail}} = \lambda T_{\text{exec}} = \lambda(\frac{W}{s} + T_C)$
- In case of failure: re-execute at speed σ: $T_{\text{reexec}} = \frac{W}{\sigma} + T_C$
- And we assume success after re-execution

- $\mathbb{E}(T) = T_{\text{exec}} + P_{\text{fail}} T_{\text{reexec}} = (\frac{W}{s} + T_C) + \lambda(\frac{W}{s} + T_C)(\frac{W}{\sigma} + T_C)$
- $T_{wc} = T_{\text{exec}} + T_{\text{reexec}} = (\frac{W}{s} + T_C) + (\frac{W}{\sigma} + T_C)$

Energy consumption, one single chunk

One single chunk of size W

- Checkpoint overhead: energy consumption E_C

- First execution at speed s: $\frac{W}{s} \times s^3 + E_C = Ws^2 + E_C$
- Re-execution at speed σ: $W\sigma^2 + E_C$, with probability P_{fail} $\left(P_{\text{fail}} = \lambda T_{\text{exec}} = \lambda(\frac{W}{s} + T_C)\right)$

- $\mathbb{E}(E) = (Ws^2 + E_C) + \lambda \left(\frac{W}{s} + T_C\right) \left(W\sigma^2 + E_C\right)$

Multiple chunks

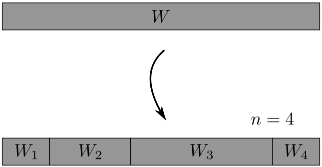
- Execution times: sum of execution times for each chunk (worst-case or expected)
- Expected energy consumption: sum of expected energy for each chunk

- Coherent failure model: consider two chunks $W_1 + W_2 = W$
- Probability of failure for first chunk: $P^1_{\text{fail}} = \lambda(\frac{W_1}{s} + T_C)$
- For second chunk: $P^2_{\text{fail}} = \lambda(\frac{W_2}{s} + T_C)$
- With a single chunk of size W: $P_{\text{fail}} = \lambda(\frac{W}{s} + T_C)$, differs from $P^1_{\text{fail}} + P^2_{\text{fail}}$ only because of extra checkpoint

- Trade-off: many small chunks (more T_C to pay, but small re-execution cost) vs few larger chunks (fewer T_C, but increased re-execution cost)

Optimization problem

- Decisions that should be taken before execution:
  - Chunks: how many (n)? which sizes (W_i for chunk i)?
  - Speeds of each chunk: first run (s_i)? re-execution (σ_i)?
- Input: W, T_C (checkpointing time), E_C (energy spent for checkpointing), λ (instantaneous failure rate), D (deadline)



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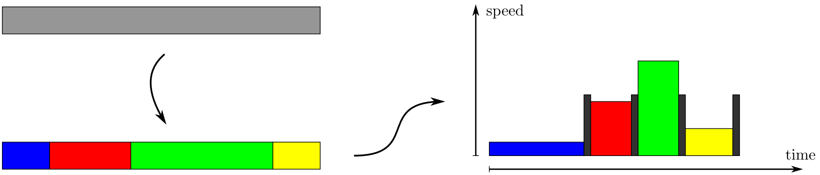

Optimization problem

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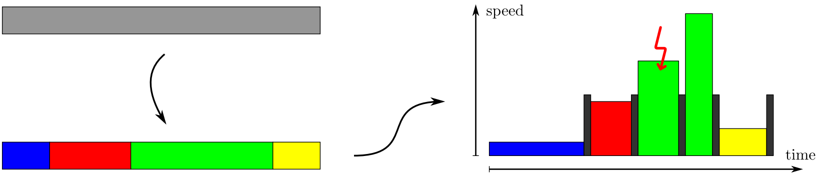


Models

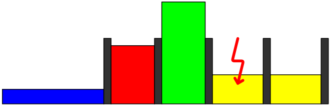
- Chunks

Single chunk of size W

VS

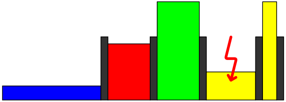
Multiple chunks (n and W_i's)

- Speed per chunk



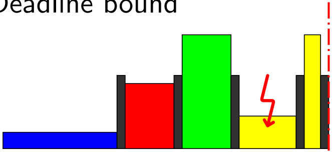
Single speed (s)

VS



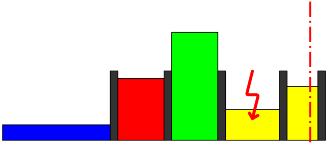
Multiple speeds (s and σ)

- Deadline bound



Hard ($T_{wc} \leq D$)

VS



Soft ($\mathbb{E}(T) \leq D$)

Single chunk and single speed

Consider first that $s = \sigma$ (single speed): need to find optimal speed

- $\mathbb{E}(E)$ is a function of s:
$$\mathbb{E}(E)(s) = (Ws^2 + E_C)(1 + \lambda(\frac{W}{s} + T_C))$$
- Lemma: this function is convex and has a unique minimum $s^\star$ (function of λ, W, E_c, T_c)
$$s^\star = \frac{\lambda W}{6(1+\lambda T_C)} \left(\frac{-(3\sqrt{3}\sqrt{27a^2-4a}-27a+2)^{1/3}}{2^{1/3}} - \frac{2^{1/3}}{(3\sqrt{3}\sqrt{27a^2-4a}-27a+2)^{1/3}} - 1 \right),$$
where $a = \lambda E_C \left(\frac{2(1+\lambda T_C)}{\lambda W} \right)^2$
- $\mathbb{E}(T)$ and T_{wc}: decreasing functions of s
- Minimum speed s_{exp} and s_{wc} required to match deadline D (function of D, W, T_c, and λ for s_{exp})

$\rightarrow$ Optimal speed: maximum between $s^\star$ and s_{exp} or s_{wc}

Single chunk and multiple speeds

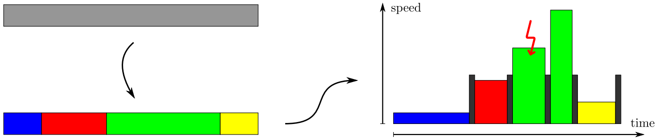
Consider now that $s \neq \sigma$ (multiple speeds): two unknowns

- $\mathbb{E}(E)$ is a function of s and σ:
  $$\mathbb{E}(E)(s,\sigma) = (Ws^2 + E_C) + \lambda(\frac{W}{s} + T_C)(W\sigma^2 + E_C)$$
- Lemma: energy minimized when deadline tight (both for wc and exp)
- $\rightsquigarrow$ σ expressed as a function of s:
  $$\sigma_{exp} = \frac{\lambda W}{\frac{D}{\frac{W}{s}+T_C} - (1+\lambda T_C)}, \quad \sigma_{wc} = \frac{W}{(D-2T_C)s - W} s$$

$\rightarrow$ Minimization of single-variable function, can be solved numerically (no expression of optimal s)

General problem with multiple chunks

- Divisible task of size W
- Split into n chunks of size W_i: $\sum_{i=1}^{n} W_i = W$
- Chunk i is executed once at speed s_i, and re-executed (if necessary) at speed σ_i
- Unknowns: n, W_i, s_i, σ_i
- $$\mathbb{E}(E) = \sum_{i=1}^{n} \left(W_i s_i^2 + E_C\right) + \lambda \sum_{i=1}^{n} \left(\frac{W_i}{s_i} + T_C\right) \left(W_i \sigma_i^2 + E_C\right)$$



Multiple chunks and single speed

With a single speed, $\sigma_i = s_i$ for each chunk

- Theorem: in optimal solution, n equal-sized chunks $(W_i = \frac{W}{n})$, executed at same speed $s_i = s$
  - Proof by contradiction: consider two chunks W_1 and W_2 executed at speed s_1 and s_2, with either $s_1 \neq s_2$, or $s_1 = s_2$ and $W_1 \neq W_2$
  - $\Rightarrow$ Strictly better solution with two chunks of size $w = (W_1 + W_2)/2$ and same speed s

- Only two unknowns, s and n
- Minimum speed with n chunks: $s^{\star}_{exp}(n) = W \dfrac{1 + 2\lambda T_C + \sqrt{4\frac{\lambda D}{n} + 1}}{2(D - nT_C(1 + \lambda T_C))}$

$\rightarrow$ Minimization of double-variable function, can be solved numerically both for expected and hard deadline

Multiple chunks and multiple speeds

Need to find n, W_i, s_i, σ_i

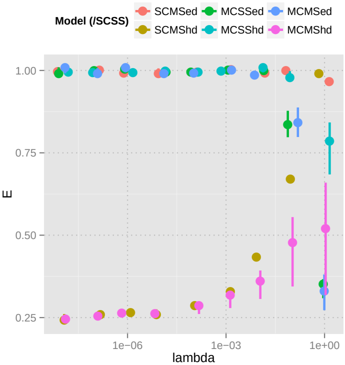
- With expected deadline:
  - All re-execution speeds are equal ($\sigma_i = \sigma$) and tight deadline
  - All chunks have same size and are executed at same speed
- WIth hard deadline:
  - If $s_i = s$ and $\sigma_i = \sigma$, then all W_i's are equal
  - Conjecture: equal-sized chunks, same first-execution / re-execution speeds
- σ as a function of s, bound on s given n

$\rightarrow$ Minimization of double-variable function, can be solved numerically

Simulation settings

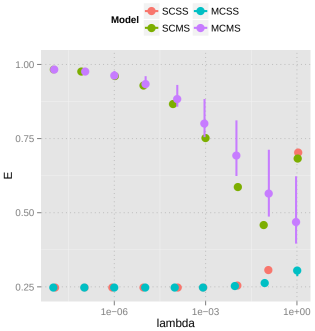
- Large set of simulations: illustrate differences between models
- Maple software to solve problems
- We plot relative energy consumption as a function of λ
  - The lower the better
  - Given a deadline constraint (hard or expected), normalize with the result of single-chunk single-speed
  - Impact of the constraint: normalize expected deadline with hard deadline
- Parameters varying within large ranges

Comparison with single-chunk single-speed



- Results identical for any value of W/D
- For expected deadline, with small λ ($< 10^{-2}$), using multiple chunks or multiple speeds do not improve energy ratio: re-execution term negligible;
  increasing λ: improvement with multiple chunks
- For hard deadline, better to run at high speed during second execution: use multiple speeds; use multiple chunks if frequent failures

Expected vs hard deadline constraint



- Important differences for single speed models, confirming previous conclusions: with hard deadline, use multiple speeds
- Multiple speeds: no difference for small λ: re-execution at maximum speed has little impact on expected energy consumption;
  increasing λ: more impact of re-execution, and expected deadline may use slower re-execution speed, hence reducing energy consumption

Outline

Conclusion

- OnLine-Greedy and OffLine-Greedy for power: tight approximation factor for any p, extends long series of papers and completely solves N_3 minimization problem ☺
- Different energy models, from continuous to discrete (through VDD-hopping and incremental)
- Tri-criteria heuristics with re-execution to deal with reliability
- Checkpointing techniques for reliability while minimizing energy consumption

On-going and future research directions

- Investigate other reliability models (for instance, local constraints on reliability of each task, or global reliability of success of the execution of the DAG)

- Consider both re-execution and replication (recent results for linear chains and independent tasks: approximation algorithms)

- Checkpointing at the exascale: find the optimal checkpointing period (with the goal of minimizing the energy consumption)

What we had:

Energy-efficient scheduling
+
frequency scaling

What we aim at: