Scheduling Algorithms for Variable Capacity Resources

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Scheduling Variable Capacity Resources for Sustainability
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Motivation

- **Online scheduling techniques**: at the heart of *batch schedulers*
- **Schedule independent jobs on parallel HPC platforms**

**Optimization objectives:**

- **Utilization** (platform owner’s perspective) – fraction of time where platform resources execute computations
- **Stretch** (user’s perspective) – minimize the maximum (or sometimes average) stretch of jobs, defined as the response time normalized by the job length
Motivation: Variable capacity

- Green computing: total available power evolves with time (cost, wind or solar energy, ...)
- How to efficiently schedule when variations in power supply imply changes in the number of available computing resources over time?
- Need to be prepared to variations: if a machine is shut down, all its jobs must be re-executed
- Design of risk-aware strategies that assign incoming jobs to the right target machine, for our optimization criteria
- Platform utilization no longer an adequate criterion (partial executions of jobs that get killed do not count as actual progress of the jobs) ⇒ Goodput – useful platform utilization, accounting only for jobs that are running or have completed
Outline

1. Framework and complexity
2. Heuristics
3. Simulations
4. Conclusion
Platform and jobs

Platform:

- Set $\mathcal{M}$ of $M^+$ identical parallel machines, each equipped with $n_c$ cores, and requiring power $P$ when switched on.
- Overall available power capacity $P(t)$: function of time $t$ (time discretized) $\Rightarrow M_{\text{alive}}(t)$ machines alive.
- $b_{m,t}$: boolean decision variable, equal to 1 if machine $m$ is active at time $t$ and 0 otherwise: $\forall t, \sum_{m\in \mathcal{M}} b_{m,t} \times P \leq P(t)$

Jobs:

- Set $\mathcal{J}$; job $\tau_i \in \mathcal{J}$ released at date $r_i$, needs $c_i$ cores, has length $w_i$; allocated to machine $m_i$ at starting date $s_i$.
- (Predicted) completion date of job $\tau_i$: $e_i = s_i + w_i$ if not interrupted.
- At any time, cores used by running jobs on a machine $\leq n_c$. 
Objective function: Goodput

- $J_{comp,T}$: set of jobs that are complete at time $T$ ($e_i \leq T$)
- $\tau_i \in J_{started,T}$: set of jobs running and not dead at time $T$ ($s_i \leq T < e_i$)

Total number of units of work that can be executed in $[0, T]$:
- at most $\sum_{t \in [0, T-1]} M_{alive}(t)n_c$,

**Goodput**($T$) – fraction of useful work up to time $T$:

$$\text{Goodput}(T) = \frac{\sum_{\tau_i \in J_{comp,T}} w_i c_i + \sum_{\tau_i \in J_{started,T}} (T - s_i)c_i}{n_c \sum_{t \in [0, T-1]} M_{alive}(t)}$$
**Theorem**

An adversary can force any schedule to achieve no goodput at all, even with a single unicore machine.

- Job $\tau_1$ of size $c_1 = 1$ and duration $w_1 = K$ released at time $t = r_1 = 0$; **Goodput** of the machine at time $T = K$

- Start $\tau_1$ at time $s_1 > 0$: machine interrupted at time $K$
An adversary can force any schedule to achieve no goodput at all, even with a single uncore machine.

- Job $\tau_1$ of size $c_1 = 1$ and duration $w_1 = K$ released at time $t = r_1 = 0$; Goodput of the machine at time $T = K$

- Start $\tau_1$ at time $s_1 = 0$: new job $\tau_2$, machine interrupted at time $K - 1$
Algorithms: Take action whenever an event occurs

- **Job Arrival Event** – *Job released*: decide when to schedule it and on which machine

- **Job Completion Event** – *Job completed*: release the cores it was using, possibly allowing for additional jobs to be scheduled

- **Machine Addition Event** – *New machine available*: decide how to utilize it

- **Machine Removal Event** – *Machine switched off*: kill jobs and decide how to reallocate them

Different heuristics take different decisions
**FirstFitAware and FirstFitUnaware**

**Baseline heuristics:**

- Machines labeled from 1 to $M^+$; jobs scheduled on the machine with the smallest available index that has enough free resources to execute it.
- Use of waiting queue for pending jobs.
- When a machine needs to be switched off, **FirstFitAware** kills the machine with the highest index.

- **FirstFitUnaware**: Not aware of the risk of shutdown incurred by the machines, and hence switches off randomly a machine rather than ordering them by index.
**TargetStretch**

- Interrupting long job $\Rightarrow$ significant work loss

Schedule smaller jobs on machines that are likely to be turned off (large indices), and longer jobs on machines that will never be turned off (small indices)

- Consider a target stretch value, and one queue per machine

For the **TargetStretch** heuristic, at each **Job arrival event**: compute the job’s target machine; consider neighboring machine if target stretch not achievable

- Set of risk-free machines recomputed at machine addition/removal events, and jobs might be reallocated
**TargetASAP and PackedTargetASAP**

- **In TargetStretch**, with large target stretch, **bad utilization** as job goes to target machine; no flexibility to go to another free machine.

- **TargetASAP** proposes a new strategy at **job arrival event**:
  - try to start job immediately on target machine or on closest machine in the neighborhood;
  - if not possible, assign on target machine if target stretch not exceeded;
  - otherwise, assign on machine where it can start ASAP (within acceptable distance)

- **Variant PackedTargetASAP**: group machines per packs, and assign jobs to first machines of the pack, to leave machines empty for future jobs with large number of cores.
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Simulation setting

- **In-house simulator**, using a combination of two traces:
  - **Resource variation trace** representing the number of machines alive at any given time – Use of a random walk, within an interval

- **Job trace:**
  - **Real traces** coming from **Borg** (two-week traces with jobs coming from **Google** cluster management software: release dates, lengths, number of cores)
  - **Synthetic traces** to study the impact of parameters (three variants: uniform lengths, log scale, and three types of jobs)
Varying the number of machines

- **FirstFitAware** and **FirstFitUnaware** never good
- **TargetStretch**: different behavior because of its lack of flexibility, some machines remain partially inactive even when jobs are waiting (better with fewer machines)
- **TargetASAP** always good, and the packed variant **PackedTargetASAP** even better
Varying the period of machine variation

- As before, limited impact of workflow
- With low period (many changes), `TARGETSTRETCH` better by preserving long jobs
- `Goodput` increases with the period: less changes means less job interruptions
- More impact of new `TARGETASAP` and `PackedTargetASAP` strategies with high variability (low periods)
Exploring other metrics

Different metrics to analyze the results for **BORG** (varying the range of the machines)

- **Increase in range** ⇒ **Degradation of the metric**
- **TARGETSTRETCH** achieves the lowest maximum stretch, as well as low aborted volume and time
- However, low utilization of machines for **TARGETSTRETCH**, with low **goodput**
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Conclusion

- Right in scope of the workshop: **Scheduling with variable capacity resources**
- **Formalization** of the problem, model and objective functions
- First attempt at providing **practical solutions** to the problem
- **TARGETSTRETCH** very good to minimize maximum stretch, but leads to a poor resource utilisation
- Clever strategies **TARGETASAP** and **PackedTARGETASAP** achieve very good **goodput**

- **On-going collaboration**, looking forward to new ideas emerging from discussions these days 😊