Scheduling Algorithms for Variable Capacity Resources

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Joint work with Y. Robert, L. Perotin, J. Cendrier, F. Vivien (ENS Lyon)
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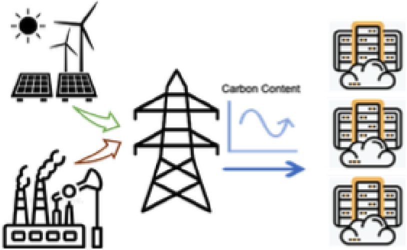
May 16, 2024 – New Challenges in Scheduling Theory – Aussois

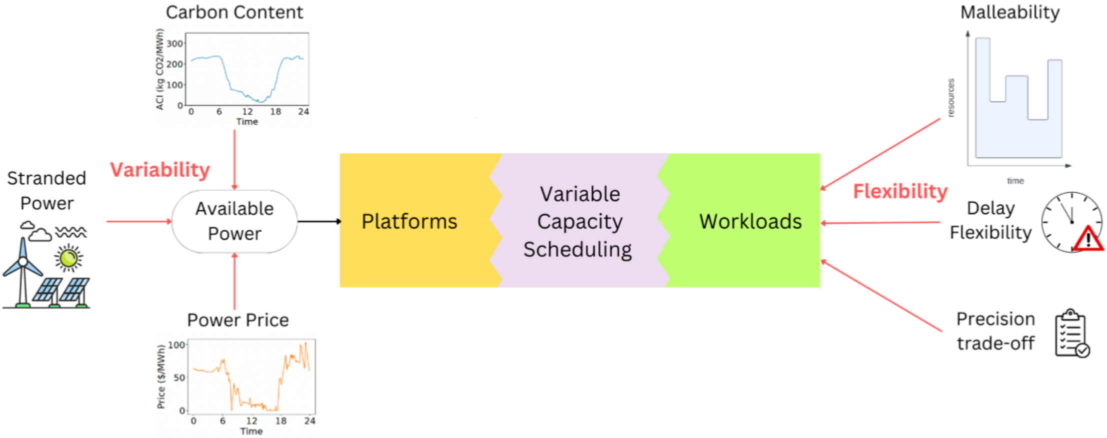
Variable power



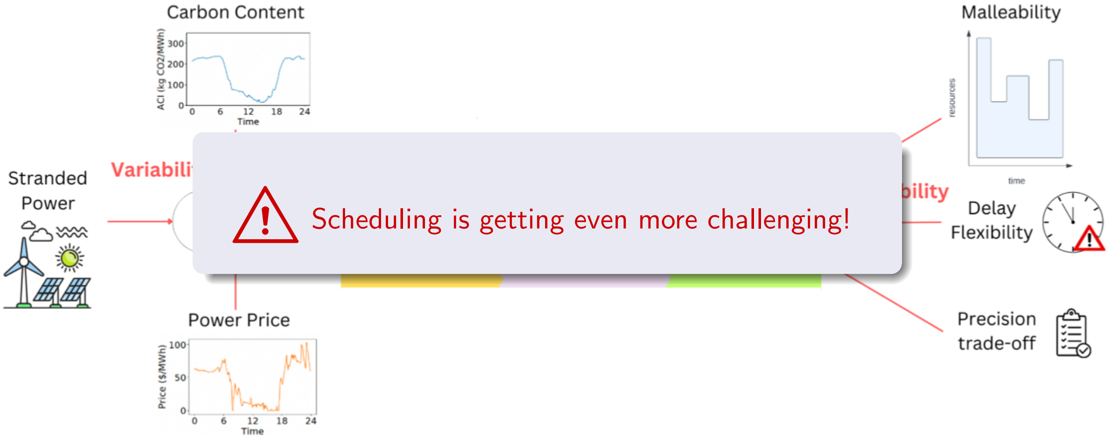
- Today's data centers assume resource capacity as a fixed quantity
- Emerging approaches:
  - Exploit grid renewable energy
  - Reduce carbon emissions

⇒ Variable power

Big picture


Carbon Content
ACI (kg CO2/MWh)
300
200
100
0
0
6
12
18
24
Time
Stranded Power
Variability
Available Power
Power Price
Price ($/MWh)
100
50
0
0
6
12
18
24
Time
Platforms
Variable Capacity Scheduling
Workloads
Malleability
resources
time
Flexibility
Delay Flexibility
Precision trade-off

Big picture

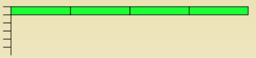


⚠ Scheduling is getting even more challenging!

Outline

1. Variable capacity scheduling
2. Case study (with U. Chicago)
3. With checkpoints
4. Conclusion

Parallel jobs



- **Rigid jobs**: Processor allocation is fixed
- **Moldable jobs**: Processor allocation is decided by the user or the system but cannot be changed during execution
- **Malleable jobs**: Processor allocation can be dynamically changed

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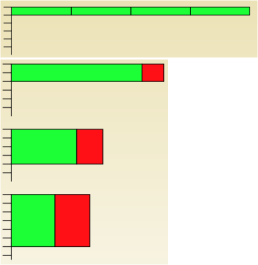

Parallel jobs

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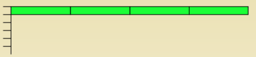

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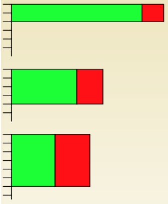

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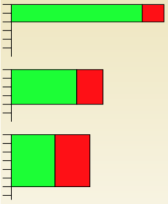


- **Malleable jobs**: Processor allocation can be dynamically changed

The case for moldable jobs:

- Easily adapt to the amount of available resources (contrarily to rigid jobs)
- Easy to design/implement (contrarily to malleable jobs)
- Computational kernels in scientific libraries are provided as moldable jobs

Checkpoints

- Some jobs cannot be interrupted
- Some jobs can be checkpointed

Half the projected load for US Exascale systems include checkpointing capabilities (from APEX worklows, Sandia/LosAlamos/NERSC report, April 2016)

Checkpoints

Scheduling opportunity

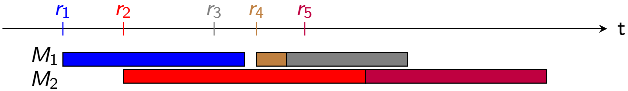
- Many checkpointable jobs are moldable
- These jobs are able to restart with a different allocation (size and shape)

⚠ Resizing impacts performance

(from APEX workflows, Sandia/LosAlamos/NERSC report, April 2016)

Risk aware?

1. **Which machine to shutdown?**



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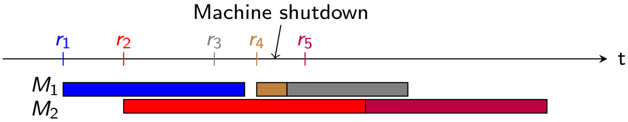

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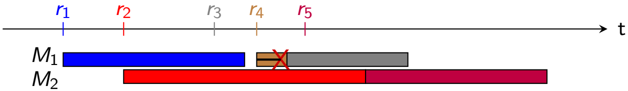

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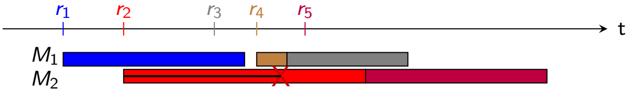

Risk aware?

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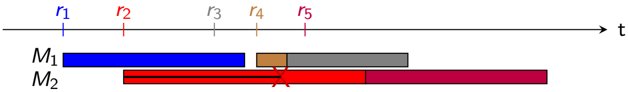

② **How to schedule jobs to minimize impact?**

Main questions

- When power decreases, which machines to power off? Which jobs to interrupt? And to re-schedule?
- Are we notified ahead of a power change?
    - Resource variation in power obeys specific parameters whose evolution is dictated by a mix of technical availability and economic conditions
    - Accurate external predictor (precision, recall)? Maybe too optimistic ☹
- Re-scheduling interrupted jobs
    - Can we take a proactive checkpoint before the interruption?
    - Which priority should be given to each interrupted job?
    - Which geometry and which nodes for re-execution?

Main questions

- When power decreases, which machines to power off? Which jobs to interrupt? And to re-schedule?
- Are we notified ahead of a power change?

Scheduling opportunity & challenge

- Nodes ordered according to non-decreasing risk, say from left to right
- Shutdown nodes starting from the right
- Assign priority jobs, such as large jobs, to nodes on the left
- Global load of the platform must remain balanced

⚠ Sophisticated algorithms that go well beyond first-fit decisions

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Platform

- Set $\mathcal{M}$ of M^+ identical parallel machines, each equipped with n_c cores, and requiring power P when switched on
- Global available power capacity $P(t)$: function of time t (time discretized) $\Rightarrow M_{alive}(t)$ machines alive, with $M_{alive}(t)P \leq P(t)$

Rigid 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 τ_i: $e_i = s_i + w_i$ if not interrupted
- At any time, total cores used by running jobs on a machine $\leq n_c$

Resource variation

- The number of alive machines evolves over time (either random-length phases, or fixed-length periods)
- The number of alive machines in the next phase/period is not known in advance
- Technically, $M_{alive}(t)$:
  - Always ranges in interval $[M^- = M_{avg} - M_{ra}, M^+ = M_{avg} + M_{ra}]$ centered in M_{avg}
  - Evolves according to some random walk, starting with M_{avg}
  - Stays constant, increases or decreases with same probability (if range bound reached, stays constant or evolves in unique possible direction, with same probability)
  - Magnitude of variation controlled by another variable

Limitations

- Rigid jobs ⇒ no flexibility in size
- Identical multicore machines
- No checkpoints
- Power consumption at time t proportional to $M_{alive}(t)$ (actual load not accounted for)
- Resource variation not known until change

Objective function: Goodput

- $\mathcal{J}_{comp,T}$: set of jobs that are complete at time T $(e_i \leq T)$
- $\mathcal{J}_{started,T}$: set of jobs running and not finished at time T $(s_i \leq T < e_i)$
- Total number of units of work that can be executed in $[0, T]$:

$$n_c \sum_{t \in [0, T-1]} M_{alive}(t)$$

- $\textsc{Goodput}(T)$ is the fraction of useful work up to time T:

$$\textsc{Goodput}(T) = \frac{\sum_{\tau_i \in \mathcal{J}_{comp,T}} w_i c_i + \sum_{\tau_i \in \mathcal{J}_{started,T}} (T - s_i) c_i}{n_c \sum_{t \in [0, T-1]} M_{alive}(t)}$$

Keep an eye on maximum stretch

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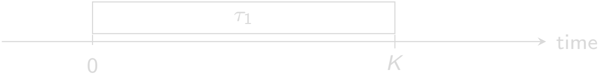
Keep an eye on maximum stretch

Complexity

Theorem

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

- Job τ_1 of size $c_1 = 1$ and duration $w_1 = K$ released at time $t = r_1 = 0$; Goodput of the machine at time $T = K$?



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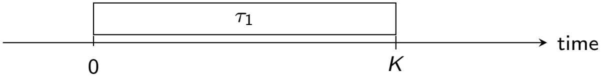

- Start τ_1 at time $s_1 > 0$: machine interrupted at time K

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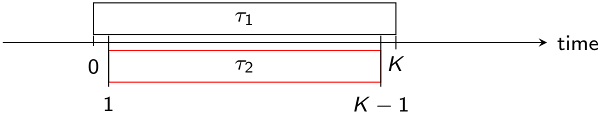
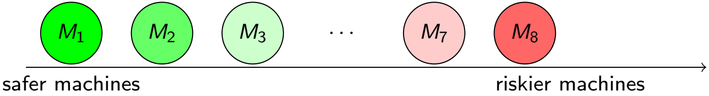


- Start τ_1 at time $s_1 = 0$: new job τ_2, machine interrupted at time $K-1$

Risk-aware



Risk-aware job allocation strategies

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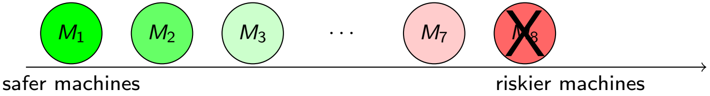

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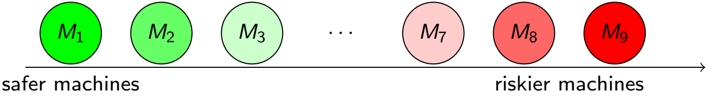

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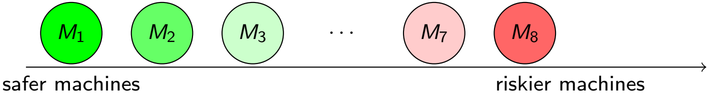

Risk-aware job allocation strategies

Events:

- **Job arrival**: When a job is released, when to schedule it and on which machine?
- **Job completion**: When a job is completed, its cores are released ⇒ additional jobs can be scheduled
- **Machine addition**: When a new machine becomes available, how to utilize it?
- **Machine removal**: When a machine is turned off, its jobs are killed and need re-allocation

FIRSTFITAWARE

- **Job arrival**
  Assign incoming job to smallest-index machine with enough free resources
  If no machine can execute the job, it is placed in waiting queue
- **Job completion**
  Check the queue for job with smallest release date that fits in the machine *m* with completed job, and assigns it to *m*
  If a job is assigned, continues to search the queue
  If empty queue or not enough cores in *m* for any waiting job ⇒ no action
- **Machine addition**
  Assign jobs to the new machine in order of increasing release date
- **Machine removal**
  Shut down machine with highest index, put all its jobs in the queue
  Assign jobs to available machines in order of increasing release date

FirstFitAware

- **Job arrival**

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  vith

Risk-aware

- Ordered list of machines
- Jobs mapped to leftmost (safer) machines whenever possible
- Rightmost (riskier) machines are shutdown whenever necessary

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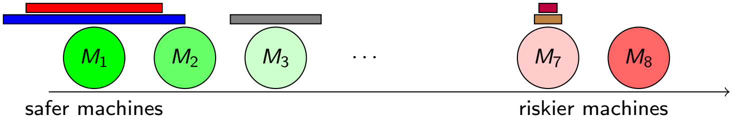
FirstFitUnaware: Shutdown random machines whenever necessary

Interrupting a long job is a big performance loss

Schedule smaller jobs on machines that are likely to be turned off

Schedule longer jobs on risk-free machines

TARGETSTRETCH



- Add one queue per machine
- Set target value for (target) maximum stretch
- **Job arrival**
  Compute job's target machine
  Consider neighboring machines if target stretch not achievable
- **Machine addition/removal**
  Set of risk-free machines recomputed
  Re-allocate pending jobs

TARGETASAP & PACKEDTARGETASAP

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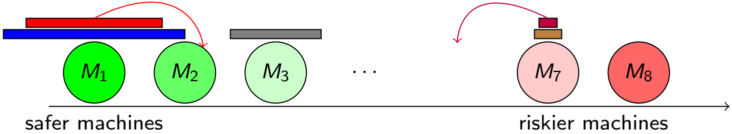

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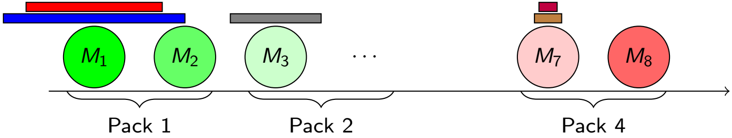
- Variant PACKEDTARGETASAP: group machines into packs, and assign jobs to first machines of the pack, to leave machines empty for future large jobs



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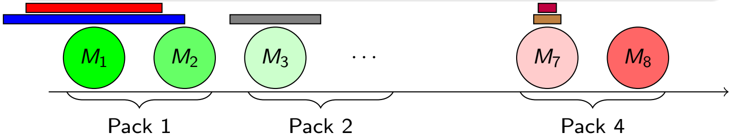
Technical and kind of painful
despite all simplifying hypotheses ☹



Simulation setting

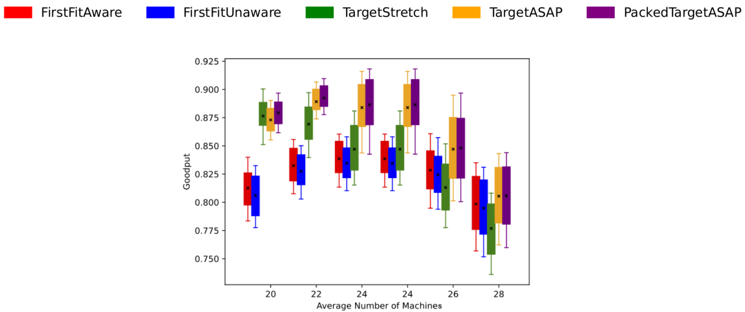
In-house simulator, using a combination of two traces:

- Resource variation trace: 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) ⇒ similar conclusions

Dimensioning

- Number of available machines always in $[M_{avg} - M_{ra}, M_{avg} + M_{ra}]$
- Total work hours $\approx$ maximum capacity of 26 machines each with 24 cores, running during 2 weeks with full peak load
- Average number of machines: $M_{avg} = 24$
- Period of machine variation: $\phi = 20mn$
- Range of machine variation: $M_{ra} = 8$; half the machines are safe
- Number of cores per machine: $n_c = 24$. Jobs typically use $1, 2, 4, 8$ cores
- Conservative backfilling at machine level

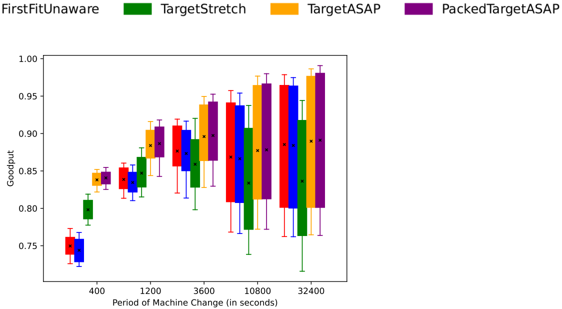
Varying the number of machines



Borg

- 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 packed variant PackedTargetASAP even better

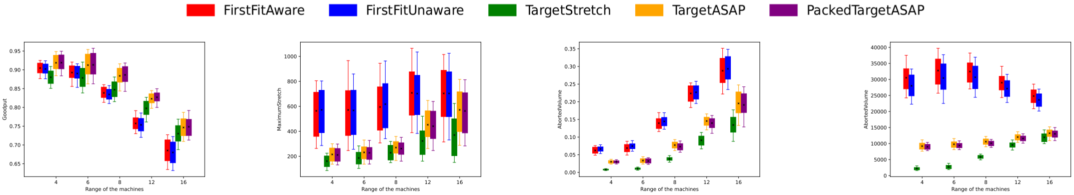
Varying the period of machine variation



Borg

- With low period (many changes), TargetStretch better by preserving long jobs
- Goodput increases with period: less changes ⇒ less job interruptions
- Better relative performance of TargetASAP and PackedTargetASAP with low periods (= high variability)

Exploring other metrics (Borg)



Goodput MaximumStretch AbortedVolume AverageAbortedTime

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

Conclusion for this case study

- A simple case-study of scheduling with variable capacity resources
- Primary challenge: when capacity decreases, running jobs need to be terminated to meet required power load reduction
- Online risk-aware scheduling strategies to preserve performance:

  map the right job to the right machine
- Algorithmic techniques: risk index per machine, mapping longer jobs to safer machines, maintaining local queues at machines, re-executing interrupted jobs on new machines, and redistributing pending jobs as resource capacity increases
- Significant gains over first-fit algorithms with up to 10% increase in goodput, and better performance in complementary metrics (maximum and average stretch)

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Model

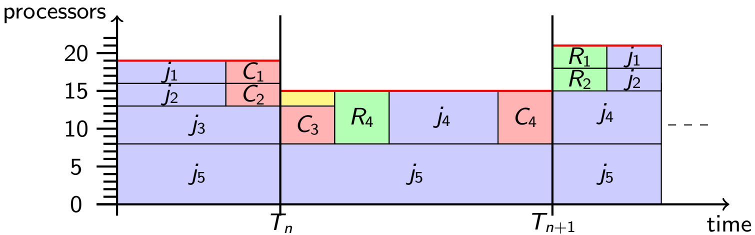
Problem: Scheduling infinite parallel rigid jobs under variable number of processors, during each *section*

Hypotheses:

- A job can be checkpointed and recovered
- Knowledge of the duration of each section, and bound on #proc difference

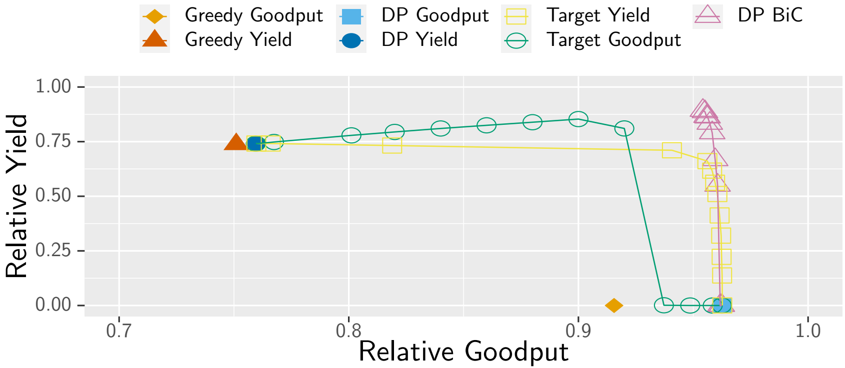
Additional constraint:

- Never lose work (i.e., checkpoint enough before section change, and never shut off a non-checkpointed job)



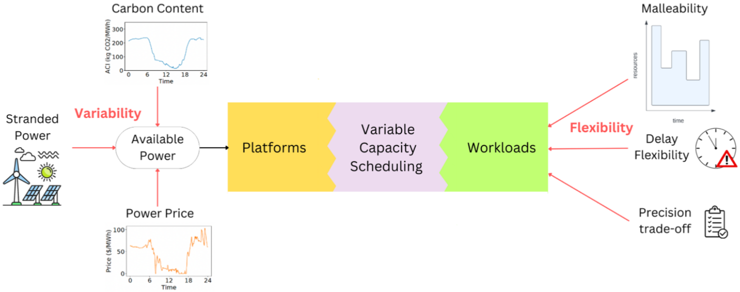
Algorithms

- Sophisticated dynamic programming algorithms to optimize goodput and/or yield at the end of a section
- Evaluation on job traces
- Improvement of novel strategies over greedy approaches



Outline

Back to the big picture



Many challenging scheduling problems ☺

Workshop report: *Scheduling Variable Capacity Resources for Sustainability*; March 29-31, 2023, U. Chicago Paris Center

Today's case study: restricted instance ☹

Risk-Aware Scheduling Algorithms for Variable Capacity Resources; PMBS workshop at SC'23

Research directions

Platforms and resources: New and more complex definitions of capacity; describe resource capacity as a function of time

Flexible workloads: Flexible start dates, allow migration or deferral

Scheduling models and metrics: New models for resource variability and job classification; New multi-criteria metrics for both performance and sustainability; Accounting for uncertainty

Policy and societal factors: Mechanisms that help people accept constraints linked to environmental rules; *Superficial feeling of abundance:* abuse of computational resources, rebound effect