

Carbon-Aware Scheduling on Multiple Edge Servers

Anne Benoit

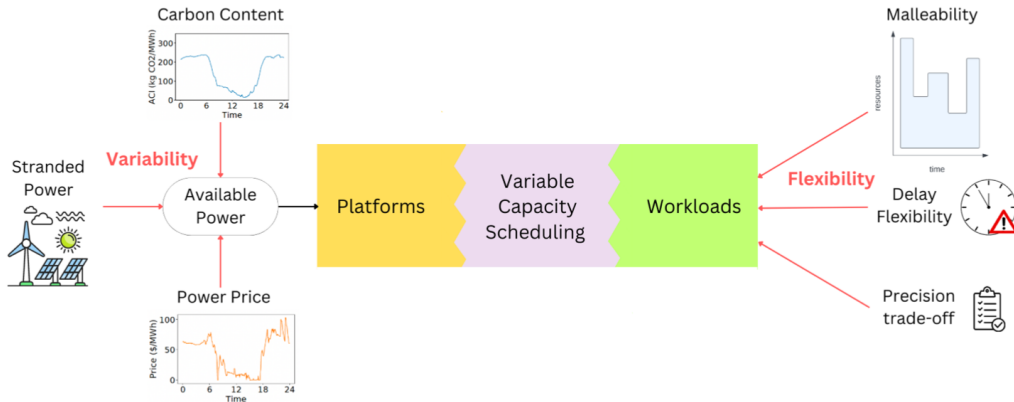
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Joint work with Y. Robert, J. Cendrier, F. Vivien (ENS Lyon)
and A. A. Chien, R. Wijayawardana (U. Chicago)

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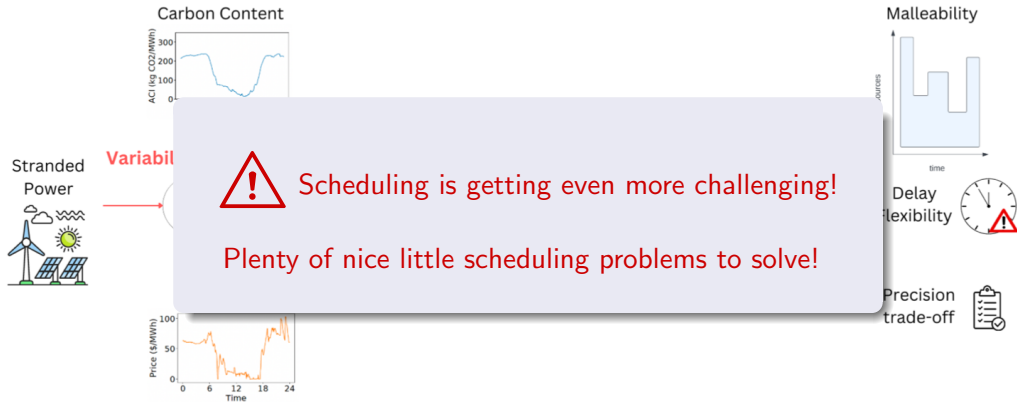
Where were we two years ago?

... Playing with variable capacity scheduling 😊

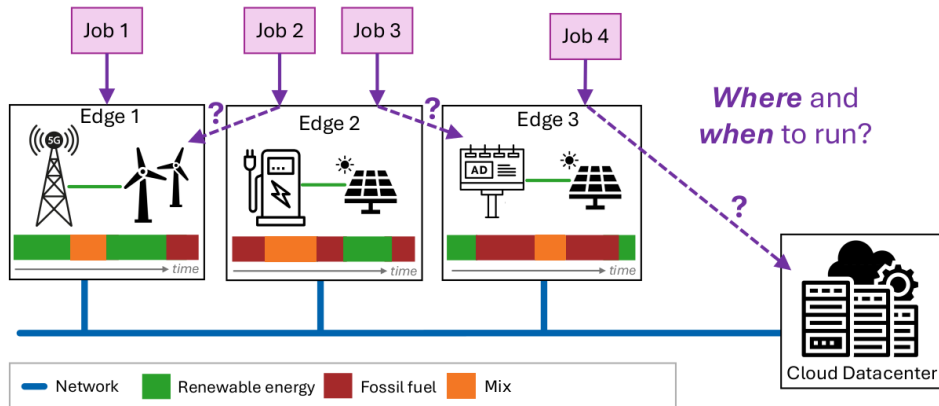


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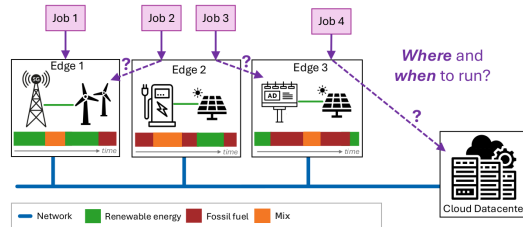
... Playing with variable capacity scheduling 😊



A nice little scheduling problem

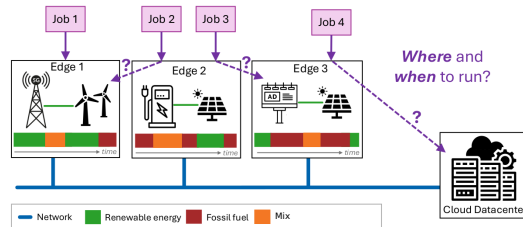


Platform



- Edge servers powered by renewable energy sources, with different levels of carbon intensity depending on time
- Migration possible between edge servers
- Powerful *cloud* server to avoid missed deadlines

Jobs



- Jobs arrive **online** with **deadlines** to respect
- Can be preempted and migrated during execution (cost for recovery/checkpoint)
- Possible execution on a big cloud server powered only by the grid
- Aim: complete all jobs before their deadlines while **minimizing the total carbon cost**

Contents

1 Theoretical results

2 Heuristics

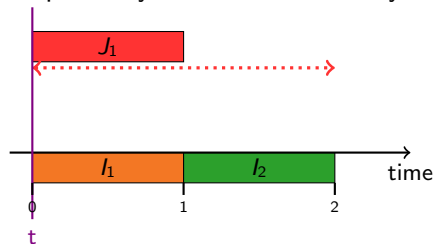
3 Simulations

Online scheduling

Assumptions:

- **Online** (release dates and deadlines are unknown)
- One edge with total knowledge of energy intervals

Exemple with $k_1 > k_2$, respectively the carbon intensity of l_1 and l_2 :



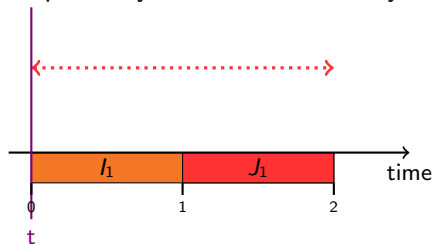
Two cases:

Online scheduling

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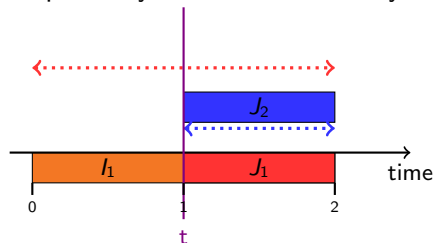
- k_2

Online scheduling

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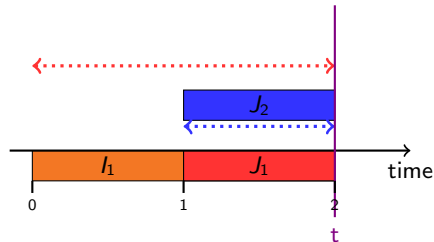
- $k_2 + K$

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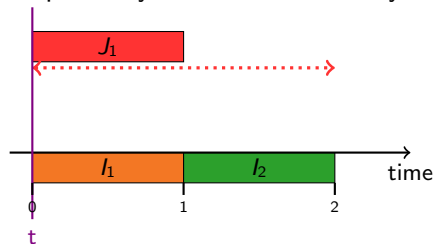
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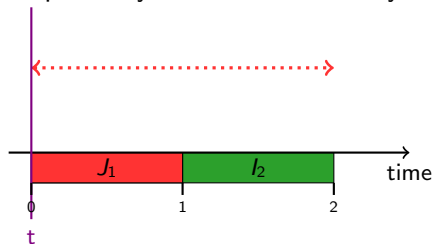
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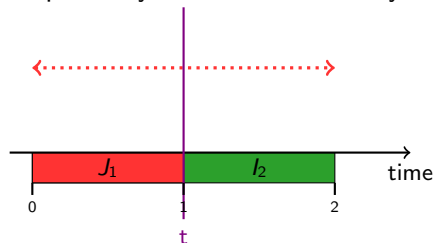
- $k_2 + K > k_1 + k_2$
- k_1

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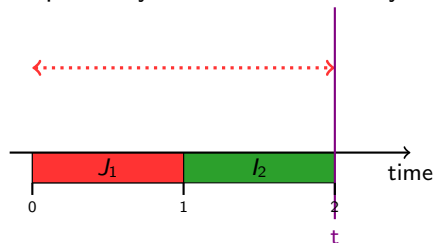
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Two cases:

- $k_2 + K > k_1 + k_2$
- $k_1 > k_2$

Offline scheduling, one edge, $R + C > 0$

Assumptions:

- **Offline** (release dates and deadlines are known)
- One edge with total knowledge of energy intervals
- One job with $R + C > 0$

Complexity of the associated decision problem (carbon cost below K_{max}):

- **NP-hard** problem: proof by subset sum

Offline scheduling, one edge, $R + C = 0$

Assumptions:

- **Offline** (release dates and deadlines are known)
- One edge with total knowledge of energy intervals
- Multiple jobs with $R + C = 0$, which admit a valid schedule on the edge and available at time 0

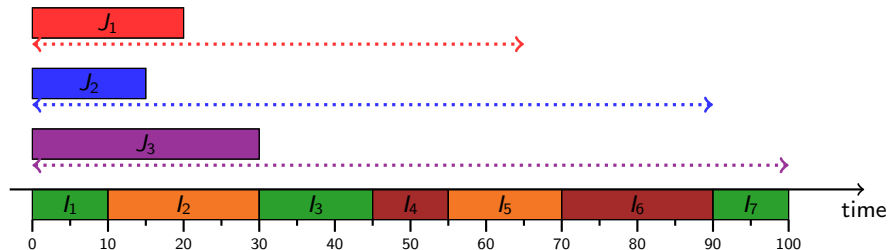
Optimal algorithm, OFFLINEGREENESTPREEMPTION, with **polynomial complexity** in: $O(u + mp + m \log(m))$

where u is the number of intervals in the edge server, m is the number of jobs and p the number of different carbon intensities

OFFLINE GREENEST PREEMPTION

One round per carbon type:

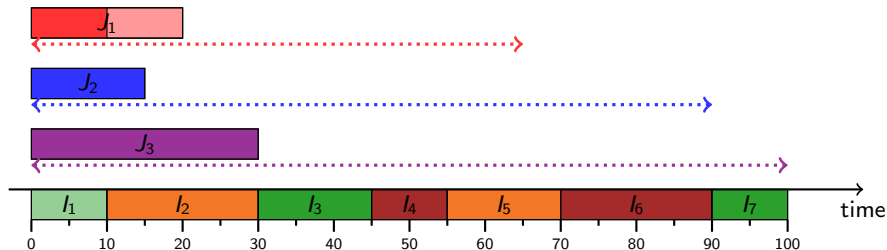
- Selection of the green intervals



OFFLINE GREENEST PREEMPTION

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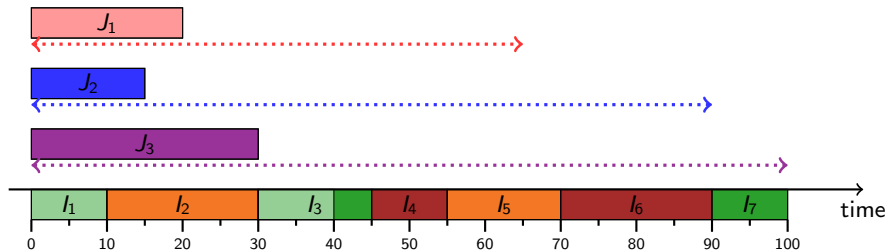
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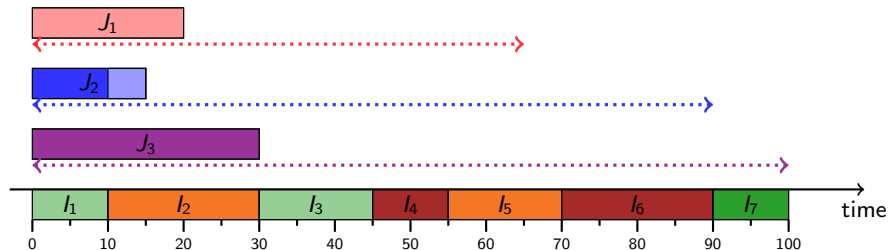
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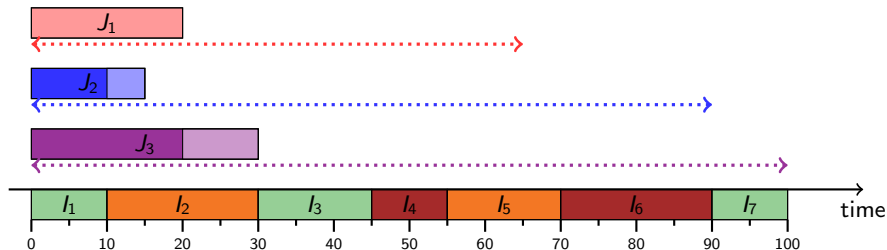
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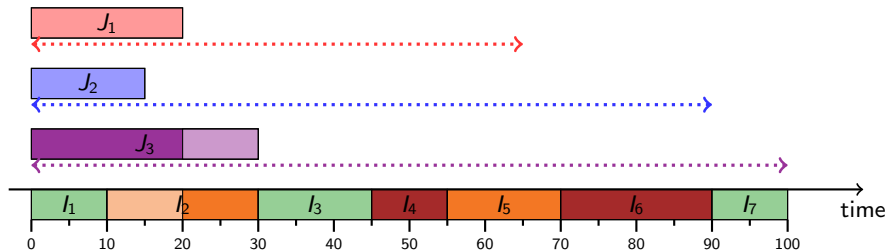
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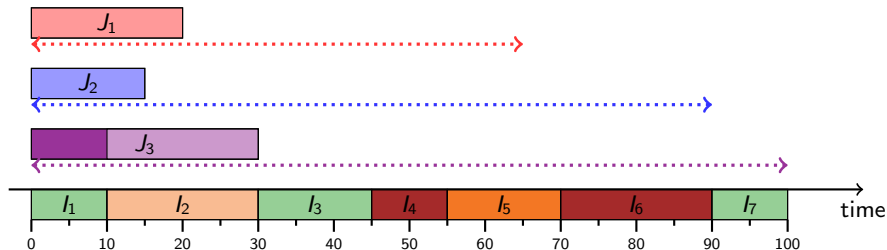
- Selection of the orange intervals



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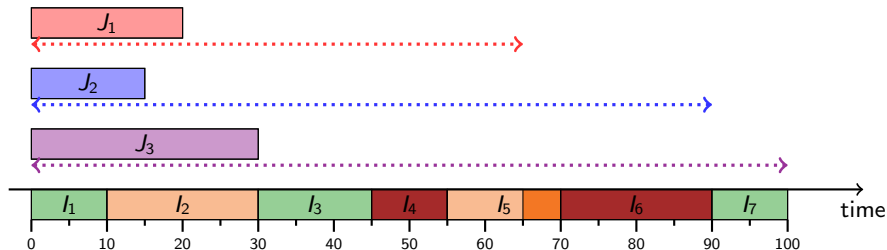
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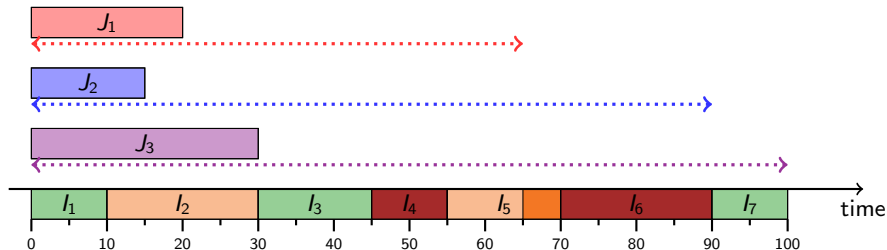
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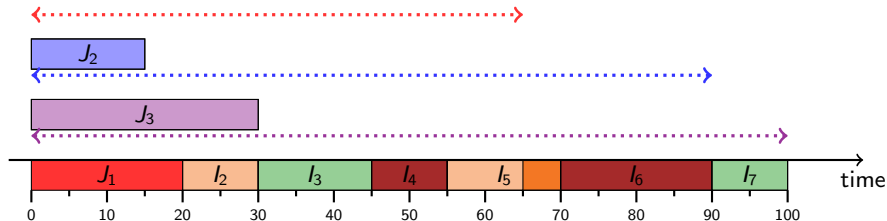
- Selection of the brown intervals



OFFLINE GREENEST PREEMPTION

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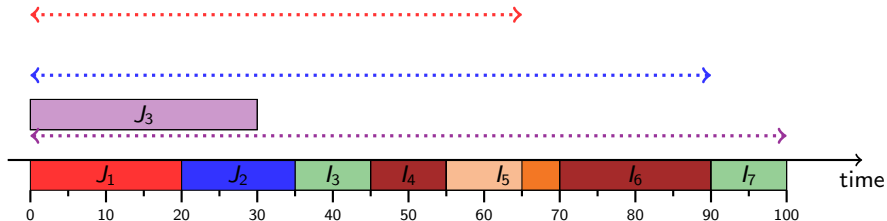


- Scheduling of jobs in the EDF order on the selected energy intervals

OFFLINE GREENEST PREEMPTION

One round per carbon type:

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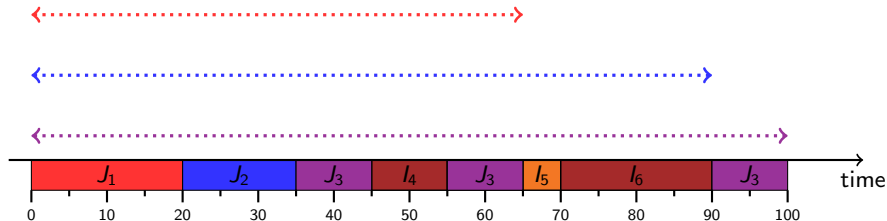


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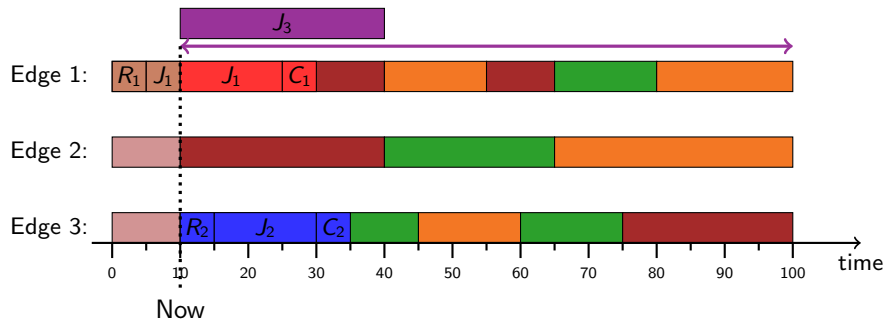
2 Heuristics

3 Simulations

Baseline heuristics

Take decisions only when a new job is released, and only for this job:

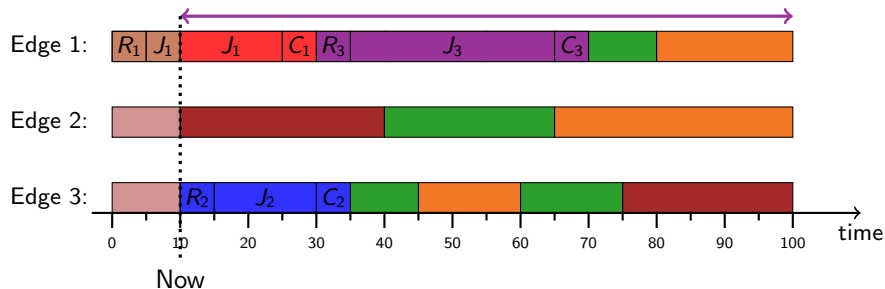
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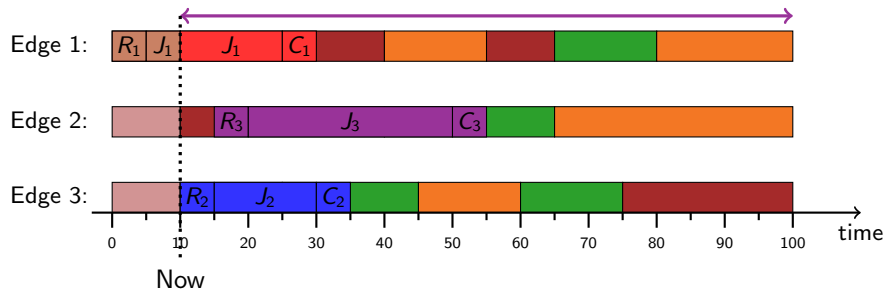
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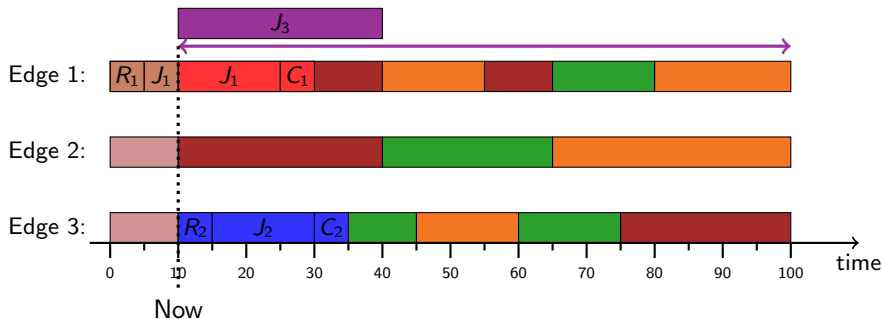
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Green-aware heuristics

Take decisions only when a new job is released, and only for this job:

- LOCALGREEN: Schedules each job at the earliest on its edge but only using greenest energy interval
- EGT: Schedules each job at the earliest on any edge but only using greenest energy interval

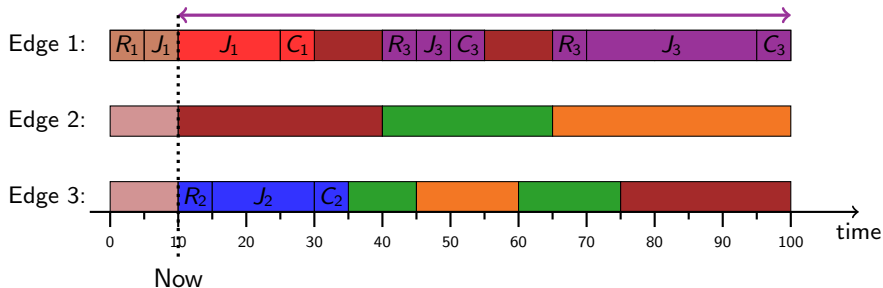


How can we define green energy? Should depend on the system load!

Green-aware heuristics

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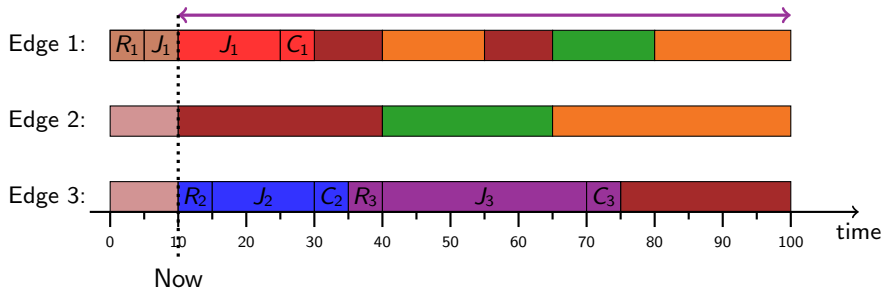


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How can we define green energy? Should depend on the system load!

Re-evaluation heuristics

General idea:

- Each time a new job is submitted, cancels the current schedule and computes a new one, job by job (in a specific order, such as EDF)

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Two strategies:

- **REALLOCMIGRATION**: Try to shedule the job on each edge server (using **OFFLINEGREENESTPREEMPTION** with the already placed jobs) and choose the server with the lowest variation in carbon cost
- **REALLOCINPLACE**: Same than **REALLOCMIGRATION**, but when a job starts its execution on an edge, it will do all of its execution on this edge

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Predictions:

- Re-evaluation of the current schedule when there is an update to the predictions of edges' energy intervals

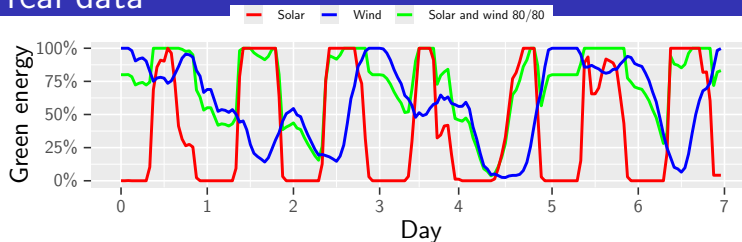
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Traces from real data



- Simulation length: $T = 30$ days
- One year of ERCOT data (2024)
- 10 edge servers, with various on-site generation models and a **3-day forecast**:
 - Solar only, Wind only, Solar and wind, **Mix**: 3 solar, 3 wind, 4 solar and wind
- CLOUD carbon cost K ; carbon cost of transfer k^{trans} : depends on the month
- b^r : 2.15 Gbit/s ; 3.5 Gbit/s for Cloud
- b^w : 2.15 Gbit/s ; 7 Gbit/s for Cloud
- b^{trans} : 10 Gbit/s

Synthetics simulation parameters

- Job duration: between 1 hour and 24 hours, with various mean, depends on job skew
- Job skew: [1.1, 1.15, 1.18, 1.2, 1.4, 1.6]
- Job data volume:
 - **proportional** to the data volume of the job, in [17, 409] Gbit
 - fixed at [1, 10, 50, 100, 200, 400] Gbit
 - uniformly distributed in [[1, 50], [1, 100], [1, 200], [1, 400], [50, 200], [200, 400]] Gbit
- Load $\in \{0.1, 0.2, \dots, 1\}$
- Looseness = $\frac{d_j - s_j}{\ell_j}$: $\{1.15, 1.5, 2, 4, 6, 10, 20\} \pm 10\%$
- Job arrival models:
 - **Uniform**: the workload is distributed uniformly across all 10 edges
 - **Clustered**: 30% of the edges receive 90% of the workload
 - **Event/Mall**: one edge receives 80% of the workload

Run experiments by selecting **default** or outsider value for each parameter (at most one outsider value by experiment)

First results

Metrics:

- Ratio full knowledge: comparison of the total carbon cost with partial / total knowledge of the energy interval costs

Heuristics	<i>GeoMean ratio full knowledge</i>		
ALLCLOUD	1.00		
LOCAL	1.00		
LOCALGREEN	1.01		
ECT	1.00		
EGT	1.00		
REALLOCMIGRATION	1.09		
REALLOCINPLACE	1.07		

Table 1: Statistics on **default** instances. Sorted by ratio ECT values.

- Prediction does not degrade performance too much

First results

Metrics:

- Ratio full knowledge: comparison of the total carbon cost with partial / total knowledge of the energy interval costs
- Ratio ECT: comparison of the total carbon cost of a heuristic for an instance with the total carbon cost of the ECT heuristic

Heuristics	<i>GeoMean ratio full knowledge</i>	<i>GeoMean ratio ECT</i>	
ALLCLOUD	1.00	2.02	
LOCAL	1.00	1.23	
LOCALGREEN	1.01	1.18	
ECT	1.00	1.00	
EGT	1.00	0.88	
REALLOCMIGRATION	1.09	0.61	
REALLOCINPLACE	1.07	0.59	

Table 1: Statistics on **default** instances. Sorted by ratio ECT values.

- Prediction does not degrade performance too much
- Good performance for re-evaluation algorithm

First results

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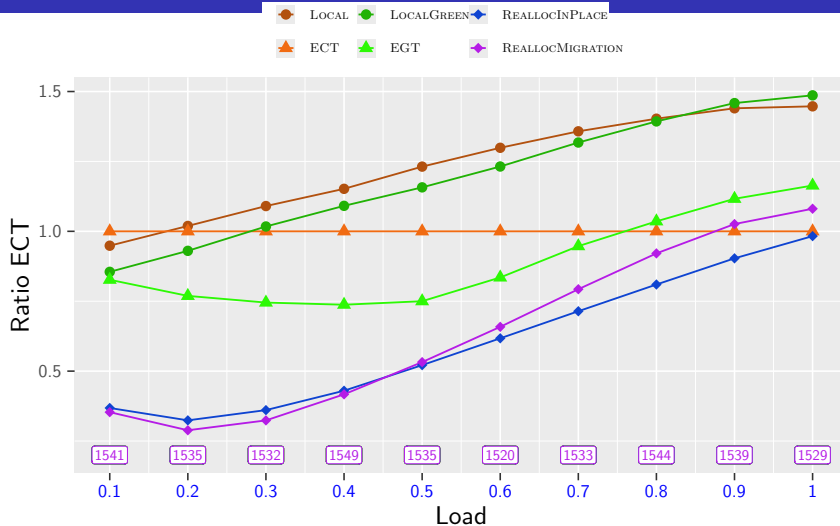
- Ratio full knowledge: comparison of the total carbon cost with partial / total knowledge of the energy interval costs
- Ratio ECT: comparison of the total carbon cost of a heuristic for an instance with the total carbon cost of the ECT heuristic
- Stretch: ratio between execution time and duration of jobs on edge servers

Heuristics	<i>GeoMean ratio full knowledge</i>	<i>GeoMean ratio ECT</i>	<i>GeoMean stretch</i>
ALLCLOUD	1.00	2.02	1.00
LOCAL	1.00	1.23	1.47
LOCALGREEN	1.01	1.18	1.99
ECT	1.00	1.00	1.07
EGT	1.00	0.88	2.21
REALLOCMIGRATION	1.09	0.61	2.57
REALLOCINPLACE	1.07	0.59	2.46

Table 1: Statistics on **default** instances. Sorted by ratio ECT values.

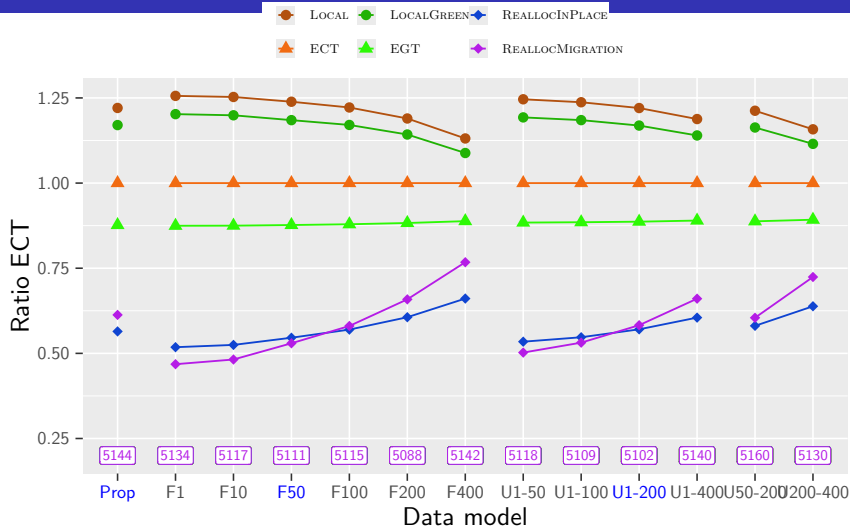
- Prediction does not degrade performance too much
- Good performance for re-evaluation algorithm at the expense of the stretch

Impact of the load on ratio ECT



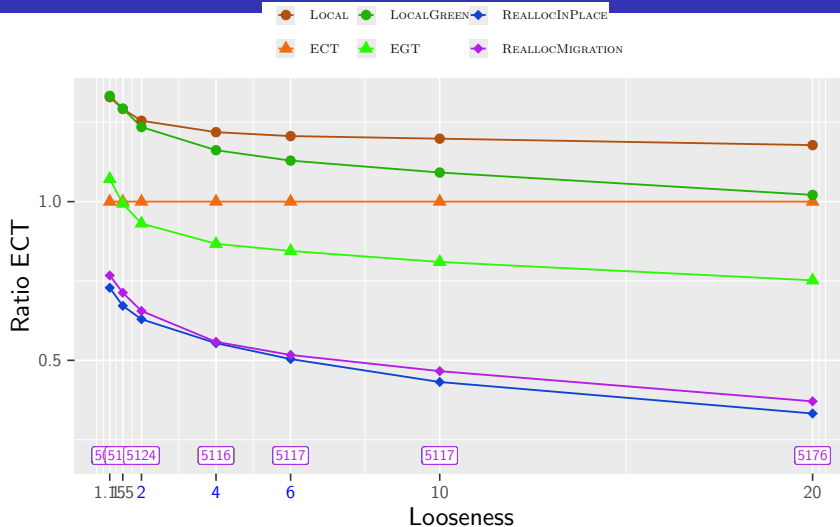
- Re-evaluation algorithms have very good gains at around 1/4 load

Impact of the data volume on ratio ECT



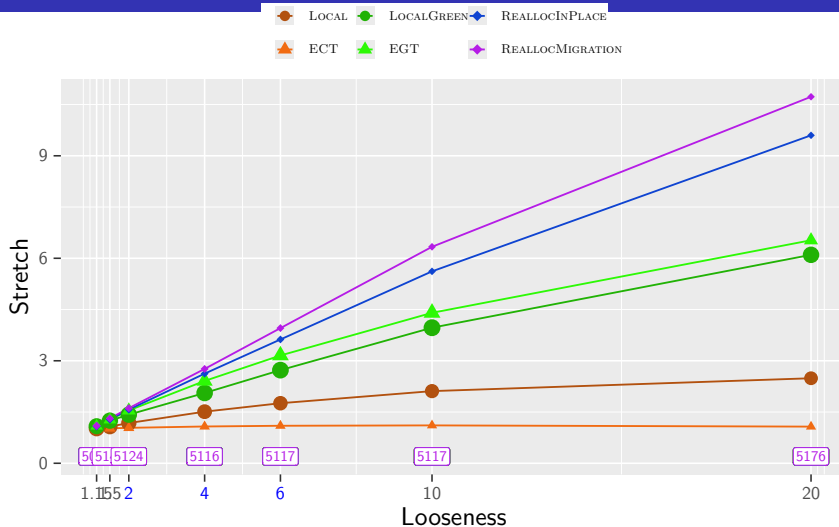
- Local-oriented algorithms are better when data volume is high

Impact of the looseness on ratio ECT



- Higher looseness implies better performance...

Impact of the looseness on stretch



● ... but at the cost of the stretch

Conclusion

- Model of a complex edge scheduling problem
- Complexity results for the general problem and its subproblems
- Optimal polynomial algorithm to schedule jobs with free preemption
- 3-day prediction is enough to avoid significantly degrading performance
- Reevaluation heuristics offer robust performance