

# Exploring scheduling solutions for Federated Learning training

**Laércio Lima Pilla** (he/him)

laercio.lima-pilla@labri.fr

# ... but before we start discussing the topic

## Who am I?

- CNRS research scientist (2018-)
- Aim to make **parallel applications more efficient\*** through **better scheduling**
  - \* faster, more energy efficient, using less or older resources, ...



[website](#)

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[website](#)

## Acknowledgements

- PhD student
  - Alan Lira Nunes
- Co-advisors
  - Cristina Boeres
  - Lúcia M. A. Drummond



- DecoHPC joint team

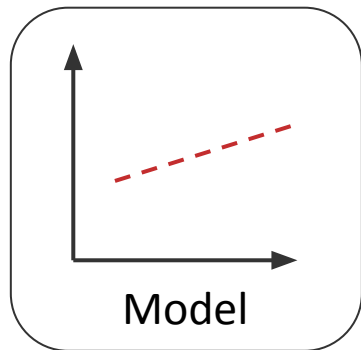
# What is Federated Learning?

**distributed learning** + **local data is never shared**

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**Communication-Efficient Learning of Deep Networks  
from Decentralized Data**

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Central  
FL server

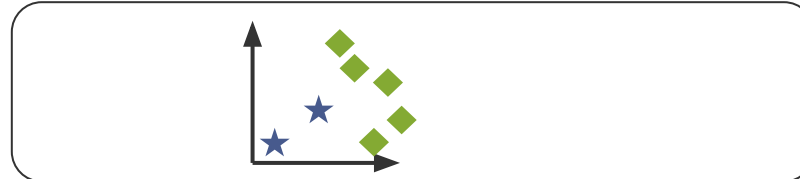
Device 1



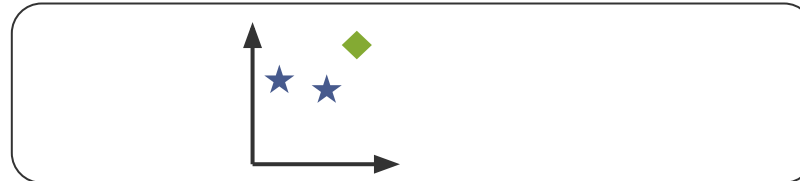
Device 2



Device 3

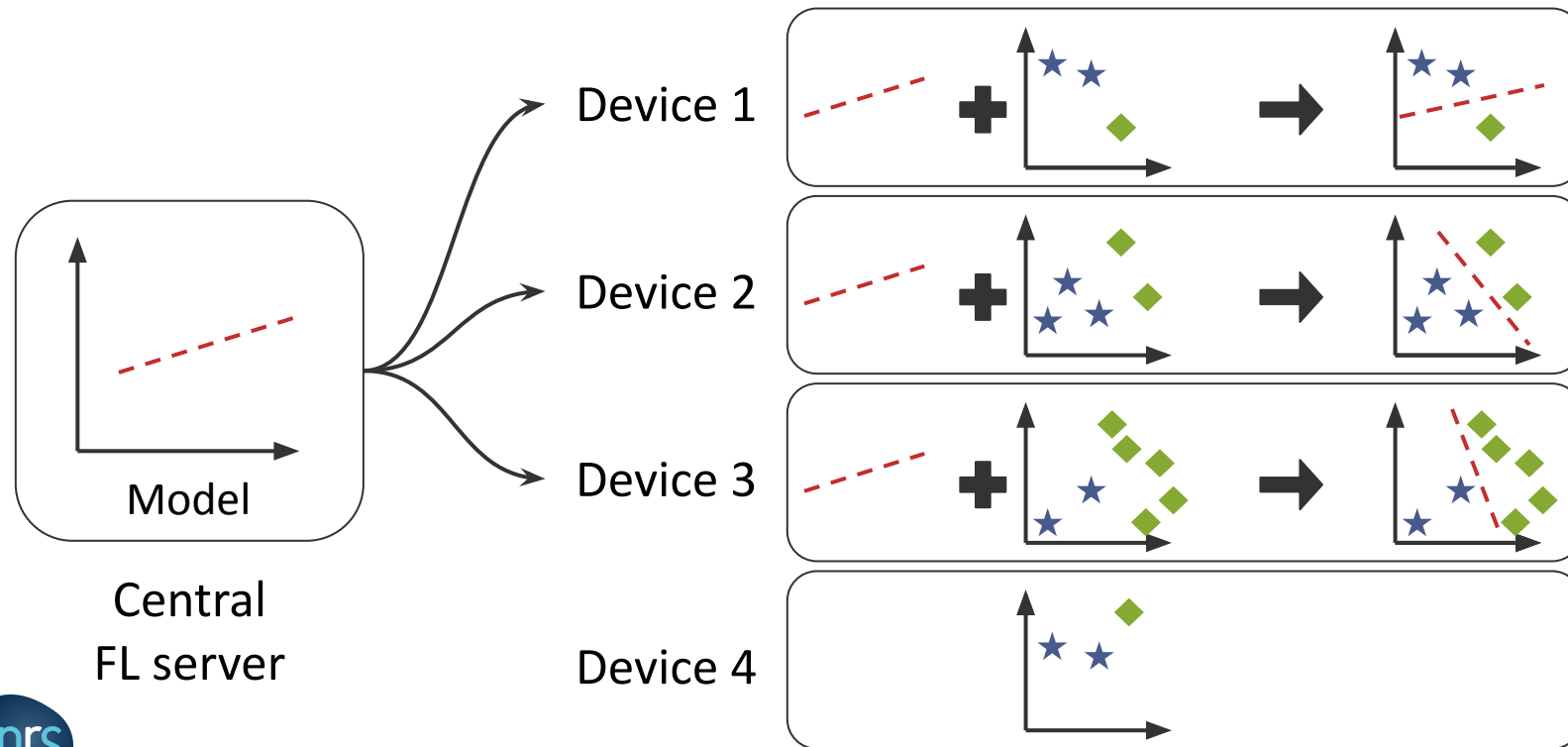


Device 4



# What is Federated Learning?

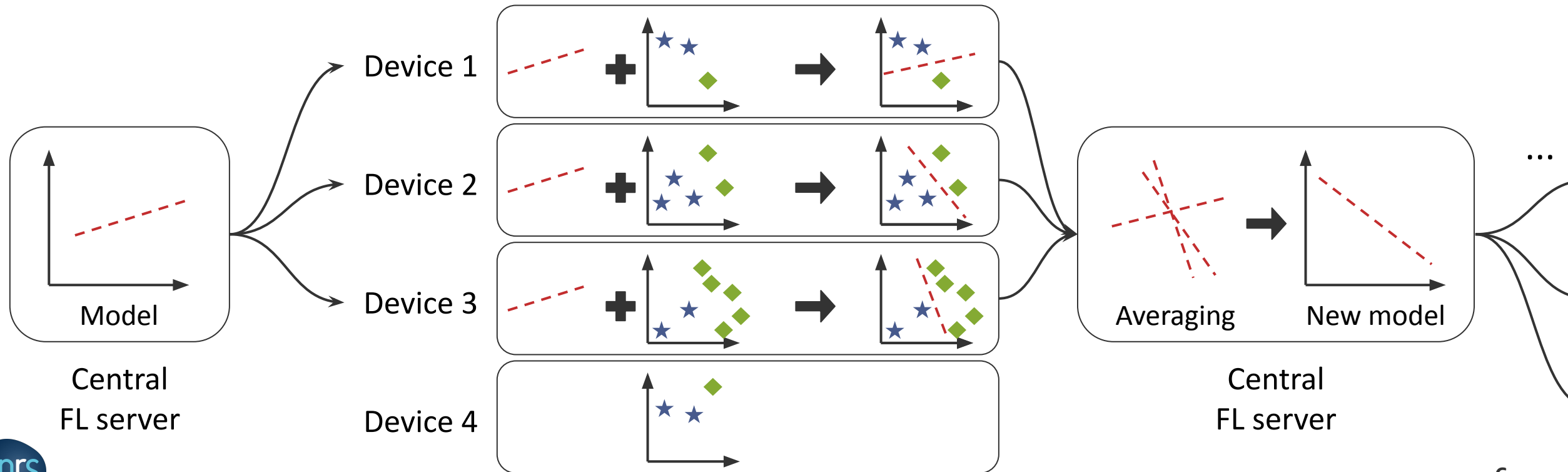
distributed learning + local data is never shared



# What is Federated Learning?

distributed learning + local data is never shared

**Applications:** next-word prediction, on-device item ranking, cyberattack detection, medical applications



# Why do we care (about optimizing it)?

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**ILLS**  
International Laboratory  
on Learning Systems



**ÉTS**  
ÉCOLE DE  
TECHNOLOGIE  
SUPÉRIEURE  
Université du Québec



## 18th **Scheduling for large-scale systems** workshop

École de Technologie Supérieure, Montréal, Québec, Canada, July 8-10, 2025



*[...] this year edition will be focused around  
"Scheduling and AI" [...]*



# Why do we care (about optimizing it)?

## Characteristics of cross-device FL

device and data **heterogeneity**



## Issues

duration of training

energy costs and emissions of ML\*

battery or energy available

convincing people to participate in training

\*[Qiu, Xinchu, et al.](#) "A first look into the carbon footprint of federated learning." Journal of Machine Learning Research 24.129 (2023): 1-23.

# What the problems look like?

## For a training round, given

- some heterogeneous **clients**
- amount of **data** to be used for training

## try to optimize

- the **time**
- the **energy** (or the emissions)
- both

## it takes by

- defining **how much data each client should use locally**

# What the problems look like?

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- amount of data to be used for training

## try to optimize

- the time
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## it takes by

- defining how much data each client should use locally

## Requires estimations of

- the amount of **local data**\*
- **functions** of
  - **time per data unit**
  - **energy per data unit**

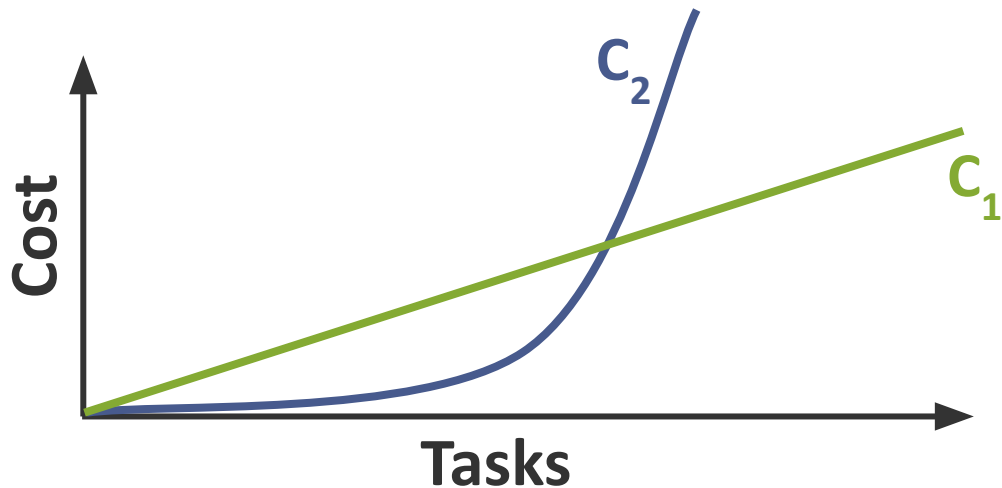
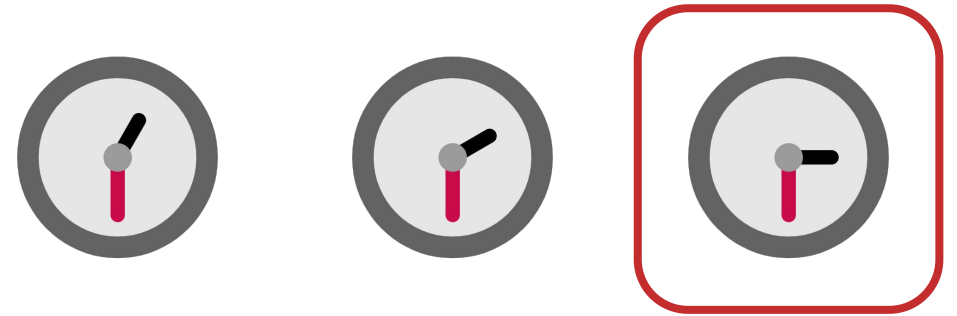
## per client

\*or upper and lower limits

# Optimizing time (2021)

**Problem:** given  $T$  tasks and  $n$  resources with different cost functions  $C$ , find an assignment that minimizes the **maximal cost**  $C_{\max}$ .

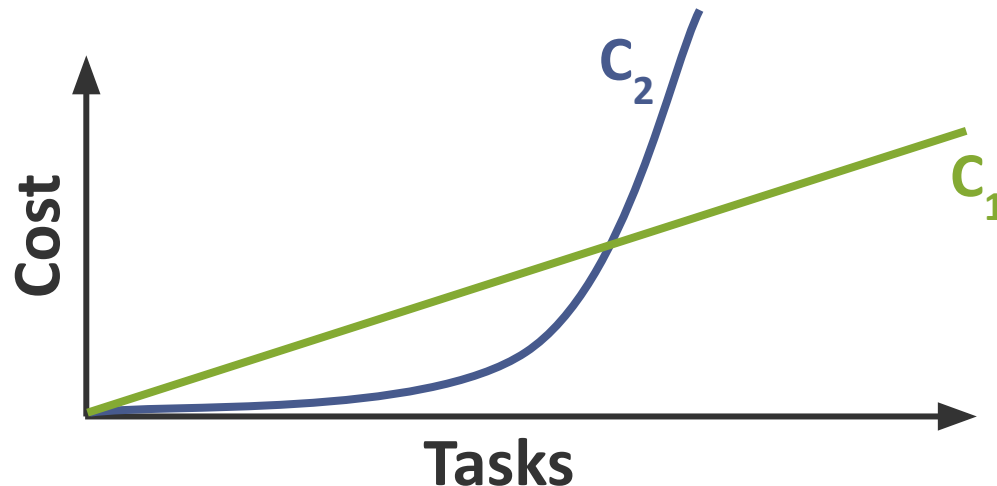
**Assumption:** all cost functions are monotonically increasing and known



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Find a task assignment  $A_i \in \mathbb{N}$  to each resource  $i \in R$  that minimizes the **makespan**  $C_{\max}$  while assigning all tasks among the resources and respecting their lower and upper limits.

$$C_{\max} := \max_{i \in R} C_i(A_i)$$

$$\sum_{i \in R} A_i = T$$

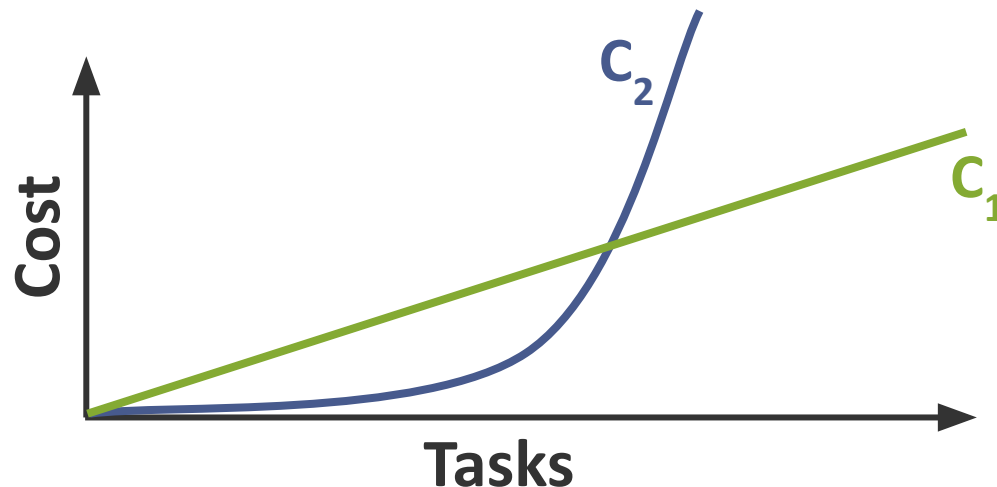
$$L_i \leq A_i \leq U_i, \forall i \in R$$

[Pilla, Laércio Lima](#). "Optimal task assignment for heterogeneous federated learning devices." 2021 IEEE International Parallel and Distributed Processing Symposium (IPDPS). IEEE, 2021.

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**Problem:** given  $T$  tasks and  $n$  resources with different cost functions  $C$ , find an assignment that minimizes the **maximal cost**  $C_{\max}$ .

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**Solution** in  $O(T \log n)$ : assign the **next task** to one of the resources that increases the execution time the least.

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**Algorithm 1:** OLAR

---

**Data:** Tasks  $T$ , Resources  $\mathcal{R}$ , Cost functions  $C_i(\cdot)$ ,

Lower and Upper limits  $L_i$  and  $U_i$  ( $i \in \mathcal{R}$ )

**Result:** Assignment of tasks to resources  $A_i$  ( $i \in \mathcal{R}$ )

```
1  $h \leftarrow \text{min-heap}()$  ▷ Heap sorted by cost
2 for  $i \in \mathcal{R}$  do
3    $A_i \leftarrow L_i$  ▷ Resources start at their lower limit
4   ▷ Checks if the resource can receive more tasks
5   if  $A_i < U_i$  then
6     ▷ Inserts the cost of the next task on  $i$ 
7      $h.\text{push}(C_i(A_i + 1), i)$ 
8   end
9 end ▷ Main loop
10 for  $t$  from 1 to  $T$  do
11   ▷ Extracts the next optimal assignment (Eq. (9))
12    $(c, j) \leftarrow h.\text{pop}()$ 
13    $A_j \leftarrow A_j + 1$  ▷ Assigns  $t$  to  $j$ 
14   ▷ Checks if the resource can receive more tasks
15   if  $A_j < U_j$  then
16     ▷ Inserts the cost of the next task on  $j$ 
17      $h.\text{push}(C_j(A_j + 1), j)$ 
18   end
19 end
```

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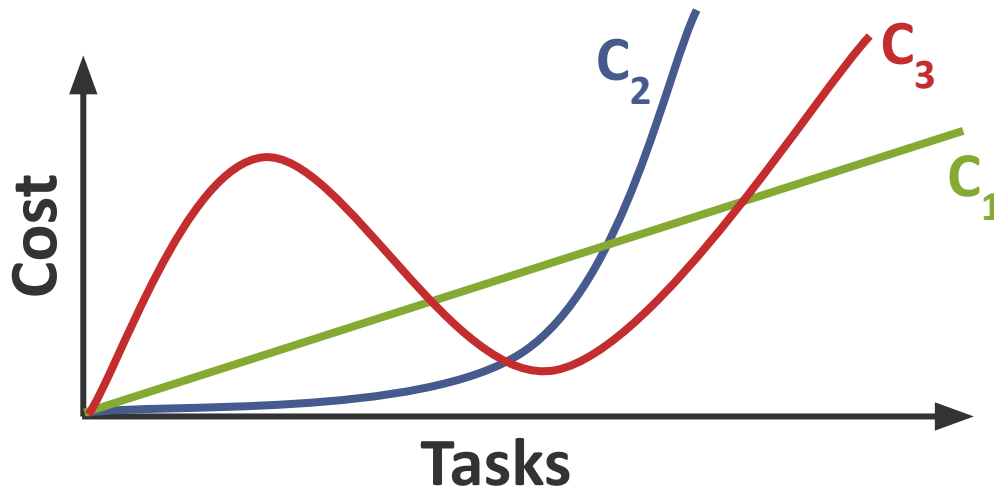
# Optimizing time (**2022**)

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**Assumption:** all cost functions are ~~monotonically increasing and known~~

**Solution** in  $O(T^2n)$ : a bit more complex

- Dynamic programming solution
- (to be shown soon) ;)
- SotA was  $O(T^3n^3)$

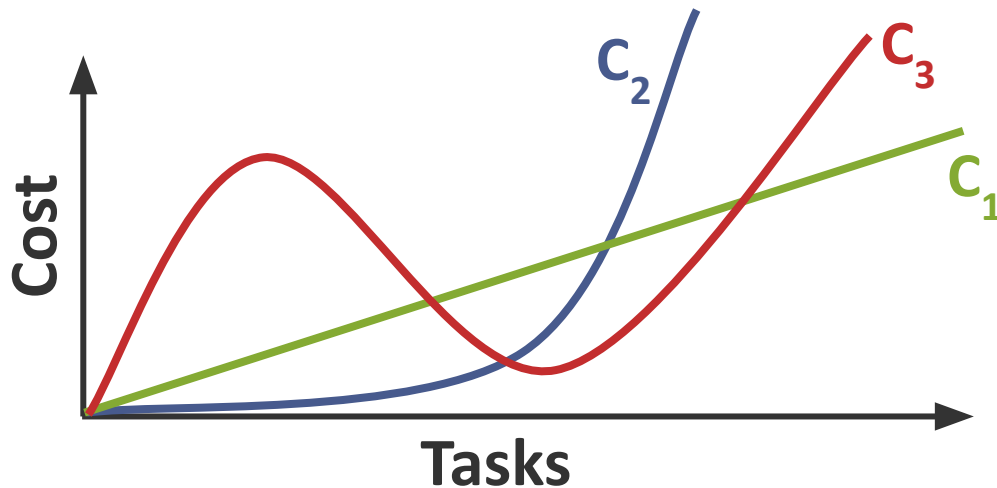


[Pilla, Laércio Lima](#). Optimal workload scheduling algorithm for data-parallel applications on heterogeneous platforms based on dynamic programming. Diss. CNRS; LaBRI; Inria; Université de Bordeaux; Bordeaux INP, 2022.

# Optimizing **energy** (2023)

**Problem:** given **T tasks** and **n resources** with different cost functions  $C$ , find an assignment that minimizes the **total cost**  $\Sigma E$ .

**Assumption:** all cost functions are known

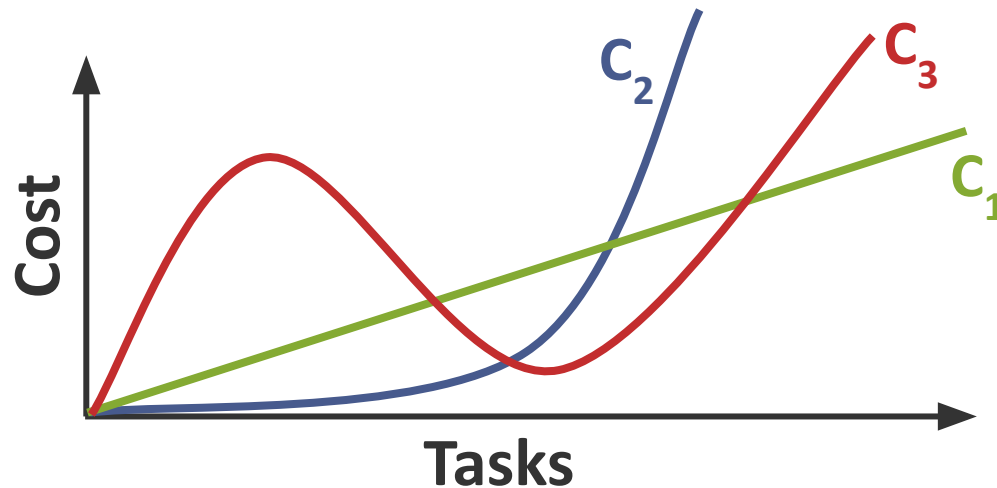




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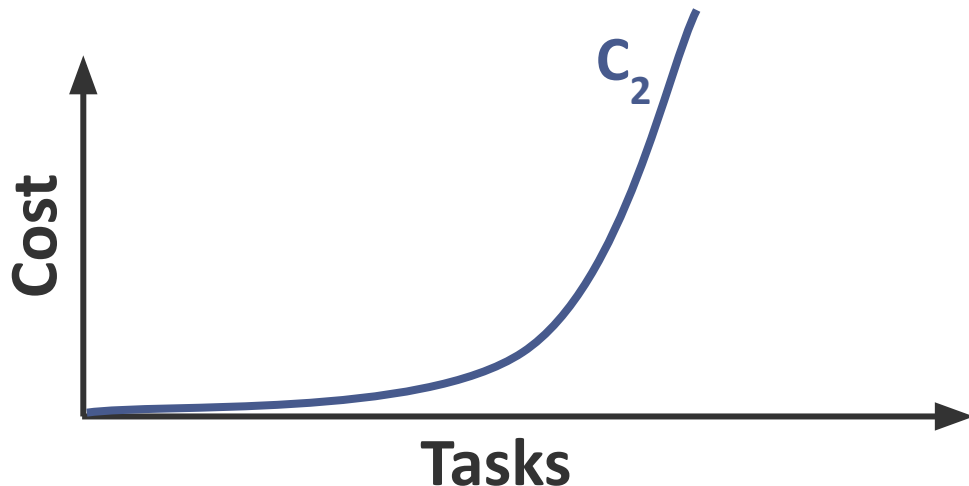
# Optimizing energy (2023)

**Problem:** given **T tasks** and **n resources** with different cost functions  $C$ , find an assignment that minimizes the **total cost  $\Sigma E$** .

**Assumption:** all cost functions are known **and superlinear**

**Solution** in  $O(T \log n)$ : assign the **next task** to one of the resources that increases the total cost the least.

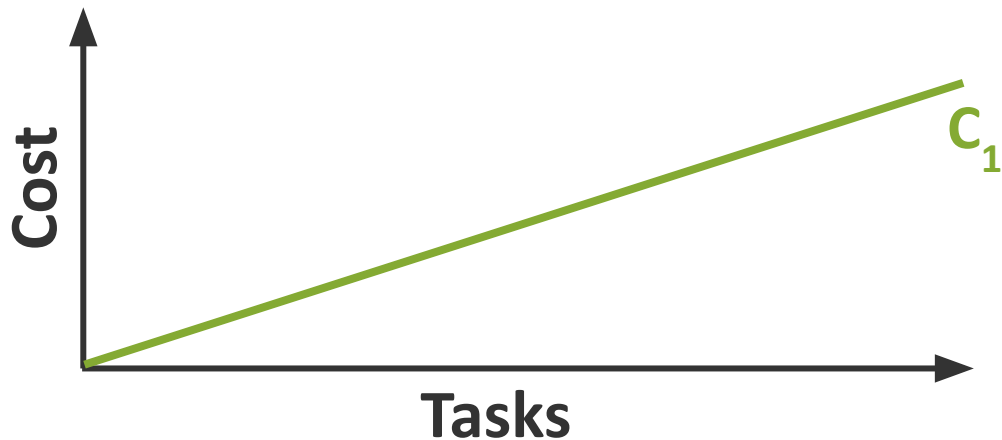
- similar to OLAR



# Optimizing energy (2023)

**Problem:** given **T tasks** and **n resources** with different cost functions  $C$ , find an assignment that minimizes the **total cost  $\Sigma E$** .

**Assumption:** all cost functions are known **and linear**

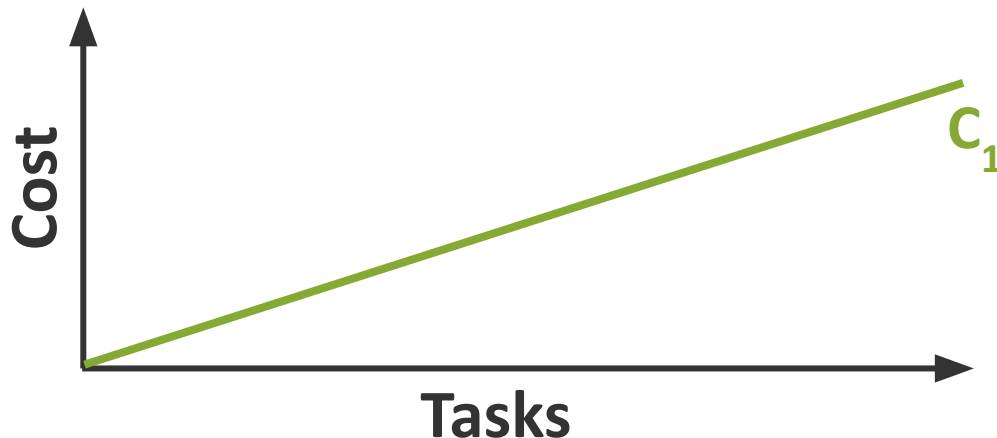


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**Problem:** given  $T$  tasks and  $n$  resources with different cost functions  $C$ , find an assignment that minimizes the **total cost  $\Sigma E$** .

**Assumption:** all cost functions are known **and linear**

**Solution** in  $O(n \log n)$ : assign the **most tasks possible** to one of the resources with the least cost per task.



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**Algorithm 3:** MarCo.

---

**Input:** Set of resources  $\mathcal{R}$ , number of tasks to schedule  $T$ , set of upper limits  $\mathcal{U}$ , set of cost functions  $\mathcal{C}$ .

**Output:** Optimal schedule  $X$ .

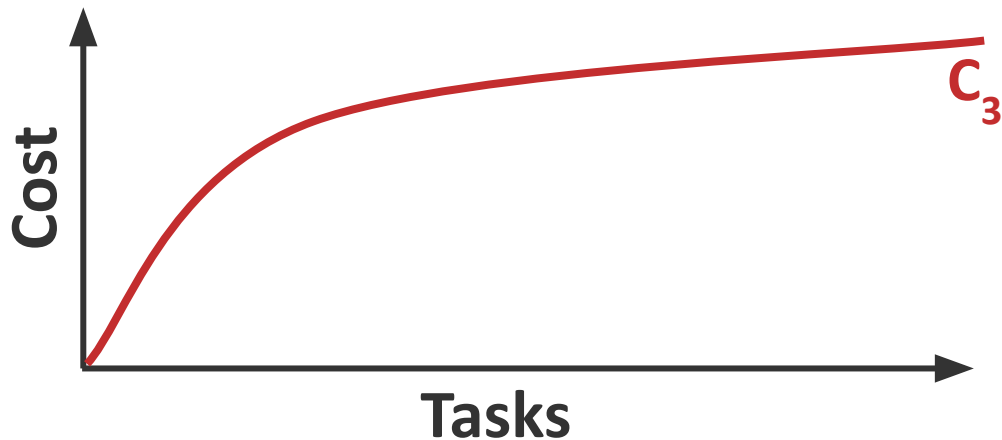
```
1: for all  $i \in \mathcal{R}$  do
2:    $x_i \leftarrow 0$   $\triangleright$  All resources start without any tasks.
3: end for
4:  $t \leftarrow 0$ 
5: while  $t < T$  do
6:    $k \leftarrow \arg \min_{i \in \mathcal{R}, x_i \neq U_i} M_i(1)$ 
7:    $x_k \leftarrow \min(U_k, T - t)$   $\triangleright$  Assigns the most tasks possible.
8:    $t \leftarrow t + x_k$ 
9: end while
10: return  $X$ 
```

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# Optimizing energy (2023)

**Problem:** given **T tasks** and **n resources** with different cost functions  $C$ , find an assignment that minimizes the **total cost  $\Sigma E$** .

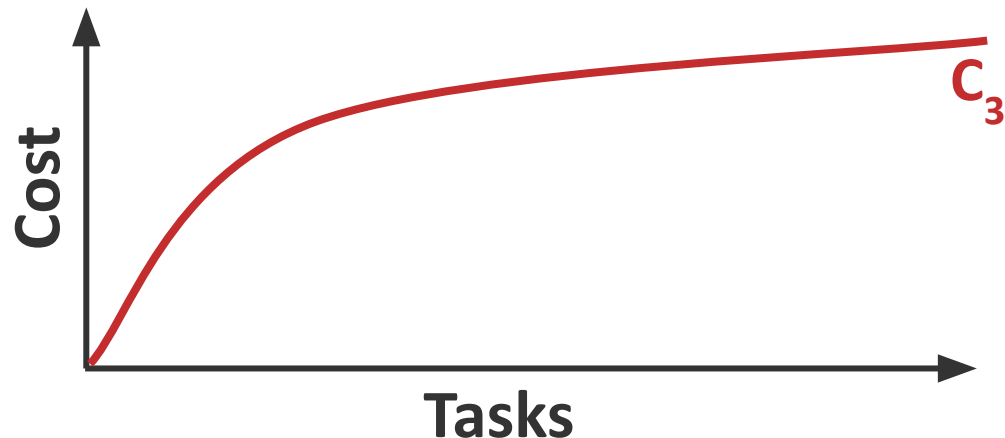
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# Optimizing energy (2023)

**Problem:** given  $T$  tasks and  $n$  resources with different cost functions  $C$ , find an assignment that minimizes the **total cost  $\Sigma E$** .

**Assumption:** all cost functions are known **and sublinear**



**Solution without upper limits** in  $O(n)$ : assign **all tasks** to one of the resources with the least total cost.

---

**Algorithm 4:** MarDecUn.

---

**Input:** Set of resources  $\mathcal{R}$ , number of tasks to schedule  $T$ , set of upper limits  $\mathcal{U}$ , set of cost functions  $\mathcal{C}$ .

**Output:** Optimal schedule  $X$ .

1: **for all**  $i \in \mathcal{R}$  **do**

2:    $x_i \leftarrow 0$     $\triangleright$  All resources start without any tasks.

3: **end for**

4:  $k \leftarrow \arg \min_{i \in \mathcal{R}} C_i(T)$

5:  $x_k \leftarrow T$     $\triangleright$  Assigns all tasks to the same resource.

6: **return**  $X$

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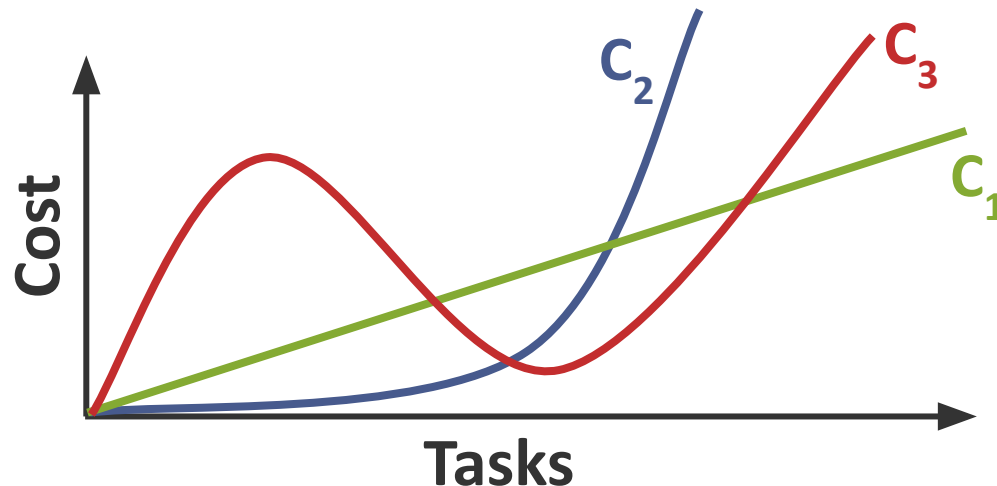
**Solution with upper limits** in  $O(Tn^2)$

- More complex (and related to our previous mystery) ;)

# Optimizing energy (2023)

**Problem:** given  $T$  tasks and  $n$  resources with different cost functions  $C$ , find an assignment that minimizes the **total cost**  $\Sigma E$ .

**Assumption:** all cost functions are known



**Solution** in  $O(T^2n)$ : **(MC)<sup>2</sup>MKP** - Knapsack w/ DP implementation

- **M**ultiple-**c**hoice
  - One item per group (resource)
- **M**inimum-**c**ost
  - Minimizes cost (instead of maximizing profit)
- **M**aximum **K**napsack **P**acking
  - Fills the knapsack as much as possible

# Optimizing **time** and **energy** (2024)

**Problems:** given **T tasks** and **n resources** with different cost functions **P** and **E**, find an assignment that

- minimizes the **maximal cost  $C_{\max}$**  and then **total cost  $\Sigma E$** 
  - Minimal Makespan and Energy Consumption (**MEC**)
- or **vice-versa within a deadline D**
  - Minimal Energy Consumption and Makespan under Time Constraint (**ECMTC**)



$$C_{\max} := \max_{i \in \mathcal{R}} P_i(x_i) \quad (1)$$

$$\begin{aligned} \text{lex min}_X \quad & C_{\max}, \Sigma E \quad (3a) \\ \text{subject to} \quad & \sum_{i \in \mathcal{R}} x_i = T, \quad (3b) \\ & x_i \in A_i, \quad \forall i \in \mathcal{R} \quad (3c) \end{aligned}$$



$$\Sigma E := \sum_{i \in \mathcal{R}} E_i(x_i) \quad (2)$$

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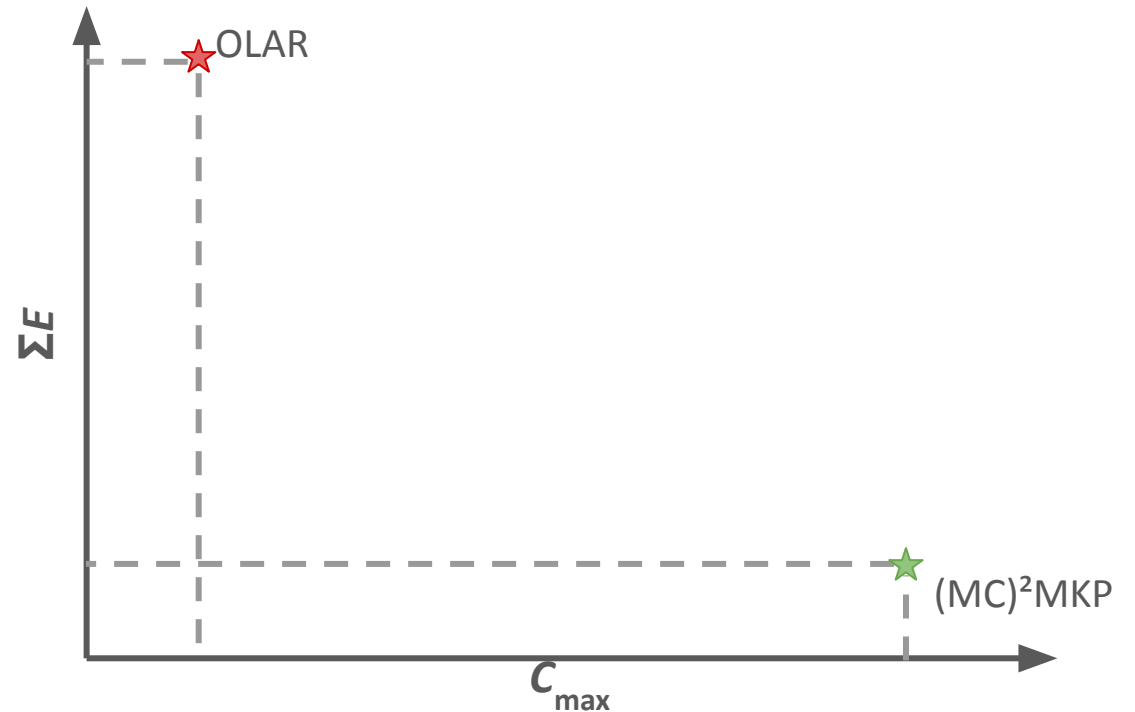
[Nunes, Alan L., et al.](#) "Optimal time and energy-aware client selection algorithms for federated learning on heterogeneous resources." 2024 IEEE 36th International Symposium on Computer Architecture and High Performance Computing (SBAC-PAD). IEEE, 2024.



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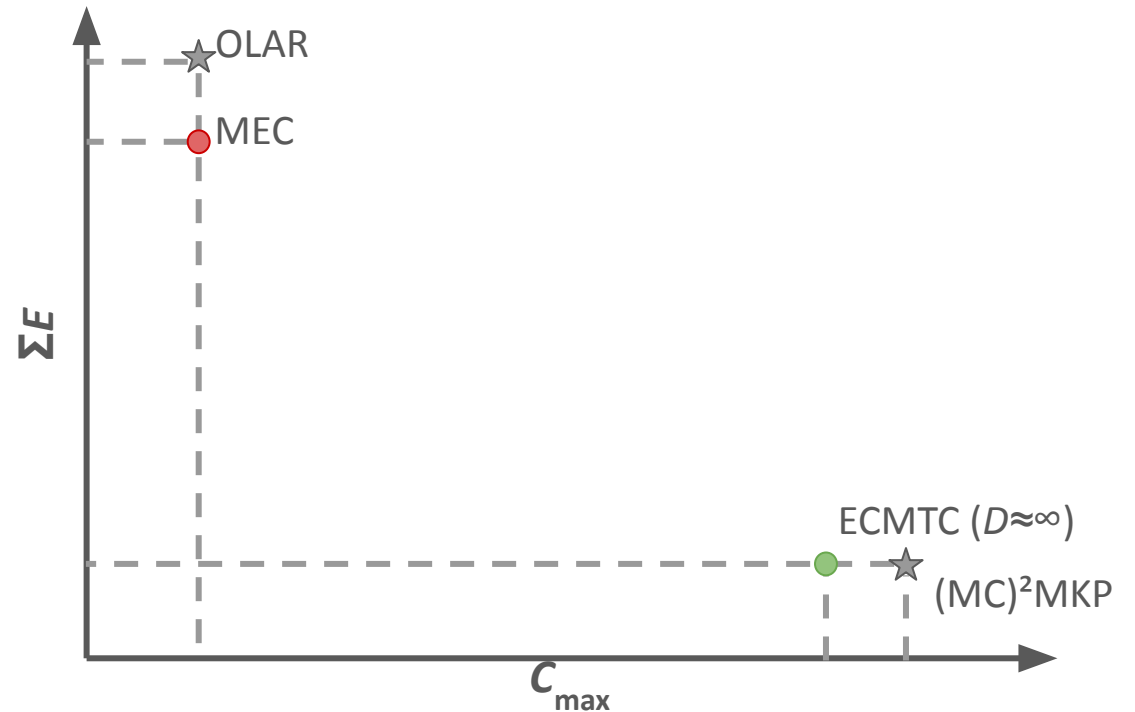
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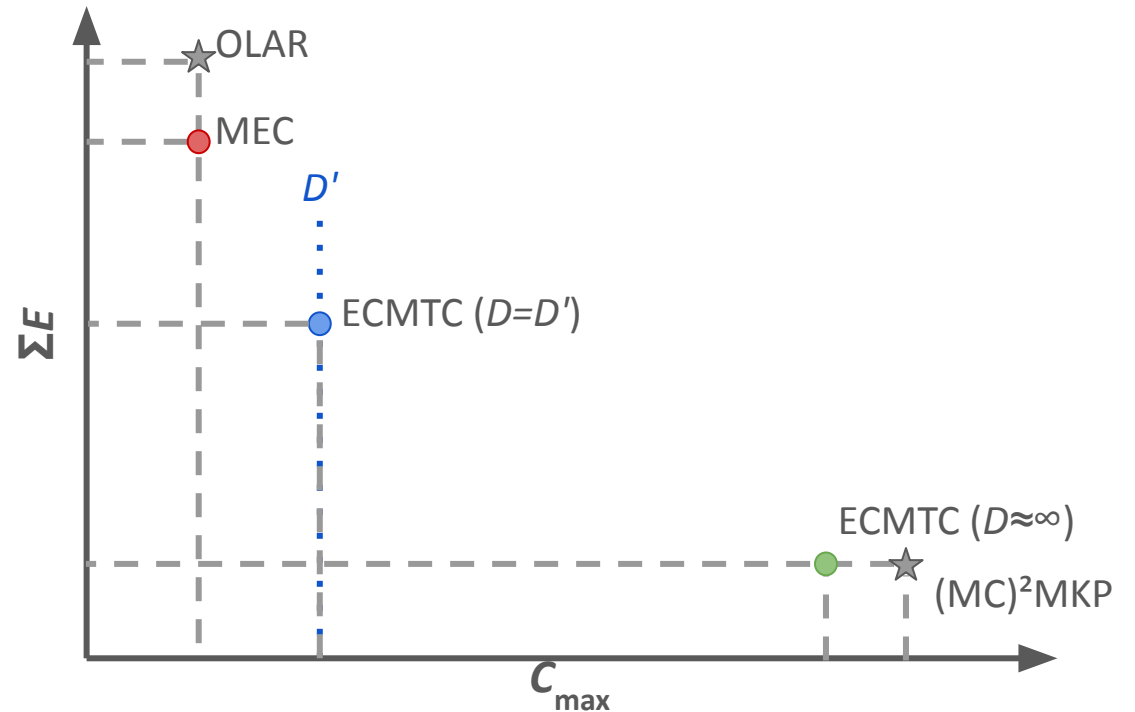
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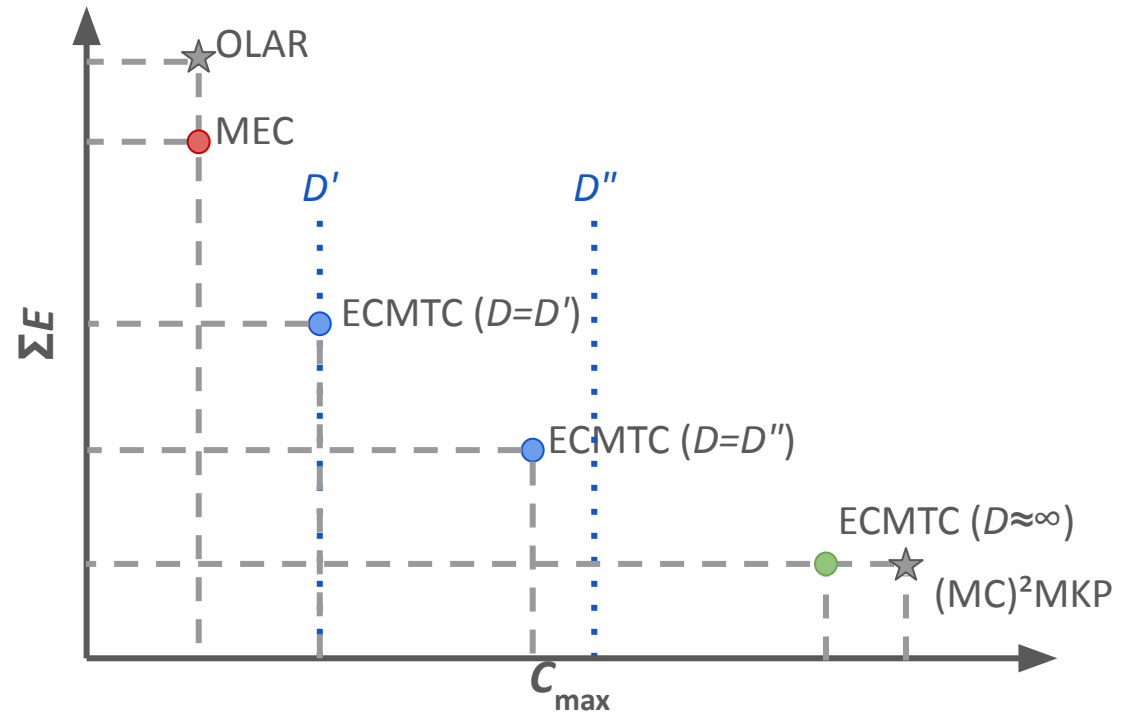
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**All solutions are Pareto optimal!**

# Optimizing time and energy (2024)

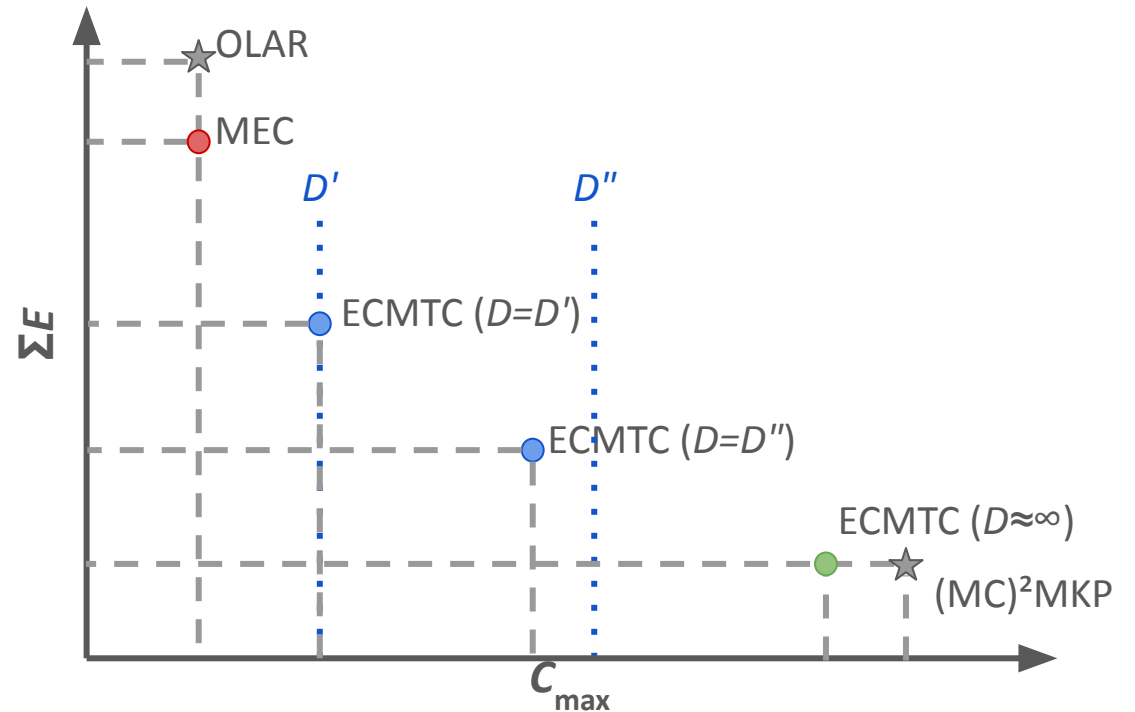
**Solutions** in  $O(T^2n)$  based on  $(MC)^2MKP$

## MEC

- Find minimal makespan, set it as deadline
- Filter assignments based on deadline
- $(MC)^2MKP$

## ECMTC

- Filter assignments based on deadline
- As  $(MC)^2MKP$ , but solve ties for the minimal total time



# Optimizing **over multiple rounds** (2025)

## General problem:

1. get an optimal schedule
2. reuse it over multiple rounds
3. only see "the same" data
4. the model requires more rounds to converge/achieve a given accuracy
5. total **time and energy increase**



# Optimizing over multiple rounds (2025)

## General problem:

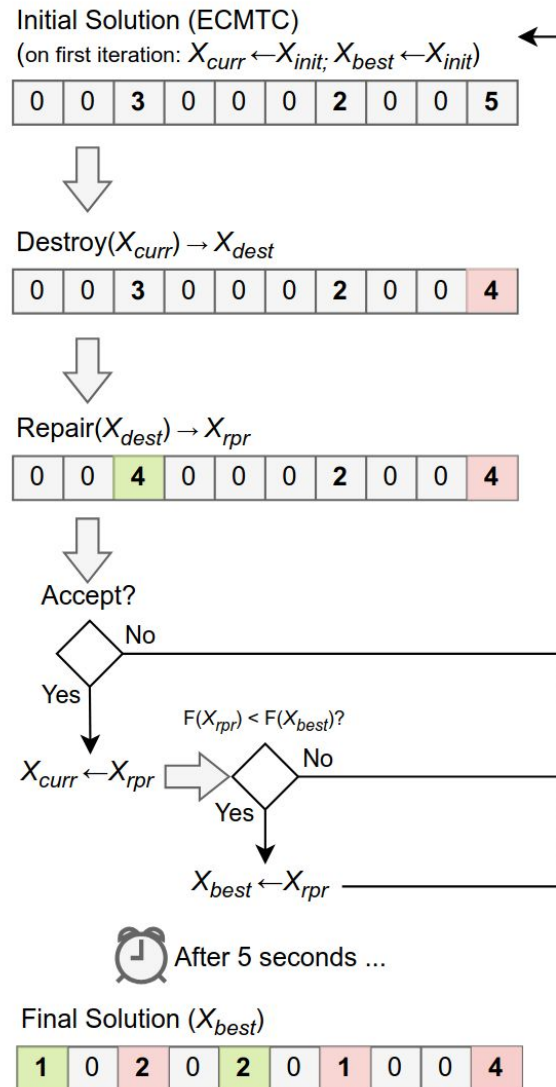
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## Possible approaches:

- Select a random subset of resources before computing each schedule
- **Change a schedule to add diversity**
  - **Large Neighborhood Search**
- etc

Nunes, Alan L., et al. "MetaCS-FL: A Metaheuristic-Based Framework for Client Selection in Federated Learning Systems." to be submitted.

# Optimizing over multiple rounds (2025)



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# Optimizing over multiple rounds (2025)

**Preliminary results:**  $M_{\text{total}}$  = time;  $\Sigma_{\text{total}}$  = energy;  $S_{\text{fair}}$  = Jain's Fairness Index; figures -> rounds to accuracy

TABLE VI: Performances for CIFAR-10 IID. NaN means the method did not achieve the target testing accuracy.

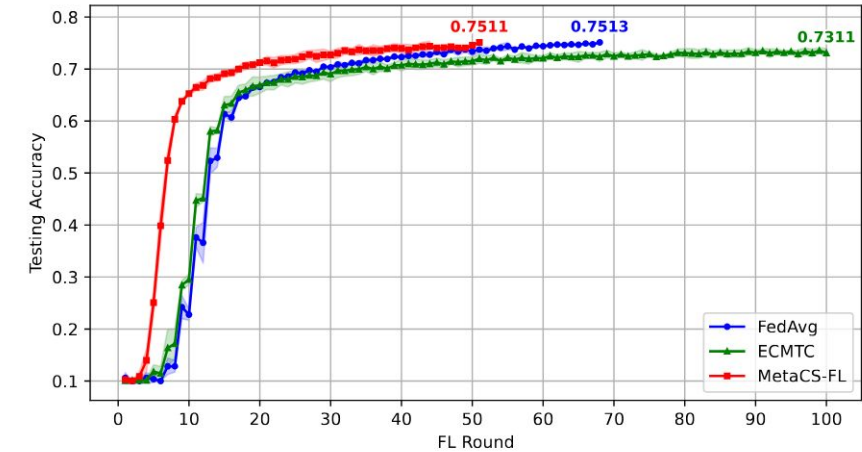
CS Approach	$M_{\text{total}}$	$\Sigma_{\text{total}}$	$S_{\text{fair}}$	RoA@0.75
FedAvg (Baseline)	10,696.79	2,077,926.08	0.98	$62 \pm 5.4$
ECMTC	8,615.93 (-19.45%)	2,019,645.24 (-2.8%)	0.45 (-53.85%)	NaN
MetaCS-FL	3,762.31 (-64.83%)	897,893.30 (-56.79%)	0.67 (-31.54%)	$46 \pm 3.6$

Units:  $M_{\text{total}}$  in seconds;  $\Sigma_{\text{total}}$  in joules.

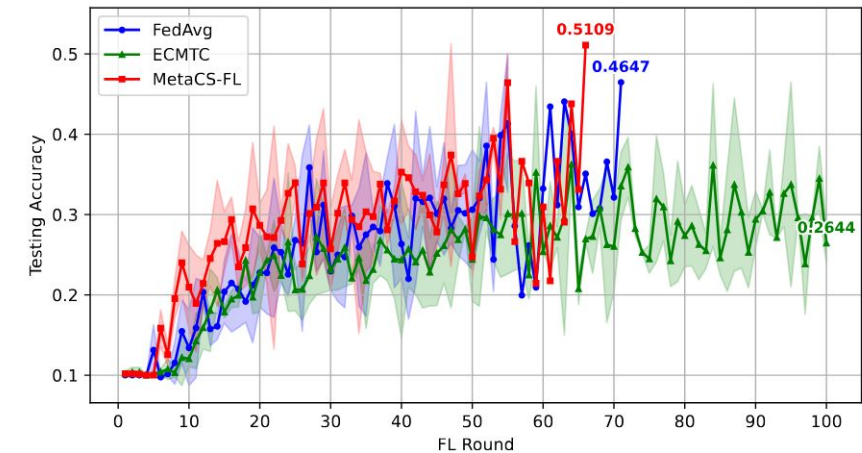
TABLE VII: Performances for CIFAR-10 non-IID. NaN means the method did not achieve the target testing accuracy.

CS Approach	$M_{\text{total}}$	$\Sigma_{\text{total}}$	$S_{\text{fair}}$	RoA@0.45
FedAvg (Baseline)	10,010.54	1,976,410.31	0.98	$59 \pm 8.3$
ECMTC	8,389.58 (-16.19%)	1,822,920.56 (-7.77%)	0.46 (-53.12%)	NaN
MetaCS-FL	5,106.6 (-48.99%)	1,151,546.44 (-41.74%)	0.71 (-27.76%)	$56 \pm 7.8$

Units:  $M_{\text{total}}$  in seconds;  $\Sigma_{\text{total}}$  in joules.



(a) CIFAR-10 IID



(b) CIFAR-10 non-IID

# Concluding remarks

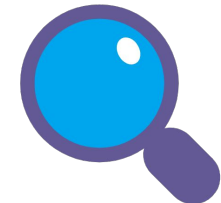
We take FL and optimize its performance and/or energy consumption by controlling how much work each device should do.

## Advantages of our approaches



- ★ Given the required information, we can find optimal solutions
  - Time, energy, both
- ★ It should be easier to control how much work to give to a resource than to control other aspects of the resources
  - e.g. DVFS

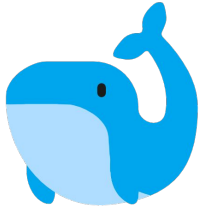
## Limitations



- ❖ We require more information from the resources
- ❖ Optimizing for one objective can lead to worse outcomes for other objectives

# Concluding remarks

We take FL and optimize its performance and/or energy consumption by controlling how much work each device should do.

- Can we get energy or carbon-equivalent emissions **information**?
  - Should we? (privacy issues)
  - Can we trust this information?
- **How far from the best performance** (%) do I accept to be if it improves my energy consumption (and vice-versa)?
- How to optimize considering more options (e.g., edge device offloading)?
- **White whales**
  - Optimize energy if monotonically increasing [faster than  $O(T^2n)$ ]? 
  - Optimize time given an energy budget in  $O(T^2n)$  or less?

That's all folks!