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Auction-based and Distributed Optimization Approaches for Scheduling Observations in Satellite Constellations with Exclusive Orbit Portions

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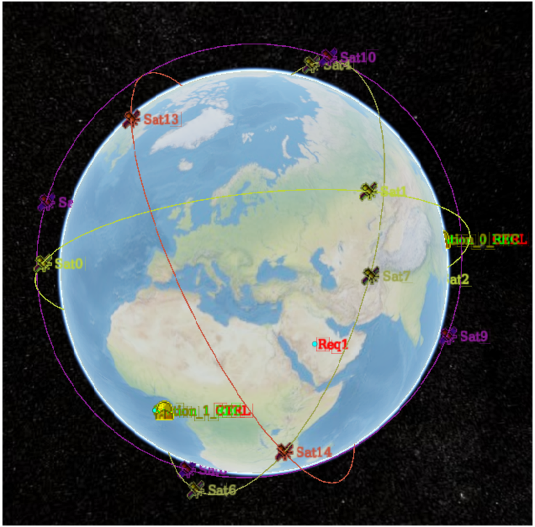
ONERA, DTIS-SYD, Université de Toulouse

Context and Motivations

- Increasing size of deployed EOS constellations

⇒ Observe any point on Earth at higher frequency, e.g. Planet [SHAH et al., 2019]

- **but**, requires to improve coordination and cooperation between assets and stakeholders



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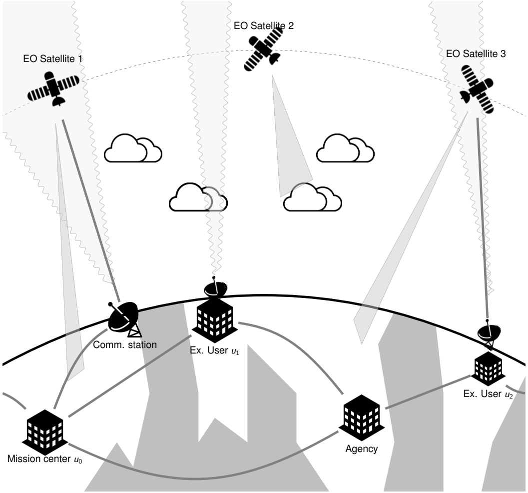
⇒ Observe any point on Earth at higher frequency, e.g. Planet [SHAH et al., 2019]

- **but**, requires to improve coordination and cooperation between assets and stakeholders

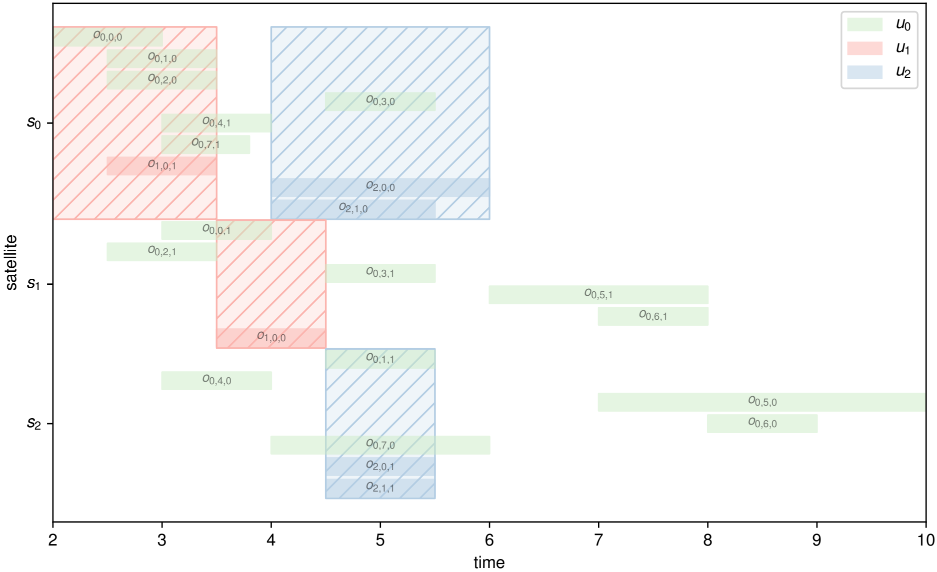
- We focus here on collective observation scheduling on a constellation where some users have exclusive access to some orbit portions

⇒ Answer to strong user expectations to benefit both from a shared system (to reduce costs) and a proprietary system (total control and confidentiality)



Scheduling Observations with Multiple Exclusive Orbit Portions

Illustrative Example



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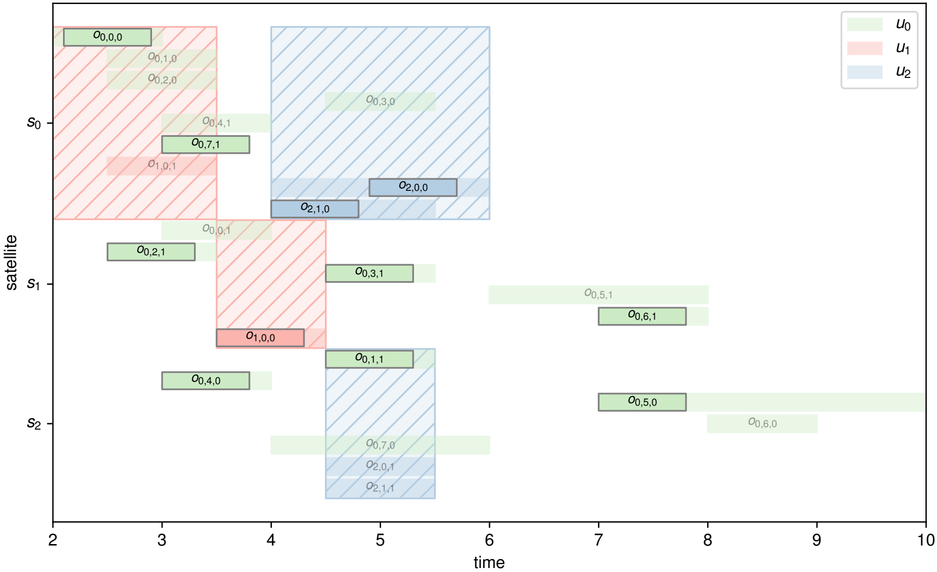

EOSCSP Model

Earth Observation Satellite Constellation Scheduling with Exclusives Problem is a tuple

$$P = \langle \mathcal{S}, \mathcal{U}, \mathcal{R}, \mathcal{O} \rangle$$

- $\mathcal{S} = \{s = \langle t_s^{\text{start}}, t_s^{\text{end}}, \kappa_s, \tau_s \rangle\}$ is a set of satellites
- $\mathcal{U} = \{u = \langle e_u, p_u \rangle\}$ is a set of users
- $\mathcal{R} = \{r = \langle t_r^{\text{start}}, t_r^{\text{end}}, \Delta_r, \rho_r, p_r, u_r, \theta_r \rangle\}$ is a set of requests
- $\mathcal{O} = \{o = \langle t_o^{\text{start}}, t_o^{\text{end}}, \Delta_o, r_o, \rho_o, s_o, u_o, p_o \rangle\}$ is a set of observation opportunities

A *solution* to an EOSCSP is a mapping $\mathcal{M} = \{(o, t) \mid o \in \mathcal{O}, t \in [t_o^{\text{start}}, t_o^{\text{end}}]\}$
s.t. the overall reward is maximized (sum of the rewards of the scheduled observations):
$\arg\max_{\mathcal{M}} \sum_{(o,t) \in \mathcal{M}} \rho_o$

How to Solve EOSCSPs?

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- Centralized allocation

How to Solve EOSCSPs?

$$\underset{x_{s,o}}{\text{maximize}} \quad \sum_{o\in\mathcal{O},s\in\mathcal{S}} \rho_o x_{s,o} \tag{1}$$

$$\text{s.t.}$$

$$2-\beta_{s,o,p}-\beta_{s,p,o} \geq x_{s,o} \qquad \forall s\in\mathcal{S},\forall o,p\in\mathcal{O},o\neq p \tag{2}$$

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$$\beta_{s,o,p}+\beta_{s,p,o} \leq 3-x_{s,o}-x_{s,p} \qquad \forall s\in\mathcal{S},\forall o,p\in\mathcal{O},o\neq p \tag{4}$$

$$\beta_{s,o,p}+\beta_{s,p,o} \leq 1 \qquad \forall s\in\mathcal{S},\forall o,p\in\mathcal{O},o\neq p \tag{5}$$

$$t_{s,p}-t_{s,o} \geq \tau_s(o,p)+\Delta_o-\Delta^{\text{max}}_{s,o,p}\beta_{s,o,p} \qquad \forall s\in\mathcal{S},\forall o,p\in\mathcal{O},o\neq p,\text{s.t.}\Delta^{\text{max}}_{s,o,p}>0 \tag{6}$$

$$t_{s,o}-t_{s,p} \geq \tau_s(p,o)+\Delta_p-\Delta^{\text{max}}_{s,p,o}\beta_{s,p,o} \qquad \forall s\in\mathcal{S},\forall o,p\in\mathcal{O},o\neq p,\text{s.t.}\Delta^{\text{max}}_{s,p,o}>0 \tag{7}$$

$$\sum_{o\in\mathcal{O}} x_{s,o} \leq \kappa_s \qquad \forall s\in\mathcal{S} \tag{8}$$

$$\sum_{o\in\theta(r)} x_{s,o} \leq 1 \qquad \forall r\in\mathcal{R} \tag{9}$$

$$x_{s,o}\in\{0,1\} \qquad \forall s\in\mathcal{S},\forall o\in\mathcal{O} \tag{10}$$

$$t_{s,o}\in[t_o^{\text{start}},t_o^{\text{end}}]\subset\mathbb{R} \qquad \forall s\in\mathcal{S},\forall o\in\mathcal{O} \tag{11}$$

$$\beta_{s,o,p}\in\{0,1\} \qquad \forall s\in\mathcal{S},\forall o,p\in\mathcal{O},o\neq p \tag{12}$$

$$\text{with} \quad \Delta^{\text{max}}_{s,o,p}=t_o^{\text{end}}-t_p^{\text{start}}+\Delta_o+\tau^s(o,p)$$

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  - Exact solving (e.g. MILP), but won't scale-up

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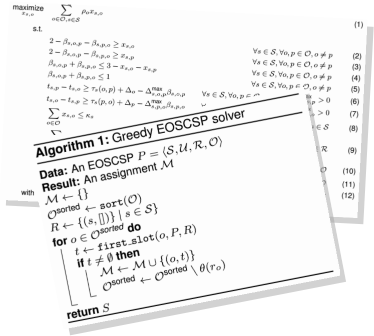

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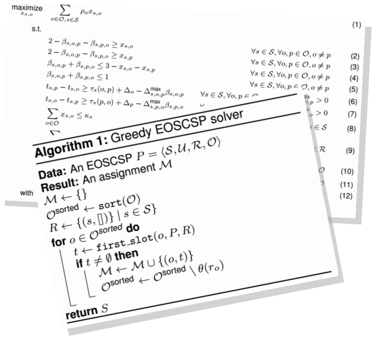
$$\underset{x_{s,o}}{\text{maximize}} \sum_{o \in \mathcal{O}, s \in \mathcal{S}} p_o x_{s,o} \quad (1)$$

s.t.

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Algorithm 1: Greedy EOSCSP solver

Data: An EOSCSP $P = \langle \mathcal{S}, \mathcal{U}, \mathcal{R}, \mathcal{O} \rangle$

Result: An assignment $\mathcal{M}$

$\mathcal{M} \leftarrow \{\}$

$\mathcal{O}^{sorted} \leftarrow \texttt{sort}(\mathcal{O})$

$R \leftarrow \{(s, [])\} \mid s \in \mathcal{S}\}$

for $o \in \mathcal{O}^{sorted}$ **do**

  $t \leftarrow \texttt{first\_slot}(o, P, R)$

  if $t \neq \emptyset$ **then**

    $\mathcal{M} \leftarrow \mathcal{M} \cup \{(o, t)\}$

    $\mathcal{O}^{sorted} \leftarrow \mathcal{O}^{sorted} \setminus \theta(r_o)$

return S

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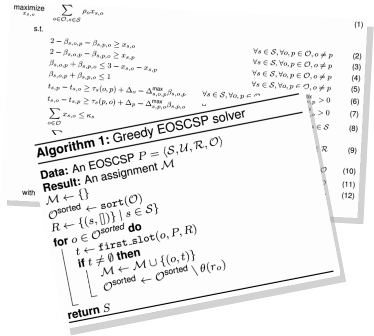

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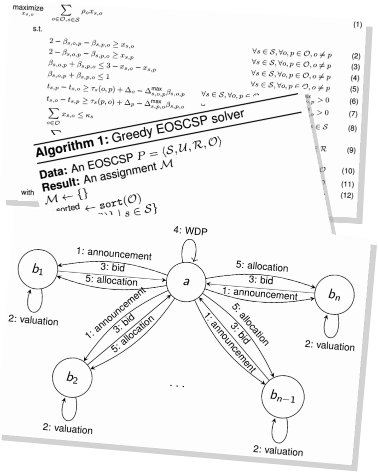

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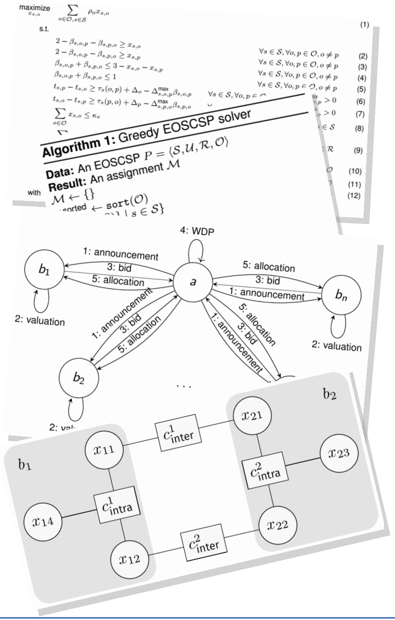

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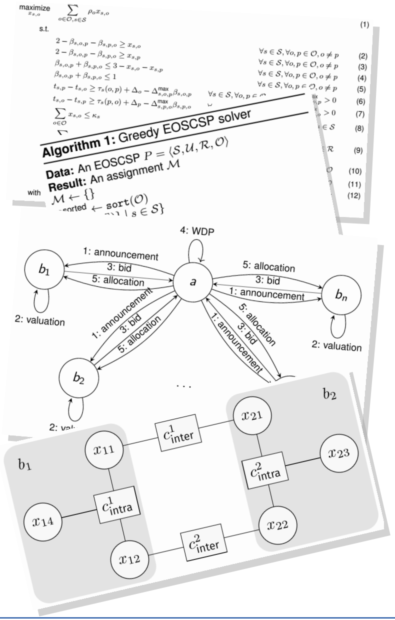

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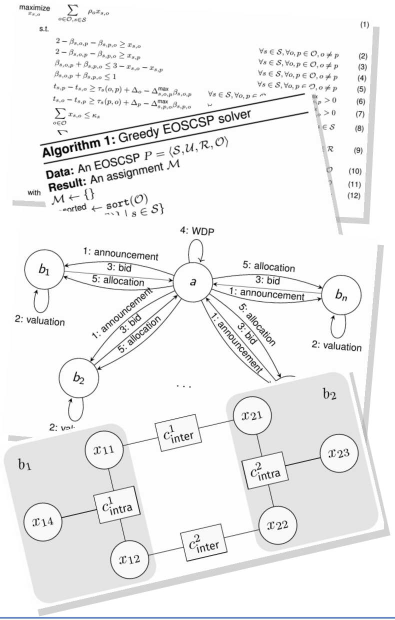
    - ✓ plans remain private
    - ⚠ requires some coordination/communication



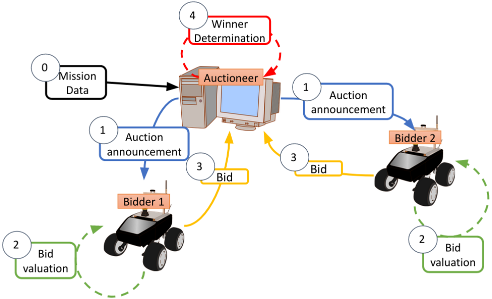
Plan

Auction-based Coordination for EOSCSP
Focus on Resource/Task Allocation

Many application fields, as Collective Robotics, make use of market-based approach to allocate tasks/resources to robots

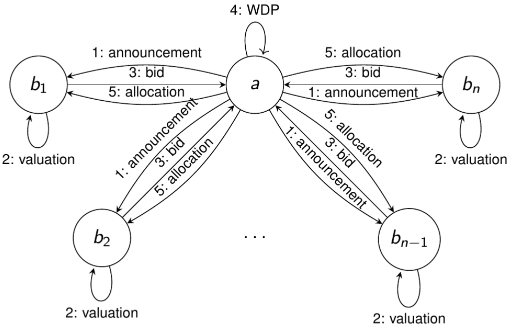
- A set of **resources** (robots, satellites, etc.), $R = \{r_1, \ldots, r_{|R|}\}$
- A set of **tasks**, $T = \{t_1, \ldots, t_{|T|}\}$, each having a time-related and operation constraints
- Find an allocation of tasks to resources, wrt. some consistency constraints

≈ **multi-item allocation**: each resource is allocated several tasks (bundle)



Auction-based Coordination for EOSCSP
Allocating non exclusive observations to best exclusive portions

Auction-based approches are relevant for satellite task allocation [PHILLIPS and PARRA, 2021]



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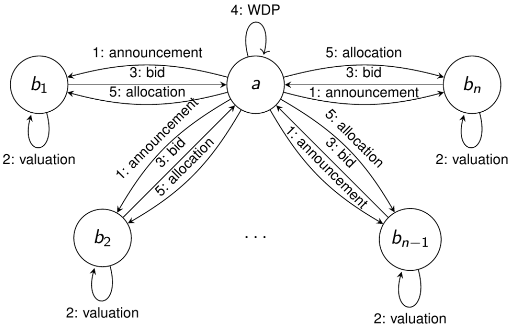

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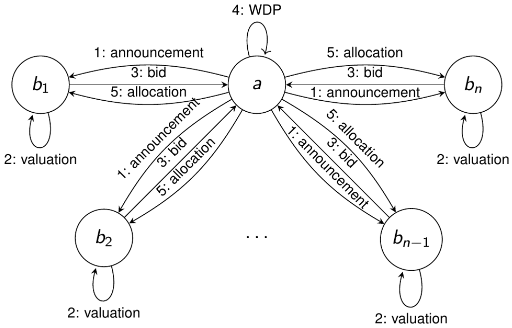

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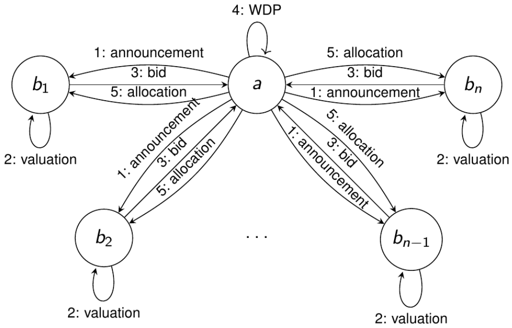

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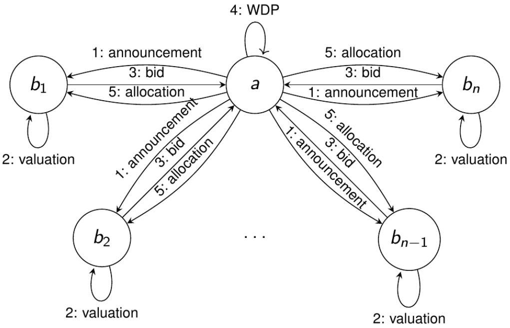

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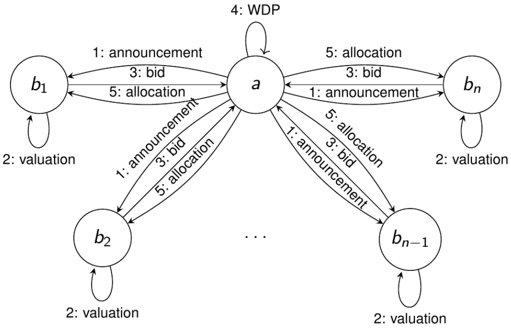

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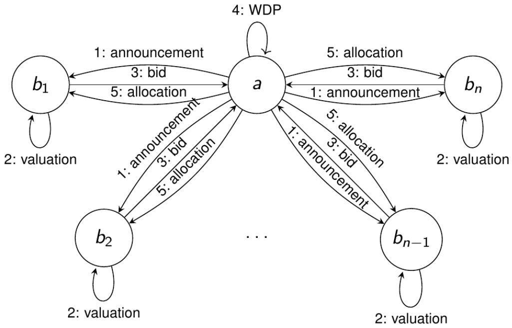

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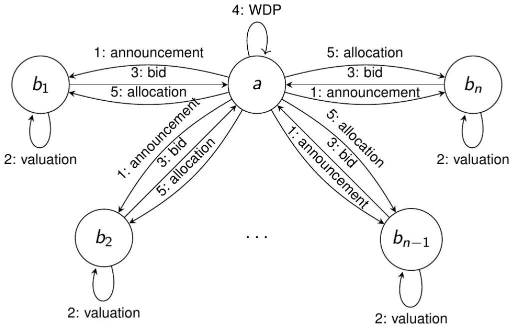

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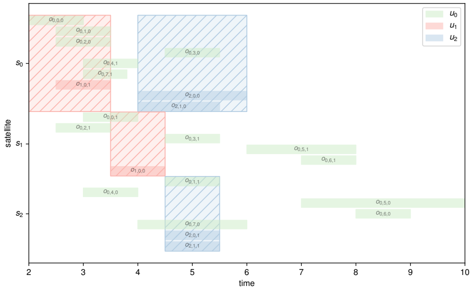
- **Consensus-based Bundle Auction** (CBBA) [CHOI et al., 2009]
  - Each agent bids on some *bundle of tasks* and *converge to a consensus* with other agents

1. Identify non exclusive requests possibly fulfilled in exclusive portions
2. Send identified requests to exclusive users
3. Solve the allocation problem using PSI, SSI or CBBA
   - Bids are computed as the **best marginal costs** of integrating requests in their current plans (which amounts to solve scheduling problems...)
4. Allocate as many remaining requests outside exclusive windows

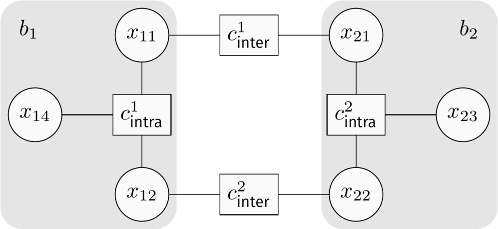


Plan

DCOP-based Coordination for EOSCSP

Allocating non exclusive observations to best exclusive portions

- Consider the **collective decision** for allocating non exclusive tasks to exclusive windows
- Collective decision to coordinate exclusive users' decisions modeled as a **distributed constraint optimization problem** (DCOP)
- As for auctions, exclusive users aim to **minimizing the marginal cost** of integrating non exclusive tasks in their schedule, while meeting some operational constraints



DCOP-based Coordination for EOSCSP
General Scheme

1. Identify non exclusive requests possibly fulfilled in exclusive windows
2. Send each identified request r to exclusives users, one by one
3. Solve the problem of r using a DCOP solution method (e.g. DPOP [Petcu and Faltings, 2005])
   - Costs are computed as the **best marginal cost** of integrating requests in their current plan (which amounts to solve a scheduling problem...)
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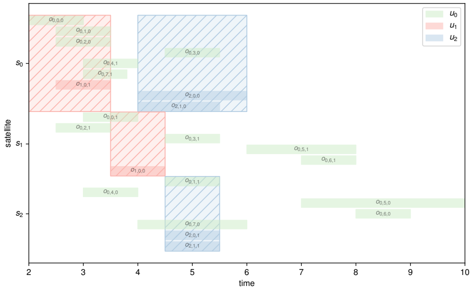

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- The agents are the exclusive users which can potentially schedule r:

$$\mathcal{A} = \{u \in \mathcal{U}^{\text{ex}} | \exists (s, (t_u^{\text{start}}, t_u^{\text{end}})) \in e_u, \exists o \in \theta_r \text{ s.t. } s_o = s, [t_u^{\text{start}}, t_u^{\text{end}}] \cap [t_o^{\text{start}}, t_o^{\text{end}}] \neq \emptyset\} \quad (1)$$

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- Each agent u owns binary decision variables, one for each observation $o \in \mathcal{O}[u]^r$ and exclusive e in its exclusives e_u, stating whether it schedules o in e or not:

$$\mathcal{X} = \{x_{e,o} | e \in \textstyle\bigcup_{u \in \mathcal{A}} e_u, o \in \mathcal{O}[u]^r\} \quad (2)$$

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with $\mathcal{O}[u]^r = \{o \in \theta r | \exists (s, (t_u^{\text{start}}, t_u^{\text{end}})) \in e_u, \text{ s.t. } s_o = s, [t_u^{\text{start}}, t_u^{\text{end}}] \cap [t_o^{\text{start}}, t_o^{\text{end}}] \neq \emptyset\}$ are observations related to request r that can be scheduled on u's exclusives

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$$\mathcal{A} = \{u \in \mathcal{U}^{\text{ex}} | \exists (s, (t_u^{\text{start}}, t_u^{\text{end}})) \in e_u, \exists o \in \theta_r \text{ s.t. } s_o = s, [t_u^{\text{start}}, t_u^{\text{end}}] \cap [t_o^{\text{start}}, t_o^{\text{end}}] \neq \emptyset\} \quad (1)$$

- Each agent u owns binary decision variables, one for each observation $o \in \mathcal{O}[u]^r$ and exclusive e in its exclusives e_u, stating whether it schedules o in e or not:

$$\mathcal{X} = \{x_{e,o} | e \in \textstyle\bigcup_{u \in \mathcal{A}} e_u, o \in \mathcal{O}[u]^r\} \quad (2)$$

$$\mathcal{D} = \{\mathcal{D}_{x_{e,o}} = \{0, 1\} | x_{e,o} \in \mathcal{X}\} \quad (3)$$

  with $\mathcal{O}[u]^r = \{o \in \theta r | \exists (s, (t_u^{\text{start}}, t_u^{\text{end}})) \in e_u, \text{ s.t. } s_o = s, [t_u^{\text{start}}, t_u^{\text{end}}] \cap [t_o^{\text{start}}, t_o^{\text{end}}] \neq \emptyset\}$ are observations related to request r that can be scheduled on u's exclusives

- μ associates each variable $x_{e,o}$ to e's owner

DCOP-based Coordination for EOSCSP (cont.)

DCOP Model

- Constraints should check that at most one observation is scheduled per request (4), that satellites are not overloaded (5), that at most one agent serves the same observation (6)

$$\sum_{e \in \bigcup_{u \in \mathcal{A}} e_u} x_{e,o} \leq 1, \quad \forall u \in \mathcal{X}, \forall o \in \mathcal{O}[u]^r \tag{4}$$

$$\sum_{o \in \{o \in \mathcal{O}[u]^r \mid u \in \mathcal{A}, s_o = s\}, e \in \bigcup_{u \in \mathcal{A}} e_u} x_{e,o} \leq \kappa_s^*, \ \forall s \in \mathcal{S} \tag{5}$$

$$\sum_{e \in \bigcup_{u \in \mathcal{A}} e_u} x_{e,o} \leq 1, \quad \forall o \in \mathcal{O} \tag{6}$$

DCOP-based Coordination for EOSCSP (cont.)

DCOP Model

- Constraints should check that at most one observation is scheduled per request (4), that satellites are not overloaded (5), that at most one agent serves the same observation (6)

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$$\sum_{e \in \bigcup_{u \in \mathcal{A}} e_u} x_{e,o} \leq 1, \quad \forall o \in \mathcal{O} \tag{6}$$

- The cost to integrate an observation in the current user's schedule should be assessed to guide the optimization process

$$c(x_{e,o}) = \pi(o, \mathcal{M}_{u_o}), \quad \forall x_{e,o} \in \mathcal{X} \tag{7}$$

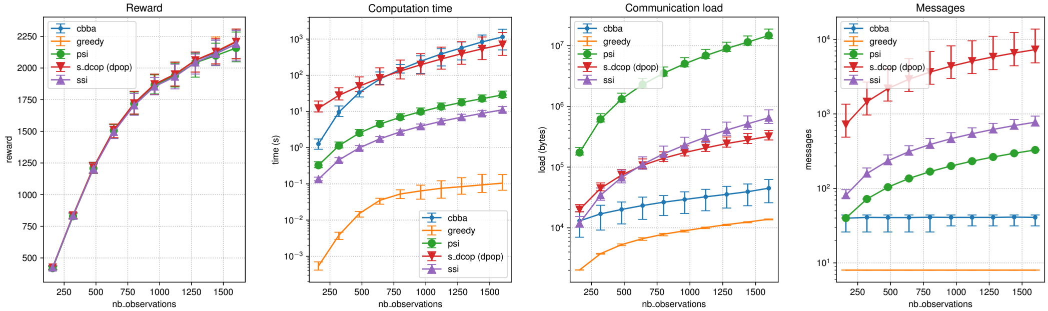
where π evaluates the best cost obtained when scheduling o and any combination of observations from $\mathcal{M}_{u_o}$, as to consider all possible revisions of u_o's current schedule

$$\mathcal{C} = \{(4), (5), (6), (7)\} \tag{8}$$

Plan

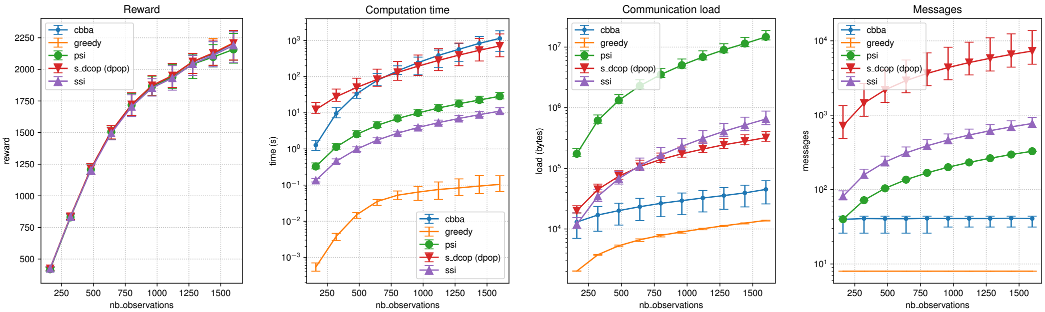
Highly conflicting randomly generated problems

5-min horizon with overlapping requests and limited capacity



Highly conflicting randomly generated problems

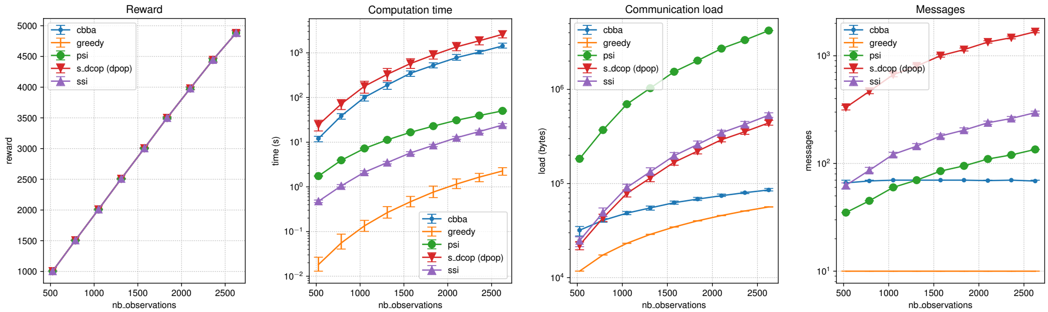
5-min horizon with overlapping requests and limited capacity



- ✗ cbba and s_dcop requires extra-computation time (≈ 1000s)
- ✓ cbba and s_dcop provide the best solutions wrt. reward
- ✓ cbba exchanges fewer messages of small size
- ✓ ssi remains the best compromise wrt. solution quality, computation time and communication load

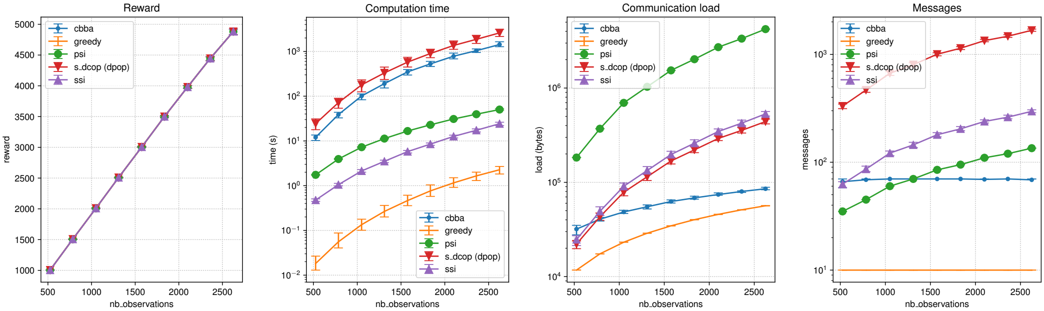
Realistic randomly generated problems

6-hour horizon with numerous requests and large capacity



Realistic randomly generated problems

6-hour horizon with numerous requests and large capacity



- ✓ cbba does require less time to compute than s_dcop
- ✓ s_dcop and cbba can perform many computation concurrently
- ⇒ There is room for computation speedup in real distributed settings

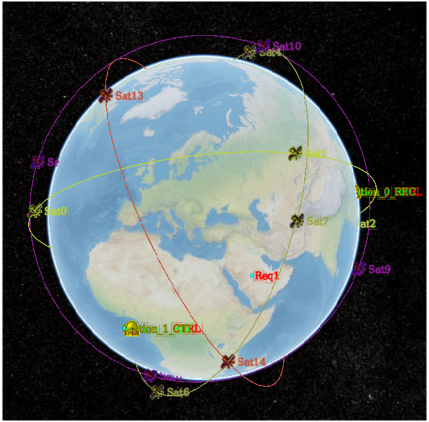
Plan

Conclusions and Perspectives

- We proposed the **EOSCSP model** for allocating observation tasks in private orbit portions
- We proposed several distributed allocation methods based on **auctions and DCOPs**
- We evaluated the performance of these techniques on **randomly generated (but realistic) instances**

⇒ **SSI** is a good compromise with good performance with faster computation but slightly higher communication load

- Ideas for future developments
  - Investigate **exclusive windows allocation** (prior to EOSCSP) [MAQROT et al., 2022]
  - Approximate marginal cost instead of computing bundle marginal costs
  - Evaluate on larger realistic EOSCSP instances



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Auction-based and Distributed Optimization Approaches for Scheduling Observations in Satellite Constellations with Exclusive Orbit Portions

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