Appears in the 18th International Conference on Space Operations, Montreal, Canada, 26 - 30 May 2025.

Federated Autonomous Operations: A New Paradigm for Large-Scale Observation Systems

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Abstract

The number of spacecraft available for observation has grown rapidly in the last few years, opening the door for larger and larger observation systems. Coordinated observation systems can provide new insights and measurements of phenomena on Earth and in space. However, the vast suite of observing assets available for observation is not operated by a single omnipotent entity. Instead, fleets of assets have different operators. We envision a *federated* observation system composed of many operating entities. A federated observation system can leverage all observing assets across operators for timely and coordinated measurement. A federated system requires novel federated autonomous operations to address the distributed control of the system. This work discusses federated scheduling, an approach to autonomously coordinating the observing assets across a federated observing system. Federated scheduling enables (1) the use of all available assets for observation, (2) distributed tasking of the system, and (3) resolving contention among competing campaign objectives. We discuss large federated autonomous systems including how they would be operated, the underlying artificial intelligence that autonomously coordinates entities and assets, and the novel capabilities enabled by such an observing system.

Keywords: remote sensing, observation scheduling, multi-agent systems, constellation operations, federated operations

1. Introduction

Recent years have seen a proliferation of Earth-observing spacecraft and their capabilities which can enable faster response times to both static and transient phenomena as well as coordinated remote sensing. Reduced launch costs have led to a growing number of commercial constellations including diversity in sensor types [1]. This increase in the number of spacecraft available for observation not only results in an increase in total observation volume but also means shorter revisit times to target observation locations on Earth. Reduced revisit times are key to both efficient single observation responses and coordinated measurements such as stereographic imaging which requires multiple spacecraft simultaneously observing from different viewing angles. New commercial spacecraft possess edge hardware capable of obtaining rapid insights from data, such as whether an observation was successful (e.g. non-cloudy) [2]. Edge data insights can also be leveraged to identify time-sensitive phenomena like volcanic eruptions, wildfires, or flooding. Inter-satellite links (ISL) enable persistent low-data rate communications among spacecraft in space and stations on the ground resulting in low-latency communication [3]. Therefore, onboard detection of failed acquisitions or time-sensitive phenomena can be rapidly alerted for rapid response to these events.

These capabilities are particularly important for supporting science campaigns that require time-sensitive and coordinated measurements. Science campaigns refer to the monitoring of Earth phenomena and the collection of measurements to understand Earth processes. These campaigns are not comprised of single observations, but long-term goals such as global monitoring of all volcanic activity or flooding events. Measurements before, during, and after dynamic events like natural disasters can both inform response teams and deepen understanding of environmental processes by collecting data as they develop. However, without timely observations (e.g. hours to same day), key measurements of these processes may be missed. For example, when monitoring a wildfire, ground responders require at least 30-minute updates [4]. These campaigns often manifest in workflows such as “observe volcano daily and if thermal emissions detected, observe as much as possible” or “if flood detected, acquire hourly non-cloudy observations of flood extent”. For these science campaigns to be successfully implemented, we require the real-time event detection and alerting enabled by edge computing and ISL as well as the reduced revisit times provided by having many observing assets.

While these capabilities support the theoretical advancement of remote sensing systems for science campaigns, there are challenges to their realization. There are institutional boundaries preventing access to the large number of spacecraft available for observation. Consider early warning signs of a volcanic eruption are detected by a spacecraft operated by Entity X and it is necessary to rapidly re-observe the volcano. The soonest available overflight is likely not from a spacecraft operated by Entity X. This problem is further highlighted when we consider diversity in sensors and stereographic imaging. Certain sensor types, such as thermal infrared, are rarer compared to visible-range instruments, yet necessary for applications like thermal activity detection from volcanos and wildfires. The necessary sensors for science measurements and overflights for stereographic observations are distributed across operating entities.

We must conform to the reality that all in-space assets are not under the operation of a single omnipotent entity. Therefore, to leverage all observing assets (including space, but also ground, air, marine, etc...), we require *federated* operations in which needed observations are requested of entities controlling their respective assets. The emergence of new capabilities to task spacecraft from electronic interfaces opens the door to complete autonomous coordination of a federated system. This new operational paradigm harmonizes numerous entities (e.g. commercial, federal, etc.…) and their assets into one large-scale, coherent observation system without single unified control. By requesting the observations from assets across entities, a federated system can provide the timely observations required for science campaigns.

A federated system not only improves observation efficiency through leveraging greater spatial and temporal coverage but also has enhanced robustness. A federated system is inherently robust to disruptions; there is no single-point failure. If a single spacecraft, or even an entire constellation of spacecraft, is operationally unavailable, a federated system can leverage the suite of other spacecraft in orbit to fulfill observation requirements. This robustness is unique to a federated system; in a single-entity observation system, non-functional spacecraft or operations result in failures (i.e. no observations).

Tasking assets in a federation will require novel federated scheduling algorithms that utilize state-of-the-art planning and scheduling autonomy. Scheduling observing assets often culminates in solving a complex task allocation problem in which we reason about spacecraft orbits and target visibilities, instrument capabilities, operational constraints including spacecraft resources, and competing campaign objectives [5-11]. However, in a federated system, information such as spacecraft resources is not globally available to a single controller, and no single controller has permission to command every spacecraft operated by external institutions. Federated scheduling differs from traditional scheduling in that tasks get allocated to entities that then schedule their assets; when allocated tasks are not scheduled, the federated scheduler must re-allocate. Tasking the federation will culminate in a simple, service-oriented interface for users, such as commanders, scientists, and automated software protocols. Users specify desired measurements and workflows while all operations and analyses are automated. The user requests are the input to the federated scheduler which will optimize the allocation of tasks to entities. We require continuous and contingent scheduling capabilities to accommodate user workflows and dynamic requests. This results in solving a complex, hybrid centralized and decentralized, multi-agent combinatorial optimization problem with uncertainty.

Previous work on large-scale observation systems for science campaigns has focused on sensorwebs. These efforts coordinate multiple assets to observe a single physical phenomenon. There have been multiple deployments leveraging the Earth Observing One (EO-1) Mission from 2004-2017 [12]. Applications of deployed sensorwebs include tracking volcanic activity [13], flooding [14], and wildfires [15].

More recent efforts to demonstrate sensorwebs have included modeling to demonstrate tracking of flooding events [16]. That work included demonstrations using Planet Dove, SkySat, and Capella SAR measurements. More recent large-scale demonstrations have leveraged the Planet Dove and SkySat constellations to track volcanic activity [17] (also using the ECOSTRESS instrument onboard ISS) and flooding worldwide [18].

Sensorweb technologies offer the opportunity to acquire unique coordinated complementary observations, as well as enable the narrow field of view measurements to be more effectively targeted as for volcanoes [13] which demonstrated an over 30% hit rate for capturing active thermal signatures over an order of magnitude increase of blind monitoring. For flooding applications [14], using global coverage moderate resolution MODIS to target the narrow field of view, but high spatial resolution sensors on EO-1, Worldview, Geo-Eye, and others enabled a doubling of temporal coverage with high spatial resolution sensors. More recent demonstrations highlighted the utility of integrating science (hydrological) models in targeting sensors [16]. While sensorwebs are effective for some applications and can task assets based on alerts [17,18], they have limitations. In a non-federated system, it is not possible to address unfulfilled requests efficiently as there is no distributed coordination or feedback from entities/agents. Previous sensorwebs are also not scalable to multiple applications since there is no reasoning about how to handle competing campaign objectives.

There is minimal prior work on federated scheduling. Previous work did not consider complex workflows, tasking from multiple channels, or coordinated measurements [19,20]. The scheduling approach in previous work leveraged a single centralized planner to perform task allocation, whereas distributed planning offers much more effective solutions which we discuss in the next section.

Federated scheduling enables (1) the use of all available assets for observation, (2) distributed tasking of the system, and (3) resolving contention among competing campaign objectives. This work envisions large federated autonomous systems including how they would be operated in a lights-out fashion, the underlying artificial intelligence that coordinates entities and assets, and the novel capabilities enabled by such an observing system.

2. Federated Observation Systems

A federated observation system consisting of the following parts:

1. *F:* a set of federated entities,
2. *A:* a set of observing agents, and
3. *U:* a set of users.

Each agent in the federation is operated by one entity in the federation. It is assumed that all federations can communicate with the other federations for planning purposes, but agents cannot necessarily communicate with agents in other federations. An agent can be any observing node, including a satellite, a ground sensor, or a marine sensor.

Users submit requests for a fixed planning horizon (e.g. 1 week). However, requests can be submitted at any point during the horizon. The requests can be fulfilled by any agent and entities/agents can also serve as users that request from the entire federation.

To autonomously plan the observations of a federation, we must define the following parts in addition to the above sets:

4. *H:* a planning horizon and
5. *R:* a set of requests for observation.

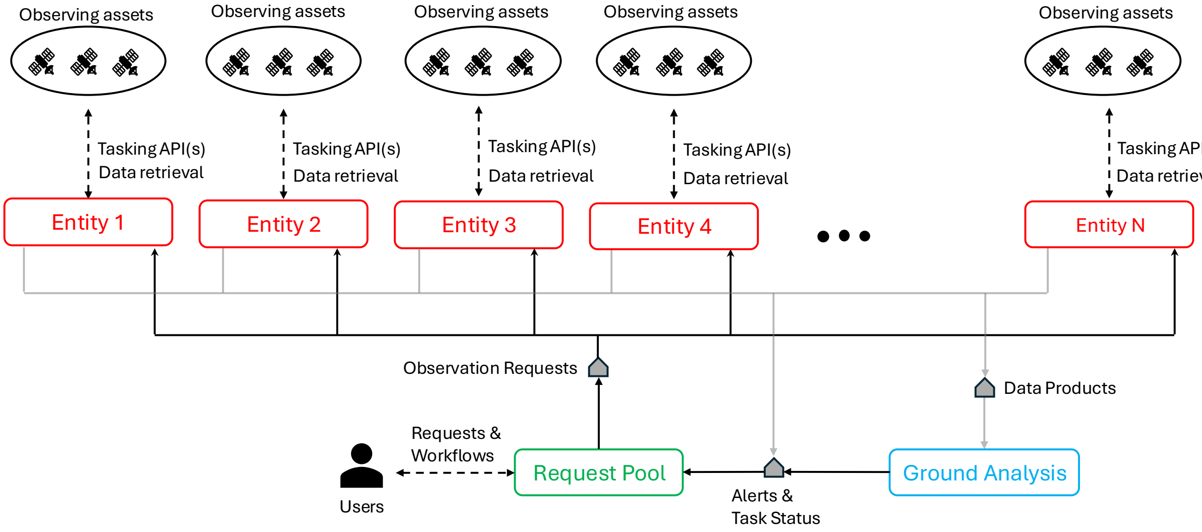

Fig. 1. Overview of a federated observation system. Entities get allocated requests to schedule for their observing assets based on a federated scheduler. The federated system interfaces with requests through several channels such as users, alerts, and task status.

The planning horizon defines the time frame for scheduling observing assets. The requests specify the desired observations from users. As mentioned previously, a federated system can effectively tackle complex workflows of requests. Individual requests have observation modes that define the type in addition to standard data such as target location, time horizon, and science measurement as shown in Figure 1. The Rosetta Orbiter used a similar paradigm to define complex observation types [21]. Coordinated measurements can be represented using a hierarchy of tasks. Complex workflows (e.g. daily monitoring) will be automatically translated into schedulable atomic tasks (e.g. single observations). Each workflow is parsed into *N* sets of observation requests with *N-1* (or *N*) conditions. Every time a condition is met, the next set of requests become active, and the previous set becomes void. For example, consider the workflow "observe volcano daily with TIR and if thermal emitting, observe as much as possible with TIR until not thermal emitting". This gets translated to a 3-step workflow: (1) Daily periodicity request to observe with TIR with end condition of thermal emission detection, (2) Continuous request to observe with TIR with end condition of no thermal emission detection, (3) End observation (or alternatively repeat step 1). Workflows will be translated intelligently to avoid obsolete observations. In the above workflow a night acquisition cannot distinguish between cloud cover and volcanic inactivity whereas a day acquisition can. This is reflected in the time horizon of the requests defining the workflow.

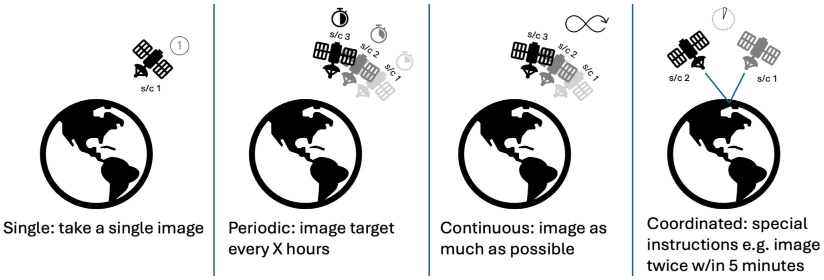

Fig. 2. Request modes for a federated system.

The goal of the federation is to collectively satisfy all the requests in *R* during the horizon *H* while adhering to all constraints of the agents *A.* These constraints include data volume limits, mechanical restrictions such as slewing, energy usage, and more. These constraints are known by the federation controlling each agent, but not by other federations.

A federated observation system inherently requires distributed coordination to schedule observations. A centralized controller is not able to command all the agents and does not have the sufficient information regarding agent constraints to develop a schedule for each agent that satisfies all constraints. While a *federated scheduler* may be a centralized computing source, this scheduler would only be able to request that observations are fulfilled by the agents of a federated entity. The final actions of observing agents are determined by the operating federated entity. A federated scheduler does know the overflights of every agent in the federation along with details of the instruments onboard. Federated scheduling differs from traditional scheduling in that tasks get allocated to entities that then schedule their assets; when allocated tasks are not scheduled, the federated scheduler must re-allocate. A federated scheduler can employ different planning techniques, which we discuss below.

2.1 Centralized Allocation

The most basic federated scheduler uses just the knowledge of the satellite overflights to compute a task allocation of observation requests to entities. This task allocation is a constraint optimization problem and requires no communication between federated entities. The federated scheduler assigns requests to the entities, and they schedule their assets accordingly with no guarantees on request fulfilment. While simple, this solution technique is not robust against the uncertainty of how each entity operates their agents and the entities do not contribute to the allocation of requests. This approach is also not as effective at scheduling workflows as this requires knowledge of request satisfaction which may only occur after data is collected and delivered.

2.2 Decentralized Allocation

An alternative is to leverage a completely decentralized approach in which the entities reason about the capabilities of their agents and communicate to converge to an optimal task allocation. This paradigm solves the task allocation problem as a distributed constraint optimization problem [22]. Solving satellite observation allocations as distributed constraint optimization problems has been shown to produce effective solutions for large-scale satellite systems [23]. In addition, distributed constraint optimization can handle continuous planning to accommodate the dynamic allocation of workflows and rolling requests [24].

2.3 Market-based Approaches

One drawback of solving the problem as a distributed constraint optimization problem is that this requires entities to communicate with each other. If this is not desired, we can leverage market-based techniques in which a centralized auctioneer communicates with each entity via bids for observation requests. Auction-based techniques have also been examined in previous work for satellite observation allocation [25]. However, an auction for a federated system would require a hierarchical structure in which entities bid for observation requests for their entire observing fleet.

Finally, in combination with any of these paradigms, we can deploy model-free solutions to learn the behaviour of the entities. Reinforcement learning can be used to either learn a direct policy that maps requests to entities or to learn heuristics that support allocations such as the probability entities accept or reject a request.

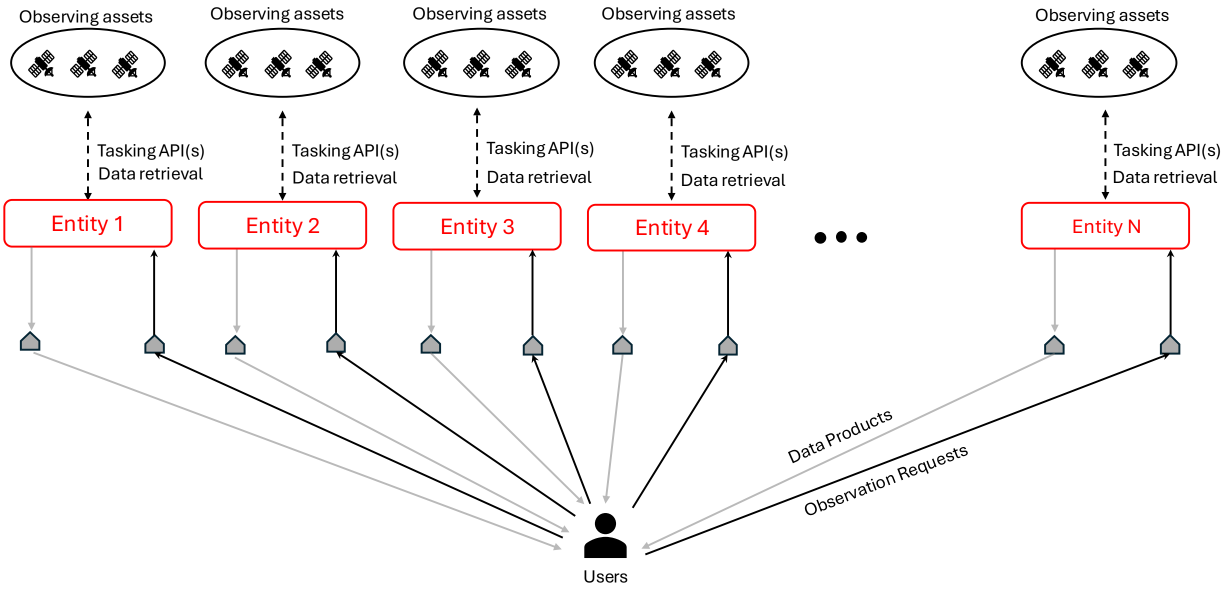

Fig. 3. Without a federated scheduler, each user must allocate requests to entities.

2.4 Alternatives to Federated Scheduling

We discuss two alternatives to federated scheduling that serve as baselines in evaluation. These approaches assume that a user can interface with each entity and the user is responsible for submitting requests. This alternative is shown in Figure 3. The first approach is for the user to submit *all* requests to all the entities. There are several drawbacks of this approach. First, the overhead for the user is increased substantially as the number of entities grows. For N entities, a user would need to specify each request N times. This approach also fails to coordinate the actions of the observing assets across entities. This results in redundant observations (i.e. two or more collects for the same request) which both wastes spacecraft resources and may be expensive for users. Finally, there is no possibility of scheduling workflows autonomously as all feedback from observations would be returned to the user who would have to manage data analysis and re-tasking. There is also no coordination among requests from different users, therefore the load on the entire observation system cannot be managed.

The second alternative is for the user to independently allocate requests to the entities. In this approach, instead of submitting all requests to all entities, a user can determine which observations to request of which entities. A user could decide this by examining the overflights of all the satellites. While this approach may be more effective at reducing redundant observations, it increases the overhead on a user even further. It also does not leverage the suite of observing assets in the federation for efficient completion as requests are allocated to only certain entities. Again, there is no possibility of scheduling workflows autonomously as all feedback from observations would be returned to the user who would have to manage data analysis and re-tasking.

Without federated scheduling, a federated observation system losses the capabilities to execute observations efficiently, react to dynamic events and workflows, and easily support useability.

3. Results

We show through simulation the improvement in request satisfaction when leveraging federated scheduling versus the two alternatives mentioned above.

3.1 Experimental Setup

We consider a satellite constellation modelled after the Planet SkySat [26] configuration with 6 orbital planes at an 88° inclination and 14 satellites per plane. There are an additional two planes at a 51.6° with 12 satellites per plane. Each satellite is constrained by a data volume limit of 125 GB and has an agile sensor that can slew to 45 degrees off-nadir. The constellation is shown in Figure 4.

We consider a target set of 634 major cities and generate random user requests by selecting a target and a time interval to observe the target within a day-long interval. We consider requests over a day long horizon that is randomly initialized during a week-long interval. Each request is a single image request to be taken between a specified interval. An observation consumes data volume that is sampled from a normal distribution with mean 50 MB and standard deviation 10 MB and requires 63 seconds to complete. We consider day long campaigns with between 3000 and 5000 requests.

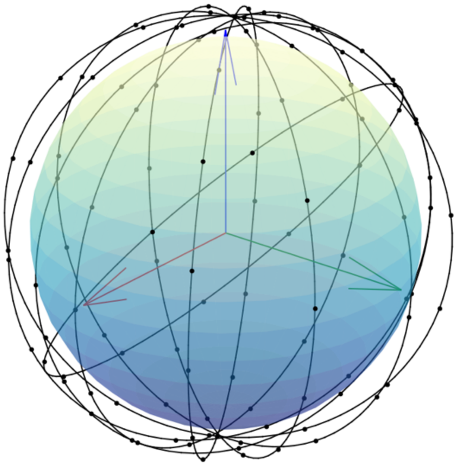

Figure 4. The satellite constellation used in evaluation. Satellites are dots and the lines depict orbital planes.

3.2 Evaluated Algorithms

We assume that there is one user, and each satellite is operated by a different federated entity. Each satellite constructs its own schedule of observations such that no observations are scheduled to overlap, and all data volume constraints are met.

We consider two baseline approaches mentioned above. In the first approach, the user requests all observations from all entities (i.e. satellites). This approach is referred to as *User Broadcast.* Each satellite constructs its own schedule by considering its overflights of the request locations. A satellite greedily constructs its schedule by examining all overflights for all requests and inserting into its schedule sequentially based on the start time of the overflight. An overflight is successfully scheduled if it does not overlap a scheduled observation, and the data volume of the observation does not exceed the maximum onboard capacity.

In the second baseline approach, referred to as *User Allocation*, the user decides which requests to submit to which entities. The user examines the orbits of all satellites in the federation and allocates requests to satellites by selecting the satellite that has the least allocated requests and breaking ties by selecting the satellite with the overflight for the request. Once the requests are submitted to the satellites, each satellite individually constructs its own schedule using the same procedure as above.

The federated scheduling algorithm we consider is the *Neighbourhood Stochastic Search Algorithm* (NSS), which is a decentralized allocation approach [19]. In this approach, the user submits requests to a single source that distributes requests to all satellites. All the satellites then communicate with each other according to the NSS algorithm to converge on an allocation of requests.

Table 1. Results of 10 simulations of different scheduling approaches for a federated system

Algorithm	Type	Request Satisfaction (%)
User Broadcast	Non-federated scheduler	64.34
User Allocation	Non-federated scheduler	68.98
NSS	Federated (Decentralized Allocation)	79.16

3.3 Experimental Results

We evaluate each algorithm on 10 randomly generated simulations and report the average request satisfaction shown in Table 1. The request satisfaction refers to the percent of total requests fulfilled during the day-long horizon. The results show the immense improvement in request satisfaction when using federated scheduling compared to non-federated scheduling baselines. The NSS algorithm achieves almost 80% request satisfaction within the day-long horizon, which is more than 10% more than either baseline. These results support the motivation for using federated scheduling to coordinate assets within a federated system.

4. Conclusion

In this work, we have motivated the use of federated scheduling to coordinate a large-scale observation system consisting of many operators. We have shown through simulation, that leveraging federated scheduling to autonomously coordinate observing assets across federated entities greatly improves the completion of observation requests compared to baseline approaches. However, these results only scratch the surface of the capabilities of federated observation systems. In future work, we will examine how to schedule complex workflows that leverage automated data analysis and tasking from entities within the federation to tackle science campaigns. We will explore both centralized and decentralized allocation as well as market-based techniques for task allocation. As opposed to previous work where observation campaigns were static, future work will consider dynamic campaigns in which requests are added and removed during the planning horizon.

Market-based techniques also open the door for commercial entities to bid on requests for cost of completion. This would result in a marketplace in which customers are able to obtain the minimum cost for an acquisition. While this application is of interest for commercial entities, it is beyond the scope of this work.

Acknowledgements

This work was performed by the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (80NM0018D0004).

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