Efficient and Responsive Task Allocation in Distributed Satellite Systems: The Role of Central Nodes

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Abstract

Efficient and responsive satellite operation planning is essential for monitoring short-lived transient events on Earth, such as floods, wildfires, and thunderstorms, as well as for observing objects in space, including satellites, debris, and natural bodies. Most operations rely on centralized planning, which introduces dependency on a central node and causes delays, particularly as the number of satellites increases. These operations require responsive data collection, onboard processing, and seamless communication among satellites. To address this, we propose a method for decentralized scheduling of operations that minimizes inter-satellite data transmission, onboard computational requirements, and power consumption. This paper evaluates the performance of the proposed decentralized task allocation method as a planning strategy for space object detection in Distributed Satellite Systems. We focus on analyzing the performance of the task allocation mechanism in terms of time for propagating the task and capability of performing the observation for Distributed Satellite Systems with different numbers of observers and numbers of central nodes. Our findings highlight the importance of balancing the flexibility and scalability of decentralized networks with the limited complexity of centralized networks to optimize operational efficiency.

Introduction

Traditional satellite operation planning is heavily based on centralized architectures, where a single node orchestrates all tasks. Although effective in smaller networks, this approach becomes increasingly inefficient as the number of satellites increases, leading to communication bottlenecks, delays, and a high dependency on the central node. Decentralized planning, on the other hand, distributes decision-making across the network, offering the potential for greater scalability and fault tolerance. However, achieving optimal performance in such systems requires careful management of network complexity, data exchange, and on-board computational demands, as analyzed by (Ben-Larbi et al. 2021). Responsiveness plays a critical role in the case of urgent observation of short-lived transient events, such as floods, wildfires, and thunderstorms, as well as observation of objects in space, including satellites, debris, and natural bodies. If an event is detected from a satellite in orbit, nowadays, the detection needs to be down-linked to the ground station, where an observation task will be scheduled to an available satellite and up-linked to it. This brings delays in performing the operation, being unacceptable for urgent missions. When the number of satellites to coordinate increases, it is difficult to have real-time telemetry data available. This brings uncertainty to the identification of the best satellite to perform the task, not knowing the exact conditions of each subsystem of the satellites. Performing the task allocation in space by implementing a distributed evaluation of the capabilities is the key to a rapid and high-quality allocation of the task considering the real-time properties of the satellite.

This paper provides a method for decentralized task allocation in Distributed Satellite Systems (DSS), enabling satellites to make decisions while ensuring consensus across the network. The method assigns the task of observing an object in space with specified orbital parameters to a single satellite. The satellite can independently define the necessity of performing the task, or it can be requested from ground. The DSS satellites exchange the task and once received, each satellite independently evaluates its capability of performing the observation using a reward function (RF). For each time step, the RF considers different onboard factors, such as angular separation from the target, observable object distance and detectability, power availability, data storage, availability of the schedule, and the instrumentation onboard. The maximum value of the RF, evaluated onboard, together with the ID of the satellite and the task, are selectively propagated across the network to find the best satellite and the best time step to perform the observation.

Many of the methods for decentralized task allocation consider a reduced number of satellites in the network, that all the satellites receive the task simultaneously, and that all the satellites are capable of communicating with each other (Johnson et al. 2011) (Pearl, Miller, and Lee 2025). We consider DSS with up to 10,000 satellites, where the network topology evolves during the propagation of the satellites in orbit, and the number of satellites capable of establishing communication links is limited. We focus on analyzing the time needed to distribute the task among the satellites and identifying the best satellite to perform the operation, varying the number of central nodes in the network. We refer to central nodes as the satellites that act like hubs for task coordination and data propagation, being the only ones able to communicate with the rest of the nodes. By evaluating the method performance across networks with varying levels of centralization, this work aims to identify the optimal balance between centralized and decentralized approaches.

The use-case presented in this paper focuses on the allocation of a task for the observation of an object in Sun Synchronous Orbit (SSO) with an altitude of 800 km, using a Walker Delta constellation of 6U-Cubesats distributed among 10 planes. The initial conditions for the parameters and variables of the power subsystem, communication subsystem, and data handling are the same for all the satellites, having a homogeneous constellation. The real-time variables evolve depending on the orbit position and illumination condition of the spacecraft, i.e. the energy production and consumption depend on the sunlit and eclipse conditions. The results analyze the time to distribute the task among the network and the maximum achieved value of the RF, varying the numbers of satellites in the constellation, from 500 to 10,000 satellites, and central nodes, from 10 to 100.

This approach is particularly relevant for missions requiring rapid and adaptive task execution, such as Earth observation for transitory events (e.g., volcanic eruptions, earthquakes, dust storms, and monsoons), space situational awareness for tracking satellites and debris, and autonomous deep space exploration where real-time ground communication is limited. By distributing decision-making among satellites, the method improves operational efficiency, reduces dependence on centralized control, and enhances resilience against communication disruptions. This study evaluates the effectiveness of the proposed method by analyzing its performance across networks of varying scales and levels of centralization. The main contributions of this work are:

- Introduction of a scalable, decentralized consensus-based task allocation method designed for space-based object detection missions.
- Demonstration of the value of more interconnected satellite architectures for faster task convergence.

The remainder of this paper is structured as follows: Section 2 outlines the related works. Section 3 focuses on the problem formulation and methodology. Section 4 presents the results and discusses their implications. Finally, Section 5 concludes the paper with a summary of findings and directions for future research.

Related Works

Task allocation in distributed satellite systems has been widely studied, with different approaches focusing on optimizing scheduling, communication efficiency, and resource management. Many existing methods emphasize maximizing the number of allocated tasks while resolving conflicts between competing observation requests. Fewer studies prioritize rapid task assignment based on execution quality. Most prior research considers either fully centralized or fully decentralized architectures, with limited exploration of hybrid models that balance coordination efficiency and resource constraints. Below, we highlight key contributions in this field and position our work within the broader landscape of satellite task allocation. For a complete survey on satellite scheduling problems, we refer the reader to (Ferrari et al. 2024).

(Li 2020) focus on the online task allocation problem, where individual satellites must determine a schedule with stochastic arrival of urgent tasks. They rely on a modified consensus-based bundle algorithm (m-CBBA) and a modified asynchronous consensus-based bundle algorithm (m-ACBBA) to allow satellites to achieve mutual consensus via a greedy bidding process of tasking scenarios while accounting for various communication constraints between satellites and ground. They demonstrate the effectiveness of their approach on a joint geostationary and low Earth orbit satellites coordination tasking problem. Their approach achieves a higher completion percentage of scheduled tasks and a higher total profit rate when compared to sequential, centralized techniques. (Jaramillo et al. 2020) extends the work of (Li 2020) by evaluating each satellite's ability to detect targets and increasing the complexity of the problem by focusing on dynamic target scheduling.

(Zilberstein et al. 2025) use a heuristic-based approach to decompose the global distributed constraint optimization problem into a set of sub-problems. In satellite scheduling problems, local adjustments, such as reordering tasks between satellites, can lead to significant improvements in resource utilization. Leveraging this principle, (Zilberstein et al. 2025) employs a Neighborhood Stochastic Search heuristic to develop a scalable, constraint-based technique that balances the trade-offs between centralized, globally informed techniques and decentralized, independent techniques. They demonstrate that using this heuristic to solve well-constructed sub-problems can generate high-quality solutions, but (Zilberstein et al. 2025) are unable to provide formalized quality guarantees of the produced solutions.

(Parjan and Chien 2023) seek to provide a less computationally intensive, heuristic search-based approach to request allocation and propose two broadcast algorithms that maximize the number of requests satisfied by agents and minimize the number of future requests that agents cannot observe due to data volume or slew constraints. Through experiments across various orbit distributions, they demonstrate that broadcast decentralized algorithms outperform communication-free approaches, and are robust to problems where the number of requests and associated number of agents are variable.

With respect to the discussed literature, our method prioritizes task urgency and execution quality, enabling satellites to bid immediately upon receiving a task, unlike previous approaches that first resolve scheduling conflicts. We analyze different levels of centralization, whereas other studies focus only on fully centralized or decentralized architectures. Our goal is to demonstrate that, although our method may not always yield the highest possible performance, it strikes a balance between efficiency and resource constraints, maintaining robust results while reducing computational load, power usage, and communication demands. In comparison, alternative approaches may offer superior performance but typically require satellites with substantially greater onboard resources.

Problem Formulation

We study the problem of allocating the observation task of an object in space across N_{sat} satellites, each equipped with an imaging payload, while minimizing communication overhead and optimizing resource utilization.
We define the task allocation as follows:

1. $[T_0, T_e]$ is the overall mission duration for the performance of the observation, starting at time T_0 and ending at time T_e. T_e is discretized by a time step size $\Delta t > 0$ to result in the finite number of discrete time steps $T = T_e/\Delta t$. The set of time steps, defined as $T = \{1, 2, ..., T_e\}$, contains all time steps at which a task can be performed.
2. $S = \{1, 2, ..., N_{sat}\}$ is a set of observer satellites containing the associated orbital elements, attitude, and the properties of each satellite. The initial parameters and variables of the communication subsystem, power subsystem, and data handling are equal for all the satellites. In our implementation, the number of observer satellites varies within the range of $[500, 1000, 2000, 3000, 5000, 10000]$.
3. $C = \{1, 2, ..., N_{cent}\}$ is a set of central nodes acting as hubs for task coordination and data propagation. We vary C in the range $[10, 20, 30, 40, 50, 60, 70, 80, 90, 100]$.
4. $O = \{1, 2, ..., N_{target}\}$ is the set of targets to be observed with their orbital elements, in Two-Line Element (TLE) format. In our case, the target is only one object in an SSO with an altitude of 800 km and a dimension of 1 m.
5. R represents the request of observation of element O to be performed within $[T_0, T_e]$.
6. D_{tot} represents the information to be sent among the satellites of the network, composed by the optimal reward function, D_{RF}, together with the satellite ID, D_{ID}, and the associated task, D_{task}, when two satellites are within a range r and communicate for enough time t_{comm} with the same bandwidth b and enough energy available p.

Methodology

To address these challenges, we propose a decentralized coordination method for Distributed Satellite Systems.

Decentralized Task Allocation

The core components of the methodology are:

1. Reward Function (RF): Evaluates the capability of each satellite S of observing a target in space O within the time $[T_0, T_e]$, based on resource availability.
2. Selective Data Propagation Mechanism: Reduces communication overhead by selectively sharing only the most critical information.

Reward Function: Evaluation of observation capability Each satellite evaluates its capability for performing a given observation task R using a reward function RF, defined as expressed in Eq. (1).

$$RF_i(T) = q_i a_i(T) \Bigg[A p_i(T) + B d_i(T) + C \left(1 - \left| \frac{\varphi_i(T)}{FoV_i} \right| \right) \Bigg] \quad (1)$$

For each satellite i at each time step T, considering the following variables:

- q_i : A binary variable representing the availability of the required instrumentation for the task, in this case, an imaging payload. If the necessary instrumentation is available, $q_i = 1$; otherwise, $q_i = 0$.
- a_i: A binary variable indicating the availability of the satellite to perform the task. If the satellite is free of conflicting tasks, $a_i = 1$; if it is engaged in another incompatible task, $a_i = 0$.
- p_i: A continuous variable representing the percentage of energy available on board the satellite.
- d_i : A continuous variable representing the percentage of data storage available on the satellite.
- φ_i: The angular separation between the observer pointing direction and the target position.
- FoV_i: Field of View of the imaging payload of each satellite i.

The different variables are scaled depending on the mission, with the scaling parameters A, B, and C. These parameters have a value of 1 in the presented results. The maximum ideal value of the reward function RF_{ideal} is 3.0; this represents the status of the satellite where the pointing direction of the imaging payload aligns perfectly with the target, the satellite has full energy and whole storage available, and the instrumentation and schedule are available for the new observation task.

Selective Data Propagation Method To coordinate task assignments without a fully centralized control, we implement a lightweight data-sharing mechanism, as shown in Figure 1, it shows:

1. Initial Task Assignment: The first satellite receiving a task computes its RF over the task's time window $[T_0, T_e]$, identifying the optimal time step T and corresponding RF value.
2. Data Exchange: The satellite broadcasts its RF, satellite identifier ID, and task details O to nearby satellites when within communication range.
3. Iterative Evaluation: Neighbouring satellites independently compute their RF for the task in $[T_0, T_e]$. If their RF exceeds the received RF, they update the propagated values RF_{max} with their own. Otherwise, they forward the received data unchanged.

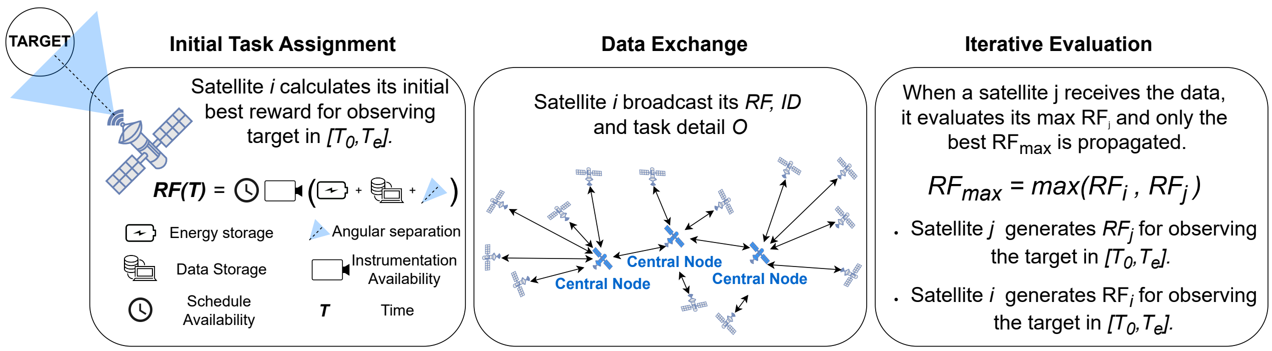

Figure 1: Selective Data Propagation Method Schematic

The objective of this data propagation mechanism is to coordinate the operation, distributing the information among the network as fast as possible.

Two satellites i and j can communicate if the data sent during the communication, corresponding to the product of the communication time t_{comm} and the data rate in the link between the two satellites $Drate_{i,j}$, is larger than the total data sizes D_{tot} to be sent, as expressed in Eq. (2).

$$t_{comm} \times Drate_{i,j} > (D_{RF} + D_{ID} + D_{task}) \quad (2)$$

This transfer of information does not require a fully centralized control structure; instead, each satellite autonomously assesses incoming data as new encounters occur within the network. This process continues until one of the two stopping criteria is met. The first criterion considers the maximum allowable time to complete the task, $T\Delta t = T_e$. The second criterion considers when the reward function reaches a predefined RF threshold, as the constraint expressed in Eq. (3)

$$RF_{max} > 0.95 RF_{ideal} \quad (3)$$

The study has two objectives that we formalize mathematically as follows. Given a couple of satellites i and j, the first objective is to find the minimum of the time for task allocation, as Eq. (4) represents.

$$min \sum_{i=1}^{N_{sat}} \sum_{j=1}^{N_{sat}} [\Delta T_{ij}(\mathbf{x}, T) \cdot c_{ij}(\mathbf{x}, T)] \quad (4)$$

The second objective is to maximize the quality of observation performed by the satellite, as Eq. (5) represents.

$$max[RF_i(T)] \quad (5)$$

The main variables are:

- $\mathbf{x} = [x, y, z, v_x, v_y, v_z, K_{RF}]$: representing the state vector of the satellite depending on time T, including his position, velocities, and the knowledge of the RF K_{RF}, that is a binary variable equal to 1, if the node has a new RF value to be broadcasted, and 0 otherwise.
- ΔT_{ij}: represents the time it takes for information to travel from satellite i to satellite j.
- c_{ij}: is a binary decision variable, where $c_{ij} = 1$, if there is a communication link from satellite i to satellite j, and $c_{ij} = 0$ otherwise.

This method is adaptable to various observation applications and is not limited to space object detection. In the described approach, the reward function (RF) is evaluated based on the angular distance from a moving object in space. It can be modified for other applications, such as Earth observation, where the RF could instead consider alignment with a specific ground target or other mission-specific metrics. Despite these adaptations, key factors such as energy availability, data storage, schedule availability, and the presence of required instrumentation remain fundamental across different applications. Additionally, the selective data propagation mechanism and iterative task evaluation process would remain unchanged, ensuring efficient task allocation regardless of the specific observation objective.

Simulation framework

We implement the methodology using a custom-made simulator in Python, presented in previous work (Messina and Golkar 2025). Figure 2 extracts an overview of the different modules of the simulator with inputs and outputs. The Distributed Satellite Systems Simulator models the task allocation and observation capabilities of a network of satellites operating with different central nodes. The simulator consists of multiple interconnected modules that simulate key spacecraft subsystems, including orbit and attitude propagation, power management, data handling, communication, and imaging payload performance. The Satellite Class initializes the parameters of each satellite, including the orbit and initial parameters of the various subsystems. The Orbit Propagator and Attitude Propagator update the position and orientation of the satellite over time. The Power Module and Data Handling Module track the availability of onboard resources, while the Communication Module determines the effective data transfer rates between satellites. The Imaging Payload Module evaluates the feasibility of an observation task based on the angular separation between the observer and the target. The simulator quantifies the ca-

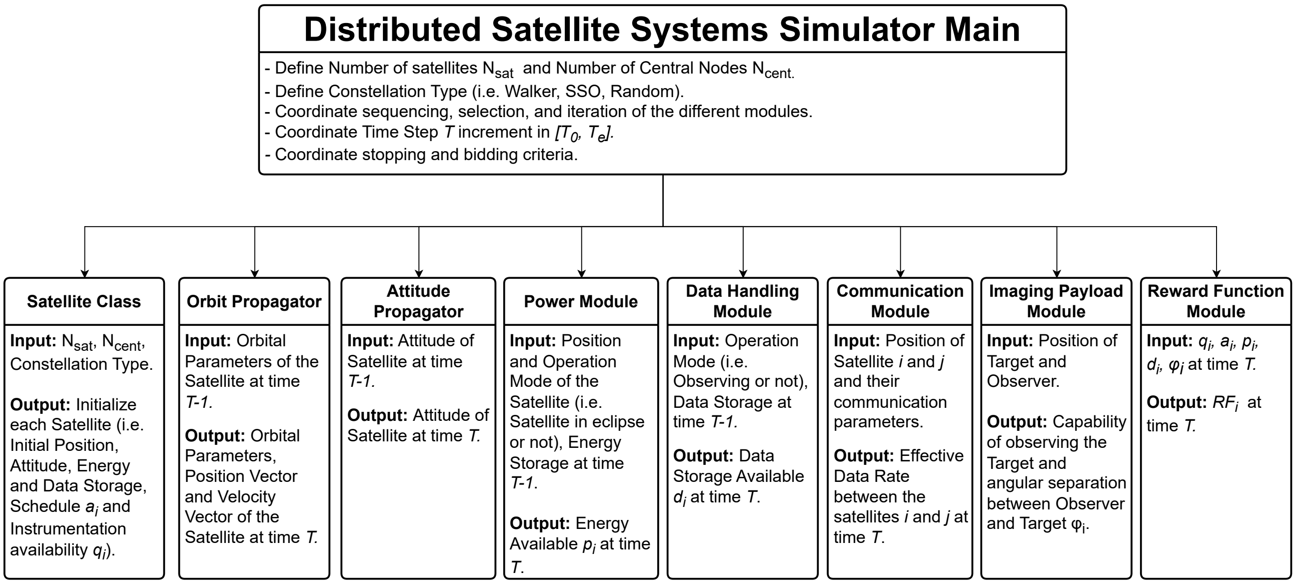

Figure 2: Distributed Satellite Systems Simulator Modules with Inputs and Outputs

pability of each satellite to execute the task in $[T_0, T_e]$ using the Reward Function. The simulator implements the selective data propagation mechanism, ensuring that only the most relevant information is shared across the network, reducing communication overhead. This modular architecture enables the simulation of various constellation types, including Walker, Sun-Synchronous, and randomly distributed configurations, and allows for systematic evaluation of task allocation efficiency in networks ranging from hundreds to thousands of satellites. In this paper, the simulated satellites are equally distributed among a Walker Delta constellation with 10 planes and an altitude of 550 km and equally spaced along the orbit. The initial true anomaly for the first satellite assigned to a plane is varied for creating different distributions of the satellites in the constellation. We define the initial values of the true anomaly $TA_{init} = [5, 10, 11, 30, 70]$ for not repeating configurations with the same exact distribution of satellites. Combining all the possible alternatives of the presented N_{sat}, N_{cent}, and TA_{init}, we performed a total of 300 simulations.

Results and Discussion

This section evaluates the effect of adding observer satellites and central nodes in the decentralized allocation of an observation of an object in space. Central nodes serve as high-connectivity hubs within the network. These nodes have greater communication capabilities, being able to communicate with all the other nodes and enabling faster data propagation and improved coordination. We analyze how the different presented configurations influence task propagation speed and reward function performance.

Effect of numbers of central nodes on the maximum time for task allocation

To assess the practical feasibility of applying the presented methodology to DSS in a time-critical scenario, we analyze the maximum time for distributing the task among all the satellites of the network, as presented in Figure 3.

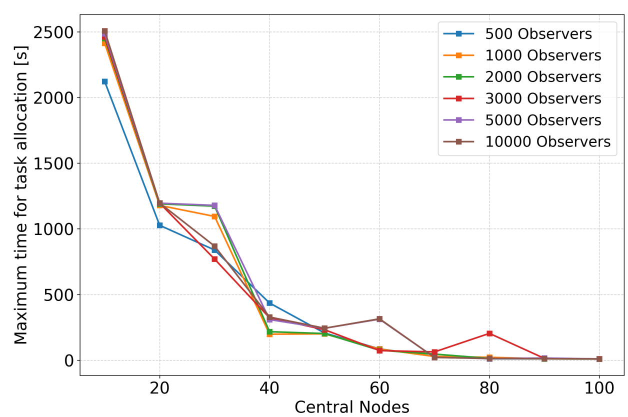

Figure 3: Evolution of time for propagating the task for different N_{sat} and N_{cent}.

The temporal evolution consistently shows that increasing the number of central nodes reduces the time for task allocation. This is expected as more central nodes improve communication efficiency and minimize delays in distributing the task. When the number of central nodes increases, the reduction in propagation time becomes less relevant. For example, the time for task allocation from 10 to 20 central nodes has an average absolute improvement of 1243 s, corresponding to 51.65 %, while from 90 to 100 nodes it has an average absolute improvement of 2.67 s, corresponding to 20.5%. This suggests that after a certain threshold, adding more central nodes does not provide significant benefits. We will consider further investigation on the threshold for future work, aware that it is dependent on the initial positions and properties of the satellites. For 500 satellites, the task propagation time decreases from 2,122 seconds with 10 central nodes to 10 seconds with 100 central nodes, corresponding to a 99.53% reduction. A similar reduction happens for 10,000 satellites; the time reduces from 2,507 seconds for 10 central nodes to 9 seconds for 100 central nodes, showing an improvement of 99.63%. We analyzed that the standard deviation on the time reduces increasing the number of central nodes, highlighting a reduced impact of the variation of different satellite configurations, in particular the number of observers and their initial true anomaly, on the time to allocate the task, for a fixed N_{cent}. We observe that for the case of 10,000 observers and 60 central nodes and for 3,000 observers and 80 central nodes, the results show an offset with respect to the main trend. In these specific cases, even in the presence of a larger number of central nodes, we notice an increased standard deviation depending on the initialization of the position of the satellites; however, further analysis is to be performed to confirm the reason for this behavior.

Effect of adding central nodes on the evaluation of the Reward Function

A relevant aspect of this study is to understand how the number of central nodes in the network affects the performance of the decentralized task allocation method. We analyze how the maximum achieved value of the reward function RF_{max}, corresponding to the best satellite to perform the task, varies depending on the number of satellites and number of central nodes. Table 1 highlights the importance of introducing a larger number of observers to improve the performance of the observation.

The results of the RF_{max} in Table 1 show the mean maximum values of the reward function for each N_{sat}, with a variation depending on the number of the central nodes and initial true anomalies.

The standard deviation has relatively small values with respect to the RF_{max}, varying from 0.001 to 0.035, suggesting consistent results across different configurations of N_{cent} and TA_{init}. The highest value of the reward function corresponds to the best satellite that can perform the observation, the introduction of central nodes influences the time for reaching the best satellite, but does not directly affect the quality of the task. The $RFmax$ increases from 2.702 for 500 satellites to 2.926 for 10,000 satellites, reflecting an 8.3% improvement. Adding observers in the network brings a higher value of the RF, corresponding to an improved quality of the observation of the object.

Table 2 shows that the time for identifying the best satellite to perform the task T_{max} decreases significantly with more central nodes.

More central nodes mean higher communication overhead, showing a reduction of over 99% in the identification of the best RF_{max}. For a given number of central nodes, we notice an increment in T_{max} when adding observers satellites in the network. The task is initially allocated to a single satellite that corresponds to one of the central nodes; for larger N_{sat}, more hops are necessary to achieve the best-performing satellite, leading to delays. The increase of T_{max} attenuates when the N_{cent} increases, a higher connectivity of the network limits the hops necessary to reach the satellite with RF_{max}, further connectivity study are necessary for confirming this trend.

Figure 4 shows the time evolution of the maximum value of the reward function for the configuration with 10,000 observers and different numbers of central nodes, with $TA_{init} = 10$. The various configurations reach a similar value of RF_{max}, represented in the plot by the star mark, but the configuration with better-expected connectivity requires less time to converge to the best-performing satellite. The initial positions of the satellites capable of communicating with each other influence the hops necessary to reach the best reward function, causing in the first seconds of the simulation an overlapping of the different curves. Different configurations lead to a different time evolution for each time step, but converge at a similar time to the maximum value of the reward function.

The results of this study demonstrate the advantages of decentralized task allocation in large-scale satellite networks, revealing key practical implications for space operations. One of the primary benefits is the ability to achieve faster response times for time-critical missions. The reduction in task propagation time observed in this study—up to 99.6% with increased central nodes—suggests that such methods can significantly enhance real-time observation capabilities, which is crucial for applications like disaster monitoring, environmental surveillance, and transient event detection. The scalability of the proposed method further supports its applicability to next-generation mega-constellations and DSS missions, where centralized planning becomes a bottleneck as the number of assets increases. The approach maintains efficient task allocation across networks ranging up to 10,000 satellites, while also improving system resilience by eliminating single points of failure. This allows the network to remain operational even in cases of partial failures or communication disruptions.

Another important advantage is the optimization of energy and bandwidth usage. The selective data propagation mechanism ensures that only relevant information is transmitted across the network, reducing overall communication overhead. This is particularly beneficial for energy-constrained CubeSat and small satellite missions, where onboard energy and data transmission capabilities are limited. The method has broader applicability beyond Earth observation. It can enhance space situational awareness by enabling satellites to collaboratively track objects in orbit with minimal ground intervention, increasing responsiveness to potential collision risks or new object detections. Additionally, in deep space exploration, where communication delays make centralized planning infeasible, decentralized task allocation can enable self-organizing spacecraft swarms to au-

Table 1: Maximum reward function RF_{max} for different N_{sat} with standard deviation across 5 runs.

N_{sat}	500	1,000	2,000	3,000	5,000	10,000
RF_{max}	2.702 ± 0.001	2.776 ± 0.001	2.884 ± 0.001	2.862 ± 0.035	2.888 ± 0.001	2.926 ± 0.001

Table 2: Time to reach the RF_{max} (T_{max}) in seconds for different N_{sat} and N_{cent}.

Number of Central Nodes (N_{cent})	**Number of Satellites** (N_{sat})				
	500	1,000	3,000	5,000	10,000
10	2122.2	2413.4	2463	2486.4	2507.2
20	1027	1178.4	1196	1195.2	1196.2
30	838.6	1094.4	1196	1178.8	868.2
40	435	197.8	769.4	309	328.4
50	206.8	200.4	322.6	243	243
60	86	84.6	231.8	312.2	314.8
70	28.4	28.2	73	21.2	20.8
80	10.8	21.8	62.8	12	12.8
90	10.4	10.2	203.8	16	11
100	10	8.6	13.2	9.2	9.2

tonomously schedule observations and data relay tasks.

In large heterogeneous satellite constellations, it is unfeasible for all satellites to participate in decentralized decision-making and communication with all the other satellites, as variations in onboard capabilities and communication terminals limit the possible links. Studying the effect of central nodes helps to understand what could lead to optimal allocation, by avoiding both extreme centralization and full decentralization, and suggesting a hybrid strategy to improve operational efficiency, responsiveness, and scalability in Distributed Satellite Systems.

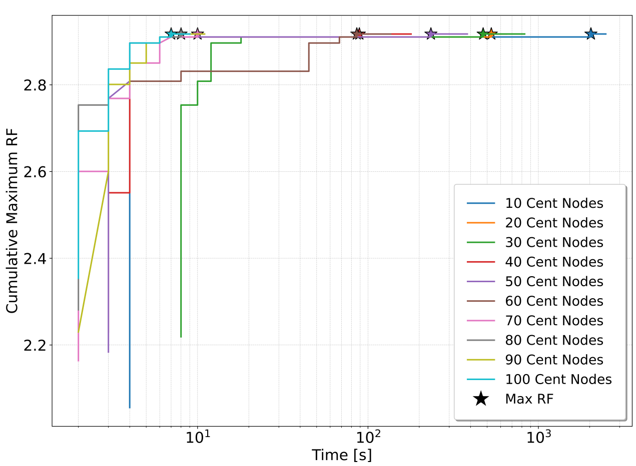

Figure 4: Evolution of the maximum RF for 10,000 satellites with different N_{cent}.

Future Work and Conclusion

Future research should consider a wider range of configurations for implementing the proposed method. We could consider different constellation architectures with different initial orbital parameters, and different use cases, i.e. wildfire detection or other Earth Observation tasks. The evaluation of the power consumption implications of different network configurations could provide further insights into the selection of centralized and decentralized methods. A highly decentralized system may introduce a significant number of communication hops, consuming overall more energy.

The current study assumes a fixed number of central nodes. An adaptive approach that dynamically adjusts the number and location of central nodes based on real-time network conditions could further optimize performance.

Future studies include further adaptability, robustness and scalability investigations, comparing the method with existing ones in terms of task allocation performance, computational capabilities required and communication overhead. This paper focuses on the influence of the number of central nodes and satellites on task allocation, additional sensitivity analysis of the parameters of the reward function, and of the initial conditions of the satellites needs to be performed, together with an uncertainty analysis on the data acquisition and communication rates. We will aim to demonstrate that while our method may not always achieve the highest performance, it maintains strong results while minimizing computational demands, power consumption, and communication overhead. In contrast, other methods and algorithms might achieve better performance but require satellites with significantly greater resources. The presented method demonstrated scalability in the applicability of task allocation in Distributed Satellite Systems with up to 10,000 satellites, with different configurations and conditions. The introduction of satellites to the network influences the efficiency of the task allocation. The increment of observers reveals an effect on the quality of the observations for an object in space. The RF_{max} represented the metric for evaluating the capability of performing the task; Table 1 shows that its value has an improvement of 8.3% when moving from a network of 500 to 10,000 satellites. The maximum RF achieved in various scenarios approaches the theoretical limit of 3.0, with a peak value of 2.926, corresponding to 97.53% of the theoretical maximum, observed for the network with 10,000 observers.

Adding central nodes significantly influences the performance, in terms of efficiency and responsiveness, of the implemented method. Highly centralized networks offer simplicity in their architecture and rely on well-established, state-of-the-art methods for planning and task allocation. The dependence on few central nodes introduces potential bottlenecks, and delays in decision-making, especially in scenarios requiring real-time responsiveness. They reduce the responsiveness of the task allocation as demonstrated in the results and, in particular, in Figure 3 and Table 2. These results demonstrated that reducing the central nodes from 100 to 10 reduces the task propagation time up to a 99.6% decrease. The results highlight the trade-offs between centralization and decentralization, demonstrating that increasing central nodes significantly improves task propagation time while maintaining high task execution efficiency. This improvement diminishes as the number of central nodes increases, suggesting that a higher number of central nodes is required for faster communication, but an excessive increase in central nodes should be avoided to prevent unnecessary complexity while maintaining good performance. These findings underscore the potential of adaptive, autonomous network architectures that dynamically optimize task allocation and responsiveness in large-scale Distributed Satellite Systems.

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