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Coopetitive Lunar Mapping: A distributed non-proprietary Multi-Robot Coordination using Blockchain-based Cost Optimisation

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***Abstract*— Recent advancements in in-situ resource utilization (ISRU) exploration lead to a new space economy trending towards *coopetitive* multi-robot systems (MRS). This trend highlights the need for a robust, transparent, and universally accessible cross-organization platform for coordinating these complex systems. To fill this gap, we present in this paper a novel approach to address the challenge of globally optimising distributed mapping tasks in *coopetitive* heterogeneous MRS within ISRU lunar scenarios. Thereby, we propose a cost function that combines the perspectives of both robotic operational metrics and economic principles to elevate ISRU global efficiency. Our approach leverages blockchain-based auctioning mechanisms to overcome the computational complexity of global coordination more efficiently. Our focus is on improving distributed mapping and utilizing blockchain technology to create a trustworthy digital platform for auction-based coordination. This non-proprietary and non-discriminatory platform aims to optimize costs in the context of ISRU. We demonstrate that our system outperforms traditional random task allocation methods by 17.5% on average. We validate our scenario in a simulated lunar environment, supporting robots with competing interests yet collaborating for mapping tasks.**

I. Introduction

The resurgence of interest in space exploration, fueled by both governmental and private sector initiatives [1], has given rise to a new space economy [2], explored by multi-robot systems. As these agencies began to shape this evolving landscape via guidelines for in-situ resource utilization [3], the industry is transitioning from a traditional antitrust model to a more decentralized, consumer-focused free-market approach [4]. This shift has led to a unique setting of *coopetition* [5], where firms both collaborate and compete. This new environment necessitates innovative solutions for efficiently coordinating MRS [6].

Historically, the coordination of MRS in decentralized exploration has been a research topic since the 1980s [7]. However, the market-based multi-agent coordination approaches, especially those emerging in the 2000s [8, 9], are particularly relevant for *coopetitive* space exploration scenarios. These approaches often employ auction systems, which have proven effective for spatial mapping explorations [10]. Despite these market-based approaches being computationally intensive, the optimal planning problem for MRS remains *NP-Hard* [8]. This computational complexity and the latency in Earth-space communication render real-time decision-making impractical for space missions. This issue makes the potential of market-based approaches more apparent [6].

However, designing a universal cost/reward function for robotics is still one of the unresolved challenges in this context. Existing research has proposed various terms to enhance the bid valuation process [11], ranging from the most common distance-based metrics to performance indexes or computational complexity. Moreover, the communication architectures of multi-robot teams have also been improved by considering coupling constraints, energy capacities, time windows, and possible coalitions. The computational complexity of combinatorial auctions is also recognized as highly intensive [12]. Thus, works have identified solutions, from simple single-item auctions to the more complex consensus-based bundle algorithms. However, these solutions often rely on proprietary and centralized frameworks, lacking the transparency and trust economic digital platform required in the emerging space economy [4], nor try outsourcing to other companies' MRS that may be willing to sell their mapped data via a make-or-buy decision framework [13].

Although digital platforms operated by a distinguished company or institution could efficiently coordinate interactions and services through economic incentives and value exchange [14], discussions about the platform operator's market power and corresponding concerns regarding security aspects and political dependencies can impede MRS operators from actively participating on such a digital platform [15]. Many actors may hesitate to join a centralized platform due to concerns about monopolistic ownership, conflicts of interest, and treaty violations [1]. Here, blockchain technology offers an innovative approach for MRS [16, 6]. Its decentralization (i.e., non-proprietary) and transparency make it an ideal candidate for fostering *coopetitive* market-based transactions and bridging the trust gap among stakeholders, enabling information and value exchange [17], thus leveraging the capabilities of multiple stakeholders to significantly reduce the redundancy and costs associated with every organization

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launching individual robotic missions.

In light of these challenges and opportunities, this paper aims to display the following contributions.

- We propose the make-or-buy decision framework [13] to guide robots in deciding whether to perform or outsource mapping tasks to enhance ISRU efficiency.
- We leverage blockchain technology to automate the lower complexity MRS coordination through an *coopetitive* single-item auction-based system.
- This paper introduces a cost function that allows each robot to offer its most competitive price for the area to be mapped, given its constraints focusing on reducing the global travelled distance. The blockchain programmatically lists the cheapest options for external buyers
- We validate our platform and cost function by integrating them with the Algorand blockchain and ROS2, comparing efficiency in coopetitive scenarios.

Through this work, we aim to provide insights into the adaptability of MRS in the new space economy.

The rest of the paper proposes the following structure. Section II describes the related work and state of the art of the fields involved. Section III presents the scenario acting as a basis for the project. Section IV presents the solution and its application on a simulated robotic system, while Section V presents the results of a comparative study with a random allocation system. Section VI concludes the work and offers insights into the planned work.

II. State of the Art

The concept of ISRU has emerged as a cornerstone for the future of space exploration, offering a sustainable and economically viable approach to long-term missions [18]. However, the complexity and multifaceted nature of ISRU tasks often exceed the capabilities of single robotic systems. This complexity has led to adopting MRS, which offers the advantages of distributed intelligence and labor [10]. However, effectively coordinating these MRSs from different companies remains a significant challenge, particularly in task allocation, adaptability, and decentralized operation. Market-based approaches are particularly promising in addressing these challenges. This section critically examines the intricate interplay between ISRU, blockchain technology, and MRS coordination, thereby identifying the challenges and untapped potential at this multidisciplinary intersection.

A. Blockchain for Space MRSs Coordination

Distributed Ledger Technology (DLT), through its most common application, Blockchain, has gained attention for supporting decentralized systems in various sectors like finance and healthcare [17]. Its relevance to space exploration is particularly noteworthy [19], given the increasing need for a trustless, transparent, and economically viable digital platform [4]. While existing literature has explored the role of blockchain in robotics and distributed control systems [16], there is a gap in research focusing on its utility in *coopetitive* auction-based space scenarios [20] where various stakeholders both collaborate and compete.

Therefore, we identify a research gap: a platform is needed that allows MRS members to automate tasks like bidding for resource usage and receiving immediate compensation. This would provide idle robot resources and enable stacking intermediary tasks to compensate for operational costs automatically. Ultimately, this could increase ISRU efficiency and make space exploration more cost-effective.

B. Market-based Multi-Robot Coordination

Many approaches to market-based robotic systems have been proposed over the years, however, they remain classifiable. The authors of [21] proposed a taxonomy for market-based approaches. They can classify each problem as three pairs of letters and propose a study of each case and the standard solutions. They distinguish the following:

- **Single Task Robots (ST)** versus **Multi-Task Robots (MT)**, ST refers to the robot able to perform only one task at a time, while MT can parallelize tasks.
- **Single Robot Task (SR)** versus **Multi-Robot Task (MR)**, SR refers to a task that requires exactly one robot, and MR tasks that can require multiple robots.
- **Instantaneous Assignment (IA)** versus **Time extended assignment (TA)**, IA represents tasks to be instantaneously assigned, while TA can be assigned over time.

Conducted surveys [9] propose that when it comes to finding the best solution for a team working in an unknown environment, it is an *NP-Hard* problem similar to the Traveling Salesperson Problem (TSP). They note that most market-based approaches fall under the SR-ST category, which can be further subdivided into IA and TA taxonomies, with IA's faster but fewer solutions. The surveys also identified two main market schemes for the MRS task allocation problem: Auction-based methods are a scheme where robots bid selfishly for their interests like in [22]. And consensus-based approaches, where all robots try to reach a consensus, produce more communication and network overhead like in the approach of [18].

It is detailed that even if we talk of free market and market-based approaches, the robots do not exchange currencies in any of them. The work done in [23] is one of the few implementations of a pricing function for MRS, providing a price depending on each robot.

While various market-based approaches offer frameworks for task allocation and coordination, the effectiveness of these models largely hinges on the underlying cost and utility functions used for task valuation. This brings us to another crucial aspect of multi-robot systems: the design and selection of cost, utility, and pricing functions.

C. Cost, Utilities and Pricing functions

Cost and utility functions are the backbone of any market-based approach to MRS coordination. However, the existing literature offers many approaches with little consensus on standardization and no detailed design choice [9]. Although most existing approaches use measures such as distance, time, or energy consumption to calculate costs, the choice

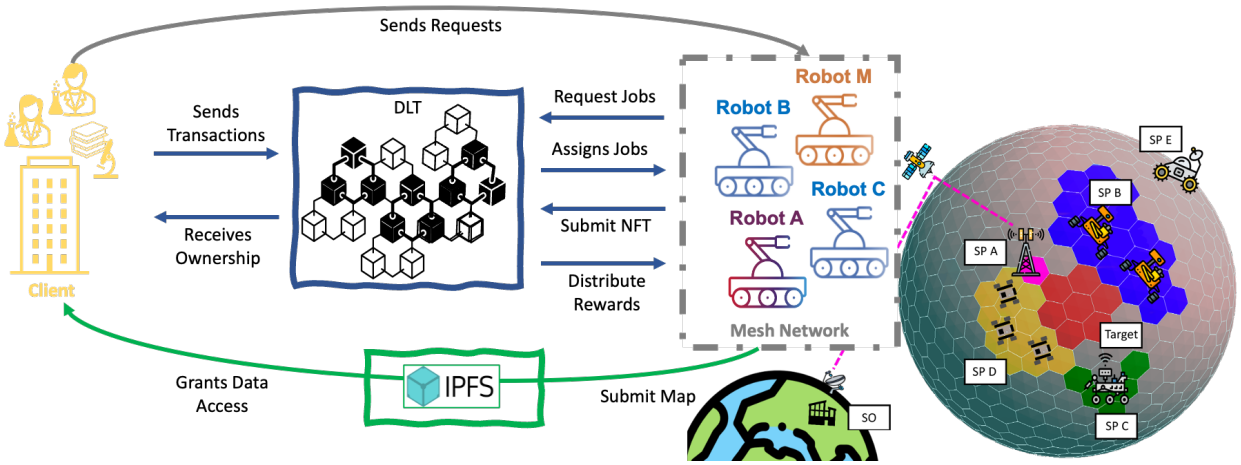


Fig. 1: Scenario graph, displaying each SP and their assets, along with the planned solution

of cost function is often not detailed in relation to the other aspects of the proposed solutions.

The authors of [22] propose using the wavefront propagation function [24] to calculate the distance and, thereby, cost. The work of [21] proposes a utility function based on the quality at which the robot can perform the task subtracted by the cost of the task. However, the computation of these parameters needs standardization, and finding the proper set of weights makes the problem more complex.

It is important to note that the cost proposed by the robots in our approach corresponds to pricing, which is a significant deviation from the existing literature. In [23], one of the only approaches to use a pricing function, the pricing itself, was accepted as existing and not reviewed by the paper. Our work introduces a novel pricing model as a cost function that offers a more accurate and comprehensive approach to task valuation. The existing literature often assumes pricing functions without critically examining or integrating them into the overall system, which is another major difference between our approach and the literature.

III. Scenario

We present an expected future scenario in Fig.1 needing collaboration among organizations for space mapping and exploration. We distinguish two kinds of organizations: the service orderer (SO) and the service providers (SP). SO, SP A, SP B, SP C, SP D, and SP E are involved in the system.

- Organization SO is interested in a piece of unmapped territory on a celestial body.
- SP A provides communication services.
- SP B, SP C, SP D, and SP E are independent and potential competitors. Each operates its own MRS fleet.
- All the robots maintain a global lunar network

When an SO desires to map a specific lunar area to prospect some resources, such as in figure 1, the obvious solution would be to set up and develop a whole robotic mission. However, if robots are already mapping the moon, they might propose their mapping functionality as a service. The scenario requires a set of robots R, such as

$$R = \{r_1, r_2, r_3, \ldots, r_n\}$$

where n robots are interconnected on the same network. Each robot is owned by a company that might not share common economic interests with the other, and each has its own capabilities. The study focuses on how to minimize the global cost for the user.

To answer this scenario, we propose the following:

- The SO requests a mapping task, specifying the required information and level of detail they need.
- The SP B, SP C, and SP D MRSs proposes prices meeting SO's requirements.
- The decentralised platform facilitates the bidding process, ensuring fair competition and transparency. It executes the smart contracts between SO and the organisation (SP B, C or D) that provide the best solution.
- Once a mapping task is complete, data is securely stored using non-fungible tokens (NFTs), ensuring its immutability and accessibility to all stakeholders.
- Other organisations and researchers can access the mapped data, enabling collaboration, validation, and further scientific studies.
- The decentralised nature of the platform ensures that all participating entities have equal access to the data and can verify the results independently.

IV. Materials and Methods

A. Cost Function

We propose optimising the ISRU mapping process by integrating MRS with economic factors through a cost function.

System Flexibility: It is essential to highlight that this system allows every robot to include its own cost function, depending on the system's. However, we propose a general cost function with adaptable parameters for each robot.

Proposed Cost Function: For a given robot r_i, there is a cost function C_i which gives the price (in the decided

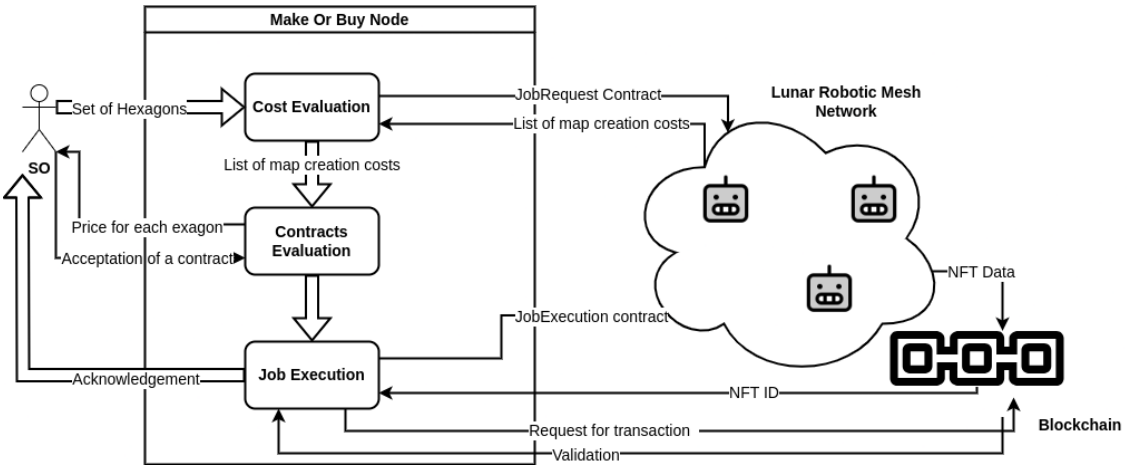


Fig. 2: Architecture of the Make or Buy client node, featuring the SO and the Robotic network, on the moon.

monetary unit) the robot asks to operate a given task. The cost function is the following:

$$C_i = E \times F_E \times LU \times P_u \tag{1}$$

Where:

- E: Represents the energy consumed by the robot during the mapping process with:

$$E = \Delta D \times E_d \tag{2}$$

  - ΔD is the distance to perform the task given by the global planner of the robot. It is a planned distance that can be less precise due to terrain irregularities.
  - E_d represents the energy consumption per unit of distance, part of the design of every robotic mission (e.g. the Scarab mission from NASA [25])
- F_E is the fee per unit of energy consumed
- LU: provides a straight-line lifespan depreciation proportion of how much of a robot is depreciated by performing a specific task, expressed as:

$$LU = \left(\frac{\Delta t}{L} + 1\right) \tag{3}$$

  - Δt is the estimated time to perform the task $\Delta t = \frac{\Delta D}{V} + t_{task}$ with V the estimated velocity of the robot. t_{task} is an additional constant time in case the robot needs to stay in place to perform the task. In the case of mapping, this value is null since the robot is always moving between waypoints.
  - L denotes the expected lifespan of a robot in space missions. With the level 1 requirement of 90 sols, past missions have ranged from 78 hours to 2.7 years. Notably, the last third quartile approaches two years [26].
- P_u: Embodies the navigational uncertainty as a Gaussian distribution [27].

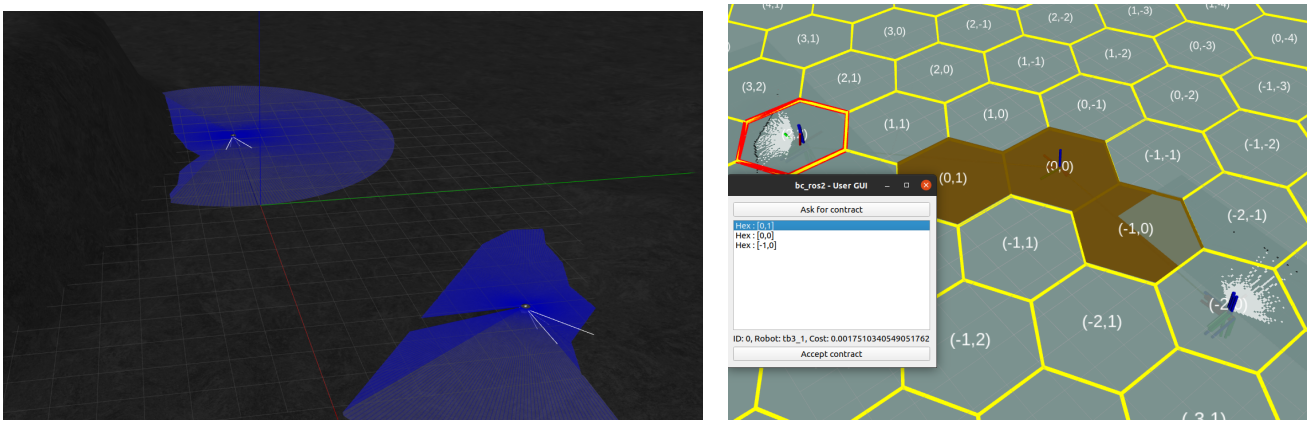
The framework guides robots in deciding whether to acquire or manufacture maps. It is based on the "make or buy" decision framework [13], which consists of seven steps. We adapted these steps to account for the trigger (SO ordering) and proceed by analysing internal processes (does the robot already own the map, or can it outsource), cost estimations (acquisition and manufacturing estimations), supply chain management (verify who has the mapped area), and support systems (quality and technical supports). After going through all the behaviour steps, our system considers performance measurements closely linked to the triggers, which means the system aims to evaluate the extent to which the task targets ordered by the triggers (SO) are met. Since our trigger is cost reduction, cost-saving should be the primary performance measure while considering flexibility, resource usage, and quality measurements such as energy and time. Furthermore, we assess the mapped area based on clients' requirements. Performance measures assess the extent to which the targets suggested by the triggers are achieved, such as cost reduction or quality. We aim to reach the lowest price and highest global ISRU efficiency.

Actors of the solution:

- Operator: A company or individual desiring to buy maps
- Client Node: A ROS node, operating like the blockchain as explained in section IV-B.
- Robots 0 to n: All the robots connected to the network
- Algorand blockchain: The implemented blockchain

The process is encapsulated in three primary stages as visible in Fig. 2:

1) **Cost Evaluation**:
   - The operator requests a set of maps represented by hexagons as detailed in IV-B
   - The client node generates a "Job Request" contract, which is disseminated to all robots for cost estimation.
   - Each robot evaluates its map creation costs locally, which are relayed to the client node.
2) **Contract Bidding Creation**:
   - Based on the collected cost evaluations, the client node ranks the job contracts and proposes them to the operator. It periodically recomputes until the operator accepts the job for the selected hexagon.



(a) View of the simulated lunar environment, running with Gazebo. It features a lunar landscape with two robots and their laser scans.

(b) User interface on RVIZ 2, featuring both robots on the hexagonal grid. The user can select any hexagon, turning them brown, then request for prices and accept the contract.

Fig. 3: Experimental simulation environment along with the user interface allowing a user to request maps in set of hexagons

- Post acceptance, the map-making initiative is triggered, creating a "Job contract" with the robot.

3) **Execution of Job Contract**:
   - If needed, the designated robot makes the map and uploads it as an NFT.
   - This robot then conveys the NFT and job metadata to the Client Node for validation.
   - Upon successful validation, the client Node oversees the payment procedure, and the map's ownership NFT is transferred to the operator.

In summary, our framework introduces a streamlined "Make or Buy" decision-making methodology [13], matching robot capabilities with blockchain's transparent notoriety.

B. Blockchain Network and NFTs

The use of the blockchain covers two main functionalities: ensuring a reliable auctioning system between competing actors and authenticating maps as NFT. The reliable auctioning protocol should rely on the smart contract technology. However, this current implementation offers a ROS node that simulates the concept of smart contracts as detailed in [6], called the **client node**.

To save maps as NFT, we propose a novel approach inspired by [28] visible in Fig. 1. A Goldberg polyhedron is a solution to subdivide a sphere into H hexagons and a fixed number of $P = 12$ pentagons [29]. This solution especially fits our approach due to the following properties:

- **Uniformity**: Each cell has a fixed size, making it easier to make defined NFT collection-sharing properties
- **Geometry**: Hexagons offer the possibility to tesselate well, covering the designated surface, providing an easy set of coordinates assuring the unicity of each NFT
- **Scalability**: A Goldberg sphere is defined by two parameters l and m that can be adjusted for any astral body and cell size.

The Goldberg parameters l and m are the number of divisions along the triangular edges of an icosahedron's face. Being a widely studied topic, it is easy to calculate the parameters l and m to get a given cell size by knowing the size of the moon [29].

The subdivision of the mapping zone as a subset of multiple hexagons allows the turn of a single **Multi-Task Robots (MT)** to a set of **Single Task Robots (ST)**. It allows us to have a subset of ST-MR-IA problems, described in [21] as the simpler.

In the current implementation, the mapped hexagons are saved on InterPlanetary File System (IPFS) using the Pinata interface and then uploaded on the Algorand test blockchain.

C. Communication protocols, Mesh Network and ROS2

Reliable communication is crucial in MRS, particularly in extreme, unexplored environments where pre-established networks are absent. Mesh networks, in synergy with ROS 2, offer a robust solution [30].

In a mesh network, each robot acts as a node, ensuring network resilience by rerouting data if a node fails [31]. ROS 2 complements this by facilitating seamless data communication in decentralized systems. This combination enhances MRS *coopetition* by offering:

- **Resilience**: Data rerouting ensures network integrity.
- **Scalability**: Network reliability increases as robots join.
- **Dynamic Adaptation**: The network adapts to changing robot positions.
- **Enhanced Exploration**: Robots can venture further without communication loss.

1) **Data Sharing Transparency**: Fosters reduced information asymmetry [32].
2) **Robot Agnostic System**: Scalable and compatible with various platforms [8].
3) **Data Loss Resistance**: Ensures data integrity [4].

We demonstrated in a real-world experiment [33] the efficacy of mesh networks and ROS 2 in facilitating map creation, storage, and trade among robots during a proof-of-concept experiment in a lunar analogue environment (Fig. 3a)

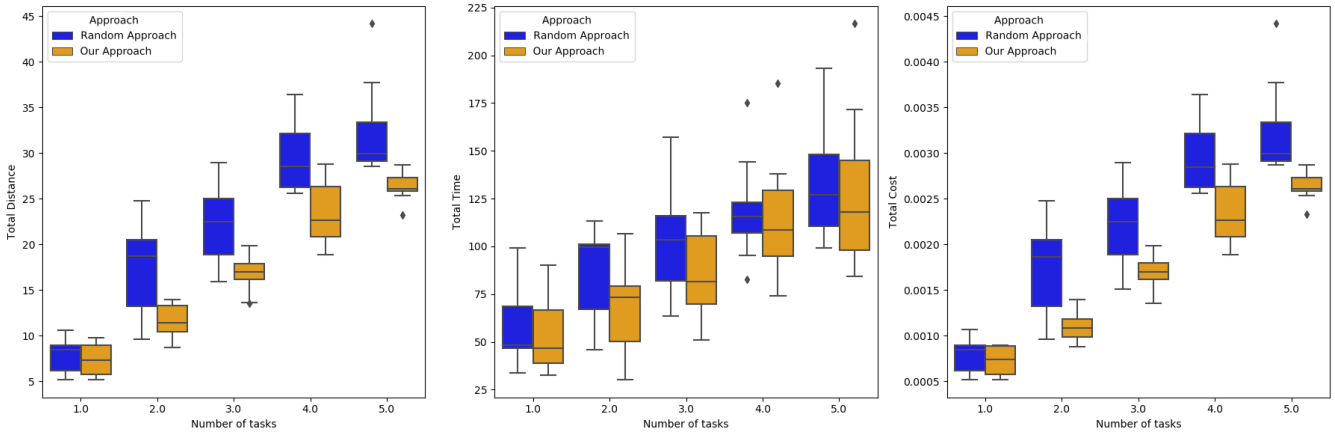


Fig. 4: Comparison of the metrics given the number of tasks proposed to the system for the two approaches. The first graph shows the distance travelled by all the robots, while the second one displays the time to map the requested hexagons.

D. Autonomous exploration

Most of the crucial work for autonomous exploration has been covered by the work of Yamauchi [34] and the related papers. The author highlights the need for three layers, crucial in any exploring robot: the mapping layer, discovering the environment; the navigation layer, ensuring the robot can move to the desired places; and finally, the exploration layer, sending to the navigation layer the points to explore. In our experiment, we rely on a simple but reliable implementation since it is not the focus of the paper:

1) Mapping layer: Our system relies on a turtlebots3, which has a Lidar sensor to map an environment. The software SLAM toolbox in ROS2 provide a 2D map using the lidar readings.

2) Navigation layer: ROS2 offers the implementation of the nav2 stacks, which take charge of navigation with a high level of customisation. For the experiment, the robots use the standard configuration.

3) Exploration layer: For simplicity, the exploration algorithm passes through the centre of gravity of the six triangles composing the hexagon. For future applications on a real system, we consider implementing a more robust approach, such as frontier-based.

E. Experimental setup

For the experiments, we consider a subdivision of the moon as a Goldberg sphere, as explained in section IV-B. The simulation used for the study is an area A such as $A << A_{moon}$, allowing it to be in a case of local flatness. The size of the hexagon edge is 4 meters to represent the local hexagon map as a plane, as seen in Figure 3b.

V. Results and Discussion

The evaluation of the presented work is performed over a simulation while the functionnality has already been proven in a real world system in [33]. The simulation is composed of a lunar analogue environment, as explained in the section IV-E. For the evaluations, we admit a scenario with one user and 2 robots owned by 2 companies. We compare the previously proposed framework to a simple approach where each task is distributed to a random robot. This approach is selected because existing task allocation solutions are not applicable to our system or would not provide comparable results. The tests are executed over a fixed set T of 7 hexagons, chosen to put the random allocation approach in its best situation. Each system receives the same random subset $\tau \in T$ of a fixed number of hexagons to map.

We compare three main data, primarily the global distance travelled by the robots, the cost contracted and the real robot's operational cost for a specific task. For each test run with a given τ, we measure these data for both approaches. As illustrated in figure 4, the experimental results suggest our approach improves the distance travelled, offering a $17,5\%$ less global average distance than the random allocation approach. It is worth noticing that the random allocations is highly dependent on the set T of this experiment and that a more sparse set produces significantly worse. However, the set of this experiment was selected to be in the best situation for the random allocation approach, showing that even in "the worst situation", our approach outperforms it. In cases where $\Delta t << L$, the cost function (1) primarily relates to the distance travelled rather than the time, which aligns with the fact that traveling is a robot's primary cost.

We also compared the computed cost of the robot with the effective cost, and it is worth noticing that with the experimental setup, the computed cost is 2.18 times bigger than the real robot cost, ensuring that the robot owner is making benefits from every transaction.

VI. Conclusion and Future Work

This study proposed a make-or-buy framework tailored for *coopetitive* multi-robot systems engaged in exploratory missions. The framework allowed robots from multiple companies to collaborate on tasks while safeguarding their individual economic and operational interests. It relied on blockchain technology to ensure trust via transparency between the participants. The lunar surface to be mapped was subdivided as a Goldberg sphere, allowing standardized uniform maps to be uploaded on the blockchain as NFTs. A user,

referred to as the service orderer (SO), could request a set of hexagons corresponding to the maps. Through the blockchain interface, which was simulated by a *ROS* node, each robot could offer contracts for mapping specific hexagonal regions. We also proposed an price function, enabling each robot to propose a contract for a given task, considering the specificity of a robotic exploratory mission. The SO could then receive the most interesting contract and decide to accept it.

The coordination flow involves creating, trading, and validating NFTs through a blockchain network. This enables real-time decision-making for multi-robot coordination. Entities control metadata and configurations of their NFTs, creating a market for data access. NFTs contain map data and facilitate trade within the network for ISRU. As it refers to a novel approach, we compared it in a simulated lunar environment with a randomized task assignment approach and showed a 17.5% improvement over such methods. The improvement minimized the total distance travelled, which is a significant cost factor in such space missions.

This study remained an introductory work to a new domain on a simple scenario. Future work would require more variety in tasks and capabilities while handling scenarios with Multi-Robot Tasks and Multi-Task Robots. Future work should also investigate scenarios where some robots have already formed alliances to compete for optimal pricing. This approach was also presented as a basis for comparison with future approaches to competition problems.

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