# AI Approaches to the Automatic Optimization of Instrument Acquisition Scheduling in Space Missions

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## INTRODUCTION

- In the context of planetary missions, the **optimization** of the scheduling of the acquisitions of instruments in the payload is of great importance in order to maximize the scientific return. To this end, specific **acquisition plans** are defined, deciding which instruments can operate at different times in order to optimize coverage while respecting both the physical constraints imposed by the target scenario and the mission resources.
- Despite some automatic/semi-automatic approaches have been developed for scheduling activities of Earth observation satellites, only few studies have considered the case of space missions focused on other planets, where the usually **temporal length of the schedule and the many constraints** make the problem more complex.
- This research work attempts to address the problem of **instrument acquisitions optimization** through the use of new methodologies based on **AI**. The study is developed with respect to the operations of radar instruments, even if the methodology is general.

## BACKGROUND AND AIM OF THE WORK

- Planning problems with constraints are complex optimization problems that are generally addressed using metaheuristics.
- Among the most widely used algorithms there are those based on a **local search in the solution space**, such as in Simulated Annealing [1], where a succession of probabilistic transitions attempt to gradually improve the current solution.
- More advanced techniques include the use of **genetic algorithms** that can generate good solutions as a result of the evolution of a population of candidate solutions. In [2], the authors started from the NSGA-II [3] genetic algorithm and adapted it with a set of specific evolutionary operators designed for the planetary scheduling problem.

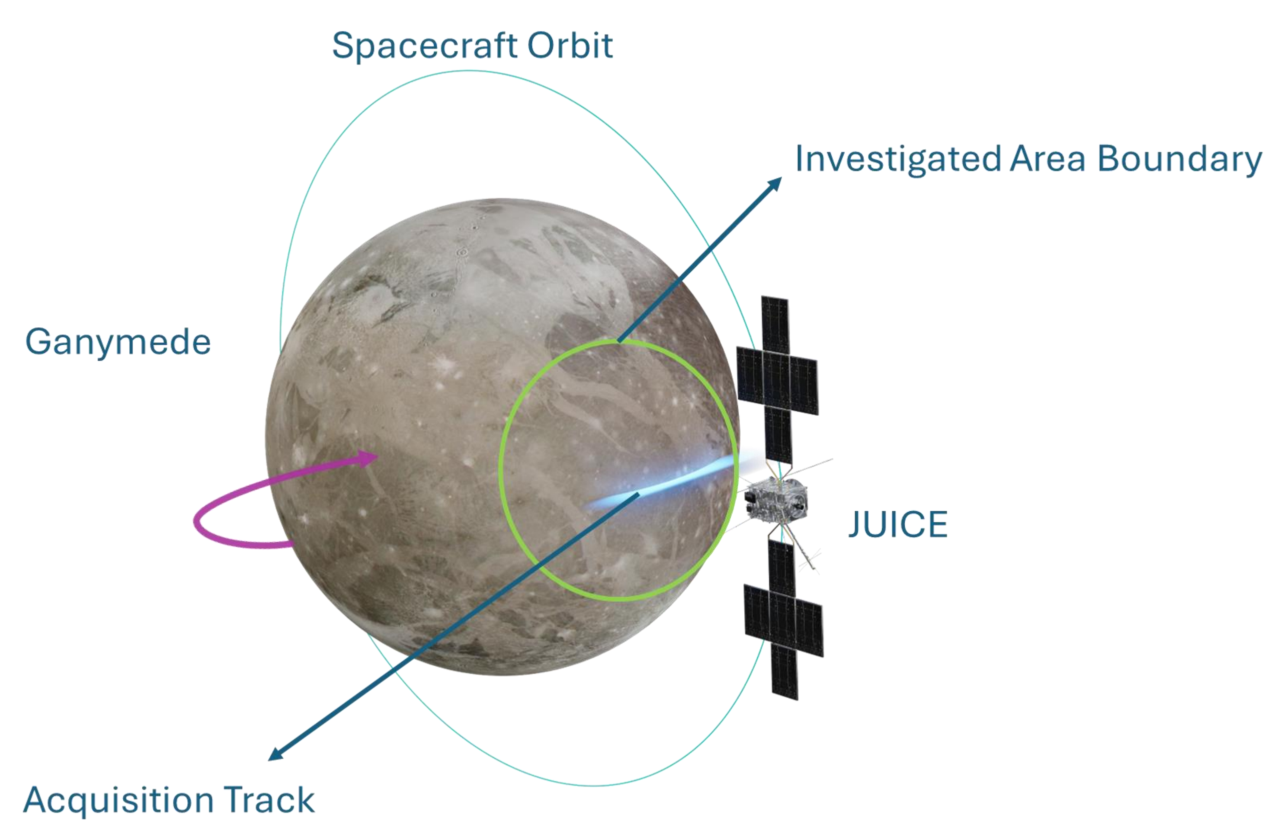


**Fig 1.** Acquisition scenario at Ganymede of the radar RIME mounted on the satellite JUICE.

- Some planning/scheduling approaches based on the use of AI have been explored in the literature. Techniques based on an unsupervised training of the optimizer are of particular interest.
- **Reinforcement learning** (RL) is a branch of machine learning in which intelligent agents are trained through a trial-and-error mechanism.
- Some successful applications of (deep) RL to combinatorial optimization can be found in [4] and in [5]: the former trains a solution-generating recurrent neural network with a policy gradient method, while in the latter a combination of two RL agents is used to implement a local search approach.
- However, **most optimization algorithms are limited by the size of the solution space in which they can operate**. In the case of scheduling for long-term space missions, it is therefore necessary to develop new methods capable of managing the very large dimensionality of the search space.

## METHODOLOGY

- The problem is initially addressed by focusing on the acquisition of a single instrument and will then be extended to a multi-instrument and multi-objective scenario.
- Starting from a large set of land segments visible from the s/c (**ground tracks**), the goal is to determine a subset of them to be acquired by radar/other instrumentation in order to maximize our objective function.
- The problem is formalized as a **multi-dimensional knapsack** with several constraints given from the satellite instruments and the mission probe.
- The solution to optimize is represented as a **binary vector, where each component is associated to a specific ground track.**
- The very high dimensionality of the solution space requires an innovative approach: use of **(deep) reinforcement learning combined with stochastic methods** for performing the optimization as a local search.

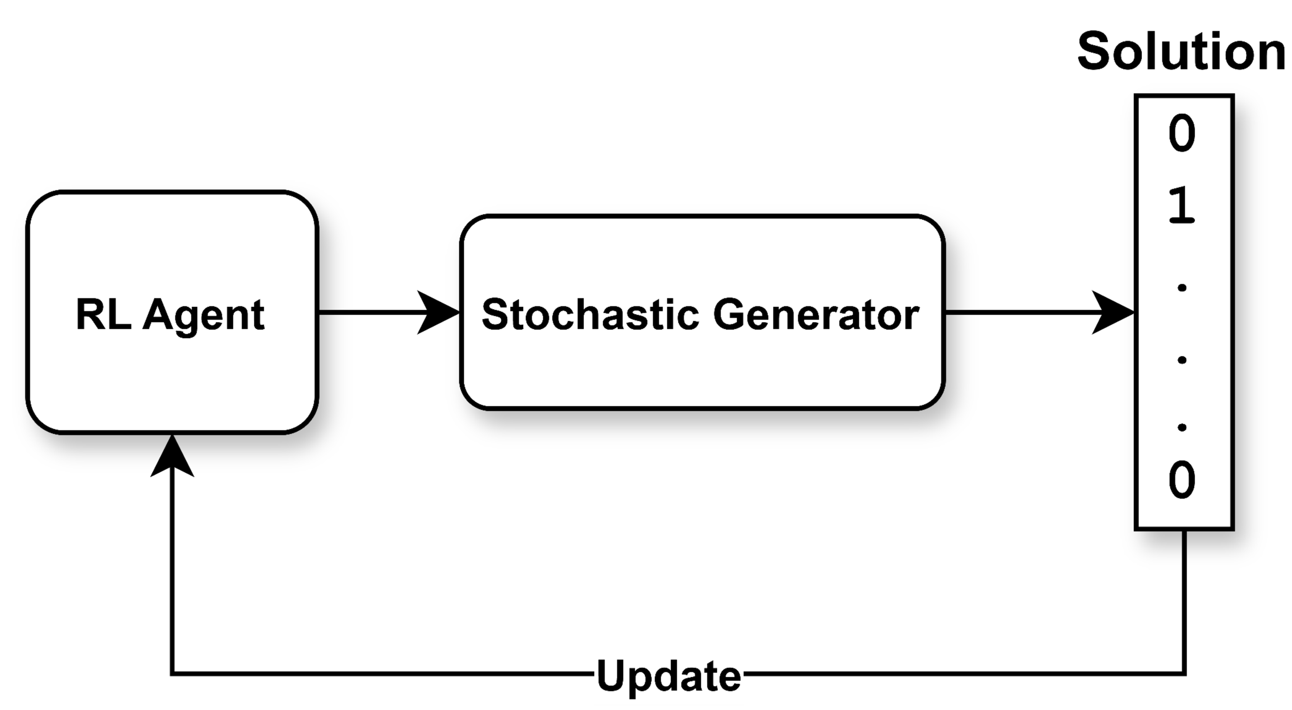


**Fig 2.** Reinforcement learning architecture which is currently being tested.

## EXPECTED RESULTS AND FUTURE PERSPECTIVES

- The problem addressed is part of a **wider category of optimization problems**. An algorithm capable of solving it would be easily generalizable to solve many other tasks.
- The complexity of scheduling makes finding an optimal solution challenging. More studies will be needed to develop an effective methodology.
- If successful, the optimizers could be used to support space missions such as **JUICE** and **EnVision**.

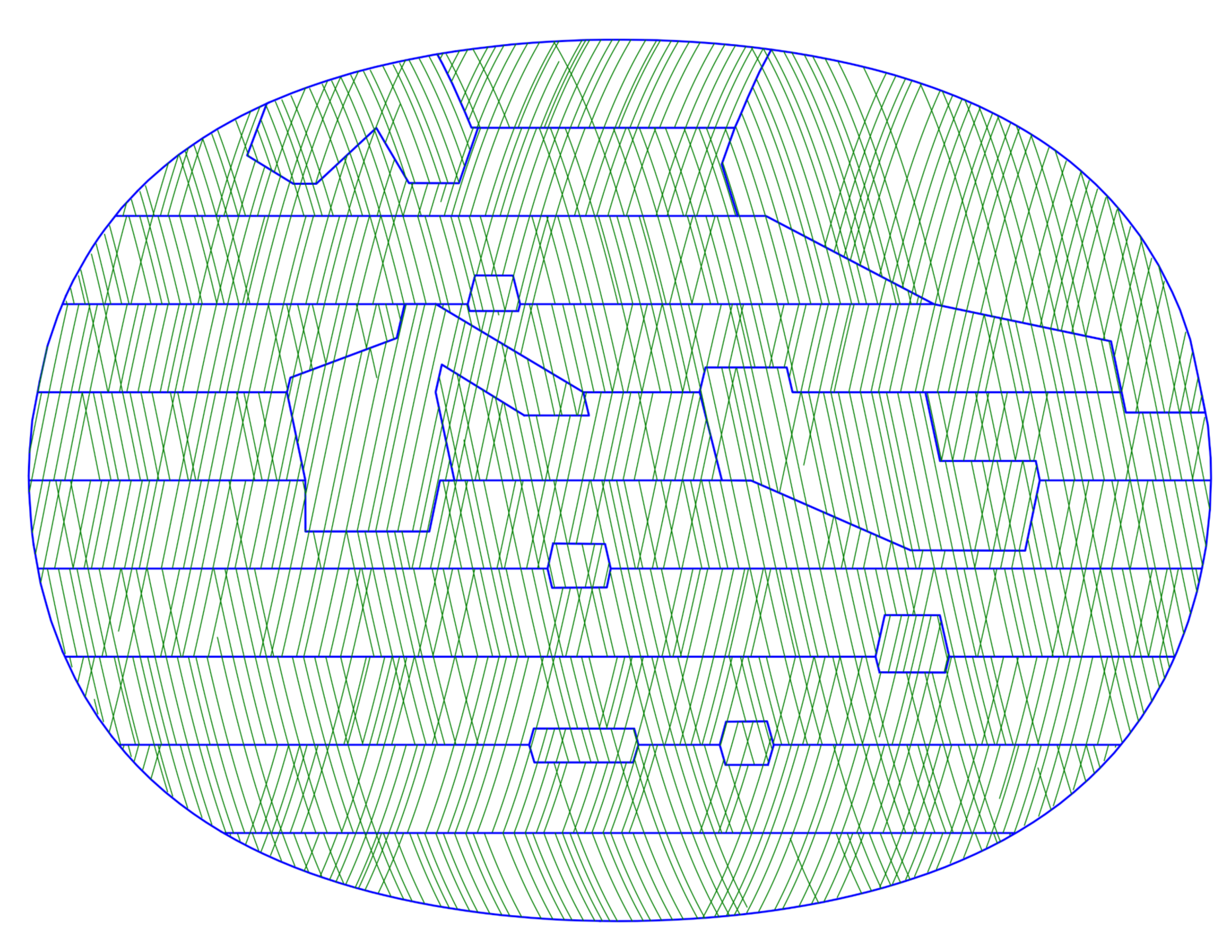

**Fig 3.** Visualization of a possible acquisition plan produced by our algorithm. The image depicts the investigated area boundary of the Ganymede surface we want to examine, divided into regions to separate the different targets of interest. Each green line represents a ground track that has been chosen by the algorithm for acquisition among all possible tracks. Those will be the only segments that will be sensed by the radar.

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