

# Towards Large-Scale Satellite Acquisition Scheduling with Hybrid Quantum-Classical Optimization

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shown promising results on small satellite acquisition scheduling problems, e.g., using QA (Stollenwerk et al. 2021; Makarov et al. 2023) and QAOA (Quetschlich et al. 2023; Makarov et al. 2024). However, scalability remains limited, due to algorithmic limitations, current quantum hardware constraints, and the difficulty of mapping large problems to existing quantum systems. For example, QAOA has only been tested in simulation, already showing degrading performance with more than 10 requests, and QA can only realistically solve problems with less than 100 requests.

In the optimization literature, hybrid quantum-classical methods have emerged as a practical strategy for tackling large, NP-hard problems that exceed current quantum hardware limits. A common pattern is to use a classical algorithm, such as metaheuristics, mathematical programming, or constraint-based search, to generate and maintain a feasible global solution, then identify smaller, well-defined sub-problems that can be mapped to a quantum solver. This approach has been applied in domains such as scheduling (Tran et al. 2016), routing (Feld et al. 2019), and portfolio selection (Sakuler et al. 2025). Makarov et al. (Makarov et al. 2024) also successfully solved satellite acquisition scheduling problems with up to 209 requests with the D-Wave LeapBQMHybrid solver. However, it cannot be determined whether and to which extent this specific solver benefits from quantum optimization, leaving the door open to research in the direction of hybrid optimization.

In this paper, we present a hybrid quantum-classical method designed for large-scale satellite acquisition scheduling problems. The method relies on a classical heuristic to generate a global candidate solution, from which local, constraint-aware sub-problems are extracted and solved using a quantum annealer. This hybridization allows us to exploit quantum hardware without being limited by its size. We validate the approach on large problem instances with up to 20000 requests using the Advantage quantum annealer from D-Wave Systems (D-Wave Systems, n.d.). The rest of the paper is structured as follows: Sect. 2 provides a problem formulation for satellite acquisition scheduling. Sect. 3 introduces the proposed approach. Sect. 4 provides results from experimental validation. Sect. 5 concludes the paper and summarizes possible future research directions.

## Introduction

The growing demand for timely and high-resolution Earth observation data has led to a rapid increase in both public and commercial imaging satellite constellations (Celesti et al. 2022; Denby and Lucia 2020). These systems are expected to support diverse applications, ranging from environmental monitoring and disaster response to defense and agriculture (Bovolo et al. 2020). However, fully exploiting these satellite resources requires intelligent and efficient scheduling of imaging tasks (Zhang et al. 2022). Acquisition scheduling involves assigning requests to specific satellites in a way that maximizes acquisition value while satisfying a wide set of operational constraints. The total value of an acquisition schedule can be related to economic return, for the case of commercial imaging systems, or to urgency in performing the acquisition, for the case of rapidly evolving extreme events such as fires or eruptions. The underlying constraints can involve satellite orbits, sensor agility, on-board resources, weather conditions, and ground station availability.

Due to the problem's combinatorial complexity, exact solutions are often infeasible for large scenarios. Heuristic and metaheuristic algorithms, such as greedy methods, genetic algorithms, or SA, are commonly used to find good-enough solutions within reasonable time frames (Agnès et al. 1996). However, as the problems become larger in practical cases, the performance of existing methods degrades. In recent years, quantum optimization has been explored. Early studies have



### ... Problem Formulation for Satellite Acquisition Scheduling

Satellite acquisition scheduling varies significantly across systems and applications. It fundamentally involves assigning acquisition requests to satellites in a way that maximizes the overall value of collected data while minimizing acquisition time. These problems are subject to a range of operational constraints, which may involve satellite configuration, sensor characteristics, on-board memory capacity, cloud coverage, illumination conditions, or ground station communication windows.

In this work, we focus on a simplified acquisition scheduling formulation, first introduced in the work of Quetschlich et al. (Quetschlich et al. 2023). The setup involves a single satellite tasked with fulfilling up to  $R$  acquisition requests  $\{r_i; i=1, \dots, R\}$  during one orbital pass. Each acquisition  $i$  is associated with a binary decision variable  $x_i \in \{0, 1\}$ , where  $x_i=1$  indicates that the acquisition is selected. Each request also has an associated value  $v_i$ , representing, for instance, economic importance or urgency, as highlighted in Sect. 1.

The primary constraint arises from the time required to rotate the satellite's sensor between targets located at different off-nadir angles. Let  $T_{\text{rotation}}(i, j)$  denote the sensor rotation time between acquisitions  $i$  and  $j$ , and  $T_{\text{transition}}(i, j)$  the available orbital transition time between the two. The optimization problem is:

$$\max_{x \in \{0, 1\}^R} \sum_{i=1}^R x_i v_i \quad \text{subject to: } T_{\text{rotation}}(i, j) \leq T_{\text{transition}}(i, j) \quad \text{if } x_i = x_j = 1 \quad (1)$$

A visual depiction of this acquisition setup is provided in Fig. 1.

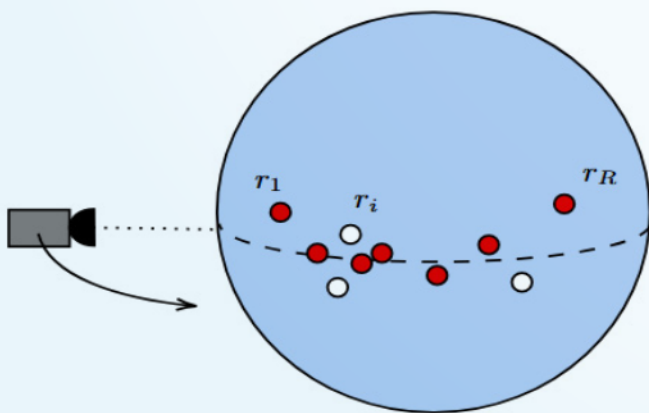


Figure 1: Considered setting for satellite acquisition scheduling, with acquisition requests  $r_i$  represented as circles along the satellite trajectory projection on the Earth's surface. The objective consists in finding a subset of acquisition requests (here, a possible subset is indicated in red) that maximizes the acquired value and satisfies the rotation constraint. The image was first introduced in (Delilbasic et al. 2024).

The problem is reformulated as a QUBO problem, the constraint being integrated into the energy (objective) function as a penalty term:

$$\max_{x \in \{0, 1\}^R} \sum_{i=1}^R x_i v_i - p \cdot \sum_{i=1}^{R-1} \sum_{j=i}^R x_i x_j \cdot c(i, j) \quad (2)$$

Here,  $p$  is a penalty coefficient, and  $c(i, j)=1$  if  $T_{\text{rotation}}(i, j) > T_{\text{transition}}(i, j)$ , and 0 otherwise. This ensures compatibility with quantum optimization methods such as QA (Kadowaki and Nishimori 1998), as this formulation is fundamentally equivalent to the Ising model. Note that we effectively convert Eq. 2 to a minimization problem by inverting the sign of the terms, as this is a standard for optimization. Despite being a simplified formulation with a linear cost function, one satellite and one set of constraints, computational limitations arise when the number of requests  $R$  increases, as sensor rotation constraints increase at an even faster rate.

### Hybrid Quantum-Classical Optimization for Satellite Acquisition Scheduling

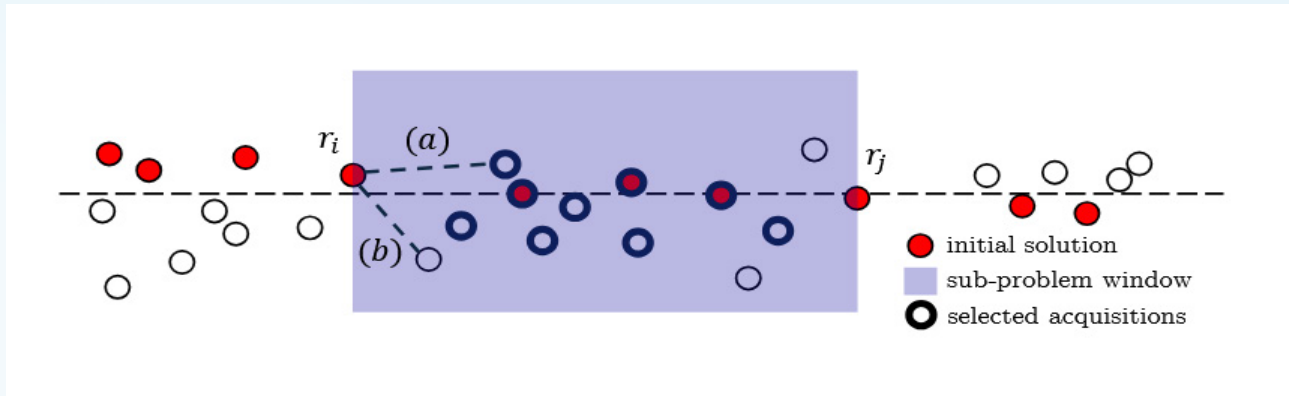
As mentioned in the previous sections, finding optimal acquisition schedules for a high number of acquisition requests  $R$  is prohibitive. Heuristic methods based on quantum optimization cannot be directly applied, due to the aforementioned limitations in computational capabilities. Here, we introduce an iterative approach to integrate quantum optimization within an acquisition scheduling algorithm.

#### Full problem solution sampling.

A conventional (classical) heuristic method can start tackling the large problem and sampling candidate solutions. The solution associated with the lowest energy, corresponding to a sub-optimal acquisition schedule, can be the initial solution for a subsequent local refinement.

#### Sub-problem generation.

In order to locally improve on the initial solution, a suitable sub-problem is generated. In Fig. 2, the proposed sub-problem generation method is shown. The method selects a local subset of acquisition requests within a window, for which rotation constraints (see Eq.1) are in place with respect to the acquisitions delimiting the window. First, two acquisitions  $r_i$  and  $r_j$  belonging to the initial solution are chosen. This ensures that the updated schedules for the selected acquisitions present no constraint violations with the initial acquisition schedule outside the window. The window is iteratively extended until a  $S$ -dimensional sub-problem is reached. An independent sub-problem is thus generated.



**Figure 2:** Example of sub-problem generation. Circles represent acquisition requests distributed along the satellite orbit projection. Two acquisitions  $r_i$  and  $r_j$  belonging to the initial solution to the acquisition scheduling (in red) define a window (in blue). The selected acquisitions for the sub-problem generation (circled in blue) are all acquisitions within the window for which the rotation constraint is satisfied, i.e.,  $T_{\text{rotation}}(r_{ij}, r) \leq T_{\text{transition}}(r_{ij}, r)$  (a), excluding the incompatible ones (b).

### Sub-problem solution sampling.

The size  $S$  of the sub-problem can be adaptively selected so that a quantum optimization algorithm, such as QA, can sample solutions for it. The initial solution can also be exploited, e.g., using advanced schedules such as reverse quantum annealing (Pelofske et al. 2020; Delilbasic et al. 2024) or for warm-starting QAOA (Quetschlich et al. 2023). The best solution is used to update the schedule, which then becomes the initial solution of the next iteration of full and sub-problem solution sampling.

## Experimental Validation

In this section, we show initial results for hybrid optimization on large acquisition scheduling problems, following the approach of Sect. 3. We generated two problems, with requests  $R=10000$  and  $R=20000$ , each request having value  $v_i=\{1,2\}$ , with overall penalty coefficient  $p=\max(x_i+x_j)+1=5$ . In order to validate the iterative approach and understand the impact of hybrid optimization, we worked with two experimental setups:

1. *Simulated annealing - simulated annealing (SA-SA)*: SA is used for both full problem and sub-problem solution sampling. It is executed on 2 Intel Xeon Cascade Lake Platinum 8260M CPUs from the DEEP HPC system located at the Jülich Supercomputing Centre (JSC) (Suarez et al. 2021).

2. *Simulated annealing - quantum annealing (SA-QA)*: in this case, forward QA is used for sub-problem solution sampling. QA is executed using the Advantage\_system\_6.4 solver, accessed through D-Wave Leap (D-Wave Leap 2025).

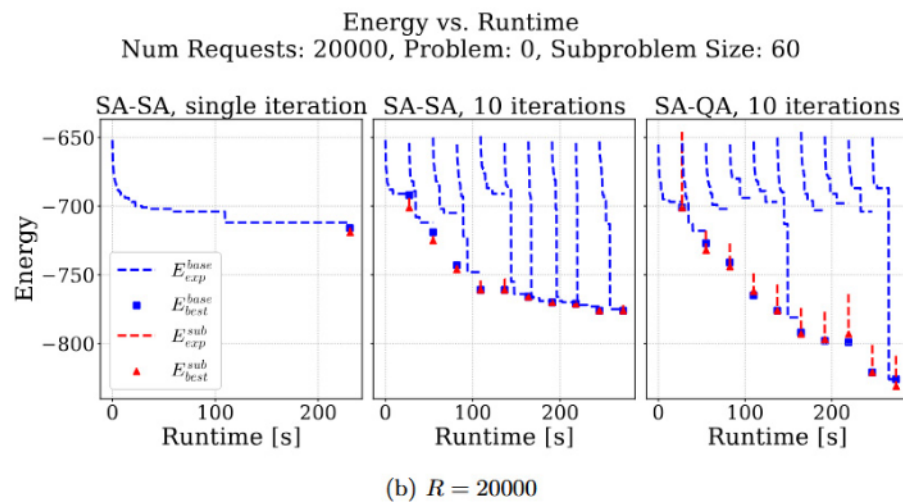
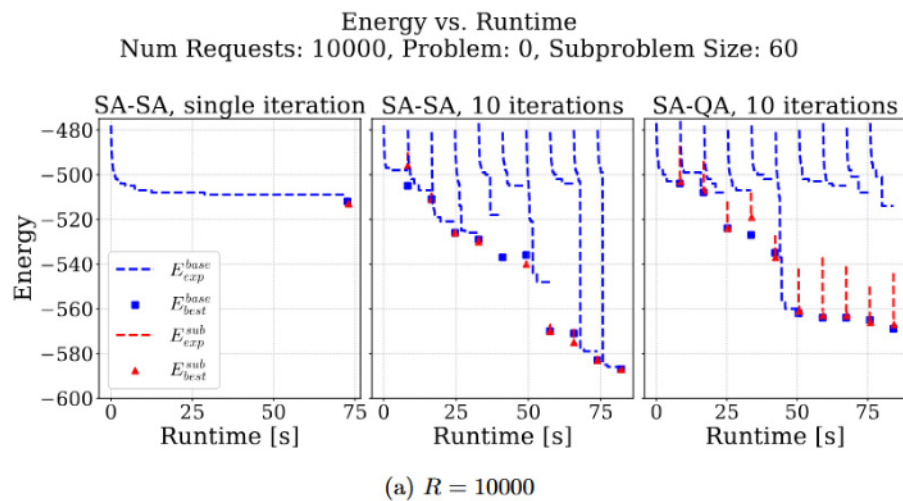
We generate subproblems of a fixed size of 60 requests, to ensure a feasible problem embedding into the Advantage system. We perform a fixed number of runs for each solver (100 runs at 1000 sweeps for SA, 1000 runs at 100 $\mu$ s annealing time for QA) and 10 iterations. The high number of runs ensures

statistical significance of the obtained results, from which we collect suitable metrics for practical use. We compute a discrete cumulative distribution function (CDF) for the statistical distribution of the sample energies collected by all the runs. We can derive the expected energy for each iteration  $I$  as the energy value for which  $\text{CDF}(\text{expected\_energy}) = 1 - 0.5^I$ . A continuous inverse CDF, needed for finding the expected energy, is obtained by interpolating the discrete CDF using PCHIP 1-D monotonic cubic interpolation (Fritsch and Butland 1984) and inverting it. The results for the two setups are compared to a single SA-SA iteration with 1000 runs. The code for the method and the experimental setup is made available for reproducibility<sup>1</sup>.

A plot for the expected and best solution energies vs. runtime is shown in Fig. 3. The best solution found in our runs for each subroutine was used as initial solution of the subsequent subroutine. This initial experiment confirms the feasibility of the iterative sub-problem generation approach, as the solution search generally improves at each iteration. QA is also able to run and sample feasible solutions for the generated sub-problems. The question is whether it is worth running QA over SA. For the  $R=10000$  problem instance, this is not the case, except for a better energy found by the SA-QA setup at iteration 6, after which no significant improvement is reached. In the  $R=20000$  problem instance, solutions updated by QA actually lead to better final acquisition schedules compared to the SA-SA setup. This could be related to the fact that a higher acquisition density leads to higher problem complexity, where QA can have an edge. The higher solution variability of QA, signaled by the varying expected sub-problem energy, also indicated a difference in the exploration of the solution space. Another indicator is the high difference between expected and best energies obtained in the SA-QA case, showing that QA shifts from the conventional statistical distribution of SA solutions.



<sup>1</sup> <https://gitlab.jsc.fz-juelich.de/sdlrs/qmp>



**Figure 3:** Hybrid optimization results for two different acquisition scheduling problems, i.e., number of requests  $R=10000$  (a) and  $R=20000$  (b), and two algorithm combinations (SA-SA, SA-QA). Results are compared to one SA-SA iteration, executed for a comparable amount of time. Blue plots show the expected ( $E_{exp}^{base}$ ) and best ( $E_{best}^{base}$ ) energies recorded on the full problem of size 60. Red plots show the expected ( $E_{exp}^{sub}$ ) and best ( $E_{best}^{sub}$ ) energies recorded on the generated sub-problem of size 60.

## Conclusion

The presented hybrid approach to optimization enables experimental validation of quantum optimization subroutines in acquisition scheduling, with initial promising results for QA. A higher contribution of quantum optimization, finding better solutions and working on larger subproblems, is an expected outcome of future quantum machines. Practical use will also benefit from tight on-premise integration of quantum machines, which will reduce communication delays. Future work will focus on extending the validation to other optimization methods, beyond standard QA, including a deeper analysis of the benefits of quantum optimization. In addition, further scalability will also be studied, working with a higher number of requests and more complex acquisition scenarios.

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## Abstract

The need for on-demand satellite acquisitions for Earth observation is rapidly increasing, along with the availability of public and commercial satellite constellations capable of fulfilling such requests. Scheduling acquisitions optimally remains a computationally challenging task, especially in complex scenarios with multiple satellites, constraints, and high number of requests. Today, heuristic algorithms are commonly used to find sub-optimal solutions that balance computational time and acquisition value, for example in terms of economic return. The potential role of quantum optimization in this domain is still an open question. While recent demonstrations have explored quantum approaches, they are limited to small problem instances due to current hardware constraints and the difficulty of simulating large quantum systems with classical hardware.

In this work, we present a hybrid quantum-classical optimization approach to address acquisition scheduling problems of any size. At each iteration, a classical heuristic generates a global candidate solution, from which a smaller local sub-problem is extracted and solved using a quantum optimization algorithm. We validate the method on large-scale instances, leveraging D-Wave Advantage to solve the sub-problems with quantum annealing. Initial results show the feasibility of the approach and highlight the capability of quantum annealing to guide the hybrid solver towards better overall acquisition schedules than simulated annealing in a comparable amount of time, in particular as the complexity increases. ■

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