REVERSE QUANTUM ANNEALING FOR HYBRID QUANTUM-CLASSICAL SATELLITE MISSION PLANNING

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ABSTRACT

The trend of building larger and more complex imaging satellite constellations leads to the challenge in managing multiple acquisition requests of the Earth surface. Optimally planning these acquisitions is an intractable optimization problem, and heuristic algorithms are used today for finding sub-optimal solutions. Recently, quantum algorithms have been considered for this purpose, due to the potential breakthroughs that they can bring in optimization, expecting either a speedup or an increase in the solution quality. Hybrid quantum-classical methods have been considered as a short-term solution for taking advantage of small quantum machines. In this paper, we propose reverse quantum annealing as a method for improving the acquisition plan obtained by a classical optimizer. We investigate the benefits of the method with different annealing schedules and different problem sizes. The obtained results provide guidelines on designing a larger hybrid quantum-classical framework based on reverse quantum annealing for this application.

Index Terms— Optimization, quantum computing, quantum annealing, reverse quantum annealing, mission planning.

1. INTRODUCTION

Satellite Mission Planning (SMP) consists in scheduling the acquisition of images given a set of requests, a satellite imaging system and a number of constraints. Exact and approximate methods for solving the combinational optimization problem have already been defined in the past [1]. However, as the problems become larger in practical cases, the performance of existing methods degrades.

Research on quantum computing has provided a new computational paradigm that processes information in a fundamentally different way. By comparing quantum algorithms and classical algorithms, a number of advantages and disadvantages can be found. Research efforts aim at understanding what the theoretical and practical advantages of quantum algorithms are and how different applications can benefit from them. A number of contributions on quantum computing for SMP have been recently published. In [2], the problem is reframed as a Quadratic Unconstrained Binary Optimization (QUBO) problem and solved with Quantum Annealing (QA). The idea of employing hybrid quantum-classical optimization has also been explored. In a recent work, both hybrid and full quantum solvers based on quantum annealing have been tested on different D-Wave machines [3]. A hybrid quantum reinforcement learning method has been proposed in [4]. A proof of concept using variational quantum algorithms has also been shown [5]. This last approach is generally considered as a good candidate for experimentally validating and employing NISQ devices. Nevertheless, the best way to combine quantum and classical resources for SMP is still an open question.

In this paper, we explore the computational capabilities of reverse QA. Specifically, we propose a hybrid method for the SMP problem that integrates a classical heuristic solver with a quantum optimizer. The reverse QA step serves as a local exploration of the solution space, taking a classically obtained candidate solution as input. This has been proven effective in previous work, e.g., for portfolio optimization problems [6].

Sect. 2 provides an introduction to forward and reverse QA. Sect. 3 describes the considered problem setting and proposes a hybrid quantum-classical framework for its solution. Sect. 4 contains experimental results of reverse QA instances. Sect. 5 concludes the paper and summarizes possible future research directions.

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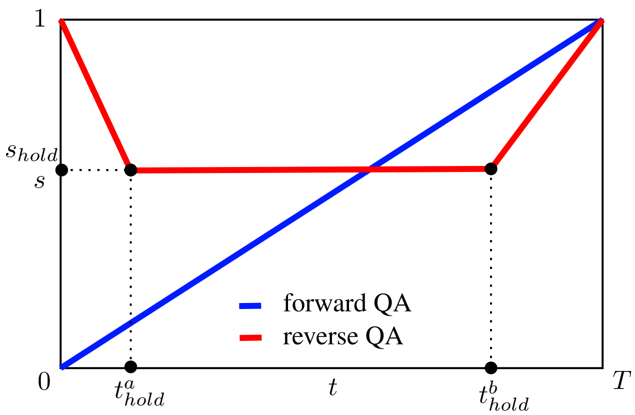

Fig. 1. Example plot of s for reverse QA compared to standard (forward) QA. Instead of simply being a normalized time, here s is a time-varying parameter that regulates the evolution of the Hamiltonian.

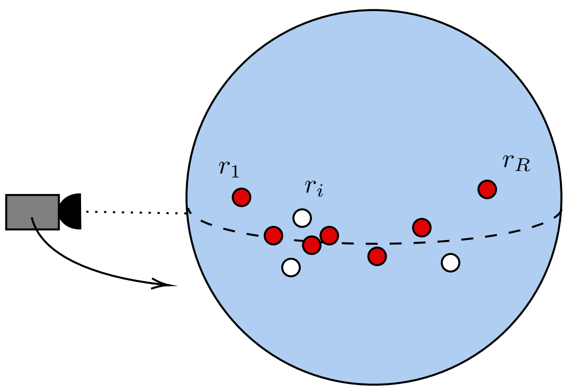

Fig. 2. Considered acquisition setting. In red, a possible solution to the SMP problem is highlighted.

2. QUANTUM ANNEALING

2.1. Forward Quantum Annealing

Adiabatic Quantum Computation (AQC) [7, 8] is a computational paradigm where the operations applied to qubits are forces acting on a quantum system. The temporal evolution of the quantum system, denoted as the state $|\varphi(t)\rangle$, is governed by Schrödinger's Equation, expressed as:

$$i\hbar\frac{\partial\,|\varphi(t)\rangle}{\partial t} = \mathcal{H}(t)\,|\varphi(t)\rangle \tag{1}$$

where i denotes the imaginary unit, $\hbar$ the reduced Planck constant, and $\mathcal{H}(t)$ a time-varying Hamiltonian describing the system. The concept of AQC involves encoding the desired outcome as the ground state of the final Hamiltonian $\mathcal{H}_F$, which is also the final state of the evolved quantum system, if the assumptions of the adiabatic theorem [9] are satisfied.

D-Wave quantum annealers are the physical implementation of a quantum system with a specific Hamiltonian of the following form:

$$\begin{aligned}\mathcal{H}(s) = &-\frac{A(s)}{2}\left(\sum_i \hat{\sigma}_x^{(i)}\right)\\ &+\frac{B(s)}{2}\left(\sum_i h_i\hat{\sigma}_z^{(i)} + \sum_{i>j} J_{i,j}\hat{\sigma}_z^{(i)}\hat{\sigma}_z^{(j)}\right)\end{aligned} \tag{2}$$

where $s = t/T$ is the normalized time, T the total annealing time, $A(s)$ and $B(s)$ are the weights of two Hamiltonians, respectively called transverse Hamiltonian and Ising Hamiltonian, and $\hat{\sigma}_x^{(i)}$ and $\hat{\sigma}_z^{(i)}$ are the Pauli x and Pauli z operators. The coefficients h_i and $J_{i,j}$ are the coefficients of the Ising problem that the Ising Hamiltonian encodes. An Ising problem is an optimization problem where the cost function is of the following form:

$$I\left(x_1,\ldots,x_n\right) = \sum_{i=1}^{n} h_i x_i + \sum_{i<j} J_{ij} x_i x_j \tag{3}$$

where the variables x_i can assume the values -1 and 1. Note that QUBO problems, commonly found in the literature, are equivalent to Ising problems where the values of the variables are set to 0 and 1, and the coefficients are adapted accordingly. For this reason, both Ising and QUBO formulations are compatible with QA.

The functions $A(s)$ and $B(s)$ of the annealing Hamiltonian in Eq. 2 are chosen so that $A(s)$ is decreasing to 0 and $B(s)$ is increasing from 0 for $s \in [0, 1]$. In this setup, the state of the system at $s = 0$ is the ground state of the transverse Hamiltonian, which is easy to prepare, and the state at $s = 1$ is expected to be the ground state of the Ising Hamiltonian, which encodes the optimal solution to the optimization problem.

2.2. Reverse Quantum Annealing

So far, the standard QA method has been presented, referred to as forward QA. However, it is possible to act on the functions $A(s)$ and $B(s)$ to change the time evolution of the system, also changing the logic of the machine. A possibility is to act on the variable s. Methods that revert the progression of s during time are referred to as reverse QA. For example, instead of a linear time progression, the annealer can start at $s = 1$, invert the time evolution, and then restart it shortly after. Fig. 1 graphically shows possible anneal paths for forward and reverse QA.

An advantage of reverse QA is that a possible solution to the optimization problem can be set as the initial state of the system. This has shown to guide the search and refine previously found solutions [10].

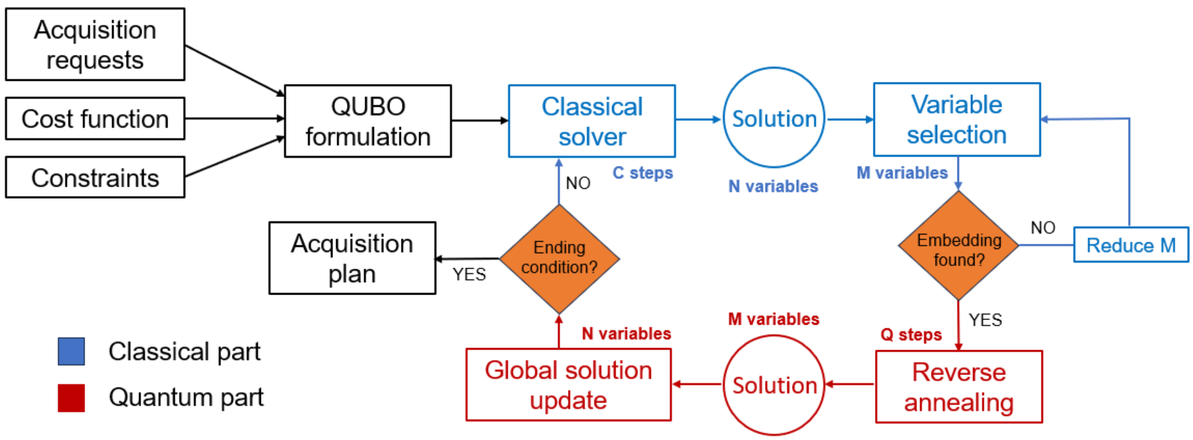

Fig. 3. General flowchart of a hybrid quantum-classical solver based on reverse QA. The classical and the quantum part are highlighted in blue and red.

3. HYBRID OPTIMIZATION FOR SATELLITE MISSION PLANNING

3.1. Problem Definition

SMP problems vastly differ between different systems and applications. Generally, the problem consists in assigning acquisition requests to satellites to maximize the value of the acquisitions and minimize the time. A number of required or desired constraints are enforced, e.g., related to the satellite constellations, sensors, on-board memory, cloud coverage, illumination, or communication with ground stations.

We consider a simple formulation of the SMP problem [5]. A set of R acquisition requests is provided, and a subset of them is to be found so that a system made of a single satellite is able to satisfy them in a single pass. This subset is defined as a binary vector $x \in (0,1)^R$, where x_i means that the area i is planned to be acquired. An arbitrary value v_i is set to each acquisition, which may correspond to economic value or urgency. The constraint is related to the fact that the satellite needs time to rotate the sensor and acquire images at different off-nadir angles. A representation of the acquisition setting is shown in Fig. 2.

The mathematical formulation of the optimization problem is the following:

$$\max_{x \in \{0,1\}^R} \sum_{i=1}^{R} x_i v_i \quad \text{with} \\ R(i,j) \leq T(i,j) \quad \text{if} \quad x_i = x_j = 1 \tag{4}$$

where $R(i,j)$ is the sensor rotation time between the acquisitions i and j, and $T(i,j)$ is the orbital transition time of the satellite between the acquisitions i and j.

This problem is reframed to a QUBO problem, equivalent to the Ising problem in Eq. 3, to ensure compatibility with QA. The constraint is included in the cost function as a penalty term:

$$\max_{x \in \{0,1\}^R} \sum_{i=1}^{R} x_i v_i - p \cdot \sum_{i=1}^{R-1} \sum_{j=i}^{R} x_i x_j \cdot c(i,j) \tag{5}$$

where p is the penalty weight, $c(i,j) = 1$ if $R(i,j) > T(i,j)$ and $c(i,j) = 0$ otherwise.

3.2. Hybrid Quantum-Classical Optimization

QUBO problems can be solved both with classical and quantum methods. Classical solvers can deal with a high number of variables, but a tradeoff between solution time and quality is needed. Solvers based on quantum annealing can be quick, but they have a strong limitation on the problem size. A possible approach to bring together such different solvers is to have the classical solver deal with the whole problem, and run the quantum solver on specific subproblems that fit the size of the machine. This problem decomposition can be done in multiple ways. For example, the method can select the M variables that have the most impact on the cost function. However, the existence of an embedding for the newly generated M-variable problem is a requirement for proceeding. For this reason, M should be carefully chosen in advance, or adapted at runtime. Once a new, hopefully better solution is obtained in the reverse QA phase, the original solution can be updated, and the cycle can be repeated until the ending conditions are met (e.g., number of repetitions or convergence). A flowchart of the proposed approach is shown in Fig. 3.

4. EXPERIMENTAL VALIDATION

The goal is to verify whether reverse QA can provide an advantage in finding optimal acquisition plans, a necessary con-

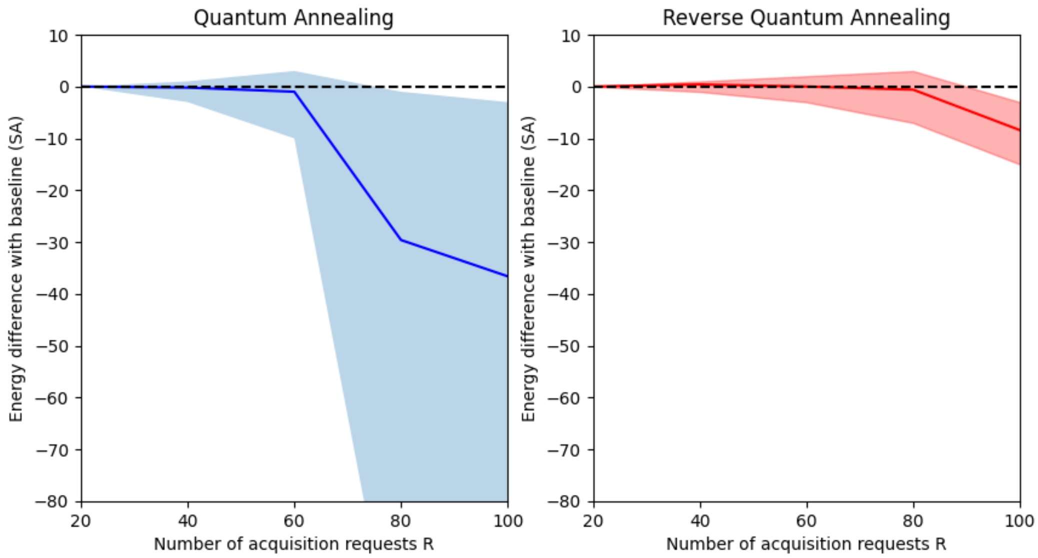

Fig. 4. Energy differences between quantum annealing-based methods and SA. Mean, minimum and maximum out of 5 problems for each number of acquisition requests R are highlighted. Only differences higher than -80 are shown.

dition for the hybrid framework in Fig. 3 to be effective. A total of 25 SMP problems has been instantiated using the *mqt-problemsolver* library [5]. Given a number of acquisitions, the library generates a collection of random acquisition requests with different values and provides a QUBO formulation of the problem, as in Eq. (5). The number of acquisitions has been chosen as $R \in \{20, 40, 60, 80, 100\}$, and 5 different instances for each R have been generated. The QUBO problem is first solved running Simulated Annealing (SA), a classical method for combinatorial optimization. This serves as a baseline method for comparison. The best obtained solution is then used to initialize the state of the quantum annealer and perform reverse QA. The anneal path regulating this step is shown in Fig. 1. The parameters that regulate the anneal path, also shown in Fig. 1, are: s_{hold}, which determines at which value of s the Hamiltonian stops its reverse path; t^a_{hold}, the time at which this value of s is reached and the reverse path stops; t^b_{hold}, the time at which the forward path is resumed; T, the total time of the QA step. In our case, we optimize the anneal path varying s_{hold} and other derived parameters: *reverse_slope*, *hold_time*, and *forward_slope*. This choice comes from the fact that quantum annealers specifically impose a limitation on the slope of the anneal path that can be implemented.

The parameters are optimized using Bayesian optimization [11]. This method ensures a relatively low number of cost function evaluations (as reverse QA can be costly), and it has been preferred to standard anneal path choices in previous work [10]. The obtained results are compared with standard QA, which requires no initial solution. Each optimizer is set to sample 500 solutions, among which the single best one is selected.

The difference between the energy of the obtained best solutions and the baseline are shown in Fig. 4. For $R = 20$ acquisitions, the problem is simple enough to be optimally solved by all the solvers. An improvement on the baseline can also be seen with QA alone, especially for $R = 60$. Nevertheless, reverse QA becomes a better choice than forward QA especially for $R = 80$. This clearly shows the positive effect of providing an initial classically obtained solution. Moreover, reverse QA can also improve on that solution in certain instances. The performance of both quantum optimizers decreases for $R = 100$, also due to the noise affecting the quantum annealer.

5. CONCLUSIONS

In this preliminary work, we showed the potential of reverse QA for SMP, which can improve the acquisition plans obtained with SA in some cases. A natural continuation of the work can provide more insights on the reverse QA method by choosing different acquisition settings, anneal paths, and configurations. Afterwards, the full framework for large-scale hybrid optimization can be implemented, taking into account the advantages and limitations of reverse QA. This approach can greatly benefit from an integration of quantum computing with high-performance computing systems, allowing parallelization and lowering communication time overheads.

6. REFERENCES

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