Efficient Earth Observation Satellites Mission Planning with Quantum Algorithm

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Efficient Earth Observation Satellites Mission Planning with Quantum Algorithm

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***Abstract*—Earth observation satellites (EOS) collect vital data for various applications such as weather forecasting, disaster management, environmental monitoring, etc. Maximizing the value of this data requires designing optimal EOS missions to capture targets with high business value or priority while satisfying complex constraints such as storage capacity, energy limits, weather, etc. However, traditional computing methods often struggle with the complexity of optimizing EOS mission schedules, leading to suboptimal target selection and reduced data collection efficiency. To address this challenge, there is a growing interest in leveraging quantum computing to enhance the efficiency and accuracy of EOS mission planning. Quantum computing provides the potential to explore vast solution spaces and find optimal schedules for EOS missions, even when faced with complex constraints and objectives.**

In this paper, we demonstrate the potential of our quantum algorithm to optimize EOS mission schedules and improve the efficiency of multiple EOS in real-time. The aim is to maximize the acquisition of high-priority targets with significant business value within the constraints of limited resources. We evaluated the performance of our quantum algorithm by comparing it with two classical optimization algorithms: simulated annealing and Gurobi optimizer. Our quantum algorithm outperformed the Gurobi optimizer by 23.46% in selecting high-priority targets, while satisfying all constraints. Although the simulated annealing executed faster than the quantum algorithm, its accuracy in providing high-value targets was poor in comparison. Moreover, the Gurobi optimizer took 39.09% longer to execute on average than our quantum algorithm. Additionally, the Gurobi optimizer failed to satisfy all constraints for 32% of the data, whereas our quantum algorithm successfully satisfied all constraints for all the data, even with an increased data size.

***Index Terms*—Earth Observation Satellites (EOS), Quantum Computing, Quantum Annealing, Simulated Annealing, Gurobi Optimizer**

I. Introduction

Earth observation satellites (EOS) are of immense use in understanding and proactively responding to various complex and dynamic natural systems of earth including climatic changes leading to natural disasters, oceanography, deforestation, forest fires, seasonal changes in the earth's environment due to cosmic showers, the sun's impact on terrestrial communications and a host of various other phenomena and influences. Satellites can probe and provide data for remote and normally inaccessible regions of the earth through other modes of information gathering. Therefore, EOS is a critical technological tool for carrying out scientific research to enhance our understanding of the planet's diverse ecosystems, geology, and atmosphere amongst various other aspects. Since there is a constant need for such information and providing intelligent insights based on the gathered data, there is a requirement for improved data acquisition and optimization techniques.

There are increasingly complex data acquisition challenges faced by EOS due to the limitations of data storage and transmission on the satellites. Some of these are the following:

(a) Volume of Data: EOS generates large volumes of data which is further increasing due to technological advancements in satellites. This results in significant challenges for data processing, storing and data transmission to ground (also called as earth) stations.
(b) Limited Data Storage Capacity: Satellites need to be compact in size since every gram of additional weight results in a significant increase in the cost for launching the satellite, the storage capacity is usually limited. Consequently, as the data volume increases, data storage on board the satellite becomes a challenge. This results in the question of optimizing which data to retain and which one to discard.
(c) Bandwidth Limitations: The transmission bandwidth available for transmitting data from satellites to the ground stations is limited due to the communication channel constraints. This in turn implies that only certain amounts of data can be transmitted at a given point in time. This can result in delays in data transmission and data can also be lost.
(d) Weather conditions: Since EOS are usually in low earth orbits, they can be affected by weather conditions including dynamically changing atmospheric conditions and cloud cover. This critically impacts the quality and quantity of data that can be received by ground stations.
(e) Trajectories and orbits: This is one of the most important aspects of data acquisition using satellites. Some areas of

earth may be more difficult to observe or access due to the satellite's trajectory and orbit. There could be multiple satellites with overlapping trajectories trying to gather data of a particular spot. Priorities of data gathering can become challenging due to such diverse conditions.

Therefore, it is important to address these data gathering challenges so that efficiency and effectiveness of EOS is enhanced. Exploring new technologies such as quantum computing techniques may be one of the directions to take to address these challenges.

Quantum computing is a form of computing that is based on three fundamental quantum mechanics principles, namely superposition, entanglement, and interference. This is a complete paradigm shift from the conventional or classical computing principles on which the current digital computers are based. The idea for quantum computing was initially mooted by Feynman [1], [2] when he discovered that simulating quantum phenomena using classical computers became unwieldy even for a small number of quantum systems. He therefore suggested that a computational machine should be developed which would use the principles of quantum mechanics. Such a computer would naturally align to simulate quantum phenomena. The concept of a universal quantum computing machine was first proposed by David Deutsch in 1985 [3], where he outlined five principles for the existence of a universal quantum computer. These are the principles of superposition, entanglement, interference, measurement, and reversibility.

Quantum computers moved out of the research mode into actual design, development, and usage in real-life phenomena in 1994, primarily due to the paper by Peter Shor [4], [5] on factoring large integers into a pair of prime numbers. Classical algorithms used for the same task are proven to be exponentially slower in comparison to the Shor's algorithm. The importance of Shor's algorithm lies in the fact that classical cryptography algorithms used for encryption of online transactions that are carried out every day can, in principle, be broken by Shor's algorithm. The other important research work that was instrumental in bringing out quantum computers out of the physics research mode was Grover's algorithm on unsorted database search [6] [7]. Grover's algorithm can search an unsorted database of N entries in O($\sqrt{N}$) time, which is exponentially faster than the classical algorithm which does the search in $O(N)$ time. In today's era, quantum computers have made significant progress in terms of their use in solving problems in quantum machine learning, quantum simulation and certain classes of optimization problems which are NP-Hard. For optimization problems, in general, quantum annealing is used, which is a heuristic optimization algorithm used in quantum mechanics to determine the global optimum (in this case the global energy minimum) of quantum mechanical systems which may be of combinatorial complexity [8].

Given the above background, we address the following research questions in this paper:

1) How do we optimize the scheduling of Earth Observation Satellite missions for maximizing the acquisition of high-quality data while addressing the efficient allocation of limited resources using a quantum optimization algorithm?
2) How does the proposed quantum optimization algorithm compare with the most effective classical optimization algorithms?

The structure of the paper is as follows. In Section II, we present the current literature that addresses the above questions. Section III gives an overview and provides mathematical details of the proposed quantum annealing algorithm. In Section IV we explain the methodology and experimental setup that is used to develop the three optimization algorithms namely, simulated annealing, Gurobi optimizer and quantum annealing. We also explain the various experiments that are carried out using the algorithms. In Section V we present the results of the various experiments carried out in Section IV and discuss the results of our experiments. We conclude the paper with some future directions in Section VI.

II. Related Works

In the first part of this section, we briefly summarize earlier work done on earth observation satellites and data acquisition challenges. An excellent summary of using EOS for gathering relevant information and analysis through remote sensing is given in the book by Cracknell. It provides details on using satellites to gather data and evaluate it for getting information about earth's surface for weather forecasting, climatology, applications to the geosphere such as geomagnetic radiation, gathering and analyzing geological data for geothermal and volcano studies and so on. The longest-running and most important satellite program for earth observation is the Landsat program [9]. Landsat 1 started the era of collecting data through satellites. These data have been extremely useful in mapping and monitoring ground resources and atmospheric conditions for developing programs which benefit everyone on earth. The work by Colwell [10] provides an analysis of how modern remote sensing techniques can facilitate the inventory and management of natural resources which are renewable, such as timber, agricultural crops as well as nonrenewable resources including minerals and fossil fuels.

In recent times, fusion data-driven algorithms which are based on machine learning tools and techniques are being used for problems on earth observation [11]. The fusion data is obtained through various sources including EOS, various types of sensors, processes and variables which have a high degree of spatial and temporal resolutions. Given that remote sensing involves data volumes from the multitude of in-orbit satellites, analyzing the data using deep learning is being considered in this paper [12]. Spectral data with high spatial resolution, (which is the number of pixels per unit area) and very high spectral dimensionality with thousands of bands are being acquired. These lead to significant challenges in data management, data interpretation and data analysis.

Quantum algorithms have been applied for satellite mission planning and scheduling to be used for earth observation [13], [14]. There is some work also being done on using Quantum Machine Learning algorithms for processing data from multi-spectral sources for earth observation [15]. Quantum Annealers have been used for image acquisition of EOS [16].

III. Overview of the Quantum Annealing Algorithm

This section gives an overview of the quantum annealing algorithm that we have developed and details the mathematical formulation. We have proposed an improved algorithm for scheduling Earth Observation Satellite (EOS) missions. This is a challenging task as it involves optimizing a large input set while satisfying numerous dynamics constraints in real-time, making it an NP-hard problem [17] which is difficult to solve using classical methods. So, the quantum algorithm is developed to optimize the EOS schedule, which can satisfy all the constraints while giving optimal and efficient results in real-time.

Our quantum algorithm can simultaneously optimize the schedules of multiple satellites. The satellites have unique imaging targets that may overlap during their respective journeys. Thus, we need to make sure that their schedules are synchronized and there is no redundancy in their acquisitions. Since the primary goal of the algorithm is to maximize the acquisition of high-quality data while ensuring the efficient allocation of limited resources, the algorithm considers the following constraints:

- Storage capacity of the satellite.
- Downlink limits of ground stations.
- Energy available for capturing the targets.
- Optimally selecting line of sight targets while considering the satellite's required adjustment time.
- Weather conditions

. Weather conditions are a critical factor and are considered in the objective function of our algorithm. The weather variable for each target indicates the probability of successful target acquisition in that weather. The algorithm tries to pick the targets with maximum weather variable values. Maximum weather variable signifies better climate conditions.

The following parameters are input to the algorithm. We have considered three sets of parameters, namely, targets, satellites, and ground stations:

(A) Targets
- Target IDs
- Priorities
- Sizes
- Energies required to acquire targets

(B) : Satellites
- Satellite IDs
- Storage limits
- Energy Limit

(C) Ground Stations
- Ground Station IDs
- Downlink Limit of Ground Stations

The amount of data that can be transmitted to a ground station from a satellite in one orbit is limited due to the limited interaction time window, and the downlink limit constraint is essential for ensuring that the captured data is effectively transmitted to the ground station without any data loss. The energy constraint is crucial in ensuring that satellites operate within their allocated energy budgets and avoid potential system failures that could lead to data loss.

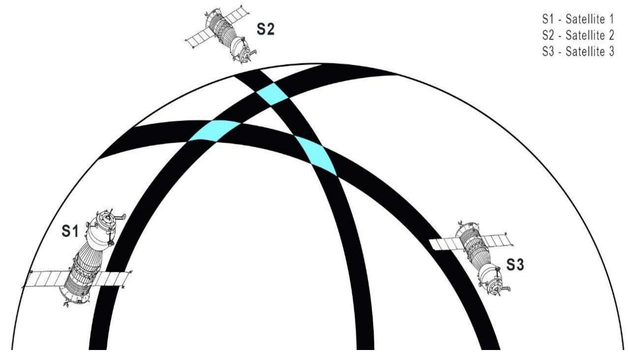


Fig. 1. Three Earth Observing Satellites S1, S2, and S3 with their lines sight (The cyan parts highlight the intersection in the orbits of two satellites)

Consider the example illustrated in Fig. 1 with three distinct EOS with a black strip representing the path of each satellite. The cyan part indicates the intersection of the paths of the satellites. Our algorithm maximizes the overall outcome while ensuring that each satellite selects targets that meet its constraints, thereby minimizing resource wastage. Therefore, the same target should not be selected by two or more satellites. The algorithm ensures that this constraint is satisfied, and each satellite chooses targets that satisfy its individual constraints thereby eliminating redundancy and increasing efficiency.

It is worth noting that the scheduling problem becomes increasingly complex as we incorporate more parameters and constraints. However, our algorithm is designed to inherently address these complexities and ensure that the scheduling process is efficient and effective.

Fig. 2 illustrates the approach we use for scheduling the acquisition of targets. Our approach involves segmenting the satellite's path into various quadrants based on the presence of ground stations. The geographical area between two ground stations in the path of a satellite is considered a quadrant. Each quadrant has its ground station and unique targets.

To capture a target, a satellite must adjust its camera to properly align with the upcoming target. The amount of time required for this adjustment varies depending on the target. This period is referred to as the adjustment time of a target. To ensure successful capture and proper camera adjustment, the satellite must complete capturing a target with enough time remaining to adjust its camera before the next target aligns with it. However, if another target appears in the satellite's path before a previous target has fully passed or if two or more targets appear simultaneously, the satellite can only capture one target completely. To address this issue, we propose an algorithm that optimizes the utilization of the satellite's resources, reducing wasted time, energy, and storage by preventing overlapping target captures. Specifically, our algorithm ensures that when multiple overlapping target requests are encountered, only one will be scheduled for capture, minimizing the negative impact of overlapping captures. By effectively managing the satellite's scheduling, our algorithm can improve the efficiency of target capture while reducing

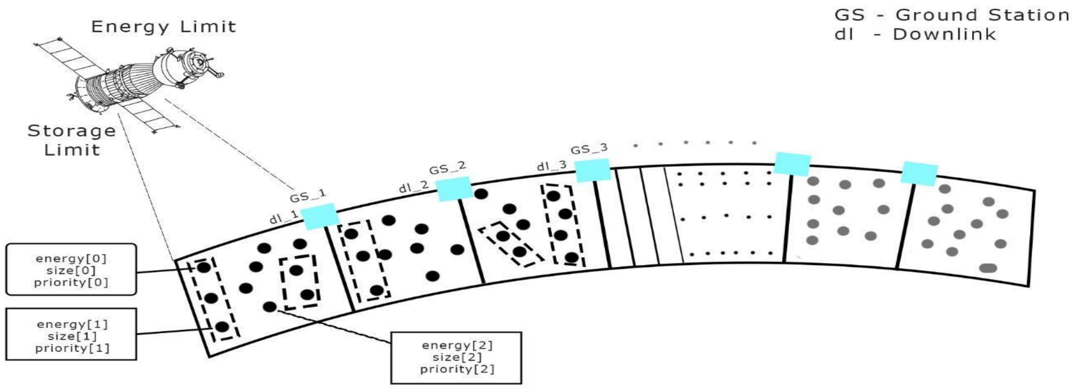


Fig. 2. Illustration of EOS operation

waste, making it a valuable tool for satellite operations.

The algorithm presented in this study is a valuable addition to the field of earth observation as it addresses crucial challenges in scheduling data acquisition. By prioritizing shared targets and considering resource constraints, the algorithm facilitates the efficient acquisition of high-quality data. This significantly enhances the effectiveness of earth observation missions.

A. Mathematical details of the quantum annealing algorithm

As mentioned above, we propose a novel quantum optimization approach for Earth Observation Satellite (EOS) schedule optimization that considers all relevant constraints, including weather constraints. The primary goal of our algorithm is to maximize the acquisition of high-quality data while ensuring the efficient allocation of limited resources in real time. In a typical data acquisition, the resources being storage capacity of the satellite, energy of the satellite and the time window available for downlinking the acquired data to a ground station can be considered as the downlinking limit of the ground station.

1) Objective function: The objective function that we have proposed is:

$$\sum p_i x_i : Maximize\ High\ Priority\ Target\ Selection \tag{1}$$

$$\sum w_i x_i : Maximize\ Good\ Weather\ Target\ Selection \tag{2}$$

To optimize for the two objectives, namely priority and weather, we must balance their importance by assigning relative weights to each.

$$Objective = \alpha \sum p_i x_i + \beta \sum w_i x_i \tag{3}$$

α and β are weighting parameters to give more bias on either weather or priority according to needs to find a solution that meets both objectives to the greatest extent possible.

2) Constraints: The following constraints apply to the problem:

(a) Total sizes of images: less or equal to the downlink limit of ground stations.
(b) Total energies of images: Less than or equal to the energy limit of a satellite.
(c) Total sizes of images: within the storage limit of the satellite.

3) The QUBO problem: Quadratic Unconstrained Binary Optimization (QUBO) is a mathematical framework for representing optimization problems as a quadratic polynomial in binary variables.

$$H = \sum_i a_i x_i + \sum_{i<j} b_{ij} x_i x_j \tag{4}$$

x_i is a binary variable that takes values 0 or 1, and a_i and b_{ij} are the coefficients that determine the cost or objective function of the optimization problem [18]. The first and second term in (4) represents linear cost and quadratic cost respectively, which depends on the pairwise interactions between the variables. As a linear optimization model that uses a grid by binary parameters, it can be transformed into a QUBO, and fit rather quickly to the quantum Ising model [19].

We use the one-dimensional Ising model to encode the proposed optimization problem, which is mathematically represented below:

$$H(\sigma) = \sum_{i=1}^{N} h_i \sigma_i + \sum_{i=1, j=i+1} J_{ij} \sigma_i \sigma_j \tag{5}$$

Where, H is Hamiltonian of the system, h_i is the linear coefficient corresponding to qubit biases and J_{ij} are the quadratic coefficients corresponding to the coupling strengths.

The Adiabatic Theorem states that if a quantum system is prepared in its ground state at the start of a slow and continuous evolution, then it will remain in its ground state throughout the evolution. This is a central concept in the field of quantum optimization.

Quantum Annealing (QA) is a specific type of AQC (Adiabatic Quantum Computing) that uses a different approach to solve optimization problems. In QA, the initial Hamiltonian is chosen to be a simple one, and the final Hamiltonian encodes the problem. The system is prepared in a superposition of all possible states and is then evolved under the time-dependent Hamiltonian that interpolates between the initial and final Hamiltonians [19].

$$H(t) = (1 - \frac{t}{T})H_0 + \frac{t}{T}H_Q \tag{6}$$

where H_0 is the initial Hamiltonian, H_Q is the QUBO Hamiltonian to be solved, T is the total annealing time, t is the instantaneous annealing time.

The initial Hamiltonian is typically a simple Hamiltonian such as the superposition of all possible states. The second term represents the QUBO Hamiltonian, which encodes the optimization problem to be solved.

The annealing parameter t varies from 0 to T, so that the system starts in the ground state of the Hamiltonian and evolves towards the ground state of the QUBO Hamiltonian [19].

IV. Methodology and Experimental Set up

In this section, we present the methodology and the experimental setup for carrying out the computational experiments. Apart from our quantum algorithm, we have considered two classical algorithms for baselining our results and to address the intricate optimization problem at hand. These algorithms are:

- Simulated Annealing, which is a heuristic optimization technique that employs a probabilistic search approach.
- The commercial optimization solver, Gurobi optimizer.
- Our Quantum algorithm which uses the quantum annealing approach as explained in Section 3 which enabled the simultaneous evaluation of multiple potential solutions using the algorithm.

A brief overview of the algorithms is given below:

A. Simulated Annealing

Simulated Annealing is a well-known heuristic optimization technique that can be used to solve optimization problems. The goal in this research is to find the optimal allocation of limited resources to maximize the acquisition of high-quality data. The simulated annealing approach involves iteratively searching through the solution space and accepting new solutions based on a probability distribution that gradually becomes more selective. The search terminates when the temperature parameter reaches a sufficiently low value or when a maximum number of iterations has been reached, and the algorithm returns the best solution found during the search. By applying the simulated annealing approach to our problem, we can effectively optimize the allocation of limited resources to maximize the acquisition of high-quality data [20]. These steps are shown in Fig. 3.

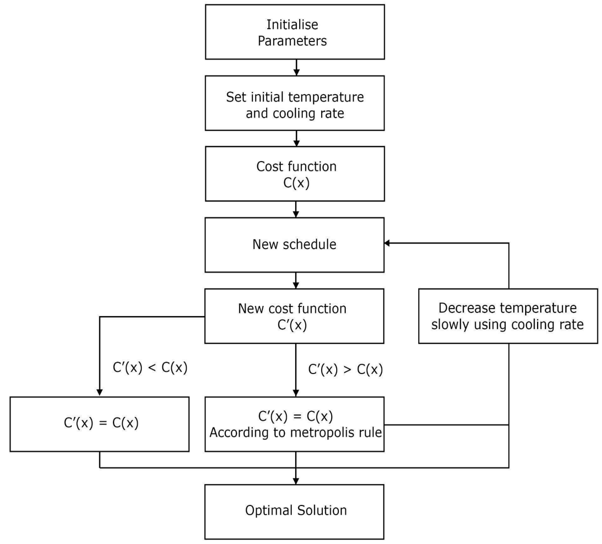


Fig. 3. Flowchart depicting simulated annealing

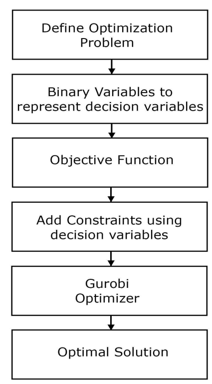


Fig. 4. Flowchart depicting optimization using Gurobi Optimizer

B. Gurobi Optimizer

In the Gurobi optimizer the approach involves the following steps as shown in Fig. 4.

- Defining the problem as an optimization problem with constraints
- Formulating it as a mathematical optimization problem,
- Inputting it into the Gurobi optimizer, and letting it solve the problem.

The Gurobi optimizer employs advanced optimization techniques, such as linear programming, mixed-integer programming, and quadratic programming, to find the optimal allocation of limited resources to maximize the acquisition of high-quality data while satisfying the constraints of the problem. The solution obtained by the Gurobi optimizer can be evaluated to verify that it satisfies the constraints of the problem and achieves the desired optimization goal.

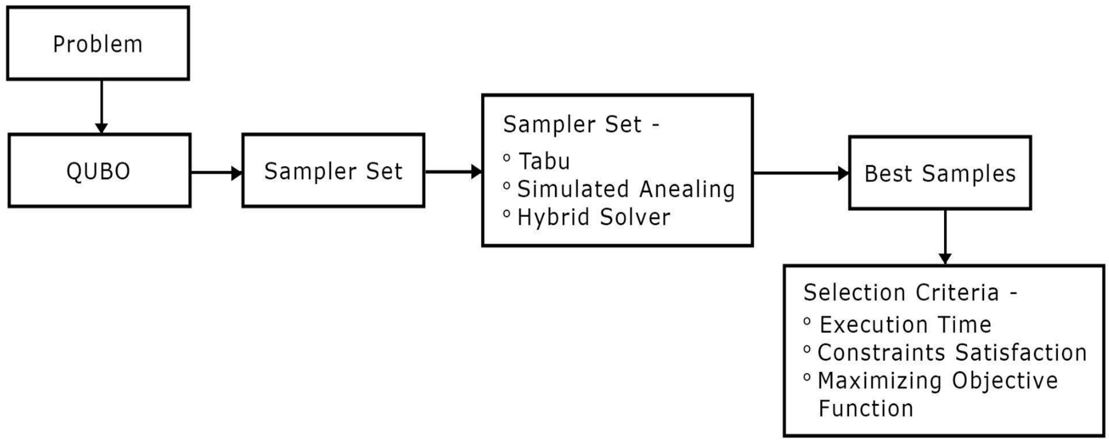


Fig. 5. Flowchart representing optimization using quantum annealing

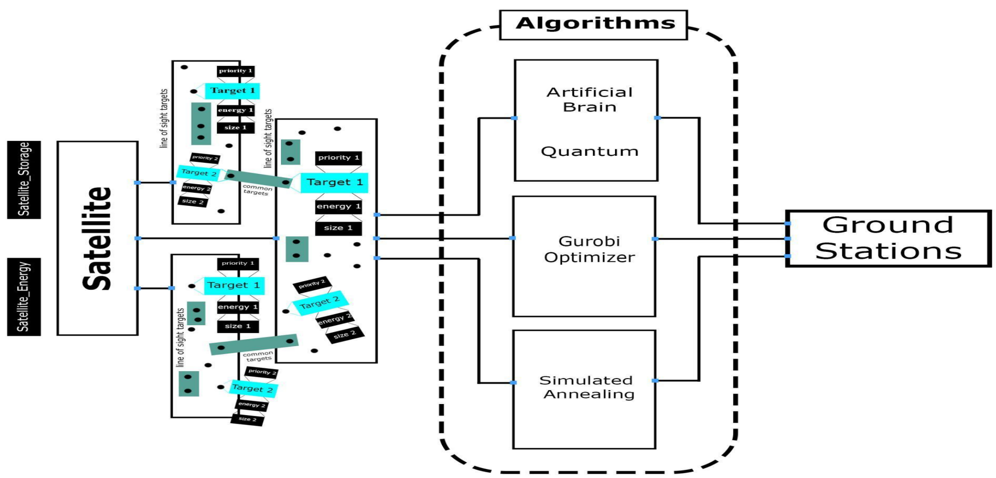


Fig. 6. Block diagram depicting quantum algorithm and other techniques used for optimization

C. Quantum Computing

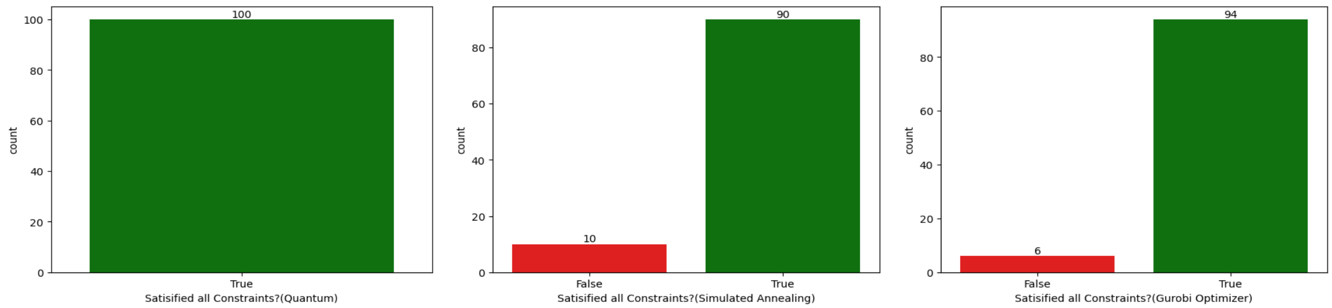
For our quantum computing algorithm, we have used the D-Wave quantum computer. The approach involves:

- Mapping the optimization problem to a quantum annealing architecture
- Using quantum annealing to find the optimal allocation of limited resources to maximize the acquisition of high-quality data while satisfying the constraints of the problem.

Quantum annealing involves encoding the problem as a set of binary variables and representing the problem as an Ising model (Fig. 5), which can be mapped onto a quantum annealing architecture. The quantum annealer then searches for the ground state of the Ising model, which corresponds to the optimal solution of the optimization problem [19].

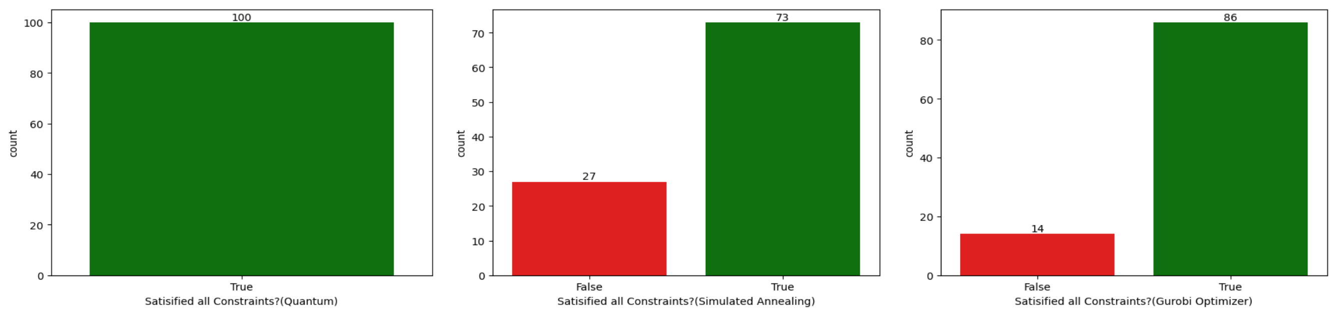
For complex problems involving numerous variables and constraints, quantum annealing has the potential to search solution spaces more efficiently and effectively, in comparison to the classical optimization methods. Nonetheless, it is crucial to acknowledge that the performance of D-Wave quantum computing heavily relies on the problem and the quantum annealer's size. As a result, additional research and development are necessary to ascertain the practicality and effectiveness of utilizing D-Wave quantum computing for Earth observatory satellite data acquisition optimization.

In the realm of earth observation satellite missions, weather conditions play a vital role in determining the success of the mission [21]. However, the effect of cloud coverage uncertainty on satellite operation has been largely overlooked in the existing research on deterministic scheduling [22]. To address this critical gap, we have integrated this key factor into our algorithm (Fig. 6), with the aim of optimizing the scheduling of satellite observations and enhancing their efficacy under diverse weather conditions [23]. Our approach is founded on extensive research and geared towards ensuring the optimal performance of the earth observation satellite mission.



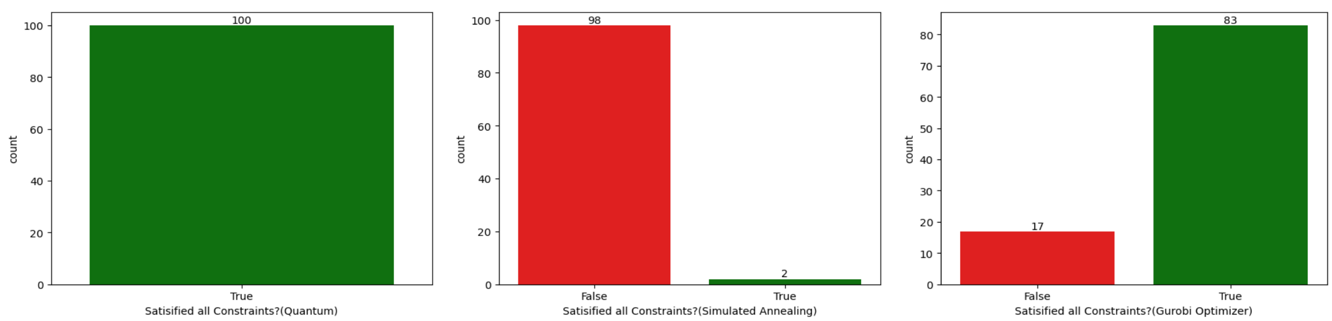
(a) (b) (c)

Fig. 7. Performance comparison of each technique on a dataset of 100 rows with each row having 20 targets.



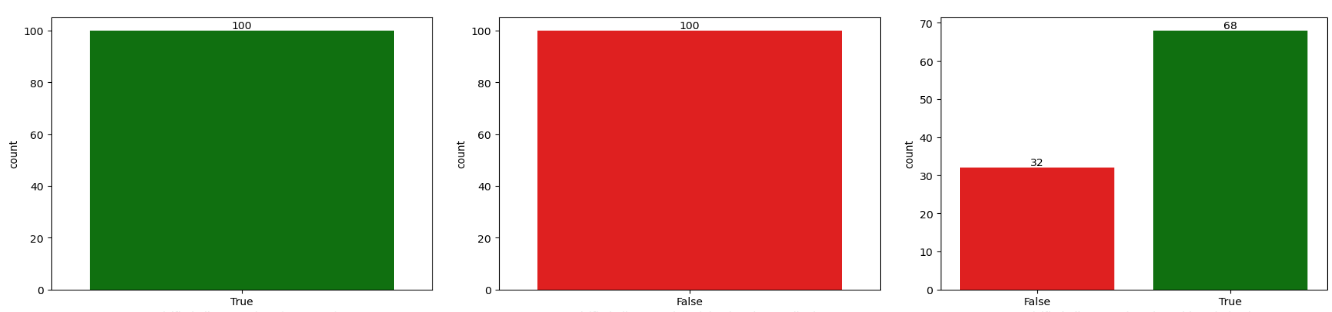
(a) (b) (c)

Fig. 8. Performance comparison of each technique on a dataset of 100 rows with each row having 100 targets.



(a) (b) (c)

Fig. 9. Performance comparison of each technique on a dataset of 100 rows with each row having 600 targets.



(a) (b) (c)

Fig. 10. Performance comparison of each technique on a dataset of 100 rows with each row having 1000 targets.

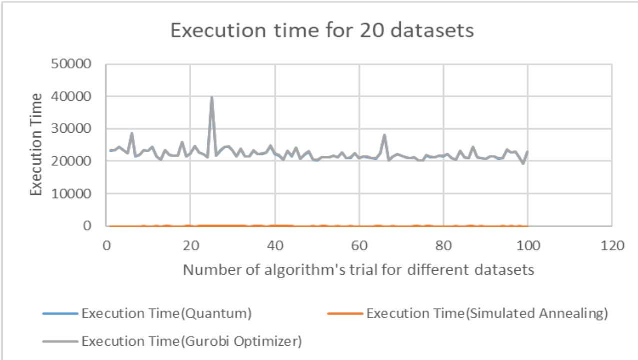


Fig. 11. Execution graph of each technique on a dataset of 100 rows with each row having 20 targets.

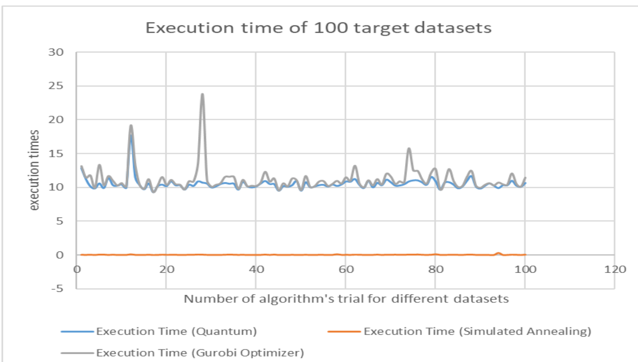


Fig. 12. Execution graph of each technique on a dataset of 100 rows with each row having 100 targets.

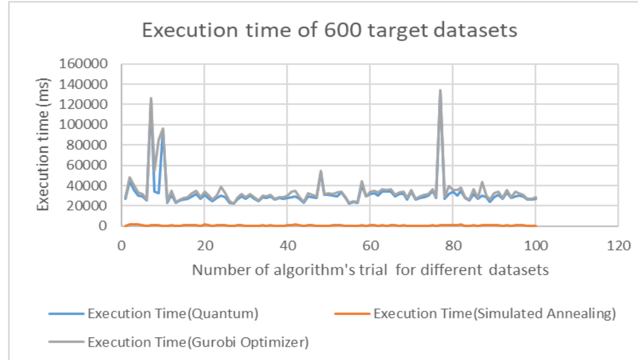


Fig. 13. Execution graph of each technique on a dataset of 100 rows with each row having 600 targets.

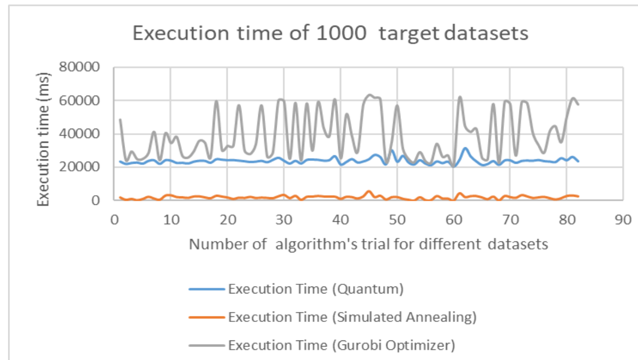


Fig. 14. Execution graph of each technique on a dataset of 100 rows with each row having 1000 targets.

V. Results and Discussion

The aim of this study was to evaluate the effectiveness of three optimization techniques - our Quantum algorithm, Simulated Annealing, and Gurobi optimization - in optimizing different datasets. As outcomes, the algorithms provide the following results:

1) Whether the algorithm satisfies all the constraints
2) A list of targets for the earth observation satellites to capture,
3) Identifying overlap of targets from multiple satellites and recommending the appropriate satellite for capturing the images.

This result will show how efficient algorithms are in optimizing weather parameters and maximizing priorities.

Using the Intel(R) Core(TM) i5 - 5257U CPU @ 2.70GHz system with 2 physical cores, 4 logical processors, and up to 4 threads, we were able to solve a maximum of approximately 12,000 targets in approximately 7 minutes for our Earth observatory satellite scheduling problem. From 12,000 targets we achieved:
Total priority: 267219
Execution time: 468856.63 ms
Total Variables: 12000
Total Constraints: 4586
Also, all the datasets below are solved using this CPU model.

A. Constraints Satisfaction Model:

We have considered 100 different datasets of 20, 100, 600 and 1000 targets each and applied Quantum, Gurobi and Simulated Annealing algorithms. These histograms represent the number of datasets the particular algorithm satisfied constraints out of 100 datasets of different numbers of targets while maximizing objective function.

Thus, we can conclude that our Quantum algorithm was the most effective method for maximizing priorities, outperforming both Gurobi optimizer and Simulated Annealing. Gurobi Optimizer was the second-best option, followed by Simulated Annealing. Furthermore, we observed that our Quantum algorithm was able to meet the constraints for all three sets of targets, while Simulated Annealing frequently failed to meet the constraints. Gurobi was able to satisfy the constraints to a moderate extent as is shown in Fig. 7- Fig. 10.

B. Execution Time Graph

In Fig. 11- Fig. 14, we have presented the execution time graphs. Our analysis revealed that simulated annealing exhibited minimal execution time; however, its effectiveness in satisfying constraints diminished with increased complexity of the dataset, and it failed to produce optimal solutions. On the other hand, the execution graph of Gurobi optimizer was comparable to that of the quantum algorithm up to a certain threshold complexity of targets. Beyond this

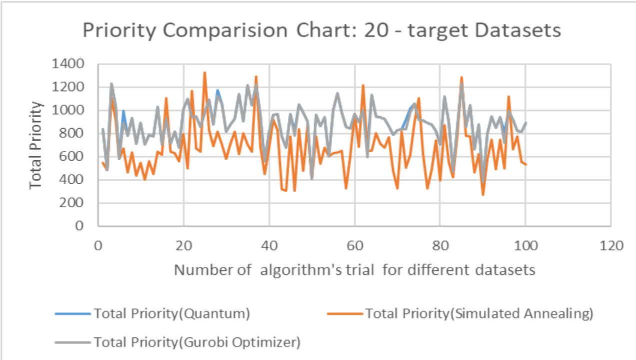


Fig. 15. Priorities comparison graph of each technique on a dataset of 100 rows with each row having 20 targets.

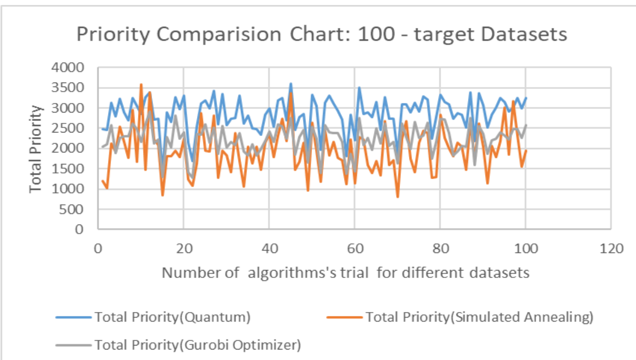


Fig. 16. Priorities comparison graph of each technique on a dataset of 100 rows with each row having 100 targets.

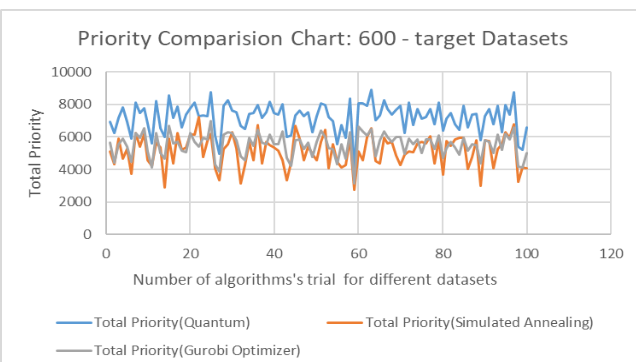


Fig. 17. Priorities comparison graph of each technique on a dataset of 100 rows with each row having 600 targets.

threshold, quantum annealing outperformed Gurobi optimizer by a considerable margin. These results indicate that while simulated annealing may be efficient for simpler problems, quantum optimization approaches may be better suited for more complex real-world scenarios. Furthermore, the findings suggest that Gurobi optimizer may be effective up to a certain complexity limit, beyond which quantum optimization should be considered for optimal solutions.

C. Priorities Comparison Graph

In Fig. 15-Fig. 18, we have presented the priorities comparison graphs. For datasets of 20 targets, Quantum algorithm

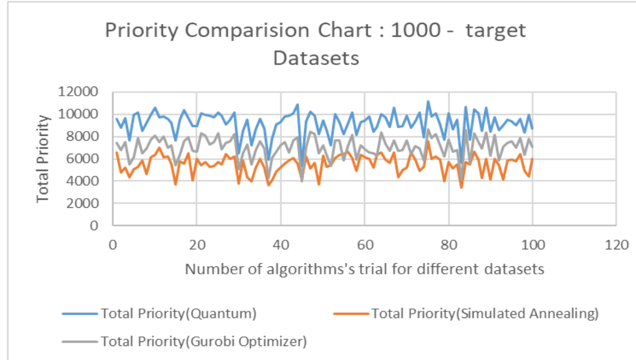


Fig. 18. Priorities comparison graph of each technique on a dataset of 100 rows with each row having 1000 targets.

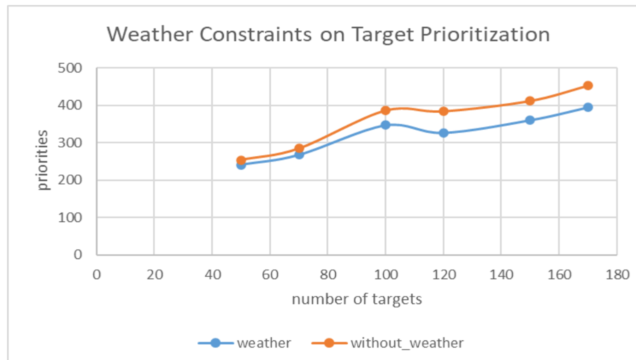


Fig. 19. Graph showing priority comparison of algorithm with and without weather constraint

and Gurobi optimizer give similar results as observed from the overlapping curves. There is a very small gap of bandwidth we see from the graphs. The separation of amplitudes of the waves represents the difference in the corresponding output priorities.

From the above graphs, we have demonstrated that in the case of a satellite scheduling problem with increasing complexity, a quantum algorithm does a much better task in allocating the resources, for maximizing priorities as well as optimizing weather parameters while satisfying all the constraints.

D. Impact of Weather Constraints on Target Prioritization: An Analysis

The graph presented in Fig. 19 illustrates the relationship between the number of targets and their respective priorities, considering the impact of weather constraints. As anticipated, our findings suggest that the incorporation of weather constraints in the system leads to a reduction in target priorities, with a larger decrease observed as the number of targets is decreased. Additionally, we observed that as the overall number of targets increased, the gap between the priorities with and without weather constraints also increased. These results provide valuable insights into the impact of weather-related factors on target prioritization and highlight the importance of considering such constraints in the optimization process for earth observation satellite missions.

These findings suggest that quantum computing may offer a more efficient and effective solution for solving constrained quadratic models in Earth observatory satellite data acquisition problems with a large number of targets. However, it is important to note that further research is needed to determine the generalizability of these findings to other datasets and problems. Overall, these results provide promising evidence for the potential of D-Wave quantum computing to address complex and challenging optimization problems, particularly those with large datasets and numerous constraints, which are common in many real-world applications.

VI. Conclusions and Future Works

In this study, we have demonstrated the potential of a quantum algorithm for optimizing Earth observation satellite (EOS) mission schedules. Our algorithm aims to maximize the acquisition of high-priority targets and high-quality data while satisfying constraints such as limited resources, storage capacity, energy limits, and weather conditions. The algorithm provided a list of targets for EOS to capture, identified overlaps of targets from multiple satellites, and recommended the appropriate satellite to capture the targets. Furthermore, the algorithm effectively captured the issue of targets orthogonal to the satellite motion, ensuring that more than one of these targets can be captured efficiently.

Our study involved a comparison of our quantum algorithm's performance with two classical optimization algorithms, simulated annealing and Gurobi optimizer. The results showed that our algorithm surpassed both of these algorithms in terms of selecting high-priority targets while satisfying all constraints. Moreover, our algorithm was also faster than the Gurobi optimizer and managed to satisfy all constraints for 100% of the data, even when the data size was increased.

Future works include demonstrating the results of the study and showing the potential of quantum computing in improving the efficiency and accuracy of EOS mission planning. Further research can be conducted to explore the application of our quantum algorithm to other problems and to incorporate additional constraints and objectives into the algorithm. In addition, it would be interesting to investigate the feasibility of implementing the algorithm in a real-world EOS mission scenario and to evaluate the performance of the algorithm under different weather and environmental conditions. Finally, the potential of using hybrid classical-quantum algorithms for EOS mission planning should be explored, as this may provide further improvements in performance and efficiency.

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