# Agile Earth Observation Satellite Scheduling with a Quantum Annealer Presentation at COMET SIL

#### **DEFENCE AND SPACE**

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# □ Context

- □ Trends for agile Earth Observation satellite scheduling
- Promises of quantum computing based optimization
- □ EO satellite scheduling with a Quantum Annealer
- Benchmarking methodology and results
- Conclusion and perspectives



## Trends for Earth Observation Mission Planning

#### Trends Very High Resolution Agile EO Satellites

- Constellation of satellites: from 2-4 to 10s to 100s of platforms
- Smaller instrument footprint  $\rightarrow$  larger volume of candidate meshes (i.e. surface elements) to plan per programming period
- Enhanced agility: multiplication of acquisition opportunities and planning solutions
- Multi-Objective optimization: priority satisfaction, capacity (surface) maximization, age of information, weather conditions...



#### **Bottom line**

- EO Mission Planning is a well-known multi-objective NP-hard optimization problem under uncertainty
- Current trends indicate a combinatorial explosion (# decision variables, # constraints) for future Earth Observation systems

#### **Expectations**

- Current Mission Planning solutions are based on (sub-optimal) heuristic algorithms (greedy or dynamic programming)
- > Experiments on smaller instances of the problem have shown gains ranging from 10% to 20% between the optimum and the solution obtained by current approximate algorithms



Airbus Amber

# Simulation of Pleiades Neo Mission

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## **EO Mission Planning Problem Statement**

Mission Planning: Must determine an optimal acquisition plan for an Earth Observation satellite

#### Input data

> R is the set of acquisition requests,  $I_r$  is the set of imaging attempts for request  $r \in R$ .

 $\triangleright \forall r \in R, \forall i \in I_r, w_{r,i}$  is the score of the imaging attempt

 $\triangleright \forall r \in R, \forall i \in I_r, t_i^r$  is the start time of the imaging attempt

#### **Decision variable**

- $> x_{r,i}$  is the binary variable indicating whether the candidate attempt i is selected in the plan
  - The number of binary variables is  $N_{\text{variable}} = \sum_r |I_r|$

#### **Constraints**

> Maximally one assigned attempt i per request r:  $\forall r \in R, \sum_{i \in I_r} x_{r,i} \leq 1$ 

> Some consecutive imagining attempts are not possible:

- $F_{r_1,r_2} = \{(i,j) \in (I_{r_1}, I_{r_2}) | t_i^{r_1} \le t_j^{r_2} \&\& t_j^{r_2} < t_i^{r_1} + T_i^{r_1,acquisition} + T_{i \to j}^{r_1,r_2 maneuver} \}$
- $\forall (r_1, r_2) \in \mathbb{R}^2$ , with  $r_1 \neq r_2$ ,  $\forall (i, j) \in F_{r_1, r_2}$ :  $x_{r_1, i}$ .  $x_{r_2, j} = 0$

Objective: Total score of the schedule

> Minimize  $C = -\sum_r \sum_{i \in I_r} w_{r,i} x_{r,i}$ 



## Quantum Computing in a Nutshell

#### **Superposition Principle**

• A qubit can be seen as a superposition of two basis vectors

 $|\psi\rangle = \alpha |0\rangle + \beta |1\rangle$ 

 A n-qubit register represents a 2<sup>n</sup>-dimensional vector space, allowing for exponentially greater information processing

### **Classical vs Quantum Computing**





### Quantum Computing in a Nutshell

### Quantum Annealing Computer (D-Wave)

- Not a general purpose quantum computer, but uses quantum properties to solve discrete optimization problems
- Natural evolution of quantum-mechanical system (using quantum tunnelling) towards a ground state minimizing its energy



### General Purpose Quantum Computer (IBM, Google)

- Quantum circuits are composed of elementary gates and operate on qubits
- QC equivalent to classical boolean feed-forward networks, except they are reversible (i.e. quantum circuits can be evaluated in both directions)



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## Quantum Annealer in a Nutshell

### **Quantum Computing for Combinatorial Optimization**

### **Quantum Annealing**

- Solves Quadratic Unconstrained Binary Optimization (QUBO) problems i.e. minimmize  $H(\{x_i\}) = \sum_i Q_{ii}x_i + \sum_{i < j} Q_{ij}x_ix_j$ , where  $x \in \{0, 1\}^N$
- Requires to formulate your discrete optimization problem as a QUBO
- QA can be seen as a stochastic process: several annealing runs are performed from a given initial state (e.g. uniformly distributed quantum superposition of all possible states)
- After a fixed elapsed time, the final state is measured providing a solution sample
- After a fixed number of runs, the solution sample having minimum energy is kept
- QA remains an approximate optimization technique, but the number of runs can be increased to reach a given probability of finding the exact solution





# EO Mission Planning Problem as a QUBO

### Quadratic Unconstrained Binary Optimization (QUBO) formulation

- > QUBO: min  $q(x) = x^T Q x = \sum_{j=1}^n Q_{j,j} x_j + \sum_{j,k=1}^n Q_{j,k} x_j x_k$  with Q an upper-triangular quadratic matrix
- > Constraint equations in a quadratic form:
  - (1) : Max one imaging attempt per request :  $C_u = \sum_r \sum_{i,j \in I_r, i < j} \min\{w_{r,i}, w_{r,j}\} x_{r,i} x_{r,j}$
  - (2) : Non feasible maneuver  $C_t = \sum_{r_1, r_2} \sum_{i, j \in F_{r_1, r_2}} \min\{w_{r_1, i}, w_{r_2, j}\} x_{r_1, i} x_{r_2, j}$
- > Constraints are taken into account in the QUBO formulation to minimize
  - $q = C + \lambda_u C_u + \lambda_t C_t$
  - With :
    - ♦  $C = -\sum_{r} \sum_{i \in I_r} w_{r,i} x_{r,i}$  is the objective function in the original problem
    - \*  $\lambda_u$ ,  $\lambda_t$  are penalty weights
- Choice of the penalty weights
  - Sufficiently large enough such that  $\hat{x} = \arg \min_{x} q(x)$  verifies our constraints, i.e.  $C_u(\hat{x}) = 0$  and  $C_t(\hat{x}) = 0$
  - We can demonstrate that any choice of penalty weight values such that both  $\lambda_u > 1$  and  $\lambda_t > 1$  gives valid solutions



## Mapping a logical QUBO into a physical QUBO

#### Embedding

Due to D-Wave architecture (chimera graph), a physical qubit is not connected to every other qubit

Embedding is the process of linking physical qubits together to virtually enhance connectivity

In our case, problem instances need to stay below
80 logical qubits to be embeddable on the D-Wave machine

#### **Weight Distribution**

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- > Couple physical qubits to chain
- > Find chain coupling  $J_C$

 $\succ$  Distribute weight  $h_j$ 

- Classical Approach:
  - Choose J<sub>c</sub> according to maximum coupling
  - Split weight equally  $h_{j,i} \rightarrow \frac{h_j}{n}$
- Advanced Approaches:
  - $\succ$  Find minimal  $J_c$  without breaking chain
  - Map to problem of graph expansion

$$C = \sum_{i} h_{i}s_{i} + \sum_{ij} J_{ij}s_{i}s_{j} \xrightarrow{\text{Embedding}} C' = \sum_{a} h'_{a}s'_{a} + \sum_{ab} J'_{ab}s'_{a}s'_{b}$$

 $x_i \rightarrow \frac{s_i + 1}{2}$ 



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# **Mission Planning Simulation**

### Mission Planning problem instances

- Generated thanks to Airbus DS Mission Simulator (TEAM)
- Reduced instances with a small number of requests and a coarse access discretization compared to real operations
- Different scenarios are considered to generate multiple instances, enabling sensitive analysis and statistics on average performance
- Main parameters
  - Number of acquisition requests
  - Access discretization step
  - Latitude range for Area of Interest
- → Drives the number of decision variables
- → Drives the "NP-hardness" of the planning problem





Nb of requests = **11** Discretization step = **12s** Latitude range = **10°** 



Nb of requests = **12** Discretization step = **16s** Latitude range = **1°** 





### **Evaluation on Classical Hardware**

#### Two classical algorithm have been considered

- An exact MIP solver with two variants
  - pairwise exact solver: based on ILP where constraints correspond to pairs of conflicting attempts
  - clique exact solver: based on ILP where constraints are reformulated through the enumeration of all maximal cliques
- A greedy algorithm (similar to operational software), showing a linear runtime (at least for small instances)



**Exact solver** 

**Greedy algorithm** 





## Evaluation on D-Wave 2000Q Quantum Annealer

### Performance Assessment methodology

- > A number of annealing runs is configured
- > A success probability is derived:  $p = \frac{\# exact \ solutions}{\# \ annealing \ runs}$  (probability to yield an optimal solution)
- Assuming independence between runs, a time-to-solution with 99% chance of optimality can be expressed

as 
$$T_{99} = \frac{\ln(1-0,99)}{\ln(1-p)} T_{Annealing}$$

#### **D-Wave Configuration**

- Number of annealing runs (10000)
- > Annealing time (20  $\mu s$ )
- $\blacktriangleright$  Choice of intra-logical qubit coupling  $J_F$
- Embeddings: using all 5 D-Wave heuristic embeddings
- Unembedding strategy: majority vote





### Benchmark 1: Classical vs Quantum Time to Exact Solution

### Time to Exact Solution Benchmark

- Run time is averaged over all problem instances having the same number of binary variables
- Execution time for the pair-wise exact solver increases exponentially with the number of binary variables
- Quantum annealing results (worst-case treatment, i.e. classical weighting approach) shows a similar slope and a constant offset of about one order of magnitude.
- By optimizing the coupling chain strength (optimizedvalue), quantum annealing performs much better
- Clique exact solver performs better than all other methods for larger instances



Time to exact solution benchmark



### Benchmark 2: Classical vs Quantum Quality of Solution

### Quality of Solution Benchmark

- A fixed time budget is allocated to the solver (.i.e a fixed number of runs for the quantum annealer)
- The approximation ratio corresponds to the objective value of the best found solution divided by the optimal objective value
- The greedy heuristic outperforms the quantum annealer for similar execution times
- Only for larger execution times, the quantum annealer yields better results than the greedy heuristic for smaller instances



**Quality of solution benchmark** 



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# **Conclusion and Perspectives**

arXiv paper: https://arxiv.org/abs/2006.09724

### **Technical achievements**

- Classical vs Quantum benchmarks for a broad range of (small) satellite mission planning problems
- Limited qubit connectivity, **precision issues** and coherence time remain a major bottleneck for the D-Wave 2000Q processor.
- Although **no quantum speedup** was observed, the run-time performance on D-Wave Q Annealer (at its current scale) is very promising

### Perspectives

- Extra research will be required to make a better use of Q technology (embedding techniques and mitigation of precision/errors for QA)
- To draw further conclusions, we need the Q technology (HW and SW) to increase in maturity, which will happen in a short timeframe
  - D-Wave Pegasus showcasing 5000 qubits and 16-connectivity
  - QAOA on Google Sycamore and IBM Q 53-qubit machines ۰







AIRBUS



