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EQUALITY

Efficient QUantum ALgorithms for IndusTrY

WP5: PoC trials/ aerodynamics and space

D5.1 Problem Specification Sheets (Aerospace)

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Document description	This deliverable will define clearly articulated problem statements for each of the four trials (Aerodynamics simulations. Space mission optimisation. Space data analysis and processing. Multidisciplinary design optimisation) including detailed descriptions of the problem scenario, the chosen methods, its implications, and its impact on the different stakeholders.

[1]R: Document, report (excluding the periodic and final reports); DEM: Demonstrator, pilot, prototype, plan designs; DEC: Websites, patents filing, press & media actions, videos, etc.; DATA: Data sets, microdata, etc.; DMP: Data management plan; ETHICS: Deliverables related to ethics issues.; SECURITY: Deliverables related to security issues; OTHER: Software, technical diagram, algorithms, models, etc.

[2]PU – Public, fully open, e.g., web (Deliverables flagged as public will be automatically published in CORDIS project's page); SEN – Sensitive, limited under the conditions of the Grant Agreement; Classified R-UE/EU-R – EU RESTRICTED under the Commission Decision No2015/444; Classified C-UE/EU-C – EU CONFIDENTIAL under the Commission Decision No2015/444; Classified S-UE/EU-S – EU SECRET under the Commission Decision No2015/444

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Abstract

A quantum revolution is unfolding, and European scientists are on the lead. Now, it is time to take decisive action and transform our scientific potential into a competitive advantage. Achieving this goal will be critical to ensuring Europe's technological sovereignty in the coming decades.

EQUALITY brings together scientists, innovators, and prominent industrial players with the mission of developing cutting-edge quantum algorithms to solve strategic industrial problems. The consortium will develop a set of algorithmic primitives which could be used as modules for various industry-specific workflows. These primitives include differential equation solvers, material simulation algorithms, quantum optimisers, etc.

To focus our efforts, we target eight paradigmatic industrial problems. These problems are likely to yield to early quantum advantage and pertain to the aerospace and energy storage industries. They include airfoil aerodynamics, battery and fuel cell design, space mission optimisation, etc. Our goal is to develop quantum algorithms for real industrial problems using real quantum hardware. This requires grappling with the limitations of present-day quantum hardware. Thus, we will devote a large portion of our efforts to developing strategies for optimal hardware exploitation. These low-level implementations will account for the effects of noise and topology and will optimise algorithms to run on limited hardware.

EQUALITY will build synergies with Quantum Flagship projects and Europe's thriving ecosystem of quantum start-ups. Use cases will be tested on quantum hardware from three of Europe's leading vendors and two HPC centres. The applications targeted have the potential of creating billions of euros for end-users and technology providers over the coming decades. With EQUALITY, we aim at playing a role in unlocking this value and placing Europe at the centre of this development. The project gathers 9 partners and has a budget of €6M over 3 years.

Consortium

The EQUALITY consortium members are listed below.

Legal Name on Grant Agreement	Short name	Country
CAPGEMINI DEUTSCHLAND GMBH	CAP	DE
QU & CO AI BV	QC	FR
AIRBUS OPERATIONS GMBH	AOG	DE
DEUTSCHES ZENTRUM FUR LUFT - UND RAUMFAHRT EV (DLR)	DLR	DE
FRAUNHOFER GESELLSCHAFT ZUR FORDERUNG DER ANGEWANDTEN FORSCHUNG EV (FHG)	ENAS	DE
INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET AUTOMATIQUE (INRIA)	INRIA	FR
UNIVERSITEIT LEIDEN (ULEI)	ULEI	NL
DA VINCI LABS	DVL	FR

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Disclaimer

Acknowledgement

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List of abbreviations

1D, 2D	One-Dimensional, Two-Dimensional
AI	Artificial Intelligence
CFD	Computational Fluid Dynamics
DFT	Differentiable Fourier Transform
DQC	Differentiable Quantum Circuit
FEM	Finite Element Method
HPC	High-performance Computers / Computing
ML	Machine Learning
PDE	Partial Differential Equations
PINN	Physics-Informed Neural Network
QAOA	Quantum Approximate Optimization Algorithm
QC	Quantum Computing
QML	Quantum Machine Learning
QUBO	Quantum Unconstrained Binary Optimisation
RAM	Random-access Memory
SAR	Synthetic Aperture Radar
TSP	Traveling Salesman Problem
USD	United State Dollars
VQE	Variational Quantum Eigensolver
WP	Work Package

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EXECUTIVE SUMMARY

This document is a deliverable of the EQUALITY project, funded under grant agreement number 101080142. This deliverable, D5.1 Problem specification sheets (aerospace), is part of work package WP5.

Quantum technologies were identified early on by Airbus as a central building block for the future of aerospace. Quantum computing is one of the three central pillars of Airbus' quantum strategy, along with quantum communication and quantum sensors. Airbus believes that this topic will have a profound impact on the future of aerospace. Traditional aerospace tasks like structural modelling and CFD are still dominating our HPC clusters. To enable the necessary computational power, Airbus operating our own very powerful HPC systems. And we are conscious that those classical computing systems will approach their limit in the future, so we are investigating different solutions to extend our HPC toolset, including also Quantum computing. Quantum Computing is part of our HPC Ambition.

Airbus has promoted quantum computing in the global ecosystem through various actions: One example is the "Airbus Quantum Computing Challenge", in which five use cases from flight physics were brought into the quantum computing community. Airbus sees itself as an end user for quantum computing. Within this framework, Airbus focuses its activities on use cases most relevant to aerospace. These are divided into four application groups that can be processed with related algorithmic families.

- Quantum Simulation
- Quantum Optimization
- Quantum Machine Learning
- Quantum Solvers

Based on the different application Cluster we work with the different teams cross all Airbus Divisions to identify most relevant and applicable use cases with potentially would fit best with the EQUALITY consortium.

1. Quantum Simulation:
   We decided for the simulation of "Solid oxide fuel cell optimization" which is integrated in the WP4 Energy Use Cases and will have a potential large impact on future Aerospace Industry.
2. Quantum Optimization:
   We decided for "Mission optimization for space", which offers direct business opportunities for industrialization. Airbus work already in past on basics for this use case with other partners
3. Quantum Machine Learning:
   We decided for "Space data analysis and processing", a case on image recognition training, where classical methods are at their limits and faster / better processing is required
4. Quantum Solvers:
   We decided for "Aerodynamics simulations" which is the most challenging and time-consuming task at our HPC systems. This case has a Sub-Sonic and a Super-Sonic case.

All decisions have been taken together with our partners in the EQUALITY consortium, specified and discussed in detail.

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1. Quantum in Aerospace

Quantum technologies were identified early on by Airbus as a central building block for the future of aerospace. Quantum computing is one of the three central pillars of Airbus' quantum strategy, along with quantum communication and quantum sensors. Although the technological development of quantum computing is still very early, Airbus believes that this topic will have a profound impact on the future of aerospace (see Figure 1).

Figure 1: Quantum Technologies; Aerospace Enabler

- Quantum Communication: Is currently experiencing a business pull for it is interesting as Airbus can develop the aerospace parts of quantum communication infrastructure but also look at ways how to enable secure connectivity on our products
- Quantum Sensing: One key application is to deploy high-precision sensors in our platforms to improve navigation capabilities, but there is more than that - for example we are currently developing a space quantum sensor for quantum gravimetric measurements
- The focus will be on Quantum Computing: To understand why we are interested in quantum computing, why it is important and our typical problems

1.1. Quantum Computing

Traditional aerospace tasks like structural modeling and CFD are still dominating our HPC clusters. Aerospace has shifted to one of the most data-rich and data-dependent industries in the world. On average an airplane carries up to 250.000 sensors, generating vast amounts of data points to be analyzed. The value of this information is significant, for instance for predictive maintenance or autonomous flight. To enable the necessary computational power, Airbus operates its own very powerful HPC systems. However, everyone is conscious that those classical computing systems will approach their limit in the future, so Airbus is investigating different solutions to extend its HPC toolset, including Quantum computing. Quantum computing is part of the Airbus HPC Ambition (see Figure 2).

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Figure 2: Quantum Computing: HPC as Key Business Tool

Airbus has promoted quantum computing in the global ecosystem through various actions: One example is the "Airbus Quantum Computing Challenge" (see Figure 3), in which five use cases from flight physics were brought into the quantum computing community as a competition with extremely high resonance (> 800 registrations from more than 70 countries).

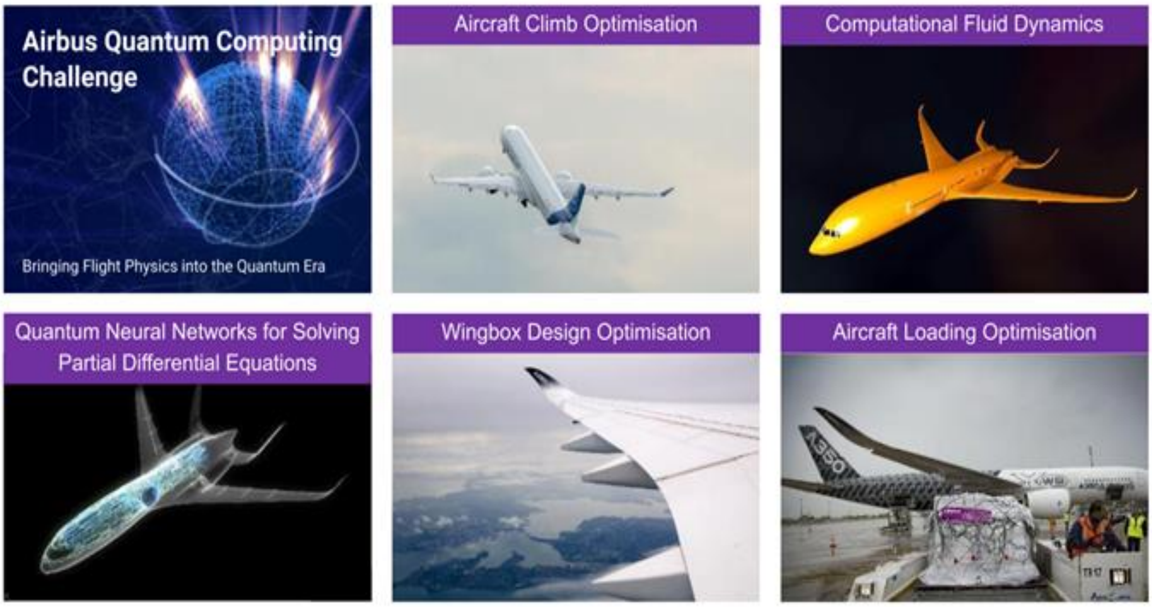

Figure 3: Overview Airbus Quantum Computing Challenge was launched in 2019. 5 different flight physics problems with different levels of complexity were presented to the quantum computing community.

Airbus sees itself as an end user for quantum computing (Figure 4). Within this framework, Airbus focuses its activities on use cases most relevant to aerospace. These are divided into four application groups that can be processed with related algorithmic families.

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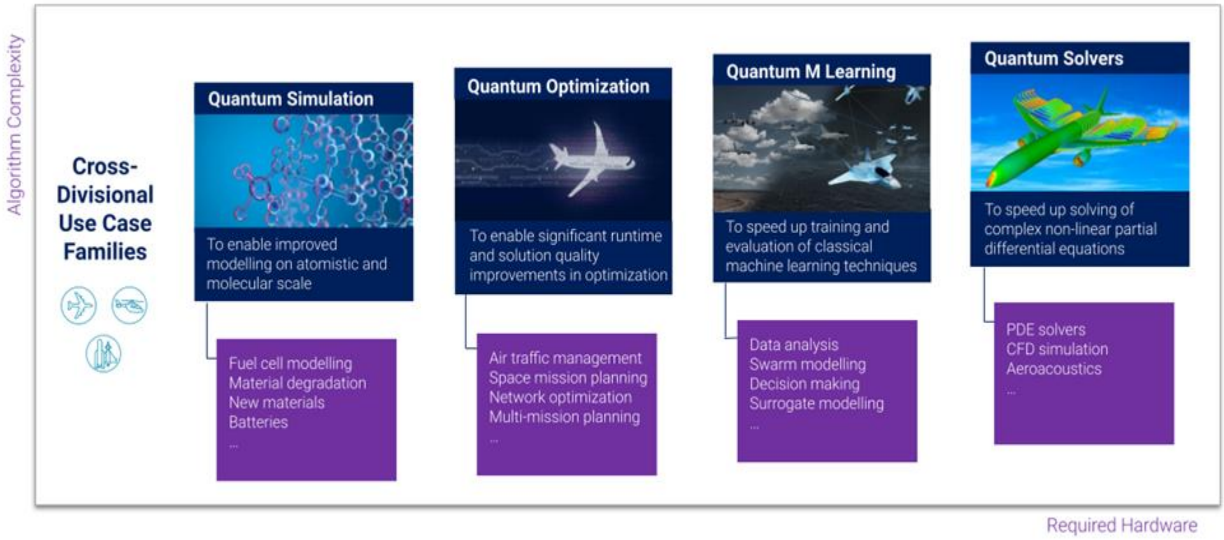

Figure 4: Representation of the application clusters used by Airbus in the field of quantum computing.

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2. Applied Methodology

Based on the different application Clusters, we work with different teams across all Airbus Divisions to identify the most relevant and applicable use cases, which would potentially fit the best with the EQUALITY consortium. For most of the envisioned use-cases, we decided inside of airbus to focus on one specific application, however, on the solver side we decided to go for a CFD approach, which would allow us to integrate the potential of a Sub-sonic and a Super-sonic use cases within the same project, which would naturally involve different teams in different Airbus Divisions.

2.1. Quantum Simulation

The focus here is on microscopic modeling, with applications ranging from energy systems to the modeling of material properties such as corrosion. Among other things, Airbus is working on the modeling of fuel cells: The oxygen reduction reaction at the cathode of the fuel cell is being investigated for various alloys (see Figure 5). For this purpose, a hybrid-classic-quantum-gate-based approach based on VQE is optimized and used for different material compositions. The aim is to be able to determine and parametrically model the responsiveness of the (strongly correlated) system more precisely than classic DFT methods. In the medium term, the performance of the energy system can be improved through design and the service life can be predicted more precisely.

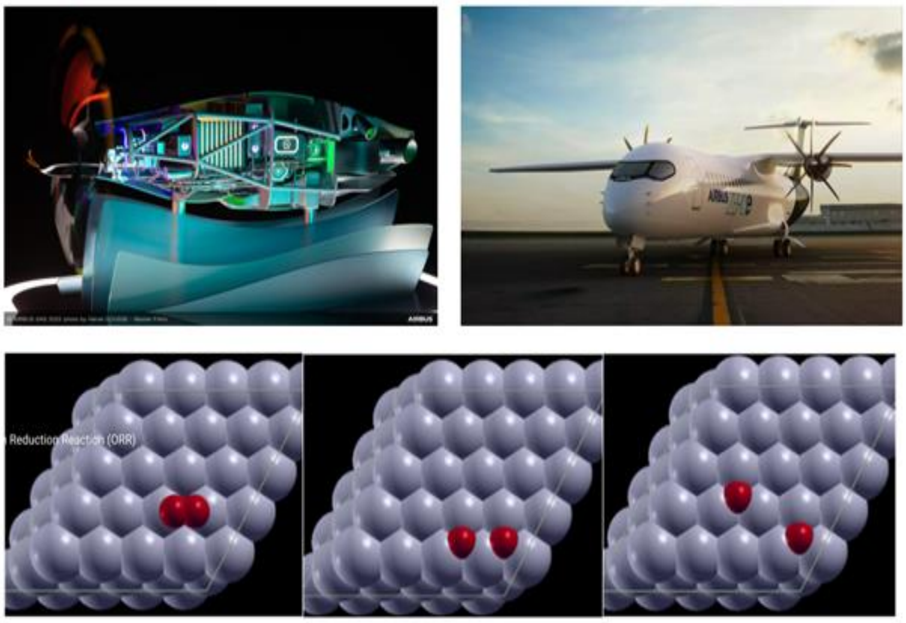

Figure 5: Airbus fuel cell propulsion and prototype for the ZeroE program. For Airbus, the oxygen reduction reaction at the cathode is of central importance.

2.2. Quantum-Optimization & Quantum Machine Learning

Airbus has been investigating various optimization applications with quantum computers over the years: One example is mission planning for satellites in optical earth observation (see Figure 6) - a business area in which Airbus operates its own fleet of satellites (Pleiades Neo). The aim is to optimize the recording sequences, which represent an np-hard problem due to boundary conditions such as orbital parameters, limitations of the payload during image recording, as well as limited storage and download options and can only be solved heuristically with today's methods. In cooperation with DLR Cologne, Airbus has researched a quantum

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annealing approach based on a D-Wave 2000 and has just been able to demonstrate a computing time for a reduced problem that is comparable to classic solutions.

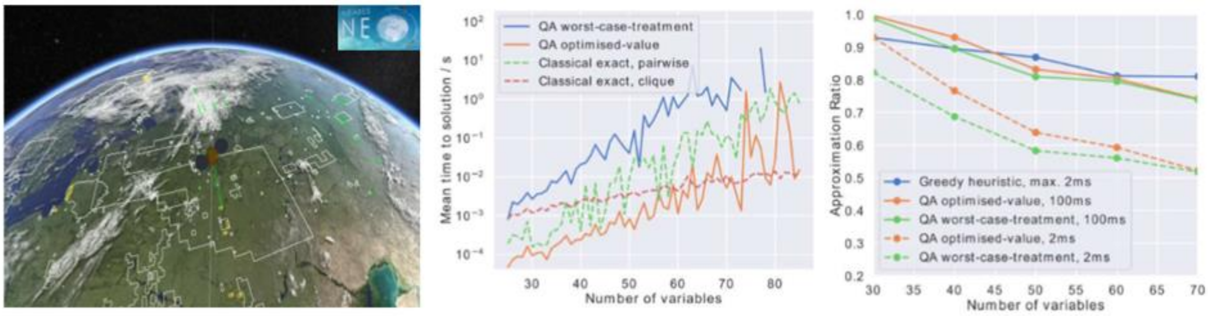

Figure 6: Representation of the complexity of the recording sequence of optical earth observation systems. Shown are time-to-solution and quality-to-solution compared between a classic and a quantum annealing approach.

In the medium term, Airbus sees gate-based solutions in particular as future-oriented for quantum optimization. In the summer of 2022, Airbus started a partnership with IonQ and is developing algorithms based on the QAOA method combined with the use of artificial intelligence. The algorithm is optimized for four combinatorial applications: TSP, MaxCut, Knapsack, MaxIndSet. The algorithms are tested on ion trap-based systems, so that complex quantum error correction is not necessary. Figure 7 shows the elaboration for the use case of loading an aircraft and the corresponding solution with a quantum computer.

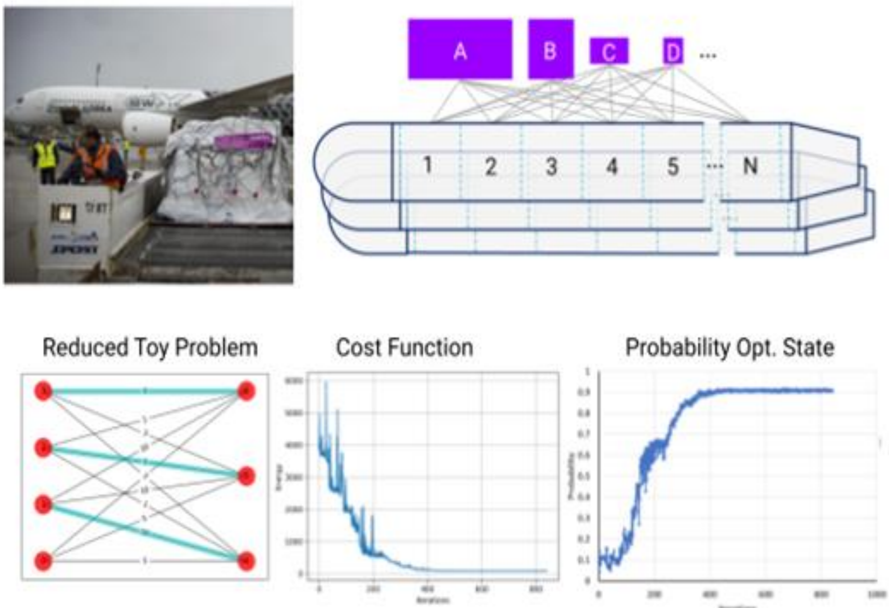

Figure 7: Quantum ML use case: loading an airplane (extended knapsack problem). The solution of a quantum computer is shown, whereby the center of mass and the shearing forces have to be optimized in addition to the loading.

The area of quantum machine learning is also being investigated at Airbus. The focus here is on being able to train systems better through the expressiveness of quantum machine learning. In the future, this could be of particular importance for the topic of trustworthy AI and the certification of AI systems.

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2.3. Quantum Solver

Computing power is required in the aerospace industry above all to solve complex nonlinear differential equation systems. Airbus operates its own high-performance clusters, which are primarily used for CFD applications. Airbus is also investigating approaches in the field of quantum computing that are based on both digital and analog quantum algorithms.

2.4. Quantum Computing and High-Performance Computing Integration

Airbus maintains a dedicated division for Scientific Computing Services. These include, among other things:

- Platform Provision of HPC supercomputers for engineering HPC workloads
- Scientific Computing Services on the HPC infrastructure
  - Application lifecycle management of HPC compute software such as CFD or FEM solvers
  - Design & configuration of a complex, interacting mulcluster middleware environment for the orchestration of HPC compute resources
  - Advice/consulting on the integration of new HPC compute applications and optimization of the use of HPC resources
  - Development, design & configuration of transparent hybrid (on-prem / cloud) HPC environments
  - Design & exploration of future requirements for HPC platforms & services for Airbus
  - Scalable data analysis pipelines
  - Design & exploration of AI relevant platforms & services (e.g. integration of AI & HPC Orchestration, MLOps, etc.)
  - Operation of non-HPC/low-tier HPC software integrations & compute platforms

End-users of HPC Services are:

- End users of applications for scientific computing in productive use (aircraft functional design, calculations relevant to certification; Figure 8)
- Developers of applications for scientific computing for future productive use (mentioned as an example, not an exhaustive list):
  - CFD solvers like CODA: the next generation flow solver (DLR, Onera, Airbus consortium)
  - Applications & toolsets in the field of structural mechanics
  - Applications & toolsets in the field of aircraft power plant
- Data Analysts for simulation data analysis

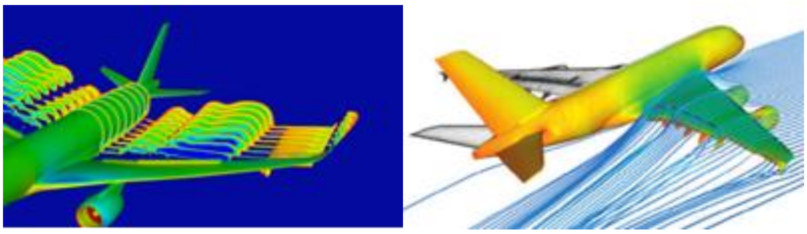

Figure 8: Visualization of Aerodynamics Simulation

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3. USE-CASE SPECIFICATIONS

3.1. Aerodynamics simulations

3.1.1. Problem scenario description

The design of an aircraft is a long, complex and expensive process as it can take up to 15 years, more than 10 billion USD and involves many human resources in the loop. To speed up the overall design process, the aircraft industry relies on an approach which considers a unique deliverable that integrates products, processes and resources. This digital thread approach can be conceptualised as a single integrated framework that allows collaborative and modular design relying on a fully connected digital toolchain. The approach has been developed to tackle two main issues that make the design process time-consuming and expensive, which are: (i) the communication and exchange between the large number of engineering teams working within specific and limited frames, and (ii) to decrease and control the cost of the additional iterations due to a minor initial modification in a single discipline that grows up to significant changes in other areas, as all these disciplines are tightly coupled [1] [2].

Computational Fluid Dynamics (CFD) is one of these disciplines. CFD software allows for the numerical resolution of the complex flow physics, governed by the Navier-Stokes equations so that the forces acting on the aircraft surfaces - including wings, fuselages, engines, landing gears and many others - can be accurately and reliably obtained (see Figure 9). Over the last decades, CFD has benefited from both the rapid growth of computing capacity and the advances in numerical methods, making it possible to use CFD simulations systematically during the aircraft design process. Therefore, CFD has become an essential enabler of the aircraft design process in the industry.

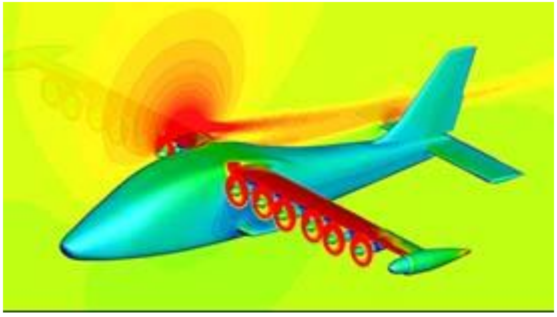

Figure 9: A CFD simulation of the X-57 Maxwell aircraft concept (source: NASA).

At the present time, the ambition of lowering aircraft emissions or even decarbonising air transport has become the key driver for the next generation of aircraft, triggering the study of innovative and disruptive concepts. In this scenario, it is expected that large campaigns of costly CFD simulations will be necessary to evaluate the complex aerodynamic phenomena that such aircraft concepts will trigger to determine their adequacy about the strict sustainability ambitions of the industry and society.

In the past, the increasing demand for numerical simulations could be satisfied by the exponential growth in computational power forecasted by Moore's law more than 70 years ago (see Figure 10). Nevertheless, this trend has become obsolete in recent decades, leading to a new scenario that puts at stake the systematic use of CFD software for the design of the future generation of aircraft - at least as we use them today. In the post-Moore scenario, it becomes necessary to consider a paradigm shift to ensure the viability of large CFD simulation campaigns in this context.

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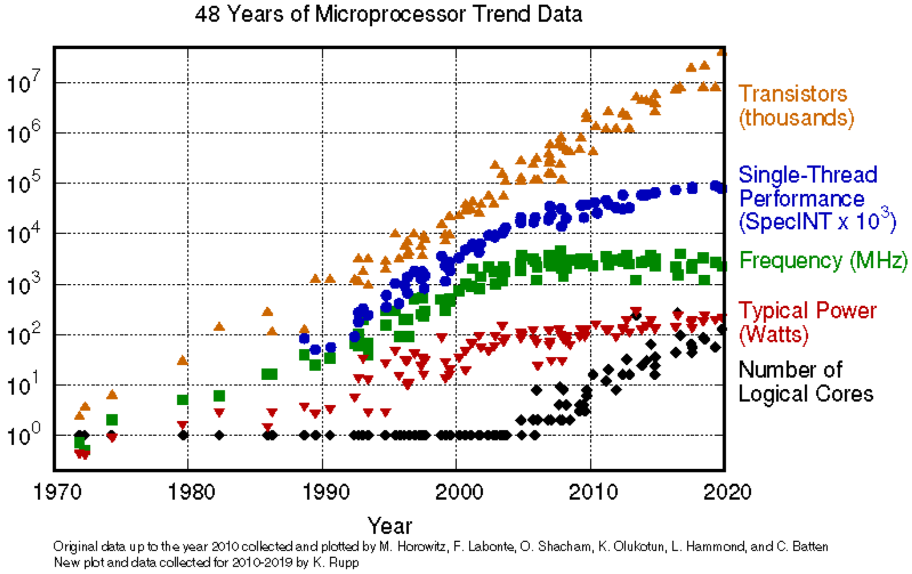

Figure 10: The evolution of computational power over the last decades.

A promising solution is the use of quantum algorithms along with their associated hardware to conduct CFD simulations. Over the past years, the research community has investigated the use of quantum algorithms for solving complex Partial Differential Equations (PDEs) - including simplified cases of the Navier-Stokes equations - highlighting the potential benefits emerging from the inherent supremacy of quantum computing [3]. The goal of this use case is to develop such approaches further, and to demonstrate them to flow configurations that can be of interest to the aerospace industry. The focus will be on understanding how both the time to solution and the number of computational resources associated with a particular problem scale when the latter's complexity is increased.

3.1.2. The chosen methods

Computationally solving the Navier-Stokes equations can be achieved with many techniques, with the finite volume method being one of the most common ones. This method consists in dividing the computational simulation domain into small control volumes in which conservation of mass, momentum and energy is enforced, as stated by the Navier-Stokes equations [4] [5]:

$$\frac{\partial}{\partial t}\rho + \nabla \cdot (\rho u) = 0$$

$$\frac{\partial}{\partial}(\rho u) + \nabla(\rho u\, u^t) \; = \; -\nabla p + \nabla \cdot \overline{\overline{\tau}} + \rho g$$

$$\frac{\partial}{\partial}(\rho E) + \nabla(\rho u\, E) \; = \; -\nabla \cdot \left(pu \; + \; \overline{\overline{\tau}} \cdot u + k\nabla T\right) + \rho g u + Q$$

where ρ stands for the density, $u = (u, v, w)$ is the vector of velocity, p is the pressure, $\overline{\overline{\tau}}$ is the viscous stress tensor, g is the gravity acceleration, E is the stagnation energy, T is the temperature, k is the heat conductivity constant and Q stands for any heat source.

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Despite its success in reproducing highly complex flow features in the presence of arbitrary body geometries such as aircraft surfaces, the finite volume method - alike any other classical method - explicitly requires the definition of a computational mesh, which brings two significant drawbacks:

- Much human time must be devoted to a correct mesh definition to ensure a robust and accurate CFD simulation.
- The control volume size must be substantially decreased when a higher degree of accuracy is required from the CFD simulation prediction, leading to an increase in the number of unknowns to be determined and, ultimately, to an increase in time to solution (see Figure 11).

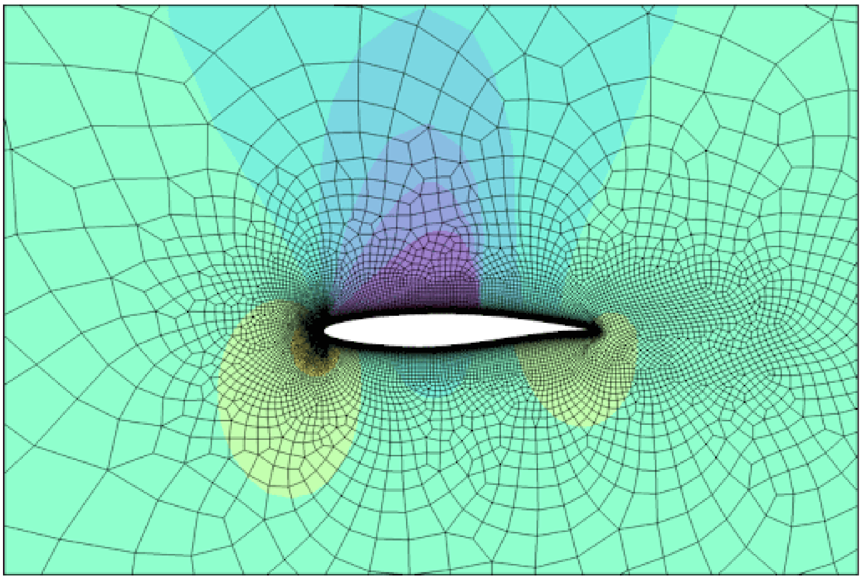

Figure 11: Unstructured computational grid of the RAE2822 airfoil. Courtesy of Airbus.

In recent years, new approaches to PDE-based problems, such Physics-Informed Neural Networks (PINNs), have emerged as an Artificial Intelligence (AI)-based counterpart of the classical methods [6] [7] [8], therefore, potentially better scalability of the associated simulations when higher degrees of accuracy are sought.

Similarly, quantum-based algorithms have recently been developed to tackle nonlinear PDEs. In particular, the so-called Differentiable Quantum Circuit (DQC) is one of the most promising techniques to address the simulation of the Navier-Stokes equations since [3] :

i. It has already been demonstrated for their inviscid, one-dimensional formulation known as the 1D-Euler flow equation and
ii. It supports implementation on near-term noisy quantum devices. In a nutshell, the DQC relies on an automatically differentiated implementation of a parameterised quantum circuit, whose parameters are updated using a classical optimiser so that a loss function representing the PDE is enforced.

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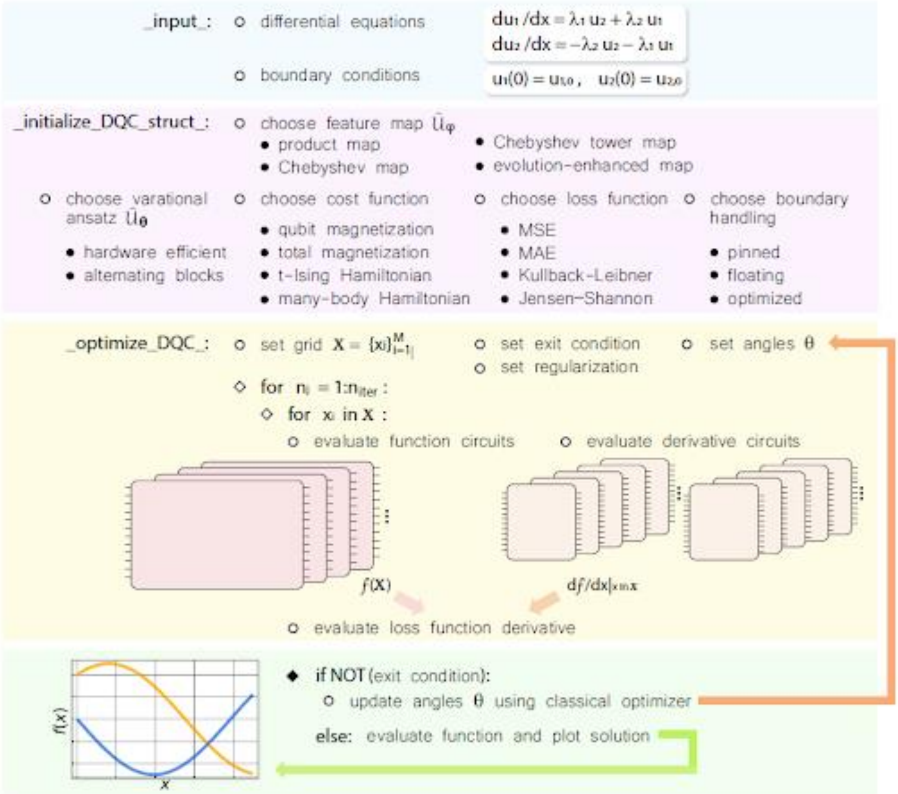

Figure 12: An overview of the DQC algorithm [3]

In this framework, the current use case proposes to extend the DQC approach (see Figure 12) to multi-dimensional problems - in space and time - involving the complete formulation of the Navier-Stokes equations, in particular including terms which require the resolution of higher-order partial derivatives of the flow variables. As such, the use case features a significant challenge, therefore it is teared down into two steps of growing complexity, each described hereafter.

Burgers equation

The first step will focus on the resolution of the so-called Burgers equation, a well-known PDE occurring in many fields of science and engineering. Although this equation can be easily solved with simple classical algorithms at a low computational cost, it features the fundamental physical mechanisms of convection and diffusion that drive the dynamics of fluid flows. Therefore, the Burgers equation provides an excellent testbed to develop and validate any numerical simulation method to be used for CFD. In its more general form, the Burgers equation reads [9]:

$$\frac{\partial u}{\partial t} + u \cdot \nabla u = \nu \nabla^2 u$$

where u stands for the unknown to be solver - which can be either a scalar or a vector field – and ν stands for a diffusion coefficient modelling the effect of viscosity.

It is first proposed to solve the time-accurate evolution of u when no diffusion is added, i.e., $\nu = 0$. In such conditions, the resulting equation

$$\frac{\partial u}{\partial t} + u \cdot \nabla u = 0$$

It is known as the inviscid Burgers equation (see Figure 13), with its immediate extrapolation to higher dimensions in space. This quasi-linear hyperbolic equation can be understood as a general conservation law of the quantity $\frac{1}{2}u^2$. As such, the equation will feature two interesting properties that must be captured by any numerical resolution method: (i) the presence of discontinuities known as shock waves, which are a well-known phenomenon happening in transonic fluid flows, (ii) the conservation of the quantity $\frac{1}{2}u^2$. Since any deviation from the quantity at $t = 0$ is purely introduced by the numerical method itself, the evaluation of the conservativeness constitutes a direct quantification of the dissipation that is artificially introduced by the numerical algorithm.

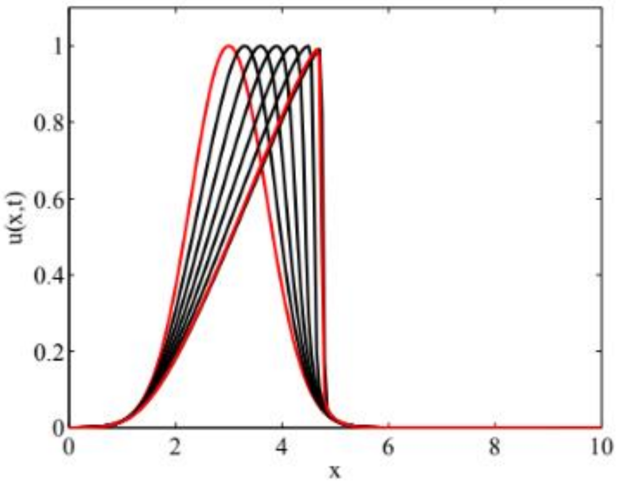

Figure 13: Solution of the inviscid Burgers equation after few time steps [10]..

As a second step towards achieving this sub-use case, it is proposed to address the complete form of the Burgers equation, i.e., including the viscous terms. In this equation, the convection and diffusion mechanism appearing in the left- and right-hand side of the equation, respectively, compete to determine the time-accurate evolution of the problem unknown and, therefore, must be captured accurately.

2D Euler equations applied to a wing airfoil

The Euler equations are a simplified form of the Navier-Stokes equation where the viscosity evaluates to zero, making term $\nabla \cdot \bar{\bar{\tau}}$ to disappear. In 2D these equations read (heat sources and gravitational effects are also dropped out):

$$\frac{\partial}{\partial t}\rho + \nabla \cdot (\rho u) = 0$$

$$\frac{\partial}{\partial t}(\rho u) + \nabla \cdot (\rho u \, u^t) = -\nabla p$$

$$\frac{\partial}{\partial t}(\rho E) + \nabla \cdot (\rho u \, E) = -\nabla \cdot (p u \, + \, k \nabla T)$$

These equations can be considered a sufficiently good approximation of the actual physics for specific applications, such as high-Reynolds flow regimes with a low-to-medium fidelity prediction requirement.

Under these conditions, the problem to solver is a nonlinear PDE system of four variables (density, x-velocity, y-velocity and energy) that describe entirely the flow motion at any given spatial location (x, y). In particular, the flow solution can be used to obtain the 2 force components acting on an airfoil immersed into a flow, commonly referred to as lift and drag, as shown in Figure 14.

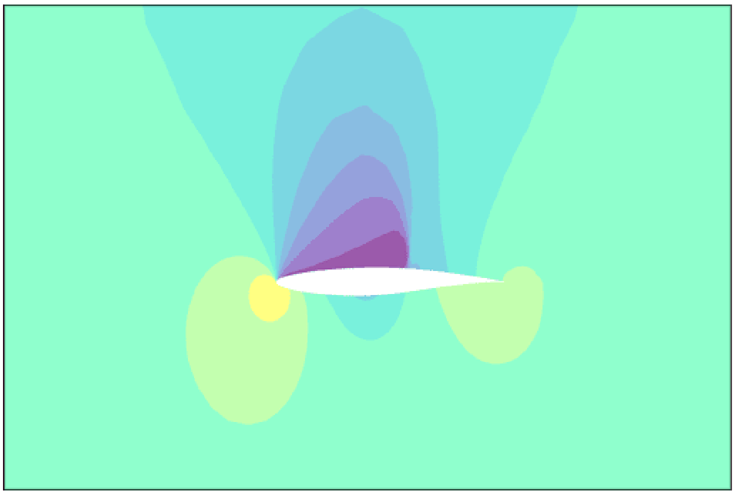

Figure 14: Solution of the 2D Euler equations on the RAE2822 airfoil case submitted to a transonic flow. Courtesy of Airbus

As mentioned earlier, DQC has been demonstrated for solving the Euler equations in a 1D flow, which is needed to meet the simulation needs of the aerospace industry. In this perspective, the current sub-use case is aimed at demonstrating the DQC capability to accurately capture the force components acting on the open-source NACA 0012 airfoil geometry. In contrast to the previous sub-use case, no other technological bricks need to be developed to tackle this problem since it only involves the use of already-demonstrated features, in particular the resolution of high-dimensional, nonlinear PDEs. Special attention is nevertheless to be paid to the specification of the boundary conditions of the problem. A non-penetration boundary condition must be imposed to avoid the flow entering in the solid domain occupied by the airfoil:

$$u \cdot n = 0$$

Where $u = (u, v)$ is the vector of velocities and $n = (n_x, n_y)$ is the vector describing the local normal to the airfoil surface.

In the framework of this sub-use case, it is suggested to assess the predictions of lift and drag force provided by the DQC algorithm in two situations:

- In the framework of an inviscid solution featured by the Euler equations, the NACA0012 airfoil should produce zero net drag force when immersed into a purely axial free stream flow. Nevertheless, most numerical methods introduce a small drag force whose evaluation directly measures the artificial dissipation introduced during resolution.
- When submitted to transonic flow conditions, shock waves develop over the airfoil surface whose position and intensity play a significant role in the magnitude of these

forces. This mechanism, already present in the Burgers equation, must be accurately captured by the DQC approach.

3.1.3. Use case implications

The application of the DQC approach to solve the Burgers equation will enable the development and validation of the following technological bricks:

- The extension of the approach to the time-accurate resolution of PDEs with arbitrary dimensionality in space.
- The assessment of the accuracy of the obtained solutions. It is sought to determine whether the effects of non-linear convection such as the presence of discontinuities in the solution can be captured.
- The assessment of the numerical properties of the solution provided by the DQC algorithm such as its ability to represent conservation laws without introducing excessive numerical dissipation.
- The extension of the approach to PDEs where second order derivatives in space appear, which are required to model the physical effects of viscosity.
- The validation of the approach in situations where the physical mechanisms of convection and diffusion are coupled.

This first step will enable us to then focus on the 2D Euler equations, which will require to overcome two additional challenges:

- The extension of the DQC approach to solve a system of PDE, where the equations are strongly coupled with each other.
- The application of arbitrary boundary conditions to enable the modelling of aerodynamic objects.

As mentioned in the previous paragraphs, the final expected result is the demonstration of the DQC approach to solve the Euler equations in presence of an arbitrary airfoil geometry such as the NACA0012 in any flow regime, ranging from low speed to transonic.

3.1.4. Use case impact on the different stakeholders.

From the aircraft industry standpoint, it must be recalled that the current in-use CFD software features a high level of maturity and reliability, and therefore it is not expected to get them replaced by disruptive algorithms such as the one explored in this use case for the short-term feature. Nevertheless, it is important to prepare the mid to long term ambition of having highly scalable and efficient algorithms to numerically simulate the aircraft aerodynamics in the context of massive CFD campaigns for innovative aircraft designs, and to take advantage of the quantum computing capabilities for this field of engineering. In this regard, the outcomes of the present use case in terms of accuracy and scalability of the developed algorithms will be of great value from the Airbus point of view.

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3.2. Space mission optimisation

3.2.1. Satellite mission planning problem description

Earth observation satellites take images of the Earth's surface through their optical sensor. They collect photographs of specific regions that users request and then send them towards ground stations. Ground stations also communicate with satellites to provide them with their mission plan describing the tasks to perform (Figure 15).

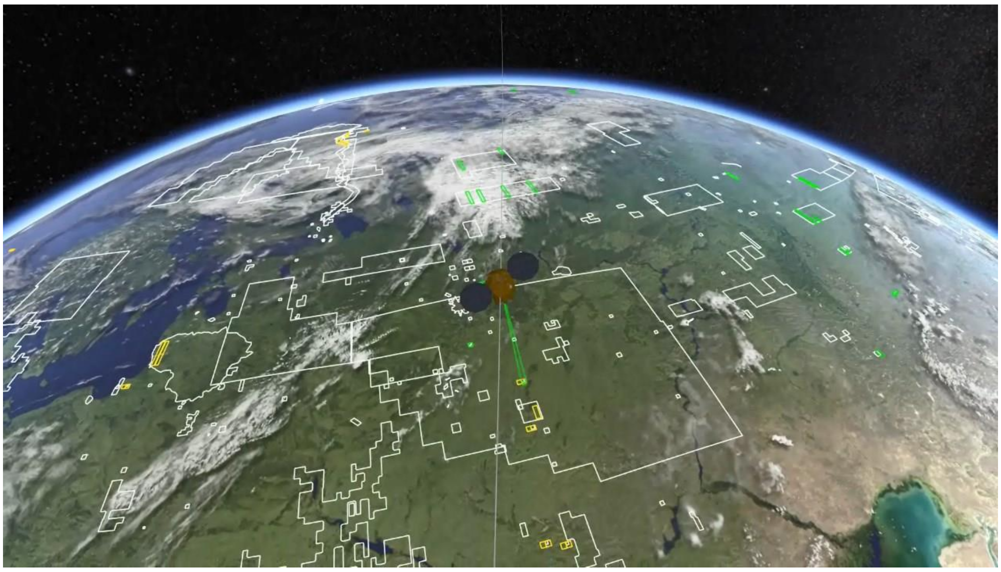

Figure 15: Realistic visualisation of an Earth observation mission plan where acquisition requests are depicted in white, planned acquisitions in yellow and already acquired observations in green.

Mission planning is a complex problem that aims at optimally selecting acquisitions among tens of thousands of user requests and ordering them in the mission timeline while respecting satellite physical constraints. While the optical instrument remains fixed on the platform, current Earth observation satellites are agile which means they can rotate on themselves to point towards different regions of interest on the Earth. The satellite's field of view is defined by the maximum angle with which it can take good quality pictures. Each acquisition has then the opportunity to be captured during a given visibility time window which is a portion of the satellite orbit where the area is accessible given this angle constraint (see Figure 16). Manoeuvre time to point from one target towards another is also an essential constraint as it limits the number of acquisitions the satellite can perform in a single pass. The timeline of a satellite mission is a sequence of manoeuvres and image acquisitions, one after the other: the satellite manoeuvres to point towards a target, then acquires an image, and then manoeuvres again to reach a new target.

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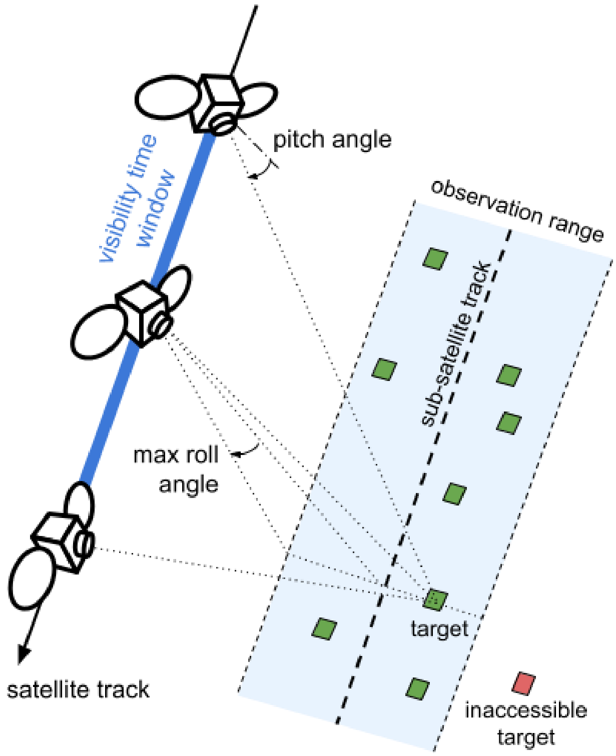

Figure 16: Agile Earth observation satellites can manoeuvre to point towards different accessible targets verifying roll and pitch angle constraints that define a visibility time window for each target

Besides satellite agility, mission planning must consider weather conditions over the acquired regions. Indeed, satellites aim at imaging the ground, and as photos are taken in the visible spectrum, clouds can hide some areas of the Earth and lower the acquisition's commercial value. Mission planning relies on weather forecasts to take as many cloudless images as possible.

Current trends in Earth observation point to an increase in the complexity of optimising mission plans because of:

- the increased number of satellites in future constellations,
- the higher resolution optical sensors leading to a smaller instrument footprint and hence a larger volume of candidate targets to plan per programming period,
- the enhanced satellite agility leading to the multiplication of acquisition opportunities and planning solutions,
- the multi-objective optimisation problem taking into consideration more planning aspects such as customer priority satisfaction, capacity maximisation, latency, weather conditions, etc.,
- managing uncertainties such as weather forecasting errors in the mission planning problem.

Mission optimisation can be treated as a multi-objective optimisation problem involving several conflicting goals and constraints. Mission operation scheduling considers factors such as customer preferences and request priorities, satellite platform and optical instrument constraints related to manoeuvring capability, onboard memory usage and power and thermal limits. It is critical to optimise these operations to ensure that resources are efficiently used and that customer demands are satisfied. The schedule must verify the maximum angle with which an image should be taken, the agility limits of the satellite to manoeuvre from pointing towards one area of the Earth to another, its memory capacity to take several images before

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downloading them to a ground station, the energy available in the batteries, the thermal limits of the satellite platform, the weather uncertainty as cloudy images are not interesting for users, etc. Objectives can be to maximise the number of images acquired in a programming period, the quality of these images, their commercial value, the satisfaction of all customers, the fairness between customers, etc.

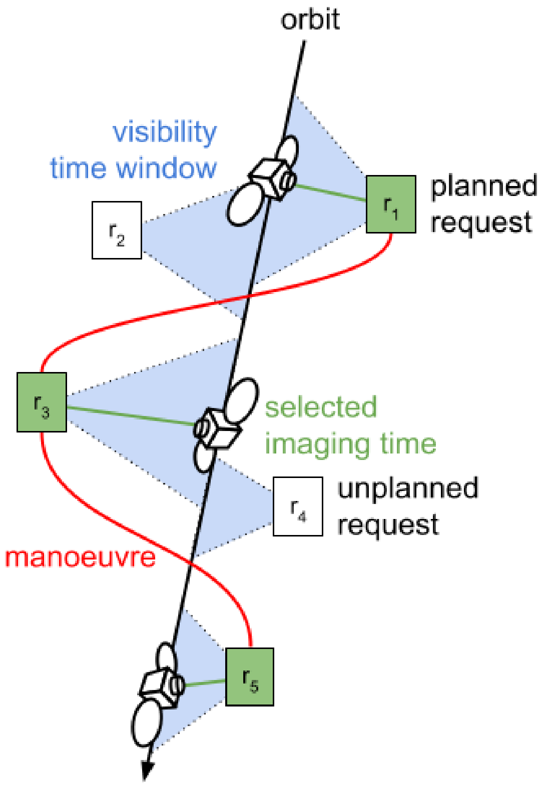

Figure 17: Scheme of an Earth observation satellite mission: each request is accessible during a limited portion of the orbit, and some requests cannot be fulfilled because of manoeuvre time constraints

Satellite mission plan optimisation is also a time-critical problem (see Figure 17). Mission plans must be established in a few minutes for each programming period (typically a few hours), considering tens of thousands of user requests. A full-size calculation using an optimal solver on a classical computer would take several hours, which is not conceivable. This computation time limit comes from the fact that planning needs to rely on fresh weather data, so cloud coverage predictions are as accurate as possible. It also allows taking into account last minute acquisition requests. It can be noted that some pre- processing is possible on the data that does not depend on weather forecasts (such as manoeuvre calculation between two acquisitions for instance). These computations can be done beforehand without impacting the planning computation time limit.

The user acquisition requests, and their parameters are inputs to the mission planning problem. An orbital physics simulator can compute satellite accesses (visibility windows) and manoeuvres between targets. These can be precomputed in advance. The aim of mission planning is not to perform these calculations but to build the best possible plan, considering these constraints. To simplify the problem, other constraints, such as onboard energy or memory, will not be handled here: it is considered that the satellite has been appropriately sized to be able to fulfil its mission. A simple single objective formulation of the satellite mission planning problem consists in selecting requests to build the mission plan and to define their start time to maximise the value of the mission.

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Considering the following notations:

- R the set of distinct acquisition requests,
- $x_r \in \{0,1\}$ the binary variable indicating whether request $r \in R$ has been selected in the mission plan,
- $t_r \in \Re$ the acquisition start time for request r,
- v_r the commercial value of the acquisition of request r,
- d_r the duration of the acquisition of request r,
- s_r the start time of the visibility window of request r,
- e_r the end time of the visibility window of request r,
- $m_{r_1,r_2}(t)$ the manoeuvre duration between acquisitions r_1 and r_2 starting at time t,

the mission planning problem can be formulated as follows:

$$\max \sum_{r \in R} x_r v_r$$

s.t. $\forall r \in R, x_r(t_r - s_r) \geq 0$ (t_r respects visibility window start time)

$\forall r \in R, x_r(e_r - d_r - t_r) \geq 0$ (t_r respects visibility window end time)

$\forall r_1, r_2 \in R^2 : r_1 \neq r_2, (t_{r_1} > t_{r_2}) \vee \left(x_{r_1} x_{r_2} \left(t_{r_2} - t_{r_1} - d_{r_1} - m_{r_1,r_2}(t_{r_1} + d_{r_1})\right) \geq 0\right)$

(t_{r_2} respects manouvre duration)

The last constraint must be verified only for the subsequent acquisition in the plan in practice. Manoeuvre duration depends on time, as the satellite orientation to point towards a given target depends on time. It is considered that there is a unique potential visibility window per user request in the programming period. This visibility window's start and end times are computed given the roll and pitch angle constraints of the acquisition request. The commercial value of an image depends on the priority of the request and on the cloud coverage forecast. As visibility windows are relatively small compared to weather variation, a single value can be inferred per request.

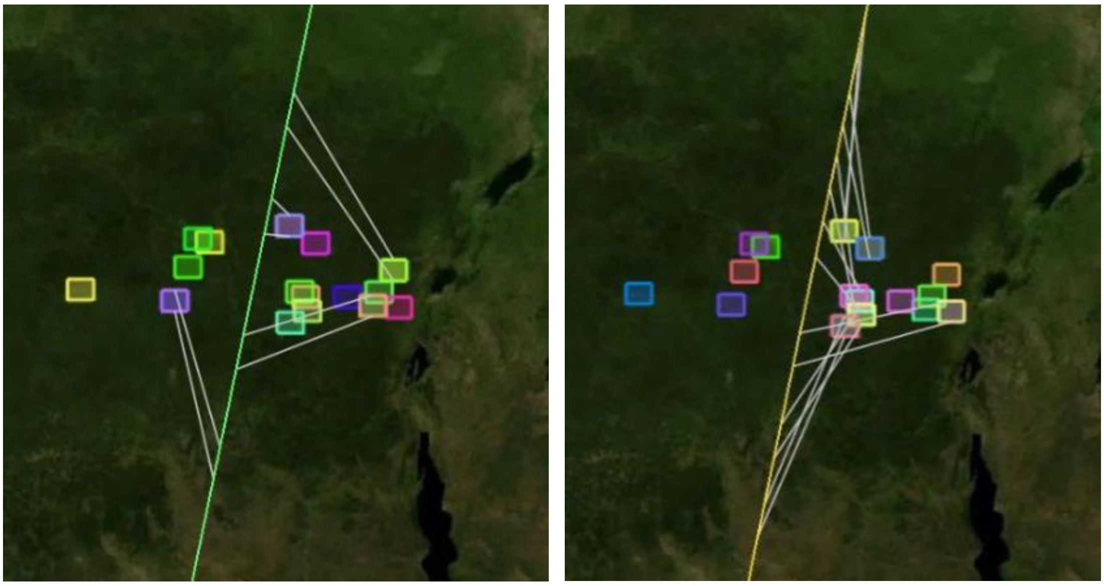

Figure 18: Two mission plan examples with selected requests and their acquisition time window among other unplanned requests

If needed, the problem can be simplified even more by considering that all acquisitions have the same commercial value and trying to maximise the number of images taken during a programming period. Acquisition duration can also be the same for all targets. For this study, the number of user acquisition requests will be limited to about a dozen so that the problem remains tractable on existing quantum computers (see examples on Figure 18). The sparsity of the problem is driven by the geographical concentration of the acquisition requests: when the request latitude range decreases, the geographical area gets denser and the number of constraints increases because the time available to manoeuvre between two requests becomes too low.

Figure 19 shows a basic example of a mission planning problem where users have made 4 acquisition requests. It is supposed that all acquisitions have the same commercial value $v_r = 1$ so the aim is to maximise the number of acquisitions in the plan. The acquisition duration is also the same for all requests: $d_r = 1$. Manoeuvre duration is supposed to be time independent and equal to 2 for all request pairs except from r_3 and r_4 that are closer to each other: $m_{r_3,r_4}(t) = m_{r_4,r_3}(t) = 1$.

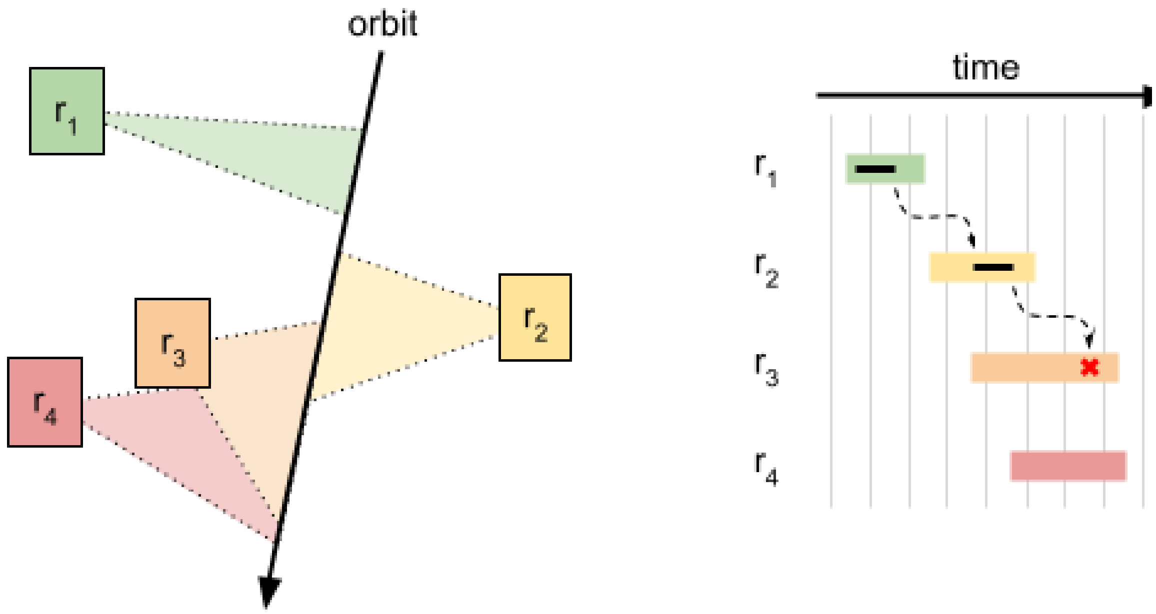

Figure 19: Small example of a mission planning problem with 4 acquisition requests.

A possible mission plan is depicted on the right of Figure 19: the satellite first acquiresr_1 during 1-time step, then manoeuvres during 2-time steps towards the target of request r_2 and acquires its image for 1-time step. It would require 2 additional time steps to manoeuvre towards request r_3, which is too late to be able to acquire its image before the end of the visibility window. So, this mission plan only satisfies requests r_1 and r_2 and has a value of 2.

3.2.2. Mission planning problem formulations

Because of the operational time constraint, mission planning is usually done using suboptimal heuristics such as greedy algorithms or dynamic programming. Solving the complete problem optimally takes too much time, but there is evidence that quantum approaches could outperform classical approaches for combinatorial optimisation problems. For this study, we consider a more straightforward case than the operational one, with fewer parameters and

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user requests so that current quantum computers can address it. Nevertheless, the test cases provided will represent the actual operational problem and allow studying suitable formulations for quantum computation.

Some possible methods and formulations of the satellite mission planning problem are described below. Several other approaches are also described in the literature [11] [12]

Greedy Algorithm

A simple but computationally efficient way to build a mission plan is to add acquisitions iteratively to the plan by selecting the one with best commercial value first. The general idea of this greedy algorithm is the following:

$S \leftarrow sort(R)$
$M \leftarrow \emptyset$
for $r$in S:
  $M' \leftarrow M \cup r$
  $M' \leftarrow order(M')$
  if $feasible(M')$:
    $M \leftarrow M \cup r$
  return M

The $order(M)$ function is a subproblem. It is expected to provide an ordering of all requests in M and set their start time t_r, to define the sequence of images that will be taken by the satellite. It can be done in a more or less sophisticated way: it can be solved optimally or built with a heuristic. A simple heuristic can be, for instance, to order requests by the start time of their visibility window s_r and to set their acquisition start time t_r sequentially by adding the acquisition and manoeuvre durations to the start time of the previous acquisition.

$order(M)$:
$M \leftarrow sort(M)$
for i in $range(M)$:
  $t_{r_i} \leftarrow \max\left(s_{r_i}, t_{r_{i-1}} + d_{r_{i-1}} + m_{r_{i-1},r}\right)$
$return\ M$

Then the $feasible(M)$ function checks whether the mission plan verifies all requests presented in section 3.2.1 so that the final mission plan returned is feasible.

This heuristic is non-optimal as it prevents removing previously inserted acquisitions. However, it is swift and compatible with operational time constraints and still provides interesting solutions that can be used as a baseline for comparison.

This algorithm produced the suboptimal mission plan (r_1, r_2) in the small example introduced in Figure 19 in the previous section.

Integer linear programming

The mission planning problem can also be formulated as an integer linear programming problem. One way to do so is to discretise time by dividing the visibility window of an acquisition into a discrete set of potential imaging attempts, that are points in time where the satellite can start the acquisition (see Figure 20). Noting:

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- I_r the set of potential imaging attempts for request r,
- $t_{r,i}$ the start time for imaging attempt i of request r,
- $x_{r,i} \in \{0,1\}$ the binary variable indicating whether imaging attempt i of request $r \in R$ has been selected in the mission plan,
- $F_{r_1,r_2} = \{(i,j) \in I_{r_1} \times I_{r_2} : t_{r_1,i} \leq t_{r_2,j} < t_{r_1,i} + d_{r_1} + m_{r_1 r_2}(t_{r_1,i} + d_{r_1})\}$ the set of forbidden pairs of imaging attempts between requests r_1 and r_2,

the problem then becomes:

$$\max \sum_{r \in R} \sum_{i \in I_r} x_{r,i}\, v_r$$

s.t.

$$\forall r \in R, \sum_{i \in I_r} x_{r,i} \leq 1$$ (at most one imaging attempt selected per request)

$$\forall r_1, r_2 \in R^2 : r_1 \neq r_2, \forall (i,j) \in F_{r_1,r_2}, x_{r_1,i} + x_{r_2,j} \leq 1$$

(no forbidden pairs of selected imaging attempts)

The more time is discretised, the more variables there are in the problem. The suboptimality of this formulation is linked to this discretisation.

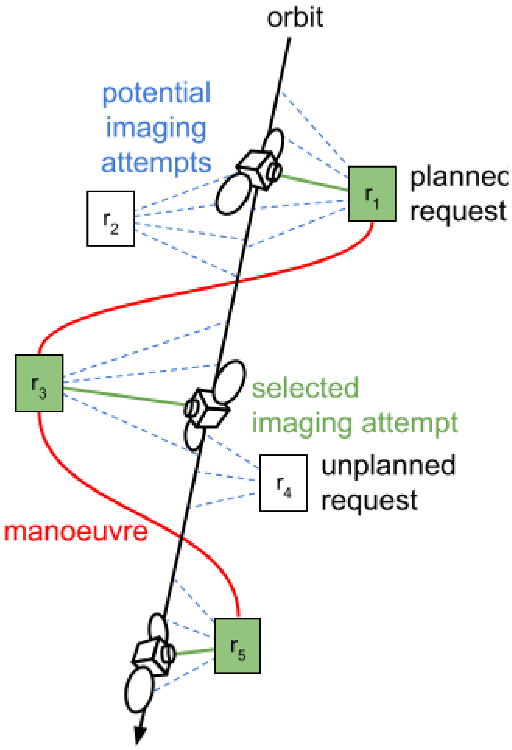

Figure 20: Scheme of an Earth observation satellite mission with discretised imaging attempts

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The small example described in the previous section with the discrete image attempts in blue depicted in Figure 21 would be formulated as:

$$\max x_{1,1} + x_{2,1} + x_{2,2} + x_{3,1} + x_{3,2} + x_{3,3} + x_{4,1} + x_{4,2}$$

s.t.

$$x_{2,1} + x_{2,2} \leq 1$$
$$x_{3,1} + x_{3,2} + x_{3,3} \leq 1$$
$$x_{4,1} + x_{4,2} \leq 1$$

(at most one imaging attempt selected per request)

$$x_{1,1} + x_{2,1} \leq 1$$
$$x_{2,1} + x_{3,1} \leq 1$$
$$x_{2,1} + x_{3,2} \leq 1$$
$$x_{2,2} + x_{3,1} \leq 1$$
$$x_{2,2} + x_{3,2} \leq 1$$
$$x_{2,2} + x_{3,3} \leq 1$$
$$x_{2,2} + x_{4,1} \leq 1$$
$$x_{3,1} + x_{4,1} \leq 1$$
$$x_{3,2} + x_{4,1} \leq 1$$
$$x_{3,2} + x_{4,2} \leq 1$$
$$x_{3,3} + x_{4,2} \leq 1$$
$$x_{4,1} + x_{3,3} \leq 1$$

(no forbidden pairs of selected imaging attempts)

An optimal solution is $(i_{1,1}, i_{3,1}, i_{4,2})$ with a value of 3 (represented on the right of Figure 21). Even after the time discretization, this optimal solving approach provides a better solution than the greedy algorithm presented above, but potentially with a larger computation time.

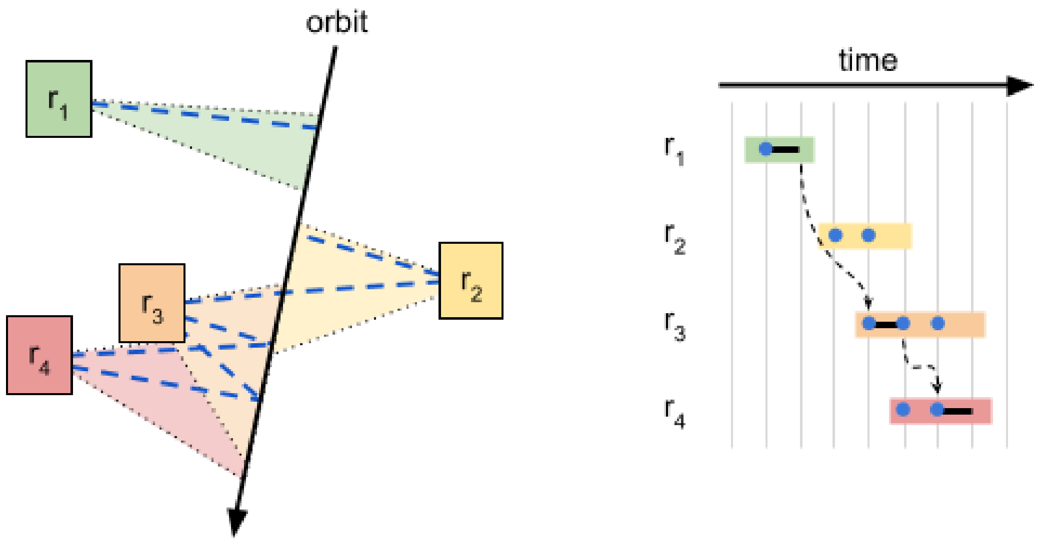

Figure 21: Small example of a mission planning problem with 4 acquisition requests.

Graph

Mission planning can also be seen as a travelling salesman problem where one needs to find an optimal path in a graph. There are several possible ways to formulate this problem as a graph. For instance, nodes can be the acquisition imaging attempts defined above, and edges can represent a possible manoeuvre between two imaging attempts. Forbidden pairs of

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imaging attempts defined above will not be linked together. Then the mission planning problem amounts to finding a path in the graph.

The small example depicted in Figure 21 can be represented with the graph in Figure 22. It is easy to see that the longest path in the graph matches the solution presented in Figure 22.

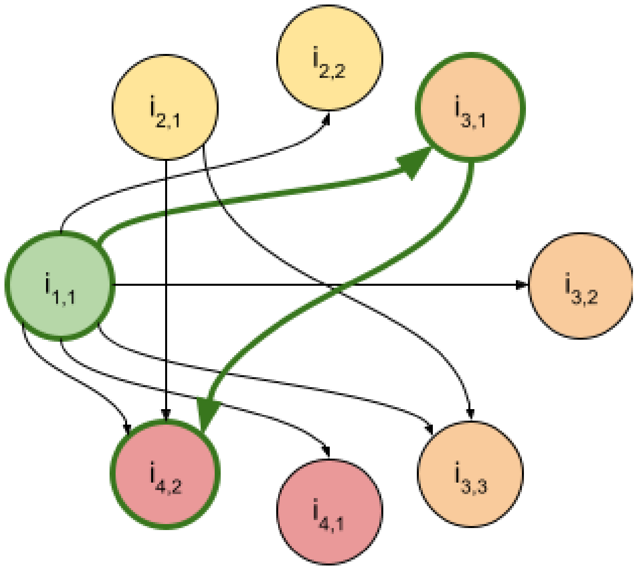

Figure 22: Graph representation of the small mission planning problem example.

Considered method for solving the mission planning problem with quantum computing

Two consortium members (AIRBUS and DLR) assessed the performance of quantum annealers for the operational planning of an Earth observation satellite. The work was concerned with the problem of acquiring high-value images while obeying the attitude manoeuvring constraint of the satellite. The work benchmarked quantum annealers against algorithms used in an industry setting. The formulation used was a quadratic unconstrained binary optimization (QUBO) problem [13].

They found that the solution quality of the quantum annealer is comparable to the heuristic method used operationally for small problem instances but degrades rapidly due to the limited precision of the quantum annealer. In this project, we expect to take this problem beyond quantum annealing and tackle it using gate-based hardware by defining a formulation that could lead to quantum advantage. The general question to answer is: can quantum computing help finding better mission plans within the computation time constraint? Some other papers in the literature address the problem of solving the mission planning problem with quantum computers [14] [15].

For solving the satellite mission planning problem on a gate-based computer, the QUBO formulation could be used with a Quantum Approximate Optimization Algorithm (QAOA). The graph formulation could also be another interesting option. These two formulations will be investigated during this study.

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3.2.3. Expected output of the study

The outputs that are expected from studying the resolution of the satellite mission planning problem on a quantum computer are one or several formulations of the problem that will be suited for quantum computing speedup, along with a comparison of the solution quality (if the problem had to be simplified) and the expected computation time. Solving this problem on current quantum computers will show the problem size that can be tackled for now, and the expected computer size that would be required to solve an operational size problem.

3.2.4. Impact of the study on the different stakeholders

For Airbus, this study will prepare the future of satellite mission planning by identifying problem formulation and algorithms that could bring a quantum speedup and provide better mission plans within the operational computation time constraint. It will allow people to learn quantum computing more in details and to understand its specificities and benefits. Studying different problem formulations for the satellite mission planning use case will also be interesting as it could improve classical computation as well in the shorter term.

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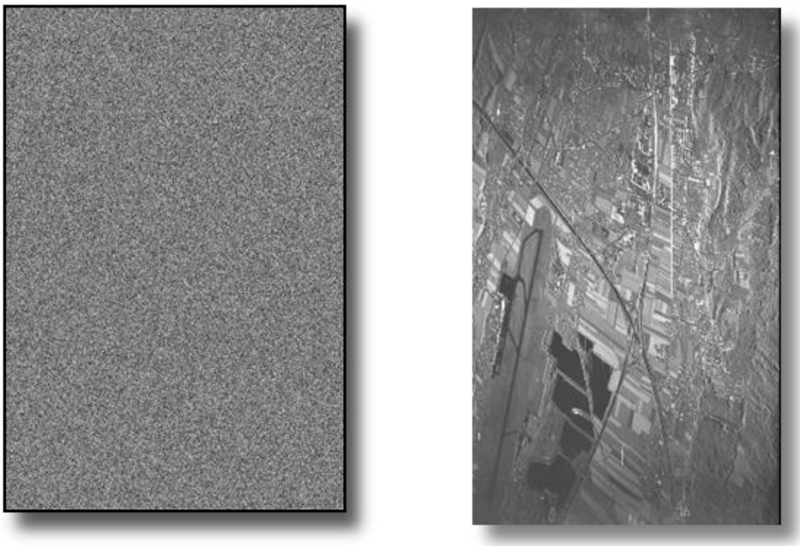
3.3. Space data analysis and processing



1 2

Figure 23: Space data processing. (1) SAR raw data (2) Processed raw data reveals image

Today, Earth observation is an essential part of the space industry. Radar systems contribute to many missions to provide images independent from weather and daylight conditions (Terra-SAR, Copernicus Sentinel, military reconnaissance). A radar sensor emits an electromagnetic wave and collects the echo, which carries the information of the surface where it has been reflected. By knowing the exact pattern sent out and the position of the sensor, it is possible to calculate an image out of the raw data by measuring the travelling time of the electromagnetic wave from the sensor to the surface and backwards. Thus, we can generate an image by simple distance measurement. The resolution of those systems strongly depends on the size of the antenna. Massive antennas would be required to generate images with reasonable resolutions, which is technically impossible for space-borne sensors. Thus, the aperture of the antenna is artificially increased by sending multiple signals during the flight, along the satellite's ground track and receiving various echoes from the area of interest. This technique is called *synthetic aperture radar* (SAR). The raw data is an overlay of complex echo patterns (see Figure 23.1) and must be processed by SAR algorithms to generate an image (see Figure 23.2). Those SAR processors are typically very sophisticated and computing intensive. Besides its core SAR processing algorithms, various errors must be treated since real SAR raw data contains distortions due to atmospheric effects and the sensor's timing and position errors. Most systems use *high-performance computers* (HPC) to provide images in a reasonable time. Quantum computers are a nascent technology with the potential to significantly accelerate the resolution of some numerical issues. In this project, we aim to explore the computational advantages that may be gained by applying machine learning techniques to SAR data processing, followed by a study of the potential further benefits that quantum computers can offer. As discussed in the following sections, we will focus on quantum machine learning techniques.

3.3.1. Methodologies

Besides the classical methods of SAR processing, in our case, the omega-k algorithm, we will introduce machine learning techniques as a baseline for quantum computing machine learning algorithms. The goal is, at first, to create a valid reference baseline and a proof-of-concept, to check the limits of a classical machine learning approach compared to the classical algorithm.

The classical algorithmic pipeline for the transformation we aim to learn (Figure 23.1) involves Fourier and other trigonometric transforms, suggesting that a succinct classifier/regressor should be amenable to learning such functions. QML models are equal to a class of generalised trigonometric polynomials [16] [17] and, consequently, may be particularly well suited for this task.

Especially the size of the data poses a problem for today's quantum computers. Hence, if possible, we first need to reduce the data while in parallel work on hybrid quantum methods, which can tackle higher dimensional data, building on [18] and other works.

3.3.2. Problem scenario description

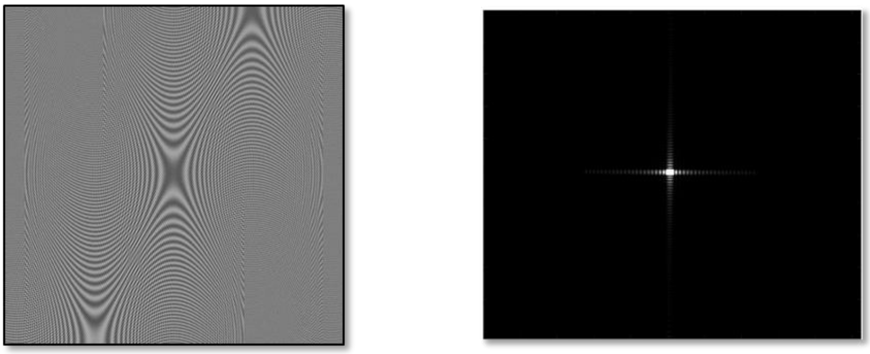


Figure 24: (left) Raw data of a single point target; (right) Processed raw data of a single point target (image data)

Since the radar raw data consists of complex interference patterns, a single point target (see Figure 24 right) is spread over the whole data matrix (see Figure 24 left). With machine learning, converting those patterns to the single-point target may be possible without using complex radar algorithms. This will give a significant advantage regarding algorithmic uncertainties, like various error correction calculations due to distortions such as atmospheric influence or the uncertainties in the exact position and time measurements of the satellite. Furthermore, an advantage in overall processing time is expected if pattern recognition is used in advance to detect targets of interest before processing the whole raw data. In this sense, a preliminary assessment could be conducted to determine whether data processing would be worthwhile.

We will start our analysis with simple cases, using simulated data with few point targets. We will proceed by adding noise or distortions in those data sets and finally, moving on to radar raw data produced by a real SAR sensor. All cases shall be first examined with the classical ML algorithm and compared to the QML approach. As a reference, a classical SAR processor will be used.

Simulated data

To reduce the complexity at the start, we will use simulated data. Radar data simulators provide a flexible way of generating simple radar raw data sets with various point targets, i.e., the radar echo from a reflection singularity, which a real sensor would measure. These single reflections will occur in the image as a cross-shaped pattern representing *sinc-function (sin x / x*), see Figure 24 right. The point targets can be generated with various amplitudes and phases, positions, and numbers. Further, distortions can be added, like background noise. For ML it is also important to have a large data base for training purpose. This can also be very well done by radar raw data simulators in an automated way. With simulated data, we aim to prove our concept of methodology.

Single point targets

First, a simple single point target without noise will be investigated. A classical machine learning algorithm will be developed and trained for this purpose. The point target will be positioned in multiple locations with varying signal strength for training. The goal is to build a neuronal network recognising a single point target from the raw data. This purpose is first to have a sanity check of our methodology and further, establishing a baseline.

We will add more point targets, again without noise, but also at various positions. Additionally, we aim to learn more specific functions that could be more succinct than the completely SAR-processed raw data.

A challenge will be devising hybrid models that will allow us to handle input dimensions that can capture the transforms' main facets. To start with a simple setup adaptable to recent quantum computing resources, we reduce the dimensionality to 1D.

Single point targets with distortions

The next step will increase the complexity by adding distortions to the raw data used in the cases before. The distortions shall be first local to the point targets and then as total background noise. This will mimic local errors, such as height levels of the targets and global errors as atmospheric distortions.

Complex targets with distortions

To increase the complexity, target patterns shall be simulated, corresponding to patterns which occurs in images generated by real radar sensors, i.e., buildings, planes, etc., again with simulated background noise.

Real data

Finally, the complete analysis will be done for radar raw data, generated by real radar sensors. The goal is recognising a complex target pattern, like buildings, planes, cars, etc., to prove, that our approach will be applicable beyond simulated data.

3.3.3. Implications for methods used and future approaches in SAR

Through this analysis, we will introduce new techniques and alternative methods for SAR processing. Besides its implications for quantum computing approaches, there will also be findings on whether complex SAR processing algorithms can be supported. Further, a training base for machine learning algorithms will be created by using automated simulated radar data.

From the perspective of quantum computing applications, many early proposals suggested quantum machine learning may be helpful in image processing due to the perceived capacity to handle extremely high dimensional data (see the review [19]). However, all these ideas were based on quantum linear algebra techniques, which required complex quantum computations and quantum RAM architectures for a chance of improvements, all of which are well beyond current capacities. The approaches based on parameterised quantum circuits, which are more amenable to near-term devices, however, did not seem to have the appropriate structure for image problems. However, they were more likely to be suitable for time-series analysis due to their trigonometric nature. This use case identifies one of the first image-processing tasks which may have the appropriate structure for modern approaches to quantum machine learning.

Due to the acute sensitivity of (quantum) machine learning to domain-specific features, identifying suitable application domains is one of the community's significant challenges.

3.3.4. Expected outcome and impact to science and industry

For Airbus, there will be an impact on upcoming space radar missions. In particular, if the approaches are applicable, the sizing of HPC systems and mission planning regarding payload data throughput from raw data acquisition to the final processed image data and delivery to the customers.

Furthermore, there will be a significant impact on radar science regarding SAR processing techniques, as the proposed methods still need to be researched, yet to our knowledge. In that sense, both techniques of classical ML and QML are not evaluated today in this context, and each finding will be very interesting for radar processing.

The field of quantum machine learning is at the critical stage, searching for concrete evidence of utility beyond very specialised contexts (e.g., in analysing certain types of quantum data). Tangible results in this direction will offer a starting point for much faster identification of broader types of real-world-relevant applications where QML can make a difference.

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4. BIBLIOGRAPHY

[1] Hunter, N. and Markiewicz, W., “Compressed Design And Validation Culture & Digital Tools,” FlyZero, 2022.

[2] Mas, F., Menéndez, J.L., Oliva, M., Gómez, A. and Ríos, J, “Collaborative engineering paradigm applied to the aerospace industry. In Product Lifecycle Management for Society,” in *Product Lifecycle Management for Society*, Berlin, Heidelberg, 2013.

[3] Kyriienko, Oleksandr, Annie E. Paine, and Vincent E. Elfving, “Solving nonlinear differential equations with differentiable quantum circuits.,” *Physical Review A,* vol. 103, no. 5, p. 052416, May 2021.

[4] C. Hirsch, Numerical computation of internal and external flows: The fundamentals of computational fluid dynamics, Elsevier, 2007.

[5] Landau, L.D. and Lifshitz, E.M., luid Mechanics: Landau and Lifshitz: Course of Theoretical Physics Volume 6, Elsevier, 2013.

[6] Lu, Lu and Meng, Xuhui and Mao, Zhiping and Karniadakis, George Em, “DeepXDE: A Deep Learning Library for Solving Differential Equations,” *SIAM Review,* vol. 63, no. 1, pp. 208-228, 2021.

[7] Qin Lou and Xuhui Meng and George Em Karniadakis, “Physics-informed neural networks for solving forward and inverse flow problems via the Boltzmann-{BGK} formulation,” *Journal of Computational Physics,* vol. 447, p. 110676, Dec 2021.

[8] Zhiping Mao and Ameya Dilip Jagtap and George Em Karniadakis, “Physics-informed neural networks for high-speed flows,” *Computer Methods in Applied Mechanics and Engineering,* vol. 360, p. 112789, 2020.

[9] M. Landajuela, “Burgers equation.,” BCAM Internship report: Basque Center for Applied Mathematics., 2011.

[10] U. Münster, “Vorlesung Numerische Methoden WS 09/10,” 2010. [Online]. Available: https://www.uni-muenster.de/Physik.TP/archive/fileadmin/lehre/NumMethoden/WS0910/ScriptPDE/Burgers.pdf.

[11] Globus A, Crawford J, Lohn J, Pryor A., “A comparison of techniques for scheduling earth observing satellites,” in *IAAI'04: Proceedings of the 16th conference on Innovative applications of artifical intelligence*, 2004.

[12] Lemaître M, Verfaillie G, Jouhaud F, Lachiver JM, Bataille N, “Selecting and scheduling observations of agile satellites,” *Aerospace Science and Technology,* vol. 6, no. 5, pp. 367-381, 2002.

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[13] Tobias Stollenwerk and Vincent Michaud and Elisabeth Lobe and Mathieu Picard and Achim Basermann and Thierry Botter, “Image Acquisition Planning for Earth Observation Satellites with a Quantum Annealer,” *arXiv: Quantum Physics,* 2020.

[14] Ye Zhang and Xiaoxuan Hu and Waiming Zhu and Peng Jin, “Solving the Observing and Downloading Integrated Scheduling Problem of Earth Observation Satellite with a Quantum Genetic Algorithm,” *Journal of Systems Science and Information,* vol. 6, no. 5, pp. 399--420, 2018.

[15] Serge Rainjonneau and Igor Tokarev and Sergei Iudin and Saaketh Rayaprolu and Karan Pinto and Daria Lemtiuzhnikova and Miras Koblan and Egor Barashov and Mohammad Kordzanganeh and Markus Pflitsch and Alexey Melnikov, “Quantum algorithms applied to satellite mission planning for Earth observation,” *arXiv,* vol. 2302.07181, 2023.

[16] Schuld, Maria and Sweke, Ryan and Meyer, Johannes Jakob, “Effect of data encoding on the expressive power of variational quantum-machine-learning models,” *Phys. Rev. A,* vol. 103, no. 3, p. 032430, 2021.

[17] Matthias C. Caro and Elies Gil-Fuster and Johannes Jakob Meyer and Jens Eisert and Ryan Sweke, “Encoding-dependent generalization bounds for parametrized quantum circuits,” *Quantum,* vol. 5, p. 582, Nov 2021.

[18] Dunjko, Simon C. Marshall and Casper Gyurik and Vedran, “High Dimensional Quantum Machine Learning With Small Quantum Computers,” *arXiv,* vol. 2203.13739, 2022.

[19] Vedran Dunjko and Hans J Briegel, “Machine learning & artificial intelligence in the quantum domain: a review of recent progress,” *Reports on Progress in Physics,* vol. 81, no. 7, p. 074001, Jun 2018.

[20] Stuart Hadfield and Zhihui Wang and Bryan O'Gorman and Eleanor Rieffel and Davide Venturelli and Rupak Biswas, “From the Quantum Approximate Optimization Algorithm to a Quantum Alternating Operator Ansatz,” *Algorithms,* vol. 12, no. 2, p. 34, Feb 2019.

[21] Stollenwerk, Tobias and Michaud, Vincent and Lobe, Elisabeth and Picard, Mathieu and Basermann, Achim and Botter, Thierry, “Agile Earth Observation Satellite Scheduling With a Quantum Annealer,” *IEEE Transactions on Aerospace and Electronic Systems,* vol. 57, no. 5, pp. 3520-3528, 2021.

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