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Quantum Computing for Space: Exploring Quantum Circuits on Programmable Nanophotonic Chips

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Abstract

Quantum circuits are the fundamental computing model of quantum computing. It consists of a sequence of quantum gates that act on a set of qubits to perform a specific computation. For the implementation of quantum circuits, programmable nanophotonic chips provide a promising foundation with a large number of qubits. The current study explores the possible potential of quantum circuits implemented on programmable nanophotonic chips for space technology. In the recent findings, it has been demonstrated that quantum circuits have several advantages over classical circuits, such as exponential speedups, multiple parallel computations, and compact size. Apart from this, nanophotonic chips also offer a number of advantages over traditional chips. They provide high-speed data transfer as light travels faster than electrons. Photons require less energy to transmit data than electrons, so nanophotonic chips consume less power than conventional chips. The bandwidth of nanophotonic chips is greater than that of traditional chips, so they can transfer more data simultaneously. They can be easily scaled to smaller sizes with higher densities and are more robust to extreme temperatures and radiation than classical chips. The focus of the current study is on how quantum circuits could revolutionize space technology by providing faster and more efficient computations for a variety of space-related applications. All the in-depth analysis is carried out while taking currently available state-of-the-art technologies into consideration.

Keywords: Quantum computing for space, Space technology, Quantum circuits for space , Quantum chips for space, Quantum algorithms for aerospace

1. Introduction

In recent times, there has been a significant surge in the development of quantum technologies [1][2]. The application of quantum information science to practical technologies holds significant potential benefits for specific functions in communication [3], computation [4], and simulation [5]. The technology of quantum computing presents a distinct approach to computational problems, allowing for more effective problem-solving capabilities compared to present day classical computations. In 1994, Peter Shor introduced the Shor's prime factorization algorithm [6], which acted as a driving force for the progression of quantum computing technology and the exploration of quantum computers. Within the framework of quantum computation, quantum operations are executed on quantum registers. The quantum register is characterised by the presence of quantum states that give rise to quantum superposition. On the other hand, in a quantum circuit, the quantum states exhibit entanglement. These phenomena give rise to a system characteristic that is fundamentally distinct from that found in a conventional computer [7].

The current state of quantum computing (QC) has progressed to the point where quantum computers have demonstrated superior computational capabilities compared to leading supercomputers in certain specific challenges [8]. Additionally, the emergence of noisy intermediate-scale quantum (NISQ) computing systems that are accessible outside of laboratory environments has ushered in the industrialization phase of QC [9]. The field of QC holds the potential to resolve computationally challenging problems that are deemed infeasible through classical means. These problems span across various industry sectors, including space technology such as optimization, machine learning, and simulation. In the field of material science, QC finds application in various areas such as quantum-inspired imaging techniques [10], prediction of chemical reactivity in molecular quantum chemistry [11] simulation of the dynamics of molecules, development of materials and drugs using quantum simulations [12], and battery research [13]. QC can be used for surrogate modeling of partial differential equations, design optimizations for electric drives using numerical simulation and finite element methods [14], testing of wingbox design optimization software, and proving correctness when designing and engineering complex structures [15]. QC also plays a great role in the production and logistic fields, it finds application in various fields such as fleet management, path optimization, shift scheduling [16], decide on a production plan given predicted customer demand [17], supply chain planning, and vehicle routing problems [18]. There is also a new area of research emerging known as Quantum Machine Learning (QML) [19], which blends Machine Learning (ML) and Quantum Computing (QC). The objective of Machine Learning (ML) is to develop models that possess the ability to learn from past experiences, without requiring explicit formulation. However, executing these operations necessitates significant amounts of time and computational resources. QC have the potential to be utilized for the manipulation and analysis of extensive tensors, rendering them a highly desirable option for the integration of machine learning (ML) algorithms. Multiple QML algorithms have been developed, including Quantum Principal Component Analysis (QPCA) [20], Quantum Support Vector Machine (QSVM) [21], Quantum Reinforcement Learning (QRL) [22], Deep Quantum Learning [23] and Kernel Methods [24].

With the growing application of QC across various industries for practical application has led to a surge in research on the medium to implement QC [25] [26]. Photons have been identified as effective and low-noise vehicles for the transmission of quantum information. A photon can be used to represent the quantum bit by encoding the information in the polarization axis. Therefore, it can be stated that a photon possesses the characteristics of a qubit in relation to its polarization state. A photon that is linearly polarized can exhibit either a horizontal or vertical polarization orientation relative to a specific direction within the plane that is perpendicular to the direction of the photon's motion. Photons also exhibit weak coupling with their surrounding environment, which results in the absence of decoherence problems that are commonly observed in matter-based systems. Consequently, there is no need to handle photons at extremely low temperatures or in a vacuum environment [27]. Apart from this, Nanophotonic devices integrated onto a chip, which utilize photons for information transmission and processing at the nanoscale, offer the benefits of high bandwidth and low energy consumption. It provides high-speed data transfer as light travels faster than electrons. Nanophotonic chips possess a higher bandwidth in comparison to conventional chips, thereby enabling them to facilitate the simultaneous transfer of a greater volume of data. The researchers have recorded a new data transmission speed record of 1.84 PB/S (petabits per second) using a photonic device and a fiber optic connection [28]. They can be also easily scaled to smaller sizes with higher densities and are more robust to extreme temperatures and radiation than classical chips. The utilization of integrated optical quantum circuits holds significant importance in the field of quantum information science, alongside optical fiber photonic quantum circuits, which have already been showcased in quantum key distribution and quantum logic gate applications [29].

There are several technical challenges associated with modern-day space technology. The performance of propulsion systems are a significant problem for enabling interplanetary space travel [30]. It is difficult to simulate complex space systems and unknown space environments [31]. The limitation of on-board processing for Guidance Navigation and Control (GNC) as well as the size of the controlling circuit unit [32] [33]. QC promises to exceed traditional computer technologies in terms of speed, productivity, and size. It could be beneficial to investigate the implementation of the QC on the issues associated with modern day space technology. QC can be used along with the existential methods available in space technology. Until now, the application of quantum science in space technology has been studied from the informational point of view. It includes the application of Quantum Key Distribution (QKD), Quantum sensing and Quantum communication [34][35] [36] [37]. To the best of the author's knowledge, there are very few or no studies which covers the applications of the quantum computing in the modern day space technology. Therefore, this study is the first of its kind which presents the application of quantum computing in space technology.

In this research, we explore the application of quantum science in space technology from a computing perspective. We identify certain domains of space technology that are difficult to deal with present day classical computing methods and provide a strategy for the application of quantum computing in such domains. To utilise quantum computing for a given problem, it is necessary to transform the problem into a quantum-based problem by converting parameters and encoding the Hamiltonian as an energy function. Once we have mapped a classical problem into a quantum nature problem, we proceed to apply the quantum algorithms. A quantum algorithm is typically described by a certain quantum circuit that acts on some input quantum bits, manipulates them with unitary operations in between, and finally terminates with a measurement. Quantum gates are unitary operators that are used to manipulate the qubits. Quantum circuits are acyclic and reversible in nature. The fan-in and fan-out are always equal in quantum circuits, which means a qubit is never created or destroyed. Depending on the nature and requirements of the problems, different types of quantum circuits have been proposed. In the current study, different types of circuits are proposed for different types of problems in space technology. The focus of the current study is on how quantum circuits could revolutionise space technology by providing faster and more efficient computations for a variety of space-related applications.

This paper is structured as follows: In Sect. 2, we provide an basic introduction to Quantum computing. We have discussed about the Quantum states, Quantum gates and gates operations in the same section. Sect. 3 provides the introduction to the Quantum algorithms with their quantum circuits. Sect. 4, we provide the various quantum algorithms along with their operational quantum circuits. In Sect. 5, we identified the domains of the space technology where quantum computing could be beneficial. In Sect. 6, we devised he methodology for application of the quantum computing to the identified domains in the previous section. We presented the challenges in the application of quantum computing in space technology in Sec. 7. In Sec. 8, we finally conclude the paper with the discussions and way forward.

2. Quantum Computing

Quantum computing is a multidisciplinary field that encompasses physics, computer science, and mathematics. It uses the principles of quantum mechanics to provide exponential speedup which is beyond the capabilities of classical computers. Traditional computers use bits, representing discrete states of 0 or 1, to encode and process information. While quantum computers use quantum bits also known as qubits. Qubit is a superposition state, representing coherent combinations of 0 and 1 states. It is continuous and can take infinitely many values. This property empowers quantum computers with high processing capabilities, enabling the exploration of multiple computational paths simultaneously. Qubit is a two level system with the states $|0\rangle$ and $|1\rangle$. $|.\rangle$ is called *Dirac bra-ket notation* [38], it is used to represent quantum states. A qubit can be represented as:

$$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \tag{1}$$

α and β are complex coefficients and known as the amplitudes of the states such that $\alpha, \beta \in \mathrm{C}, \quad |\alpha|^2 + |\beta|^2 = 1$. The states $|0\rangle$ and $|1\rangle$ are known as *computational basis states*, and are orthonormal basis for this vector space. Geometrically, a qubit can be represented by a point on the unit three-dimensional sphere known as *Bloch sphere*. By using the condition $|\alpha|^2 + |\beta|^2 = 1$, the Equation 1 can be written as:

$$|\psi\rangle = \cos\frac{\theta}{2}|0\rangle + e^{i\varphi}\sin\frac{\theta}{2}|1\rangle \tag{2}$$

θ and φ defines a certain point on the *Bloch sphere* with the condition $0 \le \theta \le \pi$ and $0 \le \varphi < 2\pi$.

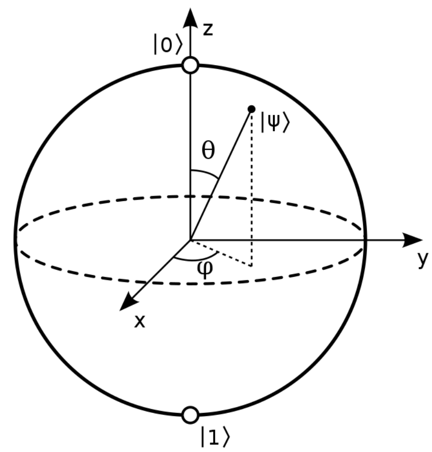


Figure 1: Bloch sphere representation of a qubit [39].

Qubit can exist in a continuum of state $|0\rangle$ and $|1\rangle$ until it is observed. Being physical systems, qubits can have any protocol for determining their state imagined for them. It is merely a measurement of the energy of the system to determine the state of the qubit in this basis, if the states $|0\rangle$ and $|1\rangle$ correspond to the spin-down and spin-up states of an electron in a magnetic field, respectively. Measurement, according to the postulates of quantum physics, must change the state of a system if it is in a superposition of the possible results of the measurement. Measurement destroys the information stored in a qubit's amplitudes because the system collapses to the measured state [39]. If a qubit is measured, it only ever gives '0' or '1' as the measurement result probabilistically.

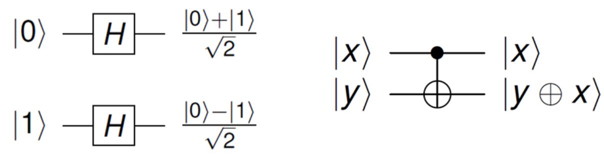
Consider a two qubit system with four computational basis states $|00\rangle, |01\rangle, |10\rangle, |11\rangle$,. It can adopt any superposition of the mentioned states with all the probability amplitudes following the normalization condition $\sum_{x\in\{0,1\}^2} |\alpha_x|^2 = 1$. One of the most important two qubit state is the Bell state or Einstein–Podolsky–Rosen (EPR) pair, given by:

$$|\psi\rangle = \frac{(|10\rangle + |01\rangle)}{\sqrt{2}} \tag{3}$$

If we measure the first qubit, we obtain two possible results: 0 with probability 1/2 and 1 with probability 1/2. Any measurement on the second qubit will result in $|1\rangle$ with a probability of 1 if the result of the first measurement was $|0\rangle$, indicating the system collapsed to the $|01\rangle$ system, and vice versa. This implies that the results of a subsequent measurement of the second qubit are affected by an operation applied to the first qubit. Hence, we can say that the measurement outcomes are *correlated*. In 1935, Einstein, Podolsky and Rosen pointed out the strange properties of states like the Bell state. The measurement correlations in the Bell state are stronger than could ever exist between classical systems. It was the initial indication that quantum mechanics enables the manipulation of information beyond the limitations of classical world. It is the main ingredient in quantum teleportation [40], super-dense coding [41] and quantum entanglement [42]. Quantum entanglement is essential for quantum computation. It has been demonstrated that any quantum algorithm that does not use entanglement may be implemented in a classical computer with no advantageous speed difference [43]. The obvious explanation is the massive amount of information that a quantum computer can handle. If a N qubit system is not entangled, the 2N amplitudes of its state can be characterized by the amplitudes of each single-qubit state, that is, 2N amplitudes. If the system is entangled, all of the amplitudes will be independent, and the qubit register will form a 2N-dimensional vector. Similar to the structure of a classical computer, which involves an electrical circuit comprising of wires and logic gates, the structure of a quantum computer involves a quantum circuit that comprises of wires and elementary quantum gates. These components are utilized to transport and manipulate quantum information. In the next subsection, we briefly describe about the Quantum gates.

2.1. Quantum Logic Gates

A quantum logic gate is a fundamental quantum circuit that operates on a limited number of qubits. They serve as the foundation for quantum circuits in the same way that classical logic gates serve as the foundation for ordinary digital circuits. The key difference is that the quantum logic gates are reversible in nature, unlike many classical logic gates. In principle, it can be inferred that quantum gates do not experience information loss. The entanglement of qubits during their entry into the quantum gate is maintained during their exit, thereby preserving the integrity of their information during the transition. In contrast, numerous classical gates present in traditional computers exhibit a loss of information, thereby rendering them incapable of retracing their operations. Quantum logic gates are used to manipulate the quantum information (qubits), while classical logic gates are used to manipulate classical information (bits). A rudimentary quantum circuit that operates on a small number of qubits can be conceptualized as a quantum logic gate.



(a) (b)

Figure 2: Basic quantum logic gates with single qubit (a) Hadamard Gate (H-Gate) and two-qubits (b) Controlled NOT gate or Feynman Gate (C-NOT Gate).

Alternatively, the quantum logic gates can also be represented by the their corresponding unitary matrices with the dimensions depending on the number of qubits. The postulates of quantum mechanics impose certain conditions on the nature of quantum logic gates in closed systems. The behavior and properties of quantum logic gates, which serve as fundamental building blocks for quantum computations and information processing, are governed by these conditions.

$$\frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \qquad \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

(a) (b)

Figure 3: Matrix equivalent of basic quantum logic gates with single qubit (a) Hadamard Gate (H-Gate) and two-qubits (b) Controlled NOT gate or Feynman Gate (C-NOT Gate).

To begin with, quantum logic gates must be unitary operators. This means that they maintain the normalization of the quantum state vector, ensuring that the probability of all potential outcomes add up to one. Unitary transformations are reversible and deterministic in nature, which allows the precise control of quantum states. In addition, it is essential that quantum logic gates are capable of operating on superposition states. The concept of superposition states enables quantum systems to exist in a coherent amalgamation of multiple states concurrently.

Quantum logic gates have the capability to manipulate superposition states, thereby facilitating parallel computations and the simultaneous exploration of all potential outcomes. Moreover, quantum gates must follow the no-cloning theorem. According to this theorem, it is impossible to produce a perfect copy of an arbitrary unknown quantum state. Due to the linearity and unitarity of quantum mechanics, quantum logic gates cannot fully copy quantum information.

Quantum logic gates can also generate and manipulate entangled states. Quantum entanglement is a fundamental phenomenon in quantum physics in which the states of two or more particles become correlated in such a way that the behavior of one particle is intrinsically related to the behavior of the other, regardless of distance. Quantum logic gates can generate, modify, and exploit entangled states, which are required for a variety of quantum information processing applications. In general, the constraints imposed on quantum gates operating in enclosed systems guarantee unitary evolution, superposition ability, no-cloning restriction, and manipulation of entanglement. These are all essential characteristics of quantum mechanics and crucial for exploiting the potential of quantum computing and information processing.

2.2. Quantum Circuits

A quantum circuit is a network of quantum logic gates, which operate on quantum bits or qubits. The qubits in a quantum circuit are denoted by horizontal lines, while the gates are represented by boxes that operate on these lines. The qubits are subjected to fixed transformations upon entering the gates, and later exit the gates. The sequencing of gates and connection among qubits are the key factors that determine the progression of the computation.

The construction of quantum circuits typically involves the combination of fundamental quantum gates in order to generate higher-level operations. The realization of the intended quantum computation is accomplished through the sequential application of gates to the qubits in a certain order. The ultimate state of the qubits, following to the application of all gates, represents the outcome of the computation. Quantum circuits are a fundamental component of the quantum computing framework for programming and executing quantum algorithms on quantum computers or simulators. They enable the creation and improvement of quantum technologies by providing an organized and visual approach to express and manipulate quantum information.

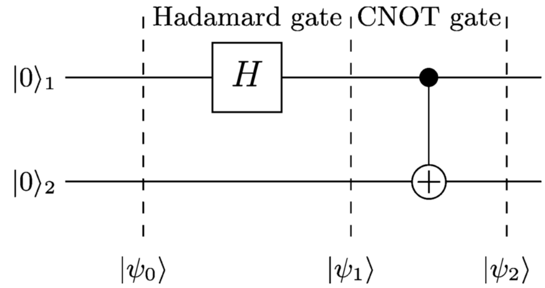


Figure 4: A simple quantum circuit made up of H-Gate and C-NOT Gate for the generation of EPR pairs (Entanglement generation).

In Figure 4, the circuit is initialized with the two qubit state $|\psi_0\rangle = |00\rangle = |0\rangle \otimes |0\rangle$. The manipulation of qubits through a specific gate can be represented through their respective matrices, as illustrated in Figure. 3. $|\psi_1\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |10\rangle)$ represents the intermediate state whereas $|\psi_2\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle)$ represents the maximally entangled state or Bell state.

The extraction of information from quantum systems is obtained by quantum measurement, an important process in quantum circuits. In a quantum circuit, this is indicated by a measurement gate or other dedicated measurement symbol. It is typically performed at the end of a computation or at intermediate steps to obtain classical information from the corresponding quantum state. The measurement gate is placed at the particular qubit(s) where the measurement is to be performed. When a qubit is measured, the associated quantum state is collapsed into one of its eigenstates. The measurement's result corresponds to one of the possible eigenvalues of the measured observable, with the chance of receiving each eigenvalue defined by the squared magnitudes of the corresponding coefficients of a quantum state.

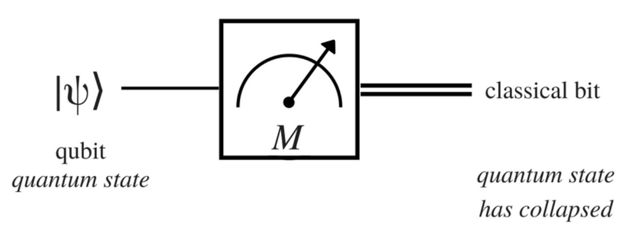


Figure 5: Quantum measurement operation, where 'M' depicts the measurement gate or measurement symbol.

3. Quantum Algorithms

Quantum computing is now being studied and applied in a number of fields, including communication, quantum internet, optimization, simulation, financial modelling, and financial modelling. To accomplish the objectives in all of these application areas, particular quantum algorithms are needed. A quantum algorithm is a computational method that is intended to be implemented on a quantum computer, employing the principles of quantum mechanics in order to solve specific problems with greater efficiency than classical algorithms [44].

David Deutsch created one of the first quantum algorithms in 1985, known as the Deutsch algorithm. It was the first method to show speed improvements over classical algorithms for a particular task [45]. The problem Deutsch's algorithm solves the Deutsch problem, or the Deutsch-Josza problem. The problem involves determining whether a given unknown function is constant or balanced. A unknown function takes an input and produces an output based on an underlying rule that is not known to the algorithm. In the case of the Deutsch problem, the function takes as input a string of bits and produces a single-bit output. In the classical world, to determine if an unknown function is constant or balanced, one would need to query the function twice: once with input 0 and once with input 1. This would require two function evaluations. However, Deutsch's algorithm solves the problem using a single function evaluation on a quantum computer, offering a speedup over the classical method.

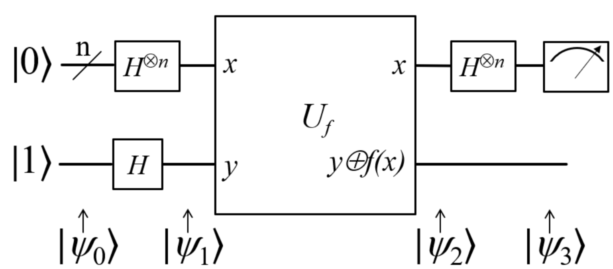


Figure 6: Quantum circuit for Deutsch-Jozsa algorithm. $|\psi_i\rangle$ shows the qubit state after each operation and for a given $f(x)$, provided we have the function f implemented as a quantum oracle, which maps the state $|x\rangle|y\rangle$ to $|x\rangle|y \oplus f(x)\rangle$, where $\oplus$ is addition modulo 2.

There are several other types of quantum algorithms, each designed to solve specific types of problems more efficiently than classical algorithms. For example: Quantum Simulation Algorithms simulate quantum systems more accurately and efficiently than classical simulations [46]; Quantum optimization algorithms, such as the Quantum Approximate optimization Algorithm (QAOA) to find the best solution among a large number of possible options [47]; Quantum factorization algorithms, like Shor's algorithm, provide exponential speedup over classical algorithms for factoring large numbers [6]; Quantum search algorithms, like Grover's algorithm, are designed to perform faster searches on unstructured databases compared to classical search algorithms [48]; Quantum Machine Learning Algorithms to improve pattern recognition, data analysis, and optimization tasks within the field of machine learning, potentially providing speedup or enhanced performance in certain cases [19]; Quantum communication algorithms for secure transmission of information using quantum properties, such as quantum key distribution [49].

4. Quantum Computing for Space Technology

In this section, we identify the major domains in space technology that could be the best fit for the application of quantum computing. We present a framework to apply quantum computing to the identified problems. In general, we chose the approach described below to apply quantum computing to space technology:

4.1. Quantum Encoding

The process of converting data, whether classical or quantum, into the state of a collection of input qubits. It plays a critical role in using quantum algorithms to solve a classical problems such as problem from space technology. It is the initial step for execution of any quantum computation task that processes the input data. Every algorithm assumes a specific data encoding and subsequently conducts computations on the data. The loading process run-time is influenced by both the chosen encoding and the data itself. Loading can take an exponential amount of time in the worst-case scenario. The criticality of this matter lies in the fact that quantum algorithms, which offer the potential for acceleration, require that the process of loading data can be executed at a faster rate, either in logarithmic or linear time. Encoding data in qubits is not simple. Number of required qubits and the run-time complexity for the encoding process are the critical part of quantum ending. Current devices have a finite number of stable qubits. Because qubits decay quickly and quantum gates are prone

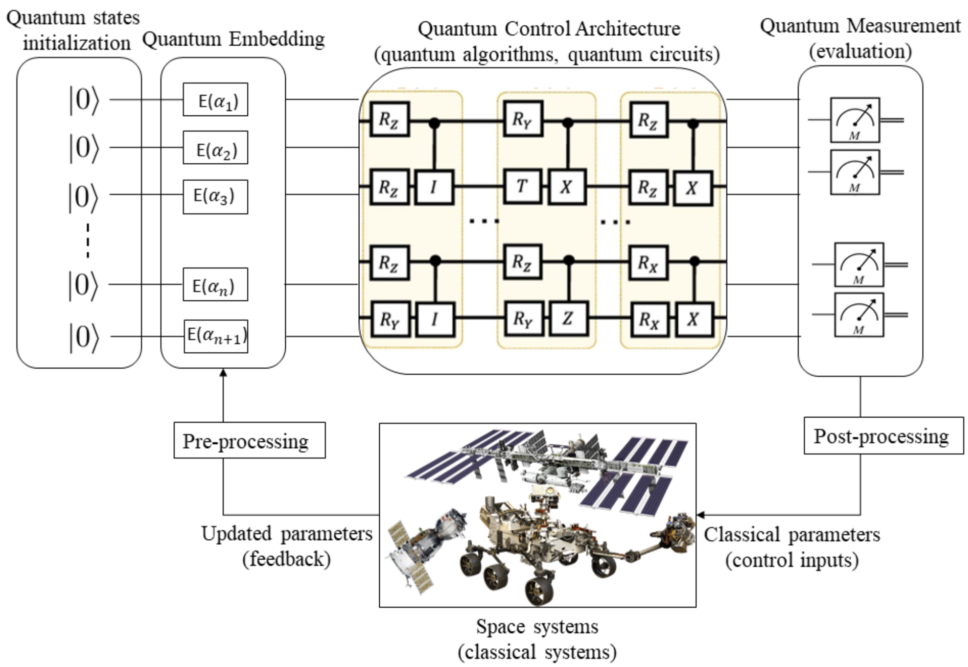


Figure 7: Exemplary illustration of proposed approach for quantum computing-based space system control architecture. Using quantum embedding techniques, the initial parameters are encoded into quantum states. The specifically designed quantum algorithm is used to perform unitary operations on these encoded states. Finally, during the measurement phase, the quantum states collapsed to provide classical control outputs for the space systems.

to errors, the number of actions required to prepare the quantum state must be kept to a minimum. A logarithmic or linear run-time is appropriate for efficiently encoding even a large number of data items. Quantum encoding is a challenging task because of the constraints imposed by quantum mechanics law such as no cloning property which states that a single quantum object cannot be replicated, which complicates the encoding schemes. Quantum embedding is one of the means by which data is encoded. Quantum embedding represents classical data as quantum states in a Hilbert space via a quantum feature map. Few of the embedding methods used are amplitude embedding, basis embedding, and many more. Few of them are described in the next subsection along with their use cases in space technology:

4.1.1. Basis Encoding

The encoding of classical information into a quantum state through basis encoding is widely regarded as the most straightforward and easily comprehensible method. It links each classical input with a computational basis state of a qubit system. It encodes an n-bit binary string x to an n-qubit quantum state $|x\rangle = |i_x\rangle$, where $|i_x\rangle$ is a computational basis state. The quantum state that is embedded refers to the translation of a binary string into the corresponding states of the quantum subsystems, on a bit-wise basis. Basis encoding is typically employed when real numbers must be mathematically altered in the course of quantum computations. In the computational basis, such an encoding depicts real numbers as binary numbers before transforming them into a quantum state.

Let's consider classical input dataset $\mathcal{X}$ consisting of M examples, with N features each, $\mathcal{X} = x^{(1)}, \ldots, x^{(l)}, \ldots, x^{(M)}$, where $x^{(l)}$ is a N-dimensional vector for $m = 1, \ldots, M$. $x^{(l)} = (b_1, \ldots, b_n)$ with each $b_i \in 0, 1$ for $i = 1 \ldots N$. The entire classical dataset $\mathcal{X}$ can be encoded in quantum superpositions of computational basis states as

$$|\mathcal{X}\rangle = \frac{1}{\sqrt{M}} \sum_{m=1}^{M} \left| x^{(m)} \right\rangle \tag{4}$$

As an example, let's consider 6D pose of spacecrafts. The 6D pose of a spacecraft refers to its relative position and orientation in 3D space. It consists of three components representing the spacecraft's position and three components representing its orientation. The position is commonly described using three Cartesian coordinates (x, y, z), while the orientation is commonly represented by Euler angles (ψ, θ, ϕ) or quaternion parameters $\tilde{\boldsymbol{q}} = \begin{bmatrix} q_1 & q_2 & q_3 & q_4 \end{bmatrix}$. It can be computationally demanding, especially for real-time applications that require fast and accurate pose updates. The computational complexity for processing the 6D pose of a spacecraft depends on various factors, including the specific algorithms and techniques used for processing, the complexity of the sensor data, the desired accuracy, and the computational resources available onboard.

The inherent complexity and computational challenges associated with classical methods make 6D pose estimation an ideal candidate for quantum computing applications. Let's encode a 6D pose data of spacecraft into qubits. Consider two vectors $\tilde{\boldsymbol{p}} = \begin{bmatrix} x & y & z \end{bmatrix}$ and $\tilde{\boldsymbol{o}} = \begin{bmatrix} \psi & \theta & \phi \end{bmatrix}$, which represent the spatial and angular configuration of the spacecraft. The corresponding basis encoding uses three qubits to represent as

$$|\Psi\rangle = \frac{1}{\sqrt{2}}|xyz\rangle + \frac{1}{\sqrt{2}}|\psi\theta\phi\rangle \tag{5}$$

where, $|xyz\rangle$ and $|\psi\theta\phi\rangle$ will take the form depending on the nature of $\tilde{\boldsymbol{p}}$ and $\tilde{\boldsymbol{o}}$ vectors. Let us consider $\begin{bmatrix} \psi & \theta & \phi \end{bmatrix} = \begin{bmatrix} -0.2 & 0.1 & 0.3 \end{bmatrix}$ and $\begin{bmatrix} x & y & z \end{bmatrix} = \begin{bmatrix} 0.7 & -0.6 & 0.8 \end{bmatrix}$. It is necessary to initially convert the given data into a binary sequence. This involves a binary fraction representation with a precision level of $\tau = 4$, with the first bit serving to encode the sign. The quantum superpositions of computational basis states for the 6D pose of the spacecraft can be written as:

$$|\Psi\rangle = \frac{1}{\sqrt{2}}|010111100101100\rangle + \frac{1}{\sqrt{2}}|100110000100100\rangle \tag{6}$$

4.1.2. Amplitude Encoding

In the amplitude encoding, amplitudes of the quantum system are used to represent data values. A quantum system is described by its wave-function Ψ which also defines the measurement probabilities. The utilisation of amplitude encoding is an essential requirement for numerous quantum machine learning algorithms. The main advantage of utilising amplitude encoding is that a dataset comprising M inputs, each with N features, can be encoded using only $n = \log(MN)$ qubits. A normalized classical N dimensional datapoint x is represented by the amplitudes of a n-qubit quantum state $|\psi_x\rangle$ as

$$|\psi_x\rangle = \sum_{i=1}^{N} x_i |i\rangle \tag{7}$$

where $N = 2^n, x_i$ is the i-th element of x, and $|i\rangle$ is the i-th computational basis state. Let's consider the same classical dataset $\mathcal{X}$ which was considered in the previous case. The conversion of the given information into quantum information can be achieved through amplitude encoding as well. Its amplitude embedding can be easily understood if we concatenate all the values $x^{(m)}$ together into one vector, i.e.,

$$\alpha = C_{norm} x_1^{(1)}, \ldots, x_N^{(1)}, \ldots, x_1^{(M)}, \ldots, x_N^{(M)}$$

where C_{norm} is the normalization constant; this vector must be normalized $|\alpha|^2 = 1$. The corresponding quantum information can be represented in the computational basis as

$$|\mathcal{X}\rangle = \sum_{i=1}^{2^n} \alpha_i |i\rangle, \tag{8}$$

where α_i are the elements of the amplitude vector α and $|i\rangle$ are the computational basis states. The number of amplitudes to be encoded is $N \times M$.

Consider the four-dimensional quaternion vector $\tilde{\boldsymbol{q}} = \begin{bmatrix} 0.625 & 0.3 & 0.4 & -0.6 \end{bmatrix}$, we want to encode it using amplitude embedding. The first step is to normalize it, i.e., $q_{norm} = 1$. The corresponding amplitude encoding uses two qubits to represent q_{norm} as

$$|\psi_q\rangle = 0.625\,|00\rangle + 0.3\,|01\rangle + 0.4\,|10\rangle - 0.6\,|11\rangle \tag{9}$$

4.1.3. Angle Encoding

In angle encoding, the phase information of quantum states is used to encode the classical data. In angle encoding, the phase information of quantum states is used to encode the classical data. In angle encoding, the phase information of quantum states is used to encode the classical data. This type of encoding is important for processing data in quantum neural networks. Angle encoding is performed by applying a gate rotation about the $x-axis$ $R_x(\mathcal{X})$ or $y-axis$ $R_y(\mathcal{X})$, where $\mathcal{X}$ is the value to encode.

$$|\mathcal{X}\rangle = \bigotimes_{i}^{n} R\left(\mathbf{x}_i\right)|0^n\rangle \tag{10}$$

where R can be one of $R_x, R_y R_z$. Consider the amplitude encoding example if we want to encode the corresponding quaternion $\tilde{\boldsymbol{q}} = \begin{bmatrix} 0.625 & 0.3 & 0.4 & -0.6 \end{bmatrix}$ in angle encoding. We can individually represent a qubit corresponding to each queternion as

$$\begin{bmatrix} \cos(0.625)|0\rangle \\ \sin(0.625)|1\rangle \end{bmatrix}$$

Similarly, angle encoding rotates every qubit around $X - axis$ (if we choose R_x) for degree equal to the each quaternion. The corresponding quantum state can be written as

$$\bigotimes_{i=1}^{4} R_y\left(x_i\right)|1111\rangle \tag{11}$$

Aside from the strategies mentioned above, there are several other encoding techniques that can be used to encode classical information into qubits. Such as Instantaneous Quantum Polynomial or IQP style quantum encoding, Hamiltonian Evolution Ansatz Encoding etc. It is worth mentioning that all of the embedding techniques uses a specific method or formula for encoding. For example with IQP, a classical dataset $\mathcal{X}$ can be encoded in qubits as follows

$$|\mathcal{X}\rangle = \left(\mathrm{U_Z}(\mathbf{x})\mathrm{H}^{\otimes n}\right)^r |0^n\rangle \tag{12}$$

where r is the depth of the quantum circuit, indicating the repeating times of $U_Z(\mathbf{x})\mathrm{H}^{\otimes n}$. $\mathrm{H}^{\otimes n}$ represents a layer of Hadamard gates acting on all qubits. $\mathrm{U_Z}(\mathcal{X})$ plays a vital role in IQP encoding scheme and can be expressed as:

$$\mathrm{U_Z}(\mathcal{X}) = \prod_{[i,j]\in S} R_{Z_i Z_j}\left(x_i x_j\right) \bigotimes_{k=1}^{n} R_z\left(x_k\right) \tag{13}$$

where, S is the set containing all pairs of qubits to be entangled using R_{ZZ} gates. First, we consider a simple two-qubit gate: $R_{Z_1 Z_2}(\theta)$. Its mathematical form $e^{-i\frac{\theta}{2}Z_1\otimes Z_2}$ can be seen as a two-qubit rotation gate around ZZ, which makes these two qubits entangled.

4.2. Quantum control architecture

The overall structure and organisation of the systems and components responsible for guiding and managing the spacecraft's operations is referred to as the control architecture. It consists of a number of subsystems and functions that coordinate to ensure the spacecraft's stability, attitude control, trajectory, and overall mission objectives. It provides a framework for implementing control algorithms, coordinating system components, and managing the flow of information. When designing a control architecture, basic arithmetic operations play a crucial role such as system modeling, controller design, and performance analysis. Similar to classical computing, in quantum computing, an adder is a fundamental building blocks for quantum control architecture which performs addition of quantum states.

Quantum addition circuits are mainly classified into two kinds: 1) Toffolli-adder circuits, which employ solely classical reversible gates (CNOT and Toffoli), and 2) QFT-adder circuits, which use the quantum Fourier transformation. The QFT transfers a quantum state from the time domain to the frequency domain, allowing frequency components and phase information to be extracted. QFT-adders are considered to be NISQ-compatible due to their depth and gate counts [50]. In QFT-adder circuits, the QFT is applied to the input quantum states that represent the numbers to be added. By conducting the QFT on these states, the Fourier amplitudes corresponding to the sum of the numbers can be derived. This enables for parallel computation and can provide speed advantages for certain applications. The circuit for QFT-adder are shown in Figure. 8.

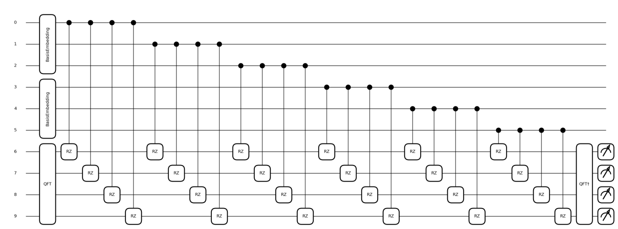


Figure 8: Quantum circuit for 6-qubits QFT-adder. The initial qubits from 0 to 6 are to be added while 7 to 10 qubits are for the measurement purpose.

As shown in Figure.8, a sequence of quantum gates applied to the set of input qubits during process while the QFT and Inverse-QFT are only applied on qubits to be measured. Similarly, a QFT-based multiplier circuits can be described for the multiplication of quantum states. The circuit for QFT-adder are shown in Figure. 9.

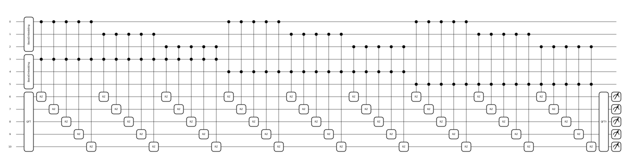


Figure 9: Quantum circuit for 6-qubits QFT-multiplier. The initial qubits from 0 to 6 are to be multiplied while 7 to 10 qubits are for the measurement purpose.

Note that both QFT-adder as well as QFT-multiplier takes $|0\rangle$ or $|1\rangle$ computational basis of the quantum states as their inputs. Therefore, it is necessary to convert the classical states into the corresponding quantum states. We have already discussed about various quantum embedding techniques along with their working principles in Section. 4.1. As both of the operation requires computational basis as their inputs therefore Basis Encoding (as described in Section. 4.1.1) could be the best fit. It encodes a classical input with a computational basis state of a qubit system. Once we have classical states in $|0\rangle$ or $|1\rangle$ computational basis and basic arithmetic quantum circuit, we can proceed to design the control architecture.

Proportional-Integral-Derivative (PID) controllers have found extensive use in various applications within space technology such as Spacecraft Attitude Control, Thruster Control, Solar Array Tracking and Temperature Control. PID controllers provide a balance of simplicity and efficiency in controlling various subsystem of space technology. Their widespread use in aerospace applications is a evidence to their robustness, flexibility and ability to deliver precise power in dynamic and complex space environments. A PID controller is a control algorithm that utilizes feedback to regulate a system's behavior. It consists of three components: Proportional (P) Control, Integral (I) Control and Derivative (D) Control. A simple time-domain PID controller can be represented as:

$$u(t) = K_p \times e(t) + K_i \times \int_0^t e(t)dt + K_d \frac{d}{dt} e(t) \quad (14)$$

where $u(t)$ is the control output to be implemented to the plant in order to compensate the error $e(t)$ where $e(t) = r(t) - y(t)$ and K_p, K_i and K_d are the constant gains for the proportional, integral and derivative components of the controller respectively.

Approximating the integral and the derivative terms to get the discrete form, using:

$$\begin{aligned} &\int_0^t e(t)dt\sigma \approx \sum_{k=0}^{n} e(k) \\ &\frac{de(t)}{dt} \approx \frac{e(n) - e(n-1)}{T} \\ &t = nT \end{aligned} \quad (15)$$

Where n is the discrete step at time t. It can be represented as:

$$u(n) = K_p e(n) + K_i \sum_{k=0}^{n} e(k) + K_d(e(n) - e(n-1)) \quad (16)$$

Where:

$$K_i = \frac{K_p T}{T_i} \quad K_d = \frac{K_p T_d}{T}$$

We can design corresponding Quantum-PID (QPID) by utilizing the QFT-adder and multiplier. Each component of the discrete PID can be modelled separately and ultimately they can be integrated together.

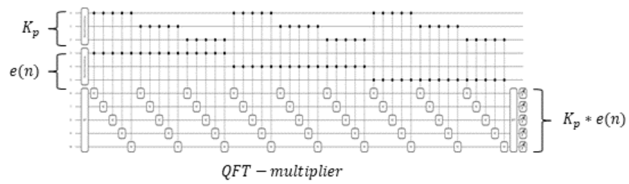


Figure 10: Quantum circuit for Proportional control.

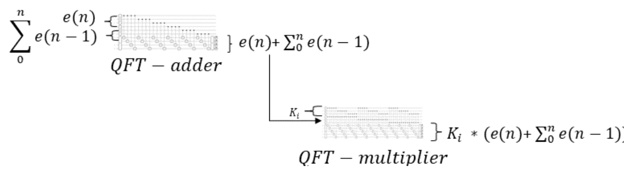


Figure 11: Quantum circuit for Proportional control.

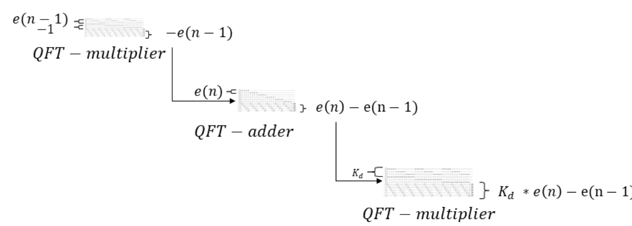


Figure 12: Quantum circuit for Derivative control.

$$\begin{aligned} &Proportional\ Control : K_p * e(n) \\ &Integral\ Control : K_i * (e(n) + \sum_0^n e(n-1)) \\ &Derivative\ Control : K_d * (e(n) - e(n-1)) \end{aligned}$$

Similarly, quantum logic gates can be used to design other complex control techniques for space technology such as Model Predictive Control (MPC), Adaptive Control, Sliding Mode Control (SMC), Linear Quadratic Regulator (LQR) and Linear Quadratic Gaussian (LQG) control.

4.3. Quantum Optimization

The implementation of quantum computing principles and algorithms to solve optimization problems more effectively than classical computing approaches is referred to as quantum optimization. Quantum optimization algorithms leverage the properties of

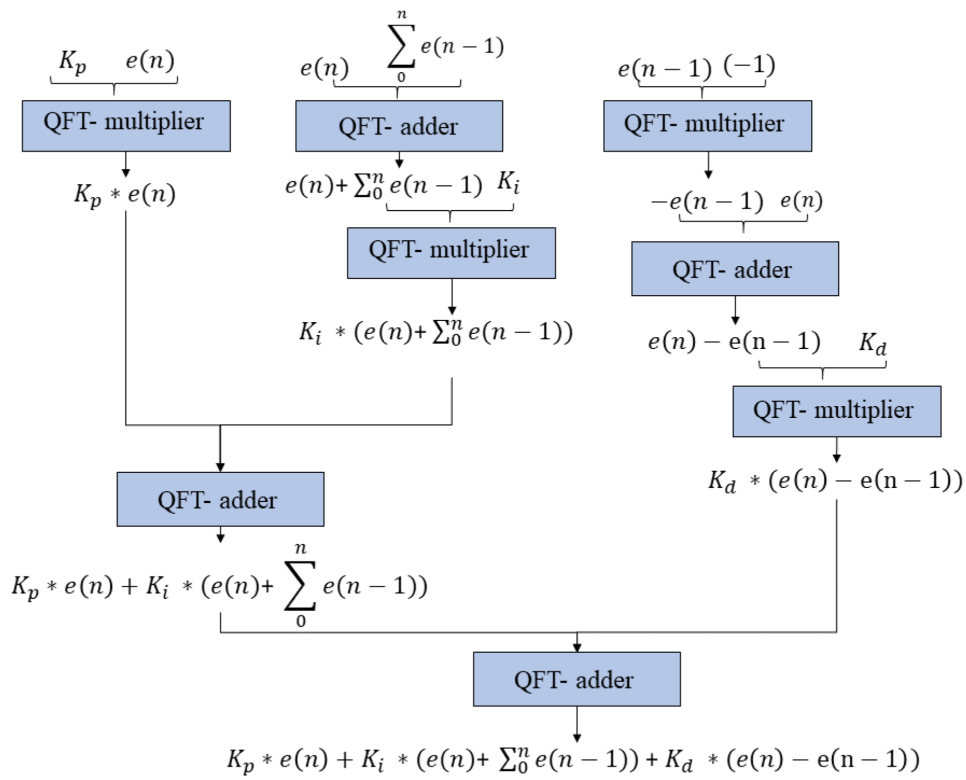


Figure 13: Illustration of quantum computing based Proportional-Integral-Derivative (QPID) controller.

quantum mechanics, such as superposition and entanglement, to explore and evaluate multiple optimized solutions simultaneously. Quantum optimization has the potential to optimize complex problems that seems infeasible or time-consuming for classical computers. There are several quantum optimization techniques such Quantum Approximate Optimization Algorithm (QAOA), Quantum Annealing, Quantum Variational Optimization, Quantum Walks, Adiabatic Quantum Optimization. There exist several optimization problems which are impossible or computational intensive to solve with classical computers in space technology such as Satellite Scheduling Problem, Satellite Constellation Design, Launch Vehicle Payload Integration, Mission Planning and Resource Allocation, Trajectory Optimization, Spacecraft Routing Problem, Satellite Network Design, Orbital Slot Assignment, Mission Sequencing Problem. In the next subsections, a few of the quantum optimization techniques are described along with their use cases in space technology.

Let us discuss QAOA and its applications in space technology. The Quantum Approximate optimization Algorithm (QAOA) is a quantum optimization algorithm that can run on present day NISQ devices and has a wide range of applications [47]. It was proposed by Edward Farhi in 2014, and its goal is to approximate the solution of combinatorial optimization problems. Many combinatorial optimization problems are NP-complete or even NP-hard, implying that classical computers may be unable to solve them efficiently. A more efficient technique is to identify the approximate optimal solution to such situations.

QAOA can find an approximate optimal solution of such combinatorial optimization problem.

In the initial step of QAOA, a cost Hamiltonian H_C and a mixer Hamiltonian H_M is formulated based on the nature of the problem such that the ground state of H_C encodes the optimized solution to the given problem while the ground state of H_M should be easily preparable state. Then the circuits corresponding to $e^{i\alpha_n H_M}$ and $e^{i\gamma_n H_M}$ are constructed known as cost and mixer layers with some parameters α and γ respectively. An operator $U(\gamma, \alpha)$ is prepared with the repeated application of the cost and mixer layers with repeating parameter $n \geq 1$ as shown below:

$$U(\boldsymbol{\gamma}, \boldsymbol{\alpha}) = e^{-i\alpha_n H_M} e^{-i\gamma_n H_C} ... e^{-i\alpha_1 H_M} e^{-i\gamma_1 H_C} \quad (17)$$

n is also known as depth of the QAOA circuit. An initial state $|\psi_0\rangle$ is prepared and $U(\boldsymbol{\gamma}, \boldsymbol{\alpha}$ is applied on this state. A classical optimization technique is used to optimize the parameters $\boldsymbol{\gamma}, \boldsymbol{\alpha}$. For some value of

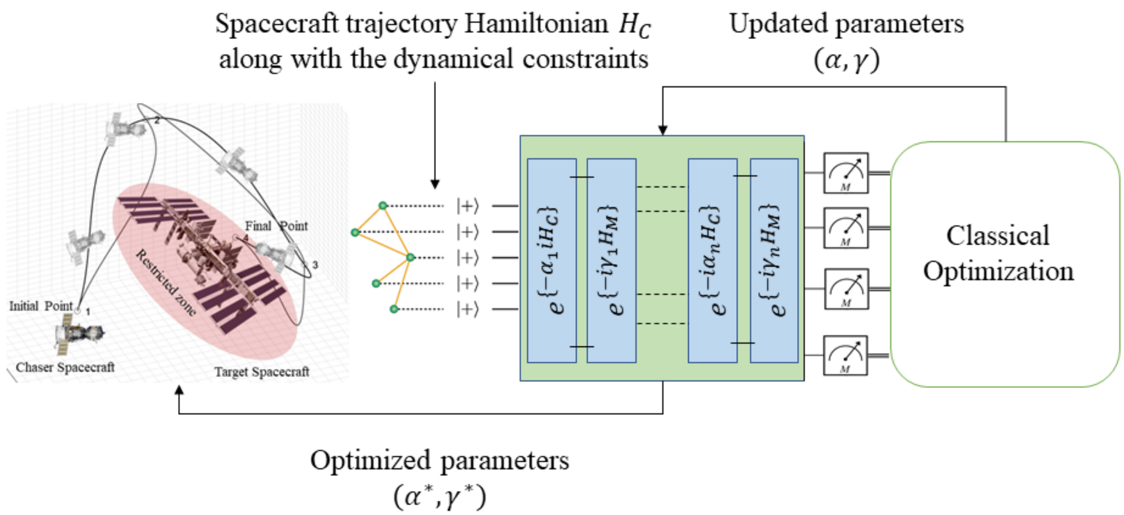


Figure 14: A quantum-classical architecture showing the application of Quantum Approximate optimization Algorithm (QAOA) for the spacecraft trajectory optimization.

optimal parameters $\boldsymbol{\gamma}^*, \boldsymbol{\alpha}^*$, it represents the ground state of H_C. Once the circuit has been optimized, measurements of the output state reveal approximate solutions to the given optimization problem. In summary, the formulation of cost and mixer Hamiltonians is the beginning step for QAOA. We then employ time evolution and layering to build a variational circuit and optimise its parameters. The process concludes with measurement from the circuit to obtain an approximate solution to the optimization problem.

Consider a simple spacecraft trajectory and model H_C which can be optimized with QAOA, the corresponding trajectory can be also modelled as:

$$H_C = \sum [L(x(t), y(t), z(t)) + \lambda(t)^T G(x(t), y(t), z(t), u(t))] \tag{18}$$

where, H_C represents the Hamiltonian i.e, the total energy or cost of the spacecraft trajectory. L represents the Lagrangian term, which represents the immediate cost or penalty associated with the spacecraft's state variables (position, velocity, etc.) and control inputs (maneuvers, thrust, etc.) at each time step t. $\lambda(t)$ represents the costate or Lagrange multiplier, which is associated with the dynamic constraints or state equations that govern the motion of the spacecraft. It is used to enforce the constraints, such as collision avoidance (e.g., where the constraint is that the signed distance between the spacecraft's geometry and the obstacles stays positive). G represents the dynamic constraint equations that describe the spacecraft's motion, linking the state variables (position, velocity, etc.) and control inputs (maneuvers, thrust, etc.) at each time step t. These constraints relate the current state and control inputs to the derivatives or rates of change of the state variables. It includes equations of motion, kinematic relationships, and other physical or operational constraints. The Lagrangian term L typically includes components that capture the desired behavior or performance criteria, such as distance from a target position, fuel consumption, time, etc. This term represents the immediate cost or penalty associated with the current state and control inputs. The costate or Lagrange multiplier $\lambda(t)$ is introduced to enforce the dynamic constraints or state equations that govern the spacecraft's motion.

The Hamiltonian H_C represents the sum of the immediate costs captured by the Lagrangian term L and the penalties associated with enforcing the dynamic constraints through the Lagrange multiplier $\lambda(t)$ and the dynamic constraint equations G. Depending on the mission objective and constraints, the Lagrangian term L, costate $\lambda(t)$, and dynamic constraint equations G will vary. By optimizing the Hamiltonian, one can find the optimal trajectory that minimizes the overall cost or maximizes a desired performance criterion.

Most of the other quantum optimization algorithms work in a similar structure as described by the quantum-classical architecture in the Figure.14. A Hamiltonian corresponding to the system must be modelled along with the dynamical constraints and penalties imposed on it. Some of the potential applications of quantum optimization algorithms for addressing optimization problems encountered in diverse areas of space technology are presented in the

Use Case in Space Technology	Quantum Optimization Algorithms
Trajectory Optimization	*Quantum Approximate Optimization Algorithm (QAOA)*: Involves defining objective functions and constraints, mapping it onto the QAOA framework, designing a quantum circuit, and iteratively updating parameters. *Quantum-Inspired Genetic Algorithm (QIGA)*: Involves chromosome encoding, quantum-inspired genetic operations, fitness evaluation, genetic evolution, and convergence and solution analysis. It considers mission requirements, fuel consumption, travel time, radiation exposure, and natural evolution. *Quantum Annealing*: Involves mapping to the Ising model. The goal is to minimize energy and find the ground state of the optimized spacecraft trajectory. Translate the problem formulation into a Hamiltonian, which governs the annealing process. After completing the process, post-process and analyze the obtained solution to extract the optimized trajectory.
Routing and Scheduling	*Quadratic Unconstrained Binary Optimization (QUBO)*: Involves defining variables, objective functions, and constraints. The objective function captures optimization goals, while constraints capture communication requirements, data relay, and task coordination. The problem is converted into a binary quadratic equation, and solved using classical solvers or quantum annealing hardware. *Quantum-inspired Particle Swarm Optimization (QPSO)*: Formulate the spacecraft routing and scheduling problem as an optimization problem, using particles as potential solutions. Initialize particles, update positions using classical and quantum-inspired mechanisms, evaluate fitness, track global best, introduce quantum-inspired techniques, and iteratively optimize.
Mission Planning	*Quantum-enhanced reinforcement learning (QRL)*: Encode states and actions using quantum-inspired techniques, design a quantum circuit for policy learning, simulate environment dynamics, enhance exploration and exploitation, optimize policy and reinforcement learning objectives, and evaluate the effectiveness of the policy. *Quantum Approximate Optimization Algorithm (QAOA)*: Formulate spacecraft mission planning as an optimization problem considering objectives, constraints, resources, and requirements. Map the problem onto the QAOA framework, design a quantum circuit, and execute the QAOA algorithm iteratively to find the optimal mission plan. Post-process and analyze the optimized plan for feasibility, scalability, and performance.
Onboard Power Management	*Quantum-inspired Simulated Annealing (QISA)*: Initialize the system with an initial power allocation and usage configuration, use quantum-inspired perturbation to introduce exploratory changes, evaluate energy, perform simulated annealing iterations, control cooling schedule, and analyze solutions. Quantum-inspired simulated annealing techniques incorporate quantum-inspired concepts within classical optimization algorithms, resulting in performance improvements depending on the problem's complexity.

Table 1: The following table presents some of the potential applications of quantum optimization algorithms for addressing optimization problems encountered in diverse areas of space technology.

Table. 1. The quantum optimization algorithms are generally used to find the ground state of the problem hamiltonian which in turn provides the optimized solution of the system. Some quantum optimization algorithms accept a specific type of Hamiltonian known as *Ising Hamiltonian*. The Ising Hamiltonian is widely used in the field of optimization, particularly in the context of Ising models and quantum annealing. It represents the energy or cost function associated with the system composed of interacting spins or qubits. Any general hamiltonian can be modelled as the *Ising Hamiltonian* with little modification.

4.4. Quantum Machine Learning

Quantum Machine Learning (QML) is an interdisciplinary field that blends the concepts of quantum physics and machine learning to generate novel algorithms and approaches for data analysis and pattern recognition [51, 52]. It aims to harness the power of quantum computing to enhance and speed up traditional machine learning tasks by utilising quantum parallelism and quantum entanglement.

Quantum machine learning methods, including quantum kernel methods, involve a quantum embedding of classical data and evaluation of an objective function applied to the embedding. The aim is to ascertain whether a quantum advantage exists in a particular problem that the objective function describes. A rigorous test was conducted by *Google Quantum AI* [53] to compare a quantum embedding, kernel, and data set to classical kernels, assessing potential quantum advantage across objective functions. A geometric constant g is defined, which quantifies the amount of data that could theoretically close the gap. This technique helps determine if a quantum solution is right for a given problem based on data constraints. The geometric test revealed that existing quantum kernels often had memorization-based geometry, leading to the development of a projected quantum kernel. This representation allows for better integration with classical non-linear kernels, allowing for a better description of non-linear functions, reduced resource consumption, and better generalization at larger sizes as shown in Figure. 15. This approach also expands the geometric g, ensuring the greatest potential for quantum advantage.

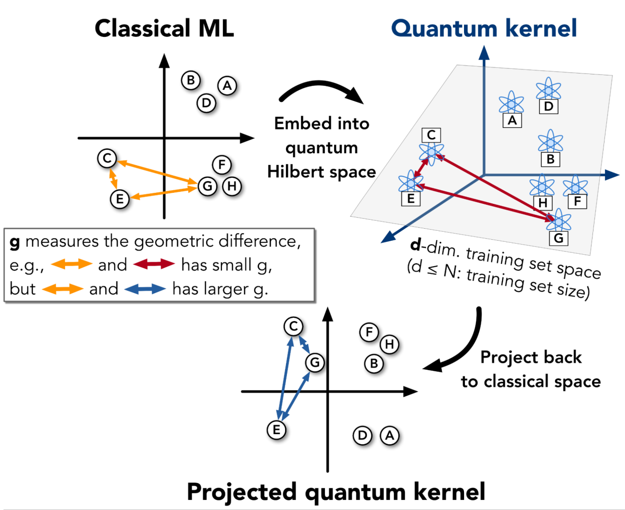


Figure 15: Illustration of projected quantum kernel approach proposed in [53].

Machine learning typically involves handling a vast amount of data and designing algorithms that are able to handle and process these datasets rapidly. A n-classical bit register can only store a n-size binary string, whereas a n-qubit register can store a 2^n n-size binary string by encoding the information in the amplitudes as described in Section 4.1.2. Therefore, quantum registers possess a significantly higher capacity to process data compared to classical registers. However, the extraction of multiple strings poses a significant challenge due to the phenomenon of state collapse during measurement, resulting in the retrieval of only a single amplitude or string. However, these qubits possess inherent parallelism, enabling the development of algorithms capable of simultaneously processing all 2^n strings. This parallel processing capability yields an exponential improvement in computational speed compared to classical algorithms.

There exist four distinct strategies for integrating machine learning and quantum computing, which depend on the classification of the data source as either classical (C) or quantum (Q), as well as the computational system employed for data processing, classified as either classical (C) or quantum (Q) as depicted in the Figure.16. (i) The Classical-Classical approach (CC) involves utilising classical algorithms that have been influenced by the principles of quantum mechanics, quantum processing, or quantum information. These algorithms are commonly referred to as quantum-inspired algorithms. They are designed to be implemented on classical computers and operate using classical data. (ii) The Classical-Quantum approach (CQ) involves the application of quantum machine learning algorithms to classical data in order to achieve efficient machine learning tasks. In general, the objective is to explore quantum renderings of classical machine learning techniques and existing quantum algorithms. The aim is to identify approaches that can effectively perform machine learning tasks and offer quantum advantages over classical algorithms. (iii) The Quantum-Classical approach (QC) involves the application of classical machine learning methods and algorithms to quantum data, enabling quantum computers to acquire knowledge and extract meaningful information from this data. (iv) The Quantum-Quantum approach (QQ) is a theoretical framework that is used to analyse and understand quantum phenomena. This approach involves the use of both quantum algorithms and quantum data. In essence, the QML algorithms engage in the manipulation of quantum states with the purpose of comprehending the fundamental patterns and acquiring knowledge about the data.

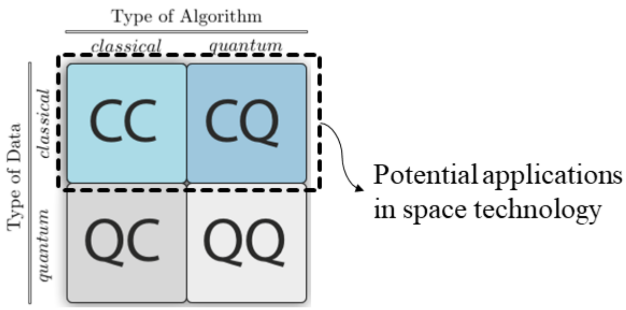


Figure 16: Illustration of four distinct ways to combine the fields of quantum computing and machine learning, along with categories marked that have potential applications in space technology. The first letter indicates whether the system under study is classical or quantum, while the second letter specifies whether a classical or quantum information processing unit is used.

In the field of space technology, there exist classical systems that employ two out of four techniques, namely CC and CQ, which have proven to be highly valuable. Based on the Quantum inspired machine learning (CC Approach), Quantum Inspired Neural Networks (QNNs) with Quantum computing and a multi-agent system were proposed, which resulted in a quicker training time due to the tremendous parallel processing capacity [54]. Quantum Translations of machine learning algorithms (based on the CQ technique): This machine learning approach entails creating quantum counterparts of normal machine learning algorithms and applying them to machine learning issues. The advantage of this approach is that it can provide exponential speedup, where quantum k-means clustering is used, as well as better privacy because only an exponentially small percentage of data is analysed, hence improving data security.

QML algorithms possess an outstanding data handling capacity, rendering them suitable for diverse applications within the domain of space technology. These applications encompass Satellite Communication and Networking, Space weather prediction, disaster monitoring, Spacecraft GNC, Satellite Image Analysis, Astronomical Data Analysis, Space Debris Tracking, Collision Avoidance, Anomaly Detection and Fault Diagnosis, Space-based sensing and remote sensing.

Quantum machine learning (QML) possesses numerous potential applications in space technology, specifically in the domain of spacecraft image processing. Few of the potential applications are presented in the Table. 2. QML leverages the phenomenons of quantum mechanics in image processing that offers several potential benefits over classical image processing. Quantum computers possess the capability to execute specific calculations at a significantly faster pace compared to classical computers. Quantum algorithms intended for image processing tasks can take advantage of this increased computational capacity to process and analyse satellite photos more effectively. This can lead to faster image processing, enabling real-time or near-real-time analysis of the captured satellite data. Quantum superposition allows simultaneous processing of multiple image pixels or features, enabling parallel computation and accelerating pattern recognition tasks. This capability significantly improves both the effectiveness and speed of analysis, thereby facilitating the accurate analysis of spacecraft images. In contrast, quantum interference utilises the constructive or destructive interaction between quantum states to amplify signals corresponding to relevant patterns while suppressing noise or irrelevant features. The deliberate enhancement of significant patterns serves to enhance the accuracy and reliability of pattern recognition.

Additionally, quantum entanglement captures complex interaction among image pixels or features. By considering the interdependencies and correlations within the image data, quantum algorithms can achieve more accurate and robust pattern recognition. Entanglement facilitates the identification of hidden patterns and uncovers subtle relationships that may be challenging for classical algorithms to detect. Quantum algorithms can produce more accurate and resilient pattern identification by taking into account the interdependencies and correlations within image data. The phenomenon of entanglement enables the recognition of hidden patterns and reveals sophisticated connections that may be challenging for classical algorithm to detect. Let us briefly examine some of the potential benefits.

4.4.1. Quantum Encryption and Compression

The concept of quantum encryption and compression involves the process of transforming data into a low-dimensional representation of the corresponding quantum states. A variety of quantum image encryption and compression schemes have been proposed by researchers, including Qubit Lattice [55], Real Ket [56], Entangled Image [57], FRQI (Flexible Representation of Quantum Images) [58], NEQR (Novel Enhanced Quantum Representation of Digital Images) [59], GQIR (Generalised Quantum Image Representation) [60], JPEG based [61] and others. Let us see the compression and decompression in detail using JPEG based quantum algorithm.

QML Algorithms	**Potential applications in space technology**
Quantum Support Vector Machine (QSVM)	It could be used in space applications to categorise celestial objects, analyse satellite photos, and detect anomalies in telemetry data. The potential advantage of QSVM is its capacity to effectively compute kernel functions using quantum methods, which could lead to faster and more accurate classification.
Quantum Neural Networks (QNNs)	QNNs possess the capability to augment a wide range of space-related endeavours. The potential applications of it encompass pattern recognition in astronomical images, enhancement of satellite communication systems, and optimization of spacecraft control systems. Quantum neural networks (QNNs) have the capability to capture intricate quantum correlations, thereby exhibiting the potential to outperform classical neural networks in specific domains.
Quantum Clustering Algorithms	Quantum clustering algorithms have the potential to be utilised in the analysis of extensive datasets obtained from space missions, including satellite telemetry data and astronomical observations. Algorithms such as quantum k-means clustering have the capability to discern patterns, group data points that exhibit similarity, and extract significant information for various purposes, such as anomaly detection or data classification.
Quantum Data Compression	Quantum-inspired algorithms, such as Quantum Singular Value Decomposition (QSVD) and Quantum Principal Component Analysis (QPCA), have the potential to facilitate the compression of extensive quantities of satellite imagery, telemetry data, and scientific measurements. This compression capability would result in reduced storage demands and improved efficiency in data transmission processes.
Quantum Bayesian Networks	Bayesian networks are a type of probabilistic graphical model that is employed for the purpose of representing and conducting reasoning about uncertain relationships that exist among variables. Quantum Bayesian networks possess the potential to serve as effective tools for the modelling and analysis of intricate space systems. Their utilisation can facilitate various tasks, including fault diagnosis, risk assessment, and decision support, within the domains of satellite operations and space mission planning.
Quantum Kalman Filters and Quantum Particle Filters	Quantum Kalman Filters can help with the tasks like spacecraft navigation, space debris tracking, and satellite attitude determination. By fusing data from sensors like star trackers, IMUs, and GNSS, they can estimate spacecraft position, velocity, and attitude with greater precision, even in measurement noise or uncertainties. Quantum Particle Filters enhance state estimation in nonlinear and non-Gaussian systems. These filters can assist in localizing spacecraft or satellites, coordinate sensor measurements, and create accurate maps of surrounding terrain.
Quantum Feature Selection	Quantum feature selection algorithms, such as Quantum Mutual Information Maximisation (Q-MIM), have the potential to be utilised for the purpose of extracting informative features from space-related data. This application can prove beneficial in various tasks, including but not limited to anomaly detection, data classification, and dimensionality reduction.

Table 2: Table presents some of the potential applications of Quantum Machine Learning (QML) in space technology.

Consider a grey scale image as shown in Figure. 17. The initial step is to encode information using Discrete cosine transform. The image is split into blocks of 8×8 pixels, and each block (denoted as $f(i,j)$, $i = 0,1,\cdots,7, j = 0,1,\cdots,7$) undergoes the discrete cosine transform (DCT) to get frequency spectrum $F(u,v)$ as shown in Equation. 19.

$F(0,0)$ is the direct-current coefficient, and the bigger u and v, the higher frequency components $F(u,v)$. Although humans have excellent contrast sensitivity, we struggle to determine the precise magnitude of high-frequency variations in brightness. As a result, it is possible to drastically cut down on the data included in the high-frequency parts.

$$F(u,v) = c(u)c(v)\sum_{i=0}^{7}\sum_{j=0}^{7}\left\{f(i,j)\cos\left[\frac{(i+0.5)\pi}{8}u\right] \times \cos\left[\frac{(j+0.5)\pi}{8}v\right]\right. \tag{19}$$

where $u = 0,1,\cdots,7, v = 0,1,\cdots,7$, and

$$c(u) = \begin{cases} \frac{1}{2\sqrt{2}}, u = 0 \\ \frac{1}{2}, u \neq 0 \end{cases}$$

To accomplish this, we divide each frequency-domain component by its associated constant and round the results to the nearest integer. This process is known as Quantization. It is represented by 8×8 matrix in which the elements control the compression ratio, with larger values producing greater compression. The quantized DCT coefficients are computed as:

$$F_Q(u,v) = \text{round}\left(\frac{F(u,v)}{Q(u,v)}\right) \tag{20}$$

During quantization, many of the e higher frequency components are rounded to zero,and many of the rest become small positive or negative numbers, which take fewer bits to represent. Due to the truncation of numerous coefficients to zero values in the DCT image, the treatment of zero coefficients differs from that of non-zero coefficients. The data is encoded utilising a Run-Length Encoding (RLE) algorithm. The Run-Length Encoding (RLE) algorithm provides a measure of the number of consecutive occurrences of zero values in an image. The compression achieved by RLE is directly proportional to the length of these consecutive runs of zeros. One potential method for extending the duration of runs involves rearranging the coefficients within the zigzag sequence, as depicted in Figure 17. These coefficients are finally normalized and embedding into corresponding quantum states using amplitude encoding as described in Section. 4.1.2. As, we can encode 2^n classical input parameters in n-wire quantum circuits. Therefore, we require 5 wires to encode the 21 elements of final normalized vector. Hence, the proposed algorithm compressed 21 values to 5 values, resulting in 76%.

In order to decompress and retrieve the pixel values for the purpose of displaying the image on a screen, the inverse process is performed. At the end of each wire, a Pauli-Z measurement operator converts the embedded quantum data back to the classical domain. Rearrange the compressed data to 8×8 blocks and multiply each 8×8 block with the quantization matrix Q.

$$F'(u,v) = F_Q(u,v) \times Q(u,v) \tag{21}$$

Performing inverse DCT (IDCT) to each 8×8 block to get the recovered pixel value $f'(i,j)$:

$$f'(i,j) = \sum_{u=0}^{7}\sum_{v=0}^{7}\{c(u)c(v)F'(u,v) \times \cos\left[\frac{(i+0.5)\pi}{8}u\right]\cos\left[\frac{(j+0.5)\pi}{8}v\right] \tag{22}$$

where $i = 0,1,\cdots,7, j = 0,1,\cdots,7$, and

$$c(u) = \left\{ \begin{array}{c} \frac{1}{2\sqrt{2}}, u = 0 \\ \frac{1}{2}, u \neq 0 \end{array} \right\}$$

4.4.2. Quantum Convolutional Neural Network

The majority of image processing approaches make use of the Artificial Neural Network (ANN), notably the Convolutional Neural Network (CNN). In space technology, ANN and CNN have several applications such as anomaly detection [62], space debris detection [63], space object tracking [64], spacecraft pose estimation [65], spacecraft component detection [66] etc. Classical CNNs are a type of artificial neural network that can identify specific features and patterns in a given input. As a result, they are frequently utilised in image identification and audio processing. In CNN, the input image is processed by a succession of alternating convolutional (C) and pooling (P) layers, which recognise and associate patterns to a specific subclass. The final output is provided by fully connected layer (FC) supplies. QCNN exhibit analogous behaviour to classical CNN [67]. Initially, the pixelated image is encoded into a quantum circuit by employing a predetermined feature map. Following the encoding process of our image, we proceed to implement a sequence of alternating convolutional and pooling layers. Through the implementation of these alternating layers, the dimensionality of our circuit is diminished until it reaches a single qubit. The input image can be classified by evaluating the output of this remaining qubit. Parametrized circuits are present in each layer, allowing us to modify the

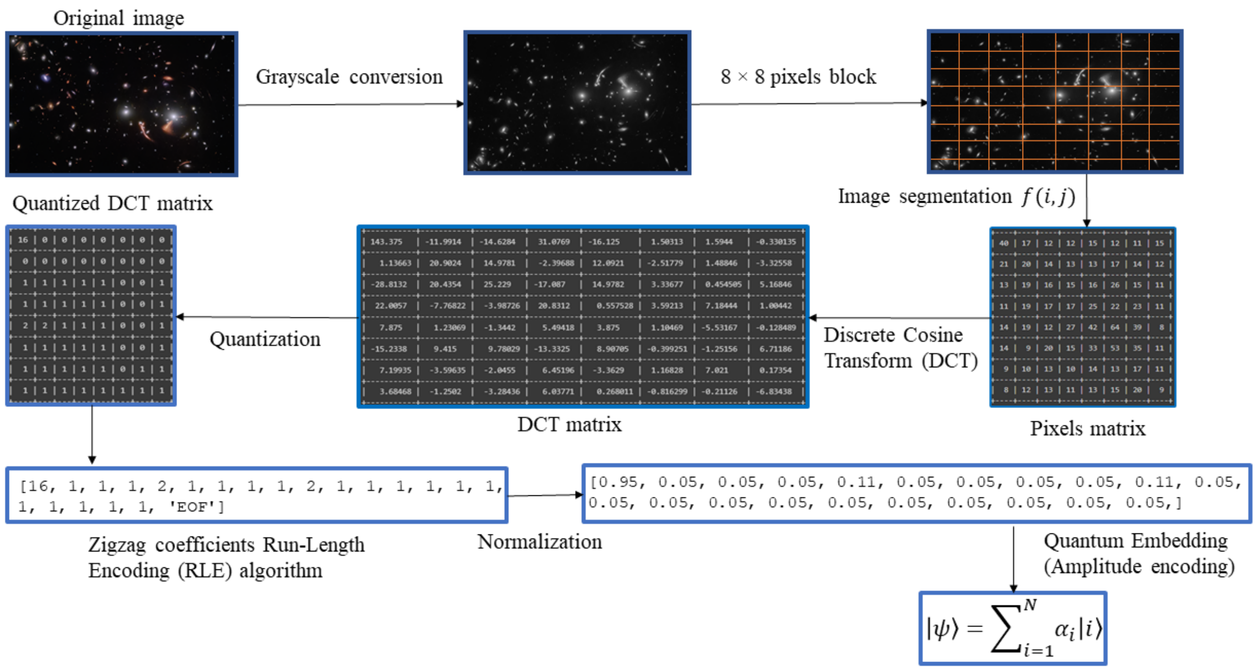


Figure 17: Illustration of Quantum Encryption and Compression architecture based on classical compression JPEG algorithm. The proposed algorithm compressed 21 values to 5 values, resulting in 76%.

final output by modifying the values of individual parameters. These settings are modified during QCNN training to minimise the loss function.

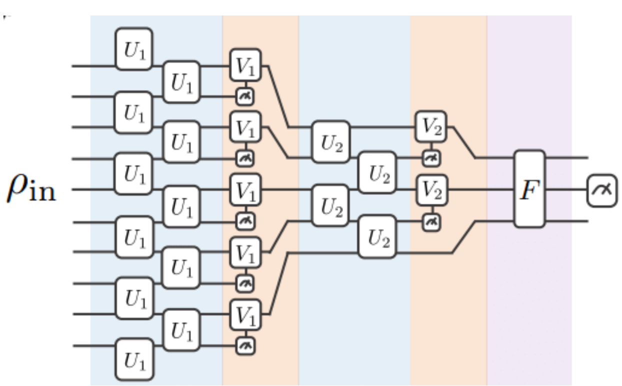


Figure 18: The QCNN architecture comprises a convolutional layer responsible for identifying new state, followed by a pooling layer that decreases the system's dimensions [67].

Let's do a conceptual analysis of using QCNN for spacecraft component detection. The initial step is to gather a dataset of spacecraft images with various components of interest. These photos can be captured by spacecraft cameras or received from other sources. Annotate the photos using bounding box coordinates or pixel-level labels to show the location of each component such as developed in [68]. The next step is quantum data encoding. Using quantum data encoding techniques, transform the input spacecraft photos into a quantum representation. This procedure turns visual input into a quantum state that can be processed by a QNN. To represent images in a quantum manner, many encoding approaches, such as amplitude encoding or quantum feature mapping as described in Section. 4.1. Then, construct the quantum convolutional layers of the QNN architecture. These layers use convolutions on quantum-encoded data to extract features and find patterns important to spaceship components. Quantum gates and circuits are used to execute convolution operations, capturing the quantum character of the data. Use quantum pooling procedures to lower the dimensionality of the feature maps created by convolutional layers. Quantum pooling approaches, such as quantum max pooling or quantum average pooling, can be used to downsample the features while keeping the quantum qualities. Create quantum classification layers to produce predictions and detect spaceship components. Quantum operations and measurements are used to extract the essential information from the quantum state and determine the presence and placement of the components within the images. The final step is to train the QNN by optimising the parameters of the quantum gates or circuits using quantum optimization techniques. Quantum algorithms, such as quantum gradient descent or variational quantum algorithms, can be used to update quantum parameters depending on a given cost function. The training approach seeks to minimise the discrepancy between anticipated component positions and ground truth annotations. Once trained, the QNN may be used to process new satellite photos and find the components of interest. The QNN analyses the quantum-encoded image data and outputs the expected locations or labels of the identified components.

4.5. Quantum implementation

In the field of classical information theory, the notion of the universal computer can be defined through various models that are equivalent in nature, each corresponding to distinct scientific methodologies. From a mathematical perspective, a universal computer refers to a device that possesses the ability to compute partial recursive functions. In the field of computer science, the Turing machine is commonly employed as the preferred conceptual model. Alternatively, an electrical engineer may refer to logic circuits, while a programmer is likely to favour a universal programming language [69]. These are fundamentally comparable in the framework of classical computation, producing the same outcomes yet relying on quite different underlying formalisms.

This oneness is less clear in the field of quantum computation. As an illustration, a quantum computer's fixedpoint algorithm might incorporate a superposition of all fixed points, not just the stable one achieved via repetitive replacement. This implies that various classical formalisms may generalise to the quantum domain in diverse ways. Multiple state-of-the-art models have been proposed for quantum computing. These models employs diverse approaches for the representation, manipulation, and execution of quantum information and computations. Some of the major models are Circuit models [70], Topological Model [71], Quantum Turing Machine (QTM) [72], QCL (quantum classical language) [73], Quantum annealing and annealers [74] and Quantum Hopfeld model [75].

The primary area of investigation in this present study relates to the quantum circuit model. In the following section, we will examine the topic in a comprehensive manner. The circuit model of quantum computation is one of the most extensively used and researched models. It represents quantum algorithms as a series of quantum gates applied to qubits. The functional and practical viability of quantum computers requires technology for the formalisation of a set of operators that is essential in mimicking quantum parallelism behaviour, thus a model for performing quantum algorithms mapping for the design of formalised quantum hardware schemes. The circuit model of quantum computation provides a versatile framework for building and implementing quantum algorithms. It permits precise control over the growth of qubits and the execution of complicated quantum calculations. It can be also utilised to create standard quantum processors and quantum chips.

In order to realise circuit-based quantum computing, it is crucial to develop dedicated hardware platforms for the purpose of manipulating and controlling qubits. The generation and sustaining of qubits, which serve as the fundamental components of quantum information, pose numerous difficulties owing to the delicate characteristics of quantum systems and their vulnerability to external disturbances [76]. There exist various challenges associated with the qubits, including but not limited to decoherence, error correction, scalability, qubit connectivity, and readout and measurement. Several qubit modalities are now being researched by industry and academia for quantum computing applications. These modalities include superconducting qubits, silicon quantum dots, trapped ions, neutral atoms, photonic qubits, nitrogen vacancy centers, and topological qubits.

Quantum chips envisioned for space technology applications must meet specific requirements due to the unique challenges and limits of the space environment. Considerations for quantum chips in space technology include radiation hardening, remote programming, power efficiency, size, weight, and integration as shown in Figure. 19. Photonic qubits are a promising strategy for developing quantum computing that takes advantage of the features of photons as qubits. While photonic qubits have distinct advantages such as reduced sensitivity to decoherence and the capacity to transport quantum information over great distances via optical fibres. A novel programmable nanophotonic chip hardware-software system has been recently introduced for the purpose of executing many-photon quantum circuit operations through the use of integrated nanophotonics as shown in Figure. 20 [77].

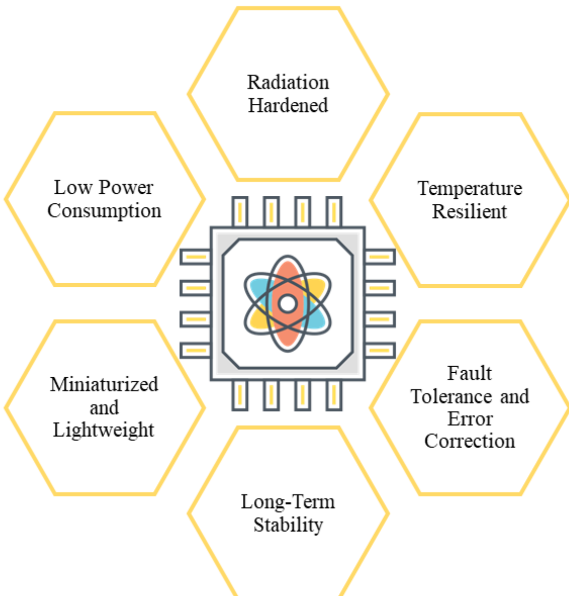


Figure 19: The schematic representation essential characteristics for the successful deployment and operation of quantum chips in space technology applications. They handle the particular challenges and limits of the space environment, enabling space missions to perform reliable and precise quantum computations.

This system consists of a programmable chip that operates at room temperature and is interfaced with a fully automated control system. The aforementioned system facilitates the execution of quantum algorithms by remote users. The algorithms necessitate the utilization of up to eight modes of strongly squeezed vacuum, which are initialized as two-mode squeezed states in single temporal modes. Additionally, the system comprises a fully general and programmable four-mode interferometer and a photon number-resolving readout on all outputs. Using strong squeezing and high sampling rates has made it possible to find multi-photon events with more and faster photons than any other programmable quantum optical demonstration before. The programmable nature of the hardware allows for remote configuration through a customized application programming interface, facilitating deployment for cloud accessibility. The core of the device is only about $10mm \times 4mm$ photonic chip. Due to all these features, it can be said to be the ideal platform as of now for practically implementing quantum circuits for space technology.

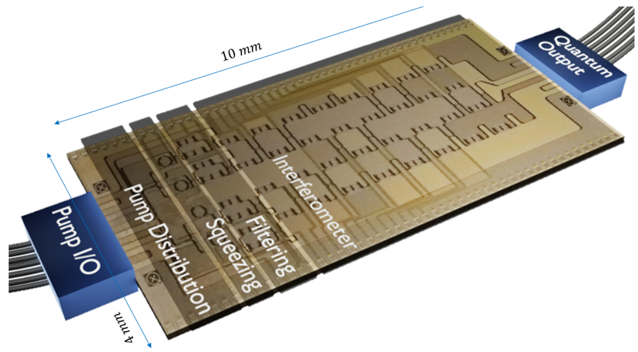


Figure 20: The schematic representation of the chip, derived from a micrograph of the physical device, illustrates the presence of fibre optical inputs and outputs. Additionally, the chip incorporates on-chip modules responsible for coherent pump power distribution, squeezing, pump filtering, and programmable linear optical transformations [77].

4.6. Challenges

Quantum computing is an emerging area of research and development. The field is undergoing rapid evolution, with the continuous emergence of novel technologies and platforms. Academic researchers are continuously engaged in the exploration of novel algorithms aimed at performing complex computations, optimization, minimising errors, achieving greater scalability, and improving control over quantum systems. Several software tools and programming languages, such as Qiskit and Cirq, have been created to enhance the process of designing and simulating quantum algorithm by circuits. Although significant progress has been made in achieving impressive results in quantum supremacy at a technical level [78] [8], there are still several challenges that need to be addressed in order to effectively apply these results to large-scale practical implementation of quantum computing. Additionally, due to the unique characteristics and limits of the space environment, the implementation of quantum computing in space technology presents extra challenges as depicted in Figure. 19. Therefore, the development of quantum computing hardware that is appropriate for utilisation in space applications poses a significant challenge. In order to facilitate space missions, it is imperative to utilise quantum processors that possess characteristics such as miniaturisation, lightweight construction, and power efficiency. These processors must also be capable of enduring the challenging environmental conditions encountered in space, which include radiation exposure, extreme temperature variations, and mechanical strains. The attainment of necessary technological advancements in the domains of quantum chip design, fabrication, and packaging holds crucial importance. Apart from this, space missions can last for a long time. Maintaining long-term stability and dependability in quantum systems is difficult. Maintaining the reliability of quantum computations during the mission requires careful management of factors such component ageing, drift in system parameters, and deterioration of quantum coherence.

In addition to technical challenges, the implementation of quantum computing in space technology encounters several non-technical challenges as well. The development of quantum computing technologies for space applications necessitates substantial financial investments and resources allocation. Ensuring sufficient financial resources, fostering partnerships among research institutions, industry stakeholders, and space agencies, and optimising resource allocation are critical non-technical obstacles. Policy and regulatory considerations must be taken into account when deploying quantum computing technologies in space. These considerations encompass various aspects, ensuring responsible and secure use of quantum technologies, data security, and international cooperation.

In order to successfully integrate the quantum computing in space technology, the active participation of policymakers, regulatory bodies, funding agencies, industry leaders, and stakeholders are required. This collaborative effort is crucial in establishing a conducive environment that supports the effective implementation of quantum computing in the field.

4.7. Discussion

We have presented the potential applications of quantum computing for space technology, such as quantum optimization of spacecraft trajectories, QML for compression and encryption, QCNN for spacecraft image processing, and a quantum computing-based control architecture for the attitude control of spacecraft. We have presented the corresponding conceptual analysis for the application of quantum algorithms to a few open problems in space technology.

The proposed quantum computation algorithms are implementable on quantum circuits, which in turn can be implemented on any available quantum hardware. We have discussed the hardware realisation of the proposed quantum algorithms in space technology, considering several constraints, particular challenges, and limits of the space environment We have also presented the current best platform for the possible implementation of the proposed quantum computing algorithms on a re-programmable nanophotonic chip developed in [77]. Overall, quantum computing holds tremendous potential for applications in space technology. By exploiting the quantum nature of the world, quantum computing opened a new area of research in space technology.

References

[1] VO Tolcheev. Scientometric analysis of the current state and prospects of the development of quantum technologies. *Automatic Documentation and Mathematical Linguistics*, 52:121–133, 2018.

[2] Masoud Mohseni, Peter Read, Hartmut Neven, Sergio Boixo, Vasil Denchev, Ryan Babbush, Austin Fowler, Vadim Smelyanskiy, and John Martinis. Commercialize quantum technologies in five years. *Nature*, 543(7644):171–174, 2017.

[3] Daniele Cozzolino, Beatrice Da Lio, Davide Bacco, and Leif Katsuo Oxenløwe. High-dimensional quantum communication: benefits, progress, and future challenges. *Advanced Quantum Technologies*, 2(12):1900038, 2019.

[4] Andreas Bayerstadler, Guillaume Becquin, Julia Binder, Thierry Botter, Hans Ehm, Thomas Ehmer, Marvin Erdmann, Norbert Gaus, Philipp Harbach, Maximilian Hess, et al. Industry quantum computing applications. *EPJ Quantum Technology*, 8(1):25, 2021.

[5] Dan Browne, Sougato Bose, Florian Mintert, and MS Kim. From quantum optics to quantum technologies. *Progress in Quantum Electronics*, 54:2–18, 2017.

[6] Peter W Shor. Algorithms for quantum computation: discrete logarithms and factoring. In *Proceedings 35th annual symposium on foundations of computer science*, pages 124–134. Ieee, 1994.

[7] Andrew Steane. Quantum computing. *Reports on Progress in Physics*, 61(2):117, 1998.

[8] Han-Sen Zhong, Hui Wang, Yu-Hao Deng, Ming-Cheng Chen, Li-Chao Peng, Yi-Han Luo, Jian Qin, Dian Wu, Xing Ding, Yi Hu, et al. Quantum computational advantage using photons. *Science*, 370(6523):1460–1463, 2020.

[9] Kishor Bharti, Alba Cervera-Lierta, Thi Ha Kyaw, Tobias Haug, Sumner Alperin-Lea, Abhinav Anand, Matthias Degroote, Hermanni Heimonen, Jakob S Kottmann, Tim Menke, et al. Noisy intermediate-scale quantum algorithms. *Reviews of Modern Physics*, 94(1):015004, 2022.

[10] Yoann Altmann, Stephen McLaughlin, Miles J Padgett, Vivek K Goyal, Alfred O Hero, and Daniele Faccio. Quantum-inspired computational imaging. *Science*, 361(6403):eaat2298, 2018.

[11] Martin P Andersson, Mark N Jones, Kurt V Mikkelsen, Fengqi You, and Seyed Soheil Mansouri. Quantum computing for chemical and biomolecular product design. *Current Opinion in Chemical Engineering*, 36:100754, 2022.

[12] Parichehr Hassanzadeh. Towards the quantum-enabled technologies for development of drugs or delivery systems. *Journal of Controlled Release*, 324:260–279, 2020.

[13] Alain Delgado, Pablo AM Casares, Roberto Dos Reis, Modjtaba Shokrian Zini, Roberto Campos, Norge Cruz-Hernández, Arne-Christian Voigt, Angus Lowe, Soran Jahangiri, Miguel Angel Martin-Delgado, et al. Simulating key properties of lithium-ion batteries with a fault-tolerant quantum computer. *Physical Review A*, 106(3):032428, 2022.

[14] Bayerstadler Andreas, Becquin Guillaume, Julia Binder, Botter Thierry, Hans Ehm, Thomas Ehmer, Marvin Erdmann, Gaus Norbert, Harbach Philipp, Maximilian Hess, et al. Industry quantum computing applications. *EPJ Quantum Technology*, 8(1), 2021.

[15] Shaukat Ali, Tao Yue, and Rui Abreu. When software engineering meets quantum computing. *Communications of the ACM*, 65(4):84–88, 2022.

[16] Wanneng Shu and Bingjiao He. A quantum genetic simulated annealing algorithm for task scheduling. In *Advances in Computation and Intelligence: Second International Symposium, ISICA 2007 Wuhan, China, September 21-23, 2007 Proceedings 2*, pages 169–176. Springer, 2007.

[17] Maria Schuld, Ilya Sinayskiy, and Francesco Petruccione. Prediction by linear regression on a quantum computer. *Physical Review A*, 94(2):022342, 2016.

[18] Stuart Harwood, Claudio Gambella, Dimitar Trenev, Andrea Simonetto, David Bernal, and Donny Greenberg. Formulating and solving routing problems on quantum computers. *IEEE Transactions on Quantum Engineering*, 2:1–17, 2021.

[19] Jacob Biamonte, Peter Wittek, Nicola Pancotti, Patrick Rebentrost, Nathan Wiebe, and Seth Lloyd. Quantum machine learning. *Nature*, 549(7671):195–202, 2017.

[20] Seth Lloyd, Masoud Mohseni, and Patrick Rebentrost. Quantum principal component analysis. *Nature Physics*, 10(9):631–633, 2014.

[21] Hong Li, Nan Jiang, Rui Zhang, Zichen Wang, and Hailiang Wang. Quantum support vector machine based on gradient descent. *International Journal of Theoretical Physics*, 61(3):92, 2022.

[22] Daoyi Dong, Chunlin Chen, Hanxiong Li, and Tzyh-Jong Tarn. Quantum reinforcement learning. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 38(5):1207–1220, 2008.

[23] Nathan Wiebe, Ashish Kapoor, and Krysta M Svore. Quantum deep learning. *arXiv preprint arXiv:1412.3489*, 2014.

[24] Maria Schuld, Francesco Petruccione, Maria Schuld, and Francesco Petruccione. Quantum models as kernel methods. *Machine Learning with Quantum Computers*, pages 217–245, 2021.

[25] Xiaojiong Chen, Zhaorong Fu, Qihuang Gong, and Jianwei Wang. Quantum entanglement on photonic chips: a review. *Advanced Photonics*, 3(6):064002–064002, 2021.

[26] Eyob A Sete, William J Zeng, and Chad T Rigetti. A functional architecture for scalable quantum computing. In *2016 IEEE International Conference on Rebooting Computing (ICRC)*, pages 1–6. IEEE, 2016.

[27] Robert H Hadfield. Single-photon detectors for optical quantum information applications. *Nature photonics*, 3(12):696–705, 2009.

[28] AA Jørgensen, D Kong, MR Henriksen, F Klejs, Z Ye, OB Helgason, HE Hansen, H Hu, M Yankov, S Forchhammer, et al. Petabit-per-second data transmission using a chip-scale microcomb ring resonator source. *Nature Photonics*, pages 1–5, 2022.

[29] Mark G Thompson, Alberto Politi, Jonathan CF Matthews, and Jeremy Lloyd O'Brien. Integrated waveguide circuits for optical quantum computing. *IET circuits, devices & systems*, 5(2):94–102, 2011.

[30] Sarah A Gavit, Paulett C Liewer, Richard A Wallace, Juan A Ayon, and Robert H Frisbee. Interstellar travel—challenging propulsion and power technologies for the next 50 years. In *AIP Conference Proceedings*, volume 552, pages 716–726. American Institute of Physics, 2001.

[31] Mike Shafto, Mike Conroy, Rich Doyle, Ed Glaessgen, Chris Kemp, Jacqueline LeMoigne, and Lui Wang. Modeling, simulation, information technology & processing roadmap. *National Aeronautics and Space Administration*, 32(2012):1–38, 2012.

[32] PL Jensen, K Clausen, C Cassi, F Ravera, G Janin, C Winkler, and R Much. The integral spacecraft–in-orbit performance. *Astronomy & Astrophysics*, 411(1):L7–L17, 2003.

[33] Martin N Sweeting. Modern small satellites-changing the economics of space. *Proceedings of the IEEE*, 106(3):343–361, 2018.

[34] Dennis M Bushnell. Survey of quantum technologies in aerospace. 2023.

[35] Timothy L Howard. Aspects of quantum sensing for aerospace systems. In *AIAA Scitech 2020 Forum*, page 0711, 2020.

[36] M Mariola, A Mirza, and F Petruccione. Quantum cryptography for satellite communication. In *Proceedings of SAIP2011, the 56th Annual Conference of the South African Institute of Physics, edited by I. Basson and AE Botha (University of South Africa, Pretoria, 2011)*, pages 403–408, 2011.

[37] Rabia Abid, Bakhtawar Aslam, Sadaf Shakeel, Fahad Ahmad, and Muhammad Rizwan. Implementation of high dimensional-qkd using bb84 protocol in the security of aerospace industry. In *2019 International Conference on Innovative Computing (ICIC)*, pages 1–11. IEEE, 2019.

[38] Arianna Borrelli. Dirac's bra-ket notation and the notion of a quantum state. In *Styles of Thinking in Science and Technology. Proceedings of the 3rd International Conference of the European Society for the History of Science*, pages 361–371, 2010.

[39] Michael A Nielsen and Isaac Chuang. Quantum computation and quantum information, 2002.

[40] Dik Bouwmeester, Jian-Wei Pan, Klaus Mattle, Manfred Eibl, Harald Weinfurter, and Anton Zeilinger. Experimental quantum teleportation. *Nature*, 390(6660):575–579, 1997.

[41] Chuan Wang, Fu-Guo Deng, Yan-Song Li, Xiao-Shu Liu, and Gui Lu Long. Quantum secure direct communication with high-dimension quantum superdense coding. *Physical Review A*, 71(4):044305, 2005.

[42] Ryszard Horodecki, Paweł Horodecki, Michał Horodecki, and Karol Horodecki. Quantum entanglement. *Reviews of modern physics*, 81(2):865, 2009.

[43] Richard Jozsa and Noah Linden. On the role of entanglement in quantum-computational speed-up. *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, 459(2036):2011–2032, 2003.

[44] Ashley Montanaro. Quantum algorithms: an overview. *npj Quantum Information*, 2(1):1–8, 2016.

[45] David Deutsch. Quantum theory, the church–turing principle and the universal quantum computer. *Proceedings of the Royal Society of London. A. Mathematical and Physical Sciences*, 400(1818):97–117, 1985.

[46] Sirui Lu, Mari Carmen Banuls, and J Ignacio Cirac. Algorithms for quantum simulation at finite energies. *PRX Quantum*, 2(2):020321, 2021.

[47] Edward Farhi, Jeffrey Goldstone, and Sam Gutmann. A quantum approximate optimization algorithm. *arXiv preprint arXiv:1411.4028*, 2014.

[48] Gui-Lu Long. Grover algorithm with zero theoretical failure rate. *Physical Review A*, 64(2):022307, 2001.

[49] Harry Buhrman, Richard Cleve, and Avi Wigderson. Quantum vs. classical communication and computation. In *Proceedings of the thirtieth annual ACM symposium on Theory of computing*, pages 63–68, 1998.

[50] Himanshu Thapliyal, Edgard Muñoz-Coreas, and Vladislav Khalus. Quantum carry lookahead adders for nisq and quantum image processing. *arXiv preprint arXiv:2106.04758*, 2021.

[51] Wen Guan, Gabriel Perdue, Arthur Pesah, Maria Schuld, Koji Terashi, Sofia Vallecorsa, and Jean-Roch Vlimant. Quantum machine learning in high energy physics. *Machine Learning: Science and Technology*, 2(1):011003, 2021.

[52] Amine Zeguendry, Zahi Jarir, and Mohamed Quafafou. Quantum machine learning: A review and case studies. *Entropy*, 25(2):287, 2023.

[53] HY Huang, M Broughton, M Mohseni, R Babbush, S Boixo, H Neven, and JR McClean. Power of data in quantum machine learning nat, 2021.

[54] Qiuchi Li, Dimitris Gkoumas, Alessandro Sordoni, Jian-Yun Nie, and Massimo Melucci. Quantum-inspired neural network for conversational emotion recognition. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 13270–13278, 2021.

[55] Salvador E Venegas-Andraca and Sougato Bose. Storing, processing, and retrieving an image using quantum mechanics. In *Quantum information and computation*, volume 5105, pages 137–147. SPIE, 2003.

[56] Jose I Latorre. Image compression and entanglement. *arXiv preprint quant-ph/0510031*, 2005.

[57] Salvador E Venegas-Andraca and JL Ball. Processing images in entangled quantum systems. *Quantum Information Processing*, 9(1):1–11, 2010.

[58] Phuc Q Le, Fangyan Dong, and Kaoru Hirota. A flexible representation of quantum images for polynomial preparation, image compression, and processing operations. *Quantum Information Processing*, 10:63–84, 2011.

[59] Yi Zhang, Kai Lu, Yinghui Gao, and Mo Wang. Neqr: a novel enhanced quantum representation of digital images. *Quantum information processing*, 12:2833–2860, 2013.

[60] Nan Jiang, Jian Wang, and Yue Mu. Quantum image scaling up based on nearest-neighbor interpolation with integer scaling ratio. *Quantum information processing*, 14(11):4001–4026, 2015.

[61] Nan Jiang, Xiaowei Lu, Hao Hu, Yijie Dang, and Yongquan Cai. A novel quantum image compression method based on jpeg. *International Journal of Theoretical Physics*, 57:611–636, 2018.

[62] Mohammad Amin Maleki Sadr, Yeying Zhu, and Peng Hu. Multivariate variance-based genetic ensemble learning for satellite anomaly detection. *IEEE Transactions on Vehicular Technology*, 2023.

[63] Jiang Tao, Yunfeng Cao, and Meng Ding. Sdebrisnet: A spatial–temporal saliency network for space debris detection. *Applied Sciences*, 13(8):4955, 2023.

[64] Saeed Matar Al Jaberi, Asma Patel, and Ahmed N AL-Masri. Object tracking and detection techniques under gann threats: A systemic review. *Applied Soft Computing*, page 110224, 2023.

[65] Siddarth Kaki, Jacob Deutsch, Kevin Black, Asher Cura-Portillo, Brandon A Jones, and Maruthi R Akella. Real-time image-based relative pose estimation and filtering for spacecraft applications. *Journal of Aerospace Information Systems*, 20(6):290–307, 2023.

[66] Herbert Viggh, Sean Loughran, Yaron Rachlin, Ross Allen, and Jessica Ruprecht. Training deep learning spacecraft component detection algorithms using synthetic image data. In *2023 IEEE Aerospace Conference*, pages 1–13. IEEE, 2023.

[67] Iris Cong, Soonwon Choi, and Mikhail D Lukin. Quantum convolutional neural networks. *Nature Physics*, 15(12):1273–1278, 2019.

[68] Guangyuan Zhao, Xue Wan, Yaolin Tian, Yadong Shao, and Shengyang Li. 3d component segmentation network and dataset for non-cooperative spacecraft. *Aerospace*, 9(5):248, 2022.

[69] Inc CiteDrive. Models of quantum computation, 2022. `http://tph.tuwien.ac.at/~oemer/doc/quprog/node9.html` [Accessed: (06-07-2023)].

[70] Peter W Shor. Quantum computing. *Documenta Mathematica*, 1(1000):1, 1998.

[71] Ananda Roy and David P DiVincenzo. Topological quantum computing. *arXiv preprint arXiv:1701.05052*, 2017.

[72] Satoshi Iriyama, Masanori Ohya, and Igor Volovich. Generalized quantum turing machine and its application to the sat chaos algorithm. In *Quantum Information and Computing*, pages 204–225. World Scientific, 2006.

[73] B Omer. Quantum programming in qcl. institute of information systems, technical university of vienna (2000).

[74] Victor Martin-Mayor and Itay Hen. Unraveling quantum annealers using classical hardness. *Scientific reports*, 5(1):15324, 2015.

[75] Masha Shcherbina and Brunello Tirozzi. Quantum hopfield model. *arXiv preprint arXiv:1201.5024*, 2012.

[76] Nathalie P De Leon, Kohei M Itoh, Dohun Kim, Karan K Mehta, Tracy E Northup, Hanhee Paik, BS Palmer, Nitin Samarth, Sorawis Sangtawesin, and David W Steuerman. Materials challenges and opportunities for quantum computing hardware. *Science*, 372(6539):eabb2823, 2021.

[77] Juan M Arrazola, Ville Bergholm, Kamil Brádler, Thomas R Bromley, Matt J Collins, Ish Dhand, Alberto Fumagalli, Thomas Gerrits, Andrey Goussev, Lukas G Helt, et al. Quantum circuits with many photons on a programmable nanophotonic chip. *Nature*, 591(7848):54–60, 2021.

[78] A Morvan, B Villalonga, X Mi, S Mandra, A Bengtsson, PV Klimov, Z Chen, S Hong, C Erickson, IK Drozdov, et al. Phase transition in random circuit sampling. *arXiv preprint arXiv:2304.11119*, 2023.