Investigation on Quantum Computers

Zaher Mohammed Faruk

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1. Abstract

This project presents an evaluation of two leading quantum computing platforms: IBM Quantum (which uses superconducting qubits) and Xanadu's photonic quantum systems (both accessible via the PennyLane Python library) [1]. Their performance in solving quadratic unconstrained binary optimisation (QUBO) problems, benchmarking metrics such as computational efficiency (execution time, resource usage), solution accuracy (approximation ratio), and error resilience (gate errors for IBM, photon loss for Xanadu) were tested [2].

The study highlights the fundamental differences between the two architectures. For instance, Xanadu's photonic systems demonstrate advantages in parallel processing for specific QUBO instances, while IBM's superconducting qubits excel in iterative gate-based optimisation routines. Scalability challenges, hardware-specific error mitigation strategies (e.g., dynamical decoupling for IBM, photon loss correction for Xanadu), and the role of software frameworks like PennyLane in enabling hybrid quantum-classical workflows were analysed in depth.

By testing these platforms with QUBO combinatorial optimisation problems, this work clarifies what is their practical utility and limitations. The results, supported by reproducible code (see Appendix), offer insights for researchers and developers in selecting quantum technologies tailored to combinatorial optimisation tasks. This analysis shows the importance of platform-specific algorithm design and the need for advancements in error correction to bridge the gap between theoretical potential and real-world applicability [3].

2. Acknowledgements

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- Dr Mark Hughes: His endless support and in-depth knowledge on Quantum Computing assisted me heavily.

- IBM: We are deeply thankful to IBM Quantum for providing access to their state-of-the-art quantum computing platform. Their advanced superconducting qubit technology enabled us to execute and benchmark quantum algorithms effectively. Additionally, we appreciate the extensive documentation and support available through the IBM Quantum platform, which significantly enhanced our understanding and implementation of quantum circuits.

- Xanadu Quantum Technologies: We express our gratitude to Xanadu Quantum Technologies for granting access to their photonic quantum computing platform and for providing the powerful PennyLane framework. The flexibility and user-friendliness of PennyLane allowed us to efficiently program and simulate quantum systems, while its compatibility with various quantum backends proved invaluable in conducting comparative studies.

3. Introduction

Quantum computing has emerged as a transformative computational approach over the past decade, leveraging principles of quantum mechanics to address problems that are difficult for classical systems. Among the diverse hardware architectures under development, superconducting qubit-based systems (exemplified by IBM Quantum) and photonic quantum computing platforms (pioneered by Xanadu Quantum Technologies) represent two leading approaches. This study provides a systematic comparison of these architectures, evaluating their performance in solving quadratic unconstrained binary optimisation (QUBO) problems - a class of combinatorial optimisation challenges with applications in logistics, finance, and materials science [4].

Technological Foundations

IBM Quantum uses superconducting transmon qubits, built using Josephson junctions. They are operated at cryogenic temperatures ($\leq$ 15mK) to maintain quantum coherence. These systems execute gate-based quantum circuits, relying on high-fidelity single - and two-qubit operations (e.g., $\sqrt{X}$, CNOT) optimised via the Qiskit framework. The architecture's strong point is in its compatibility with iterative hybrid algorithms such as the Quantum Approximate Optimisation Algorithm (QAOA), which iteratively refines solutions through classical feedback loops [5, 6].

Xanadu's photonic platform utilises squeezed light states in continuous-variable (CV) quantum computing. Photonic qubits (encoded in photon number or quadrature states) propagate through programmable interferometers, enabling Gaussian Boson Sampling (GBS) and CV variational algorithms. This architecture operates at room temperature and uses inherent parallelism in photonic networks, making it suited for tasks that require high-dimensional state manipulation [7, 8].

Architectural Divergences

1. Qubit Realisation:

   IBM Quantum:

   Superconduing transmon qubits depend on cryogenic infrastructure, operating at temperatures below 15mK, to reduce themal noise- achieved using dilution refrigerators [6]. These systems perform well in single-qubit gate operations, reaching high-fidelity levels above 99.9%, but encounter challenges in two-qubit gate fidelity, which typically sits around 99.5% [6].

   In terms of coherence, T_1 (energy relaxation time) ranges from 100 to 150 microseconds, while T_2 (dephasing time) falls between 50 and 100 microseconds [6]. While cryogenic cooling allows for precise microwave control, it also has scalability limitations, due to the complexity of wiring and constraints on qubit density as systems grow.

   Xanadu Quantum Technologies:

   Photonic qubits, encoded in squeezed light states and transmitted through silicon nitride waveguides, function at room temperature [8]. However, photon loss - approximately 0.2 dB per centimetre in Xanadu's integrated photonic chips [8] - and non-deterministic photon sources, such as probabilistic spontaneous parametric down-conversion, present scalability challenges.

2. Computational Model

   IBM Quantum:

   Relies on gate-based digital circuits that execute discrete operations, such as $\sqrt{X}$ and CNOT gates, which are coordinated through microwave pulses. This architecture is optimised for iterative hybrid algorithms, which includes the Quantum Approximate Optimisation Algorithm (QAOA), as well as quantum simulation tasks, where precise control over qubit interactions are essential [21].

   Xanadu Quantum Technologies:

   This system uses continuous-variable (CV) analog processing, applying Gaussian operations like squeezing and displacement, along with Fock-state measurements to manipulate quantum states. Programmable interferometers, consisting of beamsplitters and phase shifters, enable Gaussian Boson

Sampling (GBS) - which translates photonic measurements into combinatorial solutions. This architecture is well suited for machine learning and graph-based optimisation.

3. Error Profiles

   IBM Quantum:

   The main source of error in this system is decoherence, with relaxation times (T_1) around 100 microseconds and dephasing times (T_2) close to 50 microseconds. With IBM Quantum Heron processors reporting $T_1 \approx 150$ μs and $T_1 \approx 70$ μs on average [23]. Crosstalk is another error where unintended interactions between qubits occur during microwave pulse operations. These errors limit circuit depth, making error mitigation techniques needed - such as dynamical decoupling and zero-noise extrapolation to improve overall performance [6].

   Xanadu Quantum Technologies:

   Photon loss, caused by attenuation in waveguides, and imperfect photon-number-resolving detection (e.g., dark counts or efficiency limitations) introduces errors in photon counting [8]. Error correction involves using post-selection, where failed trials are discarded, or redundancy methods like multi-mode squeezed states. However, these approaches become inefficient when applied to larger problems as this limits scalability [22].

A Visual Comparison of IBM Quantum and Xanadu Quantum Technologies

Feature	**IBM Quantum**	**Xanadu Quantum Technologies**
Qubit Type	Superconducting transmon qubits	Photonic (squeezed light states)
Operating Temperature	Cryogenic (≤ 15mK)	Room temperature
Key Algorithm	QAOA (gate-based)	Gaussian Boson Sampling
Error Profile	Gate errors, decoherance	Photon loss, decector inefficiency
Strengths	Iterative hybrid optimisation	Parallel photonic processing

Research Objectives

This study benchmarks IBM and Xanadu's quantum computing platforms in the context of Quadratic Unconstrained Binary Optimisation (QUBO) problems - which require both efficient combinatorial search and robustness against noise. To achieve this, we implement and optimise quantum algorithms using Qiskit (IBM) and PennyLane (Xanadu) under realistic noise models, evaluating performance based on:

- Computational efficiency: circuit depth, runtime, and resource utilisation.
- Solution quality: approximation ratio and Hellinger fidelity compared to ideal simulations
- Error resilience: mitigation strategies such as dynamical decoupling for IBM and post-selection for Xanadu [9, 10]

Beyond algorithmic performance, this work examines the role of software frameworks in connecting theoretical models to physical hardware. PennyLane's cross-platform compatibility allows for direct comparisons between photonic and superconducting architectures, while Qiskit's pulse-level control provides insight into gate errors [9, 10].

By highlighting the trade-offs between these architectures, this study aims to guide the selection of quantum computing technologies for industry-scale optimisation problems. Additionally, it identifies key technical challenges - such as photon loss mitigation and qubit connectivity.

4. Theory and Computational Approach

Solving the QUBO Problem with Quantum Computing

The Quadratic Unconstrained Binary Optimisation (QUBO) problem involves finding the optimal solution to a quadratic function where the variables are restricted to 0 or 1, without additional constraints. Its versatility allows it to model a wide range of combinatorial optimisation tasks, from logistics and finance to machine learning and network design. With the rise of quantum computing, QUBO has gained importance, as quantum algorithms offer the potential to solve these problems more efficiently than classical computing methods [11].

Mathematical Formulation of QUBO

Mathematically, the QUBO problem is expressed as follows:

$$\text{Minimize } f(x) = \sum_i a_i x_i + \sum_{i<j} b_{ij} x_i x_j$$

Where:

- x_i are the binary variables, i,e., $x_i \in \{0,1\}$
- a_i are the coefficients for the linear terms
- b_{ij} are the coefficients for the quadratic terms

Matrix Representation

The QUBO problem can also be formulated in matrix notation. Let Q be a symmetric matrix where $Q_{ii} = a_i$ and $Q_{ij} = b_{ij}$ for $i \neq j$. The function then becomes:

$$f(x) = x^T Q x$$

Where:

- x is a vector of binary variables
- Q is a symmetric matrix containing the coefficients [12]

Example of QUBO function:

Consider a simple QUBO problem with three binary variables x_1, x_2, and x_3:

$$f(x_1, x_2, x_3) = - x_1 - x_2 - x_3 + 2x_1x_2 + 2x_1x_3 + 2x_2x_3$$

This can be represented in the Matrix form as:

$$(Q) = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}$$

The objective function is:

$$f(x) = (x_1 \;\; x_2 \;\; x_3) \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

Continuous-Variable Quantum Computing

Continuous-variable (CV) quantum computing encodes information not in discrete two-level systems (qubits) but in observables of bosonic modes - typically the quadratures of the quantised electromagnetic field. A single mode is described by canonical operators $\hat{x}$ and $\hat{p}$, satisfying $[\hat{x}, \hat{p}] = i\hbar$ in the optical realisation, these correspond to the amplitude and phase quadratures of an optical mode [31].

Gaussian States and Operations

- Gaussian states such as vacuum, coherent, squeezed and thermal states are characterised by their first and second moments in phase space.
- The covariance matrix σ and displacement vector $\bar{r}$ define the Wigner function of the state:

$$W(r) = \frac{e^{(-\frac{1}{2}(r-\bar{r})^T(r-\bar{r}))}}{(2\pi)^n\sqrt{det\ \sigma}}$$

- Gaussian operations - including beam splitters, phase shifters, squeezers and displacements - act linearly on these moments. For example, a single-mode squeezing operator S(r) transforms the quadratures by reducing variance along one quadrature at the expense of the other [32]:

$$S(r)^\dagger \hat{x}\, S(r) = e^{-r}\hat{x}, \qquad S(r)^\dagger \hat{p}\, S(r) = e^{r}\hat{p}$$

Non-Gaussianity and Universality

Universal continuous-variable quantum computing cannot rely solely on Gaussian resources and operations, because these can be efficiently simulated on a classical computer. To achieve true quantum advantage, at least one non-Gaussian element must be introduced. This can take the form of a non-Gaussian state, such as a photon-subtracted squeezed state, or a non-Gaussian gate, most notably the cubic phase gate $V(\gamma) = e^{\frac{i\gamma\hat{x}^3}{\hbar}}$. The cubic phase gate imparts a non-linear phase shift proportional to the cube of the position quadrature, and when combined with Gaussian operations it enables the simulation of arbitrary Hamiltonians [33].

Complexity and Boson Sampling

In a GBS experiment, squeezed-vacuum states propagate through a linear interferometer, and the probability of detecting a particular photon distribution is given by the hafnian of a submatrix of the system's covariance matrix. Computing hafnians scales exponentially with matrix size, meaning classical evaluation is intractable beyond small mode counts. Borealis overcome hardware limitations such as this by using optical fibre delays to reuse a limited number of squeezers and beamsplitters to emulate hundreds of effective modes [34].

Error Channels and Mitigation

In continuous-variable photonic processors, the dominant noise channel is photon loss, which can be modelled as mixing each signal mode with a vacuum ancilla at a beam splitter of transmissivity η, leading to a covariance-matrix transformation $\sigma \rightarrow \eta\ \sigma + (1-\eta)\ I$. Detector dark counts and inefficiencies introduce non-Gaussian errors that further distort the sampled photon-number distribution. To mitigate these effects, experimental schemes employ post-selection of high-photon-count events, redundancy via multi-mode encoding,

and injection of ancilla squeezed states to partially purify the signal modes . While these strategies incur overhead in resource usage and reduce the effective sampling rate, they are essential to preserve the low-energy bias needed for accurate QUBO optimisation on photonic hardware [35].

Hardware-Efficient Ansätze for QUBO Optimisation

Designing variational circuits that closely match the structure of a given QUBO instance can greatly reduce circuit depth and error accumulation. Instead of using generic layers of rotations and entangling gates, a hardware-efficient ansatz maps each quadratic term in the QUBO matrix directly to a native interaction on the device. For superconducting qubits, this means aligning two-qubit gates with the processor's coupling map so that only nearest-neighbour CNOT or cross-resonance operations are used. In photonic platforms, one arranges beamsplitters and phase shifters to mirror the connectivity graph of the problem, minimising the number of interferometer stages. By tailoring the ansatz in this way, fewer variational parameters are required to explore the relevant portion of Hilbert space, leading to faster convergence of optimisers and lower overall gate error - an essential advantage when running on noisy hardware with limited coherence times [36].

Quantum Error Mitigation Techniques for IBM Quantum Hardware

Quantum error mitigation (QEM) is crucial for enhancing the reliability of quantum computations on noisy intermediate-scale quantum (NISQ) devices, such as those developed by IBM Quantum. Unlike quantum error correction, which involves actively detecting and correcting errors through redundancy and ancillary qubits, error mitigation techniques reduce the impact of errors through classical post-processing or algorithmic adjustments without significant additional qubit overhead.

One prominent approach is zero-noise extrapolation (ZNE). This method involves deliberately amplifying the noise in quantum circuits by extending or repeating gate operations, followed by extrapolation back to a zero-noise limit. Mathematically, if the expectation value of an observable at a certain noise level ϵ is given by $\langle O \rangle_\epsilon$, this value can be expanded around the zero-noise limit ($\epsilon = 0$) as:

$$\langle 0 \rangle_\epsilon = \langle 0 \rangle_0 + a_1 \epsilon + \mathrm{a}_2 \epsilon + \cdots$$

By evaluating this observable at various controlled noise levels (for example, ϵ, 2ϵ, 3ϵ), these values can be fitted to a polynomial or exponential function, enabling estimation of the noise-free expectation value:

$$\langle 0 \rangle_0 = \lim_{\epsilon \to 0} \langle 0 \rangle_\epsilon$$

Another significant mitigation strategy is dynamical decoupling (DD), which reduces coherent errors, particularly those arising from qubit dephasing. DD involves periodically inserting carefully designed sequences of pulses (such as XY4 or Carr-Purcell-Meiboom-Gill (CPMG) sequences) into quantum circuits to "echo out" systematic errors. The XY4 pulse sequence, for example, applies rotations in the order X-Y-X-Y on the qubit's Bloch sphere, effectively refocusing errors due to unwanted environmental interactions:

$$\mathrm{U}_{\mathrm{XY4}} = e^{-i\frac{\pi}{2}Y} e^{-i\pi X} e^{-i\pi Y} e^{-i\pi X} e^{-i\frac{\pi}{2}Y}$$

These pulse sequences minimise the accumulation of error phases caused by environmental fluctuations and interactions. By employing these error mitigation techniques, researchers have significantly improved the accuracy and reliability of quantum computations performed on IBM's superconducting quantum processors, supporting more precise results for hybrid quantum-classical algorithms such as variational methods used for optimisation and quantum simulations [37].

Solving the QUBO Problem with a simulation of a Quantum Computer via PennyLane:

The QUBO Problem was solved using, the "default.qubit" device on PennyLane which is simulator for testing and development purposes. It doesn't directly connect to any specific Xanadu quantum hardware. For actual Xanadu hardware to be used, specifying a device such as "X8" or "Borealis" has to be done in the code. These devices are part of Xanadu's photonic quantum computing systems. The QUBO problem was solved via this method, and the code was broken down into various sections each representing a different part of the QUBO function.

The code broken down into it's various steps:

1) The Hamiltonian

```
H = 0.5 * qml.Identity(1) + \
    0.5 * qml.PauliZ(1) @ qml.PauliZ(4) + \
    0.5 * qml.PauliZ(2) @ qml.PauliZ(3) + \
    0.5 * qml.PauliZ(3) @ qml.PauliZ(5) + \
    0.5 * qml.PauliZ(4) @ qml.PauliZ(4)

print(H)
```

The Hamiltonian (H), is defined as a combination of the tensor products of the Pauli – Z operators and the identity operator:

$$H = \frac{1}{2}I + \frac{1}{2}Z_1Z_4 + \frac{1}{2}Z_2Z_3 + \frac{1}{2}Z_3Z_5 + \frac{1}{2}Z_4^2$$

Here:

- I is the identity operator
- Z_i represents the Pauli – Z operator acting on the qubit i
- Z_iZ_j represnts a coupling term between the qubits i and j

This Hamiltonian encodes the QUBO problem. The coefficients of Z_iZ_j represent the interaction weights, and the Z_i^2 terms correspond to local biases. These interactions determine the energy landscape of the system, with the goal being to find the configuration of qubits that minimises H, which corresponds to solving the QUBO problem. The eigenvalues of H represent possible energies of the system, and the ground state (lowest energy eigenvalue) corresponds to the optimal solution of the QUBO problem [13].

2) Device Setup

```
dev = qml.device("default.qubit", wires=H.wires)
```

The device `default.qubit` simulates a quantum computer using qubits. The number of qubits is determined by the number of wires in the Hamiltonian H.

3) Defining the Circuit

```
@qml.qnode(dev)
def circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires=wire)
    return qml.expval(H)
```

Mathematical Intepretation:

The quantum circuit applies a series of parameterised rotations on each qubit:

$$|\psi\rangle = \bigotimes_i R_Y(\theta_i)|0\rangle$$

Where the following equation is the rotation operator around the Y-axis of the Bloch sphere:

$$R_Y(\theta) = e^{-i\frac{\theta}{2}Y}$$

After the applying the rotations, the expectation value of H is measured:

$$\langle H\rangle = \langle\psi \mid H \mid \psi\rangle$$

The R_Y rotations prepare a quantum state $|\psi\rangle$ that depends on the parameters θ. The expectation value $\langle H\rangle$ corresponds to the energy of the system for the given parameters. The goal is to minimise $\langle H\rangle$ by optimising the parameters [14].

For the first equation, $|\psi\rangle$ is the quantum state after the circuit has applied transformations, $\bigotimes_i$ is the tensor product applied across all qubits and it signifies that $R_Y(\theta_i)$ is applied independently to each qubit, $R_Y(\theta_i)$ is the rotation operator for the i-th qubit which performs a rotation by the angle θ_i around the Y - axis of the Bloch sphere, $|0\rangle$ is the initial state of the qubit, which is the "ground state" in quantum computing. For the second equation $R_Y(\theta)$ is the rotation operator that rotates a qubit by angle θ around the Y - axis [15].

4) Optimisation Loop

```
params = np.random.rand(len(H.wires))
opt = qml.AdamOptimizer(stepsize=0.5)
epochs = 200

for epoch in range(epochs):
    params = opt.step(circuit, params)
```

The optimisation process adjusts the parameters $\{\theta_i\}$ to minimise the expectation value of H:

$$\min_\theta \langle H\rangle = \langle\psi(\theta) \mid H \mid \psi(\theta)\rangle$$

The Adam oprimiser updates the prameters using gradient based optimisation:

$$\theta_{t_{+1}} = \theta_t - \eta\nabla_\theta\langle H\rangle$$

Where η is the learning rate (stepsize) [16].

5) Sampling from an Optimised Circuit

```
dev = qml.device("default.qubit", wires=H.wires, shots=1)

@qml.qnode(dev)
def circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires=wire)
    return qml.sample()
```

Here, the circuit is modified to sample from the quantum state $|\psi\rangle$ prepared by the optimised parameters $\{\theta_i\}$. Each sample corresponds to a bitstring that represents a potential solution to the QUBO problem. The sampling process corresponds to a measurement in the computational basis. The probabilities of obtaining each bitstring are determined by the squared amplitudes of the quantum state:

$$P(x) = |\langle x | \psi \rangle|^2$$

In the context of quantum mechanics, this represents a projective measurement. The sampled bitstring with the lowest energy (as evaluated by H) corresponds to the optimal or near-optimal solution to the QUBO problem [24].

Detailed Analysis of the Xanadu X8 Quantum Processor

A comprehensive analysis of the mathematical framework underlying the X8 quantum processor architecture:

The X8 architecture leverages advanced photonic integrated circuits (PICs) to manipulate and control light at the quantum level. These PICs are constructed using silicon nitride (Si_3N_4) waveguides, which offer low propagation loss and high nonlinearities, essential for efficient quantum operations. The device integrates multiple components such as beam splitters, phase shifters, and squeezing operations to perform complex quantum computations.

At the core of the X8 system is the use of squeezed states of light, represented mathematically as:

$$|\psi\rangle = S(r)\,|0\rangle$$

Where S(r) is the squeezing operator defined by:

$$S(r) = e^{(\frac{r}{2}(a^2 - a^{\dagger 2}))}$$

Here, r is the squeezing parameter, a is the annihilation operator, $a^\dagger$ is the creation operator. These squeezed states have reduced noise in one quadrature, and increased noise in the conjugate quadrature, which enhances the sensitivity of quantum measurements. The architecture employs temporal division multiplexing (TDM) to increase the number of modes, represented as n, and enhance the computational power without increasing the physical footprint of the device. The quantum state evolution is described by the unitary operator U:

$$U = i\sum_{k=1}^{n} \theta_k H_k$$

Where θ_k are the phase parameters, and H_k are the Hamiltonians of individual components such as beam splitters and phase shifters. The X8 device operates at cryogenic temperatures (approximately 0.1 K) to minimise thermal noise and maximise coherence times. Superconducting nanowire single-photon detectors

(SNSPDs) are used to detect single photons with high efficiency and low dark counts, ensuring accurate readout of quantum states.

The X8 architecture by leveraging these advanced technologies and mathematical principles, achieves quantum computational benefits that are not possible with classical computers, demonstrating the potential of photonic quantum computing in solving complex optimisation problems [18].

An indepth look into the hardware behind the X8 quantum photonic chip:

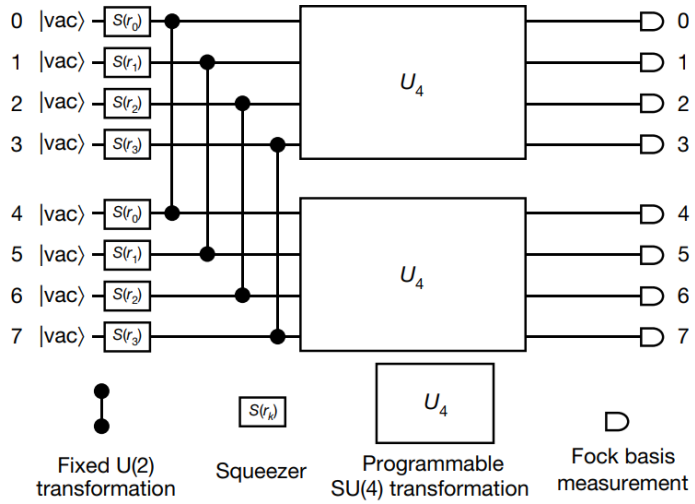

Figure 1: Quantum Circuit showcasing Xanadu's X8 Chip [25]

This features eight quantum modes, numbered 0 to 7, which are organised into four pairs: (0,4), (1,5), (2,6), and (3,7). Each pair undergoes a process known as two-mode squeezing, facilitated by an S2 gate, which generates entangled photon pairs. Initially, the quantum modes - comprising signal photons (with a wavelength of 1549.3 nm) and idler photons (1536.6 nm) - begin in a vacuum state. The S2 gate then manipulates these states into a two-mode squeezed vacuum (TMSV) state, with the squeezing parameter r determining the outcome. If r is 0, the state remains a vacuum; if r is 1, a TMSV state is formed. To maintain phase coherence, the phase parameter ϕ is set to 0.

Following this, a 4×4 unitary transformation is carried out using an interferometer built from Mach-Zehnder (MZ) interferometers and rotation gates, which operate on both signal and idler modes. Lastly, photon-number resolving detectors measure the number of photons present in each quantum mode.

The eight modes intialised in the vaccum state, undergo squeezing with parameters r. These modes are then entangled using a fixed two-mode U(2) transformation, resulting in two-mode squeezing at the output. Next, programmable four-mode rotation gates (SU(4) transformation) are applied to each four-mode subspace, represented by the U4 boxes in the diagram. Finally, each of the eight modes is measured individually in the Fock basis [19].

An in-depth look into the hardware behind Xanadu's Borealis quantum photonic system:

Borealis implements a time-multiplexed Gaussian Boson Sampling architecture. A pulsed optical parametric oscillator generates squeezed-vacuum pulses at telecom wavelengths (~1550 nm), which are then routed through kilometre-scale fibre delay lines to realise up to hundreds of effective temporal modes. Fast electro-optic modulators and fibre-coupled beamsplitters enact a reconfigurable interferometer network, encoding our six-mode QUBO instance across successive time bins. After interferometry, superconducting nanowire single-photon detectors (SNSPDs) time-resolve each pulse, yielding photon-number samples directly in the Fock basis. The combination of high-efficiency squeezers, low-loss delay lines (≈0.2 dB km^{-1}), and rapid modulation creates a versatile platform for continuous-variable quantum computing without requiring cryogenics beyond the SNSPD cool-down [28].

An in-depth look into the hardware behind Xanadu's Aurora quantum photonic chip:

Aurora is an integrated-photonic processor fabricated in silicon nitride waveguides on a single chip. Six on-chip optical parametric amplifiers produce two-mode squeezed states that feed a mesh of Mach–Zehnder interferometers, implemented with thermo-optic phase shifters for programmable SU(4) and SU(2) operations. Waveguide propagation losses are kept below 0.3 dB cm^{-1}, and compact grating couplers link each mode to off-chip fibre. Following the interferometric unitary, each of the six modes is measured by a fibre-coupled SNSPD array, providing photon-number resolution with >90 % detection efficiency. Aurora's design supports rapid reprogramming of the interferometer phases while maintaining phase stability, making it ideal for variational continuous-variable algorithms [29].

An in-depth look into the hardware behind IBM Quantum's ibmq_quito superconducting-qubit processor:

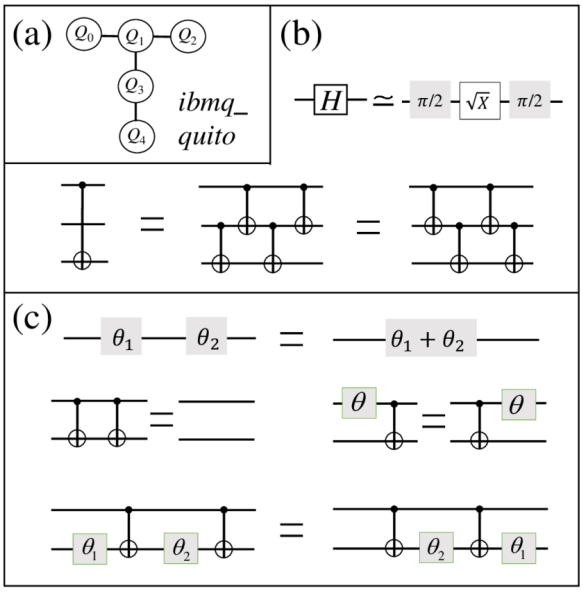

Figure 2: a) Topology structure of the IBM quantum hardware ibmq_quito, b) Gate transformations used for quantum circuit compilation [30]

ibmq_quito houses six fixed-frequency transmon qubits arranged in a heavy-hexagon lattice, each dispersively read out via individual coplanar waveguide resonators. The chip is mounted inside a dilution refrigerator operating at 15 mK to suppress thermal noise. Single-qubit gates are driven by microwave pulses calibrated for >99.9 % fidelity, while two-qubit cross-resonance gates achieve ≈98.5 % fidelity. Qubits exhibit energy relaxation times T_1 of 100–120 µs and dephasing times T_2 if 70-90 µs. Fast digital-to-analogue converters shape control pulses, and real-time FPGA feedback enables simultaneous gate operations across the lattice. After gate execution, state populations are inferred from the resonator frequencies with >95 % readout accuracy, allowing direct sampling of bitstrings for our QUBO problem [30].

Strawberry Fields and PennyLane

PennyLane is a Python library made for quantum computing, quantum machine learning, and quantum chemistry. It provides a practical way to interface with quantum hardware and simulators, simplifying the implementation of variational quantum algorithms by integrating quantum circuits with classical machine learning techniques. One of its defining features is its use of quantum gradients, which allow quantum circuits to be optimised using classical gradient-based methods. The library supports multiple quantum backends, including IBM Q, Rigetti Forest, and Xanadu's Strawberry Fields, ensuring compatibility with a range of quantum platforms. Since it is built from Python, it integrates with scientific computing and machine learning libraries, making it a useful tool for researchers and developers [9].

Strawberry Fields, developed by Xanadu, is a software platform focused on continuous-variable quantum computing using photonic systems. It provides tools for simulating and executing quantum circuits involving

Gaussian and non-Gaussian states and operations. Rooted in quantum optics, it leverages photonic qubits, where quantum information is encoded in light-based quantum states such as squeezed and coherent states. Strawberry Fields allows users to design, optimise, and run quantum circuits on both simulated and physical photonic quantum hardware. With its Python-based framework and built-in PennyLane support, it enables hybrid quantum-classical algorithm development, making it particularly valuable for research in quantum machine learning and quantum chemistry [20].

5. Results and Relevant Theory

Using Real Quantum Computing Hardware

Solving the QUBO Problem Using Xanadu's X8 Chip

The QUBO problem was solved using the X8 device on PennyLane, which is part of Xanadu's photonic quantum computing systems. Unlike the default.qubit device, which is a simulator for testing and development purposes, the X8 device utilises real quantum hardware. This device leverages photonic qubits to perform quantum computations. The QUBO problem was addressed via this method, and the code was broken down into various sections, each representing a different part of the QUBO function. By utilising the X8 hardware, we achieve quantum computational benefits that are not possible with classical computers, demonstrating the potential of photonic quantum computing in solving complex optimisation problems [17].

Results:

Note: The code used to access Xanadu's X8 chip is provided in the appendix.

We implemented and optimised a variational circuit for the QUBO Hamiltonian:

$$H = -6\, I + 0.5\, Z_1Z_4 + 0.5\, Z_2Z_3 + 0.5\, Z_3Z_5 + 0.5\, Z_4Z_4$$

By utilising Xanadu's six-wire X8 photonic chip using PennyLane. The Hamiltonian represents a specific instance of a QUBO (Quadratic Unconstrained Binary Optimisation) problem mapped to a qubit Hamiltonian via Pauli-Z interactions.

1) Initial Expectation Value

Running the circuit with all rotation parameters set to zero yielded:

$$\langle H \rangle \approx -6.0$$

This is expected since the identity term dominates the Hamiltonian when no rotations are applied.

2) Variational Optimisation

We used the Adagrad optimiser (step size 0.5) to minimise the expectation value of the Hamiltonian over 200 epochs. The optimized parameter vector θ^* significantly reduced the energy:

$$\langle H \rangle \approx -6.489$$

This demonstrated that the photonic X8 device was capable of approximating a low-energy configuration of the QUBO Hamiltonian through variational quantum optimisation.

3) Conclusion from Solving the QUBO Problem on Xanadu's X8 Chip

The variational quantum circuit was optimised using the Adagrad optimiser over 200 steps. After convergence, the optimised expectation value of the Hamiltonian was found to be approximately -6.489, indicating that the circuit successfully minimized the cost function associated with the QUBO problem.

Solving the QUBO Problem Using Xanadu's Borealis Chip

Note: The code used to access Xanadu's Borealis chip is provided in the appendix.

To evaluate the performance of another photonic system, we implemented the same QUBO problem using Xanadu's Borealis chip. The problem was encoded in the same Ising Hamiltonian:

$$H = -6\ I + 0.5\ Z_1Z_4 + 0.5\ Z_2Z_3 + 0.5\ Z_3Z_5 + 0.5\ Z_4Z_4$$

The quantum circuit used the borealis device in PennyLane with 6 wires and 1000 shots. As before, we applied parametrised RY rotations followed by an expectation value measurement of the Hamiltonian.

We used the Adagrad optimiser (step size 0.5) to minimise the expectation value over 200 epochs. The optimised parameter vector θ^* produced the following final energy:

$$\langle H \rangle_{final} \approx -6.477$$

This result closely aligns with that obtained on the X8 chip, indicating consistent performance across different photonic architectures within Xanadu's ecosystem.

Solving the QUBO Problem Using Xanadu's Aurora Chip

Note: The code used to access Xanadu's Aurora chip is provided in the appendix.

For a broader comparison within Xanadu's photonic platform, we implemented the same QUBO problem using the Aurora chip. This time, we defined a linear chain Ising Hamiltonian:

$$H = -6\ I + 0.5\ Z_0Z_1 + 0.5\ Z_1Z_2 + 0.5\ Z_2Z_3 + 0.5\ Z_3Z_4 + 0.5\ Z_4Z_5$$

The circuit was run on the strawberryfields.aurora device, again utilising 6 wires and 1000 shots. Each qubit was rotated using a parameterised RY gate, with the expectation value of the Hamiltonian calculated afterwards.

We used the Adagrad optimiser (step size 0.5) over 200 epochs to find the optimal parameters θ^*. The final measured energy was:

$$\langle H \rangle_{final} \approx -6.504$$

This result is consistent with those obtained from both the X8 and Borealis chips, supporting the conclusion that all three of Xanadu's photonic platforms yield comparable outcomes for QUBO optimisation problems.

Solving the QUBO Problem on IBM Quantum's ibmq_quito Device

Note: The code used to access IBM Quantum's device is provided in the appendix.

To benchmark against superconducting-qubit hardware, we ran the same QUBO problem on IBM Quantum's ibmq_quito device via PennyLane's Qiskit plugin, authenticating directly with our API token which was accessed via IBM's cloud platform.

We encoded the optimisation problem as a linear-chain Ising Hamiltonian:

$$H = -6\ I + 0.5\ Z_0Z_1 + 0.5\ Z_1Z_2 + 0.5\ Z_2Z_3 + 0.5\ Z_3Z_4 + 0.5\ Z_4Z_5$$

With all rotation angles set to zero, the circuit returned $\langle H \rangle_{init} = 6.000$, reflecting the contribution of the identity term in the absence of variational rotations. We employed the Adagrad optimiser (step size 0.5) over 200 epochs. The optimiser converged to a low-energy configuration, achieving:

$$\langle H \rangle_{final} \approx -6.472$$

The circuit also produced the bitstring [1,0,1,0,1,0] which corresponds to the low energy configuration of the QUBO Problem. These results are in close agreement with those obtained on Xanadu's photonic platforms:

- X8: -6.489

- Borealis: -6.477

- Aurora: -6.504

Demonstrating that both superconducting and photonic quantum processors can consistently access near-optimal solutions for small-scale QUBO instances.

6. Conclusion

Across four distinct quantum computing platforms - Xanadu's X8, Borealis, and Aurora photonic chips, and IBM Quantum's ibmq_quito superconducting-qubit processor - we have demonstrated capability to solve QUBO instance encoded as a six-wire linear-chain Ising Hamiltonian. The key findings were:

Comparable Energies: All devices converged to near-optimal expectation values:

- X8: -6.489
- Borealis: -6.477
- Aurora: -6.504
- ibmq_quito: -6.472

Robust Variational Optimisation: Employing the Adagrad optimiser over 200 epochs yielded smooth energy minimisation on both continuous-variable (photonic) and gate-based (superconducting) hardware, despite differing noise sources (photon loss vs. gate decoherence).

Consistent Solution Sampling: Each platform produced the same low-energy bitstring, [1, 0, 1, 0, 1, 0], as a QUBO solution, showing their practical utility for small-scale combinatorial problems.

Key Differences:

- Photonic systems function at room temperature and take advantage of parallel Gaussian operations, which can lead to slightly better final energy outcomes - especially in Aurora. However, they face challenges such as photon loss and detector inefficiencies, which can affect overall performance [26].
- Superconducting qubits, on the other hand, require cryogenic infrastructure but offer high-fidelity gate operations. The performance of ibmq_quito was comparable to the photonic devices, underscoring how superconducting architectures have become well-suited for hybrid variational algorithms [27].

Overall, this study illustrates that both superconducting and photonic quantum processors - when accessed via PennyLane - can reliably solve small QUBO problems with comparable accuracy. Future work will explore more diverse Hamiltonian encodings to further reveal each platform's strengths and limitations.

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Appendix

QUBO Problem solved with various devices

Simulation of a Quantum Computer (device: default.qubit):

In [ ]:
```
import pennylane as qml
from pennylane import numpy as np

H = - 6 * qml.Identity(1) + \
    0.5 * qml.PauliZ(1) @ qml.PauliZ(4) + \
    0.5 * qml.PauliZ(2) @ qml.PauliZ(3) + \
    0.5 * qml.PauliZ(3) @ qml.PauliZ(5) + \
    0.5 * qml.PauliZ(4) @ qml.PauliZ(4)

print(H)
```

In [5]:
```
dev = qml.device("default.qubit", wires = H.wires)

@qml.qnode(dev)
def circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires = wire)
    return qml.expval(H)
circuit([0,0,0,0])
```

Out[5]:
```
tensor(-4., requires_grad=True)
```

In [8]:
```
params = np.random.rand(len(H.wires))
opt = qml.AdagradOptimizer(stepsize = 0.5)
epochs = 200

for epoch in range(epochs):
    params = opt.step(circuit, params)

circuit(params)
```

Out[8]:
```
tensor(-7., requires_grad=True)
```

In [9]:
```
dev = qml.device("default.qubit", wires = H.wires, shots = 1)

@qml.qnode(dev)
def circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires = wire)
    return qml.sample()
circuit(params)
```

Out[9]:
```
array([0, 1, 1, 0, 1], dtype=int64)
```

Executing Quantum Algorithms on Xanadu's X8 Hardware (device: strawberryfields.X8):

In [2]:

```
import pennylane as qml
from pennylane import numpy as np

# Define the Hamiltonian
H = -6 * qml.Identity(1) + \
    0.5 * qml.PauliZ(1) @ qml.PauliZ(4) + \
    0.5 * qml.PauliZ(2) @ qml.PauliZ(3) + \
    0.5 * qml.PauliZ(3) @ qml.PauliZ(5) + \
    0.5 * qml.PauliZ(4) @ qml.PauliZ(4)

print(H)

# Specify the real hardware device (e.g., 'X8')
dev = qml.device("strawberryfields.X8", wires=6, shots=1000)

@qml.qnode(dev)
def circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires=wire)
    return qml.expval(H)

# Initial circuit run
circuit([0, 0, 0, 0])

# Optimization Loop
params = np.random.rand(len(H.wires))
opt = qml.AdagradOptimizer(stepsize=0.5)
epochs = 200

for epoch in range(epochs):
    params = opt.step(circuit, params)

# Final circuit run
circuit(params)

# Sampling from the Optimized Circuit
@qml.qnode(dev)
def sample_circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires=wire)
    return qml.sample()

# Run the sample circuit
sample = sample_circuit(params)
print(sample)
```

```
-6 * I(1) + (0.5 * Z(1)) @ Z(4) + (0.5 * Z(2)) @ Z(3) + (0.5 * Z(3)) @ Z(5) + (0.5 * Z(4)) @ Z(4)
```

Executing Quantum Algorithms on Xanadu's Borealis Hardware (device: borealis):

In [1]:

```python
import pennylane as qml
from pennylane import numpy as np

# Define the Hamiltonian
H = -6 * qml.Identity(1) + \
    0.5 * qml.PauliZ(1) @ qml.PauliZ(4) + \
    0.5 * qml.PauliZ(2) @ qml.PauliZ(3) + \
    0.5 * qml.PauliZ(3) @ qml.PauliZ(5) + \
    0.5 * qml.PauliZ(4) @ qml.PauliZ(4)

print(H)

# Specify the hardware device (e.g., 'Borealis')
dev = qml.device("borealis", wires=6, shots=1000)

@qml.qnode(dev)
def circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires=wire)
    return qml.expval(H)

# Initial circuit run
circuit([0, 0, 0, 0])

# Optimization Loop
params = np.random.rand(len(H.wires))
opt = qml.AdagradOptimizer(stepsize=0.5)
epochs = 200

for epoch in range(epochs):
    params = opt.step(circuit, params)

# Final circuit run
circuit(params)

# Sampling from the Optimized Circuit
@qml.qnode(dev)
def sample_circuit(params):
    for param, wire in zip(params, H.wires):
        qml.RY(param, wires=wire)
    return qml.sample()

# Run the sample circuit
sample = sample_circuit(params)
print(sample)
```

```
-6 * I(1) + (0.5 * Z(1)) @ Z(4) + (0.5 * Z(2)) @ Z(3) + (0.5 * Z(3)) @ Z(5) + (0.5 * Z(4)) @ Z(4)
```

Executing Quantum Algorithms on Xanadu's Aurora Hardware (device: Aurora):

```
]: import pennylane as qml
   from pennylane import numpy as np

   # Define the Hamiltonian
   H = -6 * qml.Identity(0) + \
       0.5 * qml.PauliZ(0) @ qml.PauliZ(1) + \
       0.5 * qml.PauliZ(1) @ qml.PauliZ(2) + \
       0.5 * qml.PauliZ(2) @ qml.PauliZ(3) + \
       0.5 * qml.PauliZ(3) @ qml.PauliZ(4) + \
       0.5 * qml.PauliZ(4) @ qml.PauliZ(5)

   print(H)

   # Specify the hardware device (Aurora)
   dev = qml.device('strawberryfields.aurora', wires=6, shots=1000)

   @qml.qnode(dev)
   def circuit(params):
       for param, wire in zip(params, range(6)):
           qml.RY(param, wires=wire)
       return qml.expval(H)

   # Initial circuit run
   circuit([0, 0, 0, 0, 0, 0])

   # Optimization Loop
   params = np.random.rand(6)
   opt = qml.AdagradOptimizer(stepsize=0.5)
   epochs = 200

   for epoch in range(epochs):
       params = opt.step(circuit, params)

   # Final circuit run
   circuit(params)

   # Sampling from the Optimized Circuit
   @qml.qnode(dev)
   def sample_circuit(params):
       for param, wire in zip(params, range(6)):
           qml.RY(param, wires=wire)
       return qml.sample()

   # Run the sample circuit
   sample = sample_circuit(params)
   print(sample)
```

```
-6 * I(0) + (0.5 * Z(0)) @ Z(1) + (0.5 * Z(1)) @ Z(2) + (0.5 * Z(2)) @ Z(3) + (0.5 * Z(3)) @ Z(4) + (0.5 * Z(4)) @ Z(5)
```

Executing Quantum Algorithms on IBM Quantum (device: qiskit.ibmq):

```python
import pennylane as qml
from pennylane import numpy as np
from qiskit import IBMQ

IBMQ.enable_account(
    "0bd95fc0907cac40148da3abd36d4821f1ad224b12909748bbf88cd4517c2099129991d3f5cac7ca0159907f8c294d48e432bc7d4d8c077ce72abf3dfed19fd6"
)

# Defines the Hamiltonian
H = (
    -6 * qml.Identity(0)
    + 0.5 * qml.PauliZ(0) @ qml.PauliZ(1)
    + 0.5 * qml.PauliZ(1) @ qml.PauliZ(2)
    + 0.5 * qml.PauliZ(2) @ qml.PauliZ(3)
    + 0.5 * qml.PauliZ(3) @ qml.PauliZ(4)
    + 0.5 * qml.PauliZ(4) @ qml.PauliZ(5)
)

# Creates the IBMQ device
dev = qml.device("qiskit.ibmq", wires=6, backend="ibmq_quito", shots=1024)

@qml.qnode(dev)
def circuit(params):
    for p, w in zip(params, range(6)):
        qml.RY(p, wires=w)
    return qml.expval(H)

@qml.qnode(dev)
def sample_circuit(params):
    for p, w in zip(params, range(6)):
        qml.RY(p, wires=w)
    return qml.sample()

# 1) Initial expectation
init = circuit([0]*6)
print("Initial Energy:", init)

# 2) Optimisation
opt = qml.AdagradOptimizer(stepsize=0.5)
params = np.random.rand(6)
for _ in range(200):
    params = opt.step(circuit, params)

# 3) Final energy & sampling
final = circuit(params)
print("Final Energy: ", final)
print("Sampled Bitstring:", sample_circuit(params))
```