National Quantum Computing Centre

Technical Report

# UK Quantum Hackathon 2024

**University of Warwick**

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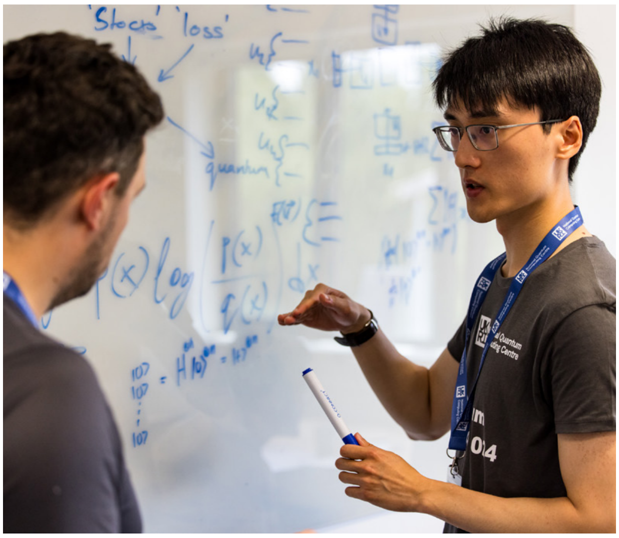


# Contents

# Executive summary

In July 2024, the National Quantum Computing Centre (NQCC) held its third UK Quantum Hackathon at the University of Warwick. Over three days, 13 teams of early-career quantum computing researchers were tasked with developing solutions to practical use-case problems provided by industrial end users.

The number of use cases demonstrated an increase in end-user organisations from 10 in 2023 to 13 in 2024. This was accompanied by a wider range of sectors being represented, including the first use case to be focused on law enforcement.

The use cases spanned different problem domains, with six exploiting quantum machine learning, five focused on optimisation and two based on simulation. Six of the end-user organisations had not participated in a previous NQCC UK Quantum Hackathon, demonstrating the growing interest in quantum computing among organisations in the UK.

The 2024 UK Quantum Hackathon also involved several quantum computing providers who hadn't engaged with the activity in previous years, such as Q-CTRL, which provided access to their 'Fire Opal' tool, and Infleqtion, which provided access to an emulator. As in previous years, various hardware platforms were available, including annealer-based and gate-based quantum hardware. Teams tested their solutions on superconducting, trapped ion, and neutral atom platforms and utilised middleware tools to enhance their solutions.

Each team consisted of four to six early career researchers supported by at least one industrial mentor from the end-user organisation that provided the team's use-case problem.

Mentors from the quantum computing providers were also present to assist teams in accessing their platforms and developing their solutions using their tools, including middleware, emulators and real quantum hardware accessed via the cloud.

As part of the hackathon, teams had the opportunity to present their solution to a panel of expert judges and their peers. The first, second and third-place teams were:

### 1st place
**Team:** KL Divergents
**Use case:** Risk aggregation evaluation for insurance losses in case of natural disaster
**Use case provided by:** Mind Foundry and Aioi R&D Lab
**Quantum computing resources provided by:** Quantinuum, IonQ and Classiq Technologies

### 2nd place
**Team:** Schrödinger's Apples
**Use case:** Efficient placement of transmitters, receivers and sensors in networks
**Use case provided by:** BT
**Quantum computing resources provided by:** D-Wave and IonQ

### 3rd place
**Team:** Trust me, I'm a Doctor…of physics…in training
**Use case:** Quantum Modelling for NHS Forecasting
**Use case provided by:** NHS England
**Quantum computing resources provided by:** IonQ, Classiq Technologies and AWS Braket

Industrial end-user mentors from each team were invited to summarise their use case and their team's solution. This report presents six summaries and three in-depth case studies, providing insights into the types of problems addressed at the hackathon and the current capabilities of quantum computing technology for solving practical problems.

*1st place: KL Divergents*

*2nd place: Schrödinger's Apples*

*3rd place: Trust me, I'm a Doctor…of physics…in training*

# Objectives and results

The objectives and main outcomes of the 2024 UK Quantum Hackathon are outlined below.

*Table 1: The results of the 2024 UK Quantum Hackathon against its objectives.*

| 2024 objectives | 2024 results |
|---|---|
| Connect the UK quantum ecosystem through networking and collaboration throughout the event. | The hackathon had 69 participants, 24 end-user mentors, 19 provider mentors, four judges, and 14 NQCC staff. |
| Explore use cases for quantum computing. | 13 use cases across 10 industrial sectors with quantum machine learning, optimisation and simulation problems represented. |
| Enable aspiring practitioners to develop their quantum computing programming and applications skills. | 95% of feedback survey respondents stated that they acquired or furthered their skills and knowledge in quantum computing through the hackathon. |
| Showcase the breadth of technology available currently and enable a broad range of users to access these tools. | Eight quantum providers, including access to emulators, quantum hardware, and middleware tools. |
| Understand the opportunities and limitations of quantum computing by demonstrating the technology's current capabilities. | A broad range of solutions developed across various sectors, with six new and seven returning end-user organisations. |

These results demonstrate the event's benefit to participants. For example, end-user organisations were able to develop and explore new use cases, developers gained new skills and knowledge, and technology providers tested practical use cases on their platforms. Compared to 2023, the 2024 hackathon hosted more developers and mentors, including those from organisations that had not previously participated in the event.

# Introduction and background

The UK Quantum Hackathon provides an opportunity for participants to gain hands-on experience of formulating computational solutions in response to practical use cases, and of coding and running quantum algorithms on real and emulated quantum processors. This facilitates an exploration of the capabilities and limitations of current cutting-edge technology.

As part of the NQCC's SparQ programme, the UK Quantum Hackathon contributes to efforts towards building an ecosystem of 'quantum ready' organisations within the UK, as well as a community of end users equipped with the tools and knowledge needed to make the most of quantum computing as the technology develops.

By ensuring that a broad range of industries are represented in the use cases and providing access to a variety of state-of-the-art quantum computing platforms, the hackathon offers a unique opportunity for participants to explore the potential of current quantum computing technology. In addition to the technical aspects of their use cases, participants are encouraged to consider the need for responsible and ethical quantum computing within the context of use-case development and quantum programming.

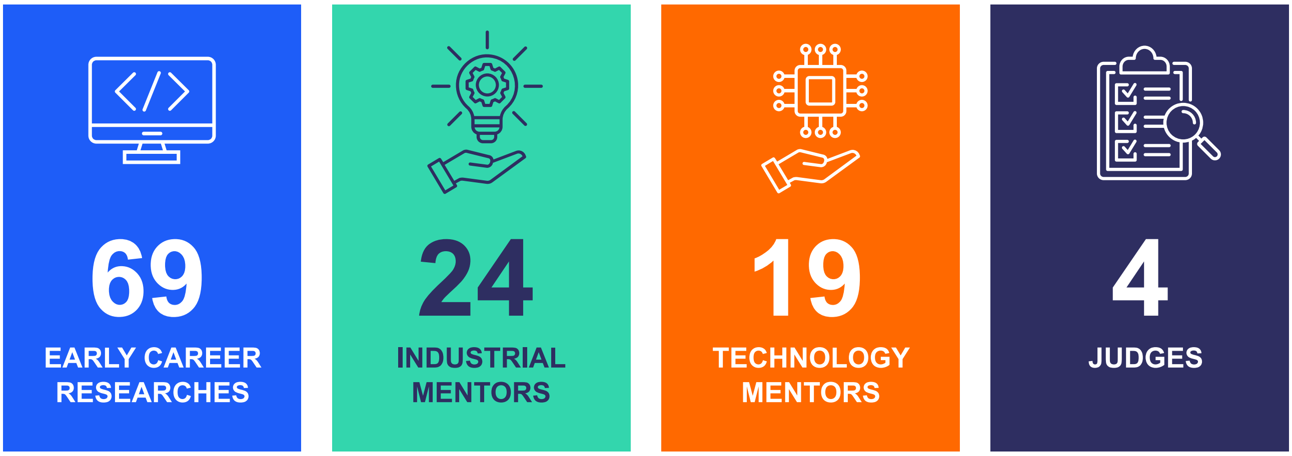



*Figure 1: Overview of the number of people participating in the 2024 UK Quantum Hackathon.*

### The UK Quantum Hackathon 2024

The 2024 edition of UK Quantum Hackathon showcased represented an evolution of the delivery model. The event was extended to three days to provide teams with more time to explore and develop their use cases.

An open competition was also introduced to enable more organisations to propose different use cases, including an event extension to three days and a 'use case competition' to enable a broader range of organisations to apply.

Any interested organisation could submit an 'expression of interest', with the NQCC selecting a shortlist based on the quality of the proposal, the suitability for the hackathon format, the opportunity for advancing learning, and the potential for societal and economic benefit.

Shortlisted applicants were invited to submit a complete use case for the full competition, with each submission reviewed and assessed against the criteria in the following table.

*Table 2. The use case competition selection criteria were shared with end users before submitting their full applications.*

1 **The suitability of the use case for the hackathon format**, including:

- Relevance to quantum computing,
- Feasibility on the available quantum computing resource (access to emulation across hardware platforms and hardware on early quantum systems such as those provided by IBMQ, D-Wave, Quantinuum, IonQ, Oxford Quantum Circuits, QuEra, and Rigetti), and
- Suitability for making meaningful progress in the timeframe of two full days of technical work

2 **The anticipated impacts of the use case and opportunities for delivering societal and economic benefit.** For example, improving resource allocation in a public service, accelerating R&D capabilities, producing more accurate results, etc.

3 **The technical interest of the use case**, including its novelty and the opportunity for advancing the learning of participants and furthering quantum computing understanding and knowledge

4 **The quality of the proposal**, including definition of the problem, background information, structure, and demonstrating a responsible innovation approach

In addition, the NQCC aims to have a diverse range of sectors, problem domains, hardware implementation, and organisations represented at the hackathon. Therefore, fit with the overall portfolio of use cases may also be considered for the final selection process.

The successful end-user organisations who provided teams with use cases were:

- BT
- CGI IT UK Ltd
- Cisco
- Homomorphic Labs
- Johnson Matthey PLC
- LTIMindtree
- Mind Foundry and Aioi R&D Lab
- NHS
- Nomura
- North Wales Police
- Rolls Royce
- UKAEA
- Unisys

Each successful end-user organisation provided an industrially relevant use-case problem for teams. As was seen in 2023, the hackathon included a mixture of end-user organisations that are already exploring the potential of quantum computing and those that are new to quantum computing. Six end-user organisations at the hackathon had not participated in the event before, while seven were returning for the second or third time. This demonstrates that many organisations are developing an interest in quantum computing, while others remain enthusiastic about using quantum computing to solve problems and drive innovation.

Later in the year, six of the 2024 hackathon end-user organisations submitted a use case for the ‘NQCC and STFC Cross Cluster Proof of Concept SparQ Quantum Computing Call’ (see appendix). While not all submitted use cases are built on work started at the hackathon, this indicates the sustained interest of these organisations in developing solutions using quantum computing.

A diverse range of quantum providers also participated in the 2024 hackathon, including an increase in middleware tools available. The providers who directly supported the event are shown in Table 3.

*Table 3. The quantum computing providers available at the UK Quantum Hackathon 2024 and the hardware modalities that they offer.*

| Quantum computing provider | Hardware modality |
|---|---|
| IBM Quantum | Superconducting circuits |
| AWS: QuERA | Neutral atoms |
| Classiq | Hardware agnostic |
| D-Wave | Superconducting quantum annealing |
| Infleqtion | Neutral atoms |
| IonQ | Trapped ions |
| Q-CTRL | Hardware agnostic |
| Quantinuum | Trapped ions |

The available emulation, hardware and matched middleware tools are mapped in the figure below.

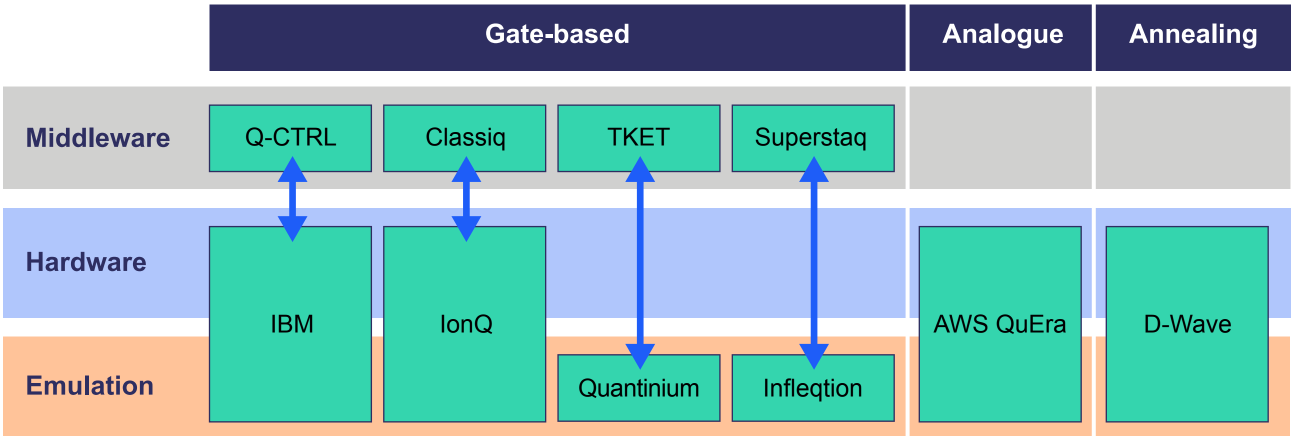



*Figure 2: The available Emulation, hardware, and middleware tools for each quantum computing hardware type. The blue arrow indicates the interface of platforms with middleware tools.*

These providers represented a broad range of technologies, giving participants access to gate-based, analogue and annealing-based quantum computers, quantum emulators, and middleware tools to enhance their solutions. Teams were allocated primary and secondary quantum hardware providers to ensure backup options were available in case of hardware access limitations. Access to quantum emulators meant that participants could compare 'ideal' emulated results to those from real quantum hardware. Benchmarking was also carried out by some teams across their primary and secondary hardware allocations, enabling participants to better understand the limitations and potential of current quantum hardware.

In the weeks before the hackathon event, quantum computing providers gave training sessions to the participants to introduce them to their platforms and allow them to start exploring the tools they would be using during the hackathon.

The hackathon concluded with short team presentations to a panel of quantum experts who assessed their solutions based on the judging criteria outlined in the appendix.

These criteria were co-developed with the judging panel, which comprised Dr Oliver Brown, Professor Animesh Datta, Professor Sarah Harris and Dr Stasja Stanisic. The judging criteria provide some structure to the work so that participants feel able to explore creative solutions whilst also considering the feasibility of their solution on today's quantum computers and the hardware requirements that would be needed for a full-scale solution.

Responsible and Ethical Quantum Computing (REQC) considerations were embedded in the hackathon via a judging criterion on this aspect of quantum computing development and innovation. A briefing introduced participants to the NQCC's recently published 'Quantum STATES Principles' (see Figure 3) and encouraged them to consider the stakeholders relevant to their team's allocated use case. In the final presentations, teams were expected to identify who might be impacted by their use case and outline how their solution could maximise the benefits and mitigate harms for these stakeholders.

| | | |
|---|---|---|
| **S** Societally beneficial | **Develop quantum computing capabilities for the benefit of society, taking a pro-active and responsible approach.** | • Pro-actively seek to understand the implications of quantum computing on wider society and the environment, leveraging our technical expertise<br>• Engage inclusively to inform the future trajectory of innovation<br>• Pursue goals for the good of all |
| **T** Trusted | **Be a trusted voice, sharing our knowledge with the quantum computing community and wider society.** | • Offer unbiased, trustworthy, informed assurance on quantum computing capabilities<br>• Manage expectations, cutting through overhype<br>• Accessibly disseminate our understanding of quantum computing and its implications |
| **A** Accountable | **Recognise our responsibility to the wider community, and hold ourselves accountable for our actions throughout our activities.** | • Put in place mechanisms to ensure the responsible development and use of quantum computing, throughout our activities<br>• Demonstrate our commitment to responsible and ethical quantum computing by sharing our efforts<br>• Champion a responsible approach among our collaborators and the quantum community |
| **T** Transparent and explainable | **Provide transparency and explainability in the quantum computing systems we develop, procure, and use, and in our decision-making.** | • Be open and honest about the capabilities and limitations of quantum computing<br>• Be clear about our intentions and decisions throughout our activities<br>• Aim for explainability, particularly where our technology informs important decisions |
| **E** Equitable, fair and inclusive | **Embed fairness and inclusivity into our activities, working to build a diverse community in which quantum computing benefits are equitability distributed.** | • Design for equitability and fairness, with particular consideration to vulnerable communities<br>• Allocate and distibute our resources through fair processes<br>• Provide inclusive opportunities to learn and benefit, building a diverse community |
| **S** Safe, reliable and secure | **Build and test for safety, reliability, and security.** | • Put in place guardrails to mitigate against harms to humans and the environment<br>• Work to ensure our systems function reliably as intended<br>• Promote and uphold best practice in data governance and information security |

*Figure 3: A summary of the NQCC's Quantum STATES Principles, which teams were asked to consider in the context of their use case solution.*

# Use cases, teams and solutions

An overview of the teams' use cases and solutions is presented in the following section, with summaries and more detailed case studies provided by the industrial end-user mentors detailed following the overview.

| Team | Use case | Problem domain | End user | Sector | Quantum provider(s) |
|---|---|---|---|---|---|
| 1 | Efficient placement of transmitters, receivers and sensors in networks | Optimisation | BT | Telecommunica-tions | Hardware: D-Wave |
| 2 | Forecasting supply, demand and price of the energy system | Quantum machine learning | CGI UK IT Ltd | Energy | Hardware: IonQ, Classiq |
| 3 | Network flow search problem – needle in a haystack | Quantum machine learning | Cisco | Cybersecurity | Hardware: IBMQ, Q-CTRL<br>Emulation: IBMQ |
| 4 | Towards a practical federated quantum learning framework for biomedical data | Quantum machine learning | Homomorphic Labs | Healthcare | Hardware: IonQ, Classiq<br>Emulation: Quantinuum |
| 5 | Quantum feature selection in surrogate time-series modelling for a chemical process | Optimisation | Johnson Matthey PLC | Manufacturing | Hardware: DWave<br>Emulation: DWave |
| 6 | Optimising car assembly lines using Flow-Shop Scheduling | Optimisation | LTIMindtree | Manufacturing | Hardware: DWave<br>Emulation: DWave |
| 7 | Risk aggregation evaluation for insurance losses in case of natural disaster | Simulation | Mind Foundry and Aioi R&D Lab | Insurance | Hardware: IonQ, Classiq<br>Emulation: Quantinuum |
| 8 | Quantum Modelling for NHS Forecasting | Simulation | NHS England | Healthcare | Hardware: IonQ, Classiq<br>Emulation: Quantinuum |
| 9 | Quantum machine learning of time series data | Quantum machine learning | Nomura | Finance | Hardware: IBMQ, Q-CTRL<br>Emulation: IBMQ |
| 10 | Quantum optimisation of forward deployment | Optimisation | North Wales Police | Law enforcement | Hardware: DWave<br>Emulation: DWave |
| 11 | Simulation of Quantum Hamiltonians with interesting properties | Quantum machine learning | Rolls-Royce PLC | Aerospace | Hardware: IBMQ, Q-CTRL<br>Emulation: IBMQ |
| 12 | Co-processing Hamiltonian Neural Networks with quantum algorithm | Quantum machine learning | UK Atomic Energy Authority | Energy | Hardware: AWS<br>Emulation: Inflegtion |
| 13 | Quantum-assisted optimisation for multi-site sub-part supply chain coordination | Optimisation | Unisys | Logistics | Hardware: DWave<br>Emulation: DWave |

# Use case summaries

## Coverage problems in telecommunications

**Author:** Catherine White
**Organisation:** BT

### Problem

Providing maximum coverage efficiently and with resilience is a critical challenge for telecommunication providers. When planning our networks, we also have to consider a range of wider issues, including our commitments to our regulators, cost constraints, and prioritising coverage in critical areas or to vulnerable groups. In addition to managing many constraints, we want to optimise service quality in multiple ways. This adds up to a problem that can be complex even to define and which can have high computational complexity to solve. Classical methods such as Simulated Annealing and Mixed Integer Programming are applied today to solve hard computational problems. Often, there is no guarantee on the 'goodness' of the solution that they will find, and if there is a guaranteed bound, it is often over 10% below the value of the true optimum solution. Finding a better solution could lead to more and better coverage for our customers.

Vertex cover problems are a very good example of problems for which it is often hard to guarantee good solutions using classical heuristics. Minimum vertex cover, in which the problem is simply to provide connections to all nodes (links) using the minimum number of vertices of a graph, is a textbook example which is both NP-hard and difficult to approximate well classically for many networks.

### Solution

Vertex cover problems arise in telecoms for a much wider range of problems than the concrete example studied in the hackathon. The team looked at a particular scenario in which we were planning the deployment of new service assurance hubs for optical fibre links into our site of exchanges. We wanted to pick an optimum set of exchanges at which to install the hubs in order to provide complete coverage over all network links.

The team then considered a version of the problem in which we had both budget constraints and a requirement to prioritise providing the new service (which would support service continuity and rapid repairs) to vulnerable and disadvantaged communities. This is not minimum vertex cover but optimum vertex assignment with constrained cost and weighted edges. For both types of problems, the DWave CQM hybrid solver approach was very successful at providing very good solutions for a representative network similar to BT's network topology. Impressively, the team also developed a QAOA approach, which also gave promising results in simulation, though the team had limited opportunity to test it on the real QPU during the short time of the hackathon.

### Outcome

Overall, BT was encouraged by the potential for quantum and hybrid methods to be useful for this type of problem and extremely impressed by the talent and persistence of the hackathon team – who won well-deserved medals.

## Forecasting supply, demand and price of the electric energy system

**Author:** German Sinuco and Rich Hampshire
**Organisation:** CGI IT UK Ltd.

### Problem

Accurate forecasting of energy demand and generation is essential for maintaining the energy system's reliability. It allows utility companies to plan their operations effectively and set competitive prices. While large-scale forecasting of electricity supply and demand is well-established, challenges persist at the consumer level, where forecasts require greater detail and faster computing times. The large-scale adoption of renewable generation and smart demand technologies, which are often inflexible and weather-dependent, further complicates the forecasting process. Traditional computing methods are likely to fall short in addressing these challenges, making it crucial to explore how quantum computing could handle the increased complexity of the system.

### Solution

The team created a new dataset by aggregating the market index data (for energy costs) and historical GB generation and demand records (Ct, Dt, Gt), which are available via ELEXON. The dataset selected records between 01/04/2023 and 31/03/2024, with a periodicity of 30 minutes.

To account for the time dependence and correlation within the dataset, the team implemented a parameterised quantum circuit (PQC) (see Figure 4). The algorithm was designed to predict the energy cost at t+1 using cost, generation and demand of the two previous time steps, i.e. t and t-1. Using angle encoding, the input layer requires six qubits to encode the values at t and t-1. The PQC consisted of Y-rotations on each qubit, followed by a cyclic sequence of CNOT gates to create entanglement.

To train the PQC, the loss function was defined by the difference between the expected value of the Z operator of the qubit encoding Ct and the cost of energy for the following time step (Ct+1). This algorithm is represented in Figure 4. Note that an ensemble of measurements is required to estimate the expected value.

The team also discussed an algorithm based on multiclass classification of the cost data, with classes defined by discretising the cost values. In this case, the training aims to predict the category (discrete value) of the cost for the following time step. This method requires fewer quantum operations, and the categories are directly read from measurements following the PQC. However, this approach uses a binary representation of the cost (as categories), which means that the number of qubits we use determines the precision to which we model costs.

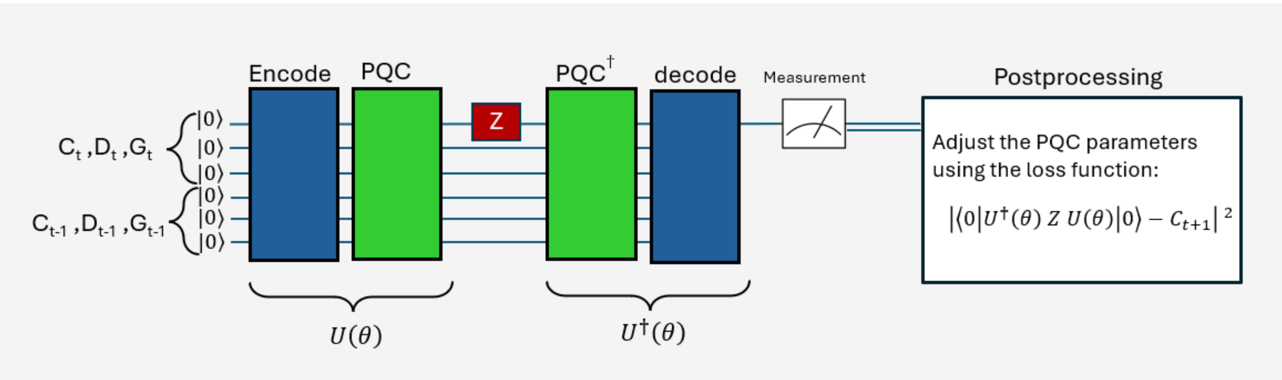



*Figure 4: Quantum circuit design to predict the cost of energy.*

## Outcome

The experiments led to several key observations:

- The number of qubits required is highly dependent on the encoding scheme used. With angle encoding, one qubit is needed per feature and time step, potentially requiring several tens of qubits. In contrast, binary encoding of a model feature demands a number of qubits proportional to the desired precision.
- The choice of loss function impacts both the number of qubits and the circuit depth, necessitating a balance between the two to leverage the hardware's capabilities fully.
- Incorporating PQCs with layers of angle encoding for additional time steps could allow for comparison with models that use more than two time steps as inputs (e.g., ARIMA, X-model). However, this approach would increase circuit depth while reducing the number of qubits.

This work represents an initial exploration of quantum computing, particularly PQCs, for forecasting in the energy sector. Future research could focus on assessing the speed and scalability of quantum computing solutions. Currently, available quantum computing platforms offer tools for the rapid development of proof-of-concept models, which can take advantage of large, publicly accessible operational datasets. This could potentially disrupt existing forecasting approaches and open up new opportunities in the energy sector.

# Quantum feature selection in surrogate time-series modelling for a chemical process

**Organisation:** Johnson Matthey PLC

## Problem

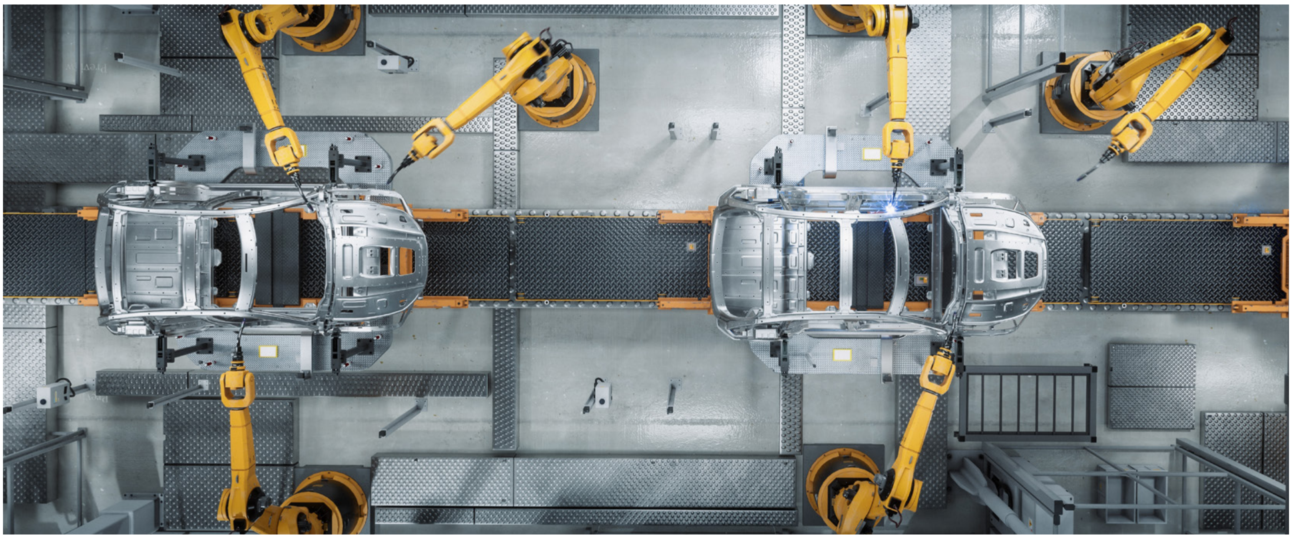
We took a business problem: selecting features for a machine learning model to predict the dynamic nonlinear behaviour of a continuous chemical process. The problem is a complex high-dimensional combinatorial problem involving finding the right combination of features from 300+ features (when including all process variables and their history) and the right model hyperparameters to optimise predictive performance.

## Solution

Over the course of the three-day hackathon, we used D-Wave's quantum annealing technology to solve the feature selection problem, leveraging existing feature selection code together with D-Wave's scikit-learn plugin to develop a quick solution. In parallel, we also tested feature selection methods with classical computing, and the best classical approach was based on a selection of features with the highest absolute mean SHAP (SHapley Additive exPlanations) values. We found that the classical approach outperformed the quantum approach to feature selection in terms of the model's predictive performance on a hold-out test set. Both approaches gave slight improvements compared to no feature selection.

## Outcome

While we were unable to demonstrate an advantage of using quantum computing during the hackathon, we are aware that the approach that we took using the quantum computer could be improved by reformulating the problem. Hence, we are hopeful that there are both software and hardware avenues to improve performance in the future. The Hackathon was a great way for Johnson Matthey to upskill and stay up to date with the progress being made in quantum computing. We feel that it has the potential to be transformative for some of the activities we undertake, e.g. in the areas of computational chemistry or process design. In the future, we are interested in exploring other use cases and attending future hackathons to be ready to embrace quantum computing when business use cases arrive.



## Optimising car assembly line using Flow-Shop Scheduling

**Authors:** Arun, Vijay Rao
**Organisation:** LTIMindtree

### Problem

In a car assembly line, each car must go through a series of operations at various workstations in a specific sequence, such as chassis assembly, engine installation, painting, and interior fittings. Optimising car assembly lines using Flow-Shop Scheduling (FSS) can significantly boost productivity while reducing costs, carbon footprint, energy consumption, and delays. Quantum computing has the potential to enhance FSS by leveraging quantum superposition to explore multiple solutions simultaneously, potentially solving complex optimisation problems more effectively and faster than classical methods.

### Solution

The problem is formulated as an integer programming model [1], and FSS benchmark instances from [2] were executed on D-Wave hardware. These instances are then solved using D-Wave's Constrained Quadratic Models (CQM) and Non-Linear Models (NLM) solvers. Both are quantum-classical hybrid solvers that combine quantum annealing with classical computing techniques for complex optimisation.We found that the classical approach outperformed the quantum approach to feature selection in terms of the model's predictive performance on a hold-out test set. Both approaches gave slight improvements compared to no feature selection.

### Outcome

The team measured the solution quality using the optimality gap, which quantifies how far the obtained solution is from the best-known solution. They observed that the NLM solver performs better than the CQM solver. As problem size increases, the optimality gap for the CQM solver grows while it remains stable (within a band) for the NLM solver. Additionally, the CQM solver cannot handle problems beyond a certain size, while the NLM solver is more scalable. The team also developed a novel approach to divide large-scale problems into smaller pieces and solve them efficiently, though this method requires further research to realize its full potential.

### References

[1] Wen-Yang Ku and J. Christopher Beck, Mixed Integer Programming models for Job Shop scheduling: A computational analysis, Comput. Oper. Res. 73, 165 (2016).

[2] E. Taillard, Benchmarks for basic scheduling problems, Eur. J. Oper. Res. 64, 278 (1993).

## Risk aggregation evaluation for insurance losses in case of natural disaster

**Authors:** Marco Caselli, Saad Hamid
**Organisation:** Mind Foundry & Aioi R&D Lab

### Problem

Risk aggregation is crucial for insurance companies as they must manage exposure to potential losses from various sources, especially insured policies and financial investments. Events like natural disasters, economic downturns, or pandemics can introduce correlations between these losses.

The complexity of risk aggregation involves modelling dynamic relationships and performing simulations, with severe scalability issues arising as the number of assets increases.

There are several papers applying quantum computing 'to risk assessment'. However, most of them focus on managing portfolios exclusively of stocks. Insurance losses have different behaviour from other types of assets, making risk aggregation more challenging.

Improvements in risk aggregation would be highly beneficial for insurance companies, leading to better risk management, enhanced decision-making, improved operational efficiency, and a stronger competitive position.

### Solution

The team extended the work in [1] with a focus on:

- Performance evaluating risk aggregation over a portfolio that contains financial assets as well as insurance losses.
- Scalability with respect to the number of assets/ insurance products.
- Quantitative evaluation against a classical implementation.

In particular, they improved the modelling of insurance losses by working on the discretisation of the cumulative distribution function, describing them as a hierarchical combination of Bernoulli and LogNormal distributions.

They also improved the scalability of the approach, which was highlighted in [1] as the prominent issue of the methodology, by using a randomised KL divergence as the loss function, introducing random binary splits of the space. This approach significantly reduces the amount of data required to fit the Copula, which is an important achievement given the limited size of the historical records.

The team also explored different quantum ansatz, training the models on emulators and comparing their performance against classical methods.

Once the model was trained, the inference was executed on real quantum hardware. The team leveraged the access to both the hardware and emulator providers: Quantinuum and IonQ + Classiq.

### Outcome

The team demonstrated the viability of using a quantum algorithm for modelling a joint distribution over sources of risk that include insurance losses due to natural disasters and losses due to a fall in the price of financial assets.

In particular, they showed that the flexibility of a variational quantum circuit can outperform classical approaches for this task. They also suggested novel approaches that could potentially improve the scalability of the state-of-the-art quantum methods.

These improvements are highly beneficial for insurance companies as they lead to better risk management, which improves insurers' robustness by reducing the likelihood that their losses will exceed their capital reserves. The team is currently working towards improving the methods and the results obtained during the Hackathon, aiming at a scientific publication outlining their discoveries.

### References

[1] https://www.nature.com/articles/s41598-023-44151-1

## Quantum modelling for NHS forecasting

**Author:** Michael Spence
**Organisation:** NHS England

### Problem

In order to efficiently allocate resources between hospitals and treatment centres, the NHS must be able to predict demand across different services. An area where demand forecasting is especially important is emergency medicine.

One tool designed to help with this problem is NHS England's A&E Forecasting Tool [1] . This tool provides a daily 3-week-ahead forecast of A&E admissions to every trust in England. However, this tool is built on top of a complicated time series forecasting model, which is quite computationally expensive.

The intention of this use case was to investigate the potential application of quantum forecasting algorithms to this problem and to determine if there was any possibility for increased model efficiency and accuracy.

### Solution

Our initial approach was to try using a quantum Markov-chain Monte Carlo (QMCMC) algorithm. The current NHS tool uses a classical Monte Carlo Collision (MCC) method, which has several benefits, such as resilience to missing training data and natural uncertainty measures for any outputs.

This approach proved unsuitable. On a technical level, the QMCMC algorithms we found [2] allow for the estimation of parameter means but not the full distributions, which is the primary advantage of classical MCMC in this case. After realising this, our team decided to focus on simpler quantum time series forecasting algorithms.

The solution we finally settled on was based on a paper published in 2022 [3]. It describes a method for quantum time-series forecasting using a variational quantum circuit. The input to our model was a 4-D real vector representing the four most recent values in a time series, and the model is trained to output a single real number corresponding to the predicted next value in the time series. The circuit had just two layers, to begin with.

The model was developed using Classiq's emulator and then tested on a 25-qubit, error-mitigated quantum computer they provided.

### Outcome

For our testing, we generated a fake time series representing linear growth. Given the limited number of qubits, we decided it was best to use very simple data with an obvious trend rather than the more complex real A&E admissions data. We initially struggled to find suitable hyperparameters for our model to learn during training, but after some adjustments, we began to get better results. We found that after training for ~20 epochs on the training data, our model began to converge, and the quality of its predictions began to improve. Some training sessions produced a model capable of detecting the linear trend in the data. Even though we were testing on fake data, this was quite an impressive feat, considering we were only making use of 25 qubits.

Although our test scenario was quite a bit simpler than the real-world problem, we believe our solution showed the potential of quantum hardware to be used in time series forecasting. One area we would have been interested in exploring more is the use of QMCMC algorithms for this problem, due to the advantages mentioned above of these approaches to forecasting.

### References

[1] https://understandingpatientdata.org.uk/case-study/predicting-ae-admissions-improve-preparedness

[2] https://www.nature.com/articles/s41586-023-06095-4

[3] https://link.springer.com/chapter/10.1007/978-3-031-19493-1_6

# Case studies

## Towards a practical federated quantum learning framework for biomedical data

**Author:** Bamborde Balde
**Organisation:** Homomorphic Labs

### Problem

Biomedical data is vital for developing machine learning models for disease diagnosis and treatment, but its sensitive nature and strict privacy regulations restrict AI researchers' access and sharing. Classical machine learning methods face issues such as the curse of dimensionality, computational complexity, and difficulty in capturing complex feature interactions. Quantum computers, with their natural ability to handle high-dimensional data due to the size of the Hilbert space, offer a promising solution for biomedical data. This use case aims to explore combining federated learning with quantum computing on NISQ devices despite current limitations like coherence times and error rates.

### Solution

A federated learning framework enables organisations to train models locally on their data, which are then aggregated to form a globally inclusive model. Since the data never leaves local servers, patient confidentiality remains protected. To enhance AI inclusivity in healthcare by providing access to diverse datasets, the hackathon team developed a framework allowing community hospitals to train quantum adversarial networks (qGANs) in a federated setup. This approach enables the generation of synthetic data, empowering AI researchers and innovators while preserving privacy and addressing the challenge of data availability.

The key motivations for exploiting quantum computing include:

- Enhanced computational advantage for high-dimensional data
- Improved data generation
- Potential security advantage via the noise generated by NISQ devices

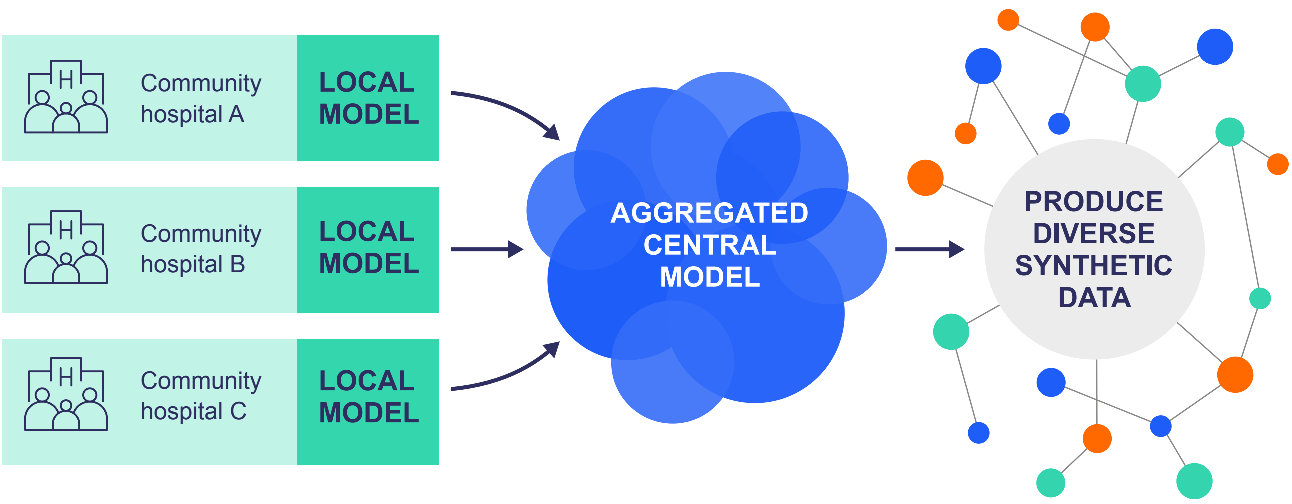



*Figure 5: An overview of the use of federated learning to generate diverse synthetic data from community hospitals. The idea is for the framework to enable community hospitals to set up a federation to help them securely generate synthetic data, which they can then make available to AI healthcare innovators.*

The team selected a quantum generative adversarial network (qGAN) to generate synthetic data. This setup involves two models: a variational quantum circuit (generator) that creates synthetic data and a classical neural network (discriminator) that distinguishes real from fake data. Bridging these models requires amplitude encoding and measurement reconstruction, both of which are computationally expensive.

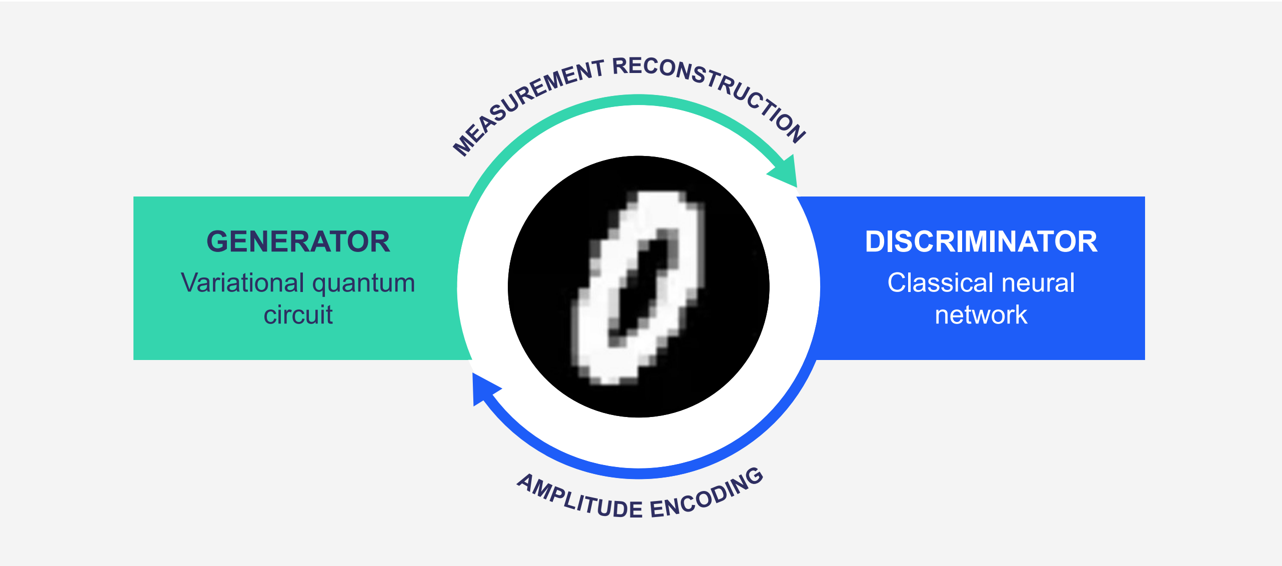



*Figure 6: An overview of the qGANs setup considered by the team.*

The team also leveraged the patch method. This means we have multiple quantum generators, each responsible for producing a different patch of the synthetic data. The advantage here is that it reduces the number of quantum resources needed for each sub-generator.

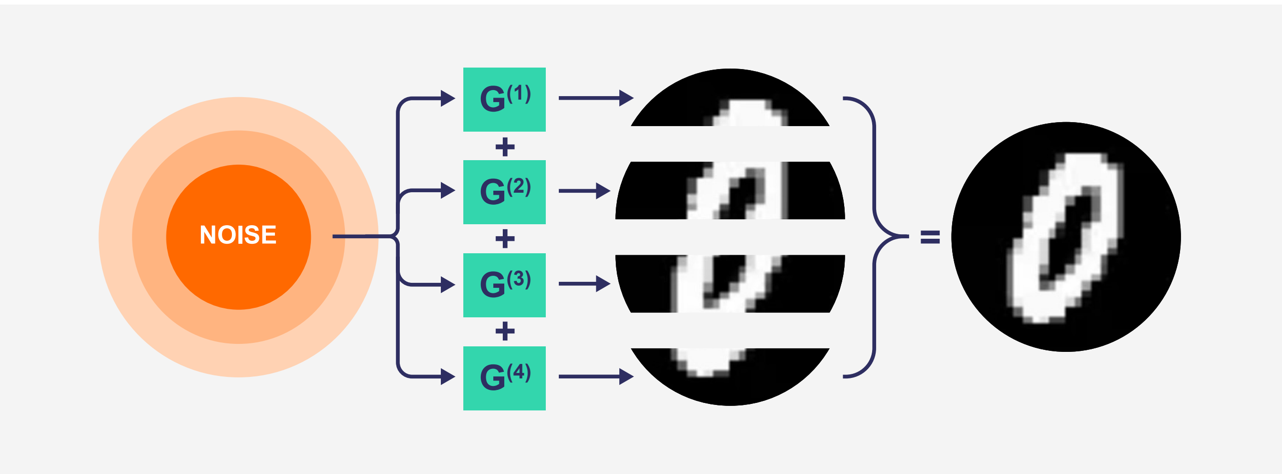



*Figure 7: An overview of the patch method used.*

## Outcome

The hackathon team used the stack seen in Figure 8 for running the experiments.

The team conducted experiments generating the image seen in Figure 6 using the stack to the right, to create the results seen in Figure 9.

An interesting idea emerged from the team, which we, as the use-case provider, hadn't considered before: incorporating a quantum discriminator so that both halves of the qGAN run on quantum devices. The key advantage is that the generator and discriminator can communicate directly, eliminating the need for costly data loading and measurement reconstruction.

Additionally, using a quantum neural network allows us to embed data symmetries into the gate set, creating an equivariant gate set. This symmetry-respecting approach enhances the model's trainability and performance.


*Figure 8: An overview of the stack used to run the experiments.*

Noiseless simulation | H1-emulator | IonQ Aria-2

*Figure 9: An overview of the initial experiment featuring a synthetic image generated by training on the devices.*

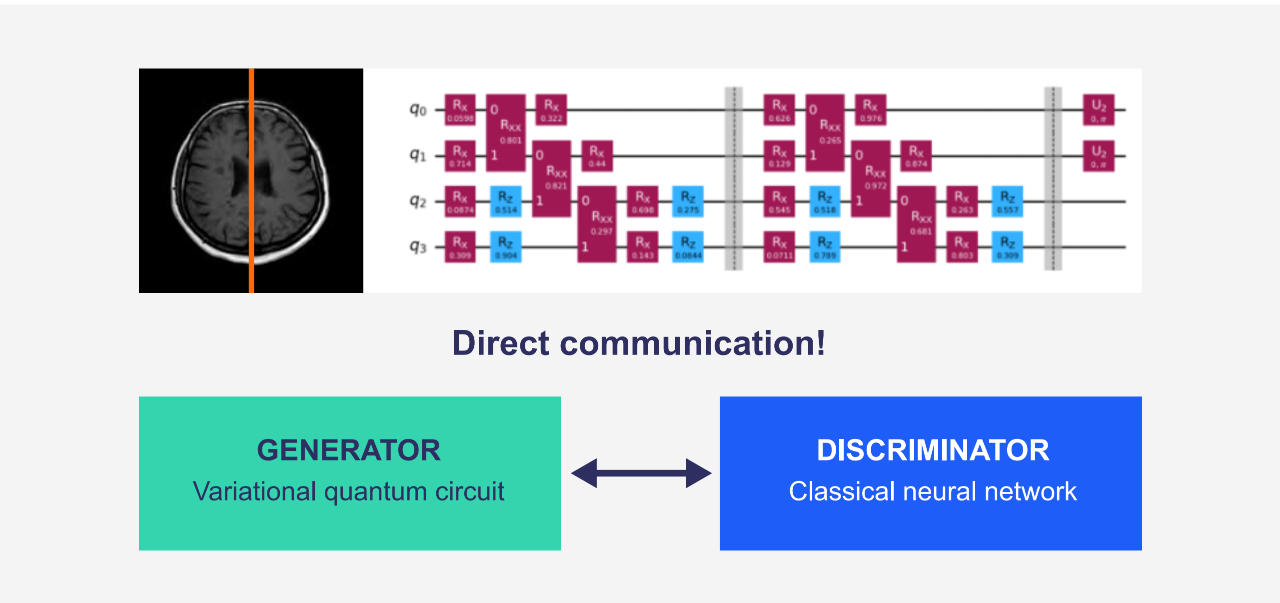



*Figure 10: An overview of the new idea provided by the team.*

As a proof of concept, the hackers ran several Quantum Neural Network (QNN) circuits, first calculating the fidelity in a noiseless simulation (which, as expected, was 1), followed by tests on an emulator and actual hardware. For a 6-qubit system with a circuit depth of around 100, the fidelity remained above 0.5, even on real quantum hardware, indicating promising robustness in practical applications.

The scalability and limitations are highlighted in figure 12.

The future directions are nicely highlighted by the hackers in figure 13.

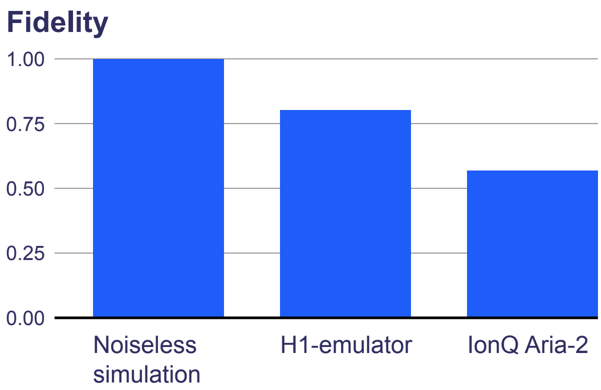



*Figure 11: The results of the experiments from running a number of QNN circuits.*

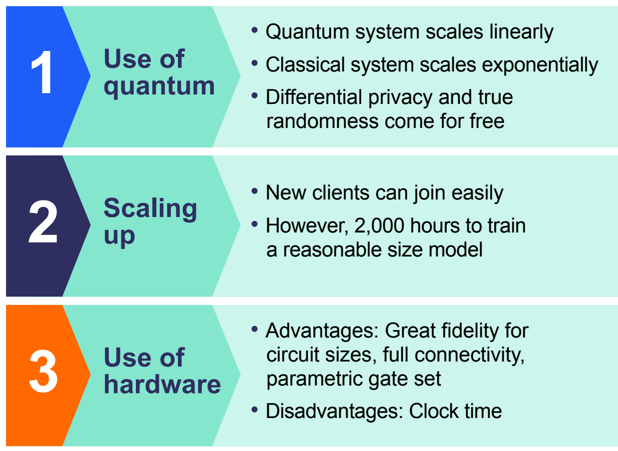



*Figure 12: Addressing scalability and limitations.*

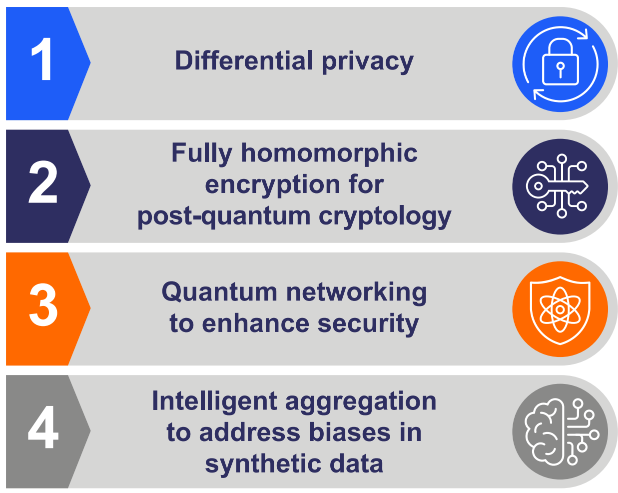



*Figure 13: The highlight of future near-term directions that are in the pipeline. We already implemented fully homomorphic encryption, and the rest, such as Differential privacy, are in the pipeline.*

## References

[1] S. Chen et al., Federated Quantum Machine Learning. arXiv:2103.12010 (2021).

[2] C. Ren et al., Towards Quantum Federated Learning. arXiv:2306.09912 (2024).

[3] Liu, Y., Arunachalam, S. and Temme, K. (2021) IBM researchers find mathematical proof of potential quantum advantage for quantum machine learning, IBM Research.

[4] Ellis, J. (2024) Quantum gans, PennyLane Demos. Available at: https://pennylane.ai/qml/demos/tutorial_quantum_gans/ (Accessed: 23 July 2024).

[5] Sun, T., Li, D., & Wang, B. (2022). Decentralised federated averaging. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(4), 4289-4301.

[6] Y. Zhang et al., (2022). Federated learning with quantum secure aggregation. arXiv preprint arXiv:2207.07444

## Quantum optimisation of forward deployment

**Author:** Alistair Hughes
**Organisation:** North Wales Police

### Problem

North Wales Police is called upon to respond to many high-priority crimes or other incidents. Response times are often dependent on the initial location of the responding officers; improving them can stop crimes and save lives. Due to resource limitations, response targets cannot always be met across the entire region, and we now need to find a way to roughly halve our response times.

To improve response times officers can be forward deployed to areas with a high probability of occurrences, it would however, be unethical to simply place all officers in the city centres and ignore the rural population. Optimising locations using classical methods can take a long time, so quantum computing is being investigated to determine whether it could improve processing times and dynamically optimise deployment locations to ensure both minimal response times and maximal geographical coverage.

### Solution

The approach taken was to treat the problem as one of optimisation. The hardware used was the D-Wave quantum annealer. The solution was formulated for use on the Leap Hybrid Constrained quadratic model solver (CQM) using binary data.

To make the problem tractable, vehicle locations were deemed to be at the centroids of council wards, and the solution was applied to one of the 10 Local Policing Areas (LPAs) at a time.

Two formulations were arrived at, one for the optimal initial configuration [1] and the other incorporating the incidence in each ward.

In order to optimise over two criteria (response time and geographical coverage), two objective functions were formulated with a tuneable parameter introduced into the cost function to adjust results according to the priority assigned to each objective:

Binary variables:

$$x_{ij} = \begin{cases} 1, \text{if car i in ward j} \\ 0, \text{otherwise} \end{cases}$$

Objective 1 – Prioritises rapid response times

$$T = \sum_{i=1}^{n_{cars}} \sum_{j,k=1}^{n_{wards}} x_{ik} J_{kj} R_j$$

Objective 2 – Prioritises geographical coverage

$$D = \sum_{i,m=1}^{n_{cars}} \sum_{j,k=1}^{n_{wards}} f(J_{kj}) x_{ik} x_{mj}$$

Cost Function:

$$C_{total} = \lambda T + (1 - \lambda) D$$

Where λ ∈ [o,1] is the tuneable parameter prioritising response time or distribution $J_{kj}$ is the travel time between ward k and j. $R_j$ represents incidence in the ward j $f$ is a function which penalises closely spaced vehicles.

## Outcome

The model was run for one LPA containing 28 wards with 15 vehicles and showed similar results to the manual process in terms of response times, but processing time was slashed from months to minutes.

The results successfully demonstrated the feasibility of using quantum computing to optimise forward deployment and further demonstrated a method for optimising over multiple objectives with prioritisation.

The prioritisation mechanism in the solution described had a very steep inversion between the objectives but demonstrated that each objective could be prioritised.

Many more constraints must be considered for a real-world solution, but the magnitude of savings in processing time alone clearly demonstrates that further development of the solution is needed.

Optimising forward deployment locations is an issue for most police forces, and once the additional constraints are incorporated, the solution could be scaled nationally, saving time, money, and lives and improving outcomes and carbon footprint.

## References

[1] O'Kelly, Morton E. "A quadratic integer program for the location of interacting hub facilities." European journal of operational research 32.3 (1987): 393-404.

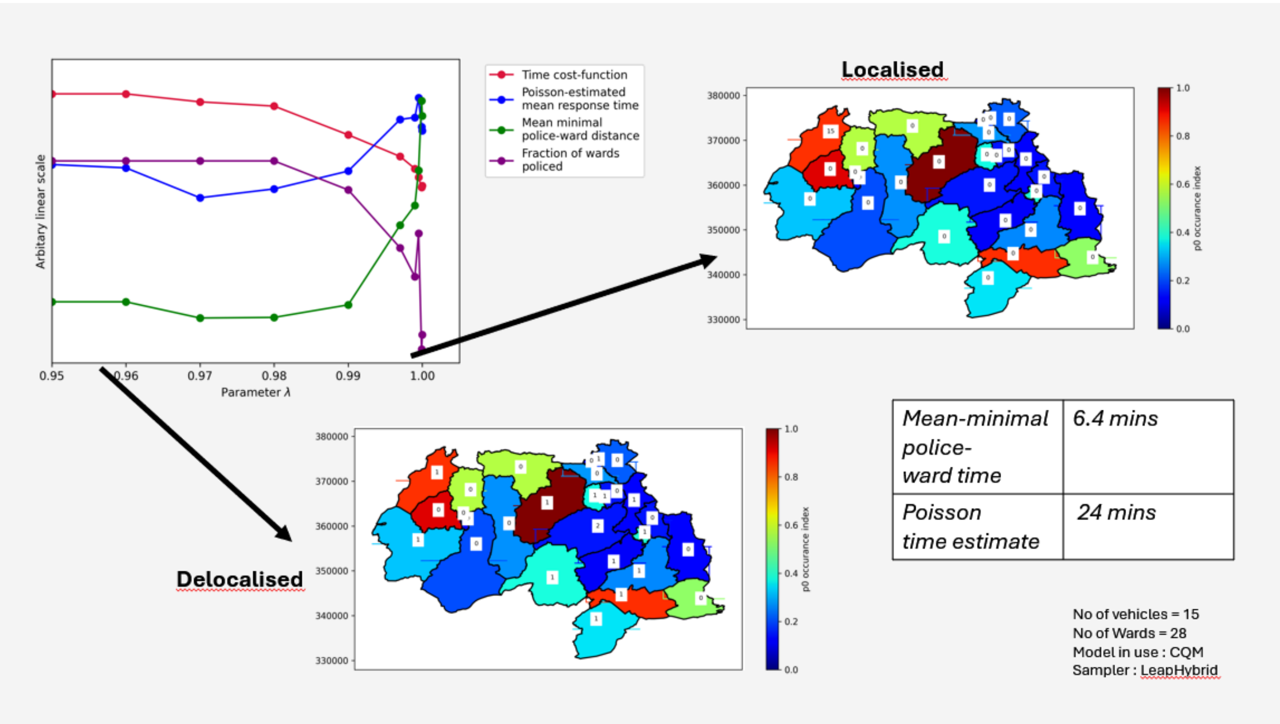



*Figure 14: The results presented by the team.*

## Co-processing Hamiltonian Neural Networks with quantum algorithm

**Author:** Fazal Chaudry
**Organisation:** UK Atomic Energy Authority

### Problem

We were attempting to train a Hamiltonian Neural Network (HNN) to learn the Hamiltonian of a dynamic mass-spring system that was mapped to a quantum computing simulation. The quantum computer was used to acquire the data needed to train the Neural Network. The HNN itself is a classical NN that is designed to learn the physics prior by learning the conservation of momentum and energy that constitutes the dynamics of physical systems. The HNN has two classical multilayer perceptrons (MLPs) that learn the potential and kinetic energy of a physical system.

This use case was attempting to train a classical neural network to learn the Hamiltonian of a mass-spring system. Whilst the use case was a small, single-degree-of-freedom system, scaling to larger systems becomes challenging when training NNs that are physics-informed. This means that we need a better way of training NNs that learn the physics prior, and HNNs are one such approach that improves the learning of the dynamic systems, such that a system can learn to converge even on points outside the original data sets. Quantum computing is particularly suited to Hamiltonian simulation.

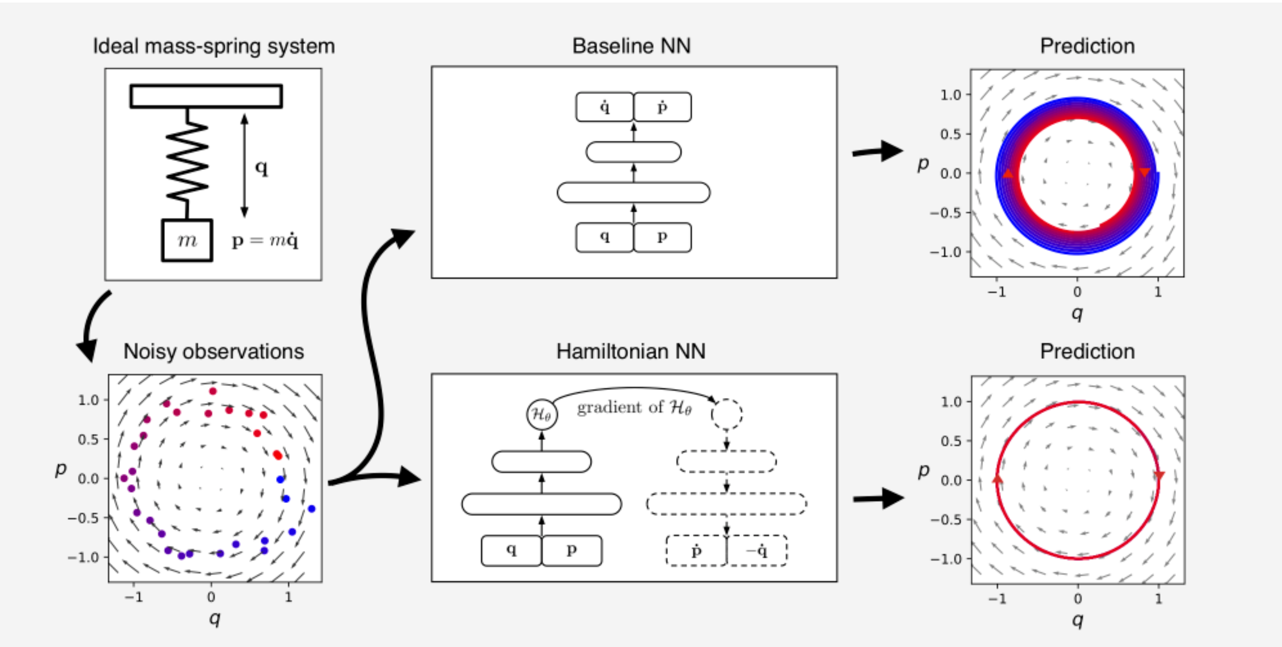



*Figure 15: Instead of crafting a Hamilton by hand, we parameterise it with a neural network and then learn it directly from data. The variables q and p correspond to position and momentum coordinates, As there is no friction, the baseline's inward spiral is due to model errors. By comparison, the Hamiltonian Neural Network learns to exactly conserve an energy-like [1] quantity.*

## Solution

The mass-spring system was first converted to an equation that represented the Hamiltonian of the system, as shown in Figure 16.

A quantum circuit was then created where we mapped the Hamiltonian of the mass-spring system to a position and moment operator using the Zero Variant point Variational Quantum Eigensolver (VQE) circuit. The quantum circuit Hamiltonian was initialised by the boundary conditions representing the problem. The position and moment operator were computed numerous times until a buildup of training data was accumulated, illustrated in Figure 17. The training data was used to train up the classical HNN, illustrated in Figure 18.

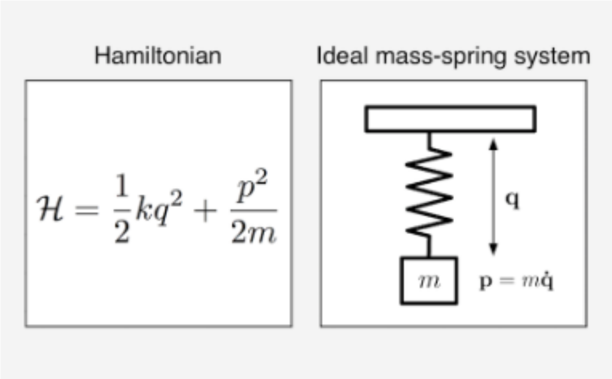



*Figure 16: Mass-spring systems as a Hamiltonian* [1]

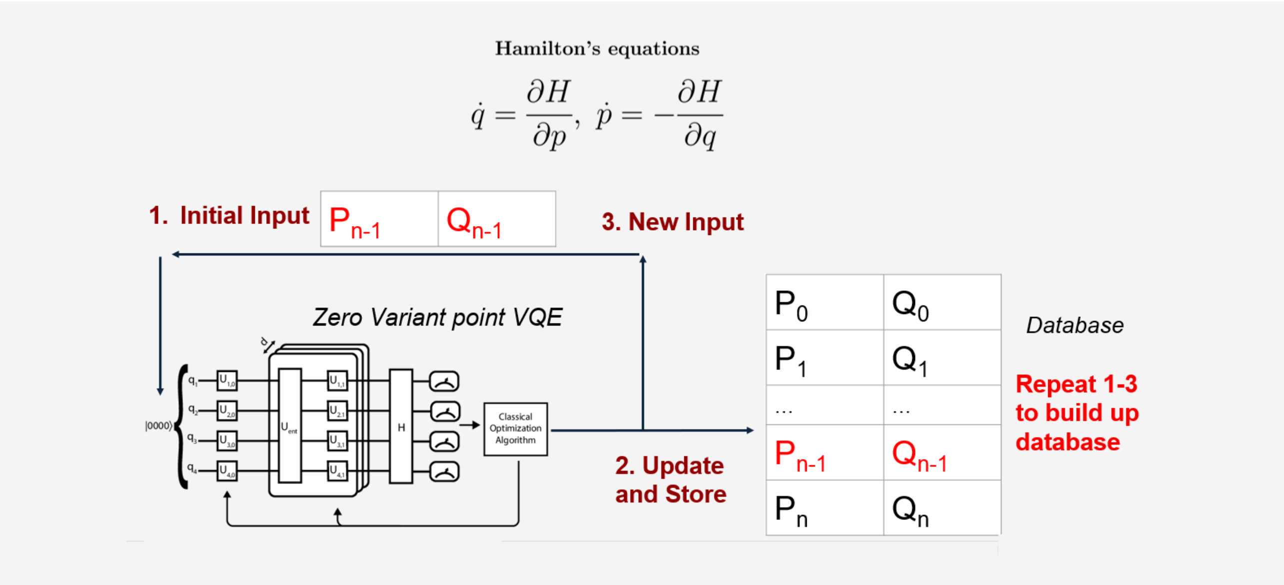



*Figure 17: Quantum circuit that computed the position and moment operator.*

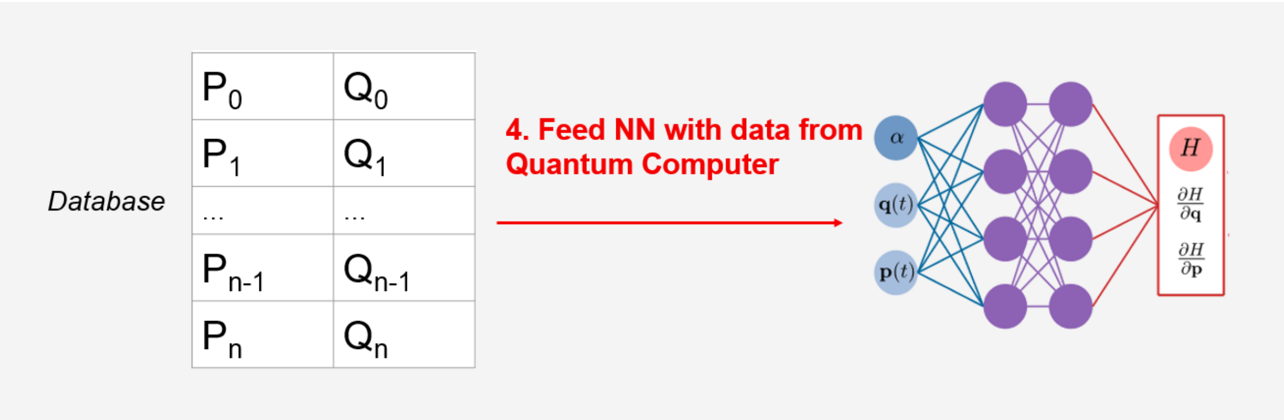



*Figure 18: Training of HNN using quantum Hamiltonian simulation.*

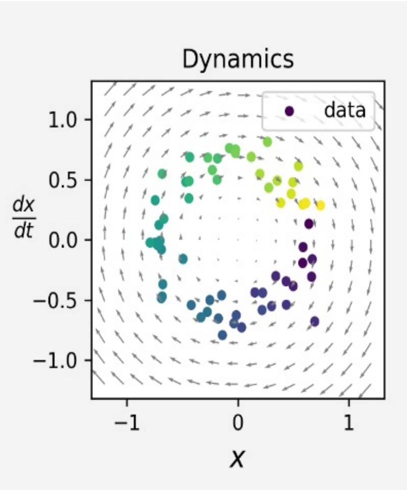



*Figure 19: Benchmark data from classical training data*

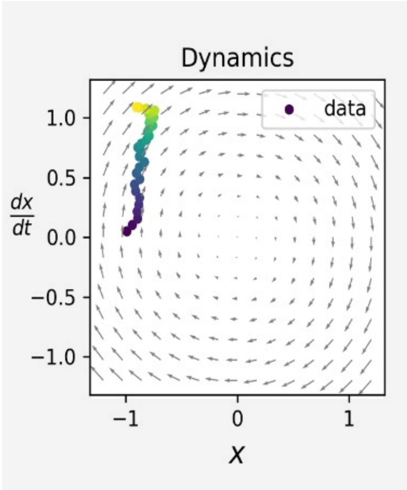



*Figure 20. Training data from Quantum Hamiltonian simulation using 30 data points*

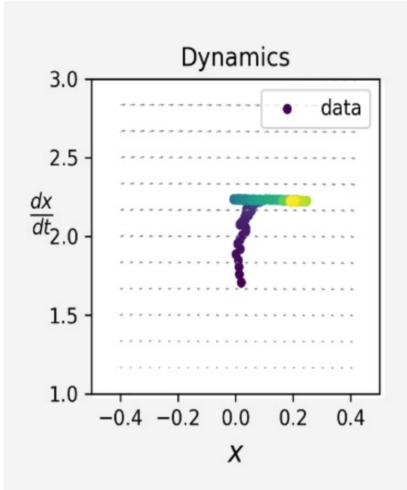



*Figure 21. Training data from Quantum Hamiltonian simulation using 140 data points*

## Outcome

The Hamiltonian simulation data from the quantum computer was compared with a classical equivalent, illustrated in Figure 19. The Quantum computing simulations started to improve as the number of data points increased, as shown in Figures 20 and 21. However, further evaluation also meant that the quantum system diverted from the physics at points, either over-constraining or shifting the initialisation point. This is largely due to the mapping errors between the physics of the problem and the quantum system and due to limited hardware, that restricted the accurate mapping of the problem.

## References

[1] Sam Greydanus, Misko Dzamba, Jason Yosinski, Hamiltonian Neural Networks [5 May 2019], https://greydanus.github.io/2019/05/15/hamiltonian-nns/

# Discussion and conclusions

The 2024 UK Quantum Hackathon showcased the state-of-the-art quantum computing available in the UK. Acknowledging the limitations of a short-term but intensive period of technical work, an incredible amount of innovation was seen at this year's event.

The increased interest in the activity from new end-users across sectors was notable, with six new end-user organisations joining the event in 2024. This may have been facilitated by the open approach taken via the use case competition or due to increasing interest and 'quantum readiness' across sectors. The 2024 hackathon also saw an increase in quantum machine learning problems presented alongside optimisation, the latter of which dominated use case domains in the 2023 event (see figure below).

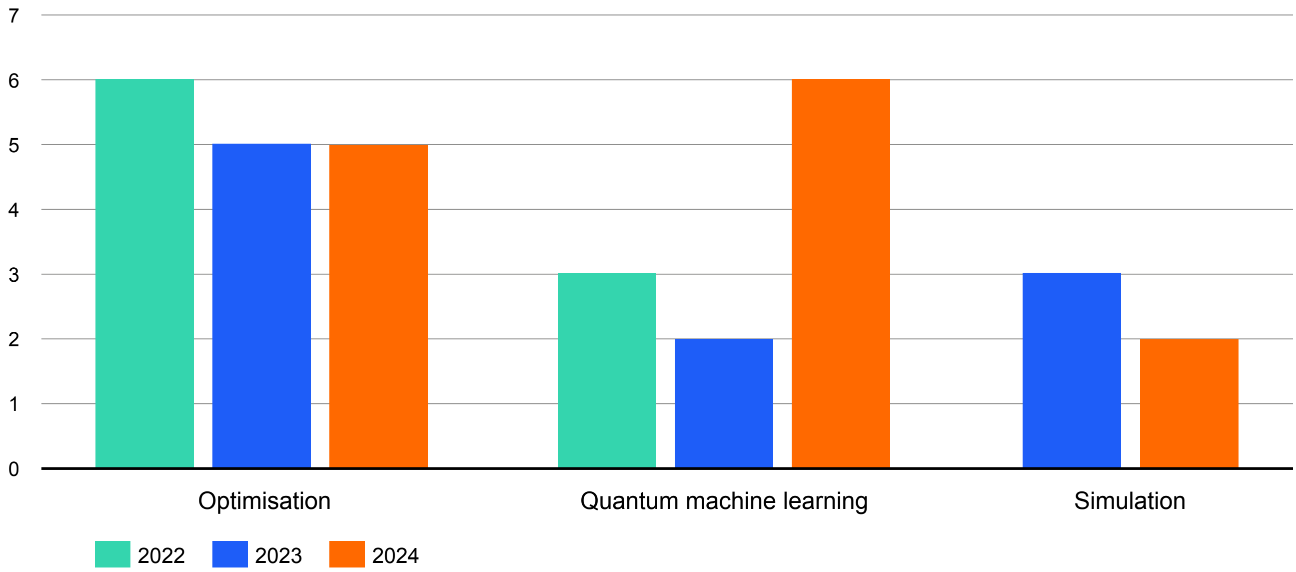



*Figure 22: The distribution of optimisation, quantum machine learning and simulation problem domains from the 2022 UK Quantum Hackathon through to the 2024 edition.*

The figure below demonstrates that this year's hackathon also showcased a wider range of sectors than in previous years.

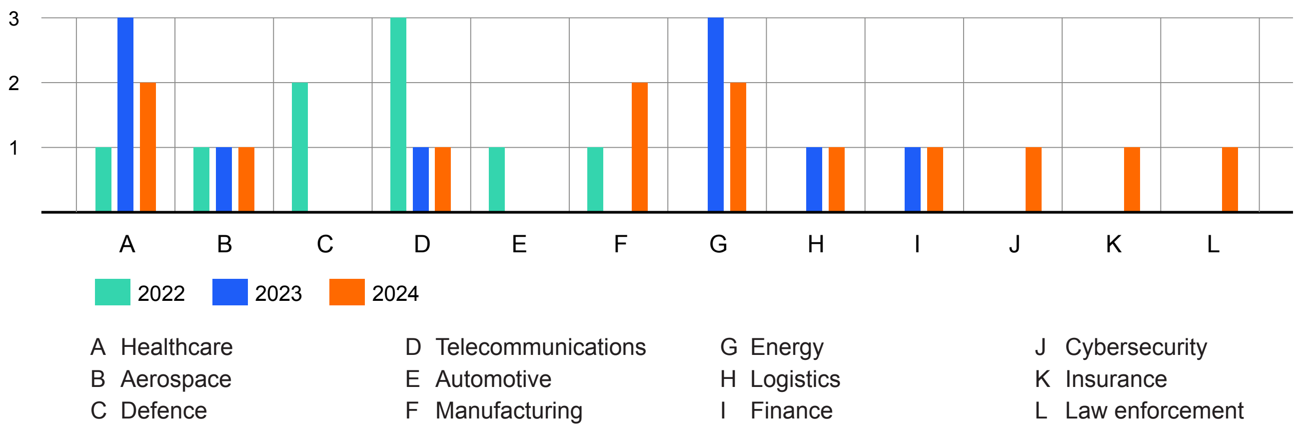



*Figure 23: The distribution of sectors represented in hackathon use cases from 2022 to 2024.*


This report reveals that hybrid algorithm approaches were successful in many cases, suggesting a way forward with near-term Noisy-Intermediate-Scale-Quantum solutions. Additionally, several teams this year were able to carry out benchmarking activities due to the three-day format, with two full days of technical work and the final day dedicated to sharing the outcomes achieved throughout the hackathon. Compared to 2023, optimisation problems were explored on gate-based hardware and annealers. Many teams could also use middleware tools such as Classiq and Q-CTRL's 'Fire Opal' to refine their solutions further. This showcases an evolution in the tools available to quantum computing developers compared to previous years.

Alongside the technical outputs presented in this report, the hackathon provided ample networking opportunities for those involved. The third day's focus on sharing results and findings allowed developers and end users to see what others had been working on, further revealing the broad applicability of quantum computing to many types of problems.

Overall, the objectives for the NQCC's 2024 UK Quantum Hackathon were successfully met, delivering clear value to the quantum ecosystem. Participants developed their skills in formulating mathematical models from use cases and implementing these on emulators and real quantum hardware. End users could explore how quantum computing can be used in their sectoral contexts, and quantum computing providers gained insights into the kinds of problems for which their platforms are suitable. The increase in the number of teams and participants compared to previous years highlights the appetite for events like the hackathon that cultivate innovation and technical progress and provide learning opportunities for all.

# Appendix

## NQCC and STFC Cross Cluster Proof of Concept SparQ Quantum Computing Call

The NQCC, in collaboration with STFC's Campus and Cluster team, ran a call for business-led proof of concept projects in quantum computing from 16th July to 10th September 2024. Funded through the NQCC's SparQ programme, this initiative aimed to facilitate the exploration of practical applications for quantum computing and use cases that are relevant to the public, private, and charitable sectors. Grants were available for up to £75,000 to develop practical applications and use cases relevant to the public, private and charitable sectors using quantum computing. More information on this initiative can be found on the NQCC's website.

## Judging criteria

**Criterion 1: Success of the solution for the given use case (out of 10)**
This criterion assesses the success of their solution, that is, how well it technically answers the use-case problem. This may require taking into consideration any relevant aspects of the hardware access, initial problem definition, challenges overcome, background information, comparison with the best classical solution, etc. It also assesses the extent to which teams have attempted to verify their solution.

**Criterion 2: Creativity and novelty of the solution given initial use case (out of 10)**
This criterion focuses on the approach the teams took in terms of creativity and novelty. Are they adding to the field through innovative approaches and solutions?

**Criterion 3: Investigation into scaling and feasibility (out of 10)**
Has the team thought about how scalable the solution is? What happens when the toy problem is extended? What can be expected with more QC resources? What are the next steps of their solution? Has the team considered the feasibility of the solution? What hardware capabilities would be required for a full-scale, realistic solution? What are the limitations and strengths of the hardware capabilities in the context of the problem?

**Criterion 4: Responsible and ethical quantum computing considerations (out of 10)**
Has the team considered how they might ensure responsible and ethical use of quantum computing in the context of their use case? To what extent have they considered the societal implications, including how benefits can be maximised and harms mitigated? How have they integrated this thinking into their solution and presentation?

**Criterion 5: Quality of the presentation – clarity, engagement, length (out of 10)**
This criterion aims to assess the quality of the presentation itself and how well the presenters are conveying their message to the audience. Both the content and the pacing should be considered. If a team is considerably late (e.g. presentation longer than 10 minutes) they will be down-scored.

**Criterion 6: Quality of the Q&A (out of 5)**
This criterion assesses how well the team handles the Q&A section of their presentation. Have they fully understood their problem and the approach they took?


# Acronyms

| | |
|---|---|
| **AWS** | Amazon Web Services |
| **BT** | British Telecom |
| **CQM** | Constrained Quadratic Model |
| **EPSRC** | Engineering and Physical Sciences Research Council |
| **FSS** | Flow-Shop Scheduling |
| **HNN** | Hamiltonian Neural Network |
| **KL divergence** | Kullback–Leibler divergence |
| **LPA** | Local Policing Area |
| **MCC** | Monte Carlo Collision |
| **MCMC** | Markov-chain Monte Carlo |
| **MLP** | Multi-Layer Perceptron |
| **NHS** | National Health Service |
| **NISQ** | Noisy Intermediate Scale Quantum |
| **NLM** | Non-Linear Models |
| **NN** | Neural Network |
| **NQCC** | National Quantum Computing Centre |
| **PQC** | Parameterised Quantum Circuit |
| **QAOA** | Quantum Approximate Optimisation Algorithm |
| **qGANs** | Quantum Generative Adversarial Network |
| **QMCMC** | quantum Markov-chain Monte Carlo |
| **QNN** | Quantum Neural Network |
| **QPU** | Quantum Processing Unit |
| **R&D** | Research and Development |
| **REQC** | Responsible and Ethical Quantum Computing |
| **SHAP** | SHapley Additive exPlanations |
| **STFC** | Science and Technology Facilities Council |
| **UKAEA** | UK Atomic Energy Authority |
| **VQE** | Variational Quantum Eigensolver |

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