Engineering QUantum Enabled Information Processing (EQUIP) – A Journey So Far!

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ABSTRACT

This paper provides an overview of the journey to date exploring the data/information processing potential of Quantum technologies based computational system, i.e. Quantum Computer (QCs), for defence applications. The journey is through the lens of UK MOD research, undertaken and managed by Dstl to advance capabilities in the Quantum field for defence and security. The aim is aligned with UK National and NATO interests in exploiting this field and the Emerging Disruptive Technologies (EDTs) that arise from it. Such work is part of the UK government's strategic thrust, and investments, to position the country and economy at the forefront of a potential 'game changing' area.

Research covered includes assessment of QCs and defence applications, with emphasis on intrinsically challenging computations, such as in optimisation and signal/image processing, and of approaches to implement Artificial Intelligence (AI)/Machine Learning (ML) algorithms. The work compared the State-Of-The-Art (SOTA) possible with commodity digital systems and QCs to understand where, and how, significant advantages could be found. We show that, with exceptions, the current limitations in Quantum system technologies and architectures (e.g. data conditioning, input/output interfaces, bandwidths, internal interconnections, and error corrections) offer many orders of magnitude lower performance than digital systems. Nevertheless, we also identify areas where with current development trends and further improvements could result in a converse finding; that in any case hybrid systems will be needed with commensurate systems engineering methodology, models, tools, and processes. These are the challenges that need to be overcome and covered in conclusions and recommendations.

Keywords: Quantum Computers, Quantum annealing, Image Processing, Machine Learning, Boltzmann machines, D-Wave

1.0 INTRODUCTION

We are currently said to be in 'the second quantum revolution' with continual emergence of new quantum technologies [1] that are predicted (perhaps 'hyped') to have a profound impact on the current trend of a globally inter-connected world supported by machines (i.e. Artificial Intelligence (AI)/Machine Learning (ML)). Consequently, the word *quantum* now precedes many active research fields (e.g. *quantum communications, quantum sensing, quantum cryptography*) advancing understanding of deeper manifestations of the quantum world and realising techniques and devices for exploitation. A particular example is Quantum Information Processing (QIP) and Quantum Computers (QCs) which is the subject of this paper. Readers can find a simple introduction to Quantum Science & Technology (S&T) via the Defence Science and Technology Laboratory (Dstl) 'biscuit book' [9].

The pressing challenge in QIP and QC is physically realising the qubits, in adequate numbers as a coupled coherent ensemble. Driving, controlling and managing the whole superposed and entangled states with low measurement errors (noise) in sufficient time to have utility as a computational system (i.e. able to program, execute processes, Input/Output (I/O) data to communicate information, internally and externally).

This is where, since the last decade, great advances are being made in the devices (systems) being built and the noise tolerant algorithms to run on them [2]. This era has been termed Noisy Intermediate Scale Quantum (NISQ) and much research directed to produce Quantum Processing Unit (QPU) devices for QCs [3]. Of these systems and type, the IBM circuit model NISQ computers[1] plus the following two are currently used in our research:

The D-Wave system[2]: This is the'world's first commercially available QC'. QPUs are superconducting circuits, and loop couplers, formed using niobium loops where current flow (clockwise/anti) (flux) qubit states are implemented with magnetic fields. This paradigm is different to other QCs, such as circuit gates, quantum logic, as it is an adiabatic quantum computer. Here system state is prepared to a reference Hamiltonian and evolved slowly (adiabatically) towards representation of the problem with the final state of the Hamiltonian representing the optimised solution. Hence the system is well suited for Quantum Annealing[3] and application to Quadratic Unconstrained Boundary Optimisation (QUBO) problems found in many sectors. We used the Advantage 2.1 system and their latest version has over 5000 qubits reporting a significant performance breakthrough, topology and connectivity [4].

ORCA system[4]: This QC is from a new UK spin-out company, established in 2019, from Oxford University. The system exploits their research work done as part of the UK National Quantum Technology Hub (NQTH) in Networked Quantum Information Technologies NQIT [8]. This includes exploiting ion traps, optical fibres and linear optics for photon circuits, detection, multiplexing, memory and spectral-temporal sampling [5][6]. A system application, with encouraging results, has been determining non-linear functions for ML algorithms (e.g. Neural Nets (NNs) including Generative Adversarial Networks (GANs)) [7].

This paper consists of a summary of the UK MOD S&T strategy supporting research programmes and projects and how this fits into the national and global landscape. The results and outcomes of one of these projects using the D-Wave Advantage 2.1 system is covered in detail in remaining sections, finishing with conclusions and the way forward.

2.0 QUANTUM LANDSCAPE AND STRATEGY

The UK was the first nation to implement National Quantum Technologies Programme (NQTP)[5] as part of the National Quantum Strategy published in 2013, and has recently refreshed both [8]. £2.5B billion is being committed cross-government to develop QTs over the ten years from 2024, doubling current public investment, and generating an additional £1B of private investment. Key pillars of the NQTP, as well as complementary initiatives by Other Government Departments (OGDs), include:- International Research Collaboration (IRC) and bi/multi-lateral partnerships (e.g. USA, Canada, Australia, NATO); the National Quantum Computing Centre (NQCC, to develop use cases with industry and help build UK supply chains); extensive university research networks and hubs (Figure 1) (e.g. centres for doctoral training and skills, 4 technology hubs for the development and commercialisation of QTs across communications, sensors and timing, enhanced imaging and computing); innovation accelerators and challenge led programmes to enhance and strengthen UK base.

The UK MOD S&T strategy (to be 'quantum ready') is also to invest in Quantum for defence and security as part of the national strategy and as a complement to the NQTP, including through partnerships with

[1] See https://quantum-computing.ibm.com/composer/docs/iqx/manage/systems/processors

[2] See https://en.wikipedia.org/wiki/D-Wave_Systems for a good summary of company history and system developments. Further in depth details available from www.dwavesys.com.

[3] An optimisation process for finding the global minimum of a given objective function over a given set of candidate solutions (candidate states), by a process using quantum fluctuations

[4] See https://www.orcacomputing.com/.

[5] https://uknqt.ukri.org/

OGDs and including IRC. Most of the research is delivered through Dstl research programmes, sponsored by the MOD Chief Scientific Advisor (CSA) and the defence services, and working with industry and academia, on defence applications exploring threats and opportunities. Quantum research reported in this paper was initiated in response to the findings of the review of the threats and opportunities landscape for UK defence and security in Quantum Information Processing (QIP) [8]. This research is part of the Dstl A2ISR (AI and Autonomy in the ISR Enterprise) multi-year project tasked under its AI programme (A2ISR) and in part by UK Strategic Command under the Quantum Enabled Intelligence (QEI) Pathfinder initiative. Conjoining QIP and AI research is deliberate as exploiting the rapid S&T advances in both may offer greater value.

3.0 QUANTUM ENABLED INTELLIGENCE RESEARCH

The QEI project explored the extent to which QC could enhance existing intelligence analysis tasks, especially imagery analysis/handling tasks, which are ubiquitous and computationally demanding. That is components of the image processing pipeline (Figure 2) where quantum processing could offer superior performance to, and overcome limitations of, State-Of-The-Art (SOTA) digital processors. The project aimed to (1) identify specific applications of QC algorithms in intelligence with their value for the MoD and to (2) perform initial experimental demonstrations. Delivered in two phases by a team comprised of researchers from BAE Systems (first phase only), Universities of Glasgow, York and Durham (via nano-spinout company Quantum Chancellor) plus OxbrdgRbtx Ltd.

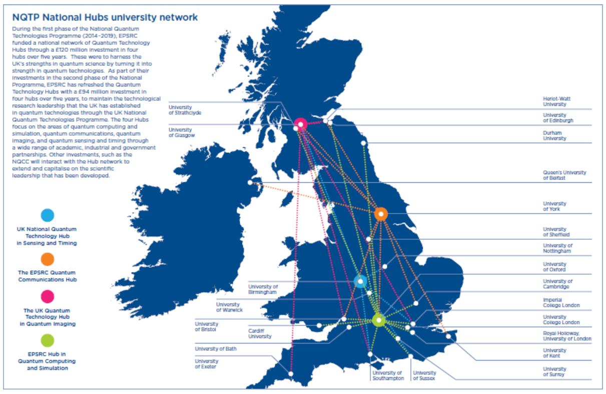

Figure 1: UK university Quantum research network and hubs.

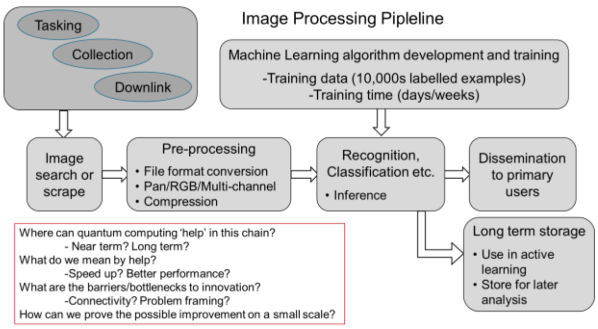

Figure 2: Simplified view of pipeline for image processing .

3.1 Phase 1 Results and Outcomes

Phase 1 consisted of preliminary work in terms of workshops, held by BAE Systems with researchers and stakeholders, to identify specific applications of QC that would provide intelligence value to MoD. Six use cases were highlighted that could be mature enough, estimated technology readiness levels and operational impact, within 5-10 years (Figure 3). The processing and classification of images is a fundamental enabler of the applications offering the highest operational advantage, namely items 4, 5 and 6 in the figure. Hence the focus of the experimental research. Furthermore, the technical reviews concluded that a hybrid approach, digital and quantum, offered with ML the best exploitation path toward defence application systems, exploiting strengths of each. As NNs are graph-based, like simpler Boltzmann Machines (BMs) and variants (Figure 4a,b,c), the selected approach was to embed such BM architectures on a quantum annealer, D-Wave system, for image classification. The selection of BMs is based on encouraging results from a growing body of research for such applications and that fewer epochs of training may be required than classical approaches [10], [11].

Therefore, in parallel with the workshops, preliminary experimental work defined and implemented a hybrid ML architecture, with digital CPUs/GPU and D-Wave QPUs, to classify images from the MNIST dataset[6] and compare with digital system results alone. Results shown in Figure 5, are using simple test images and three models trained with 5000 MNIST images, centre-cropped to 15x15, 19x19, and 27x27 pixels respectively. Once trained, the output of the first layer of the models provides binary feature data 145, 230 and 465 dimensions suitable for transfer to the D-Wave QPU. Exploratory experiments also enabled comparison of using quantum annealer to the classical calculation of weight updates by Contrastive Divergence[7]. These showed an important finding that on an iteration-by-iteration basis, faster learning could be achieved compared to the classical calculation.

Use Case	Operational advantages	Technology enablers
1. Automatically track moving targets (~10^3/6) in cluttered environments	○ Permits military end users to track multiple targets simultaneously with high accuracy	○ Quantum enhanced particle filters ○ Model-based approaches to distributions/scenes ○ Bayesian inference
2. Imaging satellite constellation optimisation	○ Exploit full use of satellite duty cycles ○ Resource management to reduce latency in imagery tasking & collection ○ Combining data collection & processing	○ Capable of dealing with large parameters for optimisation ○ Quantum annealers for optimisation ○ Quantum sensors (hyperspectral) ○ Systems engineering methods for partitioning
3. Query large-scale imagery datasets, returning results in real-time	○ Reduced cost of querying large imagery datasets ○ Increased size of datasets queried when looking for targets ○ E.g. In how many cities have I seen the same target before?	○ Search algorithms could be run on NISQ processors ○ Requires appropriate metadata and encoding ○ Fast associative memories ○ Annealers for optimisation
4. Anomaly detection, e.g. unusual tracks (part of Tasking prioritisation and collection strategy	○ Reduced burden on human analysts	○ Unsupervised ML algorithms ○ Extreme value theory ○ Sophisticated correlation analysis (2+ events) ○ Empirical distribution characterisation
5. Recognising critical image changes as they happen across vast image libraries, (living memory management)	○ Help teams to collaborate when correlated activities are recognised across vast datasets	○ Quantum entangled images? ○ Neural nets to find more interesting patterns
6. Predicting intentions of enemy targets from its behaviours, (e.g. most threatening ones)	○ Better situational awareness, highlight enemy intentions and projected threatening activities in real-time ○ Support more complex wargaming	○ Quantum simulation, high most probable events ○ Reasoning over huge probability distributions

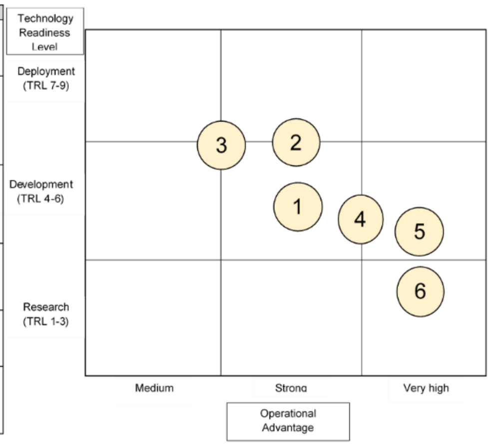

Figure 3: Use cases. Operational advantages and key technology enablers.

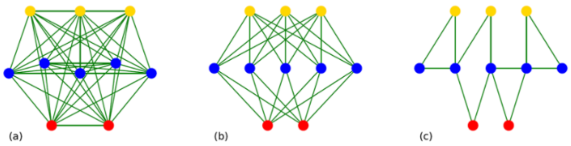

Figure 4: Network schematics, (a) Boltzmann Machine; (b) Restricted Boltzmann Machine; (c) Sparse Boltzmann Machine. [Input nodes (yellow), hidden nodes (blue), output nodes (red)].

Test Images	Model Input Size>	145	230	465
	Processor	Execution time μsecs		
10	QPU	1813.8	2014.4	2301.1
10	GPU (CPU)	272.5 (10.9)	251.8 (13.9)	231.7 (13.5)
100	GPU (CPU)	38.5 (15.2)	37.6 (15.8)	18.7 (17.2)
1000	GPU (CPU)	3 (38.5)	3 (37.6)	3 (18.7)

Figure 5: Performance using test images of QPU, GPU (CPU).

Though the D-Wave is orders of magnitude slower than GPUs (can process many images together) these experiments were encouraging. The experiments demonstrated quantum unsupervised image recognition and the automated transfer of trained RBM-based NNs between quantum and digital systems. Training an NN requires many iterative cycles and QPUs. Though this is slower, it converges much faster, requiring less epochs, than digital implementations. Thus offering opportunities in the future and an area for further research in Phase 2. Other findings from D-Wave sampling experiments to understand the limitations and potential, with system upgrades, of annealers are:

- D-Wave devices act as high-quality thermal samplers;
- Thermal sampling for ML and optimisation are two fundamentally different tasks, and we should use caution when applying results from the more studied optimisation regime;
- Integrating quantum annealers within broader classical architectures is not simply a matter of replacing a classical processor with a faster version, but one of rethinking the entire structure to make best use of highly specialised hardware.

[6] Large database of handwritten digits used extensively to test machine learning for image processing (see https://en.wikipedia.org/wiki/MNIST_database)

[7] Gradient of the Contrastive Divergence is a measure of difference between the probability distributions of the input and reconstructed data. An approach to training which closely approximates the gradient of the log probability of the training data.

Further mathematical and technical details on the challenges and approaches needed to execute ML on a D-Wave system architecture is in the paper by our co-researchers [12].

3.1 Phase 2 Results and Outcomes

In view of the findings from Phase 1 research, a full BM type NN implementation was the research focus for Phase 2 to 'benchmark' the impact on the speed and scalability of the image classification and compare to SOTA digital processors such as the Intel Neuralstick. Images from MNIST dataset were used as before but compressed[8] to embed using the native graph of the D-wave system.

The maximum size of BM that can be enacted on a QPU is limited by the size of the QPU (the number of qubits on the chip) and this in turns limits the maximum image size that can be classified. Not only does the overall number of qubits restrict the size of BM that can be implemented, the connectivity of the quantum annealer dictates the available links between qubits. Most qubits (all but those on the edges of the chip) in the D-Wave Advantage processor are connected to 15 other qubits. This prevents a fully connected BM from being implemented in all but the very smallest of cases without using additional embedding algorithms [13][14]. As the aim of the study was to exploit the native graph of the system, partially connected (sparse) BMs were designed (Figure 4c) for the larger problems.

The time-to-train, a key benchmarking metric, is a compound measurement made up of a number of sub-processes [13]. The current set up of the D-Wave application required each training sample to be sent across the internet to the D-Wave servers individually in every epoch.

It was found that using the D-Wave QPU to train a BM took longer per epoch than the simulated annealing CPU but does scale much better with image size and number of reads. This suggests that on larger problems, the QPU would be more efficient than equivalent classical methods. Additionally, when the timing was broken down into computational elements, the internet latency and queuing times were a significant portion of the time-to-train. On discovering this, the time-to-train for a hypothetical local QPU was estimated to remove internet latency – the "local epoch time" as shown in Figure 6 below. The I/O for this hypothetical local machine is unknown so the estimated time-to-train is a lower bound. Once the internet latency and queuing is removed, the most significant timing component is the gradient calculation, which is calculated on the CPU in all cases and accounts for the similar scaling between the Local QPU and CPU data.

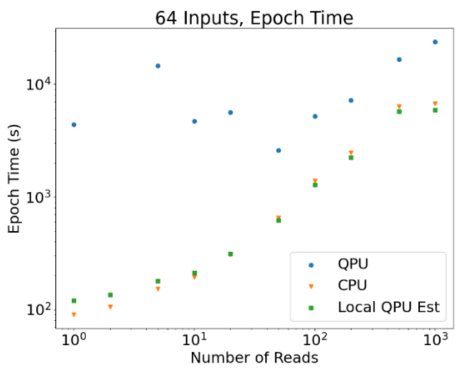

Figure 6: Time per epoch to train a BM with 64 input nodes for a Simulated Annealing CPU, a D-Wave Advantage QPU and a hypothetic local, dedicated D-Wave Advantage QPU. A BM network with 64 input nodes is capable of ingesting an 8x8 pixel image.

The D-Wave classification performance, even after what should be sufficient training, was found to be particularly poor. It is unknown if this was due to D-Wave parameter setting and/or the 'sparseness' of the

[8] Discrete Cosine Transformation compression algorithms as simple and low computational cost implementation

BM. D-Wave machines are designed to perform optimisation problems and many of the default parameters are tuned to perform well in these application. Using the D-Wave QPU to perform a BM is likely to require very different parameters and this was not explored in this research. As mentioned previously, the physical size of the D-Wave QPU (the number of qubits) limited the size and overall connectivity of the BM networks that could be executed. It is possible that the resultant networks are too sparse to perform effectively as image classifiers.

4.0 CONCLUSIONS

This paper has provided an overview of the quantum landscape, including the current state of play, key research areas and future aspirations. It has shown that the UK has a strong, growing quantum community (government, academia and industry, including new start-ups), with its MOD playing a key role in steering, funding and executing the research and development in this area. A key application being enhanced is intelligence analysis offered by quantum computer processing of imagery, analysis/handling tasks that are ubiquitous and computationally demanding. The MoD funded Quantum Enabled Intelligence research project, delivered by multi-disciplinary team (government, industry and academia), investigated this as detailed in the paper. It highlighted the processing and classification of images as a fundamental enabler offering the highest operational advantage (e.g. anomaly detection, critical change detection, enemy target behaviour and intent) and focussed the experimental research with the D-Wave Advantage 2.1 quantum annealer (computer). The research explored and assessed the implementation of ML type algorithms on the annealer to aid comparison with digital systems where ML is the state-of-the-art.

Overall, the research has successfully demonstrated, albeit for small images, the use of quantum annealers for image processing and classification, using Boltzmann Machine-based neural net algorithms. Work identified the training of ML algorithms (onerous area for digital systems) as offering most potential for quantum advantage in a hybrid system. Algorithms to automate the transfer of training weights, between quantum and digital processors, in such a system were developed and used. Benchmarking results show that the D-Wave learned faster (in fewer epochs) than the GPU equivalent but each epoch took longer to complete. The net result of this is that quantum training is only two to three orders of magnitude slower than a GPU. The notion of a ‘local QPU’ as described in section 3 showed that these results will likely be improved in the QPU’s favour with latter generations of hardware having more qubits, better connectivity and faster IO operations. Latter factors are the current barriers to progress.

Future work in this research strand will include hyper-parameter optimisation and the comparison between Boltzmann machines of varying sparsity. There are also related enquires such as whether that are alternative machine learning models that require less IO and would therefore be suitable for realising near-term quantum advantage.

5.0 ACKNOWLEDGEMENTS

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