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Quantum Computing for Agricultural Applications

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October 15, 2025

Motivation

Bringing foremost quantum computing advances into real world challenges

Business Impact :

Quantum Computing innovations (like in Quantum Machine Learning), are redefining the manufacturing landscape by giving advantage in discovery , product development and process optimization & automation. Early adoption will help to unlock the opportunities in those areas which are enormously difficult to challenge.

NISQ- Exploration

To explore inclusion of Quantum Computing with a search for an Industrial Application that can use NISQ ready hybrid Quantum Neural Network (QNN) programs to offload the heavy lifting processing, from classical computing (GPU/TPU) to Quantum Computing platforms which can be deployed today.]

Accelerate

Native randomness of Quantum Computing gets inherited by approaches like Quantum Kernel Alignment (QKA) for Hybrid Quantum Neural Networks (QNN), which helps to achieve better generalization rates for machine learning models with faster convergence during training (not mandatory, as depends on complexity of dataset & problem)[1] [2]

[1]Feature Kernel Alignment for Point Cloud Convolution : https://arxiv.org/pdf/2004.04462.pdf

[2]Covariant quantum kernels for data with group structure : https://arxiv.org/pdf/2105.03406.pdf

Why quantum? Quantum for Classical problems

- High dimensional feature space problems
- Runtime complexity
- Exploring quantum advantage
- Improved algorithms with quantum
- **(A) Abilities of Quantum Machine Learning – generalization capability, bias & variance; (B) Quantum Optimization; (C) Quantum Algorithms for Partial Differential Equations (PDEs) for Digital Twins; (D) Uncertainty quantification**

Quantum in Agriculture

Quantum computing promises to revolutionize agriculture by enabling highly accurate climate forecasting (**solving PDEs and QML**), accelerating crop genetic analysis and breeding, optimizing complex supply chains (**quantum optimization**), and facilitating advanced precision agriculture (through **quantum learning and control, uncertainty quantification, quantum-enhanced sensors and AI**).

By processing vast datasets and complex simulations, it can improve water management, predict and control diseases, analyze the soil microbiome, and support data-driven decisions for increased yields and sustainability.

Precision Agriculture & Resource Management

Climate & Weather Forecasting: Quantum algorithms can analyze massive climate datasets to provide more accurate, long-term weather forecasts, helping farmers make better decisions about irrigation, fertilization, and planting.

Water Management: Quantum irrigation systems, using quantum sensors and algorithms, can monitor soil moisture and predict water needs for different crops, optimizing water use and minimizing waste.

Precision Monitoring: Quantum computing, combined with AI and sensors, can enable digital twins for controlled environments like greenhouses, improving decision-making for crop health and growth.

Crop Science & Genetics

Genetic Improvement: Quantum computing can accelerate the analysis of genetic patterns, helping to discover optimal modifications for creating crop varieties with enhanced yield, disease resistance, and climate adaptability.

Disease & Pest Prediction: Quantum systems can analyze vast datasets of pest movements, weather, and crop conditions to accurately predict outbreaks, allowing for targeted interventions and reduced chemical use.

Soil Health: Quantum technology could help analyze the complex interactions within the soil microbiome, leading to a better understanding of soil health and more effective management strategies.

Supply Chain & Operations

Supply Chain Optimization: Quantum algorithms can solve complex logistical problems in the agricultural supply chain, reducing food waste caused by inefficiencies and unpredictable market demands.

Automated Operations: Quantum-powered robotics could optimize tasks like crop planting and harvesting, making agricultural processes more efficient.

Quantum Computing- A Glance

WHY QUANTUM COMPUTING?

Quantum computers differ from conventional computers by leveraging the properties of quantum mechanics to store and process information. This key difference allows quantum computers to represent an exponentially larger state space than conventional computers, while the power of a classical computer can be approximately doubled by doubling its number of transistors, a quantum computer's power doubles with each additional qubit.

- ***Exponential speed-up over classical techniques.***

- ***Can handle large problem spaces due to the superposition of bits between 0 and 1 called qubits, so with n-qubits we have a space of*** 2^n ***variables.***

.

Two important effects:

Superposition

Entanglement

Quantum Computers

$|\psi >= \alpha|0> \ +\beta|1>$

Qubits

Superposition

Classical computers – bit
0 or 1

Quantum states are not separable

Use case: (A) QML - Classification and monitoring

Problem Statement:

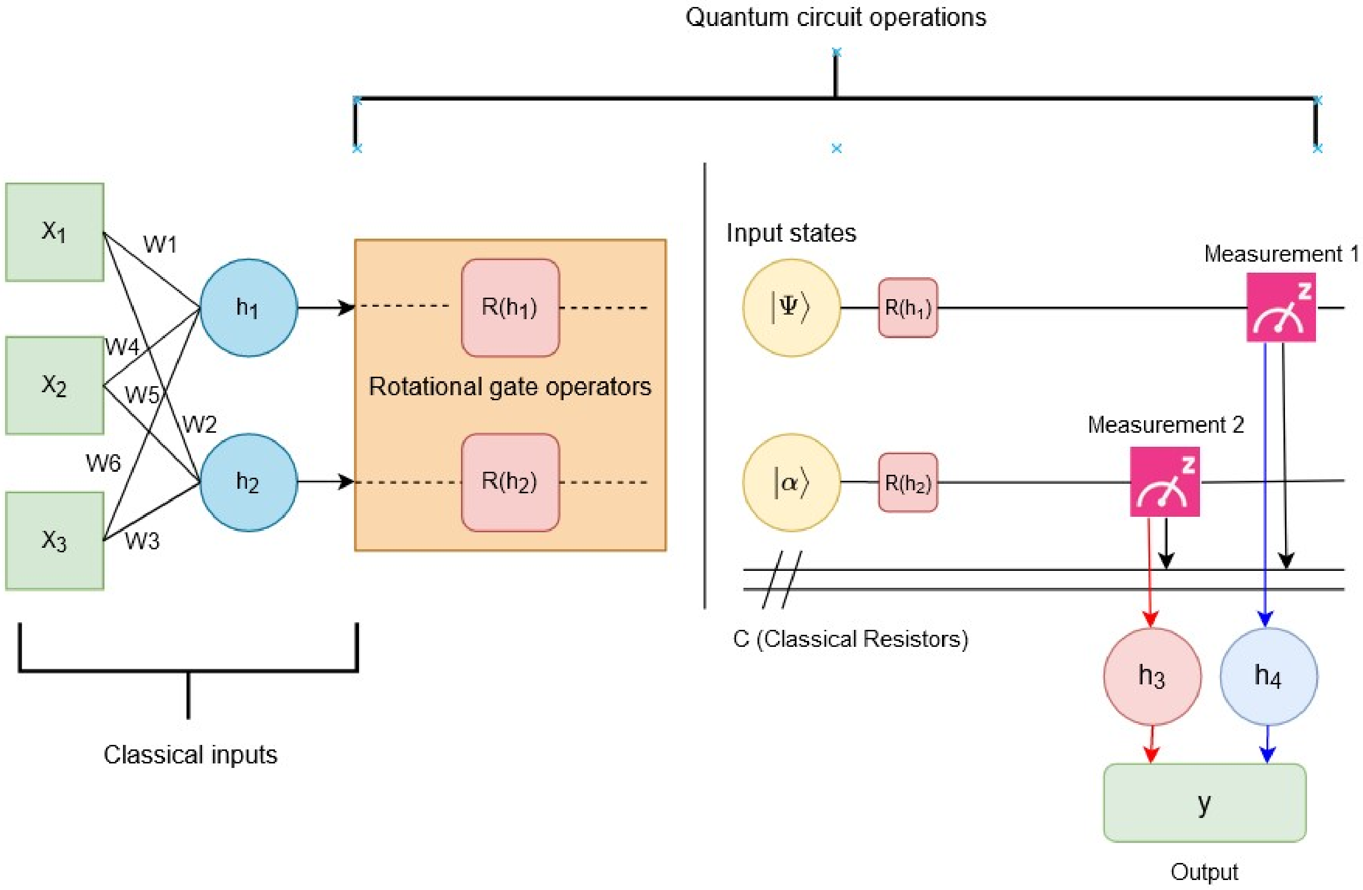
Satellite data can be used to develop novel computer vision algorithms to classify land use, vegetation, crops, deforestation, fires and other phenomena. Hybrid (quantum-classical) networks play an important role.

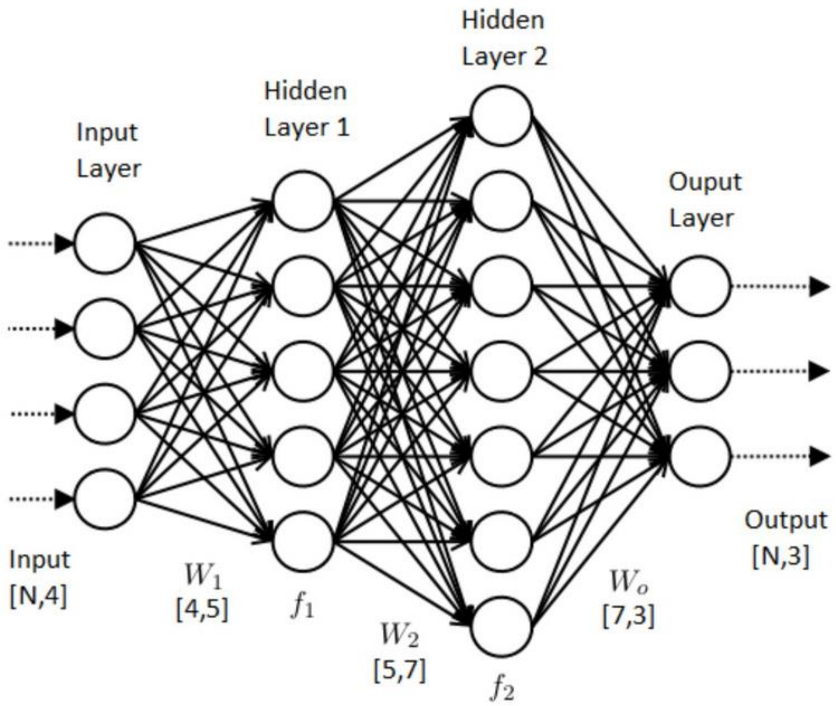
Modern imaging test the limits of advanced analytics, especially when employing machine learning and analyzing multiple variables.

Rapid developments in compute software and hardware have drastically shifted quality control and inspection from manual methods to automated routines for examination, especially in an era of Industry 4.0.

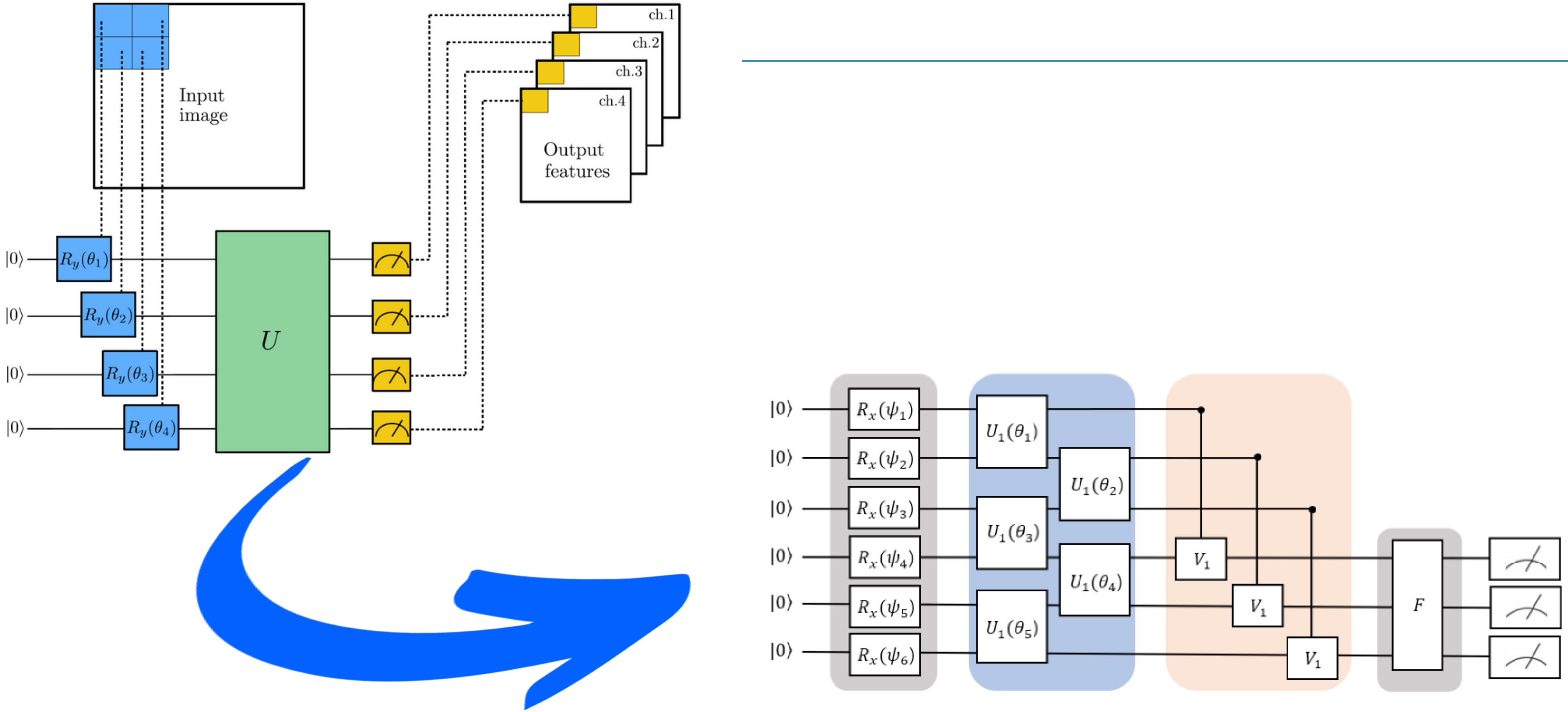
Quantum computing helps to find new correlations in data, enhance pattern recognition, and advance classification beyond the capabilities of classical computing, thus adding a digital control to Industry 4.0 technologies.

Hybrid Quantum Classical Neural Network





Quantum Convolutional NN Architecture



Hybrid Quantum Classical Neural Network (contd.)

- Parametric Quantum Circuit

$$|\Psi(x)> = F(x)|0>^{\otimes n}$$
$$|\phi(x,\theta)> = A(\theta)|\Psi(x)>$$
$$E(x,\theta) = <\phi(x,\theta)|O|\phi(x,\theta)>$$

- Feature maps
- Multilayer QNN

  (Qiskit circuit libraries can be used)

- Developing shallow Quantum Neural Networks
- Advanced architectures with prunning (Ramanujan graphs) and quantum circuits

Das M, Naskar A, Mitra P, Basu B. Shallow quantum neural networks (SQNNs) with application to crack identification. Applied Intelligence. 2024 Jan; 54(2):1247-62.

SQNNs - Combinations

A pretrained Resnet50 with last 5 NN layers modified. Image input resolution = 227x227. 20000 Positive + 20000 Negative Images , Channels = 3, Two types of images

Table 1: Different combinations of SQNNs

Model name	Data set size	NN trained model	QPC type
ResCQ-SQNNs	2000	ResNet	CircuitQNN
ResTQ-SQNNs	2000	ResNet	TwolayerQNN
VGG16VCQ-SQNNs	2000	VGG16	CircuitQNN
VGG16VTQ-SQNNs	2000	VGG16	TwolayerQNN

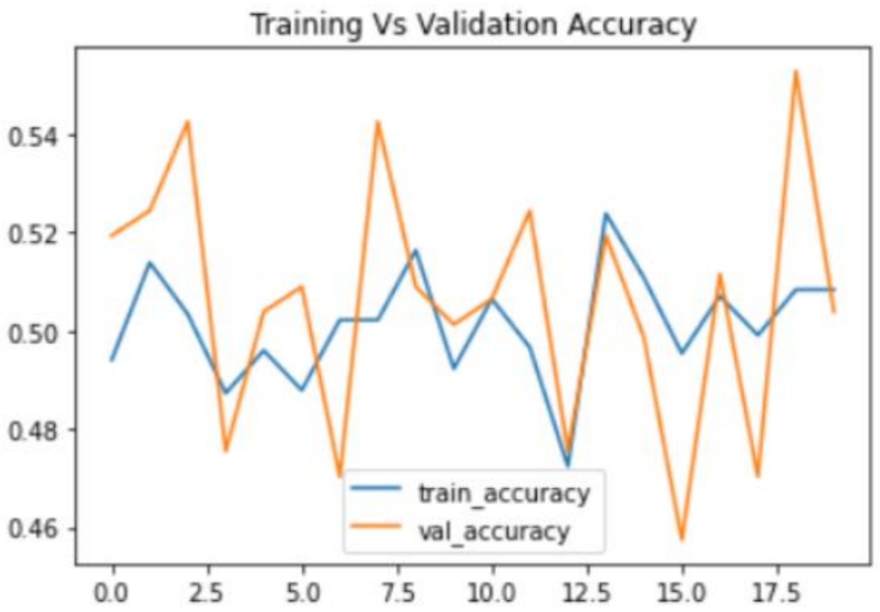
Table 2: Different combinations of classical NNs

Model name	Data set size	NN trained model
Res-NNs	40000	ResNet
Res-NNs	2000	ResNet
VGG16-NNs	40000	VGG16
VGG16-NNs	2000	VGG16

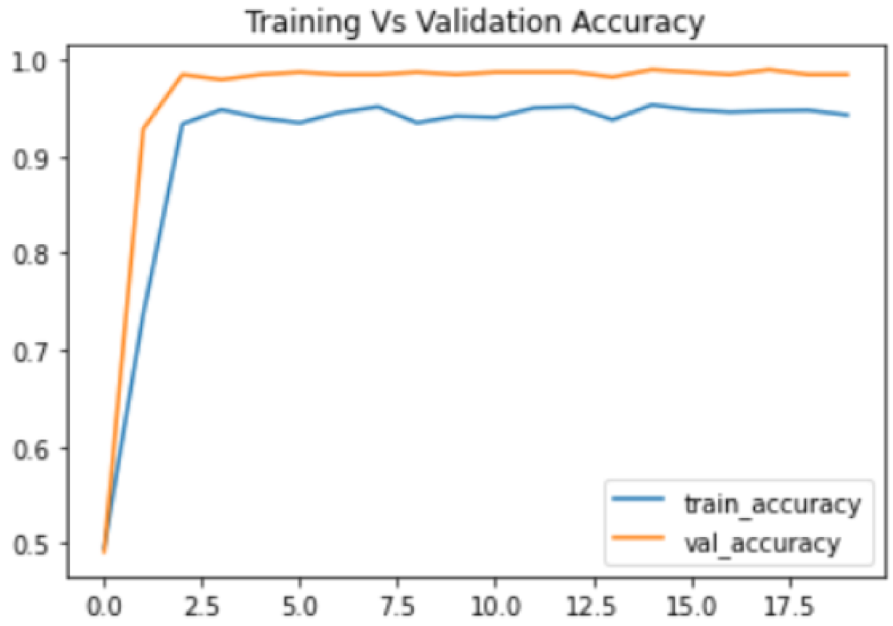
Training and Validation accuracy

Experimental results for NNs and SQNNs: Two-layer SQNN with VGG16 performs best

VGG16-NNs(2000 images)



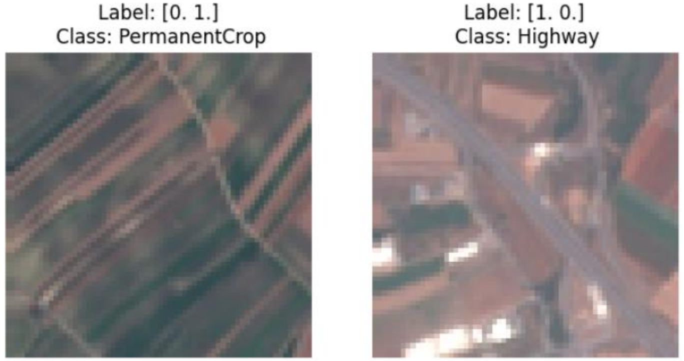
VGG16VTQ-SQNNs



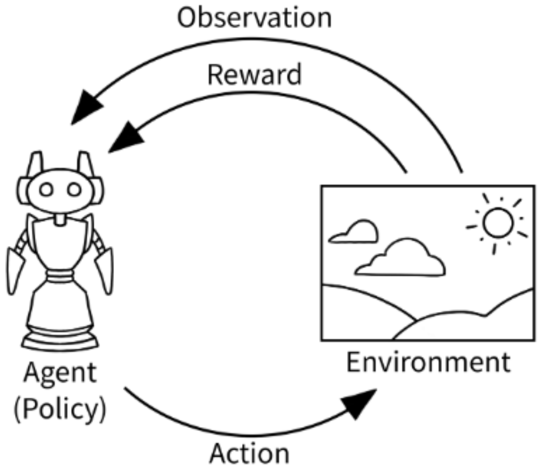
Das M, Naskar A, Mitra P, Basu B. Shallow quantum neural networks (SQNNs) with application to crack identification. Applied Intelligence. 2024 Jan; 54(2):1247-62.

Application to agriculture

Eurostat data: Agricultural land



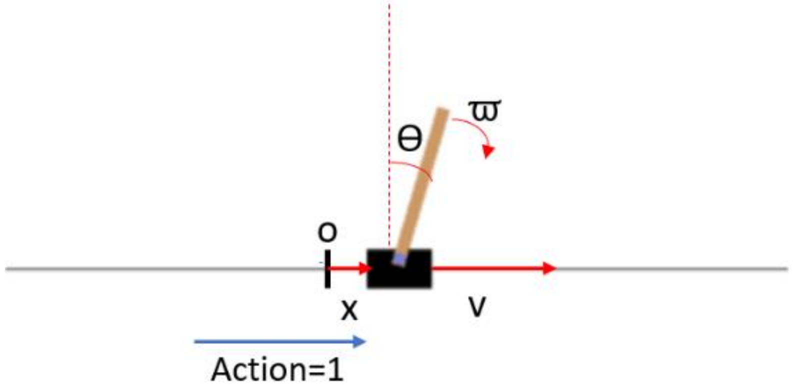
Identification and Control
Optimal control problem in an agent-environment loop



Taken from openAI gym

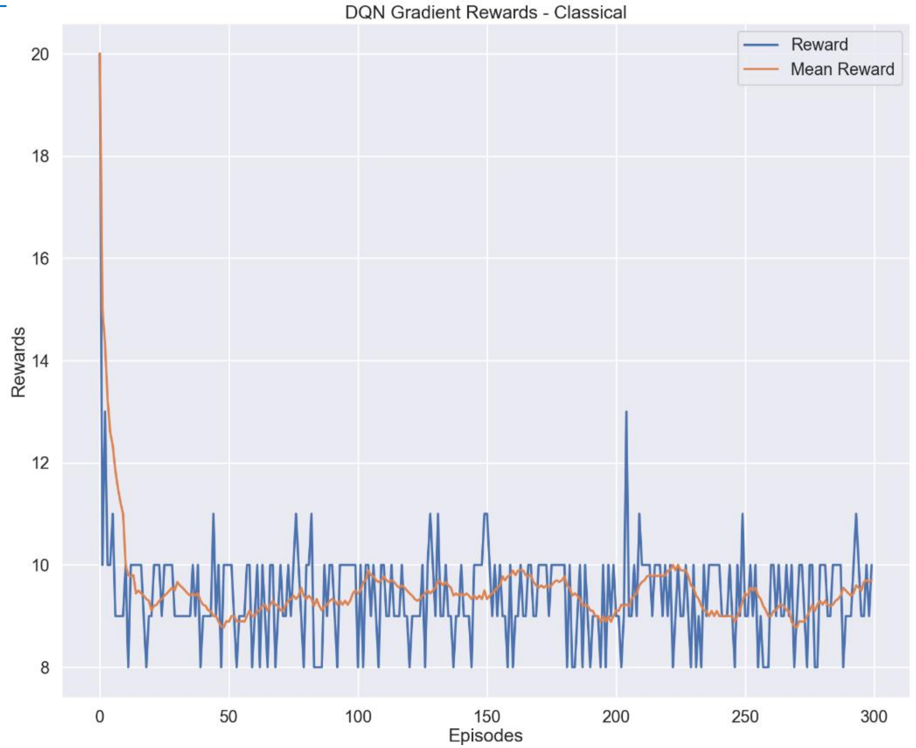
Investigation of the performance and behavioural differences that Hybrid Quantum-Classical Reinforcement Learning agents have in comparison to Classical RL agents, specifically with respect to the sample efficiency and result stability of the relevant models

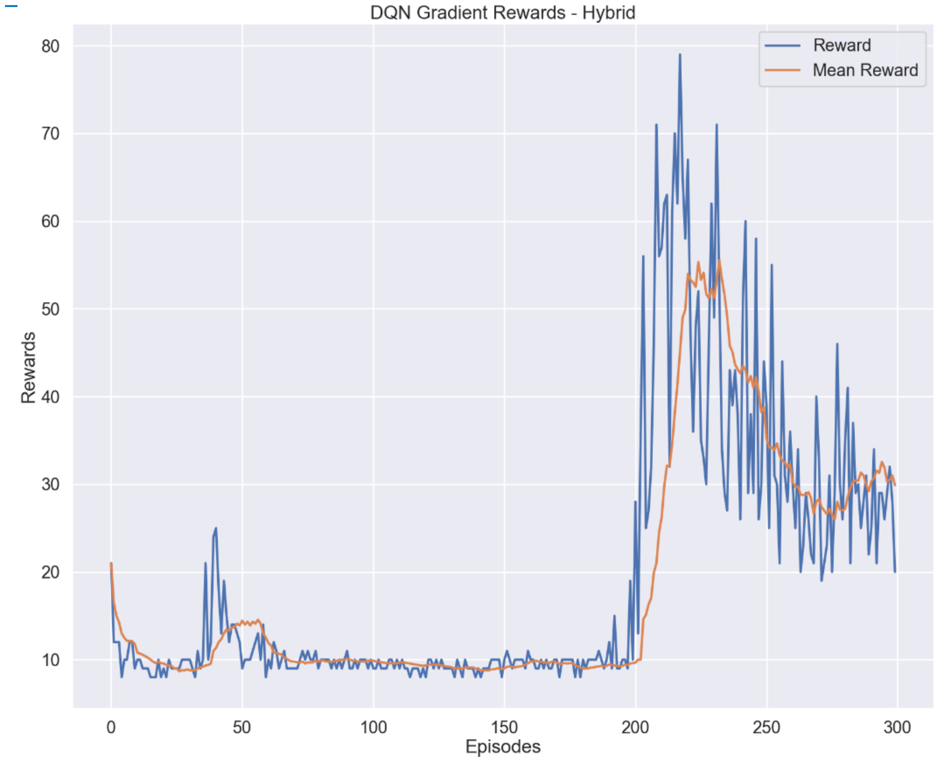
CartPole Stabilization problem



Results

The results of simple unentangled HRL models: Cartpole-v0





The hybrid model drastically improves upon the underlying classical model's baseline performance, with a sharp increase in rewards at epoch 202 up to the moving average reward value of 55, a significant increase from the baseline classical model's average

Mitchell E, Basu B, Mitra P. Performance Analysis of a quantum-Classical Hybrid Reinforcement Learning Approach. InThe Second Tiny Papers Track at ICLR 2024 2024 Jan 1.

Next steps?

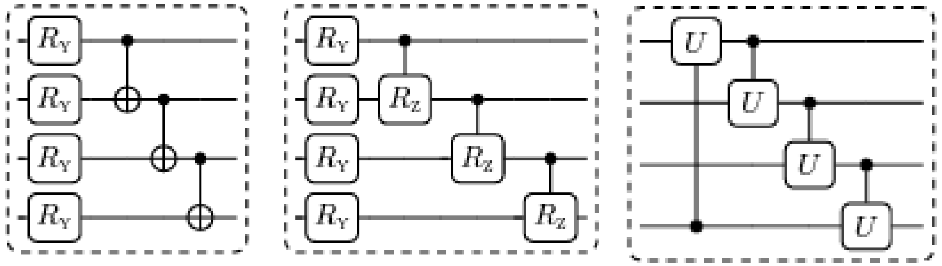
Different quantum topologies

Studies on entangled topologies

(Tensor networks and matrix product states, entanglement entropy)

Entanglement speed

Expressibility



Use Case: (B) Solving quadratic unconstrained binary optimisation (QUBO) problems

Definition of a QUBO

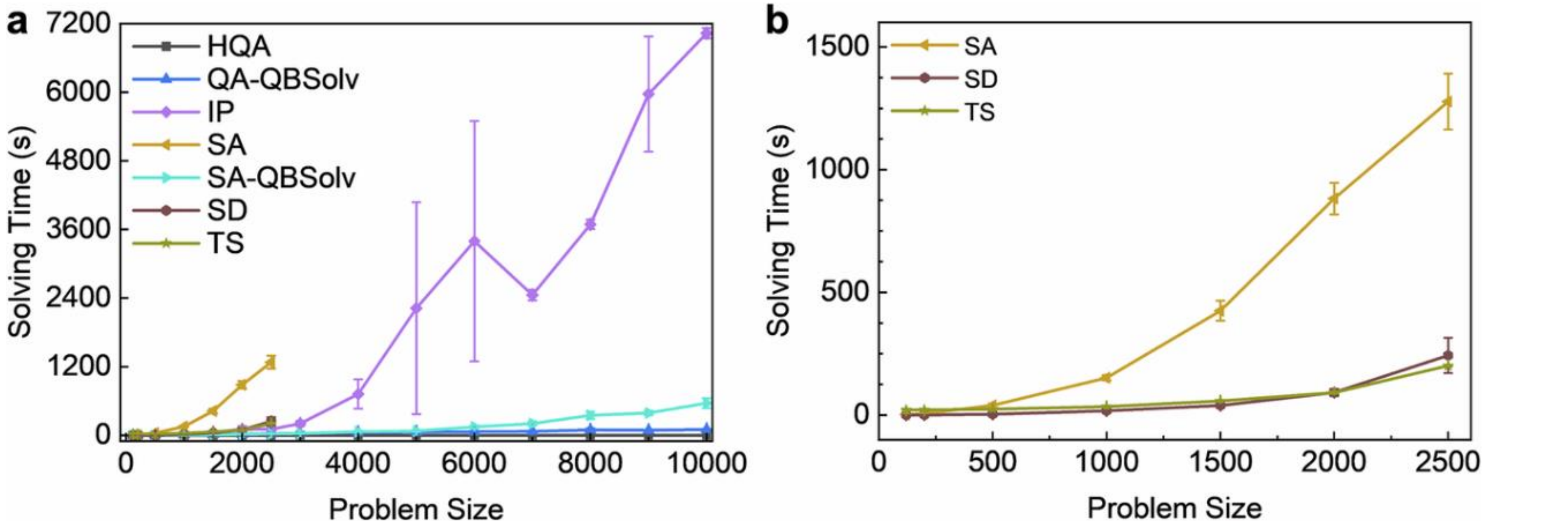
Quantum Anealing hardware is designed to efficiently solve combinatorial optimization problems that are formulated with a QUBO matrix

$$y = \sum_{i=1}^{n} \sum_{j=i}^{n} Q_{i,j} x_i x_j$$

can be solved by using quantum annealing.

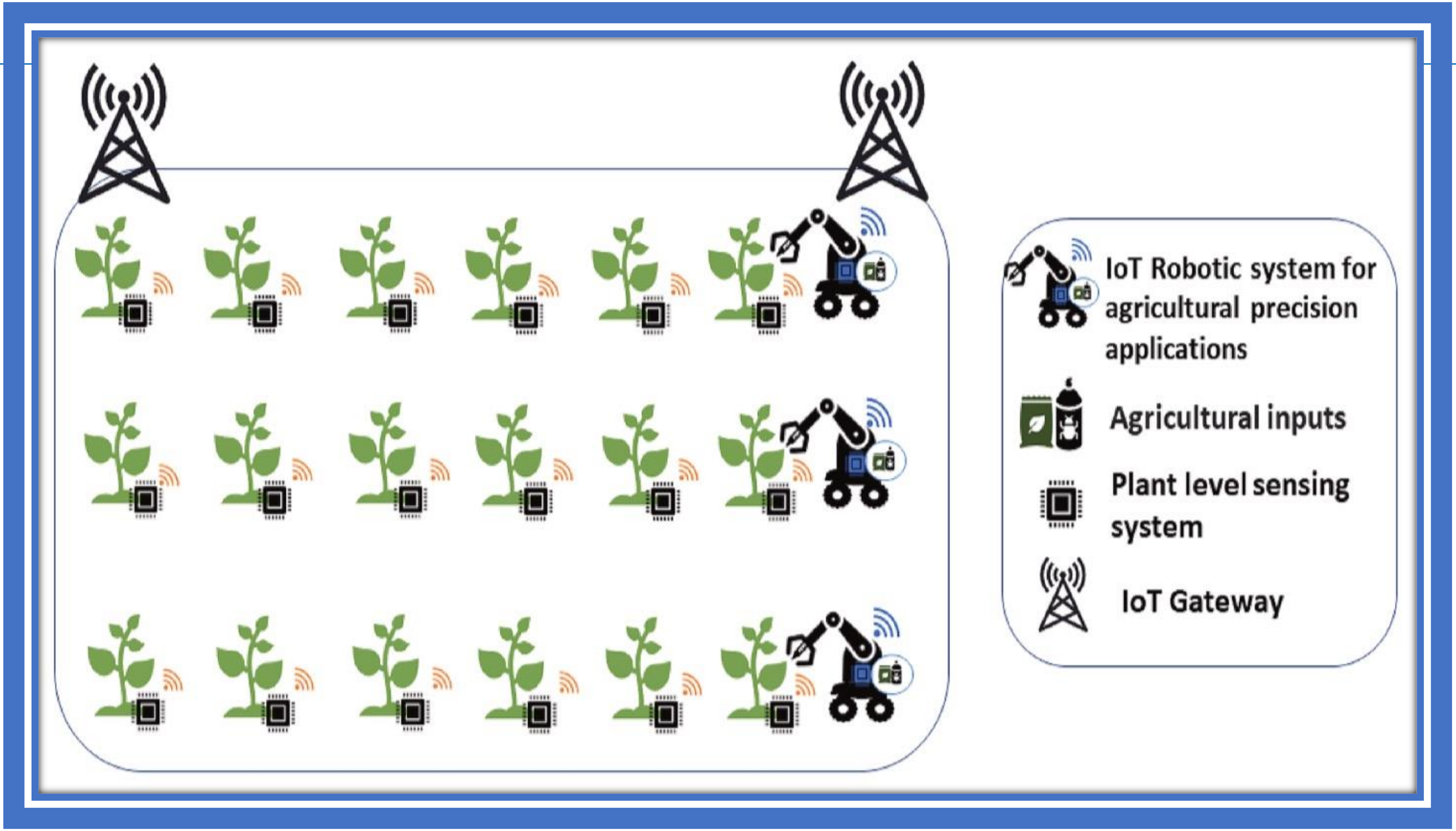
C. Smith, S. Gautheir, T. Meli, A. Staino, B. Basu Quantum optimization for energy efficient train speed profile generation, 2024 (under review).

Solving quadratic unconstrained binary optimisation (QUBO) problems



The theoretical time complexities of the classical solvers are known as $O(n^3)$ for SA, $O(n^2)$ for SD, and $O(n^2)$ for TS. On the other hand, the theoretical time complexity of the quantum solvers can be considered constant.

Use case: (C)Digital Twin in Agriculture



PDEs in Digital Twin

Aerial snapshot of the crop, with the location of the nodes marked

Problem:
Suppose we pick two nodes, A and B, in such a way that one or more other nodes are enclosed by these two. Furthermore, assume that

- The temperatures of the two nodes, A and B, are known for a period of time.
- The initial temperatures at every node are known.

Aim:
Forecast the temperature at every node enclosed within A and B for a period of time P assuming that the temperatures of A and B are known throughout the period P.

The one-dimensional homogeneous heat equation reads:

$$\frac{\partial}{\partial x}\left(c(x,t)\frac{\partial u}{\partial x}(x,t)\right) = \frac{\partial u}{\partial t}(x,t), \quad x \in (a,b),\ t > 0.$$

An approach using quantum algorithms for PDEs and optimization:

Solving for the PDE is difficult. The thermal conductivity of the soil c(x,t) depends on time and space due to factors such as: location, weather conditions, the moisture of the soil, the lack of homogeneity across the field etc.

Approach:

1) Parameterise c(x,t) or assume values in space-time domain.
2) Solve the PDE for values of temperature in space and time.
3) Match the temperature values at measured locations.
4) Minimise the error between computed and observed temperatures.

Comment: A coupled PDE-optimisation problem can be solved by quantum algorithms.

Solving Classical Problems Using Quantum Computing

Solving PDEs:

- ✓ Hamiltonian Simulation
- ✓ Lattice gas quantum computing
- ✓ Carleman approach of linearization– second quantized Lattice Boltzmann
- ✓ Schrodingerization
- ✓ Solutions inspired by HHL algorithm

- ❑ We present the extended application of a recently developed algorithm by Gaitan based on the Kacewicz' algorithm for ODE solver

QPDE algorithm

- Consists of 5 key steps (refer to Gaitan 2020, Quant Inf npj, Basu et al. 2024, Phys. of Fluids, Basu et al. 2025, Computer and Fluids)

- Among these 5 steps, the quantum part is the Novak's quantum integration algorithm QIA (2001, J. Complexity) for solving the ODEs by Kacewicz' algorithms (2006, J. Complexity)

- QIA relies on the Quantum amplitude estimation algorithm QAEA (Brassard et al. 2002, Contemporary Math) and Quantum Phase estimation algorithm QPEA (Kitaev 1995, arxiv)

Computational Complexity

Kacewicz bounds on the ε-complexity $\chi(A, \mathcal{F}, \varepsilon)$ for different types of ODE algorithms applied to Hölder class driver functions. Here ε is the error tolerance on the approximate solution; $q = r + \rho$ is the smoothness parameter, with r the highest order time-derivative retained in the truncated Taylor series and $0 < \rho \leq 1$; and $0 < \gamma \leq 1$.

Bounds	Quantum	Classical random	Classical deterministic
Upper	$\mathcal{O}\left[(1/\varepsilon)^{1/(q+1-\gamma)}\right]$	$\mathcal{O}\left[(1/\varepsilon)^{1/(q+(1/2)-\gamma)}\right]$	$\mathcal{O}\left[(1/\varepsilon)^{1/q}\right]$
Lower	$\Omega\left[(1/\varepsilon)^{1/(q+1)}\right]$	$\Omega\left[(1/\varepsilon)^{1/(q+(1/2))}\right]$	$\Omega\left[(1/\varepsilon)^{1/q}\right]$
	(almost) optimal	(almost) optimal	optimal

Speed up by decreasing the smoothness parameter q

$$\chi^{quant}(A, \mathcal{F}, \varepsilon) \sim (1/\varepsilon)$$

$$\chi^{rand}(A, \mathcal{F}, \varepsilon) \sim (1/\varepsilon)^2$$

$$\chi^{det}(A, \mathcal{F}, \varepsilon) \sim (1/\varepsilon)^{1/q}$$

Advection Equation

Advection equation

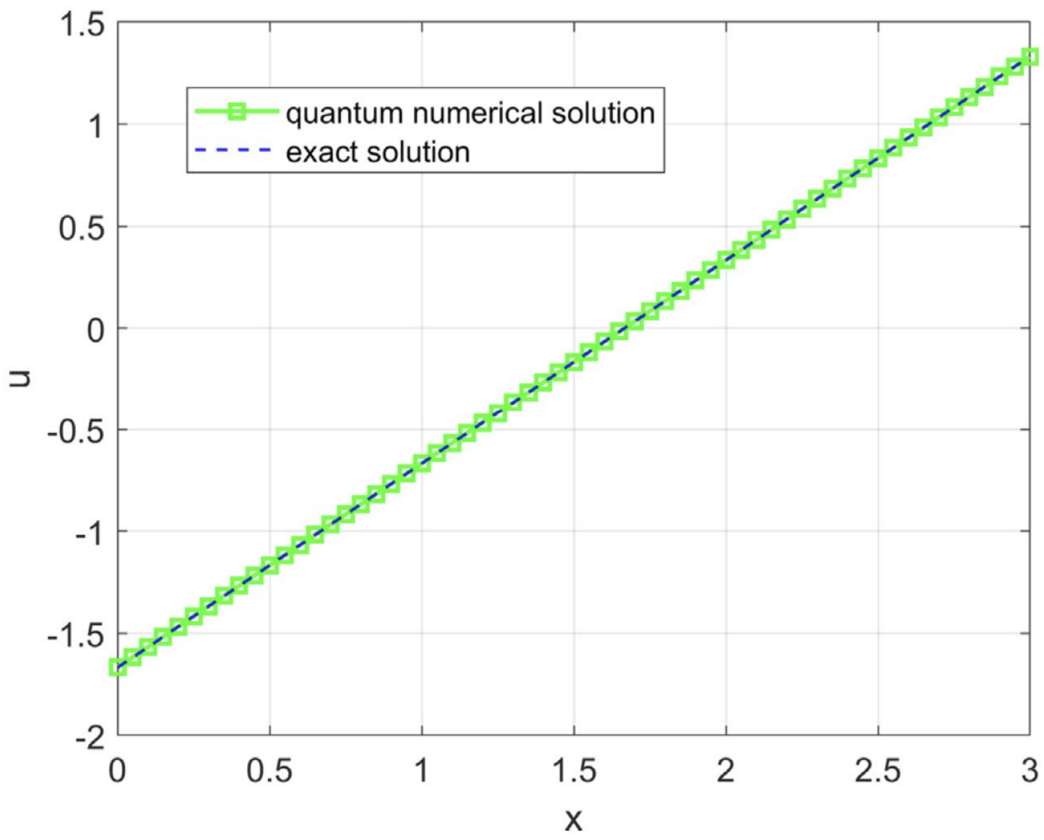
$$\frac{\partial u}{\partial t} = v\frac{\partial u}{\partial x}$$

where $u(x,t)$ is the linear flux function and v is wave speed

Spatial discretisation scheme upwinding

$$\frac{d}{dt}u(j,t) = v\frac{u(j+1,t)-u(j,t)}{\Delta x} = f(u)$$

I.C. $u(0,t) = x$



Exact solution:

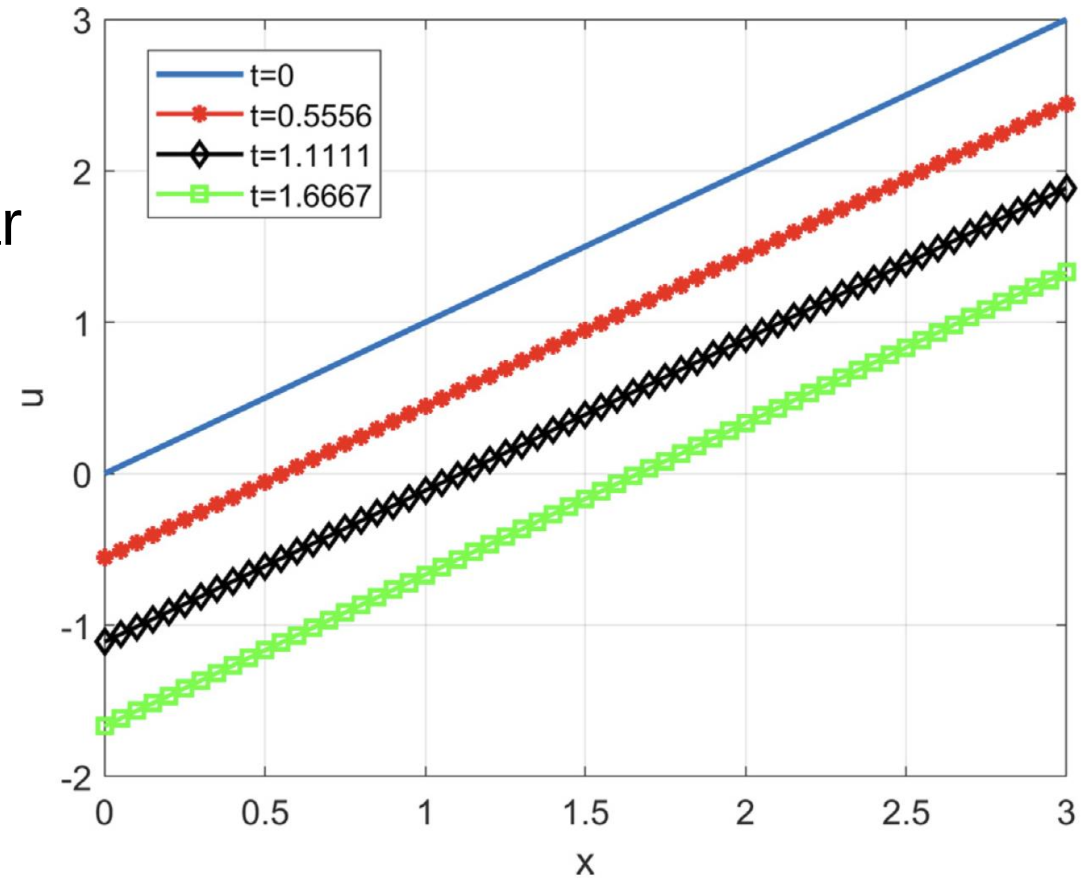
$$u(x,t) = x - vt$$

Produces travelling wave

Comparison of exact and quantum numerical linear travelling wave solution in the advection equation at the time instant $t = 1.667$.

Travelling wave solution

Time evolution of linear travelling waves in advection equation using quantum numerical solution.



- **B. Basu, A. Staino and F. Gaitan On solving for shocks and travelling waves using a quantum algorithm January (2025) Computers & Fluids 290(052355):106559**
- **B. Basu, S. Gurusamy and F. Gaitan A quantum algorithm for computing dispersal of submarine volcanic tephra, (2024) *Physics of Fluids* 36, 036607 (2024) https://doi.org/10.1063/5.0189674**
- **A. Staino, F. Gaitan and B. Basu Classical-quantum simulation of single and multiple solitons generated from the KdV equation, (2025) Physica D (under review)**

Use Case: (D) Representation of Uncertainty in Physical Processes

- **Representation in terms of stochastic process - a way to quantify uncertainty**
- **A research question: *When will a process attain a certain threshold?***
- **Approaches:**
  - Statistical modelling - classical way
  - Coupled classical-quantum uncertainty modelling proposed - an innovative and alternative way

A model developed to represent both classical and quantum uncertainties

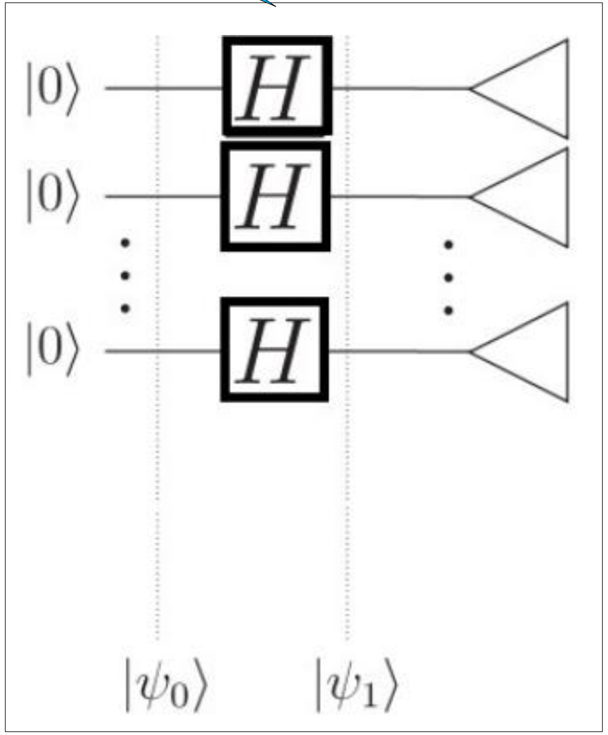
Quantum circuits implementation

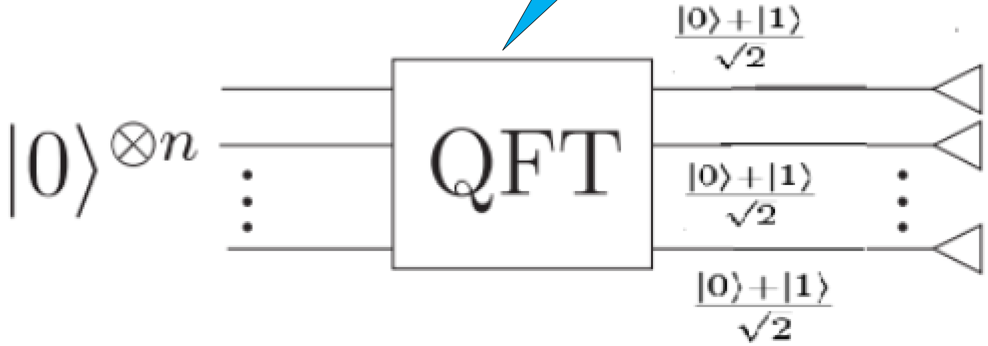
- **We generate quantum states**

$$|\alpha_1\rangle, |\alpha_2\rangle, |\alpha_3\rangle, \ldots, |\alpha_m\rangle$$

Quantum circuit for multistep prediction

A QFT circuit for multistep prediction





Alternate representation:

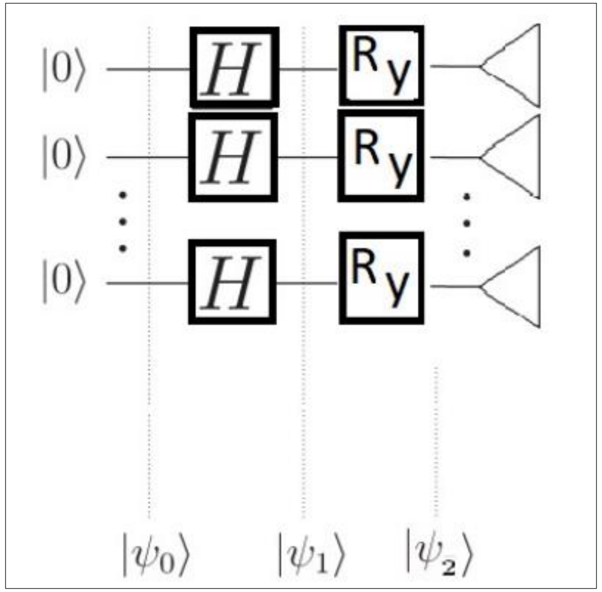
$$\mathrm{QFT}|0\rangle^{\otimes n} = \frac{1}{\sqrt{m+1}} \sum_{y=0}^{m} |y\rangle = H^{\otimes n}|0\rangle^{\otimes n}$$

Quantum circuits with rotational gates

- **We use rotation gates with Pauli operators**

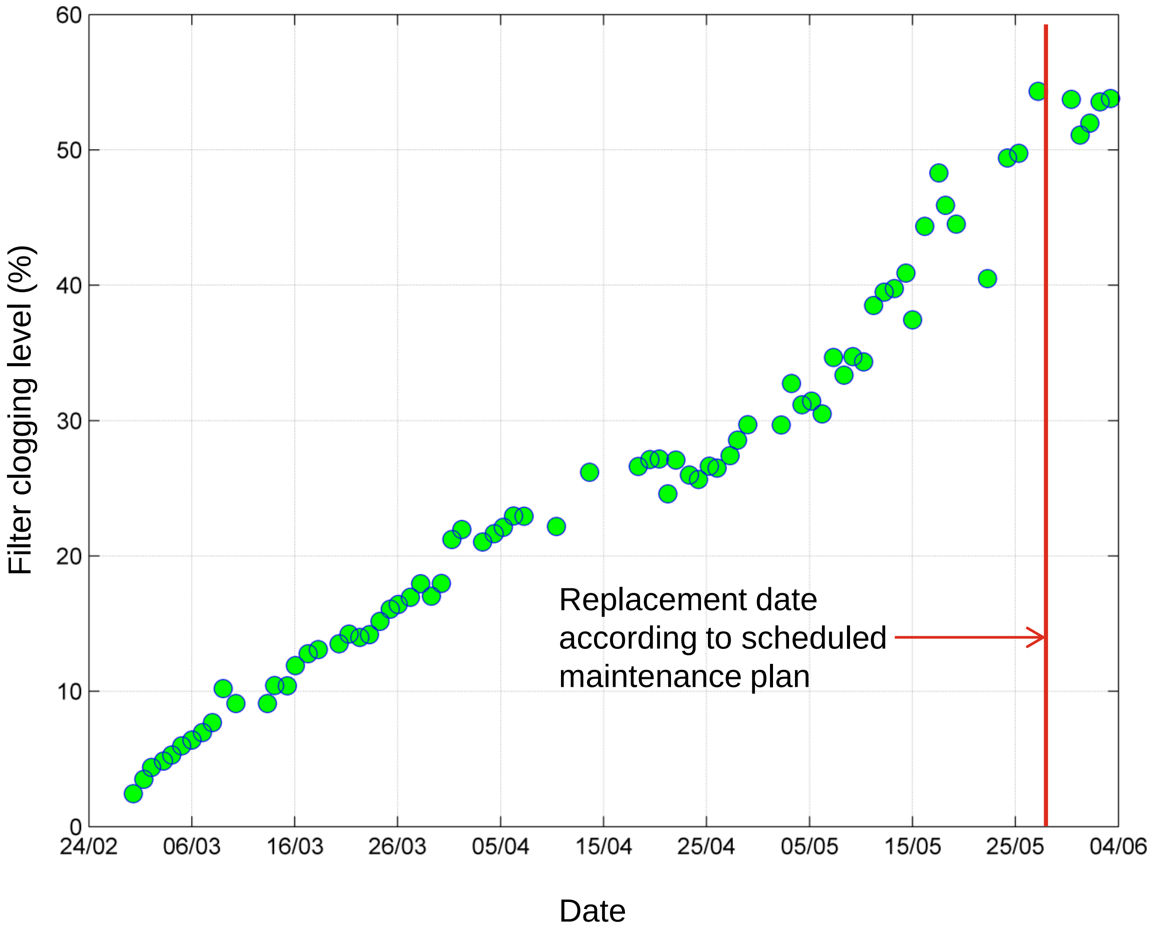
$$R_Y(\theta) \equiv e^{-\frac{i\theta Y}{2}} = \cos(\frac{\theta}{2})I - i\sin(\frac{\theta}{2})Y$$

- **Degrading systems can be modelled with $\theta > \frac{\pi}{2}$**



$$|\psi_2\rangle = R_Y(\theta)^{\otimes n} H^{\otimes n} |0\rangle^{\otimes n}$$

Challenges for Predictive Maintenance

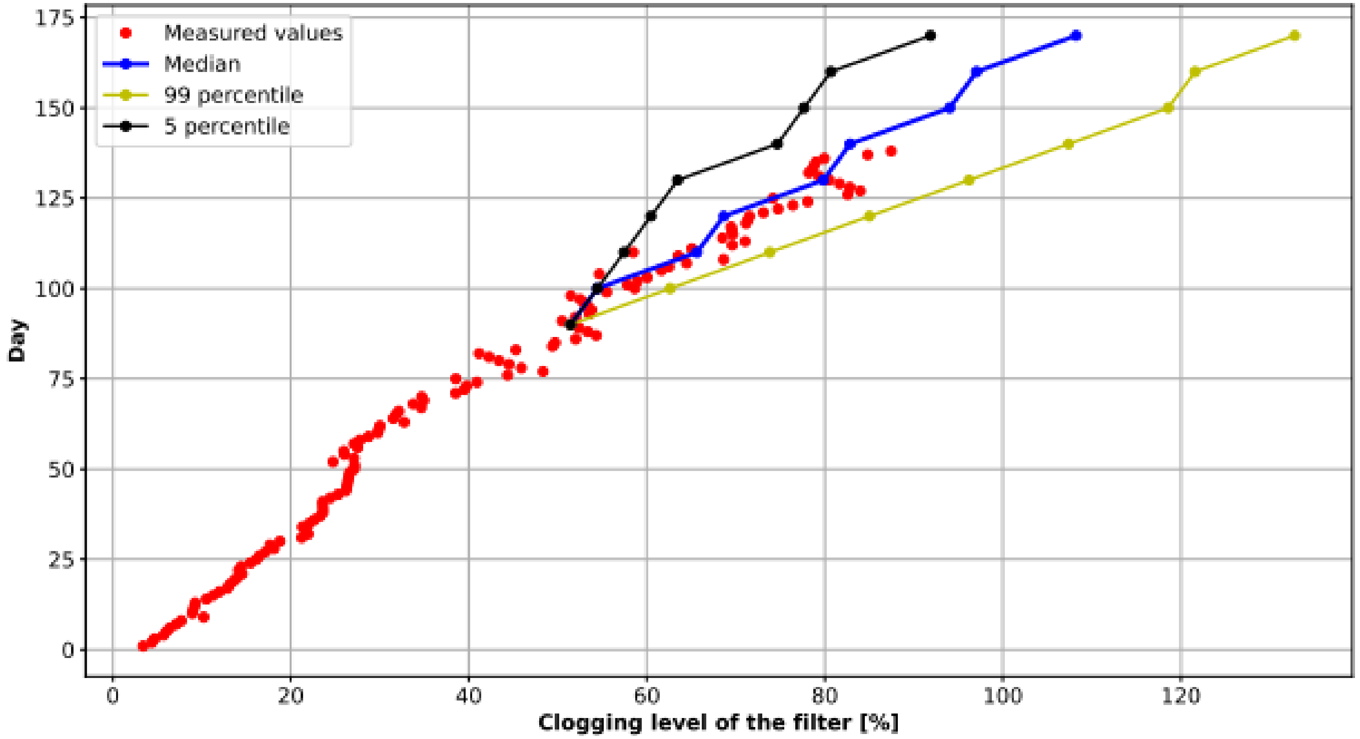


Based on available data, at what point in time will the filter reach a fully clogged condition?

Challenges for predictive maintenance

- Uncertainty affects the physical phenomenon (degradation process associated with clogging) as well as the prediction model;
    - the events of interests (e.g. failures) are intrinsically random
    - over the prediction horizon the system is subjected to unknown:
        - environmental & operating conditions
        - loading
        - mission profiles
        - unexpected events
- Prediction models are constructed based on approximations, simplifying assumptions, unknown parameters, neglected dynamics, noisy measurements, limited context….
- Quality of measured data
- **How to tackle the issue of catering for the presence of uncertainty in prognostics-oriented predictive models?**

Experiment



Predicted: 97% to 105% clogging between 160 and 170 days

Ground truth: 164 days

B. Basu and A. Staino A Quantum Computing Approach to Model Uncertainty in End of Life Prediction, 2025, J. Supercomputing (in press).

Conclusions

- Quantum computing for agricultural applications discussed

  QML

  Q optimization

  Q digital twin with PDEs

  Uncertainty quantification

- Has high potential to exploit quantum advantage in the field of agriculture
- To develop new algorithms and use cases

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Thank You
Questions?