



QuaSi

Quantum AI for CFD Simulations



BERLIN
QUANTUM
PIONEER

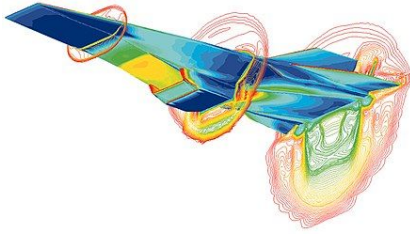
BERLIN QUANTUM Pioneer is collaboration



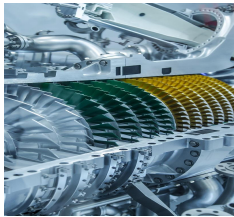
OpTecBB



Computational Fluid Dynamics



Modeling to analyse fluid flows, heat transfers, and multi-physics phenomena



**AEROSPACE &
DEFENSE INDUSTRIES**



**AUTOMOTIVE
INDUSTRY**



**CHEMICAL &
INDUSTRIAL COMPANIES**



**HEALTHCARE
INDUSTRY**

Navier-Stokes Equation

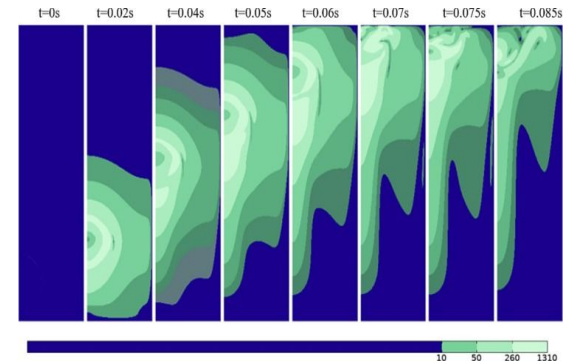
$$\rho \left(\frac{\partial \mathbf{v}}{\partial t} + \mathbf{v} \cdot \nabla \mathbf{v} \right) = -\nabla p + \nabla \cdot \mathbf{T} + \mathbf{f}$$

Biomedical CFD

Problem

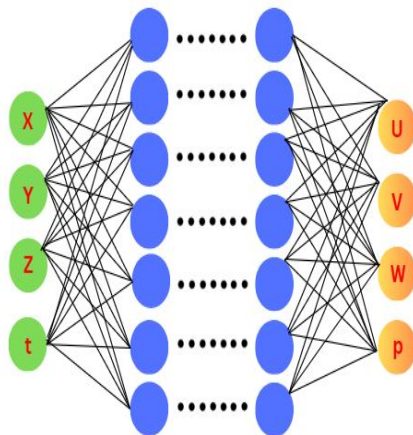
Challenges for CFD Simulations

- **High Computational Cost for Turbulent Flows**
- **Inaccuracies in Predicting Nonlinearities**
- **Expensive High fidelity simulations**



Solution

Combining Quantum with Physics-Informed Neural Networks Neural Operators, Geometry Aware Operator Transformers

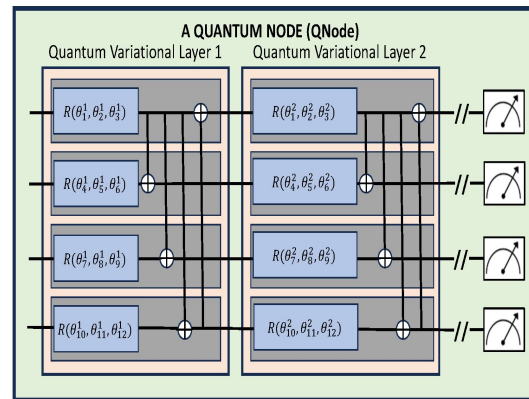


Naviers - Stokes loss

$$\begin{aligned} \rho \left(\frac{\partial u}{\partial x} + \frac{\partial u}{\partial x} + \frac{\partial u}{\partial y} + \frac{\partial u}{\partial z} \right) &= - \frac{\partial p}{\partial x} + \mu \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2} \right) + \rho g_x \\ \rho \left(\frac{\partial v}{\partial x} + \frac{\partial v}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial v}{\partial z} \right) &= - \frac{\partial p}{\partial y} + \mu \left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} + \frac{\partial^2 v}{\partial z^2} \right) + \rho g_y \\ \rho \left(\frac{\partial w}{\partial x} + \frac{\partial w}{\partial x} + \frac{\partial w}{\partial y} + \frac{\partial w}{\partial z} \right) &= - \frac{\partial p}{\partial z} + \mu \left(\frac{\partial^2 w}{\partial x^2} + \frac{\partial^2 w}{\partial y^2} + \frac{\partial^2 w}{\partial z^2} \right) + \rho g_z \end{aligned}$$

Experimental Data loss

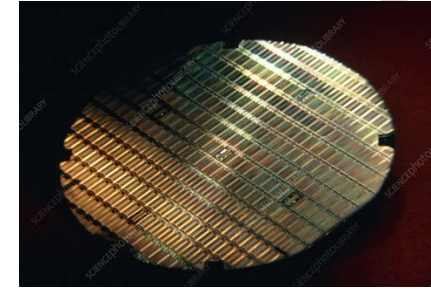
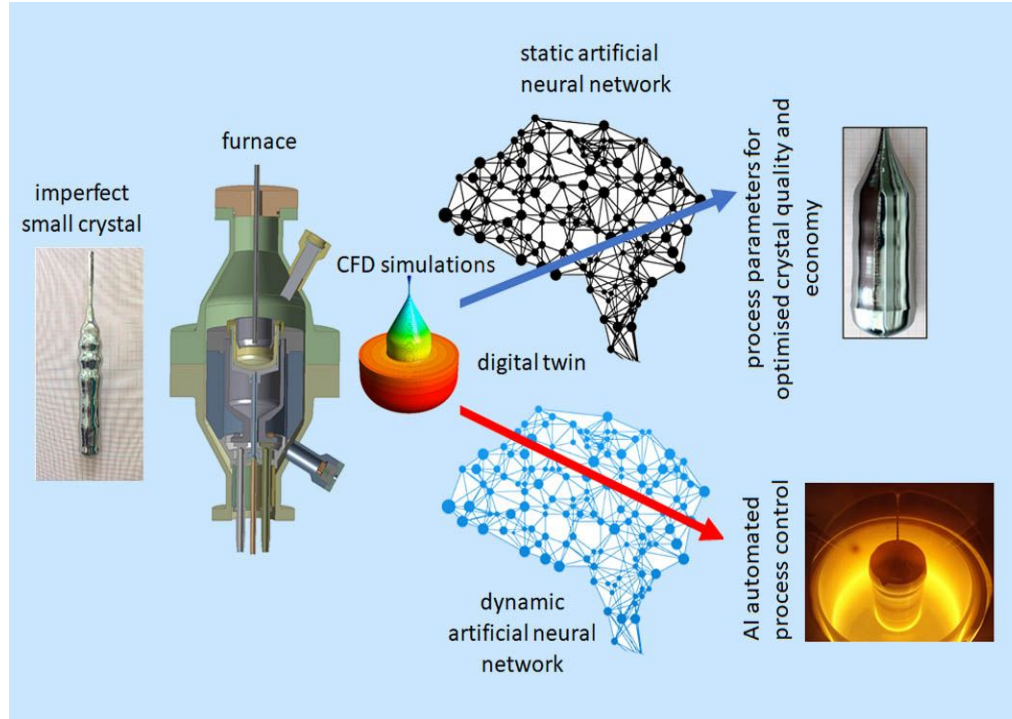
$$\| \nabla \cdot \vec{v}_{exp} \|^2$$



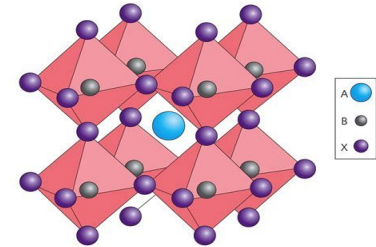
**Bringing Quantum Advantage through AI
(Hybrid Approaches on QPU/GPUs Hardware)**

Use Case (PoC)

Single-Crystal Growth Simulations



Silicon Wafers

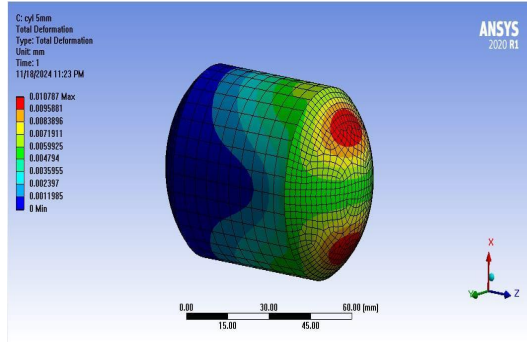


Perovskites

Accelerating CFD for Faster Chips Production

Designing Cryogenic Vessels

Accelerating CFD Reduces Design to Production Time

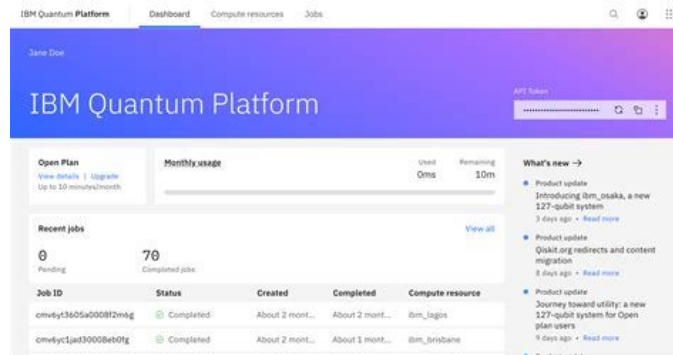
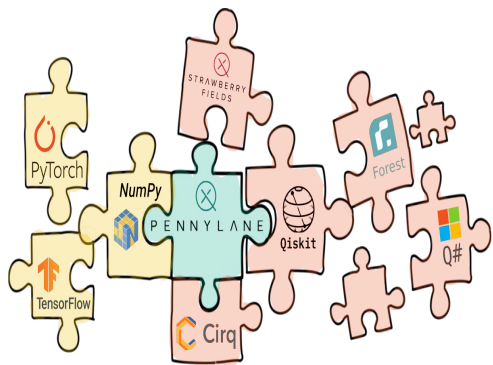
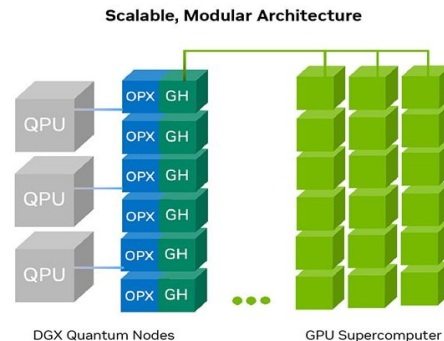
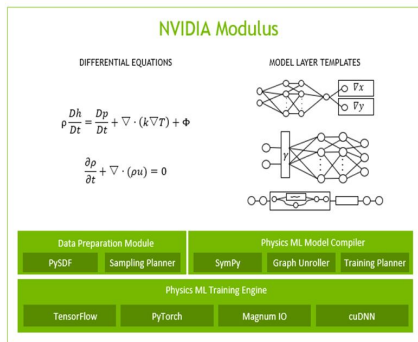


Green Hydrogen
Economy



Collaboration with Indo-Australian Startup

Frameworks & Resources



PennyLane, Nvidia Modulus, DGX Quantum, IBM Quantum Credits

<https://pennylane.ai/> developer.nvidia.com <https://quantum.ibm.com/>

Business Model



Ecosystem Integration

Integrate workflows
QuantME



Simulations as a Service

Domain Specific
QFaaS



Synthetic Data Generation

Licensing
Reselling

Timeline & Milestones

**Funding &
Collaborations**

Solutions for Cryogenics

**Integrations and API
for Simulation**

2025 Q3

2025 Q4

2026 Q2

2026 Q4

2027 Q2

Validation QPINNs

**Quantum Advantage
Hybrid Quantum-HPC**

Team

**Strong background in Quantum AI, Simulations
and Business Development**



**ADRIANO MACARONE
-PALMIERI**

CSO



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**The Institute of Photonic
Sciences**

Thank You

Collaborations & Partnerships

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<https://github.com/adytiaa/quasi.ai>

<https://adytiaa.github.io/quasi.ai/>



Classical Benchmarks

PINNs, Neural Operators, NeuralDEM, Universal Physics Transformer Models

	ShapeNet-Car		AhmedML			DrivAerML			Neural field	Mesh independent
	p_s	u	p_s	u	ω	p_s	u	ω		
PointNet	12.01	3.05	8.51	5.43	67.29	23.26	28.12	880.0	✗	✗
GRAPH U-NET	10.33	2.48	6.42	4.14	53.53	16.13	17.98	330.0	✗	✗
GINO	13.27	2.52	7.90	6.23	71.80	13.03	40.58	98.5	✓	✓
LNO	9.05	2.29	12.91	7.56	72.04	20.51	23.27	173.0	✓	✓
UPT	6.41	1.49	4.25	2.73	15.03	7.44	8.74	90.2	✓	✓
OFormer	7.05	1.60	3.55	2.22	7.78	4.48	6.64	60.4	✓	✓
Transolver	6.46	1.62	3.45	2.05	8.22	4.81	6.78	38.4	✗	✗
Transformer	4.86	1.17	3.41	2.09	6.76	4.35	6.21	47.9	✗	✗
AB-UPT	4.81	1.16	3.01	1.90	6.52	3.82	5.93	35.1	✓	✓

QC-HPC integration

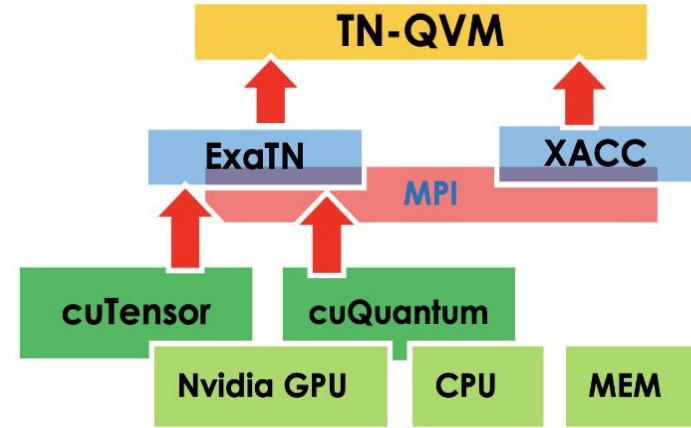
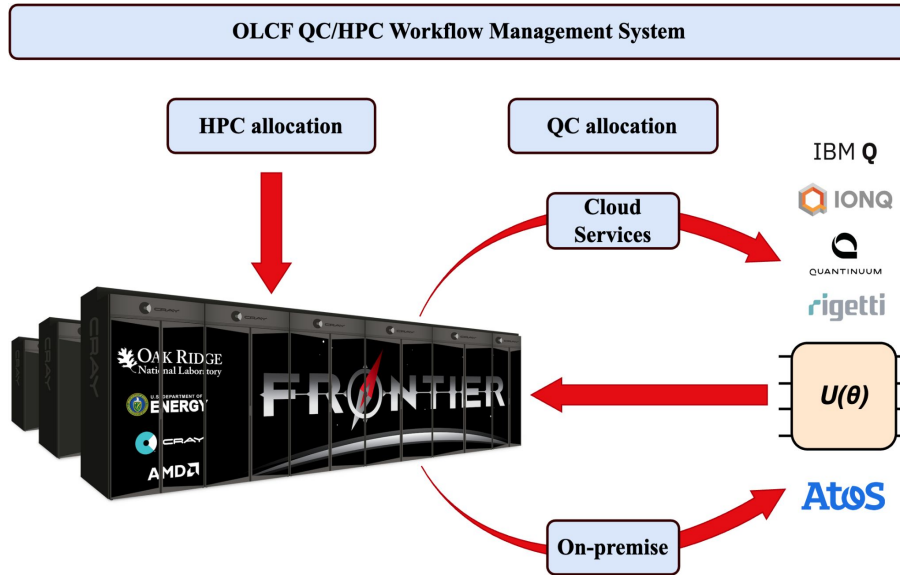


Figure 3: Schematic showing how the TN-QVM, an ORNL-developed tensor-network based accelerator, integrates with various other software packages to form a powerful tool for simulating large circuits and algorithms on HPC platforms.

Hybrid Benchmarks

Quantum PINNs/Neural Operators/Tensor Networks

Model	Harmonic		Non-harmonic		Number of trainable parameters
	Accuracy	Trainability	Accuracy	Trainability	
Classical	Medium	High	High	High	High
Quantum	High	Low	Low	Low	Low
Hybrid	Medium–High	Medium–High	Medium	Varies	Medium–High

Table 4: Qualitative assessment of PINN models in the present study.

Qubits: 4–12 qubits for initial benchmarks