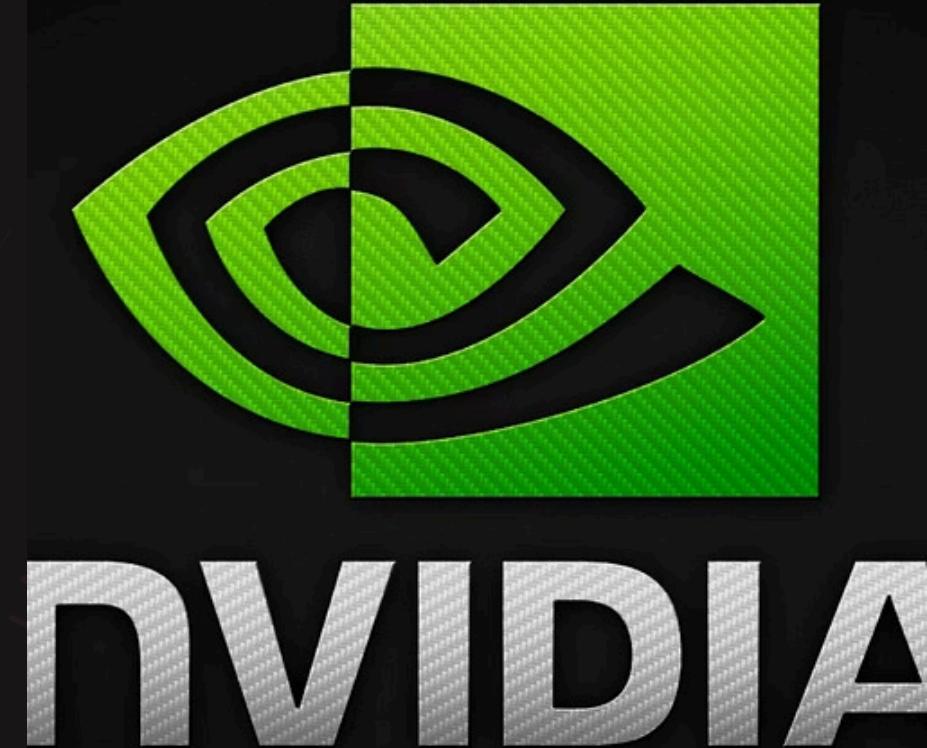
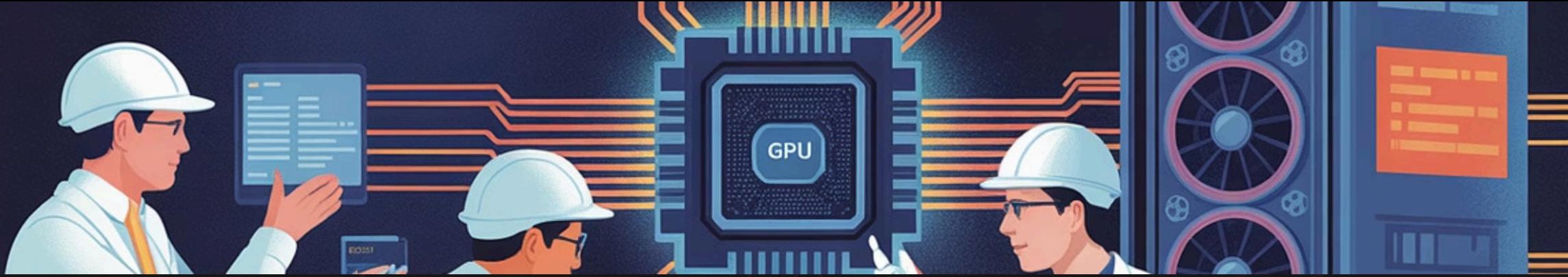


Team QuantumSpark - NVIDIA
iQuHACK 2026

Quantum-Enhanced
LABS Optimization
with GPU
Acceleration





INTRODUCTION

QRadarX: Quantum-Enhanced LABS Optimization

GPU-Accelerated Hybrid Workflow

Team QuantumSpark presents an innovative solution to the LABS optimisation problem, combining quantum computing with NVIDIA GPU acceleration for unprecedented performance.

NVIDIA iQuHACK 2026

We're Team QuantumSpark. Today we present our solution for the LABS problem using quantum-enhanced optimisation with NVIDIA GPU acceleration.

Aditya Punjani

Project Lead

Furkan Eşref Yazıcı

GPU Acceleration

Alexandre Boutot

Quality Assurance

Shreya Savadatti

Technical Marketing

The LABS Challenge

What is LABS?

Find binary sequence $s \in \{-1, +1\}^N$ that minimises:

$$E(s) = \sum_{k=1}^{N-1} C_k^2$$

where $C_k = \sum_{i=0}^{N-k-1} s_i \times s_{i+k}$

Why It Matters

- Radar systems** – Low sidelobes for target detection
- Telecommunications** – Reduced signal interference
- Cryptography** – Pseudorandom sequences



20

$N = 20$

1 million possibilities
~1 second brute force

30

$N = 30$

1 billion possibilities
~17 minutes brute force

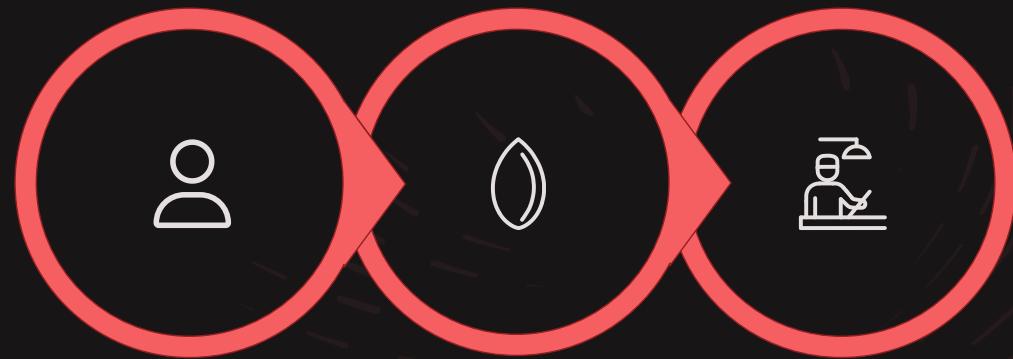
40

$N = 40$

1 trillion possibilities
~317 years brute force

LABS is NP-hard. Brute force fails quickly. We need smart algorithms.

Quantum-Enhanced Hybrid Workflow



Our innovative approach combines quantum exploration with classical exploitation, accelerating both components on NVIDIA GPUs.

01

Quantum Sampling

Generate diverse initial sequences using quantum circuits

02

Population Seeding

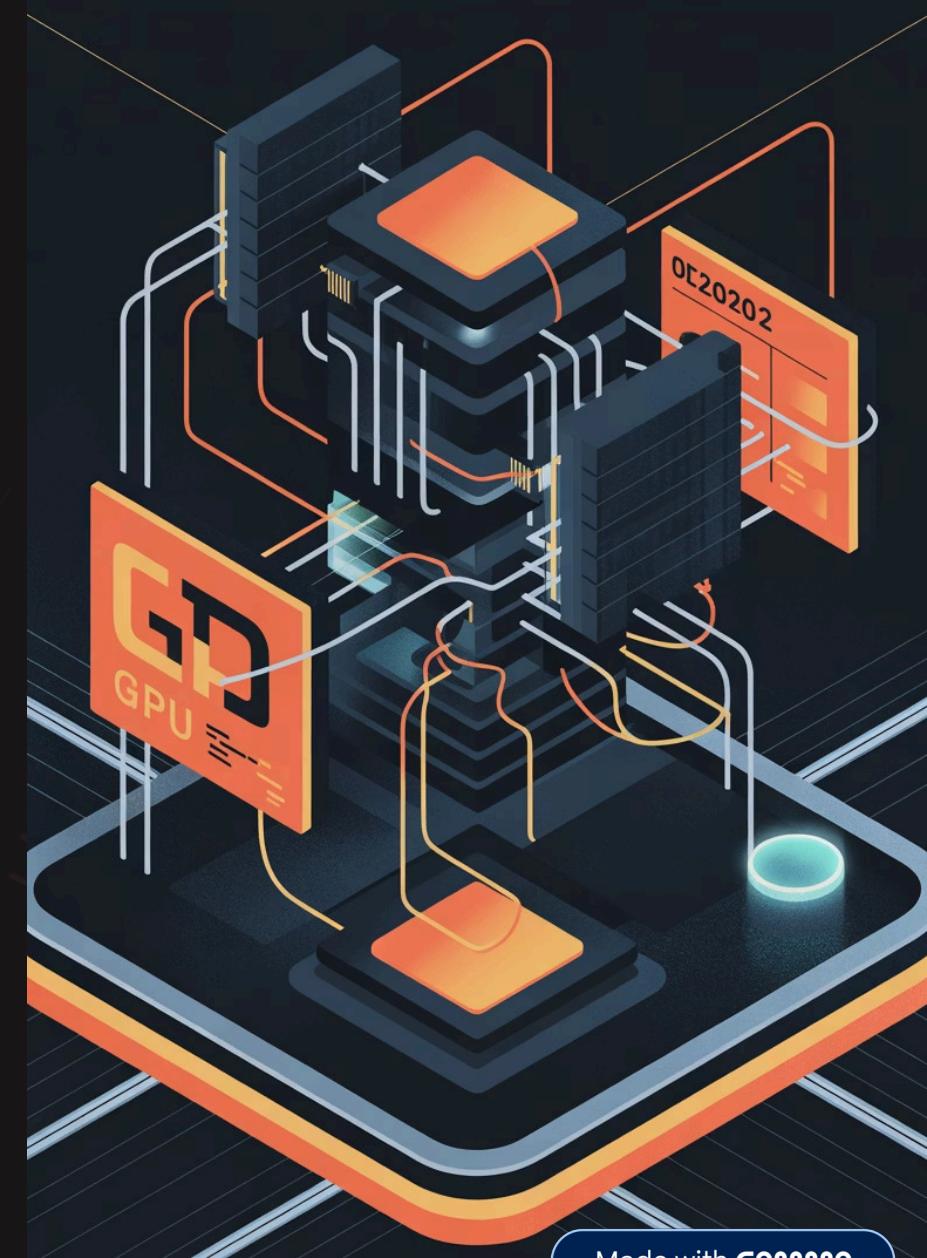
Feed quantum-generated candidates to classical optimiser

03

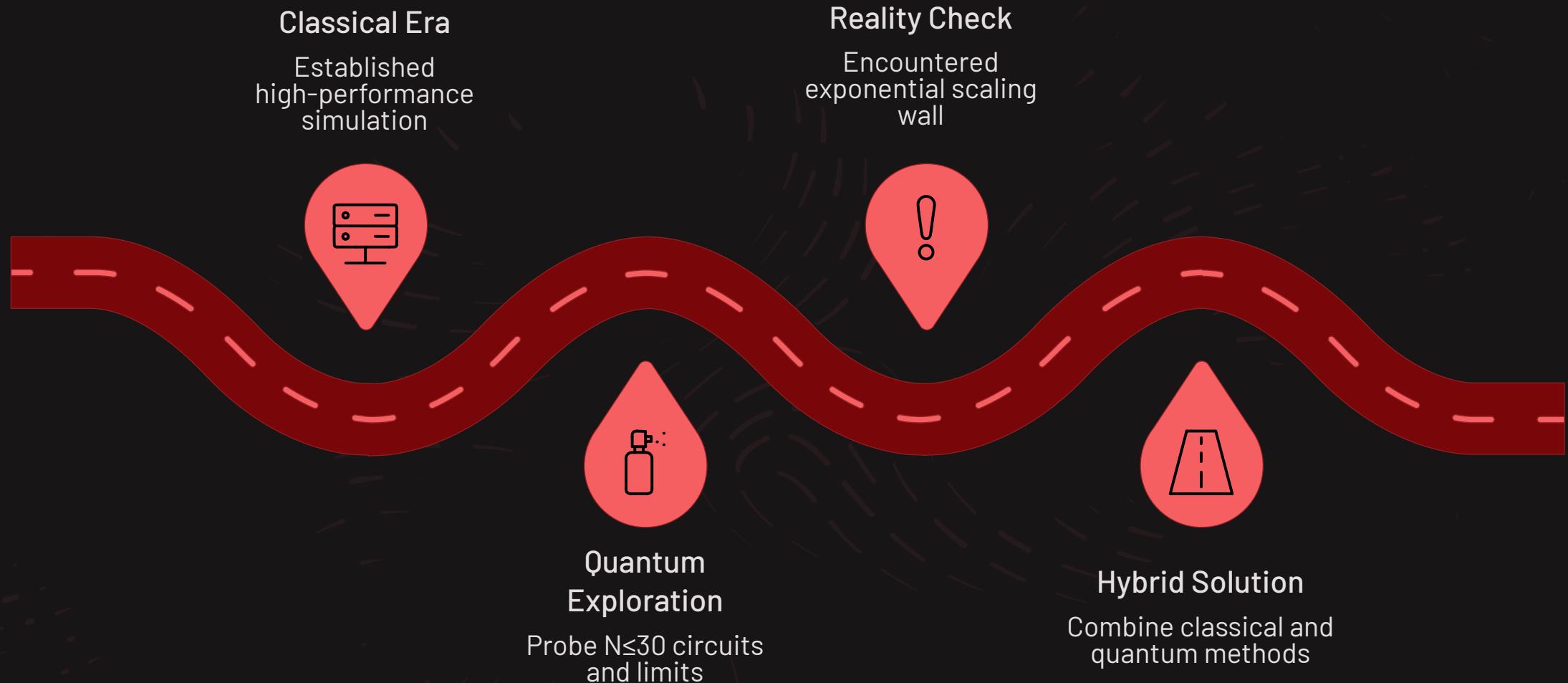
Memetic Tabu Search

Refine solutions to find optimal configurations

We don't rely on quantum alone. We combine quantum's exploration power with classical optimisation's efficiency.



The Plan & The Pivot



Original Plan X

- Scale quantum circuits to $N=40+$
- Compare quantum vs classical at same sizes

Reality Check ⚡

- **N=35 requires ~550GB RAM** – impossible!
- State vector simulation scales $O(2^N)$

Our Adaptation ✓

- Focus on $N \leq 30$ for quantum circuits
- Document memory scaling limits
- Run MTS to $N=40$ separately

☐ We hit the exponential wall. Instead of forcing it, we adapted our strategy and documented the limits. That's real engineering.



INFRASTRUCTURE

Phase 2: Brev Deployment

Hardware Configuration

GPU

NVIDIA L4

VRAM

24 GB

CUDA

Version 12.8

Platform

Brev



Seamless migration from qBraid CPU to Brev GPU

Migration Steps

```
# 1. Clone repository  
git clone https://github.com/AdityaYC/2026-NVIDIA.git
```

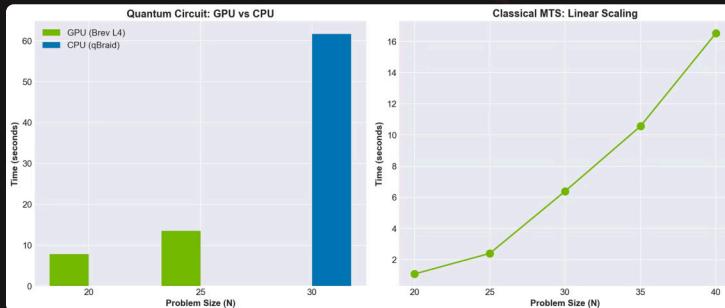
```
# 2. Set CUDA-Q target  
cudaq.set_target("nvidia")
```

```
# 3. Run benchmark  
python3 run_gpu_benchmark.py --mode gpu --n 20
```

Brev made GPU access easy. We switched one line of code and got **8x speedup**.

QUANTUM RESULTS

Quantum Circuit Performance



Benchmark Data

N	Platform	Time	Speedup
20	GPU (L4)	7.77s	Baseline
25	GPU (L4)	13.50s	—
30	CPU (qBraid)	61.68s	—

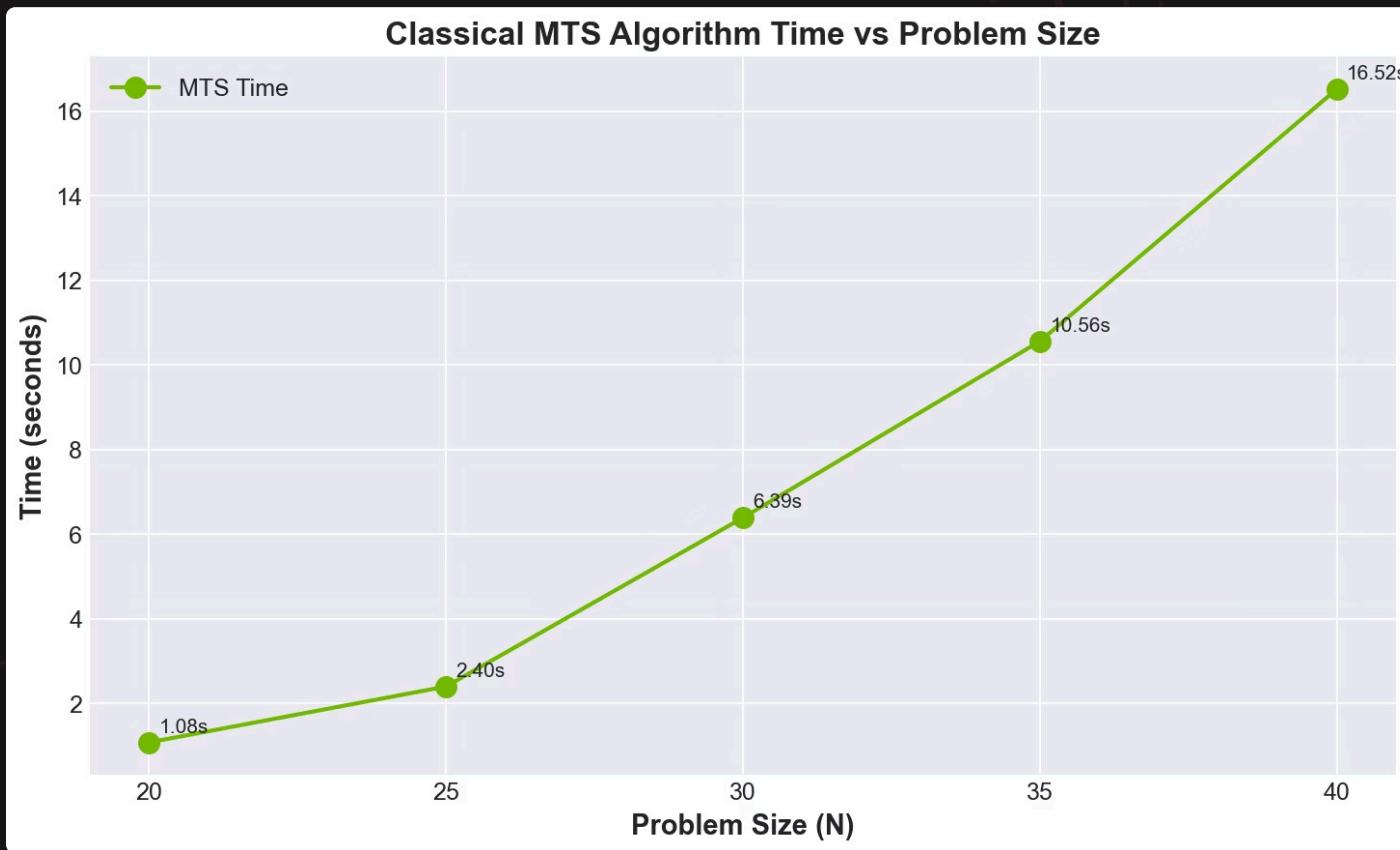
Key Insight

GPU is ~8x faster than CPU for quantum state vector simulation. N=30 on CPU takes over a minute, but N=20 on GPU completes in under 8 seconds.

Look at this chart. That's the power of NVIDIA acceleration in action.

CLASSICAL RESULTS

Memetic Tabu Search Scaling



Benchmark Data

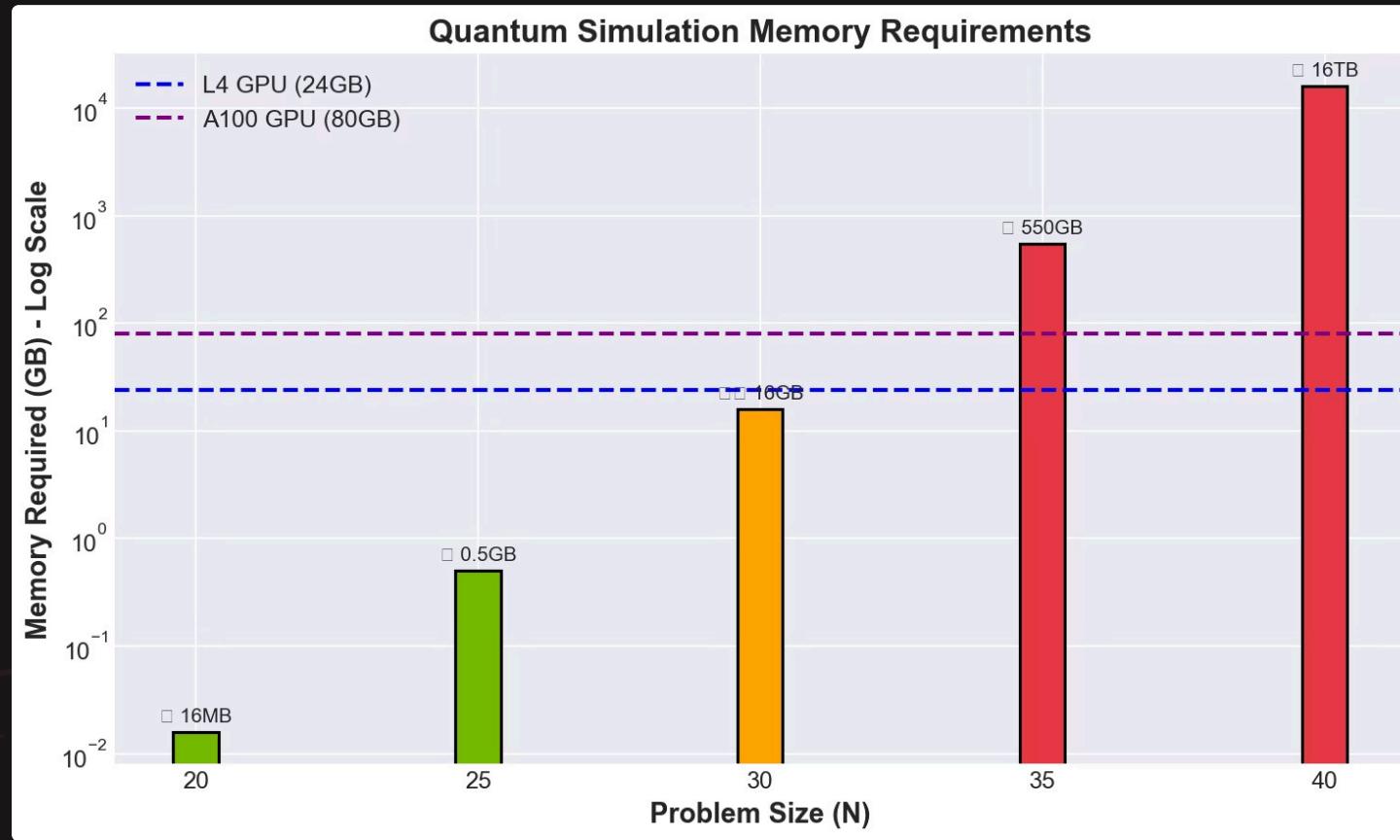
N	Time	Best Energy	Scaling
20	1.08s	26	—
30	6.39s	83	6x
40	16.52s	128	15x

Key Insight

MTS scales linearly whilst quantum scales exponentially. This is why the hybrid approach works brilliantly.

Quantum guides, but classical does the heavy lifting at scale.
N=40 in 16 seconds!

The Exponential Memory Wall



This is the exponential wall. Every +1 to N doubles memory. N=40 would need a datacentre. This is why we need real quantum computers.

The Mathematics

N	States (2^N)	Memory	Status
20	1 million	16 MB	✓
25	33 million	512 MB	✓
30	1 billion	16 GB	⚠
35	34 billion	550 GB	✗
40	1 trillion	16 TB	✗

GPU Limits

- L4 GPU: 24 GB → Max N ≈ 30
- A100 GPU: 80 GB → Max N ≈ 32
- Beyond requires tensor networks or real hardware

✓ VERIFICATION

Rigorous Testing: 26/26 Tests Passing



Energy Function
5 tests
 $E([1,1,1])=5$ ✓



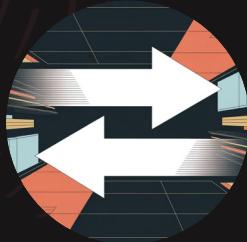
MTS Convergence
3 tests
Finds good solutions ✓



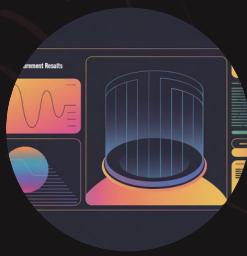
Sign Symmetry
2 tests
 $E(s)=E(-s)$ ✓



Bitstring Conversion
3 tests
Roundtrip preserves data ✓



Reversal Symmetry
2 tests
 $E(s)=E(\text{reverse}(s))$ ✓



Quantum Output
2 tests
Correct sequence length ✓



G2/G4 Indices
5 tests
Correct loop bounds ✓

AI Bug Caught

```
# AI wrote (WRONG):  
ry(theta/2, q0) # Basis change
```

```
# We fixed to (CORRECT):  
rx(1.5707963267948966, q0) # π/2 for Y→Z
```

Quality Matters

Tests caught a bug the AI introduced. The AI confused rotation angle with basis change. Rigorous testing saved us from deployment errors.