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# CROSS PLATFORM BENCHMARKING OF SHOR'S ALGORITHM FOR QUANTUM CRYPTANALYSIS

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## Introduction & Motivation

# The Quantum threat 2 Classical Cryptography

1

### The Cryptographic Foundation

Current encryption relies on the the computational difficulty of factoring large integers, safeguarding sensitive data globally. globally.

2

### Shor's Algorithm Emerges

Introduced in 1994, this quantum algorithm can factor integers in polynomial time, posing an existential threat to RSA and other widely used schemes.

3

### Our Research Goal

To evaluate current quantum computing frameworks for implementing Shor's algorithm, algorithm, assessing their performance, scalability, and practical readiness for real-world world application.

Background

# Understanding Shor's Algorithm

Shor's algorithm offers an exponential speedup over classical factoring methods by leveraging quantum mechanics. It's a hybrid approach combining classical pre and post-processing with a quantum core.

01

## Classical Pre-processing

Select a random integer 'a' co-prime to 'N' (the number to be factored). This sets up the quantum computation.

02

## Quantum Period-Finding

The core quantum step utilizes superposition and the Quantum Fourier Fourier Transform (QFT) to efficiently find find the period 'r' of the function f(x)=a^x f(x)=a^x mod N.

03

## Classical Post-processing

With 'r' determined, factors of of 'N' are calculated using the the Euclidean algorithm: gcd(a^(r/2) ± 1, N).

**The quantum period-finding subroutine is where the algorithm gains its unparalleled efficiency.**

The Tools

# The Contenders: Seven Quantum Frameworks Evaluated

We benchmarked seven leading quantum software development platforms, each with unique strengths and applications.

- **Qiskit:** IBM's framework, strong integration with IBM Q IBM Q hardware.
- **Cirq:** Google's framework, designed for near-term quantum computers.
- **PennyLane:** For hybrid quantum-classical machine learning, supports multiple backends.
- **Qibo:** High-performance framework focused on fast circuit simulation.
- **QuTiP:** Focuses on simulating quantum dynamics dynamics using symbolic operators.
- **ProjectQ:** A high-level quantum compiler framework.
- **Tequila:** An abstraction layer for variational quantum algorithms.

Each framework offers distinct advantages, from hardware integration to simulation speed and high-level abstraction.

# Quantum Frameworks: A Diverse Ecosystem

| | | |
|---|---|---|
| **Qiskit** | **IBM's open-source quantum SDK** | **Gate-level fidelity, hardware integration** |
| **Cirq** | **Google's quantum programming framework** | **Fine-grained control, hardware-agnostic** |
| **PennyLane** | **QML framework for hybrid computing** | **Symbolic differentiation, hybrid scalability** |
| **QuTip** | **Open-source library for quantum optics** | **Numerical simulation, large system support** |
| **ProjectQ** | **Quantum computing framework by ETH Zurich** | **Python-based, extensible backend** |
| **Tequila** | **Modular quantum chemistry framework** | **Variatioal algorithms, high-level abstraction** |
| **Qibo** | **Framework for quantum simulation** | **Hardware-accelerated, custom backends** |

## Our Approach

# Our Experimental Methodology

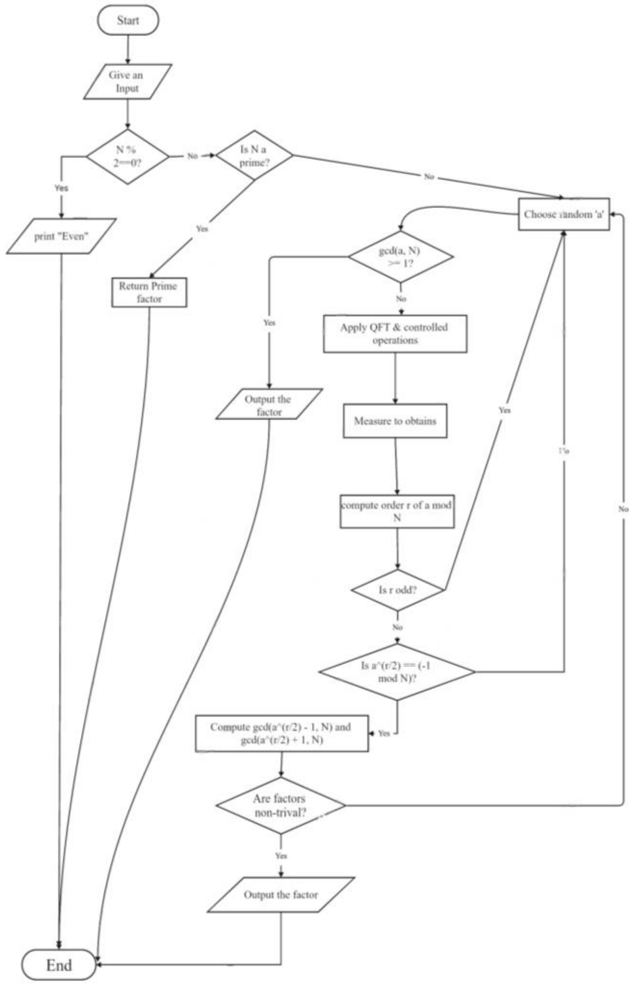
Our objective was to thoroughly assess each framework's usability, accuracy, scalability, and hardware support through a rigorous implementation of Shor’s algorithm.

### Input Data

We used a curated dataset of composite integers, ranging from small (4-bit, N=15) to considerably larger (47-bit, 15-digit numbers), to push the limits of each framework.

### Implementation Flow

A consistent workflow was maintained across all platforms: from initial input validation, through the quantum order-finding subroutine, to final classical factor extraction.




Shor's Algorithm Implementation Flowchart

# Results Overview

## Maximum Integer Factored

| Framework | Max Digits Factored | Qubits Used | Time Taken | Qubit Type |
|---|---|---|---|---|
| Qiskit | 4 (N = 1234) | 23 | 38s | Logical Qubits (Sim) |
| Cirq | 4 | 23 | 2m 17s | Logical Qubits (Sim) |
| PennyLane | 15 | 60 | 3m 05s | Logical Qubits (Hybrid) |
| Qibo | 6 | 18 | 1m 48s | Logical Qubits (Sim) |
| QuTiP | 9 | 54 | 28s | Symbolic Operators |
| ProjectQ | 5 | 28 | 35s | Logical Qubits (Sim) |
| Tequila | 6 | 18 | 5m 24s | Logical Qubits (Sim) |

```
import cirq
import numpy as np
from math import gcd
from fractions import Fraction

# Input values
N = 15         # number to factor
a = 7          # choose a value coprime with N
n_count = 4    # number of counting qubits
# 1. Initialize qubits
qubits = [cirq.LineQubit(i) for i in range(n_count)]
circuit = cirq.Circuit()

# 2. Create uniform superposition on counting register
circuit.append([cirq.H(q) for q in qubits])
# Simplified placeholder for modular exponentiation
# (In full Shor, we'd apply controlled-U gates here)
circuit.append(cirq.X(cirq.LineQubit(n_count)))  # dummy step

# 3. Measure counting register
circuit.append(cirq.measure(*qubits, key='m'))

# 4. Simulate the circuit
sim = cirq.Simulator()
result = sim.run(circuit, repetitions=1)
measured = result.measurements['m'][0]

# 5. Classical post-processing: estimate the period r
phase = int("".join(str(b) for b in measured), 2) / (2 ** n_count)
r = Fraction(phase).limit_denominator(N).denominator

# 6. Use r to compute factors of N
if r % 2 == 0 and pow(a, r // 2, N) != N - 1:
    p = gcd(pow(a, r // 2) - 1, N)
    q = gcd(pow(a, r // 2) + 1, N)
    print(f"Factors of {N}: {p}, {q}")
else:
    print("Try again with different 'a'")
```

```
Factors of 15: 3, 5
```

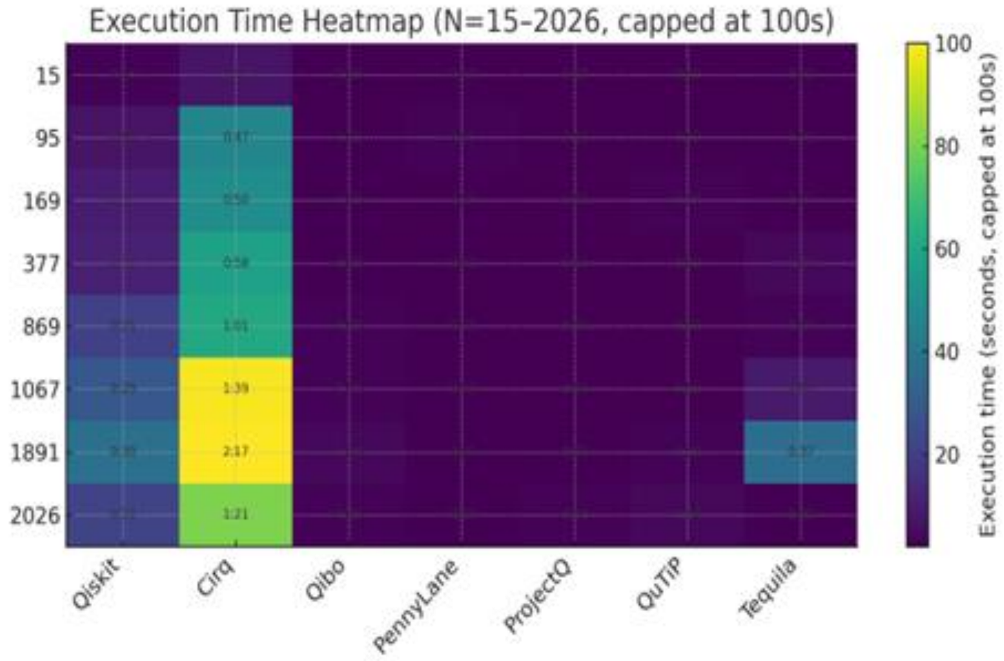
**Key Insight:** Frameworks leveraging symbolic/hybrid methods (PennyLane, QuTiP) significantly outperformed pure gate-level simulators (Qiskit, Cirq) in handling larger inputs.

**Performance Analysis**

# Runtime Performance Across Frameworks

Execution times diverged rapidly as the input integer size (N) increased, highlighting key performance differences.

- **Fast & Consistent:**
  **PennyLane** and **Qibo** maintained high efficiency, exhibiting consistently low execution times (dark purple).
- **Moderate Scaling:**
  **Qiskit** showed a modest, manageable increase in runtime as N grew.
- **Poor Scaling:**
  **Cirq** was consistently the slowest, with execution time increasing increasing substantially with N (bright yellow).



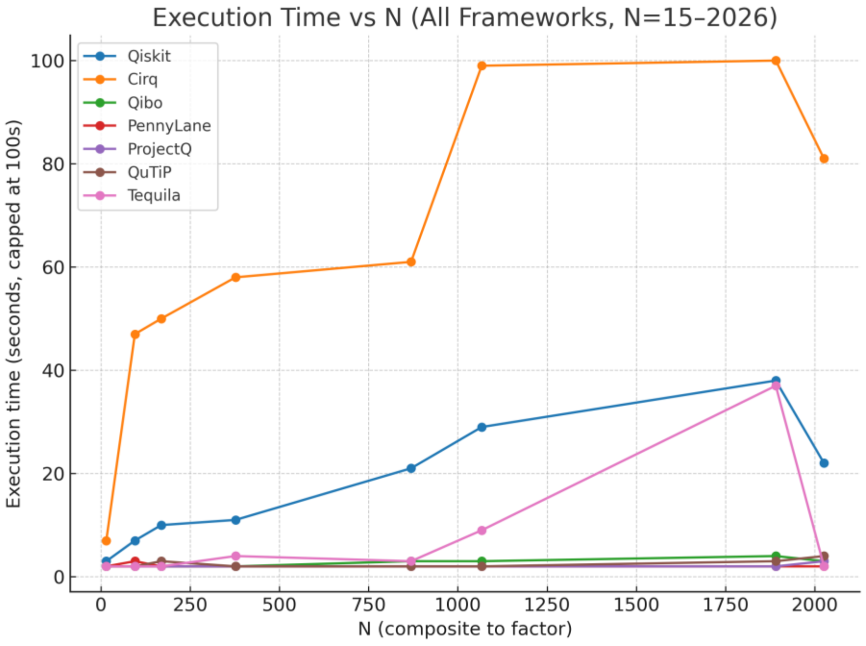

Execution Time Heatmap

## Insights

# Fidelity vs. Scalability Trade-Off

This analysis clearly visualizes the performance gap, highlighting a fundamental trade-off in quantum framework design.

- The **steep curve for Cirq** demonstrates how its high-fidelity, gate-level simulation quickly becomes computationally expensive.
- The **flat lines for PennyLane and Qibo** illustrate the significant significant scalability benefits of their symbolic and optimized optimized simulation approaches.




**Conclusion: A fundamental trade-off exists between the precision of precision of gate-level simulation and the scalability of symbolic/hybrid models.**

Standardized Comparison

# Introducing the Quantum Efficiency Index (QEI)

To provide a standardized and comprehensive comparison across frameworks, we propose a novel metric: the **Quantum Efficiency Index (QEI).**

$$QEI = \frac{\text{Qubits Used} \times \text{Circuit Depth}}{\text{Success Rate} \times \text{Max Input Bit Length}}$$

## What it Measures

The QEI balances an algorithm's accuracy and scale against its resource cost (qubits and circuit depth).

## Its Purpose

Enables researchers to assess frameworks based on overall **efficiency**, not just raw speed or the largest number factored.

# Quantum Efficiency Index (QEI): A Unified Metric

To enable a normalized, cross-platform comparison, we developed the Quantum Efficiency Index (QEI).

$$QEI = \frac{Success\ Rate \times Max\ Bit\ Lenght}{Qubits \times Circuit\ Depth}$$

This formula balances successful factorization rates, bit length, qubit consumption, and circuit complexity.

**0.0039**
**PennyLane**

Reflecting its superior balance of performance and resource usage.

**0.0005**
**Average Gate-level QEI**

Indicating lower efficiency for more complex problems.

**Impact: QEI provides a valuable quantitative measure for evaluating the practical efficiency of quantum algorithms across diverse software and hardware architectures.**

## Key Takeaways

# Discussion of Key Findings & Future Directions

## Key Findings

- **Symbolic Frameworks Excel at Scale:** PennyLane and QuTiP are ideal are ideal for large-scale algorithmic exploration where simulation simulation speed is paramount, bypassing the exponential cost of full cost of full state-vector simulation.
- **Gate-Level for Hardware Readiness:** Qiskit and Cirq, while less scalable in simulation, are crucial for hardware-focused research due to their precise circuit modeling, noise analysis, and direct QPU Integrations.
- **Major Bottlenecks Remain:** Shor's algorithm scaling is still limited limited by modular exponentiation, escalating qubit requirements, requirements, and exponential simulation time.

## Our Future Workflow

- All experiments used idealized, noise-free simulators. Real-world quantum hardware introduces decoherence and errors.
- **Proposed Hybrid Workflow:**

**Stage 1:** Symbolic Simulation (PennyLane, QuTiP) for QuTiP) for rapid logic validation.

**Stage 2:** Gate-Level Simulation (Qiskit, Cirq) for for detailed circuit analysis and hardware resource resource estimation.

**Stage 3:** Hardware Testing (Cloud Backends) for for small test cases on real QPUs in noisy environments.

# THANK YOU