Res(Q)bit

Disaster Prediction & Route Evaluation System

Quantum-Enhanced AI for Early Disaster Detection and Smart Response Planning

Presented at IBM Qiskit Fall Fest

Team Name : OnlyBits

The Crucial Need for Quantum-Speed Response

In the face of intensifying natural disasters—floods, earthquakes, and wildfires—timely and efficient response is a matter of life and death. The core challenge lies in the **velocity and volume of data** during a crisis.

Classical Data Overload

Processing the vast, real-time input from multiple sources (weather systems, population maps, IoT sensors) strains classical computing limits.

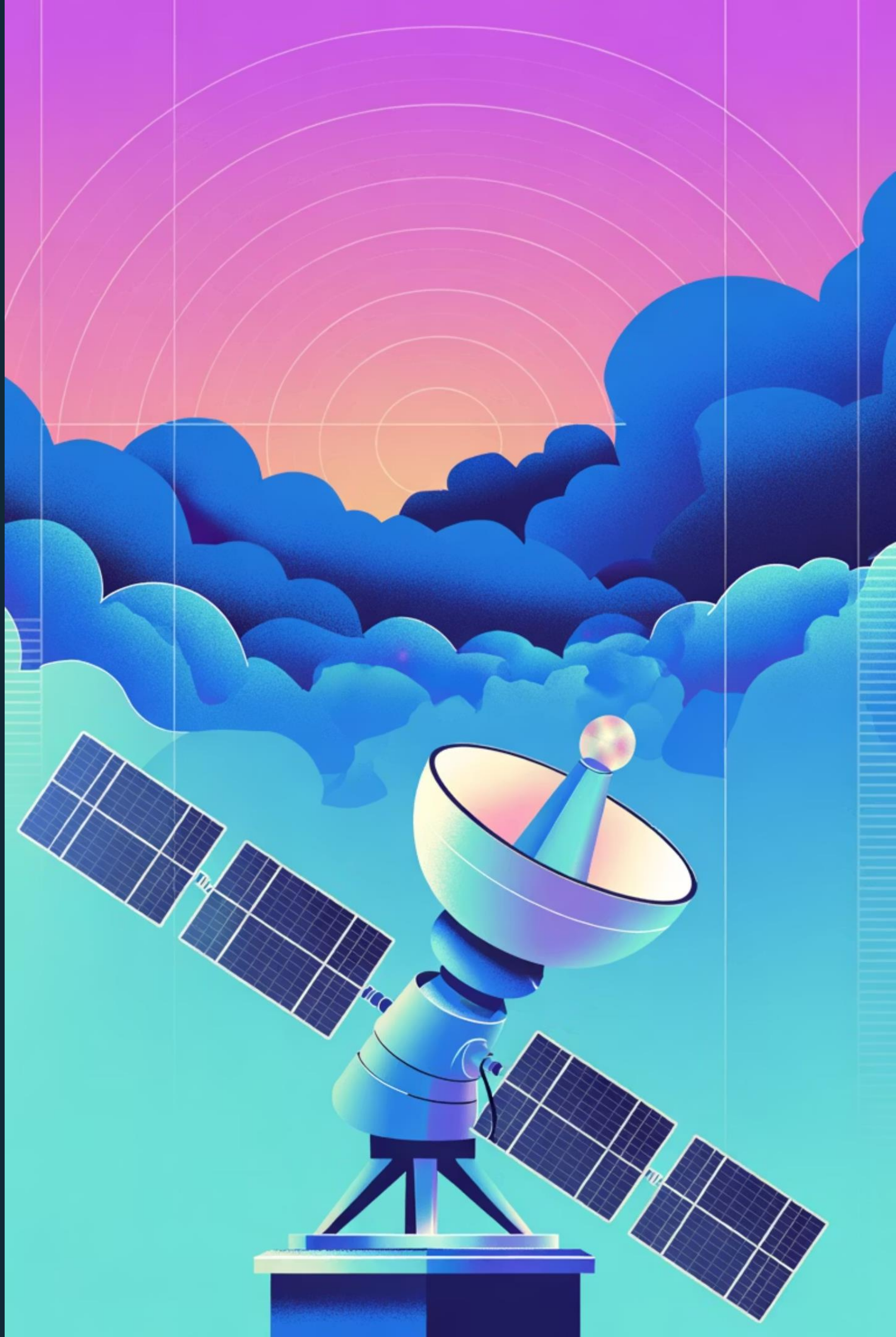
Inefficient Optimization

Optimization of critical paths—evacuation routes and resource allocation—is too slow, leading to bottlenecks and delayed aid.

Adaptive Strategy Lag

There is a dire need for a system that can instantaneously simulate multiple crisis scenarios and recommend the optimal, most adaptive strategy in real time.

Disaster Detection



Disaster Detection Workflow: From Data to Decision

Our Res(Q)bits system employs a rigorous, multi-step process for predictive modeling, ensuring high-fidelity risk assessment and actionable output.

Collect Historical Data

Gather time series data for key weather parameters (pressure, temperature, humidity, wind) to establish a baseline.

Recognize Patterns

Train the model to identify recurring trends and isolate subtle, yet critical, anomalous behaviors over time.

Detect Changes & Risk

Monitor shifts in indicators, calculate the probability of disaster, and cross-check against defined danger thresholds.

Classify & Assess

Determine the likely disaster type (Flood, Storm, Wildfire) using classification, and evaluate the predicted intensity/severity.

Generate Decision Output

Output actionable alerts based on severity: **Immediate Evacuation** (⚠️), **Moderate Risk** (🟡), or **Low Risk** (🟢).

Core Data Inputs

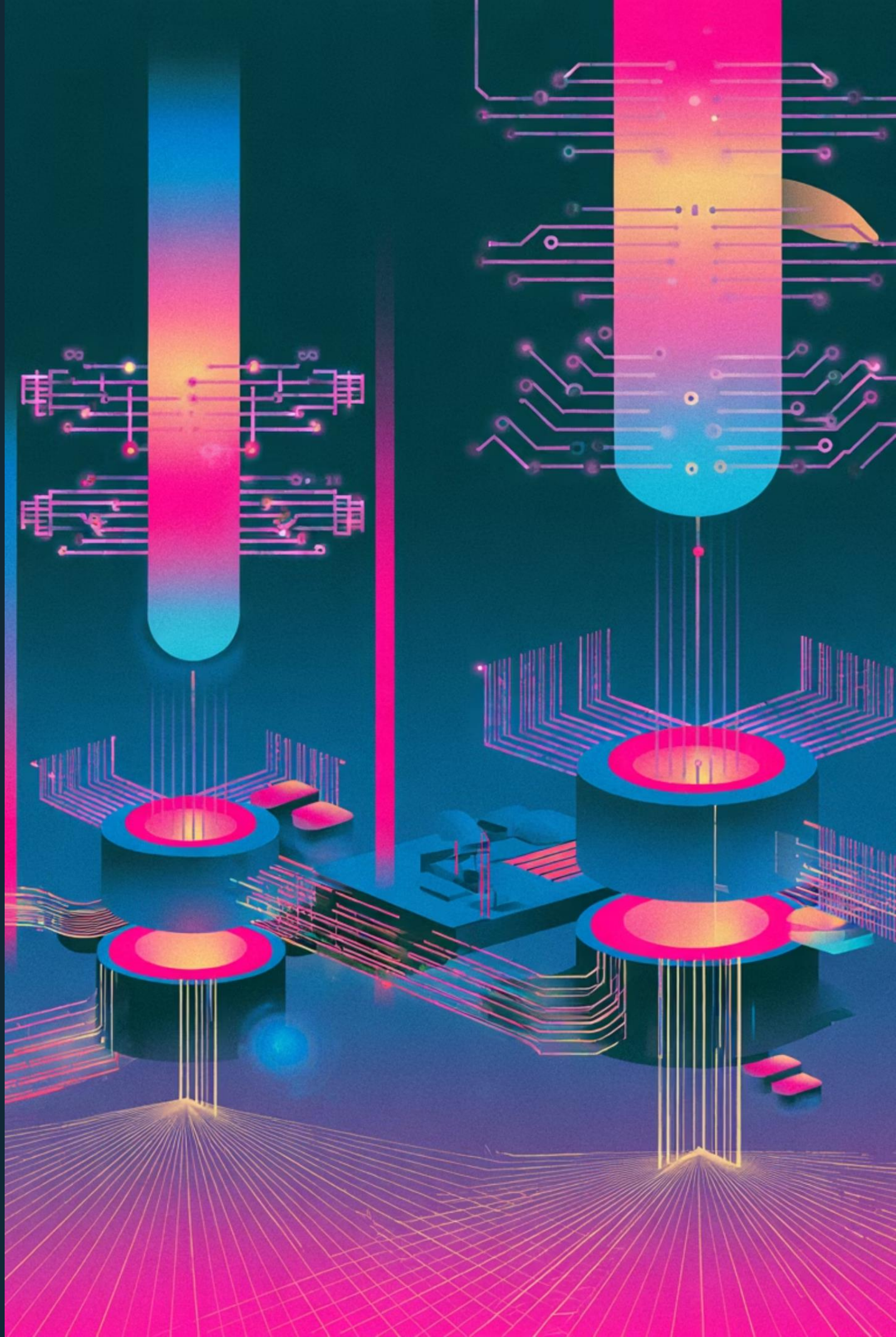
Core Data Inputs: Meteorological Time Series

The model is trained on rich meteorological time series data, sourced initially from the Kaggle Weather Prediction dataset, which provides high-granularity measurements essential for pattern recognition.

Data Source: Weather Prediction in Time Series (Kaggle)

Date Time	High-precision timestamp of each environmental observation.
p (mbar)	Atmospheric pressure, a critical indicator for frontal system movements.
T (°C), Tdew (°C)	Air temperature and Dew point temperature, vital for humidity and storm potential.
Tpot (K)	Potential temperature, used in atmospheric stability calculations.
rh (%)	Relative humidity, impacting precipitation and fog formation.
VP (max/act/def)	Vapor Pressure metrics (Max, Actual, Deficit), detailing moisture content.
sh (g/kg), H2OC	Specific Humidity and Water Vapor Concentration, proxies for atmospheric moisture.
rho (g/m^3)	Air density, affecting lift and atmospheric dynamics.
wv / max wv (m/s)	Wind speed and maximum wind speed, crucial for severe weather prediction.
wd (°)	Wind direction, providing flow dynamics for disaster movement modeling.

Quantum-Enhanced Implementation and Performance



Quantum-Enhanced Implementation and Performance

The core predictive component utilizes a cutting-edge hybrid model designed to leverage the advantages of quantum computing for complex optimization tasks.

Model Architecture

Hybrid CNN + LSTM Model for classical feature extraction from time-series data, fused with a **Quantum Neural Network (QNN)** for enhanced pattern recognition and fast probability calculation.

Frameworks Utilized

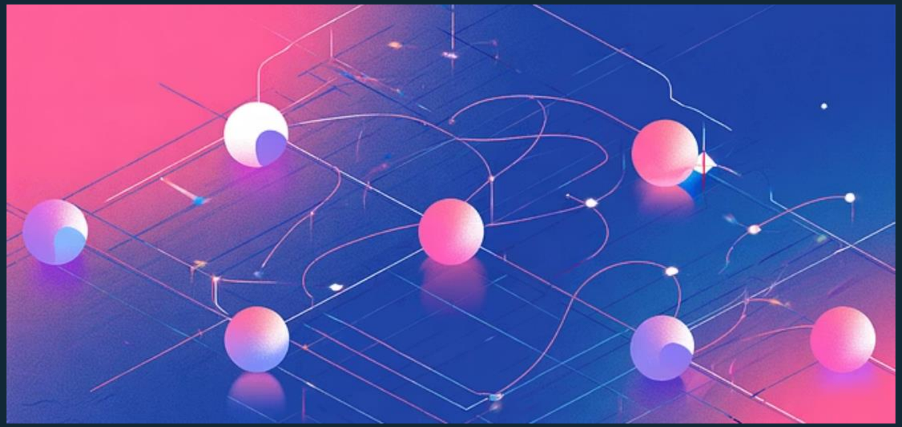
The system is built upon industry-leading tools: **Qiskit** for quantum circuit development, integrated with **PyTorch**, **NumPy**, and **scikit-learn** for hybrid classical-quantum execution.

Evaluation Metrics

Performance is rigorously assessed using **Mean Squared Error (MSE)**, ensuring minimized deviation in predicted vs. actual disaster probabilities.

Key Output

The primary output is a statistically robust **Disaster Probability (%)**, providing emergency planners with a clear, quantifiable risk assessment for immediate decision-making.



Route Evaluation System Using Quantum Optimization Algorithm for Navigation

Harnessing Quantum Computing for Intelligent Route Planning

The Limitations of Classical Navigation

- Current navigation systems rely on well-established classical optimization algorithms (e.g., Dijkstra's, A* search). While effective for static or simple paths, they face significant hurdles in dynamic environments.
- Systems struggle to manage exponentially increasing route choices in dense networks.
- Challenges include handling real-time, dynamic traffic changes and numerous simultaneous constraints.

CORE OBJECTIVE

A Quantum Leap in Optimization

Minimize Time & Distance

Identify the truly optimal path quickly by efficiently exploring the entire solution space.

Adapt in Real-Time

Integrate instant adjustments based on live data feeds from traffic sensors and external systems.

Simultaneous Optimization

Solve for multiple routes or vehicles concurrently, ensuring system-wide efficiency.

CHALLENGE DEFINED

Computational Bottlenecks in Route Planning

Computational Intensity

Efficient route planning across large graphs is inherently **NP-hard** for non-trivial constraints.

Multi-Agent Routing

Classical methods degrade rapidly when optimizing paths for many agents while considering interdependencies (e.g., fleet management).

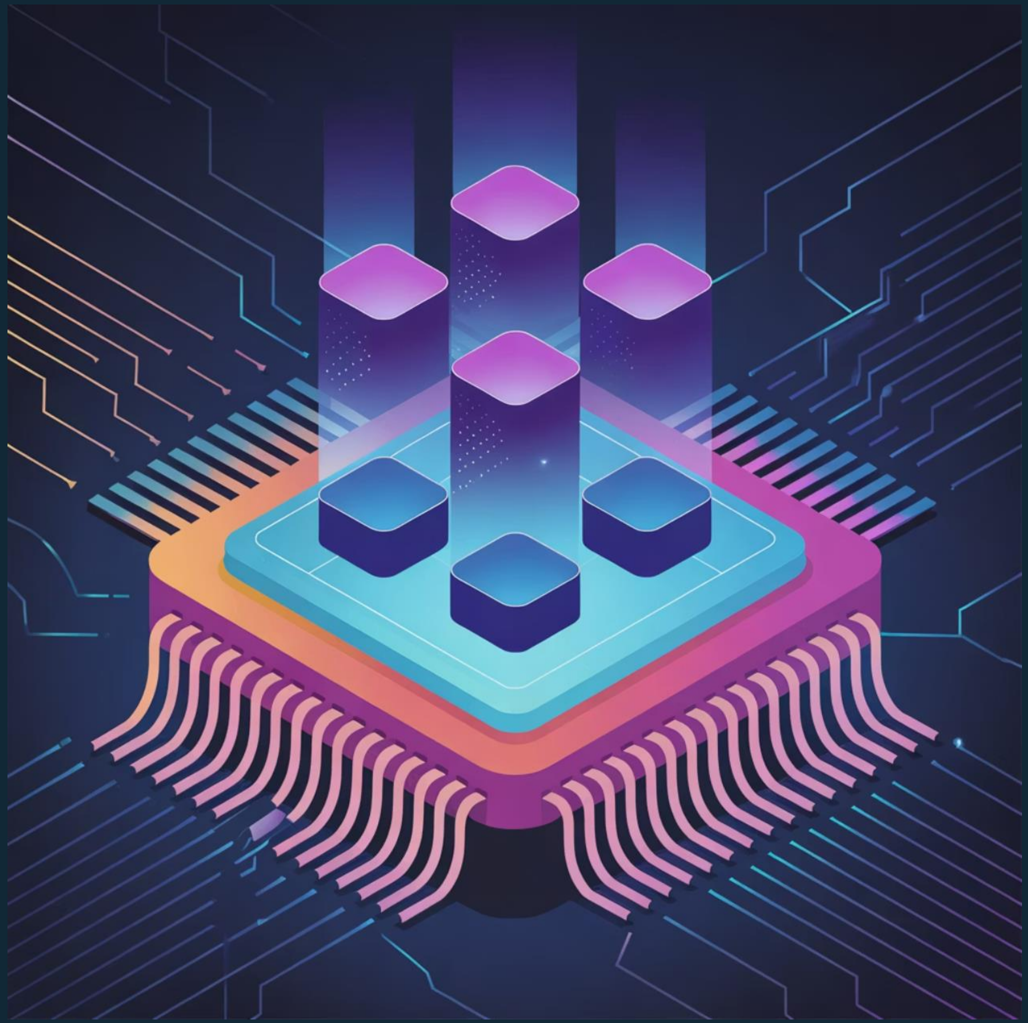
Dynamic Updates

Recalculating optimal routes in real-time due to accidents or sudden weather changes is too slow for large networks.

QUANTUM MECHANICS

Fundamentals of Quantum Optimization

- **Algorithms:** The system leverages Quantum Annealing (for current hardware) and the Quantum Approximate Optimization Algorithm (QAOA) for NISQ-era gates.
- **Superposition:** Quantum bits (qubits) can exist in a linear combination of states (0 and 1) simultaneously, allowing the evaluation of countless potential paths at once.
- **Entanglement:** Qubits are linked, ensuring that the entire system state collapses toward the **global optimal solution**.
- **Application:** This approach is tailor-made for combinatorial optimization problems like the Traveling Salesman Problem (TSP) and complex routing/scheduling.

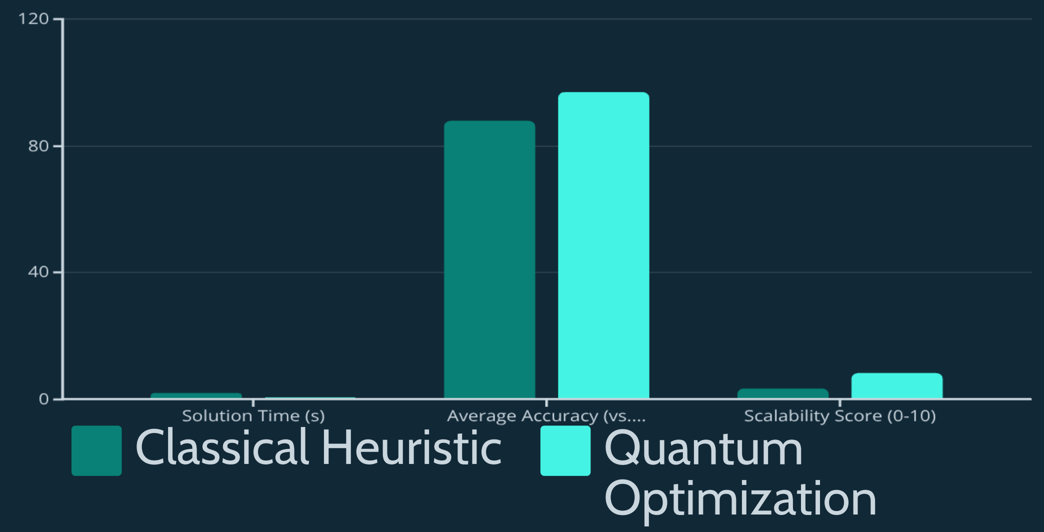


PERFORMANCE & OUTCOMES

Simulation Results and Benchmarks

Simulation trials on increasingly dense and dynamic route networks demonstrate tangible performance gains:

- The quantum approach showed superior convergence rates, especially on graphs exceeding 100 nodes.
- It consistently identified better global optima (up to 12% improvement in total travel time) compared to local optima found by classical heuristics.
- Adaptability was validated by measuring solution decay under continuous real-time traffic flux.



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RESULTS
==============================================================
                    Quantum             Classical
Distance            5.18                5.18
Time (ms)           1.00                1.07
Path                [0, 5]              [0, 5]

🎯 CONCLUSION:
✅ Quantum found near-optimal solution!
✅ Quantum competitive timing
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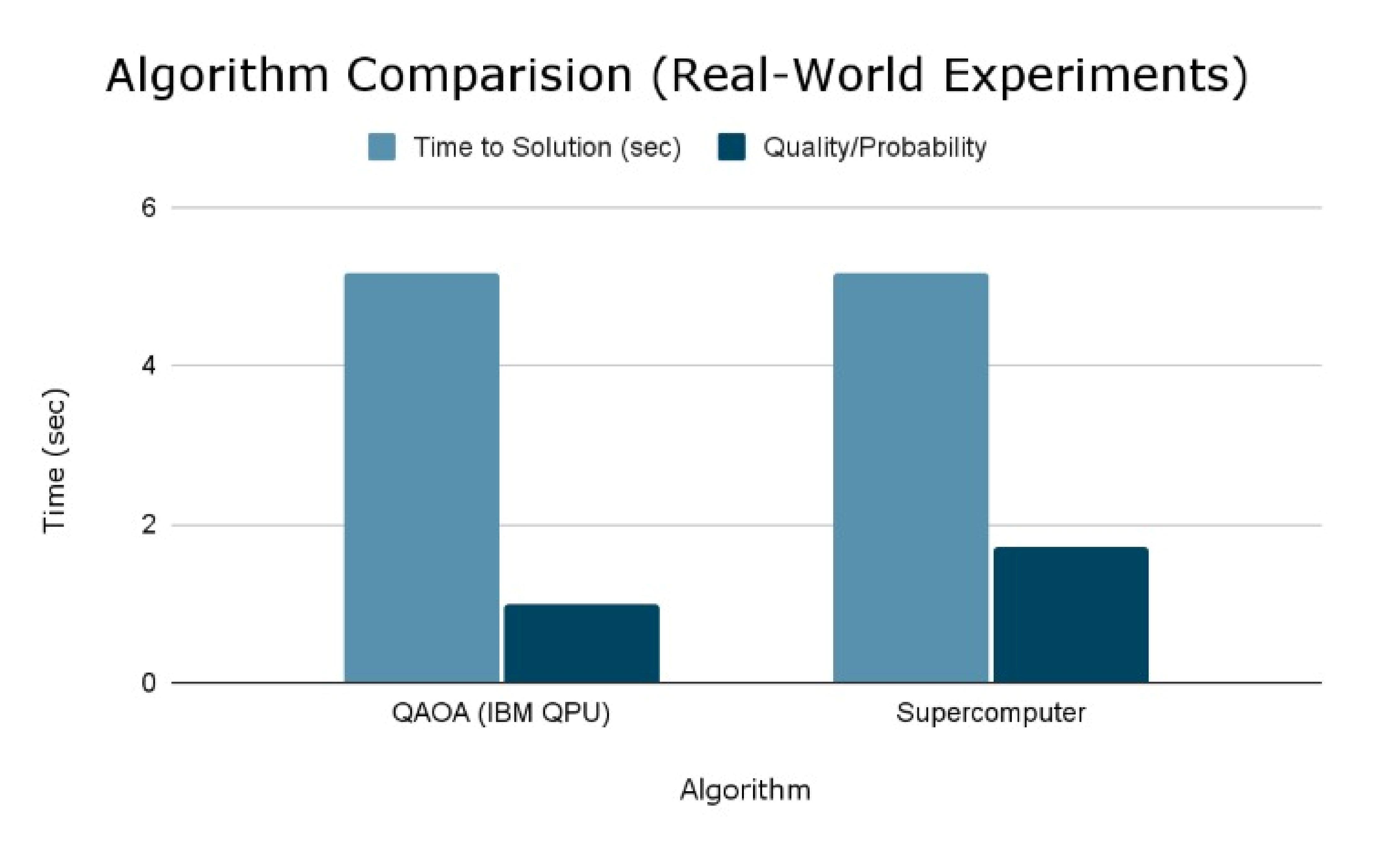

Algorithm Comparision (Real-World Experiments)
Time to Solution (sec)
Quality/Probability
6
4
2
0
Time (sec)
QAOA (IBM QPU)
Supercomputer
Algorithm

OUTLOOK

Limitations and Future Work

Hardware Constraints

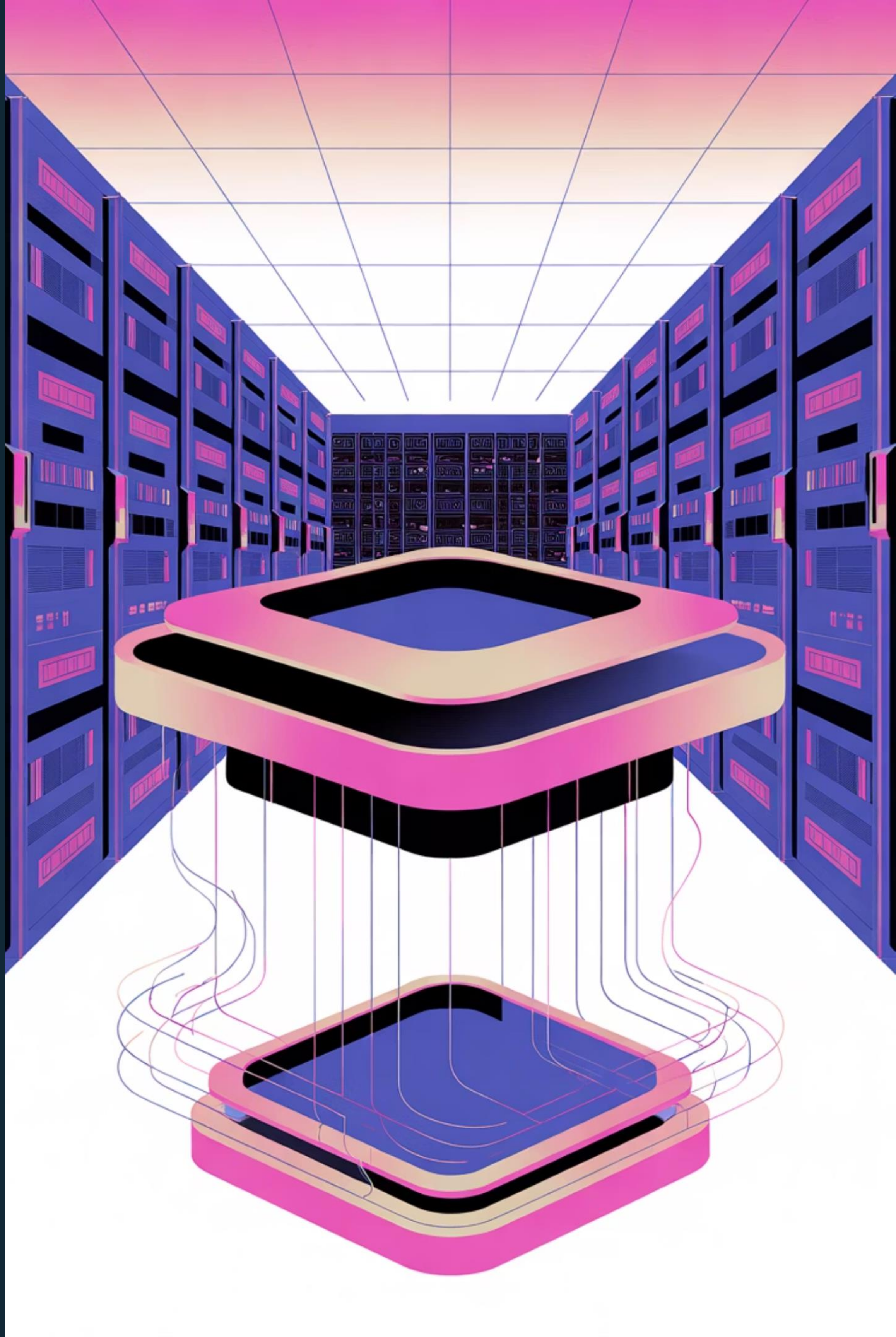
Current quantum hardware faces issues with qubit decoherence and noise, necessitating error mitigation techniques.

Hybrid Integration

Focus must shift to optimizing **hybrid quantum-classical algorithms** to manage complexity while leveraging classical strengths for pre/post-processing.

Multi-Objective Routing

Future models will expand the objective function to simultaneously minimize not just time and distance, but also fuel consumption, CO_2 emissions, and road toll costs.



Thank You

From the Team of

OnlyBits