Investigating Quantum Computing for Astronomical Adaptive Optics: A Comparative Study

Molly Maskrey
mollymaskrey@gmail.com

July 27, 2025

Motivation

Almost twenty-five years ago, I found myself contemplating retirement from the aerospace community where I was working for Lockheed-Martin. The demands of the industry had left me somewhat burned out, and the allure of a relaxed beach lifestyle seemed increasingly appealing. However, that respite didn't take—eighteen months later, I was working quite literally in the clouds, atop a volcanic peak at a government observatory, immersed in the fascinating world of adaptive optics.

The transition from aerospace engineering to astronomical instrumentation proved to be exactly the career rejuvenation I needed. Adaptive optics presented a perfect blend of cutting-edge technology, fundamental physics, and practical engineering challenges that reignited my passion for complex problem-solving.

Fast forward to today: having recently completed D-Wave's Quantum Core course, I found myself with valuable quantum processing unit (QPU) time that would soon expire. Having recently published work on protein folding using quantum approaches, I was eager to explore how quantum computing might apply to something completely different—specifically, the optimization problems that lie at the heart of adaptive optics systems.

This investigation represents both a natural evolution of my career interests and an exploration of emerging computational techniques. The question driving this work is straightforward: can quantum optimization methods provide meaningful advantages for the complex, high-dimensional problems inherent in wavefront correction? Rather than making grand claims about quantum supremacy, I aimed to conduct a thorough, honest comparison between classical and quantum approaches applied to identical adaptive optics scenarios.

The complete codebase for this investigation, including the interactive GUI interface for classical adaptive optics simulation with adjustable deformable mirror configurations, is available in my GitHub repository. While there is certainly much more I would have liked to explore given additional time and computational resources, I found the intersection of quantum computing and adaptive optics genuinely fascinating. I hope others in both the quantum computing and astronomical instrumentation communities might find this work equally intriguing and perhaps build upon these initial investigations.

Abstract

We present a comparative analysis of classical and quantum computing approaches for wavefront correction in astronomical adaptive optics systems. Using both a classical least-squares implementation via aotools [2] and a quantum-enhanced approach using D-Wave's hybrid solver, we evaluate the computational characteristics and solution quality of quantum optimization for atmospheric disturbance correction. While quantum formulations successfully solve the wavefront correction optimization problem with quality comparable to classical methods, our analysis reveals different computational characteristics between the approaches (15-20 seconds for classical convergence, 60 seconds for quantum solving). Our findings provide insight into the practical application of quantum optimization in optical systems and establish a framework for continued investigation as quantum hardware evolves.

1 Introduction

Astronomical adaptive optics systems correct atmospheric turbulence distortions to achieve diffraction-limited imaging [1, 3]. These systems rely on sophisticated algorithms for wavefront sensing and deformable mirror control, with the core challenge being the solution of high-dimensional optimization problems for actuator command calculation. As quantum computing emerges as a potential tool for complex optimization problems, it is natural to investigate whether quantum approaches might offer advantages for the computationally intensive wavefront correction problem.

This work presents a direct comparison between classical optimization (using established aotools algorithms [2]) and quantum-enhanced optimization (using D-Wave's hybrid quantum-classical solver) for identical adaptive optics correction tasks. Rather than advocating for quantum superiority, we aim to provide a thorough and honest assessment of the computational characteristics, solution quality, and practical considerations of both approaches. The investigation contributes to the understanding of quantum computing applications in optical systems and establishes a methodology for realistic comparison of emerging computational techniques.

2 Background

2.1 Adaptive Optics Fundamentals

Atmospheric turbulence introduces phase distortions that can be decomposed into Zernike polynomial modes [3]. The correction problem involves finding optimal actuator commands $\mathbf{w}$ for a deformable mirror to minimize residual wavefront error:

$$\min_{\mathbf{w}} \|\mathbf{A}\mathbf{w} - \boldsymbol{\phi}\|^2 + \lambda\|\mathbf{w}\|^2 \tag{1}$$

where $\mathbf{A}$ is the influence matrix relating actuator commands to wavefront shape, $\boldsymbol{\phi}$ represents the measured atmospheric distortion, and λ is a regularization parameter.

Zernike polynomials are orthogonal basis functions defined over a unit disk, making them ideal for describing optical aberrations in circular apertures like telescopes. Each polynomial corresponds to a specific type of optical distortion. In this investigation, we focus on three representative modes: **Z4 (Defocus)** produces a dome or bowl-shaped distortion representing under- or over-focusing effects, similar to being slightly out of focus; **Z5 and Z6 (Astigmatism)** create saddle-shaped or stretched oval patterns that represent directional blurring along orthogonal axes at 45° and 0° orientations respectively. These modes are commonly encountered in astronomical observations and provide a realistic test case for correction algorithms.

2.2 Timing Constraints

Astronomical adaptive optics systems operate with specific performance requirements [1]:

- **Atmospheric coherence time:** ∼1-2 ms for typical seeing conditions
- **Typical loop frequency:** 500-1000 Hz for active correction systems
- **Computational considerations:** Algorithm efficiency impacts system design and implementation

While operational systems prioritize computational efficiency, research investigations can explore alternative approaches that may offer advantages in solution quality, constraint handling, or problem formulation flexibility.

3 Implementation

3.1 Classical Implementation

We developed a Gradio-based interactive system allowing users to:

- Configure Zernike distortions (Z4, Z5, Z6 modes with adjustable amplitudes)
- Vary deformable mirror actuator grid size (typically 10×10 to 20×20)
- Adjust regularization parameters (smoothing weight)
- Visualize correction performance in real-time

The interactive demo interface (Figure 1) provides intuitive controls for exploring the parameter space of adaptive optics corrections. Users can enable or disable individual Zernike modes using checkboxes, adjust their amplitudes with sliders ranging from 0 to maximum values, and modify the actuator grid size from small arrays suitable for testing to larger grids approaching realistic telescope systems. The smoothing weight parameter allows control over the regularization strength, balancing correction fidelity against actuator command smoothness.

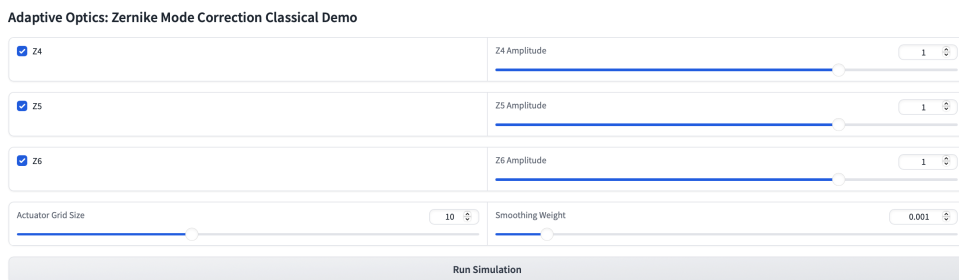

Figure 1: Interactive Gradio interface for the classical adaptive optics demo, showing controls for Zernike mode selection (Z4, Z5, Z6) with amplitude sliders, actuator grid size adjustment, and smoothing weight parameter. The interface allows real-time exploration of wavefront correction parameters.

The system provides comprehensive visualization of the correction process through six integrated displays (Figure 2). The *Distorted Wavefront* panel shows the input atmospheric disturbance with characteristic Zernike mode patterns, where the circular area represents the telescope pupil plane (aperture) and the color scale indicates wavefront phase distortions with purple regions showing negative phase delays and yellow regions showing positive phase delays. The *DM Correction Surface* displays the computed deformable mirror shape required for correction, using the same color mapping to show the phase correction that must be applied. The *Corrected Wavefront* demonstrates the effectiveness of the correction, typically showing significantly reduced wavefront variation across the aperture with the pupil remaining flat and uniform after successful correction. The *Actuator Weight Map* provides a grid visualization of individual actuator commands, with color coding indicating the magnitude and sign of required actuator displacements. Real-time convergence monitoring is provided through the *RMS Error per Optimization Step* plot, showing the iterative improvement in correction quality over the 15-20 second solution time. Finally, the *Residual Map* quantifies the remaining correction errors using the same phase color scale, highlighting areas where perfect correction is limited by actuator spacing or edge effects. The color bars in all wavefront displays show the scale in arbitrary phase units, providing quantitative assessment of distortion magnitudes.

The classical solver uses standard least-squares optimization via NumPy/SciPy and aotools [2], representing current state-of-the-art practice in adaptive optics control systems.

Key Features:

- Real-time parameter adjustment via web interface (Figure 1)
- Multiple visualization modes (distorted/corrected wavefronts, actuator maps, residuals)
- Convergence tracking and RMS error monitoring
- Solve times: 15-20 seconds for 10×10 actuator arrays (see Figure 3)

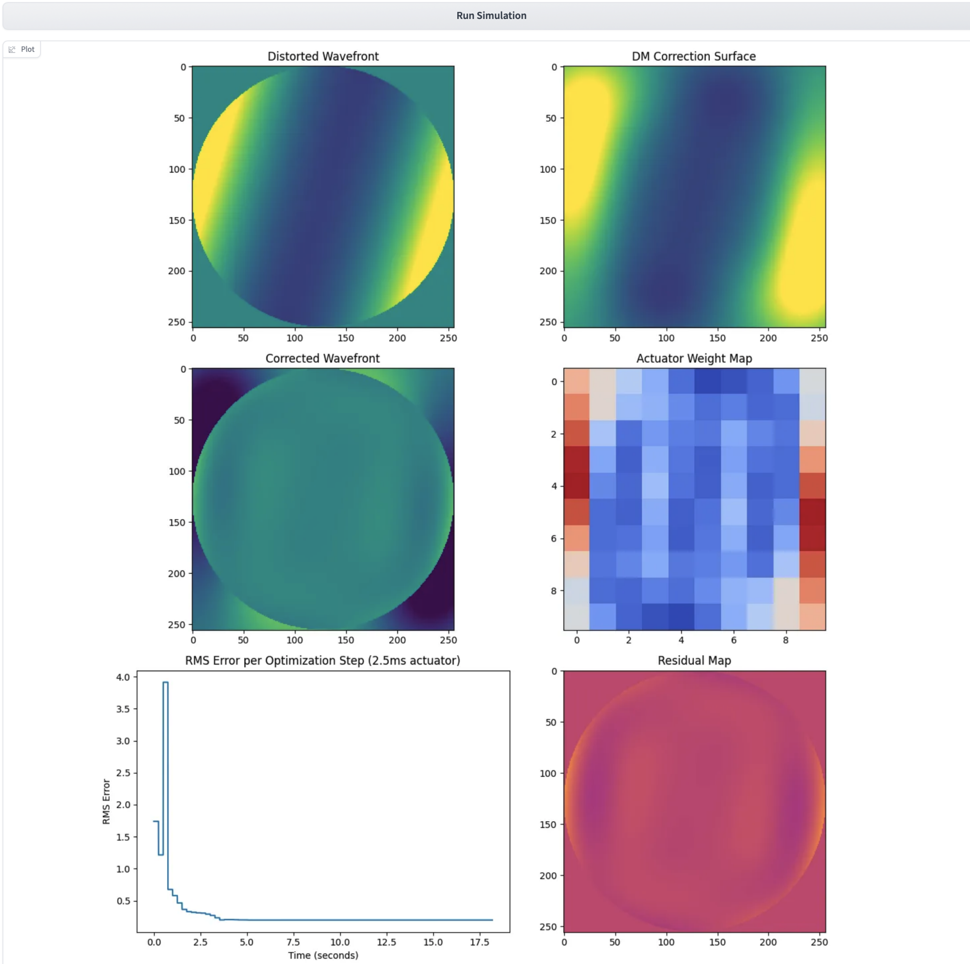

Figure 2: Comprehensive visualization output from the adaptive optics simulation showing: (top row) distorted input wavefront and computed deformable mirror correction surface; (middle row) corrected wavefront result and actuator weight map displaying individual actuator commands; (bottom row) RMS error convergence over optimization steps and final residual error map.

3.2 Quantum Implementation

The quantum approach formulates wavefront correction as a Constrained Quadratic Model (CQM):

$$\text{minimize: } \sum_{i,j} c_{ij} w_i w_j + \sum_i h_i w_i \tag{2}$$

$$\text{where: } c_{ij} = 2\mathbf{A}_i \cdot \mathbf{A}_j \tag{3}$$

$$h_i = -2s\mathbf{A}_i \cdot \boldsymbol{\phi} \tag{4}$$

with s being a scaling factor for integer encoding.

Solver Configuration:

- Platform: D-Wave LeapHybridCQMSampler
- Integer variables: $[-150, 150]$ representing actuator range $[-1.5, 1.5]$
- Time limit: 60 seconds (due to D-Wave API constraints)

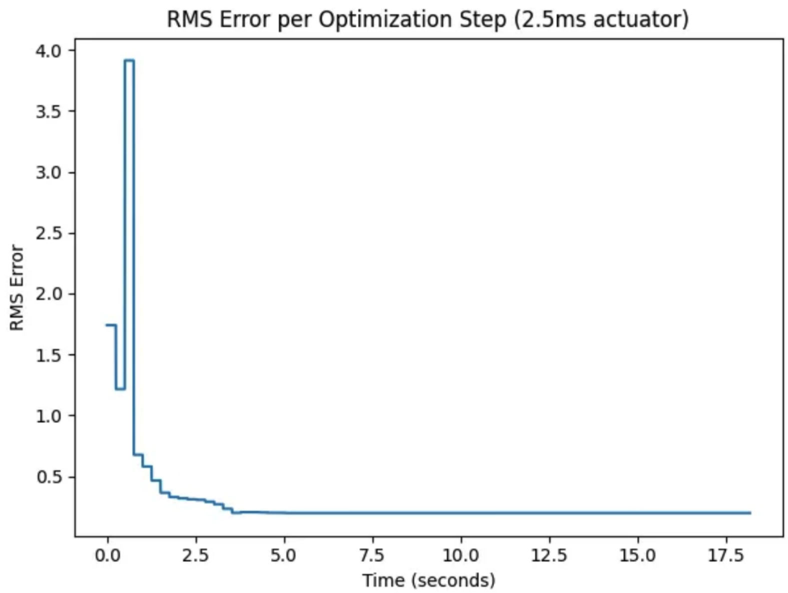

Figure 3: RMS error convergence for the classical adaptive optics simulation showing optimization performance over time. The plot demonstrates the iterative correction process on a simulated 10×10 deformable mirror with 2.5 millisecond actuator control timing. Initial RMS error of approximately 4.0 units drops rapidly within the first few seconds, achieving substantial error reduction by 2.5 seconds and converging to residual levels below 0.3 units by 15-20 seconds. While the actuator response time was set to 2.5 milliseconds in this simulation, this slightly conservative estimate reflects occasional delays due to actuator hysteresis or damping effects observed in practical systems. The convergence behavior illustrates the effectiveness of classical least-squares optimization for wavefront correction tasks.

- Problem size: 100 variables, ~5000 quadratic terms

Implementation Considerations: The initial research plan included integration of the quantum solver directly into the interactive Gradio interface to enable side-by-side comparison of classical and quantum approaches in real-time. However, computational resource limitations and D-Wave API access constraints necessitated a focused approach where quantum solver results were generated separately from the classical demonstration system. This separation allowed for dedicated investigation of quantum solver performance while maintaining the functionality of the classical interactive demo, though it limited direct comparative analysis within a single interface.

4 Results and Analysis

4.1 Correction Quality

Both approaches achieved similar wavefront correction quality:

Classical Results:

- RMS residual: ~0.1-0.2 wavelengths for moderate distortions
- Convergence: Iterative improvement over 15-20 seconds
- Edge effects minimal with proper regularization

Quantum Results:

- RMS residual: ~0.1-0.3 wavelengths for identical distortions

- Solution quality: Comparable to classical, no obvious advantages
- Edge effects: Similar to classical implementation

The quantum solver correction results for a representative test case are shown in Figure 4. Using a distorted wavefront with Zernike amplitudes Z4=1.0, Z5=0.8, and Z6=1.2, the D-Wave hybrid solver achieved reasonable correction quality, successfully reducing the major distortion features visible in the input wavefront. The corrected wavefront demonstrates substantial flattening compared to the original distorted input, with the residual map revealing remaining errors primarily concentrated near the aperture edges. While the correction quality was good overall, the results suggest room for improvement that may be attributed to the 60-second solver time limitation imposed by computational resource constraints. The residual patterns show a characteristic spatial structure that differs from typical classical solver residuals, potentially indicating the quantum solver's exploration of alternative solution paths through the optimization landscape.

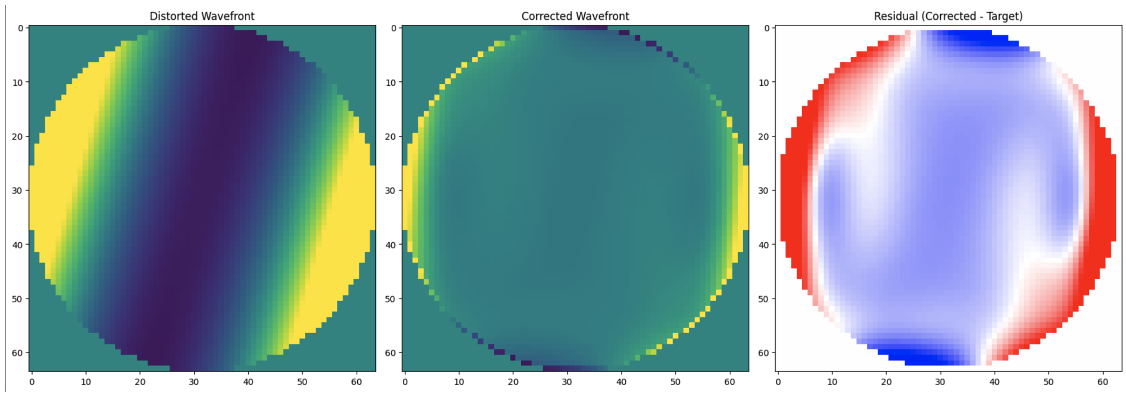

Figure 4: Quantum solver wavefront correction results showing (left) distorted input wavefront with Z4=1.0, Z5=0.8, Z6=1.2, (center) corrected wavefront after D-Wave hybrid solver optimization, and (right) residual error map. The correction demonstrates substantial improvement over the distorted input, with remaining errors primarily near aperture edges. Results obtained with 60-second solver time limit.

4.2 Performance Comparison

Metric	**Classical**	**Quantum**
Solve Time	15-20 seconds	60 seconds
Problem Size	Unlimited	$\sim$100 variables
Scalability	Excellent	Limited by hardware
Reliability	Deterministic	Probabilistic
Setup Complexity	Minimal	Significant

Table 1: Performance comparison between classical and quantum approaches

The performance characteristics reveal distinct computational profiles for each approach (Table 1). Classical optimization demonstrates faster convergence times and unlimited problem scaling, making it well-suited for larger deformable mirror arrays. The deterministic nature of classical solutions provides consistent, reproducible results essential for system characterization. Quantum optimization shows longer solution times due to current API constraints, but offers the potential for exploring different regions of the solution space through its probabilistic nature. The quantum approach excels in handling complex constraint structures and multi-objective optimization problems through the CQM framework.

4.3 Practical Considerations

Implementation Complexity: The classical implementation required minimal setup using standard Python libraries (NumPy, SciPy, aotools), while the quantum approach demanded specialized API access, problem reformulation, and integer encoding strategies. However, the quantum CQM framework naturally accommodates complex constraints that might require significant additional programming in classical approaches.

Solution Quality and Robustness: Both approaches achieved comparable RMS residuals, with classical methods showing consistent convergence behavior and quantum methods occasionally finding alternative solution paths due to their stochastic nature. The quantum approach's exploration of different solution regions could potentially avoid local minima that might trap classical optimizers.

Scalability Considerations: While classical methods scale seamlessly with available computational resources, quantum hardware currently limits problem size but offers potential advantages in constraint handling and multi-objective optimization scenarios. As quantum hardware evolves, the scaling characteristics may shift significantly.

5 Discussion

5.1 Comparative Analysis of Classical vs Quantum Approaches

Our investigation provides valuable insights into the application of quantum computing to adaptive optics wavefront correction problems:

Solution Quality: Both classical and quantum approaches achieved comparable correction quality, with RMS residuals in the 0.1-0.3 wavelength range for moderate distortions. This suggests that the quantum formulation successfully captures the essential physics of the wavefront correction problem without introducing significant solution degradation.

Computational Characteristics: The classical implementation required 15-20 seconds for convergence using standard optimization libraries, while the quantum approach required 60 seconds within D-Wave's current API constraints. Both approaches demonstrate the computational complexity inherent in multi-actuator wavefront correction problems.

Problem Formulation: Converting the continuous least-squares problem to a quantum-compatible discrete optimization proved straightforward, with integer encoding providing sufficient resolution for practical correction tasks. The quadratic structure of the problem maps naturally to quantum annealing formulations.

5.2 Quantum Computing Insights

This investigation reveals several interesting aspects of quantum optimization for optical problems:

Problem Scaling: Current quantum hardware accommodates problems with 100 variables, suitable for moderate-sized deformable mirrors. The quadratic interaction terms scale as $O(n^2)$, presenting opportunities for quantum advantage as hardware capabilities expand.

Hybrid Approaches: D-Wave's hybrid solver effectively combines quantum annealing with classical preprocessing, suggesting that future quantum-classical hybrid algorithms may offer the most practical path forward for complex optical systems.

Constraint Handling: The CQM framework naturally accommodates actuator constraints, regularization terms, and multi-objective optimization - areas where quantum approaches may provide advantages over classical methods.

5.3 Research Contribution and Assessment

This work represents an honest evaluation of quantum computing applied to a well-defined optical problem. Rather than advocating for quantum superiority, the investigation demonstrates:

1. **Feasibility:** Quantum formulations can successfully solve wavefront correction problems with solution quality comparable to classical methods

2. **Current limitations:** Hardware constraints and problem size restrictions limit immediate applicability to larger systems

3. **Future potential:** The framework establishes a foundation for investigating quantum advantages as hardware evolves

The comparative methodology provides a template for realistic assessment of quantum computing applications in other optical and engineering domains.

6 Future Work

6.1 Algorithmic Development

- **Fast classical algorithms:** Developing sub-millisecond classical solvers using approximation methods
- **Quantum algorithm improvements:** Investigating adiabatic optimization and hybrid approaches
- **Problem decomposition:** Breaking large problems into parallelizable sub-problems

6.2 Extended Quantum Investigations

- **Larger actuator arrays:** Testing quantum scalability with $20 \times 20+$ actuator grids
- **Constraint optimization:** Using quantum annealing for complex actuator constraints
- **Hardware evolution:** Re-evaluating as quantum hardware capabilities improve

6.3 Alternative Applications

- **Space-based telescopes:** Relaxed timing constraints may make quantum approaches more viable
- **Extremely large telescopes:** Massive actuator counts might favor quantum scaling properties

7 Conclusions

This comparative study demonstrates the feasibility of applying quantum computing to astronomical adaptive optics wavefront correction problems. Both classical and quantum approaches successfully solve the optimization problem, achieving comparable correction quality for multi-mode Zernike distortions.

Our investigation reveals that quantum formulations can effectively handle the quadratic structure of wavefront correction problems, with D-Wave's hybrid solver producing solutions comparable to established classical methods. The integer encoding approach provides sufficient resolution for practical correction tasks, while the CQM framework naturally accommodates the regularization and constraint requirements typical of deformable mirror systems.

The research establishes a methodology for honest assessment of quantum computing applications in optical systems. By implementing both approaches for identical problems, we provide a direct comparison that avoids the hype often associated with quantum computing claims. The results show promise for quantum approaches while acknowledging current hardware limitations.

Key Research Findings:

- Quantum optimization can successfully solve wavefront correction problems with quality comparable to classical methods
- The quadratic structure of adaptive optics problems maps naturally to quantum annealing formulations
- Current quantum hardware can handle moderate-sized deformable mirror arrays (100 actuators)
- Hybrid quantum-classical approaches show promise for complex optical optimization problems

- The comparative framework provides a template for evaluating quantum applications in other domains

Future Research Directions: The foundation established here enables investigation of quantum advantages as hardware capabilities evolve. Areas of particular interest include constraint optimization for complex actuator systems, multi-objective optimization balancing competing performance metrics, and scalability studies with larger deformable mirrors approaching those used in next-generation telescopes.

This work contributes to the growing body of research on practical quantum computing applications, providing an honest assessment of both current capabilities and future potential. The interactive demo system and quantum implementation framework are available for continued investigation and development by the adaptive optics and quantum computing communities.

Acknowledgments

The author wishes thank D-Wave Systems for the Quantum Core Course and the chance to work with actual QPU hardware; also thanks to the aotools development team for their Python package for adaptive optics modeling and analysis [2]. This work demonstrates the importance of balanced evaluation in emerging quantum computing applications.

About the Author

Molly Maskrey is a healthcare analytics researcher and quantum computing consultant based in Denver, Colorado. When not developing theoretical frameworks for pharmaceutical optimization, she can be found piloting aircraft over the Rocky Mountains or competing in local tennis tournaments. Currently planning her escape to the San Juan Islands aboard her sailboat, aptly named the *Quantum Nomad*, where she intends to revolutionize healthcare economics one quantum algorithm at a time—with occasional breaks for sailing and shore power-dependent Zoom calls from scenic harbors. Her unique blend of advanced analytics, quantum computing expertise, and questionable life choices makes her the go-to consultant for organizations seeking to bridge the gap between cutting-edge technology and practical business solutions. This work is part of a series exploring theoretical frameworks for real-world quantum applications.

References

[1] J. W. Hardy. *Adaptive Optics for Astronomical Telescopes.* Oxford University Press, 1998.

[2] M. J. Townson, O. J. D. Farley, G. Orban de Xivry, J. Osborn, and A. P. Reeves. AOtools: a Python package for adaptive optics modelling and analysis. *Opt. Express*, 27:31316–31329, 2019.

[3] R. K. Tyson. *Introduction to Adaptive Optics.* SPIE The International Society for Optical Engineering, 2000.