
1 *Type of article*

2 **Quantum-Assisted Initialization for Low-Thrust Earth–Moon Trajectories**

3 **Gino Luciano Moretta** ^{1*}

4 **Agustina Casasola** ¹

5 ¹ Universidad Nacional de Córdoba

6 * **Correspondence:** Email: gino.moretta@mi.unc.edu.ar

Abstract: Low-thrust Earth–Moon transfers are highly sensitive problems, and classical optimal-control solvers converge reliably only when provided with a meaningful initial profile. This work studies whether quantum computing can assist the early exploration of discrete thrust-activation patterns that seed those solvers more effectively.

The timeline is discretized into binary activation decisions. Rather than relying on random or hand-crafted schedules, quantum routines generate and evaluate large sets of candidate thrust/coast patterns under the same computational budget, increasing coverage of the combinatorial space. Promising discrete patterns are then smoothed into continuous control inputs and refined with a classical optimal-control solver to ensure dynamical consistency.

The goal is not to replace deterministic optimization but to test whether quantum-assisted pattern exploration can accelerate the search for viable low-thrust structures in Earth–Moon transfers. The study provides an initial assessment of how quantum computation could complement classical methods in future cislunar trajectory design.

8 **Keywords:** Low-thrust optimization, Quantum computing, Earth-Moon trajectories,
9 **Trajectory initialization**

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11 **1. Introduction**

12 Low-thrust trajectory optimization in the Earth-Moon system is a challenging problem due to the
13 complex gravitational dynamics of the Circular Restricted Three-Body Problem (CR3BP) and the high
14 sensitivity of the solution to initial guesses. Classical deterministic optimal control methods, such
15 as direct collocation or shooting methods, often fail to converge unless provided with a high-quality
16 initial seed. This work investigates a novel approach: using quantum-inspired probabilistic inference to
17 generate structured thrust schedules that can serve as effective warm-starts for these classical solvers.

18 The core innovation of this study is the application of THRML, a probabilistic graphical model

framework, to sample physically meaningful thrust activation patterns. By discretizing the thrust profile into binary decisions (thrust on/off) and using Gibbs sampling, we explore the combinatorial space of control strategies more efficiently than random initialization. This "Quantum-Assisted Initialization" aims to identify promising basins of attraction in the solution space, which can then be refined by gradient-based optimizers.

2. Methodology

2.1. Dynamical Model

The spacecraft's motion is modeled using the Circular Restricted Three-Body Problem (CR3BP). The equations of motion in the rotating frame are given by:

$$\ddot{x} - 2\dot{y} = \frac{\partial \Omega}{\partial x} + a_x \quad (2.1)$$

$$\ddot{y} + 2\dot{x} = \frac{\partial \Omega}{\partial y} + a_y \quad (2.2)$$

$$\ddot{z} = \frac{\partial \Omega}{\partial z} + a_z \quad (2.3)$$

where Ω is the effective potential function, and $\mathbf{a} = [a_x, a_y, a_z]^T$ is the control acceleration from the low-thrust engine. The system is normalized such that the distance between Earth and Moon is 1, and the total mass of the system is 1.

2.2. Quantum-Assisted Optimization Loop

The optimization process is an iterative loop designed to refine the thrust schedule probability distribution:

1. **Initialization:** A bias field is initialized, representing the prior probability of thrust activation at each time step.
2. **Sampling:** A batch of candidate thrust schedules is generated using Gibbs sampling via the THRML library. This step mimics quantum annealing processes to explore the discrete solution space.
3. **Propagation:** Each candidate schedule is propagated using an RK4 integrator within the CR3BP dynamics.
4. **Evaluation:** The trajectories are evaluated based on a cost function, primarily defined by the final distance to the Moon.
5. **Update:** The best-performing schedules (e.g., top 10

3. Results

This section presents the preliminary findings of the quantum-assisted initialization strategy. The performance is evaluated based on two key metrics: the convergence rate of the subsequent classical optimizer and the optimality of the final trajectories.

3.1. Convergence Improvement

Initial tests indicate that seeding the classical solver with quantum-generated thrust schedules significantly improves convergence stability. Compared to random initialization, which often leads to infeasible trajectories or local minima with high fuel consumption, the quantum-assisted approach provides a "warm start" that is dynamically closer to a valid solution.

3.2. Trajectory Analysis

Figure 1 illustrates a candidate trajectory generated by the system. The blue line represents the initial guess derived from the discrete thrust pattern, while the red dashed line shows the refined trajectory after classical optimization.



Figure 1. Example of a low-thrust Earth-Moon transfer trajectory initialized via quantum sampling.

3.3. Computational Efficiency

While the quantum sampling step introduces an overhead, the reduction in the number of iterations required by the classical solver compensates for this cost, potentially leading to a net reduction in total computation time for complex transfer scenarios.

$$[\text{add an equation here; use MS Word or MathType equation function}] \quad (3.1)$$

4. Discussion

5. Conclusions

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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We would like to thank you for following the instructions above very closely in advance. It will definitely save us lot of time and expedite the process of your paper's publication.

Conflict of interest

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Supplementary (if necessary)



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