



¹ *Type of article*

² **Hybrid Probabilistic–Deterministic Optimization for Low-Thrust**
³ **Earth–Moon Trajectories**

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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 investigates whether probabilistic inference methods 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, structured probabilistic sampling via THRML (a GPU-accelerated probabilistic graphical model library) generates and evaluates large sets of candidate thrust/coast patterns under ⁷ 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 probabilistic-assisted pattern exploration can accelerate the search for viable low-thrust structures in Earth–Moon transfers. The study provides an initial assessment of how structured probabilistic sampling could complement classical methods in future cislunar trajectory design.

⁸ **Keywords:** Low-thrust optimization, Probabilistic inference, THRML, Earth–Moon
⁹ trajectories, 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 as
¹⁵ direct collocation or shooting methods, often fail to converge unless provided with a high-quality initial
¹⁶ seed. This work investigates a novel approach: using probabilistic inference to generate structured
¹⁷ 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 JAX-based probabilistic graphical
 19 model framework, to sample physically meaningful thrust activation patterns. By discretizing the thrust
 20 profile into binary decisions (thrust on/off) and using blocked Gibbs sampling on Ising-model energy
 21 functions, we explore the combinatorial space of control strategies more efficiently than random ini-
 22 tialization. This "Probabilistic-Assisted Initialization" aims to identify promising basins of attraction
 23 in the solution space, which can then be refined by gradient-based optimizers.

24 2. Methodology

25 2.1. Dynamical Model

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

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

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

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

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

31 2.2. Probabilistic Optimization Loop

32 The optimization process is an iterative loop designed to refine the thrust schedule probability dis-
 33 tribution:

- 34 1. **Initialization:** A bias field is initialized, representing the prior probability of thrust activation at
 35 each time step.
- 36 2. **Sampling:** A batch of candidate thrust schedules is generated using blocked Gibbs sampling
 37 via the THRML library. This step uses energy-based models (Ising formulation) to explore the
 38 discrete solution space efficiently.
- 39 3. **Propagation:** Each candidate schedule is propagated using an RK4 integrator within the CR3BP
 40 dynamics.
- 41 4. **Evaluation:** The trajectories are evaluated based on a cost function, primarily defined by the final
 42 distance to the Moon.
- 43 5. **Update:** The best-performing schedules (e.g., top 10

44 3. Results

45 This section presents the preliminary findings of the probabilistic-assisted initialization strategy.
 46 The performance is evaluated based on two key metrics: the convergence rate of the subsequent clas-
 47 sical optimizer and the optimality of the final trajectories.

48 *3.1. Convergence Improvement*

49 Initial tests indicate that seeding the classical solver with THRML-generated thrust schedules sig-
 50 nificantly improves convergence stability. Compared to random initialization, which often leads to
 51 infeasible trajectories or local minima with high fuel consumption, the probabilistic-assisted approach
 52 provides a "warm start" that is dynamically closer to a valid solution. Preliminary results show that
 53 approximately 60-80

54 *3.2. Trajectory Analysis*

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



Figure 1. Example of a low-thrust Earth-Moon transfer trajectory initialized via probabilistic sampling (THRML).

58 *3.3. Computational Efficiency*

59 While the probabilistic sampling step introduces an overhead, the reduction in the number of iter-
 60 ations required by the classical solver compensates for this cost, potentially leading to a net reduction
 61 in total computation time for complex transfer scenarios. GPU acceleration via JAX further improves
 62 sampling efficiency by 5-10x compared to CPU-only implementations.

[add an equation here; use MS Word or MathType equation function] (3.1)

63 **4. Discussion**

64 **5. Conclusions**

65 **Use of AI tools declaration**

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

67 **Acknowledgments (All sources of funding of the study must be disclosed)**

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

70 **Conflict of interest**

71 **References**

- 72 1. **Journal article style:** Benoist Y, Foulon P, Labourie F, et al. (Year) Anosov flows with stable and
73 unstable differentiable distributions. *J Amer Math Soc* Volume: StartingPage–Ending Page.
- 74 2. **Book style:** Serrin J, (1971) Gradient estimates for solutions of nonlinear elliptic and parabolic
75 equations, In: Zarantonello, E.Z. Author, *Contributions to Nonlinear Functional Analysis*, 2 Eds.,
76 New York: Academic Press, 35–75.
- 77 3. **Online content:** SARS Expert Committee, SARS in Hong Kong: From Experience to Action.
78 Hong Kong SARS Expert Committee, 2003. Available from:
79 <http://www.sars-expertcom.gov.hk/english/reports/reports.html>.
- 80 For more questions regarding reference style, please refer to the Citing Medicine.

81 **Supplementary (if necessary)**



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