Beyond One-Step Accuracy: Closed-Loop Rollout Reveals a Validation Gap in Hankel–DMD/Koopman Models for Gravity-Gradient-Stabilized CubeSat Attitude Dynamics

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Abstract: *Data-driven Koopman operator methods, particularly* ***Extended Dynamic Mode Decomposition (EDMD)*** *and* ***Hankel Dynamic Mode Decomposition (Hankel-DMD)****, have emerged as promising reduced-order models for nonlinear spacecraft attitude dynamics. However, their performance is typically evaluated using one-step prediction accuracy, leaving their reliability for* ***autonomous long-horizon propagation*** *largely unverified. This study investigates the closed-loop rollout performance of a Hankel-DMD surrogate for a gravity-gradient-stabilized 3U CubeSat with reaction-wheel momentum bias and compares it with a conventional equilibrium linearization. The Hankel-DMD model achieves excellent one-step prediction accuracy (****RMSE = 0.049°****), but its autonomous rollout error increases from* ***7.49°*** *after* ***0.05 orbital periods*** *to* ***90.58°*** *after* ***3 orbital periods****, despite incorporating delay embedding, feature standardization, ridge regularization, and spectral-radius stabilization. In contrast, the equilibrium linearization maintains prediction errors below* ***3.5°*** *throughout the evaluated horizons and consistently outperforms the data-driven model. To quantify this discrepancy, this work introduces the* ***Rollout Amplification Factor (RAF)****, which measures the growth of autonomous rollout error relative to one-step prediction and reaches* ***1,849×*** *after three orbital periods. The results demonstrate that excellent local prediction accuracy does not necessarily imply reliable autonomous long-horizon performance and identify a previously overlooked* ***closed-loop rollout validation gap*** *in Koopman-based spacecraft attitude modelling. These findings establish that autonomous rollout evaluation against classical analytical baselines should complement conventional one-step validation when assessing Koopman-based reduced-order models for spacecraft applications.*

Key Words: *Koopman operator, Hankel Dynamic Mode Decomposition, CubeSat attitude dynamics, Gravity-gradient stabilization, Autonomous prediction, Reduced-order modelling*

1. INTRODUCTION

Data-driven reduced-order models are becoming increasingly important in spacecraft guidance, navigation, and control because they provide computationally efficient approximations of nonlinear dynamical systems. **Related machine-learning approaches have also been investigated for real-time spacecraft guidance in low-thrust transfer problems** [13]. Among these approaches, Koopman operator theory has attracted considerable attention by representing nonlinear dynamics through approximately linear evolution in a higher-dimensional observable space, enabling efficient prediction, stability analysis, and control design [1–7]. Extended Dynamic Mode Decomposition (EDMD) and its delay-coordinate extension, Hankel Dynamic Mode Decomposition (Hankel-DMD), are widely used computational realizations of this framework and have recently been applied to spacecraft attitude modelling and control [4, 5, 7, 10-12]. Despite these advances, the performance of Koopman-based spacecraft attitude models is commonly evaluated using one-step or short-horizon prediction, where the true system state is supplied at every prediction step [10, 11]. Although such validation demonstrates excellent local approximation accuracy, it does not establish whether the learned operator can reliably propagate its own predictions over extended time horizons. This distinction is particularly important for onboard attitude propagation and mission planning, where reference states are not continuously available. Gravity-gradient-stabilized spacecraft provide an appropriate benchmark for investigating this issue because their attitude dynamics exhibit nonlinear, amplitude-dependent libration about a stable equilibrium [14, 15]. These oscillatory dynamics present a challenging test for globally linear reduced-order models, making autonomous long-horizon prediction a meaningful measure of practical performance. This study evaluates the autonomous prediction capability of a Hankel-DMD surrogate for a gravity-gradient-stabilized 3U CubeSat and compares its performance with a conventional equilibrium linearization. Rather than proposing a new Koopman algorithm, the objective is to determine whether excellent one-step prediction accuracy translates into reliable autonomous long-horizon performance under recursive closed-loop propagation. The principal contribution of this work is the identification and quantitative characterization of a previously overlooked **closed-loop rollout validation gap** in Koopman-based spacecraft attitude modelling. Specifically, the proposed Hankel-DMD model achieves excellent one-step prediction accuracy (RMSE = 0.049°), yet its autonomous rollout error increases to 90.58° after three orbital periods, whereas a conventional equilibrium linearization maintains prediction errors below 3.5° throughout the same interval. To quantify this discrepancy, the study introduces the **Rollout Amplification Factor (RAF)**, a dimensionless metric that measures the amplification of prediction error during recursive autonomous rollout relative to one-step prediction. To the best of the author's knowledge, no previous spacecraft attitude study has explicitly quantified this discrepancy using a dedicated rollout amplification metric. Together, these results demonstrate that one-step prediction accuracy alone is insufficient to assess the deployment readiness of Koopman-based reduced-order models, and that closed-loop rollout evaluation against classical analytical baselines should complement conventional one-step validation for spacecraft attitude applications. The remainder of this paper is organized as follows. Section 2 describes the spacecraft dynamics and dataset generation. Section 3 presents the reduced-order modelling approaches and evaluation methodology. Section 4 reports the comparative results. Section 5 discusses the observed rollout degradation. Section 6 outlines the implications for Koopman-based spacecraft modelling, and Section 7 concludes the paper.

2. DYNAMICAL MODEL AND PROBLEM SETUP

2.1 Spacecraft and Orbit Configuration

A representative 3U CubeSat operating in a circular low-Earth orbit at an altitude of 500 km is considered. The spacecraft has a diagonal inertia tensor, **$\mathbf{J} = \mathrm{diag}(0.02, 0.018, 0.005)$ kg·m²**, and is passively stabilized using gravity-gradient torque with a fixed reaction-wheel momentum bias about the pitch axis, representing a practical low-complexity attitude stabilization architecture for CubeSat missions [14, 15]. The spacecraft state consists of a unit quaternion describing the attitude relative to the local-vertical/local-horizontal (LVLH) frame and the corresponding body angular velocity. The nonlinear dynamics are governed by quaternion kinematics and Euler's rigid-body rotational equations, including gravity-gradient torque and reaction-wheel momentum bias [14, 15]. The nominal equilibrium corresponds to the LVLH-aligned attitude with zero relative angular velocity. Perturbations about this equilibrium produce sustained nonlinear libration with amplitude-dependent oscillation frequency, providing a challenging benchmark for evaluating reduced-order models. Figure 1 presents representative nonlinear training trajectories generated over the ±40° attitude range, illustrating the persistent oscillatory behavior and amplitude-dependent dynamics that the surrogate model must accurately capture.

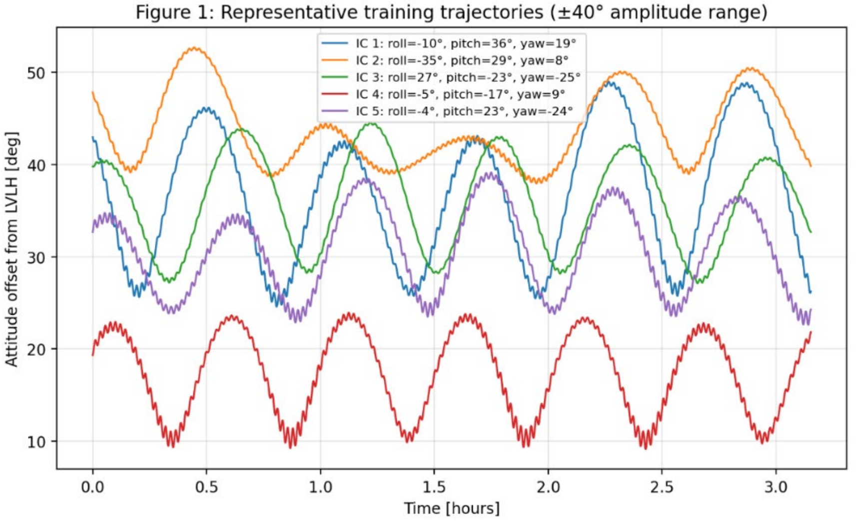

Figure 1. Representative nonlinear attitude trajectories used for training the Hankel-DMD model. The trajectories were generated from randomly sampled initial attitudes within ±40° and propagated using the full nonlinear gravity-gradient spacecraft dynamics. The sustained oscillatory motion and amplitude-dependent libration periods illustrate the nonlinear characteristics of the system that the reduced-order surrogate is required to capture for accurate long-horizon attitude prediction

2.2 Training Data Generation

Training data were generated by numerically integrating the full nonlinear attitude equations using **SciPy's solve_ivp** with relative and absolute tolerances of $\mathbf{10^{-9}}$ and $\mathbf{10^{-11}}$, respectively, to ensure high numerical accuracy. A total of **40** independent trajectories were generated, each spanning **two orbital periods** and sampled at **5 s** intervals. Initial roll, pitch, and yaw angles were uniformly sampled within **±40°**, while initial body angular rates were randomly selected within **±0.0008 rad** $\mathbf{s^{-1}}$. These limits were chosen to encompass the operating region of the validation trajectory while avoiding extrapolation beyond the training domain.

2.3 Test Case

Model performance was evaluated using a single held-out trajectory that was excluded from the training dataset. The initial condition comprised **35° roll, −30° pitch, 20° yaw**, with initial angular rates of **(0.0005, −0.0003, 0.0002) rad** $\mathbf{s^{-1}}$. The nonlinear system was propagated for **three orbital periods**, and the resulting trajectory served as the reference solution for evaluating both the classical equilibrium linearization and the Hankel-DMD model under identical closed-loop prediction conditions.

3. REDUCED-ORDER MODELING APPROACHES

3.1 Classical Baseline: Equilibrium Linearization

As a reference model, the nonlinear spacecraft attitude dynamics were linearized about the LVLH equilibrium using numerical central finite differences to compute the system Jacobian [14, 15]. The resulting continuous-time linear system was discretized using the matrix exponential with the same **5 s** sampling interval employed for the data-driven model. This equilibrium linearization represents a conventional small-angle attitude propagator and provides a physically interpretable analytical baseline for evaluating the performance of the Koopman-based surrogate.

3.2 Hankel-DMD/Koopman Surrogate

The data-driven surrogate was constructed using **Hankel Dynamic Mode Decomposition (Hankel-DMD)**, a delay-embedded implementation of the Koopman operator framework [4, 5, 7, 9]. Instead of using instantaneous system states, delay embedding was employed by stacking **d = 8** consecutive state vectors into augmented snapshots, enabling improved representation of oscillatory dynamics through temporal information. The delay-embedded snapshots were standardized to zero mean and unit variance before estimating the Koopman operator using ridge-regularized least squares. To ensure stable autonomous propagation, the fitted operator was spectrally stabilized by uniformly rescaling its eigenvalues to obtain a spectral radius of **0.999**, while preserving the learned modal structure [8]. In addition, the predicted quaternion was renormalized after each propagation step to enforce the unit-norm constraint required for physically valid attitude representation.

3.3 Evaluation Protocol

Model performance was assessed using the attitude-angle error relative to the LVLH equilibrium,

$$\theta = 2\cos^{-1}(|\, q_0 \,|),$$

where q_0 is the scalar component of the normalized quaternion. The root-mean-square error (RMSE) of this angular deviation was used as the primary performance metric.

Two evaluation strategies were considered. In the **one-step prediction** mode, the true nonlinear state was provided at every time step, allowing assessment of the local approximation accuracy of the learned operator. In the **closed-loop rollout** mode, the models were initialized only once and subsequently propagated using their own predicted states without further access to the nonlinear reference trajectory. For the Hankel-DMD model, the initial delay window was constructed from the first **d** reference states. This autonomous rollout represents the practical deployment scenario for onboard attitude prediction and forms the primary basis for comparison in this study.

4. RESULTS

4.1 One-Step Prediction Accuracy

The predictive capability of the fitted Hankel-DMD model was first evaluated using the **one-step re-anchored** validation protocol described in Section 3.3. Under this setting, the model predicts only the next state while the true nonlinear state is provided at every time step. The resulting one-step prediction RMSE over the three-orbit test trajectory is **0.049°**, indicating excellent local approximation accuracy. This demonstrates that the learned Koopman operator accurately captures the short-term dynamics of the nonlinear system.

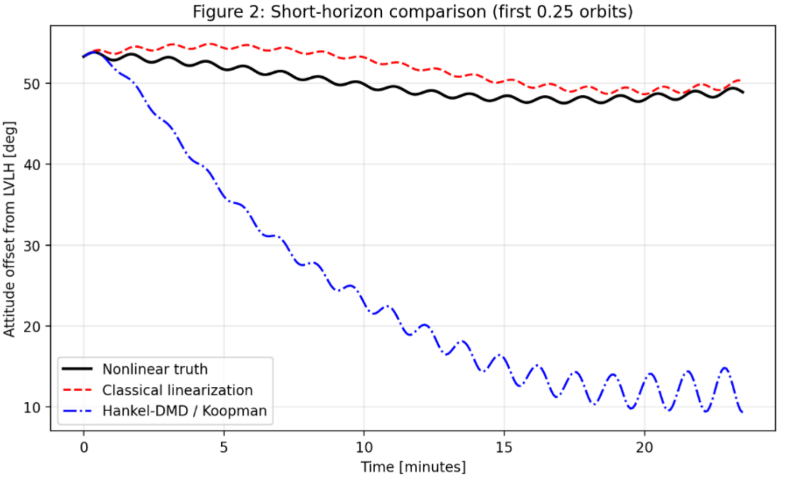

Figure 2. Comparison of nonlinear reference solution, equilibrium linearization, and Hankel-DMD closed-loop prediction during the first 0.25 orbital periods. The equilibrium linearization closely follows the nonlinear trajectory, whereas the Koopman rollout begins to deviate within the initial phase of autonomous propagation.

4.2 Closed-Loop Rollout Performance

The model behavior changes markedly during autonomous prediction. Figure 2 shows the short-horizon rollout over the first **0.25 orbital periods**, where the equilibrium linearization remains close to the nonlinear reference, while the Hankel-DMD prediction begins to diverge within the first few minutes. Figure 3 directly compares the **one-step** and **closed-loop** predictions. Although the one-step prediction closely matches the nonlinear solution throughout the simulation (RMSE = **0.049°**), the autonomous rollout rapidly departs from the true trajectory. Following an initial transient, the Koopman prediction settles into a bounded oscillation between approximately **120° and 180°**, becoming effectively decorrelated from the nonlinear dynamics. This behavior indicates that spectral stabilization successfully prevents numerical instability but does not preserve the correct long-term physical trajectory.

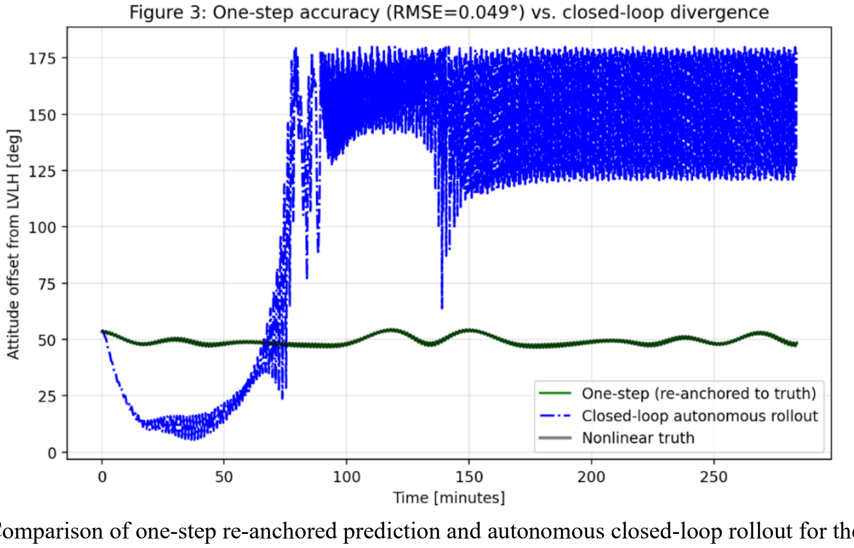

Figure 3. Comparison of one-step re-anchored prediction and autonomous closed-loop rollout for the Hankel-DMD model over three orbital periods. Although one-step prediction closely matches the nonlinear reference (RMSE = 0.049°), recursive propagation produces a bounded but physically incorrect oscillatory trajectory, illustrating the disconnect between local prediction accuracy and long-horizon autonomous performance

4.3 Prediction Horizon Sensitivity

To quantify error accumulation, the closed-loop RMSE was evaluated over prediction horizons ranging from **0.05 to 3 orbital periods**. **Figure 4** shows that the equilibrium linearization maintains low prediction error, while the Hankel-DMD model exhibits continuous error growth with increasing rollout horizon.

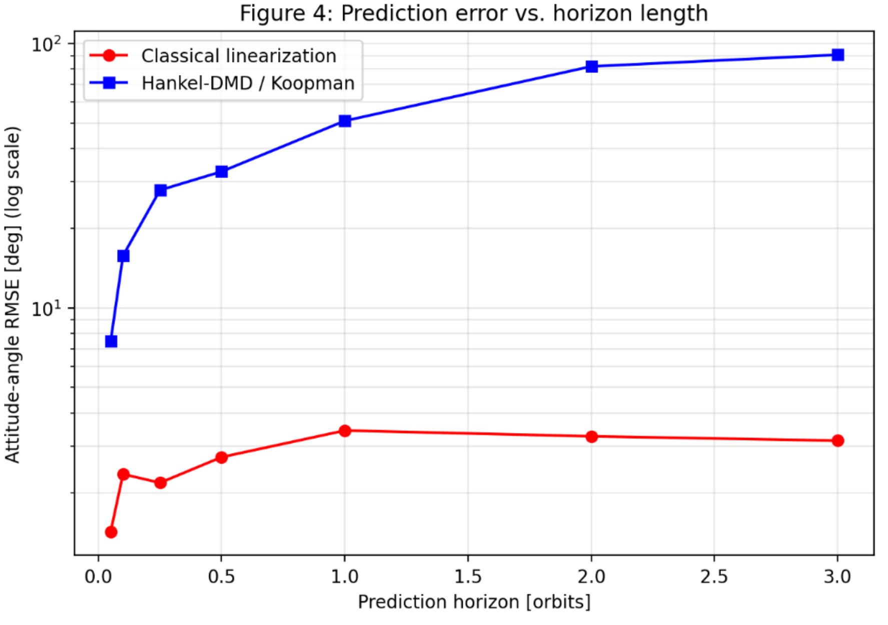

Figure 4. RMSE of autonomous attitude prediction as a function of prediction horizon for the equilibrium linearization and Hankel-DMD model. The linearized model maintains consistently low error, whereas the Koopman prediction exhibits continuous error growth with increasing rollout length.

As shown in Table 1, the equilibrium linearization maintains consistently low prediction errors across all prediction horizons, whereas the Hankel-DMD model exhibits monotonic error growth with increasing rollout duration.

Table 1. Closed-loop attitude prediction RMSE at different prediction horizons

Prediction Horizon (orbits)	Linearization RMSE (°)	Hankel-DMD RMSE (°)
0.05	1.42	7.49
0.10	2.35	15.75
0.25	2.18	27.87
0.50	2.72	32.76
1.00	3.43	50.95
2.00	3.27	81.89
3.00	3.14	90.58

The equilibrium linearization maintains a nearly constant prediction error between **1.42°** and **3.43°** across all horizons. In contrast, the Hankel-DMD model exhibits monotonic error growth, increasing from **7.49°** after **0.05 orbits** to **90.58°** after **3 orbits**. Notably, the Koopman model is less accurate than the classical linearization at **every prediction horizon**, indicating that superior one-step prediction accuracy does not translate into improved autonomous long-horizon performance.

4.4 Orbit-by-Orbit Error Analysis

To distinguish cumulative error growth from long-term steady-state behavior, the prediction error was evaluated independently for each orbital period. **As shown in Figure 5,** the equilibrium linearization maintains nearly constant orbit-wise prediction error, whereas the Hankel-DMD model exhibits rapid error growth during the first two orbits before reaching a plateau.

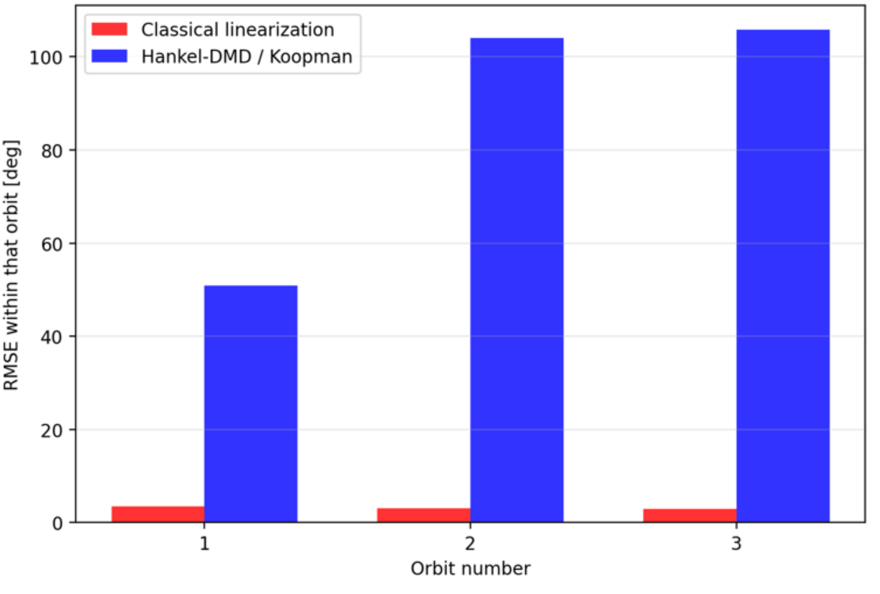

Figure 5. Orbit-wise (non-cumulative) RMSE of autonomous attitude prediction for the equilibrium linearization and Hankel-DMD model. The linearized model exhibits nearly constant prediction accuracy, whereas the Koopman model shows rapid error growth during the first two orbits before reaching a plateau.

The equilibrium linearization exhibits nearly constant orbit-wise RMSE, remaining between **2.7°** and **3.4°** throughout the simulation. In comparison, the Hankel-DMD model increases from **51.0°** during the first orbit to **104.1°** and **105.7°** during the second and third orbits, respectively. The stabilization of the orbit-wise error after the second orbit suggests that the prediction does not diverge unboundedly but instead converges to a persistent spurious oscillatory state that no longer represents the true nonlinear attitude dynamics.

4.5 Rollout Amplification Factor: Quantifying the Closed-Loop Validation Gap

Although the root-mean-square error (RMSE) provides an absolute measure of prediction accuracy, it does not directly indicate how much autonomous recursive propagation amplifies the error observed during conventional one-step validation. Consequently, models with excellent one-step performance may still exhibit substantial degradation during autonomous deployment. To quantify this discrepancy, we introduce the **Rollout Amplification Factor (RAF)**, defined as

$$\boxed{\mathrm{RAF}(h) = \frac{\mathrm{RMSE}_{\text{closed-loop}}(h)}{\mathrm{RMSE}_{\text{one-step}}}}$$

where $\mathrm{RMSE}_{\text{closed-loop}}(h)$ is the autonomous closed-loop RMSE evaluated over a prediction horizon h, and $\mathrm{RMSE}_{\text{one-step}}$ is the corresponding one-step (re-anchored) prediction RMSE. The RAF is a dimensionless metric that quantifies the amplification of prediction error resulting from recursive autonomous propagation. Figure 6 compares the one-step prediction RMSE, the autonomous closed-loop RMSE, the equilibrium linearization RMSE, and the corresponding RAF across all prediction horizons. Although the one-step prediction error remains nearly constant at **0.049°**, the autonomous rollout error increases monotonically from **7.49°** after **0.05** orbital periods to **90.58°** after **3** orbital periods. Consequently, the RAF increases from **153×** to **1,849×**, indicating that the effective prediction error during autonomous deployment becomes nearly two thousand times larger than suggested by conventional one-step validation. In contrast, the equilibrium linearization maintains a nearly constant prediction error below **3.5°** throughout the evaluation. These results demonstrate that excellent local prediction accuracy does not necessarily imply reliable long-horizon autonomous propagation and highlight the importance of complementing conventional one-step validation with closed-loop rollout assessment. **Table 2** summarizes the Rollout Amplification Factor (RAF) across the evaluated prediction horizons.

Table 2. Rollout Amplification Factor (RAF) as a function of prediction horizon

Prediction Horizon (orbits)	Koopman Closed-Loop RMSE (°)	One-Step RMSE (°)	Rollout Amplification Factor (RAF)
0.05	7.49	0.049	153×
0.10	15.75	0.049	321×
0.25	27.87	0.049	569×
0.50	32.76	0.049	669×
1.00	50.95	0.049	1,040×
2.00	81.89	0.049	1,671×
3.00	90.58	0.049	1,849×

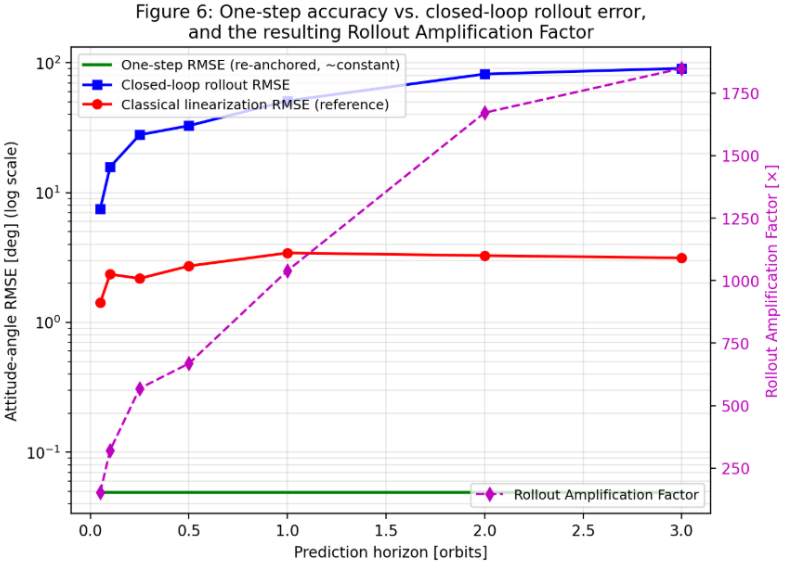

Figure 6. One-step prediction accuracy, closed-loop rollout error, and Rollout Amplification Factor (RAF) as functions of prediction horizon

Figure 6 compares the one-step prediction RMSE, the autonomous closed-loop rollout RMSE, and the equilibrium linearization RMSE across increasing prediction horizons. The secondary axis presents the corresponding Rollout Amplification Factor (RAF), defined as the ratio of autonomous closed-loop RMSE to one-step prediction RMSE. Although the one-step prediction error remains nearly constant at 0.049°, the autonomous rollout error increases steadily with prediction horizon, causing the RAF to rise from 153× after 0.05 orbital periods to 1,849× after 3 orbital periods.

In contrast, the equilibrium linearization maintains consistently low prediction errors throughout the evaluation. These results demonstrate that one-step prediction accuracy alone can substantially underestimate the degradation that occurs during autonomous recursive propagation, highlighting the importance of complementing conventional one-step validation with closed-loop rollout assessment.

5. DISCUSSIONS

The results reveal a clear distinction between excellent one-step prediction accuracy and reliable autonomous long-horizon performance. Although the Hankel-DMD model achieves a one-step RMSE of **0.049°**, its autonomous rollout error increases continuously during recursive propagation, reaching **90.58°** after three orbital periods. The newly introduced **Rollout Amplification Factor (RAF)** quantifies this discrepancy, increasing from **153×** to **1,849×** across the evaluated prediction horizons. This demonstrates that conventional one-step validation substantially underestimates the error encountered during autonomous deployment.

The observed degradation is most likely caused by cumulative phase-error growth. Gravity-gradient-stabilized spacecraft exhibit amplitude-dependent libration, whereas the learned Koopman operator represents the dynamics using a single globally linear approximation over the training domain. Small frequency mismatches that are negligible during one-step prediction accumulate during recursive rollout, eventually producing a bounded but physically incorrect oscillatory trajectory. In contrast, the classical equilibrium linearization preserves the local oscillatory characteristics of the system and maintains consistently low prediction error throughout the simulation.

Several commonly adopted improvements Including delay embedding, feature standardization, ridge regularization, expanded training data, higher-order observables, and spectral-radius stabilization improved numerical robustness but did not eliminate the rollout degradation. These findings suggest that accurate one-step prediction alone is insufficient to establish deployment readiness for autonomous spacecraft propagation. Instead, closed-loop rollout evaluation should complement conventional one-step validation when assessing data-driven reduced-order models.

6. IMPLICATIONS FOR KOOPMAN-BASED SPACECRAFT MODELING

The present results do not imply that Koopman-based reduced-order models are unsuitable for spacecraft applications. Rather, they demonstrate that one-step accuracy alone is not a sufficient indicator of autonomous prediction capability. Koopman models remain well suited to applications involving frequent state correction, such as observer-based estimation and data assimilation, where prediction errors are regularly reset. This study evaluates a single Hankel-DMD formulation for a gravity-gradient-stabilized CubeSat, and the conclusions should therefore be interpreted within that scope. Nevertheless, the identified **closed-loop rollout validation gap** provides a practical framework for evaluating autonomous prediction reliability. Future studies should compare multiple Koopman formulations and spacecraft configurations using closed-loop rollout metrics, including the **Rollout Amplification Factor (RAF)**, to establish robust validation practices for data-driven spacecraft dynamic models.

7. CONCLUSIONS

This study evaluated the autonomous prediction capability of a Hankel-DMD/Koopman reduced-order model for gravity-gradient-stabilized CubeSat attitude dynamics and compared its performance with a conventional equilibrium linearization. Although the Koopman model achieved excellent one-step prediction accuracy (RMSE = **0.049°**), its autonomous closed-loop rollout error increased from **7.49°** after **0.05** orbital periods to **90.58°** after **3** orbital periods. In contrast, the classical linearization maintained consistently low prediction errors (1.42°–3.43°) throughout the evaluation and outperformed the Koopman model at every prediction horizon. To quantify this discrepancy, this work introduced the **Rollout Amplification Factor (RAF)**, which increased from **153×** to **1,849×**, demonstrating that one-step validation can substantially underestimate the error encountered during autonomous deployment. The results further indicate that commonly adopted improvements including delay embedding, feature standardization, ridge regularization, higher-order observables, expanded training data, and spectral-radius stabilization improved numerical robustness but did not eliminate the degradation in closed-loop rollout performance. The principal contribution of this study is the identification and quantification of a **closed-loop rollout validation gap** that remains hidden under conventional one-step evaluation. These findings suggest that one-step prediction accuracy alone is insufficient for assessing the deployment readiness of Koopman-based reduced-order models for autonomous spacecraft attitude propagation. Accordingly, **closed-loop rollout testing, quantified using the Rollout Amplification Factor (RAF) and benchmarked against established analytical baselines, should complement conventional one-step validation when evaluating data-driven reduced-order models for aerospace applications.**

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Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Conceptualization, methodology, software, formal analysis, investigation, data curation, visualization, validation, writing original draft, writing review and editing.

Data Availability

The datasets and source code used to generate the results presented in this study are available from the corresponding author upon reasonable request.

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