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Orbital Phase Correction Method to Improve Custody Maintenance in LEOP

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Abstract

The Launch and Early Operations Phase (LEOP) is a critical part of any space mission, where it is crucial to maintain spacecraft custody by means of consistent and accurate knowledge of the orbital state to ensure successful communications. However, during the initial commissioning days, satellite operators frequently face severe battery budget constraints. To minimise power drain, Global Navigation Satellite System (GNSS) receivers are often duty-cycled, remaining powered only during brief intervals (e.g., ground station passes), resulting in extremely restricted datasets that might consist of only seconds or minutes of observations. With such highly sparse GNSS data, traditional sequential estimators often fail to converge or provide unreliable state estimates due to poor measurement geometry and short time span. This introduces a significant operational risk: if the predicted states deviate too far from reality, primarily due to the along-track phase error, the ground station may fail to acquire the downlink, potentially leading to loss of the mission. This paper proposes an innovative solution developed within the Competitiveness framework (Element 2) of the European Space Agency's (ESA) Navigation Innovation and Support Program (NAVISP), to be exploited commercially as part of Neuraspace's service offering. Instead of relying on full-state sequential estimation, a Phase Correction Algorithm is designed to apply discrete time adjustments to the orbit prediction from the separation state vector from the launch service provider, such that the along-track error is reduced. Focusing on the phase shift between the predicted trajectory and the brief GNSS bursts, the algorithm provides a robust state update that does not suffer from instability and convergence issues associated with classical filters with very few datasets and poor initial guess accuracy. The methodology is validated with real measurements, relying on launch separation vectors and GNSS receiver data. We demonstrate that even with as few as 5 measurements of GNSS data per orbit, the algorithm can successfully reduce the along-track drift accumulated during the initial post-launch days. The lightweight computational effort required by the proposed algorithm makes it suitable for onboard applications, such as conjunction analysis reassessment. Results indicate that this approach maintains the spacecraft within the ground station's beam-width significantly longer than uncorrected propagation, providing a "safety net" until onboard systems are fully commissioned and continuous data provision begins. This work offers a pragmatic, computationally efficient strategy for operators to ensure mission safety during the critical transition from launch to nominal operations.

Keywords: LEOP, GNSS, phase correction, along-track error

Nomenclature

Symbols

a	Semi-major axis (osculating)
C_D	Drag coefficient
d	Distance
e	Eccentricity (osculating)
H	Observation matrix
i	Inclination (osculating)
J_2	Second zonal harmonic coefficient

K	Kalman gain
M	Mean anomaly
$\bar{n}$	Mean motion
P	State variance
Q	Process noise
R	Measurement variance
R_E	Earth equatorial radius
S	Innovation variance
t	Time

u	Mean argument of latitude
x	Ephemeris state / position
y	Innovation
z	Measurement scalar
Δ	Difference or shift
μ	State estimate (mean)
ω	Argument of perigee (osculating)

Subscripts

k	Discrete time step index
$k k-1$	Prediction at step k given step $k-1$
E	Earth
$gnss$	Derived from GNSS measurement
M	Mahalanobis
$predicted$	Predicted value
$step$	Algorithm execution step

Acronyms/Abbreviations

DOF	Degrees-Of-Freedom
ESA	European Space Agency
ESTEC	European Space Research and Technology Centre
GNSS	Global Navigation Satellite System
LEO	Low Earth Orbit
LEOP	Launch and Early Operations Phase
NAVISP	Navigation Innovation and Support Program
NWBLS	Non-linear Weighted Batch Least Squares
OD	Orbit Determination
SLR	Satellite Laser Ranging
SRIF	Square Root Information Filter
TLE	Two-Line Element

1. Introduction

The recent deployment of large constellations and rideshare missions has drastically increased the number of orbiting objects, with the European Space Agency (ESA) reporting nearly 17000 active payloads by the end of 2025 [1]. Following launch, satellites undergo the highly critical Launch and Early Operations Phase (LEOP), where securing mission control and establishing communications is paramount. However, lean satellite operations teams lacking dedicated flight dynamics specialists often rely on public tracking data, such as the data from Space-Track [2]. Coupled with stringent new regulatory frameworks like ESA's Zero Debris policy [3], operators are under pressure to generate accurate orbital ephemerides almost immediately after launch.

Through extensive collaboration with satellite operators, Neuraspace has identified vulnerabilities in LEOP custody maintenance. Driven by strict battery budget con-

straints, small satellites routinely duty-cycle their Global Navigation Satellite System (GNSS) receivers, yielding extremely sparse datasets. When presented with such limited telemetry, classical sequential estimators often fail to converge. Consequently, uncorrected along-track phase errors (driven by atmospheric drag mismodelling) can cause the ground station to miss the downlink entirely, potentially resulting in total mission loss.

To address this operational gap, this paper proposes an innovative methodology developed within ESA's Navigation Innovation and Support Program (NAVISP). Rather than forcing a full-state sequential estimation on inadequate data, a lightweight Phase Correction Algorithm is introduced. This method applies discrete, 1-Degrees-of-Freedom (DOF) time adjustments to the baseline trajectory propagated from the launch separation vector.

The remainder of this paper is structured as follows. Section 2 reviews classical LEOP orbit determination challenges and sparse data tracking. Section 3 details the mathematical formulation of the proposed algorithm. Section 4 describes the validation setup using real flight data, while Section 5 presents the baseline performance and sensitivity analyses. Finally, Section 6 summarises the main conclusions and future work.

2. Literature Review

Traditional Orbit Determination (OD) methods for estimating the state of an object during LEOP can generally be divided into two main families: sequential filters and batch least-squares estimators [4]. Although different measurement types such as optical, Doppler, range or Satellite Laser Ranging (SLR) could be used in the OD process, we focus only on GNSS, since this was the data type operators tended to share with Neuraspace during LEOP campaigns.

Among the vast array of sequential filters available in the literature, the Kalman filter and its non-linear derivations are the most commonly used in operational environments, although alternatives such as the Square Root Information Filter (SRIF) can similarly be employed [5]. However, these sequential techniques present notable operational disadvantages. A primary drawback is the difficulty in reliably estimating dynamical parameters, such as the drag coefficient (C_D). Accurately resolving these parameters in a sequential framework typically requires the implementation of smoothing techniques, which considerably increase the complexity of the algorithm and the computational cost, reducing their advantages over batch estimators. Within the family of batch estimation techniques, the Non-linear Weighted Batch Least Squares (NWBLS) method [6] serves as the standard operational approach.

Throughout the LEOP campaigns Neuraspace was involved in, issues with the quality and time span of said GNSS data were very common: namely, due to power-budget or station downlink constraints, only short tracks with very few measurements might be available in the first few days immediately after launch. When these data gaps are present, the OD problem complexity increases and the non-linear orbital dynamics lead to a degradation of the prediction accuracy and eventually filter divergence [7]. Moreover, Neuraspace verified that for some of these tracks the rejection of measurements by sequential filters was very high, and convergence was not achieved.

The algorithm proposed in this paper intends to bridge the gap described above. In Low Earth Orbit (LEO), the position uncertainty of a propagated state rapidly becomes dominated by the secular growth of along-track phase error, often dwarfing radial and cross-track deviations [5].

While full-state sequential estimation struggles with sparse datasets, the physical concept of isolating and correcting this phase error has precedent in other domains. In Optical tracking and SLR, it is standard practice to compute a scalar “time bias” to shift measurements in the along-track direction [8]. Similarly, satellite operators frequently apply empirical time biases to ageing Two-Line Elements (TLEs) to artificially push the satellite forward or backward along its path [9].

However, these time-bias techniques are traditionally applied empirically, manually, or via post-pass least-squares fitting. The Phase Correction Algorithm introduces a novel approach by automating and rigorously formalising this concept specifically for LEOP. By treating the along-track time shift as a 1-DOF state variable within a probabilistic Bayesian framework, augmented by a Mahalanobis quality gate, the algorithm dynamically corrects the phase error in real-time using the highly sparse, noisy GNSS bursts that cause traditional filters to diverge. Ultimately, this provides a computationally lightweight “safety net” to maintain custody until continuous data provision allows for a full batch or stable sequential filtering OD.

3. Phase Correction Algorithm

The main goals of the proposed algorithm are to be computationally efficient by avoiding traditional full-state sequential estimation techniques, and to leverage short tracks to improve the accuracy of the orbital solution during LEOP. Instead, it employs a 1-DOF Bayesian filter to calculate a scalar along-track time shift (Δt) to reduce the phase error between the propagated baseline trajectory and the sparse GNSS measurements. The astrodynamics equations presented in this section are derived by Vallado

in [10].

3.1 Physical Equations

To take advantage of a linear Bayesian update, a relationship must be established between the state (Δt) and the physical observations. The filter achieves this by tracking how a time shift translates into an angular position error along the satellite’s track. The primary kinematic parameter used by the algorithm is the mean argument of latitude (u), which corresponds to the angular position of the satellite relative to the ascending node, as defined in Eq. 1:

$$u = \omega + M \quad (1)$$

A time synchronisation error (Δt) causes a direct mapping error in this angular coordinate. Using a first-order Taylor expansion, the spatial deviation (Δu) is related to the time offset via the time derivative of the argument of latitude ($\dot{u}$), as shown by Eq. 2):

$$\Delta u \approx \dot{u} \cdot \Delta t \quad (2)$$

Based on this mapping, a measurement scalar (z_k) can be computed as the wrapped angular residual between the predicted reference orbit and the actual state derived from the GNSS measurement, ensuring mathematical continuity within the interval $[-\pi, \pi]$:

$$z_k = \text{wrap}_{-\pi}^{\pi}(u_{\text{gnss}} - u_{\text{predicted}}) \quad (3)$$

The physical observation matrix (H_k) is defined as the time derivative of the mean argument of latitude. As derived from Eq. 1, this is the sum of the rates of change of the argument of perigee and the mean anomaly:

$$H_k = \dot{u}_k = \dot{\omega} + \dot{M} \quad (4)$$

In a perturbed space environment, computing H_k solely from Keplerian mean motion introduces tracking divergence. Thus, the model explicitly incorporates secular variations driven by the J_2 Earth oblateness perturbation, defined in Eq. 5 and Eq. 6:

$$\dot{\omega} = \frac{3}{4} \left(\frac{R_E}{a} \right)^2 \frac{\bar{n} J_2}{(1 - e^2)^2} (4 - 5 \sin^2(i)) \quad (5)$$

$$\dot{M} = \bar{n} + \frac{3}{4} \left(\frac{R_E}{a} \right)^2 \frac{\bar{n} J_2}{(1 - e^2)^{3/2}} (2 - 3 \sin^2(i)) \quad (6)$$

3.2 Bayesian Filter Formulation

The filter operates by processing the physical observations defined previously to estimate the 1-DOF scalar time

shift. To formulate the linear Bayesian update, the system dynamics and measurements are assumed to be corrupted by uncorrelated, zero-mean Gaussian white noise processes, where the process noise is defined as $w_k \sim \mathcal{N}(0, Q)$ and the measurement noise as $v_k \sim \mathcal{N}(0, R)$. The state variable then corresponds to the time correction ($x_k = \Delta t$), and the parameters of the physical domain derived in Eq. 2 map to the standard linear observation equation, $z_k = H_k x_k + v_k$. Table 1 establishes this direct correspondence between the astrodynamical physical parameters and the Bayesian filter domain.

Table 1: Variable mapping between the physical and Bayesian filter domains.

Physical Domain	Bayesian Filter Domain
Observed Deviation (Δu)	Measurement Scalar (z_k)
Angular Velocity ($\dot{u}$)	Observation Matrix (H_k)
Time Correction (Δt)	State Variable (x_k)

The filter processes each GNSS track sequentially through the prediction, validation, and correction steps, following standard linear sequential estimation practices [11].

State Prediction (Time Update)

The state is assumed to follow a random walk, meaning that the predicted state estimate ($\mu_{k|k-1}$) remains equal to the prior state, while its uncertainty ($P_{k|k-1}$) grows linearly over time due to the process noise (Q):

$$\mu_{k|k-1} = \mu_{k-1} \quad (7)$$

$$P_{k|k-1} = P_{k-1} + Q \cdot \Delta t_{step} \quad (8)$$

To assess the measurement quality and prevent anomalously noisy GNSS data from corrupting the estimator, the filter calculates the measurement innovation (or residual), y_k . This represents the difference between the actual observed scalar (z_k) and the filter's predicted scalar ($H_k \mu_{k|k-1}$):

$$y_k = z_k - H_k \mu_{k|k-1} \quad (9)$$

The Mahalanobis distance (d_M) is then computed. This represents how many standard deviations the raw measurement deviates from the filter's prediction:

$$d_M = \frac{y_k^2}{H_k^2 P_{k|k-1} + R} \quad (10)$$

The decision to accept or reject the measurement is dictated by a predefined quality gate. If $d_M \geq d_{threshold}$, the measurement is rejected as an outlier. If $d_M < d_{threshold}$, the measurement is accepted and passed to the update step.

Measurement Update (Correction Step)

For measurements that pass the validation gate, the filter computes the innovation variance (S_k) and the optimal Kalman Gain (K_k):

$$S_k = H_k^2 P_{k|k-1} + R \quad (11)$$

$$K_k = \frac{P_{k|k-1} H_k}{S_k} \quad (12)$$

Finally, the posterior state estimate and its variance are updated using the calculated gain and the accepted innovation:

$$\mu_k = \mu_{k|k-1} + K_k \cdot y_k \quad (13)$$

$$P_k = (1 - K_k H_k) P_{k|k-1} \quad (14)$$

By reducing the estimation problem from a full 6-DOF state vector to a 1-DOF scalar time shift, the computational burden is drastically reduced. The algorithm avoids the numerical integration of complex orbital perturbation models within the estimation loop, treating the baseline trajectory as a fixed reference. Moreover, during LEOP, if GNSS data is sparse and only short tracks are available due to constraints on the power-budget or ground station visibility and availability windows, a full traditional OD is generally not possible.

This lightweight formulation is highly scalable for ground-based automated pipelines processing mega-constellations and could be equally suitable for future on-board applications, such as real-time conjunction analysis reassessment under severe data constraints.

4. Test Validation Setup

To validate the Phase Correction Algorithm in a realistic LEOP scenario, the methodology was tested using real flight data from two LEO satellites, hereafter referred to as Sat. A and Sat. B (anonymised for data privacy concerns). These data were used in real LEOP scenarios by Neuraspace as part of its LEOP tracking package.

The reference or "truth" trajectory for the simulations was established using OD fitted ephemeris from the full set of GNSS tracks, considering calibrated C_D . To emulate realistic LEOP error growth, the baseline propagated trajectory was derived from post-separation state vectors with a fixed C_D (the selected value is 2.2, as is usually the standard for preliminary mission design), leading to a naturally degrading along-track state over time.

While a typical LEOP rarely exceeds two weeks before an object is catalogued, a one month data span was selected for these simulations (Neuraspace has several months of GNSS data for these objects). Rather than propagating a

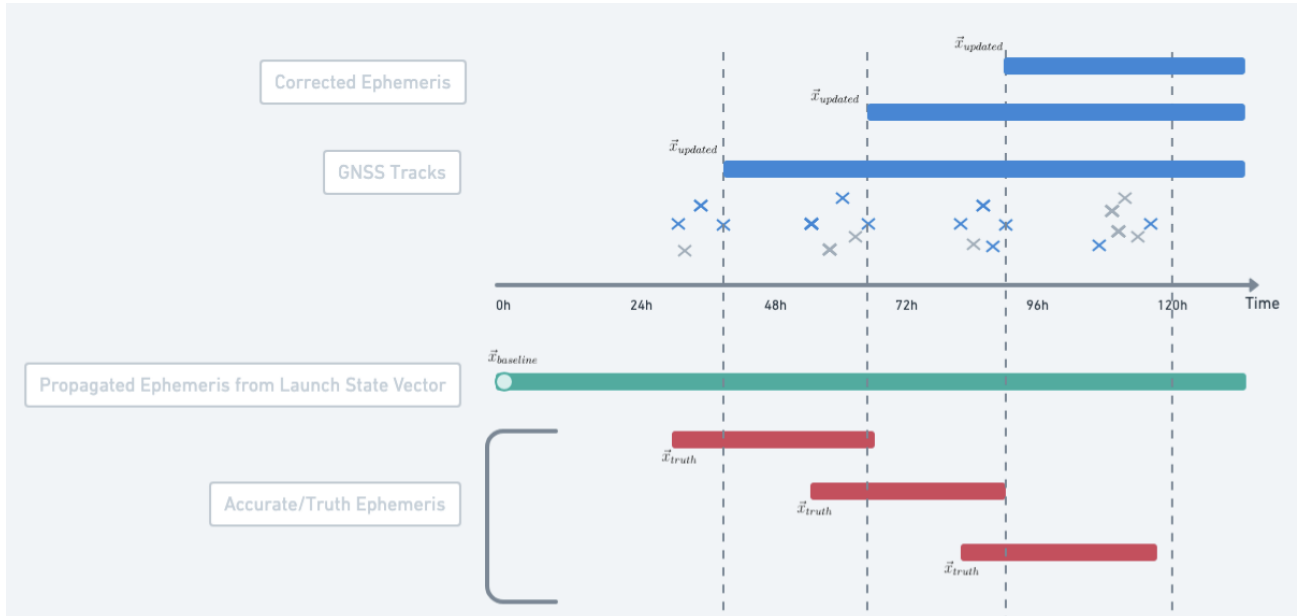


Fig. 1: Conceptual diagram of the proposed phase correction algorithm in a LEO scenario, illustrating the iterative trajectory updates using sparse GNSS tracks.

single post-separation vector for the entire month, which would be operationally unrealistic, the month of data was subdivided into multiple independent propagated orbits. Each orbit starting epoch serves as a hypothetical launch date, effectively simulating several distinct LEO scenarios spaced approximately four to five days apart. This methodology ensures the algorithm is evaluated across a variety of orbital geometries and space weather conditions, allowing for the extraction of robust statistics. The validation periods and segment breakdown (number of propagated "launch" orbits) for both test assets are detailed in Table 2.

To illustrate the operational concept, the proposed algorithm functions sequentially upon the receipt of sparse GNSS tracks. As depicted in Fig. 1, the filter processes available GNSS measurements (represented by 'X' symbols), rejecting outliers where the Mahalanobis distance exceeds the defined threshold. Upon processing a track, the time shift obtained at the last accepted GNSS measurement is used to directly shift the original baseline epochs, generating a new updated trajectory. Subsequent GNSS tracks within the window are then used to recursively correct the previously updated trajectory. This process is repeated for multiple baseline ephemeris segments spaced approximately four days apart, to be able to extract meaningful statistics on phase error reduction.

The LEO operational constraints were simulated by

randomly sampling the continuous GNSS data to emulate duty-cycled receivers. The baseline simulation parameters were configured as follows:

- **GNSS Window:** 24 to 120 hours post-separation.
- **Data Sparsity:** 4 to 10 randomly selected tracks per window, containing only 10 to 50 measurements per track (the results are reproducible since a pseudo-random generator seed value was selected).
- **Filter Parameters:** baseline process noise of $1/86400 \text{ s}^{-1}$, measurement variance of $4\text{e-}5 \text{ s}^2$, and Mahalanobis distance threshold of 5 for outlier rejection.

The selection of the baseline filter parameters is based on the physical and statistical realities of LEO operations. The process noise ($Q = 1/86400 \text{ s}^{-1}$) is designed to account for the unmodelled dynamics of the system, essentially assuming the along-track phase uncertainty grows by approximately one second per day due to atmospheric drag mismodelling. In a typical LEO orbit, a one-second time error translates to roughly 7.5 km of along-track position error. This magnitude is entirely consistent with the large secular drift observed when propagating post-separation vectors without active drag estimation. The measurement variance ($R = 4\text{e-}5 \text{ s}^2$) reflects the expected uncertainty of

Table 2: Baseline ephemeris segments, covered periods, altitude ranges, and physical properties for validation assets.

Sat.	Baseline Ephemeris Period	No. of Segments	Altitude (km)	Mass (kg)	Drag Area (m ²)
A	02/04/2025 – 01/05/2025	8	≈ 443–467	8.341	0.035
B	05/04/2025 – 02/05/2025	6	≈ 542–552	8.341	0.035

the raw GNSS measurements. Translating this variance to the physical domain yields a time standard deviation of ≈ 0.0063 s, which equates to an expected along-track position accuracy of approximately 50 m. This is a safely conservative bound for duty-cycled GNSS receivers. The algorithm’s sensitivity to these baseline choices is further explored in the tuning analyses presented in Section 5. Finally, the Mahalanobis distance threshold of 5 acts as a robust statistical quality gate, by limiting how many standard deviations a raw GNSS measurement is allowed to deviate from the filter’s prediction. A threshold of 5 is sufficiently wide to accommodate the large initial along-track mismatches inherent to propagated launch state vectors as well as GNSS quality, while remaining strict enough to reject extreme, unphysical GNSS anomalies.

A successful correction was defined as any trajectory update where the post-correction along-track error (along-track position difference between the phase shifted and the reference “truth” trajectories) was strictly less than the baseline propagation error.

The relevant error metrics are defined below (always at the last GNSS measurement of each track):

- **Baseline error:** difference between the baseline ephemeris and the reference “truth” ephemeris, $x_{baseline} - x_{truth}$;
- **Pre-correction error:** difference between the previously updated ephemeris and the accurate ephemeris, $x_{prev_update} - x_{truth}$;
- **Post-correction error:** difference between updated ephemeris and the reference “truth” ephemeris, $x_{updated} - x_{truth}$;
- **GNSS error:** difference between the GNSS derived position and the reference “truth” ephemeris, $x_{GNSS} - x_{truth}$.

5. Results and Discussion

5.1 Baseline Performance

The baseline simulation results demonstrate the algorithm’s capability to reduce the along-track error of the

post-separation propagated state vector, thus revealing itself to be useful in maintaining spacecraft custody under severe data constraints.

For Sat. A, which featured relatively clean GNSS data, the algorithm performed 304 successful updates with a 90.46% success rate against the baseline error (see Table 3). The evolution of the baseline error compared to the pre- and post-correction states, alongside the raw GNSS errors, is visually detailed in Fig. 2. Ultimately, the average final error was constrained to approximately 568 m, representing an average error reduction of 9.17 km.

Table 3: Baseline simulation statistical summary for Sat. A and Sat. B.

Sat.	Total Updates	Success Rate (%)	Avg. Error Reduction (km)	Avg. Meas. per Track	Avg. Meas. Rejection per Track (%)
A	304	90.46	9.17	30.8	59.74
B	106	94.34	20.66	33.3	71.47

The internal mechanics of the Bayesian filter during this successful run are illustrated in Fig. 3 and Fig. 4 for Sat. A. Fig. 3 depicts the evolution of the estimated delta time parameter per track, complete with 3-sigma confidence intervals. It demonstrates how the largest correction is typically applied during the first track acquisition, effectively collapsing the initial accumulated along-track error, with subsequent updates requiring much smaller magnitudes.

Fig. 4 displays the Mahalanobis distance evaluated for each GNSS measurement against the filter’s prediction quality gate (threshold of 5). This validation mechanism successfully removes outliers in the GNSS data.

Sat. B presented a significantly more challenging scenario due to inherently noisy GNSS data, resulting in a 71.4% measurement rejection rate by the filter’s Mahalanobis quality gate. Despite relying on extremely restricted and noisy accepted measurements, the algorithm achieved a 94.34% success rate for Sat. B, delivering an average error reduction of over 20.6 km (see Fig. 5). This high success rate despite massive data rejection highlights



Fig. 2: Baseline, pre- and post-correction, and GNSS errors at each track update during the LEOP simulation scenario for Sat. A.

the operational robustness of the methodology; however, it is important to note that the magnitude of the error reduction is directly dependent on the poor estimation of the C_D used to propagate the post-separation state vector.

5.2 Process Noise Sensitivity Analysis

The performance of the algorithm was evaluated by adjusting the process noise to $1/43200 \text{ s}^{-1}$ (larger) and $1/172800 \text{ s}^{-1}$ (smaller). The comparative impact of these tunings is detailed in Table 4.

Table 4: Impact of process noise (Q) tuning on algorithm performance.

Sat.	Process Noise (s^{-1})	Updates	Success	Avg. Reduct. (km)
			Rate (%)	
A	1/43200 (Larger)	315	90.79	10.07
A	1/86400 (Baseline)	304	90.46	9.17
A	1/172800 (Smaller)	282	89.72	9.14
B	1/43200 (Larger)	143	97.20	23.79
B	1/86400 (Baseline)	106	94.34	20.66
B	1/172800 (Smaller)	58	96.55	15.05

Increasing the process noise makes the filter assume the predicted time shift is less stable, thereby widening the acceptance gate. This approach increased the success rate for Sat. B to 97.20% and improved the average error reduction

to nearly 23.8 km (see Fig. 6). In contrast, reducing the process noise made the filter overconfident in its internal predictions, leading to higher measurement rejection and a degradation in the total updates for both satellites. This indicates that capturing the rapid drift dynamics typical of LEOP requires the filter to remain highly responsive to incoming measurements.

5.3 Measurement Variance Sensitivity

Tuning the measurement variance (R) further highlighted the dependency of optimal filter configurations on inherent GNSS data quality, as shown in Table 5.

Table 5: Impact of measurement variance (R) tuning on algorithm performance.

Sat.	Meas. Var. (s^2)	Updates	Success	Avg. Reduct. (km)
			Rate (%)	
A	4e-3 (Larger)	338	92.90	9.82
A	4e-5 (Baseline)	304	90.46	9.17
A	4e-7 (Smaller)	283	91.17	9.31
B	4e-3 (Larger)	140	95.00	21.12
B	4e-5 (Baseline)	106	94.34	20.66
B	4e-7 (Smaller)	84	95.24	20.78

Increasing the measurement variance to $4\text{e-}3 \text{ s}^2$ improved Sat. A's success rate to 92.9%, as the wider gate allowed more measurements to be accepted without skewing the already accurate trajectory (see Fig. 7). However, for the noisy data of Sat. B, this wider gate allowed too many outliers to pass, causing a slight divergence compared to the baseline. Implementing an adaptive tuning mechanism for these parameters based on real-time data quality assessment represents a logical next step for future operational deployment.

Although the Phase Correction Algorithm excels in highly constrained LEOP scenarios, it possesses inherent limitations due to its simplified 1-DOF parameterisation. The method provides a purely along-track correction and does not estimate or reduce cross-track or radial errors. Furthermore, it relies on a time-shift approximation of the existing ephemeris rather than dynamically re-propagating the updated trajectory. Consequently, the algorithm is applicable when the baseline error is predominantly along-track, which is the case for drag-driven uncertainties in LEO. It becomes less effective if the initial state error budget contains significant out-of-plane components, which a scalar time shift cannot mathematically resolve.

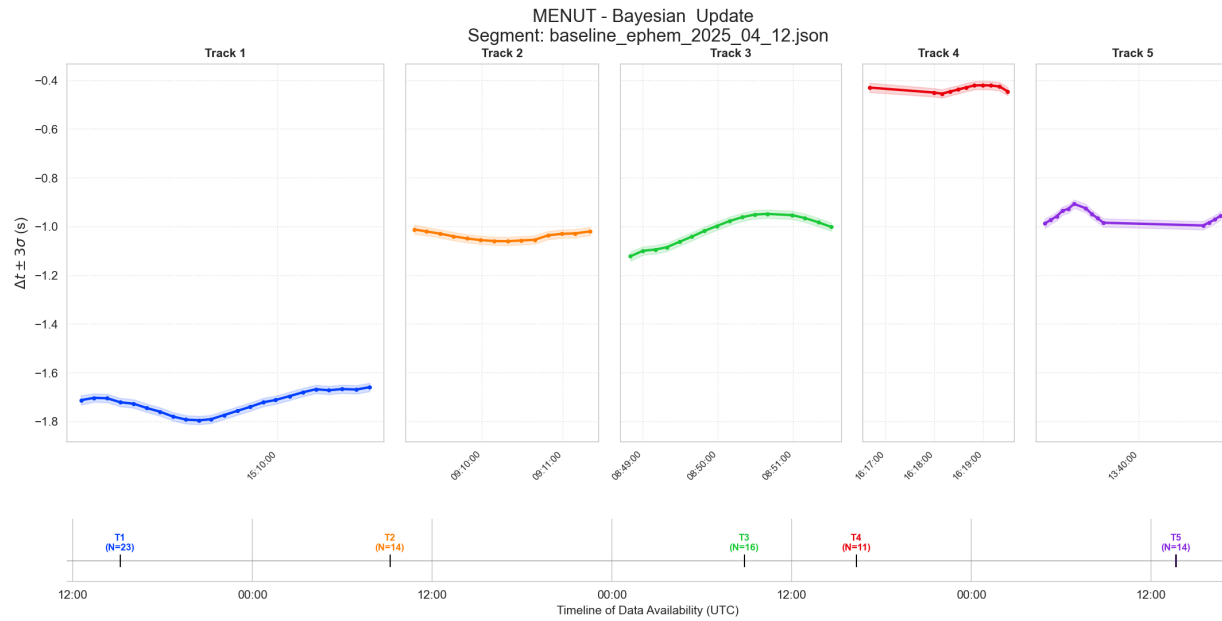


Fig. 3: Delta time parameter evolution per track (with 3-sigma confidence intervals) during the baseline LEOP scenario for Sat. A.

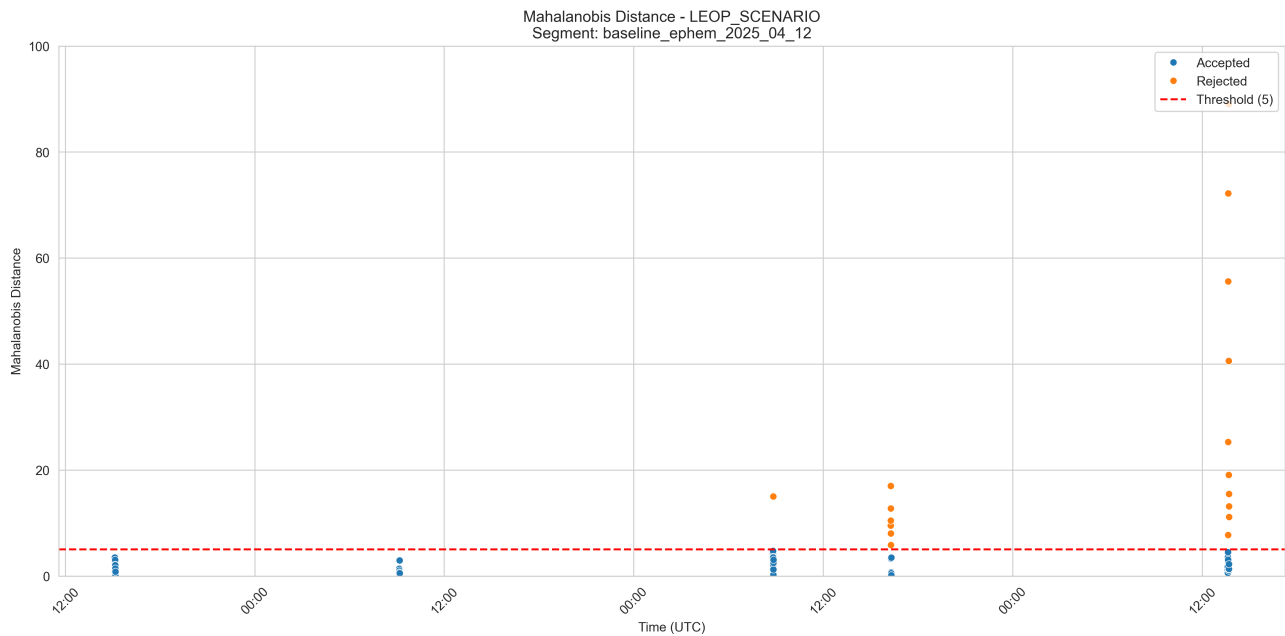


Fig. 4: Mahalanobis distance vs time, displaying accepted and rejected GNSS measurements during the baseline LEOP scenario for Sat. A. Note the y-axis is trimmed at 100 for visualization purposes.



Fig. 5: Baseline, pre- and post-correction, and GNSS errors at each track update during the LEOP simulation scenario for Sat. B.

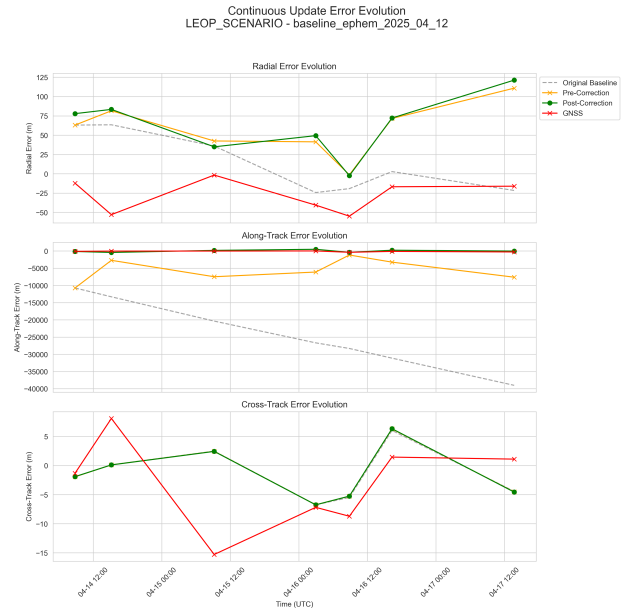


Fig. 7: Impact of increased measurement variance ($4e-3 s^2$) on the error evolution and measurement acceptance during the LEOP simulation scenario for Sat. A.

6. Conclusions

This paper presented a lightweight, computationally efficient Phase Correction Algorithm designed to maintain spacecraft custody during power-constrained LEOP operations. By applying discrete time adjustments to the propagated separation state vector using highly sparse and short GNSS tracks, the algorithm acts as an operational “safety net”. It successfully mitigates the risk of mission loss driven by rapid accumulation of along-track error, bypassing the convergence issues that plague traditional sequential estimators operating on constrained GNSS data availability.

Future work will focus on integrating this algorithm as a robust fallback mechanism within a fully automated OD pipeline for LEOP and/or nominal operations. Additional planned enhancements include replacing the time-shift approximation with a full trajectory re-propagation step based on the updated state, and implementing adaptive filter tuning mechanisms based on real-time data quality.

Furthermore, a sensitivity analysis should be performed by varying the C_D used to propagate the post-separation state vector; a better *a priori* tuning of this parameter could lead to smaller error reductions computed by the Phase Correction Algorithm.

Finally, the methodology will be validated across a broader range of orbital altitudes and inclinations, along-

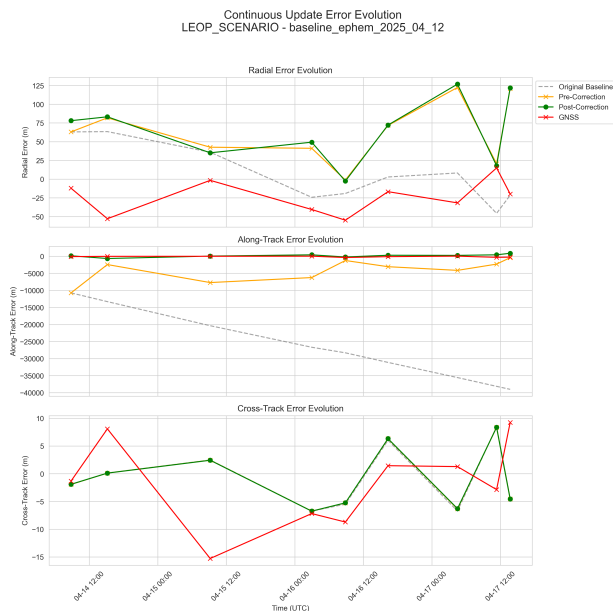


Fig. 6: Impact of increased process noise ($1/43200 s^{-1}$) on the error evolution and measurement acceptance during the LEOP simulation scenario for Sat. B.

side a detailed sensitivity analysis regarding spacecraft ballistic coefficients.

Acknowledgements

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