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A FOCUS ON NAVIGATION PERFORMANCE NEAR PERILUNE IN A NEAR RECTILINEAR HALO ORBIT FOR A CREWED STATION

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NASA's Gateway Program plans to place a crew-tended spacecraft in a southern L2 Near Rectilinear Halo Orbit (NRHO). The selected NRHO has a 6.5 day period, characterized by periods of low relative velocity punctuated by high velocity perilune passes. Determining an accurate navigation solution in this sensitive region challenging, yet it is important to understand navigation performance near perilune to support spacecraft activities planned in the vicinity. The aim of this paper is to investigate the predictive accuracy through perilune of navigation states under various operational concepts and contingencies. An error budget analysis is performed on the perturbations modeled in the simulation to gauge their impact to navigation errors. Secondly, a sensitivity analysis on the data quality investigates the impact to navigation errors near perilune. Finally, the relationship between predictive accuracy through perilune and propagation time is explored. Each analysis is performed for both non-crewed (quiescent) and crewed (active) configurations.

INTRODUCTION

A southern Earth-Moon L2 NRHO is a novel orbit with several advantages for future operations, including constant line-of-sight with Earth, extended views of the lunar south pole, and favorable eclipse properties.[1,2] The specific NRHO selected as the Gateway baseline orbit has a 6.5 day period; it varies in altitude from over 70,000 km at apolune to under 1,700 km at perilune. The time spent in NRHO is characterized by long periods of low relative velocity flight far from the Moon punctuated by brief high velocity, low altitude perilune passes. During these perilune passes, the dynamic sensitivity increases dramatically and navigation errors grow. Navigation state errors from solutions prior to perilune increase significantly as they are propagated through perilune.[3]

Navigation state errors arise from unmodeled accelerations such as gravity model errors, solar pressure model error, attitude maneuvers, venting perturbations, and orbit maintenance maneuver (OMM) execution error. Perturbations arising from attitude control, including active Reaction Control System (RCS) thrusting and reaction wheel desaturation maneuvers, may occur near perilune resulting from gravity gradient torques. The presence of a human crew also leads to periodic attitude perturbations in response to torques incurred by venting and other disturbances. The navigation state is inherently erroneous due to tracking limitations, including data quality deficits. These errors accumulate in the absence of tracking data, which are further amplified during the perilune pass.[4]

The Orbit Determination (OD) process investigated in this paper assumes data processing on the ground, with navigation solutions and commands then communicated to the spacecraft. In

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this process, tracking data from the spacecraft is received by ground operations, and some time is required for processing before an updated navigation solution is returned to the spacecraft. There is a delay between receiving tracking data and uploading a new navigation state and commands, which means that navigation performance is tightly bound to predictive accuracy (how accurate a navigation state is after some propagation time). This predictive performance is distinct from ”instantaneous” performance of the navigation solution calculated at the same epoch of the received tracking data. The duration of the delay and its placement in the NRHO determine the errors at the time of the solution; unfavorable delays result in larger errors in the state on board.

For this paper, the predictive accuracy performance to perilune is calculated as an effect of changes to the simulation. The simulation carries various parameters and assumptions that may be different than initially modeled, The current analysis assess the impact that changes to these assumptions and parameters have on the navigation performance, as measured by predictive accuracy at perilune. Three main studies are executed:

1. Error Budget Analysis. Adjust the inclusion/exclusion of modeling of physical processes in the simulation and investigate the impact on navigation performance as measured by predictions to perilune.
2. Data Quality Sensitivity Analysis. Adjust the assumed parameters of tracking data quality and investigate the impact to perilune prediction accuracy.
3. Prediction Length Analysis. Adjust the Data Cut Off (DCO) location with respect to perilune, and investigate the impact to perilune prediction accuracy due to growing prediction time span.

Each study is performed on an uncrewed and crewed vehicle. For crewed vehicles, predictions include random perturbations that can increase errors over time. For handling random perturbations on predictions from a definitive set of tracking data, predictions are *cloned* from the last tracking data point and repeatedly predicted into the future with random perturbations. This process increases the statistical robustness of crewed predictions from a smaller set of navigation solutions.

BACKGROUND AND SIMULATION

Previous Work

In previous work,[5] the authors built an orbit determination simulation for the NRHO and investigated DSN tracking pass design. The study focused on uncrewed operations with intermittent DSN tracking in different timing strategies. The work also investigated optical tracking of surface features from the Gateway near perilune to improve navigation solutions by the novel geometry introduced by optical observations.

This paper expands on previous work by introducing multiple new statistical methods to investigate navigation performance, such as position and velocity separated Mahalonobis distances, and predictive compares. Analysis is extended to include crewed scenarios, which consider periodic venting, desaturation maneuvers, and constant DSN tracking. For crewed vehicle analysis, predictions are cloned from navigation solutions and are subject to random perturbations to create multiple predictions from a single navigation solution.

NRHO Operations Overview

A spacecraft in the Gateway NRHO spend the majority of its time far from perilune. While the period is 6.5 days, it passes through the perilune vicinity- the region below 10,000 km altitude- in approximately 7 hours. State errors and perturbations prior to a perilune pass may grow quickly when propagating through Perilune. This growth is a concern for operations that require low state estimation error, such as proximity operations.[6,7] Increased errors can also impact pointing operations for communications with lunar surface assets or the Earth. These make navigation performance near Perilune important to operations, and is the driver for analyzing predictions to Perilune in this paper.

The NRHO is maintained with Orbit Maintenance Maneuvers (OMMs) nominally executed once every revolution. The OMM is placed at a True Anomaly of 200°, as depicted in Figure 1.[8] Navigation performance depends on the tracking schedule. While the spacecraft is crewed, continuous DSN tracking is assumed. While uncrewed, three 8-hour tracking passes are modeled per revolution; these passes are illustrated in Figure 1. Starting from Apolune,

1. A pre-OMM pass occurs before the data cut-off,
2. A post-OMM (*alt. pre-perilune*) data pass is scheduled between the OMM and perilune,
3. A post-perilune data pass occurs in the 24 hours after perilune.

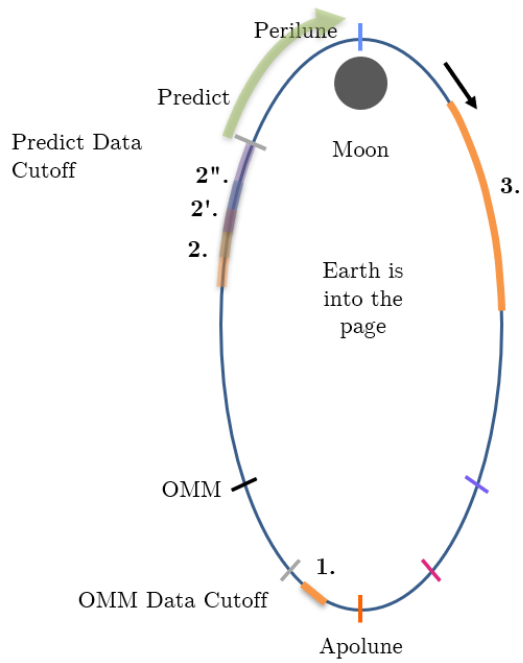


Figure 1: Tracking Data Arc Concept for Uncrewed Operations

This tracking schedule is consistent with previous analyses. The OMM is targeted after the OMM Data Cutoff (DCO) labeled (1) in Figure 1 using a receding horizon algorithm that targets the X-component of the rotating frame velocity and perilune crossing time at perilune several revolutions in the future. The algorithm is described in detail in previous papers.[3,4,8,9] There is a prediction from the DCO to OMM target epoch that short in duration and in low-velocity nearly-inertial space; this prediction is not scrutinized in this analysis.

The OMM is targeted using the navigation solution and is applied perfectly to the estimated spacecraft and imperfectly to the representative "Truth" spacecraft. Maneuver execution error is resolved by the post-OMM tracking data pass labeled (2) in Figure 1. The prediction from this predict DCO to perilune is the primary focus of this paper. Docking activities are expected to occur away from perilune; these events are not include in the current analysis.

Simulation Overview

Analysis is performed in a simulation that propagates the spacecraft through the NRHO while generating and processing tracking data measurements in a Square Root Information Filter (SRIF).

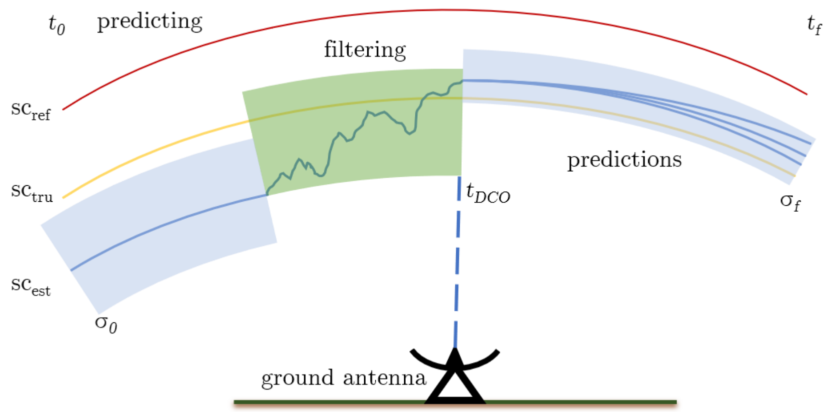


Figure 2: OD operations through time.

The simulation considers three spacecraft to emulate OD operations, which are illustrated in Figure 2 from the top as Reference, Truth, and Estimated spacecraft. The reference spacecraft is interpolated directly from the reference ephemeris and is used to generate a catalog of targets for the OMM algorithm. The truth spacecraft represents the Gateway's actual state; the OMM algorithm acts on the truth spacecraft to maintain the orbit within the NRHO. Imperfect tracking data measurements are generated from the Truth spacecraft and interpolated through a SRIF to update the state and covariance of the Estimated spacecraft.

The covariance is illustrated in Figure 2 as the blue shaded area labeled σ_0 and σ_f. Tracking data is processed Note how the width of the blue shaded area is reduced as a result of tracking data to illustrate the increase in filter confidence. Also note how the distance between the Estimated and Truth trajectories is smaller, representing improved accuracy from tracking data processing. Finally, multiple predictions originate from the single state estimate at t_{DCO} to illustrate prediction cloning for crewed predictions. Multiple predictions, each with unique random perturbations, are generated from the estimated state at t_{DCO} and propagated forward in time.

In addition to predictions to Perilune, the Mahalonobis distance of the navigation solution is calculated as a measure of the performance of the filter solution and covariance characteristics. The Mahalonobis distance is the filter state error scaled by the filter covariance "in the direction of the error". It is calculated as

$$M^2 = (x_{est} - x_{tru})C^{-1}(x_{est} - x_{tru})^T \tag{1}$$

where M is the Mahalonobis distance, x_{est} is the estimated state, x_{tru} is the truth state, and C is the filter covariance. The Mahalonobis distance is a unitless ratio of error magnitude against the covariance magnitude in the same direction. A visual representation of two errors of similar magnitude but unequal Mahalonobis distance is shown in Figure 3. The two error vectors are similar in length, but the left vector is well outside the covariance ellipse in that direction and represents an error with high M-distance relative to the right vector.

Perturbation Modeling The simulation includes off-nominal modeling, errors, and perturbations to bound the OD analysis space with reasonable uncertainty to emulate imprecise nature of tracking data in operations. Simulated error sources appear in Table 1 along with standard deviation values and operational notes.

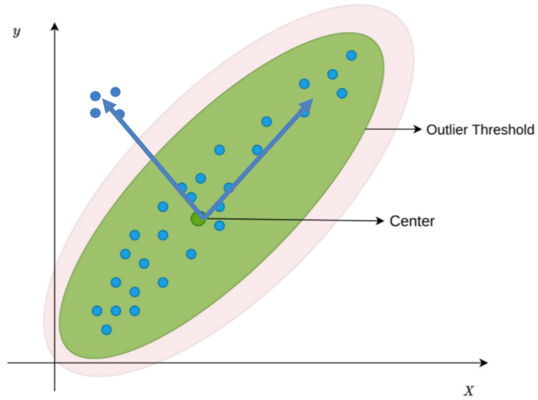


Figure 3: Two error vectors of equal magnitude but unequal Mahalonobis distance.

Table 1: Simulated Error Sources

Parameter Name	1-σ uncertainty	Notes
Initial Position Error	10 km	
Initial Velocity Error	1 cm/s	
Relative Mass Error	30%	
Relative SRP Area Error	30%	
Desaturation Maneuver ΔV	3.33 mm/s	1, 2
Uncrewed OMM Constant Error	0.47 mm/s	
Uncrewed OMM Magnitude Error	0.5%	
Crewed OMM Magnitude Error	0.5%	
OMM Pointing Error	0.333°	

[1] Desaturation occurs once before OMM execution and three times at Perilune.
[2] Crewed configurations desaturate additionally approx. every 6 hours.

Table 2: Tracking Data Quality Parameters

Parameter	Value (1-σ)
Range Noise (m)	1.0
Range Bias (m)	7.5
Range Rate Noise (mm/s)	0.1

The initial navigation state is perturbed from the truth by a random vector described in Table 1. The estimated area and mass are perturbed by relatively large values due to the simplistic "cannon-ball" SRP model and large dispersions on vehicle design mass, respectively. Uncrewed OMMs are performed with electric propulsion, which has a constant and scaled error, while crewed OMMs are performed with RCS propulsion with a scaled error. In addition to the perturbative errors described in Table 1, the truth and estimated spacecraft are propagated through spherical harmonic Lunar gravity models of degree and order $16{\times}16$ and $8{\times}8$, respectively. Of the errors in Table 11, only the desaturation and OMM execution errors are applied to the truth spacecraft, while all of the errors apply to the estimated spacecraft.

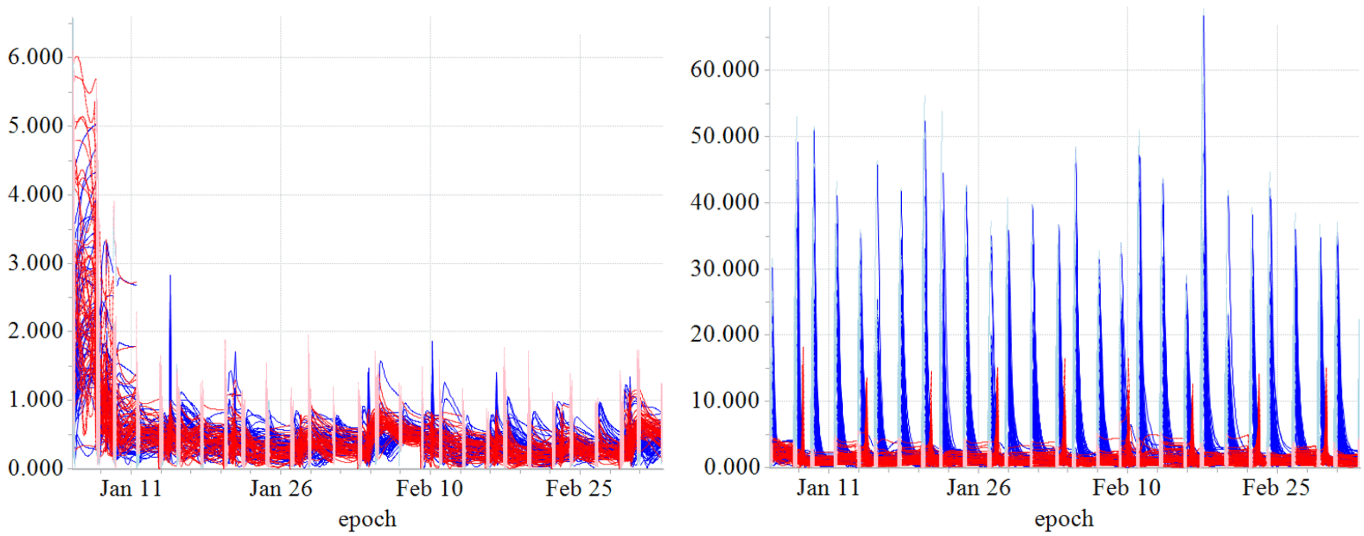
Tracking Data Modeling While the estimated spacecraft experiences additional perturbations and modeling differences that produce errors relative to the truth spacecraft, generated tracking data has errors and noise to emulate expected data quality from the Deep Space Network (DSN) X-band tracking. In Table 2, tracking data parameters are named and described. The three primary sites of Goldstone, Canberra, and Madrid are included. The range bias is modeled as a Gaussian distributed random value for each pass, but constant for the duration of that pass. DSN sites are selected automatically during simulation by selecting the most eastward site "almost" in view, which provides a long viewing time as Earth rotates in the Earth-Moon rotating frame. The simulation selects a site that is up to 5 degrees below the horizon if that is the most eastward site available. This selected algorithm results in occasional passes that are up to 20 minutes shorter than the full nominal 8 hours. DSN site handovers are not performed in this analysis to isolate tracking data quality from handover geometry.

Recall that uncrewed operations have three DSN passes per revolution while crewed operations assume constant tracking. In both cases, navigation performance is measured by predictions to perilune. This is to emulate the time it takes for tracking data to be downlinked, processed, and a navigation state uploaded to the spacecraft.

ERROR BUDGET ANALYSIS

The error budget analysis isolates drivers of prediction error by individually activating each perturbation for every permutation of error models considered. For this analysis, OMM execution error, desaturation perturbation, and data range bias are considered for the error budget analysis. Each error model case is then simulated through a representative nine-revolution mission with the nominal uncrewed tracking schedule in fifty iterations in a Monte Carlo process. Figures 4(a) and 4(b) depict the Mahalonobis distance separated by position (blue) and velocity (red) over time for the nine-revolution mission. Periods of active tracking are highlighted with light blue and pink, with predictions in dark blue and red. The positional M-distance spikes beyond 40 during active tracking, and settles during prediction. This is indicative of "filter collapse" of the navigation solution by the random range bias. Figure 4(a) has no error sources activated while Figure 4(b) has every error source activated.

In Figures 5(a) and 5(b), estimated state errors at perilune from each permutation of error modeling are displayed in a box-whisker plot. These represent the error at perilune from a nominal prediction span from the DCO. The notched line is the mean error, the box encompasses 50% of cases, the whiskers contain 99.3% of all cases, and the remaining outliers are plotted individually. Each column represents an error modeling case described with "(no) omm", "(no) desat", and "(no/rand) bias" for inclusion (exclusion) of OMM execution error, desaturation perturbations, and a random bias, respectively. The leftmost column can be thought of as the most simplified force and



(a) No errors (b) All errors

Figure 4: Mahalonobis Distance for position (blue) and velocity (red) over time, Uncrewed

error modeling, with the far right column as the nominal force and error modeling.

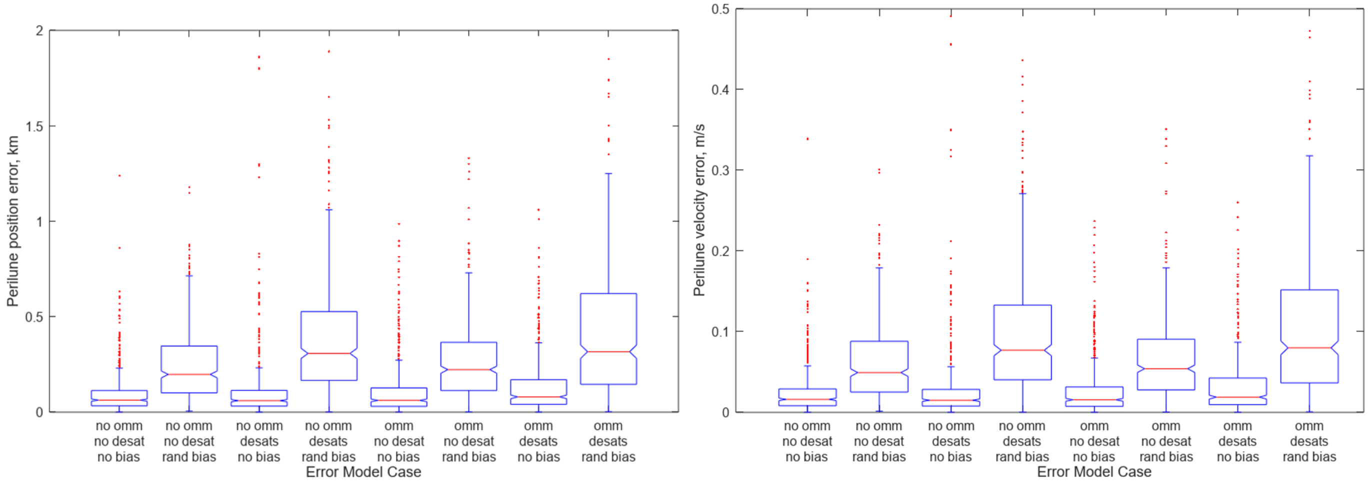
Uncrewed Analysis

Figures 5(a) and 5(b) show that the strongest driver of perilune error in both position and velocity is the inclusion of random range bias in the data. There is a smaller effect on perilune accuracy due to inclusion of random desaturation maneuver ΔV perturbations, and very little impact on accuracy from OMM execution error. The errors in the rightmost column reflect inclusion of all nominal error sources and can guide mission design as expected predictive navigation accuracy at perilune.

Crewed Analysis

The error budget analysis is run for the crewed vehicle scenario, which assumes constant DSN tracking and periodic desaturation maneuvers. To include the errors of random desaturations in predictions, many predictions from each navigation solution are propagated with random desaturation perturbations in each. Figures 6(a) and 6(b) show the Mahalonobis distances in position (blue) and velocity (red) over time for theconsideration of the crewed error budget analysis. The entire plot is highlighted in light blue and pink to illustrate continuous tracking. Figure 6(a) shows M-distances stable around 1.0 with some excursions due to perilune dynamics. Figure 6(b), however, maintains much higher M-distance values, particularly for position. There are 9 noticeable collapses of M-distance, which correspond to perilune passes, where range bias is briefly and partially observable. The high M-distance values with errors activated is due to the aforementioned “filter collapse” of the estimate around an erroneous solution offset by the DSN range bias. This filter collapse can be rectified by ideally reducing the solution error from the unobservable DSN range bias, or by reducing the information from range measurements passed into the filter to reduce its impact on covariance update.

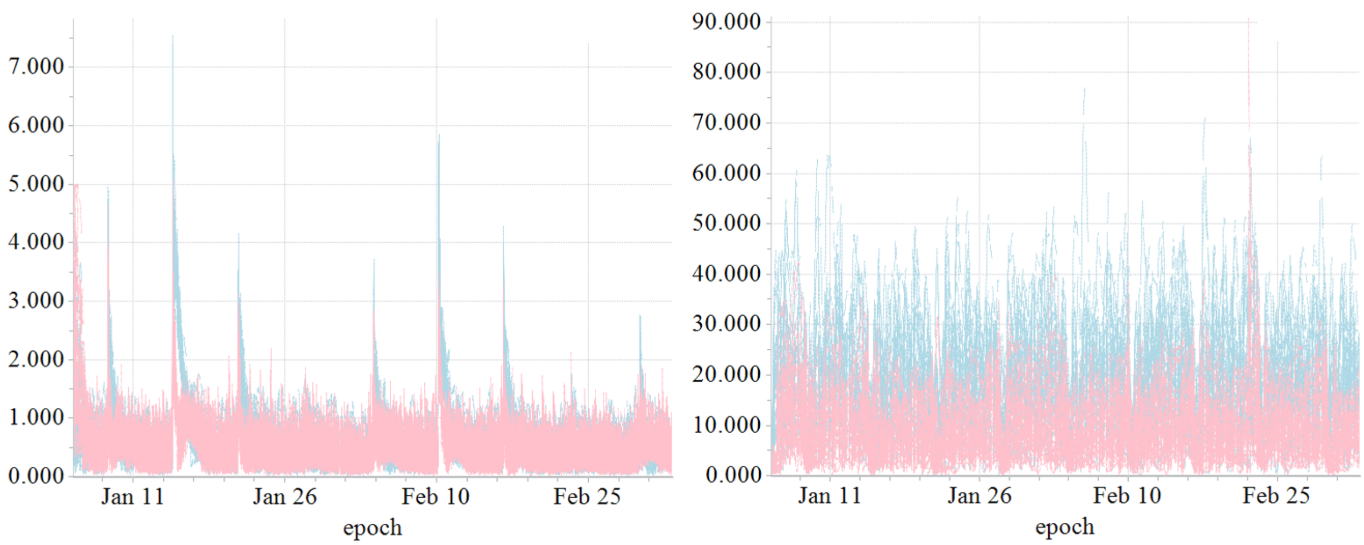
In Figures 7(a) and 7(b), perilune errors in position and velocity, respectively, are shown in a box-whisker plot for each labeled error modeling case. The perilune errors are plotted are after a nominal 16 hour propagation from the DCO. Each navigation solution at the nominal DCO is



(a) Position

(b) Velocity

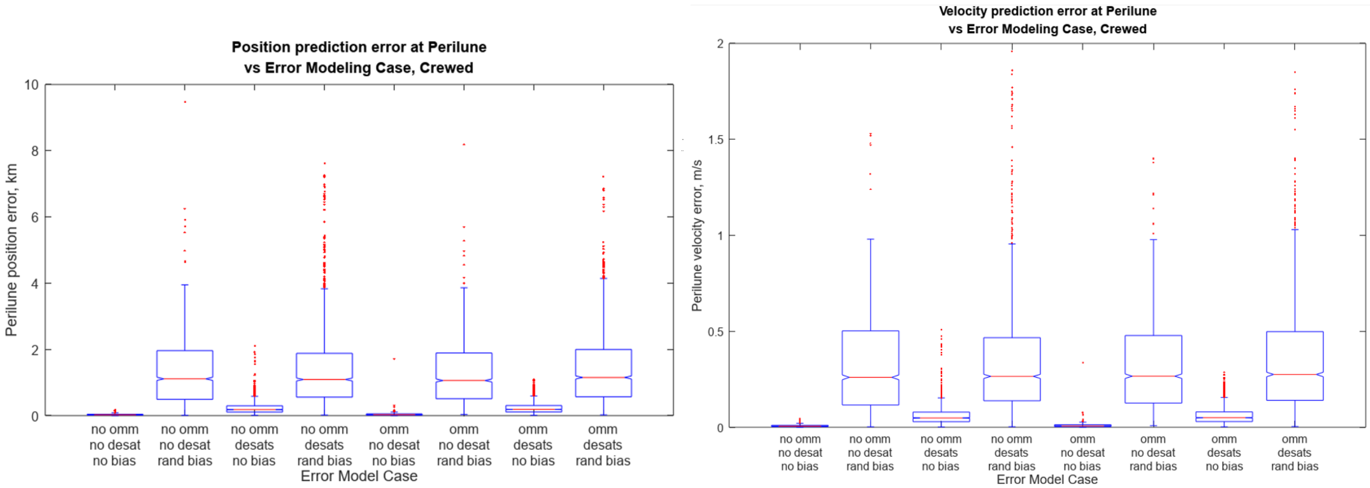
Figure 5: Errors at perilune vs Error Modeling Case, Uncrewed



(a) No errors

(b) All errors

Figure 6: Mahalonobis distance for position (blue) and velocity (red) over time, crewed



(a) Position (b) Velocity

Figure 7: Errors at perilune vs error modeling case, crewed

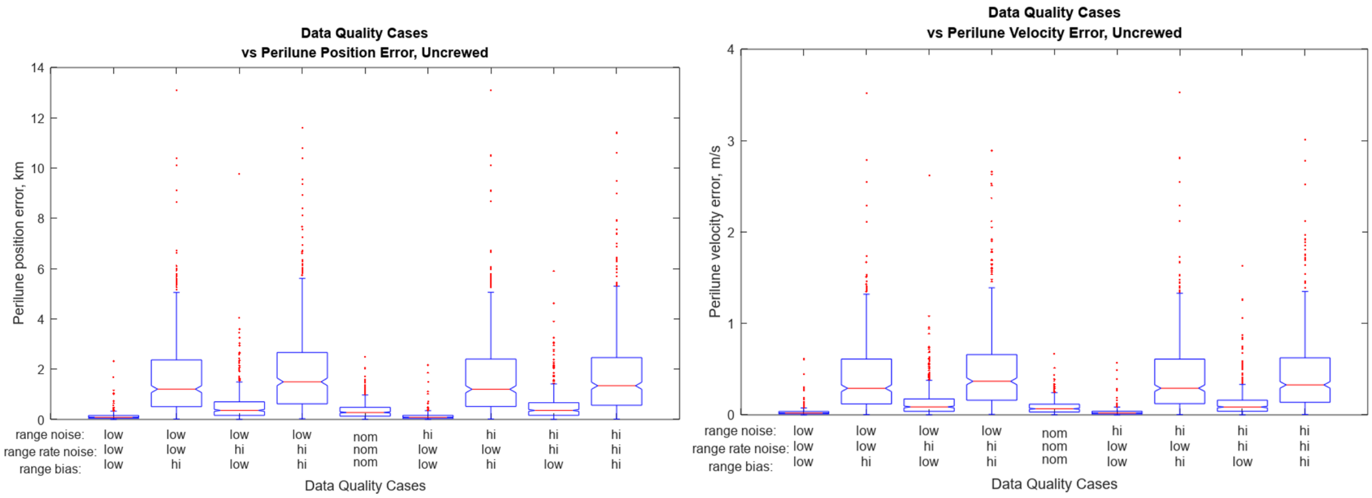
Table 3: Data Quality Parameter Cases

	Range Noise (m,1-σ)	Range Rate Noise (mm/s,1-σ)	Range Bias (m,1-σ)
Low	0.2	0.02	1.5
Nominal	1.0	0.1	7.5
High	5.0	0.5	37.5

propagated to the perilune multiple times, each with unique random perturbations from periodic desaturations (if they are activated for that case). The inclusion of a random range bias is the strongest contributor to prediction errors at perilune. Desaturations make a smaller negative impact to prediction accuracy at perilune, with OMM execution error not affecting perilune prediction accuracy. The next section investigates errors at perilune due to variations in data quality parameters, and will investigate multiple variances of range bias. Previous papers have also identified range bias as a significant driver of error budget.[10–12]

DATA SENSITIVITY ANALYSIS

The previous section shows that range data bias is the strongest contributor to perilune prediction accuracy compared to physical phenomena like random desaturation maneuvers and OMM execution error. This section focuses on the sensitivity of perilune prediction errors to changes in tracking data quality. In a similar fashion to the error budget, a representative mission of nine revolutions is simulated and processed for both uncrewed and crewed configurations under different permutations of tracking data quality. In Table 3, the values of data quality parameters simulated are listed. The variance of range noise, range rate noise, and range bias are adjusted to off-nominal values of 1/5 or 5 times their nominal value and processed in each permutation. Three data quality parameters and three values for each give rise to 27 combinations of data quality to process. For legibility, nominal values are omitted from the proceeding charts, except the "all nominal" case as the baseline.



(a) Position (b) Velocity

Figure 8: Errors at perilune vs data quality case, uncrewed

Uncrewed Analysis

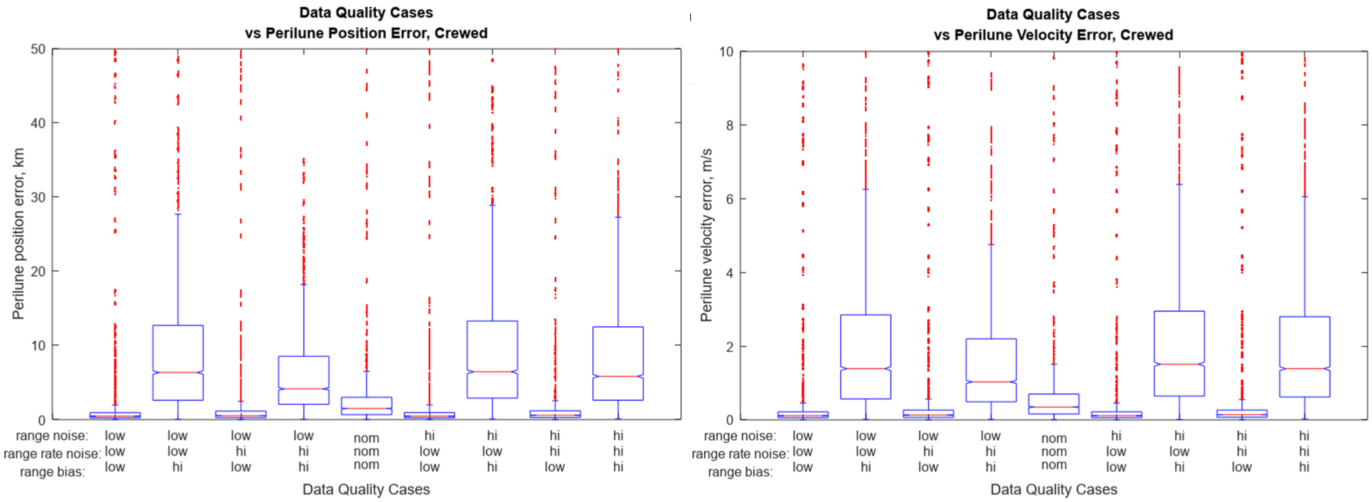
In order to isolate the sensitivity of prediction errors to each data quality parameter, each parameter is adjusted independently. The extreme-valued cases bound the expected prediction errors and highlight which data quality parameter is the most effective at controlling prediction accuracy. In Figures 8(a) and 8(b), the state errors at perilune from a nominal 16 hour prediction are plotted in a box-whisker plot for each extreme-valued data quality case, with the "all-nominal" case in the central column. The "low", "nom"(nominal), and "hi" names under each column correspond to the values listed in Table 3. Range bias has the largest impact on perilune prediction accuracy, with range rate noise variance having a smaller impact, and range noise variance having virtually no impact. It becomes more clear through these sections that tracking data range bias is important to prediction accuracy in this orbital regime. These results are consistent with previous results[10,11]

Crewed Analysis

The data sensitivity analysis is repeated for a crewed scenario, which again has continuous tracking and frequent periodic desaturation maneuvers, and for which cloned predictions with unique random perturbations are executed. In Figures 9(a) and 9(b), the position and velocity errors at perilune from cloned 16 hour predictions are shown in a box-whisker plot. The overall prediction accuracy of the crewed solutions are considerably worse due to the additional errors introduced by frequent random desaturation maneuver perturbations. In the crewed scenario, range bias is shown the be the strongest driver of perilune prediction error. Neither range noise nor range rate noise have a strong impact on perilune prediction accuracy. The next section investigates the sensitivity of perilune prediction accuracy to the time length of propagation directly.

DATA CUTOFF ANALYSIS

The studies so far have all assumed a nominal 16 hour prediction time length between the last definitive navigation solution and perilune, where state errors are documented. This section directly adjusts the time length of propagation to perilune and investigates its impact on performance at



(a) Position (b) Velocity

Figure 9: Errors at perilune vs data quality case, crewed

perilune.

Uncrewed Analysis

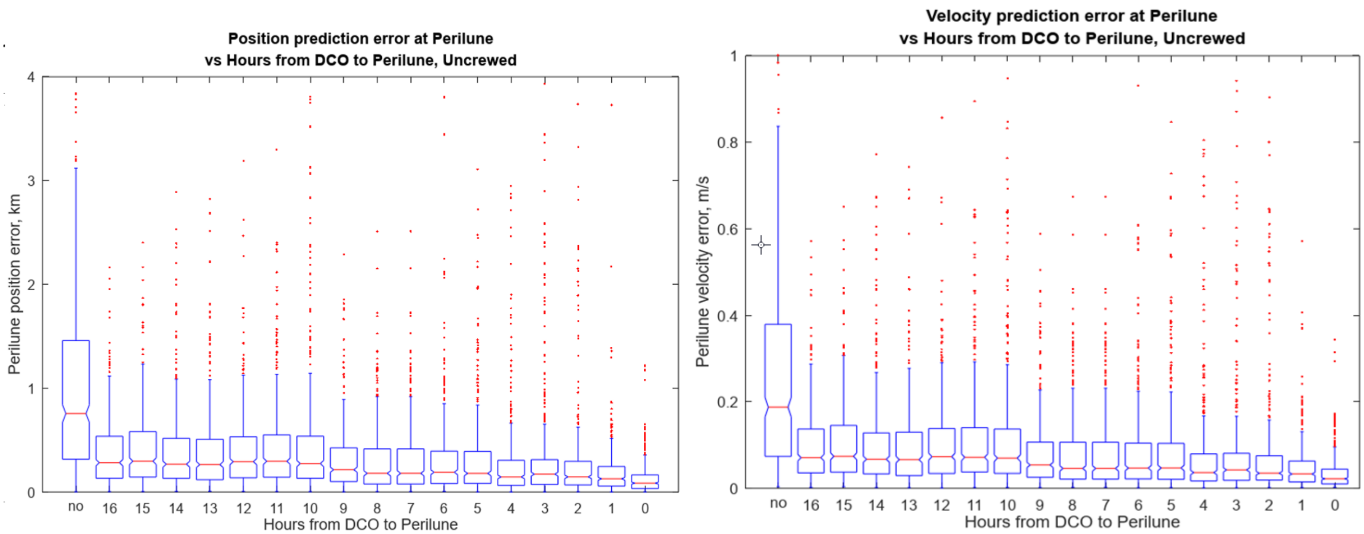
For the uncrewed scenario, the time length of propagation to perilune is reduced in one hour increments from the nominal 16 hours to zero. Additionally, a case where the post-OMM execution tracking data pass is skipped entirely is simulated. For that case, the navigation solution is effectively propagated from the end of the pre-OMM targeting data pass, which includes the OMM execution with execution error. In Figures 10(a) and 10(b), the errors at perilune from predictions of varying lengths in hours are shown in a box-whisker plot. The ”no” column represents the scenario where the post-OMM tracking data pass is skipped entirely. The errors at perilune seem to maintain their variance through decreasing propagation times until the final two columns, with ”no” post-OMM pass being the exception.

Crewed Analysis

The Data Cutoff analysis is repeated for the crewed configuration, and the navigation solutions at each propagation starting epoch are cloned and predicted with random desaturation errors. The prediction errors at perilune for position and velocity due to varying the prediction time length are shown in Figures 11(a) and 11(b), respectively. The prediction errors are universally larger compared to the uncrewed scenario. In this scenario, there is a monotonic decrease in prediction state errors that have three regions: a sharply decreasing error between predictions of 26 and 22 hours in length, a moderately decreasing error between 22 and 6 hours, and more quickly decreasing errors below for shorter prediction times.

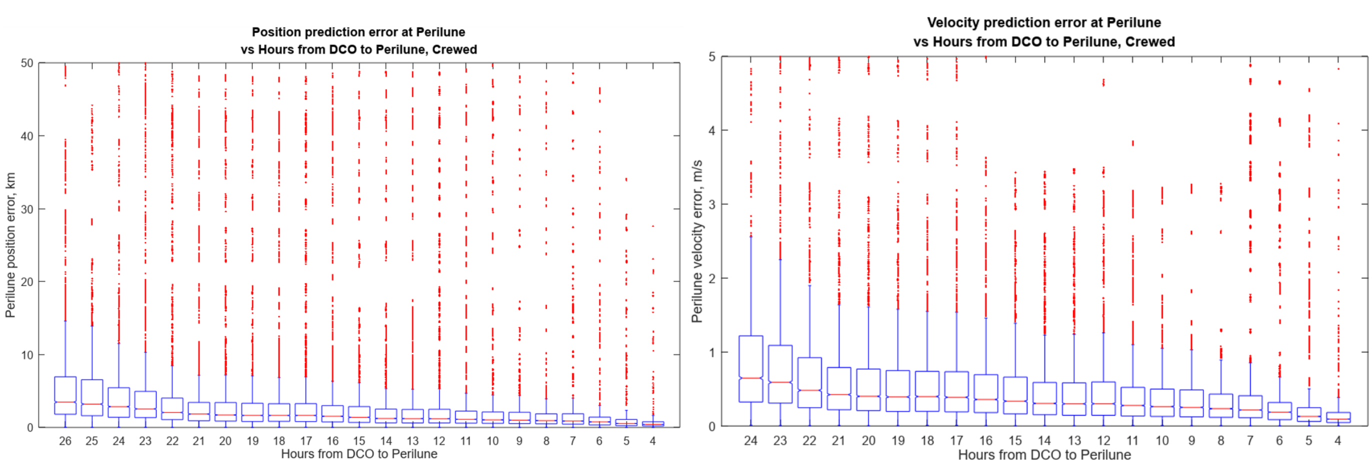
CONCLUDING REMARKS

Three studies are performed for both uncrewed and crewed configurations: Error Budget, Data Quality, and Prediction Length. In each study, a Monte Carlo simulation is performed on each of the test cases. The simulation for either uncrewed or crewed configurations represents a nine revolution



(a) Position (b) Velocity

Figure 10: Errors at perilune vs prediction length (hours), Uncrewed



(a) Position (b) Velocity

Figure 11: Errors at perilune vs prediction length (hours), Crewed

mission in the NRHO with sporadic or continuous tracking, respectively. For crewed scenarios, predictions are cloned from the last definitive solution and propagated multiple times with random errors.

The error budget analysis independently activates errors from random desaturation maneuvers, OMM execution error, and inclusion of tracking data range bias. Nominal predictions of 16 hours to perilune are documented for each test case. When tracking data bias is activated, it drives the positional Mahalonobis distance considerably higher while tracking data is actively being filtered. It is shown that for both uncrewed and crewed configurations, tracking data bias is the strongest driver among the three for errors at perilune. Desaturation maneuvers drove a small amount of error, with OMM execution error driving no error at perilune. There is a post-OMM tracking data pass that rectifies any execution error, but causes the filter to collapse around the erroneous solution offset by the range bias. For crewed scenarios, the relation is stronger: constant tracking rectifies errors from the frequent desaturation maneuvers, but range biases cause prediction errors to increase at perilune.

The tracking data quality sensitivity analysis independently adjusts the variance of tracking data range noise, range rate noise, and range bias. Nominal predictions of 16 hours are documented for each combination of tracking data qualities, and errors at perilune are documented. Range bias is the strongest driver of error at perilune, followed by range rate noise, with range noise not affecting accuracy at perilune. This trend holds for both uncrewed and crewed configurations. For both the error budget and data quality analyses, the range bias causes the navigation solution to be offset by the range bias, which in turn raises the positional Mahalonobis distance. This behavior is called filter collapse, where the errors are consistently higher in a direction of low uncertainty. It can be mitigated with additional observational geometry, data types,[13] or through process noise on the filter in the range direction.

The previous two studies both document state errors after the nominal prediction time length of 16 hours to perilune. The final study directly shifts the data cutoff epoch to document the sensitivity of prediction errors at perilune to prediction time length. The uncrewed configuration shows low sensitivity between prediction time length and perilune accuracy until the prediction time span falls below two hours. Excluding the post-OMM execution tracking data pass increases the errors at perilune substantially by not having any post-OMM data to rectify the executsion error. The crewed scenario sees a monotonic decrease in perilune errors relative to prediction time length.

The trends and values described in these analyses should help to guide feasible estimates for expected orbit determination performance for a spacecraft in this NRHO tracked by the DSN. Tracking data range bias was found to be the strongest driver of error and of high positional Mahalonobis distances. Future analyses could investigate methods to mitigate the impact to orbit determination performance due to random range biases.

ACKNOWLEDGMENTS

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