Navigation Sensor Technology Assessment Capability for Data-Driven Systems Analysis

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The capability to assess the mission performance of novel navigation technologies from a systems-level approach and to provide quantitative results is crucial. With growing interest and innovations from NASA's commercial partners, data-driven results that quantify the technological impact will guide research developments and facilitate stakeholder decision-making while requiring less time and resources. This paper presents a method to evaluate various sensor combinations and their impact on the overall system performance using an existing six degrees-of-freedom, physics-based engineering simulation for a government reference lunar lander as a testbed. Selected navigation technologies over various technology readiness levels, including Inertial Measurement Units, Navigation Doppler Lidar, and radar altimeter-radar velocimeter, were studied in this paper. Results using this testbed to perform sensitivity studies and to provide quantitative assessments are reported. One key finding is that there are diminishing returns for reducing sensor errors. The most influential sensor parameter to landing success are vehicle configuration and mission dependent. Results from this method could be used by stakeholders to make data-driven systems-based decisions and by technology developers as guidance for the specific parameter improvements that will have the most significant impact on mission success. This capability could be further used to assess alternative scenarios should one type of technology become unavailable or to re-assess initial assumptions and identify appropriate requirements from a system perspective.

I. Introduction

NASA is planning to return to the Moon through the Artemis program, with goals of landing the first woman and first person of color on the Moon and establishing the first long-term presence on the Moon. NASA will use the Human Landing System (HLS) as a mode of transportation to land astronauts on the lunar surface. Ultimately, the lessons learned on and around the Moon will support future human deep space missions to Mars.

Landing humans or payloads on the Moon, and subsequently Mars, will require collaborating with commercial and international partners to develop and build a lander with novel technologies. The capability to quantitatively assess the mission performance of these novel technologies from a systems-level approach is crucial, especially as more commercial partners innovate new technologies. These quantitative results can identify specific areas of research that will have the most impact on mission success and facilitate stakeholder decision-making. This capability to perform a technology assessment that considers mission performance metrics as success criteria is an important tool in characterizing the impact of different technology parameters.

NASA has surveyed and identified ten groups of technologies that could benefit HLS [1-10]. The Position Navigation and Timing (PNT) technology group is one of the critical groups that could have significant impact on the landing system. The focus of this study was to identify, assess, and quantify the impact of PNT technologies on

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HLS system design, risks, and operations. Through this study, PNT critical parameters, trends in performance, and their potential improvements have been identified and quantified. The outcome of this study provides guidance to stakeholders (NASA & HLS providers) and informs technology companies on ways to improve their PNT technologies. Short-term benefits of this capability are the evaluations of individual technologies. Long-term impacts of this capability are the ability to identify ways to use the technologies for specific mission requirements and the ability to pinpoint ways to improve the technologies for better mission success outcomes.

II. Method

A technology survey was performed to identify a variety of navigation sensors and related parameters for the assessment. In order to perform assessments, a testbed is needed. To that end, the team has leveraged an existing six degrees-of-freedom (6-DOF) lunar lander simulation developed by the Safe and Precise Landing Integrated Capabilities Evolution (SPLICE) Project [11]. This physics-based engineering simulation is used to evaluate the sensor suite from an integrated performance perspective and to determine its effect on the overall system performance. A rapid assessment capability was also developed and used to quickly evaluate sensor trade studies and to explore navigation filter sensitivities.

A. Overview of Simulation Model

The vehicle configuration modeled in this lunar lander simulation is a government reference design from the abbreviated NASA Design Analysis Cycle (mini-DAC) [12] that uses a storable propellant system and does not rely on cryogenics. The vehicle consists of two elements: a Descent Element and an Ascent Element. Figure 1 shows an overview of the trajectory concept of operations. The simulation begins with the "Loiter" phase, in which the vehicle loiters in a 100 km circular parking orbit. A De-Orbit Insertion (DOI) burn places the vehicle in an intermediate orbit, representing the "Coast" phase. Power Descent Initiation (PDI) begins at a distance from the landing target. A braking burn signifies the beginning of the "Braking" phase. The burn is initiated at the periapsis of the transfer orbit to reduce the vehicle's velocity and begin its descent toward the landing target. As the vehicle descends, it adjusts its orientation to facilitate the use of onboard navigation sensors and navigates its way to the landing target. As it nears the landing target, the vehicle enters the "Approach" phase and transitions into a terminal descent orientation to safely land on the surface at the last "Vertical Descent." At each phase during the Deorbit, Descent, and Landing (DDL) trajectory, the vehicle uses a different set of navigation sensors to provide information on the vehicle's state to its navigation solution. The concept of operations relating to navigation sensors is shown in Fig. 2. The Inertial Measurement Unit (IMU) provides vehicle position, velocity, and attitude measurements throughout the DDL trajectory. The Deep Space Network (DSN) provides measurements in the "Loiter" phase, and the star tracker provides additional vehicle attitude measurements during the "Loiter" and "Coast" phases. Additional vehicle position and velocity measurements during the "Braking" phase and "Approach" phase are provided by the Terrain Relative Navigation (TRN) and Navigation Doppler Lidar (NDL), respectively. Further details on the framework and simulation modelling can be found in Lugo et al. [11].

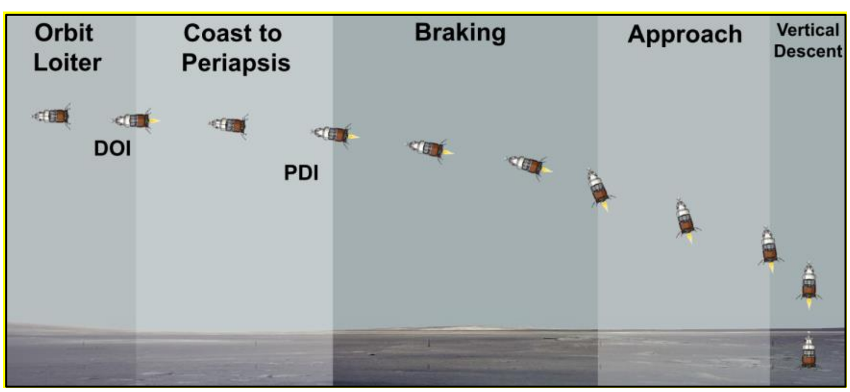


Fig. 1 NASA Design Analysis Cycle (mini-DAC) trajectory [11].

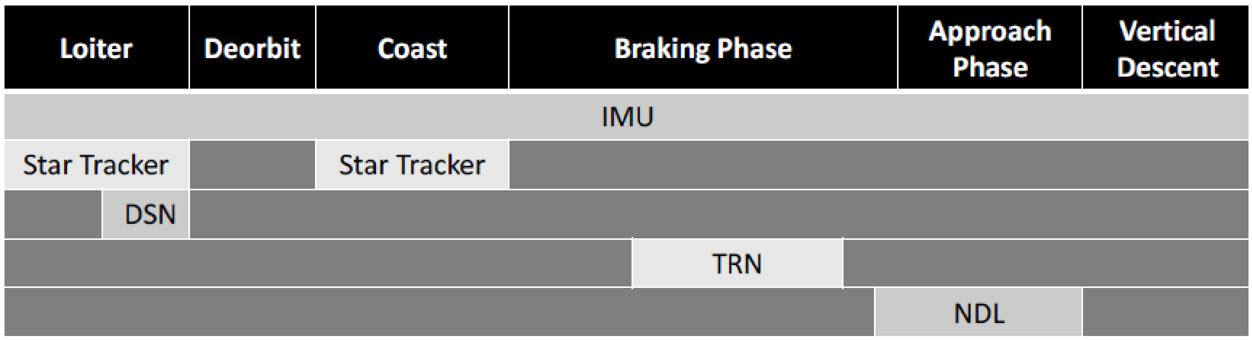


Fig. 2 Navigation sensor suite concept of operations [11].

B. Caveats and Assumptions

A caveat to using a detailed 6-DOF simulation for technology assessments is that the results are only applicable to this simulation and sensor suite. A different vehicle or trajectory design may require a different set of sensors and may have different error sensitivities. The preliminary results presented in this paper will require verification with the trajectory designed for a different sensor suite and landing mission. This paper explains the method used and how it could be used for alternative configurations. Specific results for alternative configurations may differ from this government reference design.

For this study, the focus was on technology hardware and no attempt was made to alter guidance software to account for sensor uncertainties. It is possible to use software to mitigate and compensate for some sensor uncertainties to improve sensor performance, but software cannot eliminate the effects all types of uncertainties. Therefore, it is valuable to consider the impact of hardware technology first when selecting navigation sensors for specific missions.

C. Technology Survey

A wide variety of navigation sensors were surveyed in this study, including IMUs, radar velocimeters, radar altimeters, TRN, and NDL. This paper reports results for IMUs, with ongoing progress reported for radar velocimeter, radar altimeters, and NDL. Critical parameters for these sensors were gathered by collecting publicly available data from online sources. Parameters not publicly available were obtained from the vendors who create those products. To avoid sharing any sensitive information about specific products, data has been genericized and anonymized.

1) IMUs

One of the focuses of this study is to investigate how IMU error parameters affect the landing performance of a spacecraft landing on the Moon. The three baseline IMUs used in this study were defined by the SPLICE project as high-, medium-, and low-quality, representing the state-of-the-art in current IMU technology based on performance. These were initially compared to the anticipated performance of IMUs in development. IMUs in development were labeled as “technology pull” and represented by creating two IMUs that are representative of the equivalent quality available in the near future. The two sets of composite parameters for the technology pull IMUs are listed in Table 1. The first set uses the best or lowest value of each error parameter from the entire collection of all the IMUs identified in the technology survey. The second uses the median value of each error parameter from the entire collection. The error characteristics of the individual technology pull IMUs were generally between these two bounds. None of the IMUs under development had higher sensor parameters than the high-quality IMU identified as the state-of-the-art. This is because the majority of new IMUs are focused on reducing mass, power, and cost rather than improving performance.

The exception to this is the Quantum Positioning System (QPS). There are two types of QPS, active and passive [13]. The active QPS operates similar to GPS, requiring signals from multiple satellites to determine the location of a spacecraft. The passive form of QPS is similar to an ultra-sensitive IMU. Only the passive form of QPS was included in this study. QPS is a low technology readiness level (TRL) technology and there are no prototypes with published performance parameters. It is theorized that QPS could be 1000 times as sensitive as traditional IMUs [13]. To compare with traditional IMUs, three placeholder QPS units were used with theoretical performance parameters 10, 100, and 1000 times better than the high-quality state-of-the-art IMU used in this study.

Table 1 shows a comparison of all the IMUs and error parameters used in this study, including the high-, medium-, and low-quality state-of-the-art IMUs, the best and median values of the IMUs currently under development, and the 1000, 100, and 10 times QPS units.

Table 1 IMU Technology Survey Summary

Parameter	Units	SPLICE Baseline High	SPLICE Baseline Medium	SPLICE Baseline Low	Generic (Tech Pull) Best	Generic (Tech Pull) Median	Quantum Positioning System High (1000x)	Quantum Positioning System Medium (100x)	Quantum Positioning System Low (10x)
Accelerometer Misalignment (X,Y,Z)	arcsec	17	45	20	61.8	386.25	0.017	0.17	1.7
Accelerometer Scale Factor (X,Y,Z)	ppm	450	525	900	70	555	0.45	4.5	45
Accelerometer Bias* (X,Y,Z)	micro-g	84	300	900	30	62.5	0.084	0.84	8.4
Accelerometer Velocity Random Walk (X,Y,Z)	micro-g	433	150	105	24	347	0.433	4.33	43.3
Gyroscope Misalignment (X,Y,Z)	arcsec	19	75	60	61.8	386.25	0.019	0.19	1.9
Gyroscope Scale Factor (X,Y,Z)	ppm	27	15	100	300	630	0.027	0.27	2.7
Gyroscope Bias* (X,Y,Z)	deg/hr	0.036	0.150	0.300	0.12	0.6	0.000036	0.00036	0.0036
Gyroscope Angular Random Walk (X,Y,Z)	deg/sqrt(hr)	0.015	0.018	0.210	0.01	0.0275	0.000015	0.00015	0.0015
Sample Rate (nominal)	Hz	200	200	200	200	200	200	200	200

*Reduced by a factor of 10 in the simulation to account for calibration during quiescent on-orbit period prior to deorbit and landing

2) NDL and Radar Altimeter-Radar Velocimeter Combination

A different approach was taken for the NDL and radar altimeter-radar velocimeter combination technology survey. NDL [14] is a technology being developed by NASA Langley Research Center and is not available from multiple commercial manufacturers like other sensors. As a result, this assessment used the currently available third generation (Gen-3) NDL parameters. The Gen-3 NDL parameters are shown in Table 2. There are a variety of radar altimeter and radar velocimeter sensors commercially available with a range of accuracy and precision. They are approximately an order of magnitude less precise than the NDL. Rather than evaluate commercially available altimeter-velocimeter combinations, the altimeter-velocimeter combination was assumed to have measurement errors ranging from 1 to 100 times that of the NDL measurement accuracy to facilitate expressing landing performance in terms of the NDL performance.

Table 2 NDL Technology Survey Summary

Gen-3 NDL	
Max line-of-sight range	4 km
Max line-of-sight velocity	200 m/s
Precision	
line-of-sight range	2.2 m
line-of-sight velocity	0.02 m/s
Data rate	20 Hz
Weight	14 kg
Power	80 W
Size	11x9x8 inch

D. Approach

The simulation framework was set up such that the sensor models were parametrized. This enables parametric studies of the sensor parameters. The sensor parameter values identified in the technology survey were input to the simulation framework. Multiple series of Monte Carlo simulations of 8000 runs were used to evaluate sensor sensitivities and performance. Performance metrics (e.g., landing accuracy and safe landing velocity) were identified and used to evaluate mission success. The following performance metrics were identified for this study to determine landing success. All requirements must be met to be considered a “success.”

1) Landing precision: range to the target at touchdown is 100 m.
2) Horizontal velocity at touchdown is less than 1 m/s.
3) Vehicle angle is less than 3 degrees off vertical at touchdown.
4) Maximum vehicle angular rates about all axes are less than 0.5 deg/s.

III. Results

In this section, results using this technology assessment capability are presented. Each assessment example showcases how this capability identifies improvements for low to high TRL technologies. Ongoing progress is also documented. The preliminary results presented will require verification with the trajectory designed for a different sensor suite and landing mission. Specific results for alternative configurations may differ from this government reference design.

A. Evaluating Existing IMUs

In this assessment, a series of Monte Carlo analyses was performed to determine the sensitivity of landing performance to the quality of existing IMUs. Characteristics of the IMUs from the SPLICE project were used as representative values of existing IMUs that have been used in aerospace applications. These sets were categorized as low-, medium-, and high-quality based on the overall performance of each IMU, as shown in Table 1. For this comparison, three separate Monte Carlo analyses were performed using the same vehicle configuration, with the only difference being the IMU sensor model, which was generic in nature and accounted for typical IMU errors in a parametrized fashion. The accelerometer and gyroscope bias errors listed in Table 1 were reduced by a factor of 10 to account for assumed calibration. Each analysis included 8,000 dispersed DDL trajectories beginning at deorbit from the initial 100 x 100 km parking orbit and ending at touchdown. The IMU is active for the entire duration of the DDL trajectory and other sensors are activated depending upon the specific flight phase as shown in Fig. 2. For each Monte Carlo analysis there were 88 dispersed input parameters: 34 parameters related to vehicle design and initial state uncertainties and 54 sensor-related error uncertainties (24 related to IMU and 30 related to the non-inertial sensors). The same dispersions were used in each Monte Carlo analysis, with the exception of the IMU-related error uncertainties.

The landing success metrics from Section II.D were computed for each of the three Monte Carlo analyses and used to quantify the effect that IMU quality had on overall landing performance. For the high-quality IMU, only 0.8% of cases failed to meet the safe landing requirements. There was a moderate decrease in performance for the medium-quality IMU (4.5% failure rate) and significant drop-off for the low-quality IMU (15.2% failure rate).

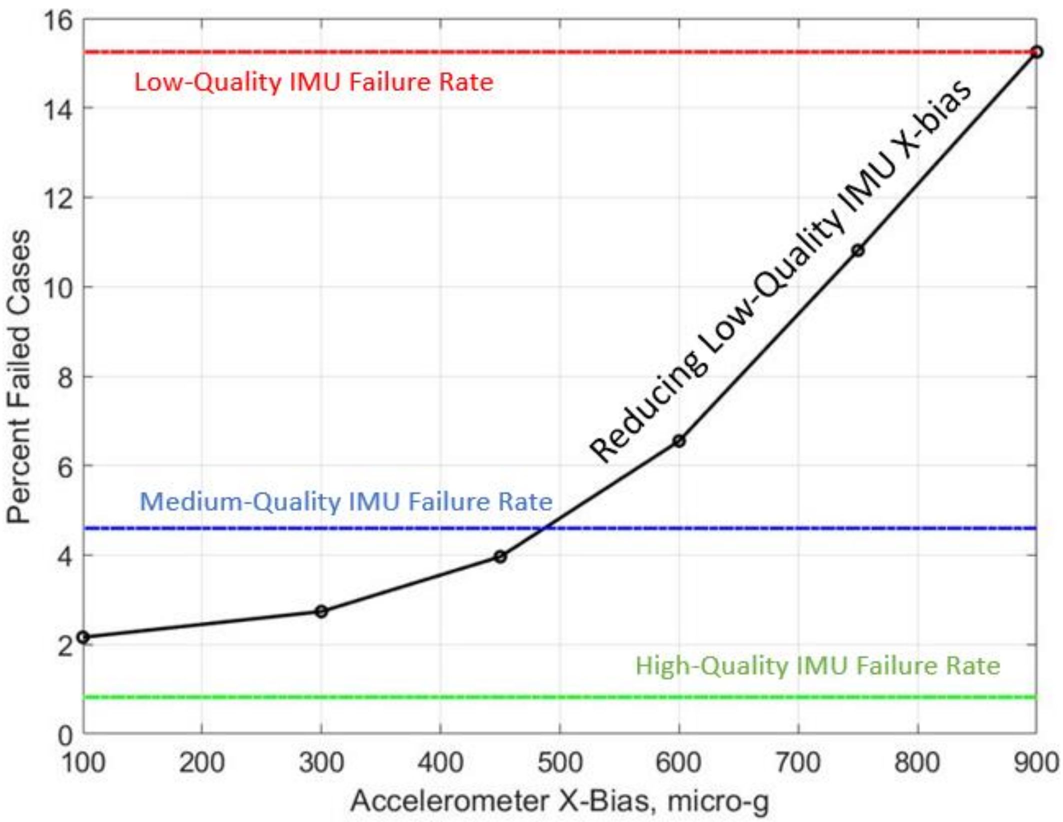


Fig. 3 Percent failed case improvement from reducing low-quality IMU accelerometer X-bias.

Additional Monte Carlo studies were performed to determine the sensitivity of landing performance to each of the individual accelerometer and gyro error parameters listed in Table 1 (i.e., misalignment, scale factor, bias, and random walk). For the three IMUs considered, the X-accelerometer bias error was the most influential parameter by a significant margin. Figure 3 shows the results of a follow-on study where additional Monte Carlo analyses were performed using all of the low-quality IMU error parameters except for X-accelerometer bias, which was varied from the low-quality level (900 micro-g) to the high-quality level (100 micro-g). The results show that the landing failure rate for this configuration decreased as this one error parameter was lowered. When the error fell below 500 micro-g, the overall landing performance of the configuration with the low-quality IMU actually surpassed the configuration with the medium-quality IMU. When the error was reduced to 100 micro-g, landing performance nearly matched that of the high-quality IMU. This assessment highlights the capability to evaluate how individual error parameters affect specific landing metrics. Results can be relayed to developers to indicate where further investment would be most beneficial

B. Evaluating IMUs Currently Under Development

Another Monte Carlo study was performed to assess the performance of the "technology pull" IMUs described in Section II.C. Table 1 lists representative values of the error parameters associated with the technology pull IMUs. These IMUs are currently under development at several vendors, with a focus on reducing mass, power, and cost rather than improving performance. The goal of this study was to determine if these future IMUs, which are currently at mid to high TRL, could be used for precision landing on the Moon, and if not, what improvements would make them suitable for this purpose.

Table 3 Comparison of Landing Performance using Representative IMUs from Technology Pull

	SPLICE Baseline			Generic (Tech Pull)	
	High	Medium	Low	Median	Best
Run to Completion (%)	99.5	98.6	88.8	29.4	98.2
Meet Horizontal Velocity Limit at Touchdown (%)	99.2	95.5	84.8	13.0	94.7
Meet Pitch Rate Limit at Touchdown (%)	99.3	96.9	85.9	17.0	96.3
Meet Yaw Rate Limit at Touchdown (%)	99.3	96.9	85.8	17.1	96.3
Meet Roll Rate Limit at Touchdown (%)	99.3	97.0	86.1	17.9	96.4
Meet Pitch Angle Limit at Touchdown (%)	99.3	96.7	85.4	14.5	96.0
Meet Vertical Velocity Limit at Touchdown (%)	99.3	96.7	85.9	15.7	96.2
Successful Land Percentage (%)	99.2	95.4	84.7	12.6	94.7

To assess performance, two 8000-case Monte Carlo analyses were conducted; one was conducted with each error parameter set to Median and the other with each parameter set to Best. The landing success metrics were computed (see Section II.D). As was done previously, accelerometer and bias terms were reduced by a factor of 10 to account for on-orbit calibration. For the representative technology pull IMU composed of median error values, the overall successful landing percentage (shown in Table 3) was only 12.6%, which is not sufficient to support a lunar landing mission. When all of the best (i.e., lowest) error characteristics were assumed, the success rate approached 95%, which is comparable to the existing medium-quality IMU considered in Section III.A. Additional Monte Carlo analyses were performed to evaluate sensitivities and identify which specific error parameters were most influential on the overall landing success rate. Initially, individual Monte Carlo analyses were performed by changing one error parameter at a time from the median value to the best value. For example, the "Best Scale Factor" case assumed median values for accelerometer/gyroscope misalignment, random walk, and bias errors but assumed the best value for scale factor errors. Results for each of these sensitivity analyses are shown in Fig. 4, where it is seen that landing performance was most sensitive to misalignment errors and random walk.

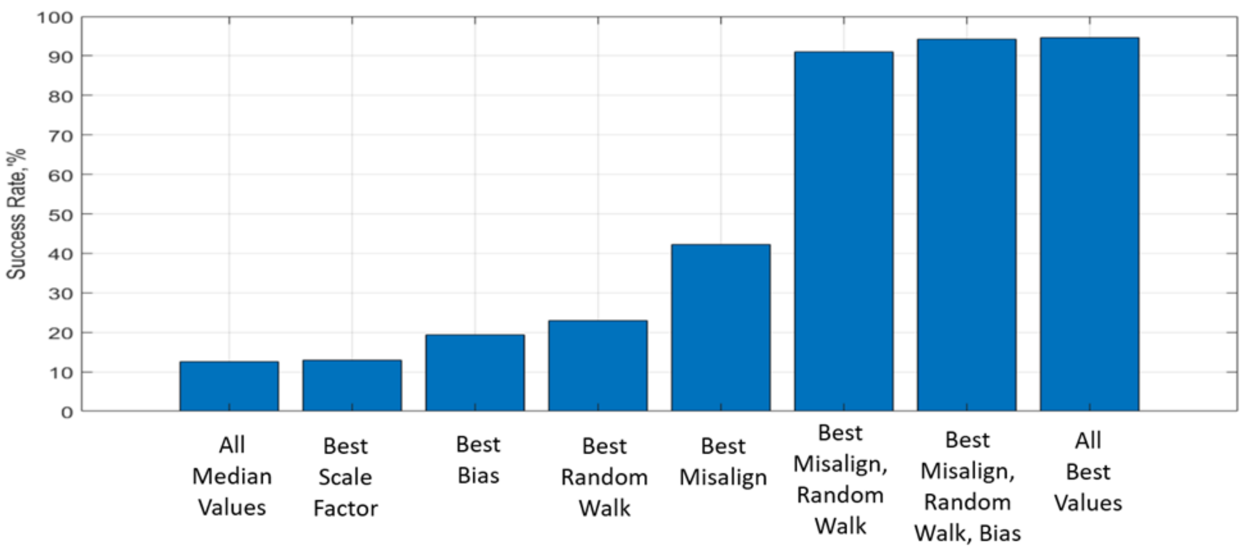


Fig. 4 Results of technology pull IMU sensitivity study.

However, even when the best value for misalignment was used, the landing success rate was still under 50%. Additional cases considered using the best values for more than one error parameter and it was found that the largest improvement occurred with best values for misalignment and random walk errors. For that case, the landing success rate exceeded 90%, and the improvement over the baseline median IMU was larger than the sum of the individual improvements when each error was increased one at a time.

The high sensitivity to misalignment and random walk errors for the technology pull IMUs differed from the previous study of existing IMUs, where accelerometer bias was found to be most influential error parameter. This difference was likely due to the smaller bias and the much larger misalignment errors associated with the technology pull IMUs, underscoring that the results of this type of analysis are vehicle and mission dependent. This assessment showcases the capability to identify sensitive parameters for an IMU with median values and the parameters to improve for better landing success for lunar missions. For vehicles that use a median value IMU, improvements in misalignment and random walk errors have the potential to improve landing success.

C. Evaluating QPS

This assessment focused on identifying the level of improvements necessary for a passive QPS that has the characteristics of an ultra-sensitive IMU. Specific parameters tied to a physical prototype were not used because the technology survey did not find prototypes for this specific technology. However, sources claim 1000 times improvement over existing IMUs [12]. Parameters of the high-quality IMU were scaled to represent three quality levels of QPS, shown in Table 1, by reducing the sensor error parameters by 10, 100, and 1000 times, which is equivalent to reducing the parameters by 90%, 99%, and 99.9%, respectively. Three Monte Carlo analyses were performed using the DDL trajectory with the IMU parameters for each QPS quality level. Landing success rates were calculated using the criteria listed in Section II.D and compared. The results showed that the landing success rate for all three exceeded 99%, and that the differences in landing success rate were within 0.1%.

Because the success rates were very high, a follow-on study was performed to explore the threshold where the landing success rate approached 99%. Additional Monte Carlo runs were performed by reducing the error parameters of the high-quality IMU by 50% and 80%. Results in Fig. 5 show that reducing IMU errors by 50% reduces failed landings significantly from the current state-of-the-art high-quality IMU. Results further show that reducing error past 50% has diminishing returns. Landing success rates for the representative IMUs with more than 50% error reduction oscillate within 0.1% due to Monte Carlo dispersions. This assessment is an example of the capability's potential to identify the level of improvements technology companies need to develop in IMUs for successful lunar landing. Instead of improving the parameters to 1000 times better than the current state-of-the-art IMU, equivalent to reducing the errors by 99.9%, resources can be allotted to improving the parameters by 50% for successful lunar landing missions. The level of improvements needed may vary depending on the vehicle and trajectory design.

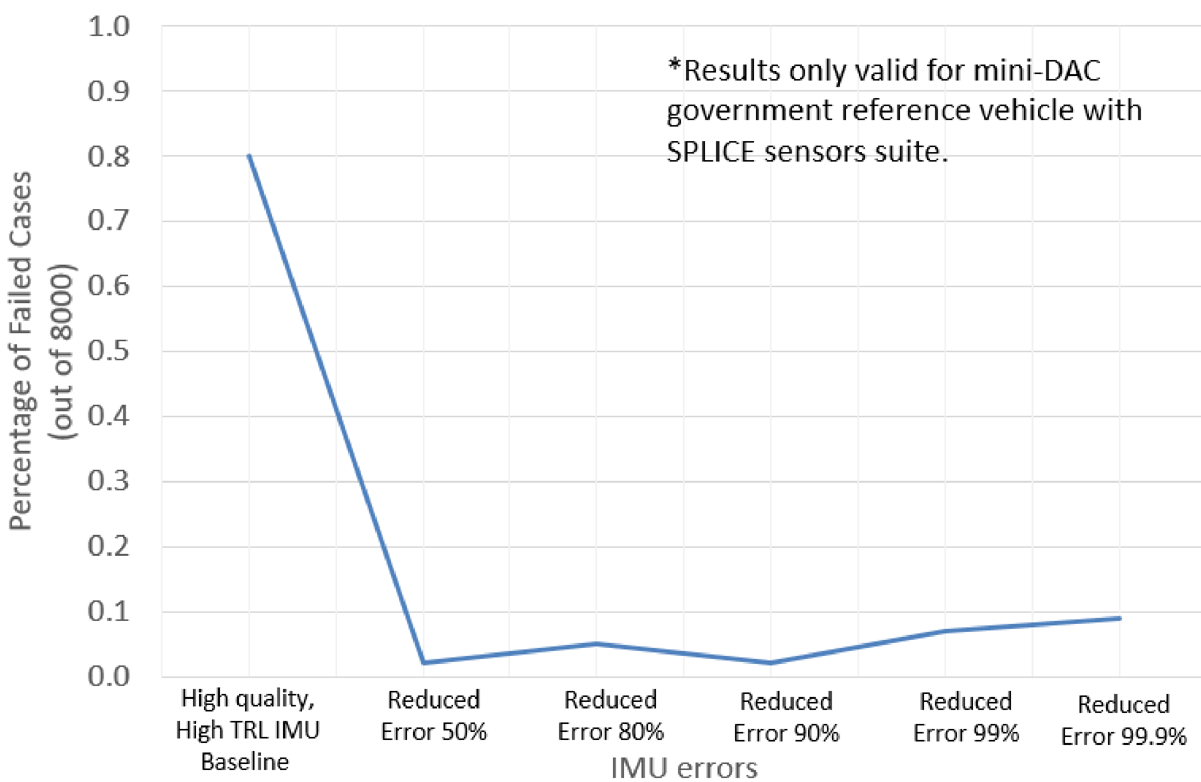


Fig. 5 Percent failed case improvement when reducing IMU errors.

D. Ongoing Work: Evaluating Radar Altimeter and Radar Velocimeter Combination as an Alternative for NDL

In the government reference design, the descent element uses a NDL sensor to measure altitude and velocity during the "Approach" and "Vertical Descent" phases of its descent trajectory shown in Fig. 1. The mini-DAC simulation incorporates a high-fidelity model of the third generation NDL (Gen-3 NDL) that begins measuring altitude and velocity at an altitude of 3 km above ground and continues measurements down to an altitude of approximately 30 m above ground.

Fig. 6 Gen-3 NDL.

The Gen-3 NDL simulation model accounts for the effects of range to ground and the vehicle's velocity on its measurements, thus its measurement uncertainty is a function of line-of-sight (LOS) range to ground and the vehicle's velocity. The Gen-3 NDL hardware is shown in Fig. 6 and its performance specifications are shown in Table 2. A fourth generation NDL (Gen-4 NDL) design has been released that increases the NDL's maximum line-of-sight range to 7 km and improves the precision of its velocity and altitude measurements. However, the Gen-4 NDL simulation model had not been released for integration into the government reference simulation at the time of this study.

Due to the high-fidelity nature of the NDL model, it was not possible to represent the Gen-4 NDL measurement precision in the mini-DAC simulation by adjusting simulation inputs, thus the effect of the Gen-4 NDL advancements on landing performance could not be quantified without the Gen-4 NDL simulation model. However, a qualitative assessment of increasing the NDL's maximum operational altitude was made by starting NDL measurements in the mini-DAC simulation at an altitude of 5 km above ground, instead of an altitude of 3 km in the original simulation. With the 5 km start altitude, the percentage of fully successful landing cases increased by 5%. An improved estimate of the lander's altitude and velocity earlier in the descent trajectory has a significant effect on the government reference mini-DAC lander making a successful landing. However, the landing performance improvement using the Gen-4 NDL model may be different than the qualitative 5% estimate.

The combination of a radar altimeter and a radar velocimeter as an alternative or redundant system for the NDL was also evaluated to determine the landing performance. The government reference mini-DAC simulation had low-fidelity radar altimeter and radar velocimeter models available for use in the navigation filter. The simulation was modified to use a radar altimeter sensor and a radar velocimeter sensor in place of the NDL. Currently available radar altimeter and radar velocimeter sensor measurements are approximately 10 to 25 times less precise than the NDL sensor and radar altimeters have a lower operational altitude than the NDL. Rather than simulate a particular radar altimeter or radar velocimeter sensor, a generic approach was used where the precision of the altitude and velocity measurements were varied from the Gen-3 NDL specifications to 100 times less precise than the Gen-3 NDL specifications. The measurement precision was varied in the simulation by applying 1, 10, 25, 50, and 100 multipliers on the Gen-3 NDL standard deviation of the sensor measurements to simulate an altitude and velocity measurement system over a range of quality. The altitudes above ground at which the radar velocimeter and radar altimeter begin taking measurements were also changed in the simulation to be representative of state-of-the-art radar altimeter and radar velocimeter sensors. This approach quantified the effect on landing performance of using more precise, state-of-the-art, and less precise radar altimeter-radar velocimeter sensor combinations. Figure 7 shows the percentage of successful landings normalized to the radar altimeter and radar velocimeter quality equivalent to the Gen-3 NDL measurement precision. The results indicate that there is little degradation in the landing performance for radar altimeters and radar velocimeters with up to 10 times less precise measurements. However, the landing performance does begin to degrade nearly linearly as the radar altimeter and radar velocimeter precision decreases more than 10 times that of the Gen-3 NDL, with a 3% degradation at 100 times less precise measurements. The altimeter and velocimeter models in the government reference mini-DAC simulation were low fidelity. Thus, the trend in landing performance may change with higher fidelity models.

This ongoing assessment evaluates the impact of an altitude and velocity measurement unit and its effects on the overall success of lunar landing missions. The trends revealed an error threshold the altitude and velocity measurement system must meet to ensure landing success.

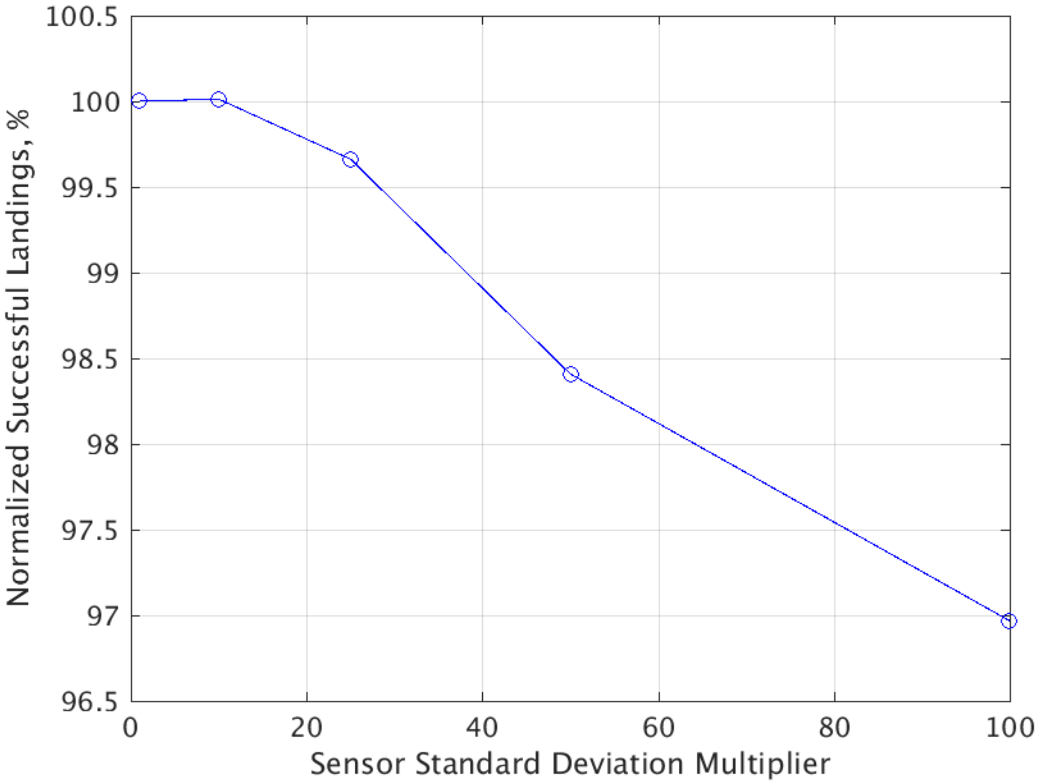


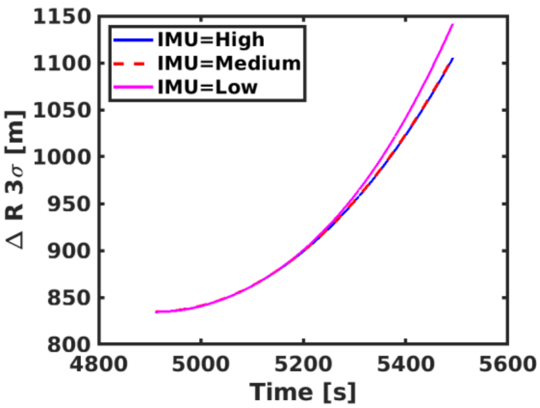
Fig. 7 Successful landing rate for radar altimeter and velocimeter combination while varying sensor measurement quality (relative to Gen-3 NDL).

IV. Enhancing the Technology Assessment Capability using NewSTEP

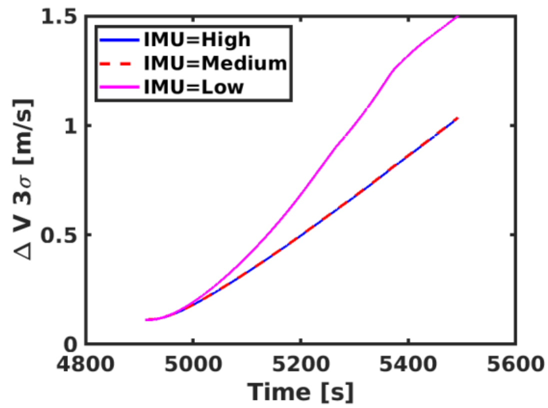
The Monte Carlo approach of assessing sensor performance can be costly in terms of the time needed to run thousands of high fidelity 6-DOF simulations. New Statistical Trajectory Estimation Program (NewSTEP) is a Kalman filter code specifically formulated for solving trajectory reconstruction problems [15]. NewSTEP can be configured to emulate navigation system performance and can produce uncertainty estimates from linear covariance analysis [16]. Linear covariance analysis enables rapid trade studies as it does not require Monte Carlo techniques for uncertainty quantification. This rapid assessment capability can be used to explore sensor capabilities or other navigation filter assumptions, which includes filter-tuning parameters to ensure filter consistency. Filter consistency is a measure of how well the filter's estimate of its navigation errors match with actual error. Inconsistent filters can cause issues: for instance, if the vehicle cannot make accurate estimation of its position above ground, it could engage its landing sequence too early or too late. However, NewSTEP’s linear covariance analysis mode does not capture dispersions as it uses a nominal trajectory to propagate uncertainty estimates. Therefore, it is complimentary to the Monte Carlo approach.

A. NewSTEP Results

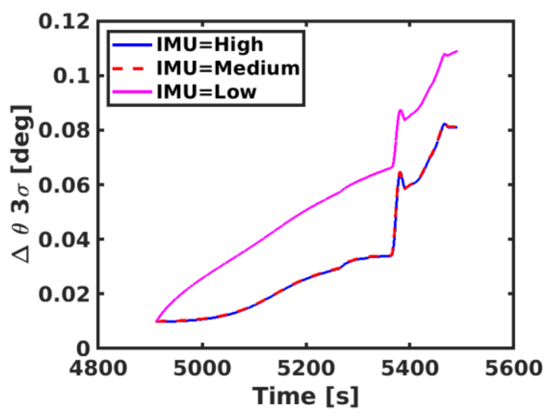
The trajectory reconstruction tool was used in its linear covariance analysis mode to assess various IMUs for the government reference vehicle. An initial linear covariance analysis was performed using the SPLICE-defined IMU parameters consisting of low-, medium-, and high-quality sensors [17]. The sensor parameters are summarized in Table 1. The results of the linear covariance analysis are shown in Fig. 8, comparing the 3-sigma values of vehicle position error (Fig. 8a), vehicle velocity error (Fig. 8b), and vehicle attitude error (Fig. 8c) measured from the IMUs over the DDL trajectory simulation. These results are for pure inertial navigation based on DSN initialization and do not consider other sensors such as TRN. It is expected that a better IMU quality would lead to smaller measurement errors. The results indicate nearly identical navigation performance between the medium- and high-quality IMUs for the DDL trajectory near touchdown. This type of result is useful for choosing sensor options, showing that there are diminishing returns as sensor quality improves.



a. Vehicle position error.



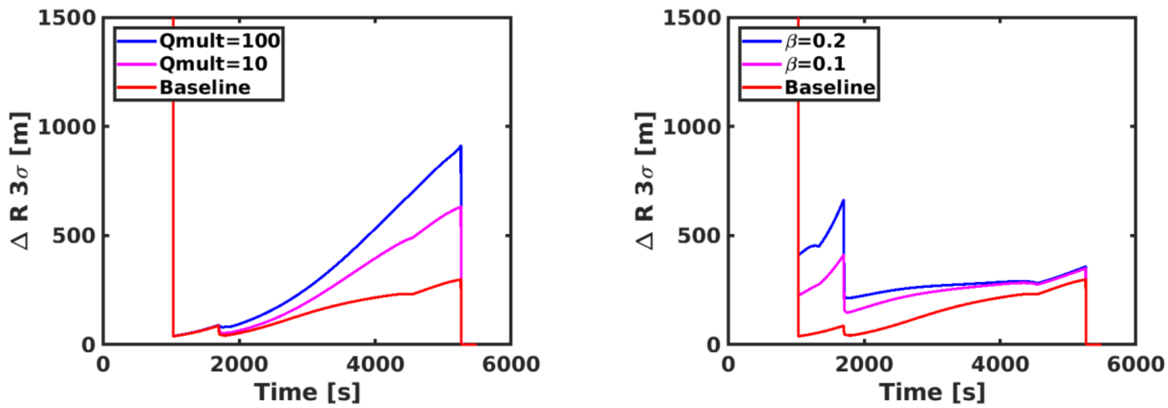
b. Vehicle velocity error.



c. Vehicle attitude error.

Fig. 8 SPLICE IMUs linear covariance results.

The linear covariance method can also be used to rapidly assess filter consistency. NewSTEP's linear covariance results are compared with Monte Carlo results, and filter tuning is conducted such that the navigation errors from the two methods are matched, i.e., the filter is consistent. This tuning can be conducted for covariance realism such that the filter predicted uncertainties match with reality, which is often not true due to various assumptions and approximations in the navigation filter design [18]. Two approaches to adjust process noise were investigated. The first approach is Q-tuning, in which a multiplier is placed on the process noise covariance matrix such that filter uncertainty predictions are increased. The second approach is known as Lear's method [19, 20], which is a form of measurement underweighting in which a term, $\beta H_k \bar{P}_k H_k^T$, is added to the residual covariance, where β is a user-specified tuning parameter, H_k is the measurement sensitivity matrix, and $\bar{P}_k$ is the predicted state covariance matrix. Sample results are shown in Fig. 9.



a. "Q-tuning" approach. **b. Lear's method.**

Fig. 9 Filter tuning sample results.

Figure 9 shows the results of the filter tuning approaches applied to a baseline case consisting of all sensor combinations set to high quality. In Fig. 9a, the results include cases for Q-tuning in which multipliers of 10 and 100 are placed on the process noise covariance. In each case the filter uncertainty is increased. Figure 9b shows the results of applying Lear's method to the filter tuning for values of β set at 0.1 and 0.2. The goal of adding the multiplier is to get the filter uncertainties to match with the navigation errors predicted in Monte Carlo simulations as the filter's prediction of uncertainty can tend to be optimistic. Results demonstrate these approaches are possible options for filter tuning purposes.

NewSTEP compliments the technology assessment by evaluating various configurations of navigation sensors and providing rapid assessment on filter-tuning parameters. The tool addresses the software requirements to match the hardware uncertainties, which improves the robustness of the overall sensor suite.

V. Summary and Future Work

Assessment examples presented in this paper show the short- and long-term impact of the technology assessment capability. Assessment results can be used to evaluate individual technologies and their impact on lunar landing missions and to identify sensitive parameters and the improvements necessary to increase landing success rates. Trends identified can impact technology-to-mission infusion and technology development decisions. It is important to reassess the results for specific mission and vehicle configurations as factors such as sensor coupling may affect results.This capability could be further used to assess alternative scenarios should one type of technology become unavailable or to reassess initial assumptions and identify appropriate requirements from a system perspective. Furthermore, the capability can also be used to assess the impact of a technology to reduce mission risks.

The current study has focused on large landers. Future study will be expanded in four areas. First, the fidelity of the technology assessment will be improved and will include additional figures of merits such as propellant usage, g-loads, and ride quality. Second, the simulation model will be expanded to include smaller landers such as Commercial Lunar Payload Services (CLPS) landers. The study will explore the importance of PNT parameters and their thresholds for smaller landers. Third, the simulation will be instrumented to assess the impact of PNT on Human Lander System risk posture. Because the current simulation assessment approach was computationally intensive, the fourth area is to continue the development of the NewSTEP rapid assessment capability to compliment the Monte Carlo analysis approach.

Acknowledgments

The authors thank Rafael Lugo (NASA Langley) and his team for providing the simulation framework, helpful insights, and discussions to facilitate this work.

References

[1] Gresham, E., Risdon, D., and Thompson, M., "Human Landing Systems Human Health Monitoring Survey Report," NASA Document ID 20230006768, May 2023, https://ntrs.nasa.gov/citations/20230006768. [retrieved July 11, 2023].

[2] Gresham, J., Hay, J. Risdon, D., Burg, A., and Thompson, M., "Human Landing Systems Thermal Control Systems Survey Report," NASA Document ID 20230006758, May 2023, https://ntrs.nasa.gov/citations/20230006758. [retrieved July 11, 2023].

[3] Gresham, E., Hay, J., Risdon, D., Burg, A., and Thompson, M., "Human Landing Systems Energy Systems Survey Report," NASA Document ID 20230006767, May 2023, https://ntrs.nasa.gov/citations/20230006767. [retrieved July 11, 2023].

[4] Gresham, E., Risdon, D., and Thompson, M., "Human Landing Systems Communications Survey Report," NASA Document ID 20230008234, May 2023, https://ntrs.nasa.gov/citations/20230008234. [retrieved July 11, 2023].

[5] Gresham, E., Craven, P., Risdon, D., Burg, A., and Thompson, M., "Human Landing Systems Human System Interaction Survey Report," NASA Document ID 20230008240, May 2023, https://ntrs.nasa.gov/citations/20230008240. [retrieved July 11, 2023].

[6] Gresham, E., Hay, J., Craven, P., and Wiley, J., "Human Landing Systems Position Navigation and Timing Survey Report," NASA Document ID 20230008242, May 2023, https://ntrs.nasa.gov/citations/20230008242. [retrieved July 11, 2023].

[7] Gresham, E., Hay, J., and Burg, A., "Human Landing Systems Plume Surface Interaction Survey Report," NASA Document ID 20230008260, May 2023, https://ntrs.nasa.gov/citations/20230008260. [retrieved July 11, 2023].

[8] Gresham, E., Hay, J., Burg, A., and Wiley, J., "Human Landing Systems Advanced Cryogenics Survey Report," NASA Document ID 20230008370, May 2023, https://ntrs.nasa.gov/citations/20230008370. [retrieved July 11, 2023].

[9] Gresham, E., Hay, J., and Wiley, J., "Human Landing Systems Radiation Environments Survey Report," NASA Document ID 20230008374, May 2023, https://ntrs.nasa.gov/citations/20230008374. [retrieved July 11, 2023].

[10] Gresham, E., Hay, J., and Burg, A., "Human Landing Systems Trusted Automation Survey Report," NASA Document ID 20230008376, May 2023, https://ntrs.nasa.gov/citations/20230008376. [retrieved July 11, 2023].

[11] Lugo, R. A., Dwyer-Cianciolo, A., Dutta, S., Williams, R. A., Green, J.S., Chen, P., and D'Souza, S., "Precision Landing Performance and Technology Assessments of a Human-Scale Lunar Lander Using a Generalized Simulation Framework," AIAA Paper 2022-0609 https://doi.org/10.2514/6.2022-0609

[12] Craig, A. S., Anzalone, E. J., Hannan, M. R., Belanger, B. L.,Burke, L. M., Condon, G. L., Joyce, R. T., Mahajan, B., Summers, A. W., Means, L. L., and Pei, J., "Human Landing System Storable Propellant Architecture: Mission Design, Guidance, Navigation, and Control," AAS 20-592

[13] Feng, D. "Review of Quantum Navigation," IOP Conference Series: Earth and Environmental Science, Volume 237, Issue 3, https://iopscience.iop.org/article/10.1088/1755-1315/237/3/032027

[14] Amzajerdian, F., Pierrottet, D., Hines, G. D., Petway, H., Barnes, B., and Carson, J. M., "Development of Navigation Doppler Lidar for Future Landing Missions," AIAA Paper 2016-5590, September 2016. https://doi.org/10.2514/6.2016-5590

[15] Lugo, R. A., Dwyer-Cianciolo, A., Dutta, S., Williams, R. A., Pensado, A., and Chen, P. "Integrated Precision Landing Performance Results for a Human-Scale Mars Landing System," AIAA Paper 2022-0607. https://doi.org/10.2514/6.2022-0607

[16] Karlgaard, C. D., Beck, R. E., Derry, S. D., Brandon, J. M., Starr, B. R., Tartabini, P. V., and Olds, A. D., "Ares I-X Trajectory Reconstruction: Methodology and Results," *Journal of Spacecraft and Rockets*, Vol. 50, No. 3, 2013, pp. 641-661. https://doi.org/10.2514/1.A32345

[17] Dwyer-Cianciolo, A., Striepe, S., Carson, J., Sostaric, R., Woffindon, D., Karlgaard, C., Lugo, R., Powell, R., and Tynis, J., "Defining Navigation Requirements for Future Precision Lander Missions," AIAA Paper 2019-0661, January 2019. https://doi.org/10.2514/6.2019-0661

[18] Lugo, R. A., Dwyer-Cianciolo, A. M., Dutta, S., Williams, R. A., Green, J., Chen, P-T., and D'Souza, S., "Precision Landing Performance and Technology Assessments of a Human-Scale Lunar Lander Using a Generalized Simulation Framework," AIAA Paper 2022-0609, January 2022. https://doi.org/10.2514/6.2022-0609

[19] Lear, W. M., "Multi-Phase Navigation Program for the Space Shuttle Orbiter," Internal Note 73-FM-132, NASA Johnson Space Center, Houston, TX, 1973.

[20] Zanetti, R., DeMars, K. J., and Bishop, R. H., "Underweighting Nonlinear Measurements," *Journal of Guidance, Control, and Dynamics*, Vol. 33, No. 5, 2010, pp. 1670-1675. https://doi.org/10.2514/1.50596