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MULTI-SOURCE RESIDENT SPACE OBJECT STATE VALIDATION AND FUSION

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ABSTRACT

The number of resident space object (RSO) orbit state solutions is rapidly increasing due to the increased RSO population and to the rise in commercial providers. Contributing to this, the operational acceptance of the Space Fence is projected to increase the RSO catalog size upwards of 100,000 objects. With multiple state solutions for a single RSO at any given instant in time, how can a satellite operator, orbit analyst, intelligence analyst, or decision maker determine which one is “correct?” This paper explores the value of aggregating, curating, and comparing these opinions from government (18th Space Control Squadron) and commercial providers (LeoLabs and Numerica), exposing insights that would normally go undetected. Precise orbit information available on various RSOs, obtained from Spire Global and MITRE, can be used to assess the accuracy of the various state solutions. Results show that commercial capabilities rival, if not exceed, performance of the existing public space catalog. Because each data source has their own strengths and weaknesses in different settings (orbit regime, global coverage, RSO type, etc.), a scheme that coalesces the various satellite state estimates into one, most accurate solution is paramount. To fuse this data into a best solution, a supervised learning regression model is developed that uses already processed provider state solutions propagated some amount of time and compared to truth data. Over a large spread of objects in GEO, this model is able to learn how to characterize the uncertainty developed during propagation and apply this to other objects in GEO to improve their solutions when compared to the standalone estimates from the various providers. This is of high value when accurate state predictions are required after propagation over many hours, such as conjunction assessment.

1. Introduction

The acceleration of the space population is staggering. With mega-constellations planned by various companies (e.g. SpaceX, Planet, OneWeb, Telesat, Blue Origin, etc) over the next few years, an order of magnitude increase in the population of active satellites within the next decade is not only imaginable, but perhaps likely. A recent search of space-track.org uncovers that approximately 5,500 active satellites are in orbit, with the addition of ~400 satellites launched in 2019 alone. Further, the vast majority of resident space objects (RSO) are debris, making the total tracked number of objects in orbit ~20,000. The operational acceptance of the Space Fence is projected to increase the RSO catalog size upwards of 100,000 RSOs by significantly lowering the RSO detection threshold [1]. Space Domain Awareness (SDA) and Space Traffic Management (STM) are clearly of paramount importance.

In addition to the rapid RSO population growth, the number of data providers is also growing swiftly. U.S. Space Command's (USSPACECOM) Space Surveillance Network is highly specified, verified and validated, but such specification is impractical for the influx of commercial providers. This creates the demand to not only aggregate, but curate and fuse the data before analytics can be meaningfully applied. During the recent SACT 19-3 (Sprint Advanced Concept Training), a week-long commercial-government exercise, in part to showcase advanced Commercial SSA capabilities to the Department of Defense and Department of Commerce, Slingshot Aerospace ingested RSO state data from several data providers (USSPACECOM, Numerica, and LeoLabs) to understand what curation was needed for various data providers. The data was curated and compared with calibration data (from Spire and MITRE). All of the data were ingested from the Unified Data Library (UDL), for simplicity.

Errors in the estimation of an object's position in space, can be introduced from both propagation and measurements (and associated modeling), and can be random (or aleatory), systematic (or epistemic), or even blunders. These errors can be very difficult to eliminate via improved modeling, especially when the source modeling is unknown. In this case, one might seek to learn, approximate and account for these unknown errors. The first objective of this study was to curate the data and examine the errors associated with multiple providers. The second objective was to determine if an improved solution could be generated at any point in time, including in the future, by fusing state data from multiple providers.

The goal is to be able to use any state information from any provider, including TLEs, which do not contain uncertainty information. Similar studies have used TLEs as pseudo-observations [3], but not with a variety of providers and actual truth data (discussed in detail below). A machine learning (ML) approach is considered to determine if we can better account for the systematic errors in the propagation, then use that knowledge to generate an improved, fused solution. ML methods have recently been implemented for astrodynamics objectives [4-7]. This includes better orbit prediction models and orbit determination of multiple RSOs. Peng and Bai [8] have also explored using support vector machines (SVMs) to improve the orbit prediction accuracy. Improvement was seen, however, only a single source (TLEs) was considered and the truth data was simulated.

The paper is laid out as follows. A quick description of the sources of data used in this paper is presented in Section 2 followed by a state error comparison in different orbital regimes in Section 3. Then, the method of producing a fused solution from multiple provider states is explored in Section 4.

2. Data Description

Sprint Advanced Concept Training (SACT) exercises are government-commercial collaboration exercises in which several real-world (and some simulated) events and scenarios unfold in the space domain. One of the main objectives of the exercise is to explore and showcase commercial capabilities to support SDA (DoD) and STM (DoC). During the SACT 19-3 exercise in December 2019, Slingshot Aerospace ingested RSO state data from LeoLabs, Numerica, U.S. Space Command's 18th Space Control Squadron (18 SPCS), Spire Global, and MITRE Corporation. 18 SPCS provided TLEs, while all others provided state vectors (SV), which are cartesian position and velocity. All of the data was curated and the LeoLabs, Numerica, and 18 SPCS ("providers") data was compared with precise states supplied by Spire and MITRE ("calibration"). The state data from each source is described in the following.

2.1 LeoLabs

Orbital state estimations at LeoLabs are achieved via an UKF [9, 10]. This class of algorithm pairs the computational efficiency of a Kalman filter with the unscented transform, which attempts to more accurately render covariance evolution in nonlinear systems by propagating a set of sample points using the full physical model. Both orbit determinations and propagations provided by LeoLabs make use of the Orekit open source orbital dynamics library5, with the following forces considered: non-uniform gravity (to degree and order 42), atmospheric drag (using the NRLMSISE-00 model), solar radiation pressure, third body forces from the Sun and Moon [11].

Computations of new orbital state estimations are initiated by a transit of the target through a LeoLabs radar and are performed at most once per hour in a cloud-based computer cluster. For targets in polar orbits, new estimations are calculated as often as six times per day. Each estimation is coupled to an eight-day propagation window that looks one day backward from state epoch and seven days forward. To assess the quality of state estimations, comparisons to ILRS-provided propagations are computed automatically for a 48-hour period centered on state epoch.

2.2 Numerica

Numerica collects data with a worldwide network of optical sensors, both fixed arrays and taskable telescopes. These observations are correlated, and orbit determination is performed by MFAST (Multiple Frame Assignment Space Tracker) a multi-target, multi-sensor tracking capability. Observations and state vectors are pushed out to the UDL and are also available on Numerica's user interface. This data is processed with little manual intervention and mis-tags are often corrected within minutes/hours, but it is currently impossible to push those corrections due to UDL limitations.

2.3 18th Space Control Squadron (18 SPCS)

The 18th Space Control Squadron (18 SPCS), assigned to the United States Space Command, is tasked with maintaining the definitive "catalog" of all RSOs, which it provides via publicly available TLEs (two-line elements). The TLEs are "mean" values obtained by removing periodic variations in a particular way. The TLEs are automatically generated with either a near-Earth or deep-space model, depending on the period of the RSO orbit [12].

2.4 Spire

Precise orbit determination of each Spire satellite center of mass is performed by utilizing multiple Global Navigation Satellite System (GNSS) signals simultaneously collected through a zenith-pointing antenna. Dual-frequency GNSS observables of carrier phase and pseudo-range are combined together with an orbit model and processed through a Kalman filter to produce position and velocity estimates during the period of GNSS receiver operation. Estimates of position and velocity are accurate to approximately 10-20 cm and 0.1 mm/s, respectively. Accuracy values have been estimated by analyzing overlapping orbit arcs and comparing solutions to those computed by the Bernese orbit processing software.

2.5 MITRE

MITRE supplies calibration ephemeris data for a large set of GNSS satellites (e.g. GPS, GLONASS, Galileo, etc.). Each GNSS satellite publishes its location on a schedule – every 30 minutes, hour, 2 hours, etc. – depending on how that country sets up their system. A GPS-style receiver takes those published values and propagates forward to "now" using that system's propagation algorithm. MITRE takes those self-published positions from the satellites, uses that system's propagation algorithm to generate state vectors in 5-minute increments, and then publishes these SVs to the UDL.

3. State Error Analysis

The first objective was to determine the accuracy of various providers through a state comparison by orbit regime. After the data was ingested, it was separated into "provider" data (Numerica, LeoLabs, and 18th SPCS) and "calibration" data (Spire and MITRE). For each provider state (TLE or SV), the calibration data was searched for corresponding SVs (i.e. same RSO and near the same time). To avoid propagation errors, the calibration data was interpolated to the time of the provider state and a position error was computed. The position error was then transformed into a satellite-based reference frame to better understand the errors: radial, in-track, cross-track (RIC). The radial direction points in the opposite direction from Earth, the cross-track direction is the orbit normal, and the in-track direction completes the frame by aligning itself near the velocity vector. With the error results, analytics can be performed, and any issues found in the data could be fed back into the data curation function (e.g. mis-matched coordinate frames or time representations, more details below). This process is illustrated in Figure 1.

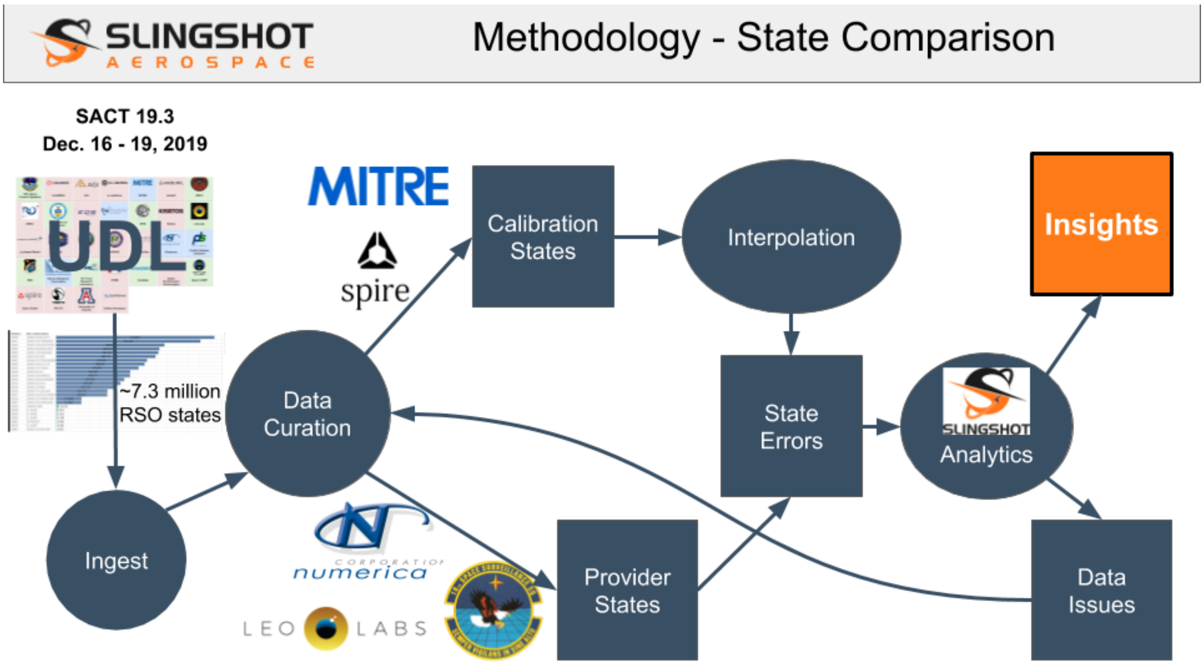

Figure 1. State Comparison Process

Once the data issues were mitigated, statistics were compiled across all provider data that corresponds to available calibration data.

Table **1** and Figure 2 show the results for GEO/MEO where 18 SPCS is the government provider, Numerica is the commercial provider, and MITRE is the calibration provider. The calibration data is based on various GNSS systems and is typically accurate to within a few meters [13]. MITRE delivered calibration for 117 RSOs. For those 117 RSOs, Numerica delivered 1363 SVs and 18 SPCS delivered 437 TLEs. After suspected cross-tags were either corrected for or removed, 1039 Numerica SVs and 397 18th SPCS TLEs are compared to calibration states to compute the associated position error.

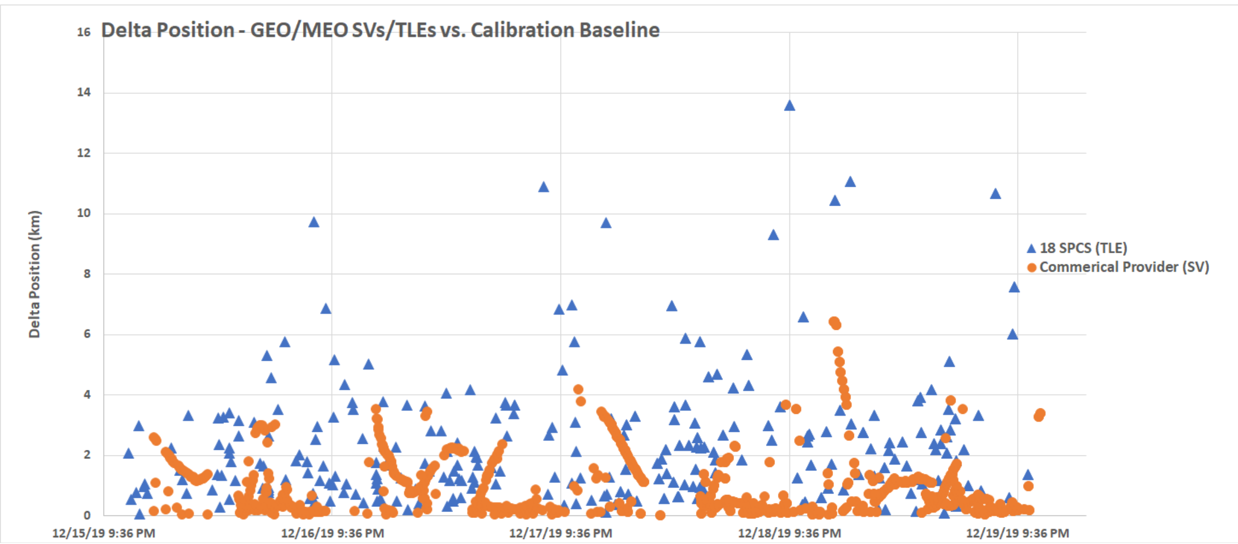

Figure 2. MEO/GEO Regime: Position errors associated with Numerica and 18 SPCS as compared to MITRE calibration states

Figure 3. MEO/GEO Regime: RIC errors associated with Numerica and 18 SPCS as compared to MITRE calibration states

Table 1. GEO Regime. RMS of Position (RSS), Radial, In-Track, and Cross-Track errors, comparing provider state estimates against calibration data interpolated to the time of the state estimate

	Numerica SVs	18th SPCS TLEs
Position RMS	1.342km	3.272km
Radial RMS	0.690km	1.09km
In-Track RMS	0.663km	2.712km
Cross-Track RMS	0.790km	1.436km

Figure 4 and Table 2 and show the results for LEO where 18th SPCS is the government provider, LeoLabs is the commercial provider, and Spire is the calibration provider. The calibration data is based on Spire's precise orbit determination, described previously, and is generally accurate to within 10-20 cm. Spire delivered calibration for 18 RSOs. For those 18 RSOs, LeoLabs delivered 35 SVs and 18 SPCS delivered 26 TLEs.

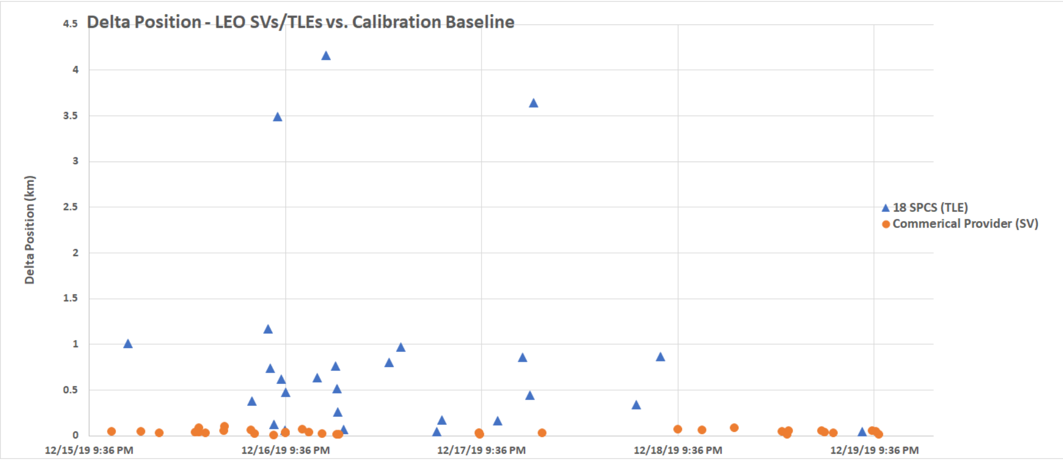

Figure 4. LEO Regime. Position errors associated with LeoLabs and 18th SPCS as compared to Spire calibration states.

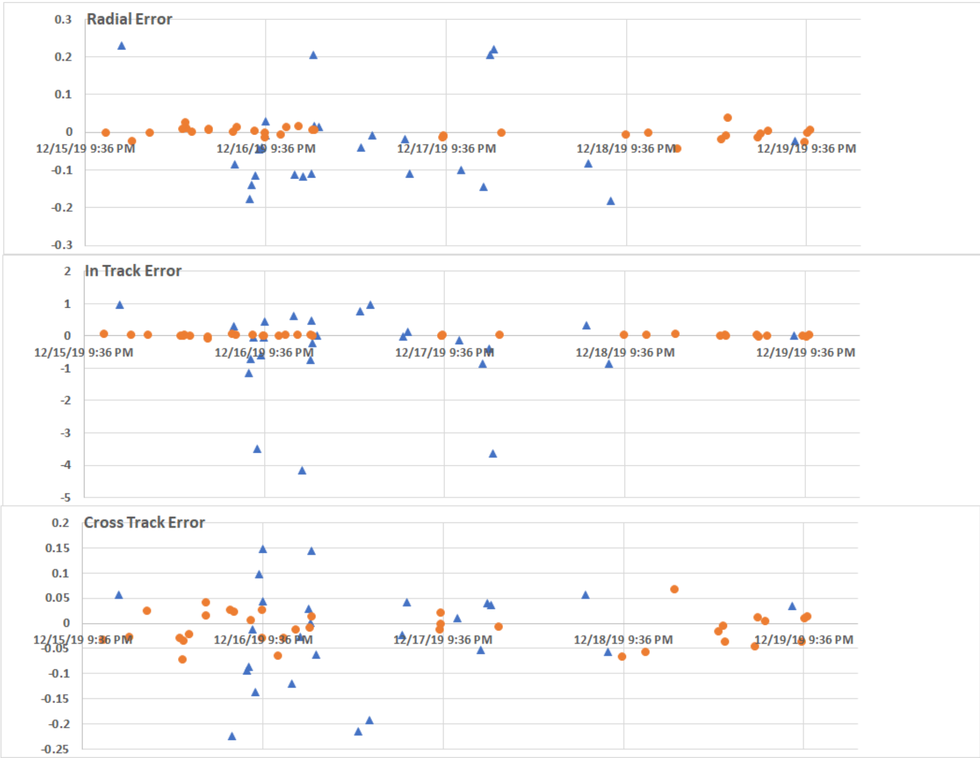

Figure 5. LEO Regime. RIC errors associated with LeoLabs and 18th SPCS as compared to Spire calibration states.

Table 2. LEO Regime. RMS of Position (RSS), Radial, In-Track, and Cross-Track errors, comparing provider state estimates against calibration data interpolated to the time of the state estimate

	LeoLabs SVs	18th SPCS TLEs
Position RMS	13.0m	303m
Radial RMS	0.79m	69.1m
In-Track RMS	7.99m	295m
Cross-Track RMS	9.76m	16.9m

From Figure 4, Figure 5 and Table 2 it is clear that commercial provider capability rivals, if not exceed, current publicly available information, especially in LEO. But that does not mean only one source should be considered. The right solution is a combination of all sources, where various strengths (global coverage, sensor accuracy/type) are accentuated and weaknesses are mitigated.

4. State Fusion Methodology and results

Two different methods were explored to determine if an improved solution could be obtained at any point in time using a combination of two provider's states. The first was a Kalman filter-based method where the provider states were used as observations in an unscented Kalman filter. Due to insufficient information about the modeling the state providers used and lack of uncertainty information, among other things, this method failed to improve upon the individual state solutions.

To contrast with the Kalman filter method, a machine learning based data fusion method was explored to attempt to properly account for systematic errors in the various source state solutions and/or orbit propagation. Various supervised machine learning models were utilized to determine if these errors could be properly identified and exploited. This analysis was applied to only the MEO/GEO data. The training and test data were generated from two different satellite state providers, 18 SPCS and Numerica, discussed above. Truth data were obtained from MITRE. States from each provider were ingested from December 16, 2019 to January 5, 2020 for 60 RSOs.

The training data was generated as follows: For each RSO, the states from Provider A were extracted. For each of these states, a range of propagation times, numbering the amount of Provider B states there were for the RSO, were generated from a triangle distribution having a median of 6 hours and a lower and upper bound of 0 and 2 days respectively. This distribution was chosen based on how far a propagated state would be still used and considered valid for operational decisions. For each propagation time calculated, the state being considered and one of Provider B's states were then propagated forward to this time, plus the amount of time required to reach the time of the next closest calibration state for the given RSO. Therefore, all provider states were at the same epoch. This process was repeated for each Provider A state solution for the given RSO. Then the whole process was repeated for Provider B for the given RSO. And finally, the process was repeated again for each RSO in the training data set.

This method minimized reusing the same initial data points to prevent overfitting while still producing enough training points to develop an accurate model. The propagation time of all the training data is represented in the histogram in Figure 6. We acknowledge that this dataset is not unique and that multiple variables can be adjusted, including reference frame and propagation time, but it will be shown that this particular dataset improved orbit prediction accuracy. The predictors from the training data were J2000 cartesian states and required propagation time from each provider (14 predictors). The propagator assumed a cannonball model and included a 20x20 gravity field, MSISE atmospheric density model, ocean tides, solar radiation pressure, and third body perturbations from the Sun and Moon. Of note, this is a different propagator than what was used to generate the original state solutions (the original propagator was not known).

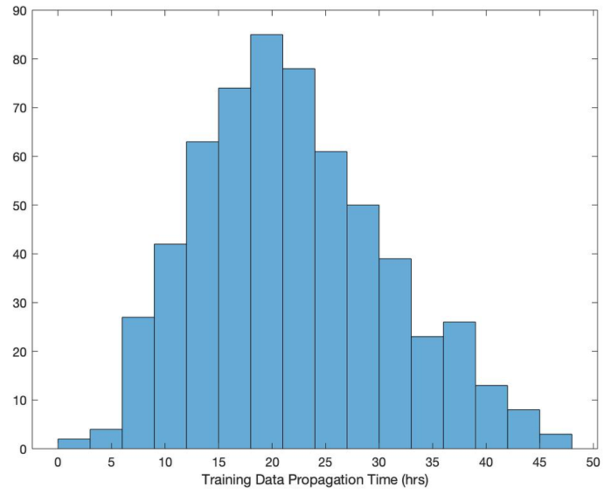

Figure 6. Propagation time sample distribution for generated training data

Nineteen different ML regression models were explored using the training data with 5-fold cross validation to prevent overfitting using the MATLAB (R2019b) [14] implementation of regression models. Various combinations of predictors were studied including converting to orbital elements and only including the respective cartesian state variable matched with the response variable (i.e. only looking at a combination of 18th SPCS' and Numerica's X position to predict the truth X position). The best performing model proved to be a linear regression model with interaction terms [15], using all 14 predictors. The interaction terms allowed for the conditional effects of propagation time to be accounted for in the linear combination of the cartesian states. The use of all variables in the state allowed for correlations amongst the state variables during propagation to be exploited.

Twenty percent of the generated data (different RSOs) were set aside for testing purposes. For the sake of evaluation, the best solution is defined as the smallest value of the position difference between the calibration state and the provider/fused state. Errors in RIC were also explored. Propagation of the provider states followed the same distribution in Figure 6, so the following statistics include any propagation errors. Of the test data, the fused solution had the best solution 58% of the time, 18 SPCS 18%, and Numerica 24% of the time. The metrics in Table 3 include varying propagation times and contain propagation errors between the two providers. See the State Error Analysis (section 3) for the actual provider state error comparison.

Table 3. Machine learning fusion technique. RMS of Position (RSS), Radial, In-Track, and Cross-Track errors, comparing individual provider and fused state estimates against calibration data propagated to the time of the calibration epoch closest to a triangle distributed propagation time (i.e. includes varying propagation error).

	Fused Solution	**18 SPCS TLEs**	**Numerica SVs**
Position RMS (km)	3.006	5.470	6.277
Radial RMS (km)	1.295	2.287	2.402
In-Track RMS (km)	2.644	4.958	5.790
Cross-Track RMS (km)	0.607	0.326	0.327

Figures 7 and 8 and show the position errors between the generated solutions (providers and fused) and the calibration source at each test point. Overall, the fused solution outperforms the two providers by reducing the error by nearly 50%. Of note is the improvement seen when both providers' solutions are used in the fused solution. The fused solutions using just a single provider actually performed worse than the corresponding provider's direct solutions. Including both providers in the fused solution allows for a more complete extraction and characterization of the propagation errors. We contend that the interaction terms of the ML model provide a model that accounts for the correlations between the propagation errors from independent state representations, allowing it to better mitigate fused propagation errors. Also, the test data does not contain any of the same RSOs as the training data, resulting in the advantage that this model can be used accurately cross RSO (but in the same orbit regime).

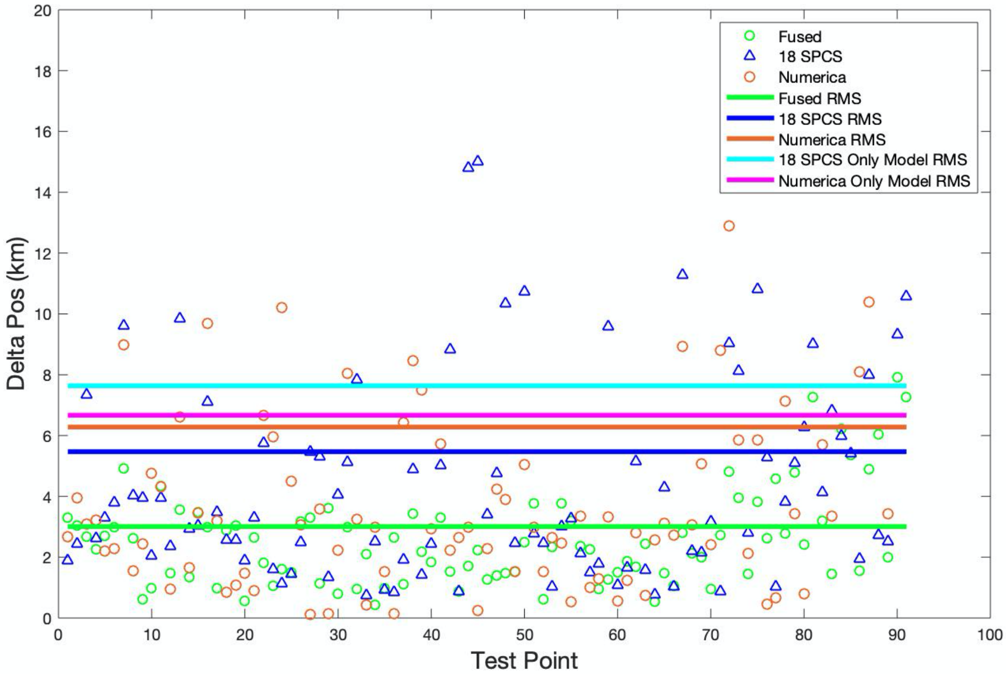

Figure 7. Machine learning fusion technique results. Position errors associated with Numerica, 18th SPCS, and fused solutions as compared to MITRE calibration states.

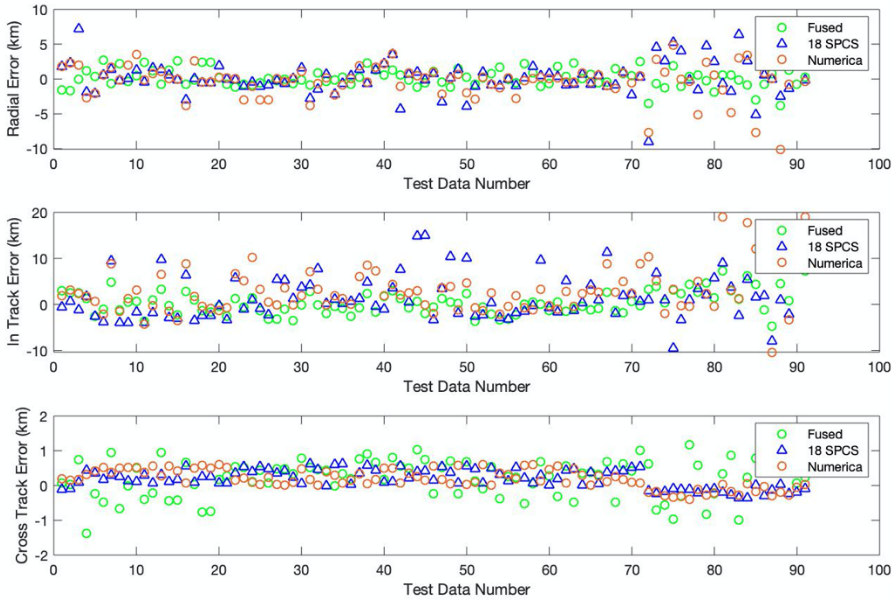

Figure 8. Machine learning fusion technique results. RIC errors associated with Numerica, 18th SPCS, and fused solutions as compared to MITRE calibration states.

Propagation time is an important variable in this analysis. Figure 9 shows how many times each solution is best as a function of total propagation time (18SPCS prop time + Numerica prop time). It shows that the fused method is the best most often after about 15 hours of total propagation, while within that time period Numerica's solution dominates.

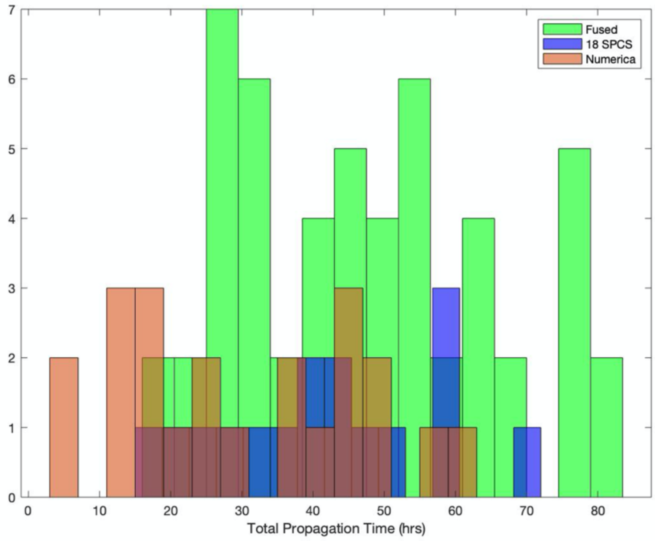

Figure 9. Number of times each solution was the best at an instant in time versus total propagation time of the providers

Examination of additional models is required to properly fuse the states at shorter propagation times, likely due to propagation not being the dominant source of error. At these short propagation times, random (or aleatory) errors may dominate over systematic (or epistemic) errors, making them more difficult to train on and overcome. Other types of predictors including covariance terms might be useful to completely define this short (or zero) propagation time region.

5. Conclusions

With the exponentially increasing amount of objects in space and an increasing diversity of observation providers, both government and commercial, to track them, it is of paramount importance to not only curate this data to allow for comparison and uncover insights, but to fuse the data into a single, more confident picture of where RSOs are and will be. A comparison of multiple providers show that commercial sources are at par, if not exceed, the accuracy of openly available data from space-track.org in the form of TLEs.

To find the best solution at any given time, including the future, a data fusion method was explored. Using a supervised ML model, we were able to properly account for the error introduced in the propagation of a satellite state and produced a fused result of two different providers that reduced the RMS of the original solutions by nearly 50%. This improvement was realized on RSOs other than what the model was initially trained on, demonstrating that these improvements may apply to all RSOs in a given regime. Future work will involve varying the predictors used in the model to better account for propagation time and to take advantage of RSO type and also include more sources of data. Additionally, methods will be explored to take provider solution uncertainties into account.

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