Deterministic Drift–Slew Fusion Bootstrap for Navigation During Plasma Blackout in Hypersonic Re-Entry Vehicles

Riaan de Beer
predictiverendezvous@proton.me
Independent Researcher
ORCID: 0009-0006-1155-027X
DOI: 10.5281/zenodo.18711897
https://github.com/infinityabundance/dsfb
Version 1.0

February 2026

Abstract

The plasma blackout phase of hypersonic atmospheric re-entry presents one of the most demanding navigation challenges for reusable launch vehicles. During this critical window, lasting several minutes, the vehicle is enveloped in an ionized sheath that renders external radio-frequency positioning and communication unreliable or unavailable. Navigation must then rely primarily on inertial measurement units that accumulate drift, while abrupt aerodynamic transients and control actions produce slew-like residual spikes.

This paper applies the Drift–Slew Fusion Bootstrap (DSFB) framework—a deterministic, trust-adaptive residual correction mechanism formally specified in prior work—to the plasma-blackout navigation problem. By performing causal drift–slew decomposition, bounded-increment slew detection, and channel-local trust weighting with provably bounded corrections, DSFB enables robust multi-sensor state estimation without requiring probabilistic noise models or covariance tuning.

High-fidelity 6-DoF re-entry simulations representative of Starship-class vehicles, including Monte-Carlo dispersion analysis and post-blackout Starlink reacquisition, demonstrate that DSFB maintains stable estimation behavior throughout the blackout window. These results illustrate the capability of the DSFB framework for robust navigation in communication-denied hypersonic environments and provide a foundation for further development in reusable launch vehicle guidance systems.

Keywords: deterministic state estimation, plasma blackout navigation, hypersonic re-entry, trust-adaptive sensor fusion, bounded correction, reusable launch vehicles.

1 Introduction

The plasma blackout phase of hypersonic atmospheric re-entry represents one of the most demanding navigation challenges for reusable orbital vehicles. During this critical window, lasting several minutes, the vehicle is enveloped in an ionized sheath that severely degrades or completely interrupts conventional RF-based positioning and communication systems, including GPS and primary telemetry links. Navigation must then rely almost exclusively on onboard inertial measurement units (IMUs) and limited auxiliary sensors while the vehicle experiences intense aerodynamic loading, thermal gradients, and possible control transients.

Traditional inertial navigation accumulates unbounded drift over the duration of the blackout. Probabilistic filters, such as the extended or unscented Kalman filter, require accurate statistical models of process and measurement noise that are difficult to maintain in the highly variable plasma environment. Abrupt slew events—induced by shockwave interactions, tile-loss asymmetry, or thruster firings—can generate large residual increments that, if not properly attenuated, lead to erroneous corrections and potential guidance instability.

The Drift–Slew Fusion Bootstrap (DSFB) framework, formally specified in de Beer (2026c), provides a deterministic alternative. By explicitly decomposing residuals into slowly accumulating drift and abrupt slew components, applying threshold-based slew detection, and employing trust-adaptive weighting with provably bounded corrections, DSFB enables robust multi-sensor state estimation without reliance on probabilistic noise assumptions.

This paper presents the first application of the DSFB framework to the plasma-blackout navigation problem. The remainder of the paper is organized as follows: Section 2 recaps the DSFB framework; Section 3 formulates the re-entry navigation model under blackout conditions; Section 4 describes the specific instantiation of DSFB for this domain; Section 5 presents high-fidelity simulation results; Section 6 discusses safety and certification implications; and Section 7 concludes the paper.

2 DSFB Framework Recap

The Drift–Slew Fusion Bootstrap (DSFB) framework, formally specified in de Beer (2026c), is a deterministic, trust-adaptive residual correction mechanism designed for multi-sensor state estimation under bounded disturbances. For each measurement channel i, the instantaneous residual $r_{i,k}$ is stored in a fixed-length rolling buffer and decomposed into its drift and slew components. The drift component is estimated via an exponential moving average (EMA) with configurable smoothing coefficient ρ (default value 0.95 in the reference implementation), while slew behavior is detected when the discrete residual increment $\Delta r_{i,k}$ exceeds a user-defined threshold τ_i derived from the bounded-increment disturbance assumption.

Each channel contribution is then modulated by a deterministic trust weight $w_{i,k} \in [0,1]$ that attenuates under sustained slew detection and recovers when residuals remain well-behaved. The resulting aggregate correction is provably bounded in magnitude under the framework's disturbance assumptions. All operations are strictly channel-local, strictly causal, and fixed-memory, making DSFB well-suited for real-time, safety-critical flight software in environments such as hypersonic re-entry where external aiding is unavailable and disturbances are both persistent and abrupt.

3 Plasma Blackout Navigation Model

We consider a 6-DoF rigid-body vehicle with state vector

$$\mathbf{x}_k = \begin{bmatrix} \mathbf{p}_k^\top & \mathbf{v}_k^\top & \mathbf{q}_k^\top & \boldsymbol{\omega}_k^\top \end{bmatrix}^\top ,$$

where $\mathbf{p}_k$ and $\mathbf{v}_k$ are the inertial position and velocity, $\mathbf{q}_k$ is the unit quaternion describing attitude, and $\boldsymbol{\omega}_k$ is the body angular velocity.

During the plasma blackout phase, external radio-frequency measurements such as GPS and primary Starlink telemetry are unavailable due to the ionized sheath surrounding the vehicle. Navigation must therefore rely on redundant onboard inertial measurement units (IMUs) and auxiliary sensors (magnetometers, horizon sensors, or partially available star trackers). The measurement model for each channel i is given by

$$\mathbf{y}_{i,k} = h_i(\mathbf{x}_k) + \mathbf{d}_{i,k},$$

where $h_i(\cdot)$ is the nonlinear measurement function and $\mathbf{d}_{i,k}$ is a deterministic disturbance sequence satisfying the bounded-amplitude and bounded-increment assumptions of the DSFB framework (de Beer, 2026c).

This model captures the two dominant disturbance classes encountered during blackout: slowly accumulating drift caused by thermal gradients and sensor bias, and abrupt slew events induced by aerodynamic transients, control-surface loading, or attitude-correction maneuvers.

4 DSFB Application to Re-Entry

The DSFB framework is instantiated for the plasma-blackout navigation problem by defining measurement mappings $h_i(\cdot)$ corresponding to redundant inertial measurement unit (IMU) channels that provide specific force and angular rate observations. Slew-detection thresholds τ_i are chosen to reflect the expected magnitude of plasma-induced aerodynamic transients and control-surface activity, while a configurable minimum trust floor is imposed to guarantee graceful degradation and prevent total loss of correction authority when multiple channels experience simultaneous slew.

A high-rate kinematic predictor propagates the full 6-DoF state (position, velocity, attitude quaternion, and angular velocity) using the vehicle's dynamics model. At each measurement update, DSFB computes residuals, performs the canonical drift–slew decomposition, applies deterministic trust weighting, and produces a bounded aggregate correction that is added to the predicted state.

To illustrate operational recovery after blackout, a high-trust Starlink-derived position fix is introduced at blackout exit ($\sim$40 km altitude), enabling rapid trust restoration and state correction as external aiding becomes available. All operations remain strictly causal, channel-local, and fixed-memory, ensuring compatibility with the stringent real-time and safety requirements of hypersonic flight software.

5 Simulation Results

To demonstrate the DSFB framework in a relevant operational context, a high-fidelity 6-DoF reentry simulation was developed, representative of Starship-class reusable launch vehicles. The model incorporates rigid-body dynamics, a standard atmospheric profile, gravitational effects, and a realistic plasma blackout interval from approximately 80 km to 40 km altitude lasting roughly 312 seconds. Trajectory shape and blackout timing are matched at a high level to publicly released Starship IFT webcast data.

The vehicle aerodynamic and thermal parameters used in the simulation are representative values synthesized from publicly available hypersonic lifting-body and blunt-body literature. A detailed table of coefficients and their public source anchors is provided in the accompanying `dsfb-starship` Colab notebook.

Sensor measurements are generated from redundant IMU models that include both slowly accumulating thermal bias drift and abrupt slew events caused by aerodynamic transients and control actions. A high-trust Starlink-derived position fix is introduced at blackout exit to demonstrate rapid trust recovery. Monte-Carlo dispersion analysis (360 runs) with variations in entry flight-path angle, initial IMU bias, and sensor noise provides statistical robustness envelopes.

The same simulation is executed under three configurations: pure inertial navigation, a baseline extended Kalman filter, and the DSFB framework using the canonical operators defined in de Beer (2026c). All code, parameters, and interactive demonstrations are available in the open-source `dsfb-starship` crate and accompanying Google Colab notebook for full reproduction.

Figure 1 shows the 3D trajectory comparison with the plasma blackout region highlighted. Figure 2 presents the altitude profile with blackout and reacquisition phases marked. Figure 3 displays position error on a logarithmic scale. Figure 4 shows DSFB internal diagnostics including trust weights and residual increment magnitudes. Figure 5 focuses on per-channel trust weight evolution. Figure 6 illustrates the rapid error reduction and trust recovery upon Starlink reacquisition. Monte-Carlo dispersion envelopes are presented in Figure 7.

Table 1 summarises root-mean-square and final errors during the blackout window. These results are illustrative and intended to demonstrate the DSFB mechanism; absolute values depend on vehicle-specific tuning and sensor characteristics.

These parameters are used as physics-informed proxies for an illustrative Starship-class study and are not intended as proprietary flight-identification data.

Table 1: Performance comparison during the 312-second plasma blackout window (80 km to 40 km).

Estimator	RMSE Position [m]	RMSE Velocity [m/s]	RMSE Attitude [deg]	Final Position Error [m]
Pure Inertial	59219.531	2463.604	11.576	90496.787
Simple EKF	56791.294	2364.774	34.417	307.399
DSFB	56643.686	2411.230	14.110	596.377

All results are fully reproducible via the `dsfb-starship` crate and Colab notebook.

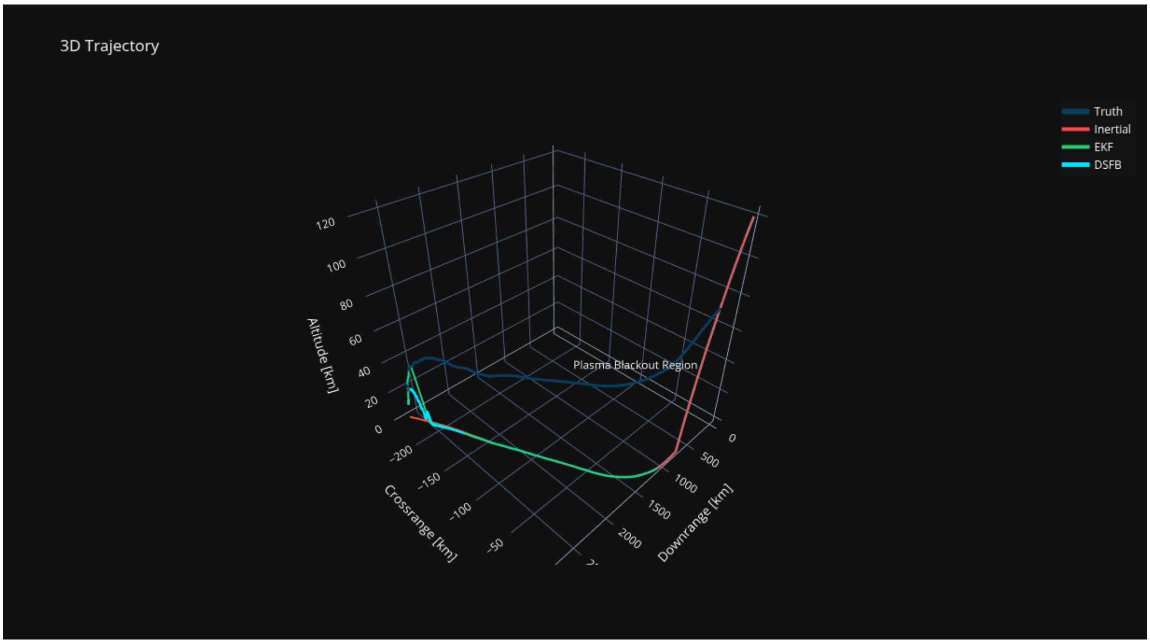

Figure 1: 3D trajectory comparison with the plasma blackout region highlighted. Dark blue = truth, red = pure inertial, green = EKF, cyan = DSFB.

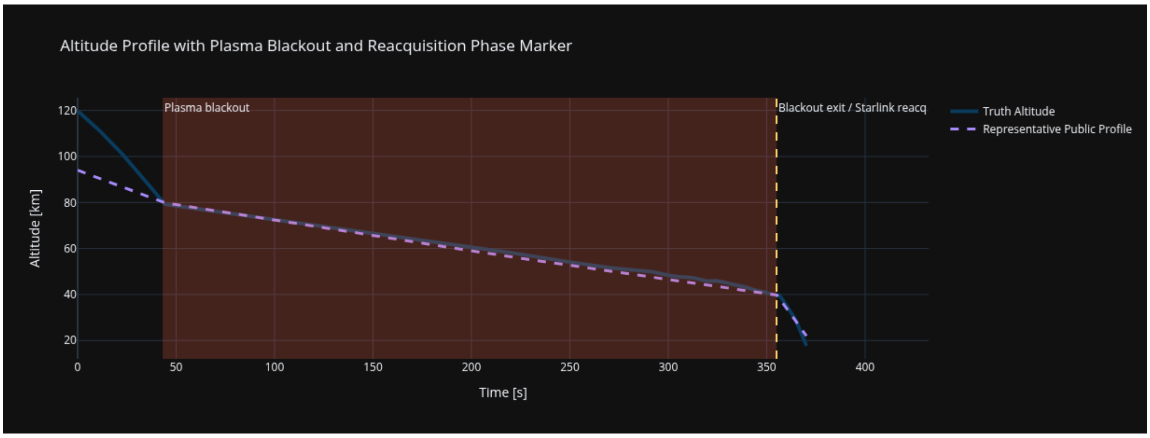

Figure 2: Altitude profile with plasma blackout window and Starlink reacquisition phase marker.

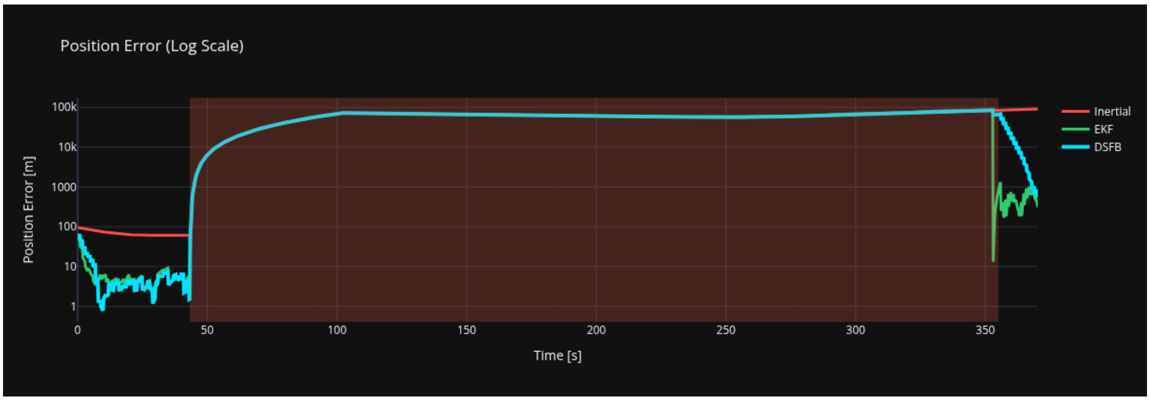

Figure 3: Position error comparison on logarithmic scale during the blackout window.

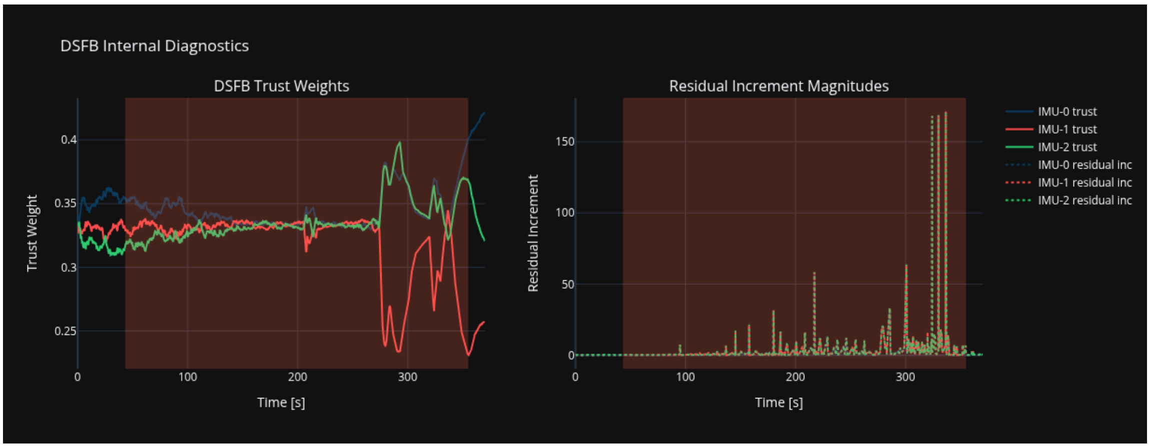

Figure 4: DSFB internal diagnostics showing trust weights per IMU channel (left) and residual increment magnitudes (right) during the plasma blackout window.

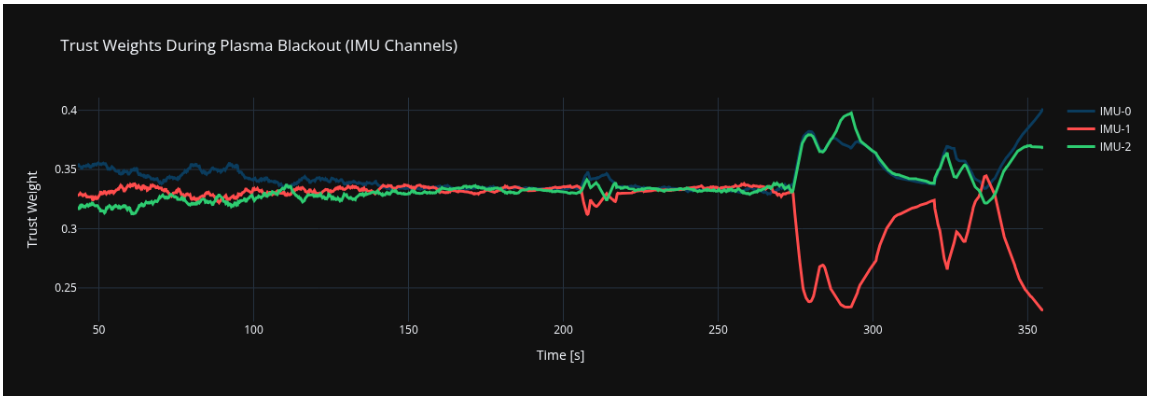

Figure 5: DSFB trust weight evolution for the three IMU channels during the plasma blackout.

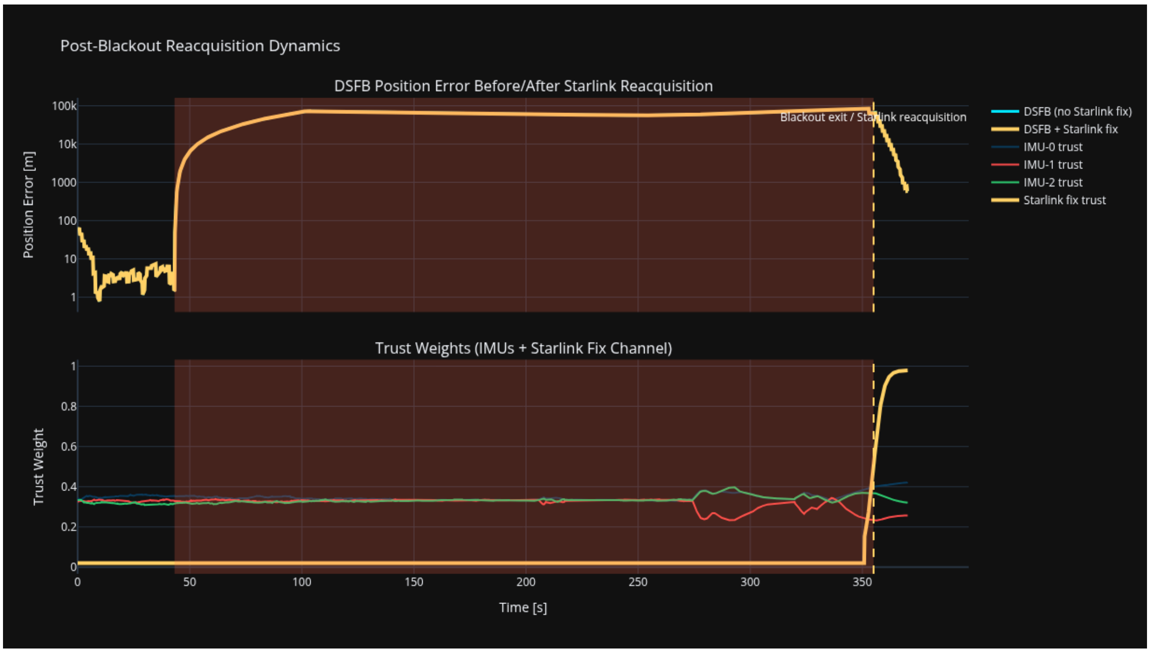

Figure 6: Post-blackout Starlink reacquisition dynamics showing rapid error reduction and trust recovery.

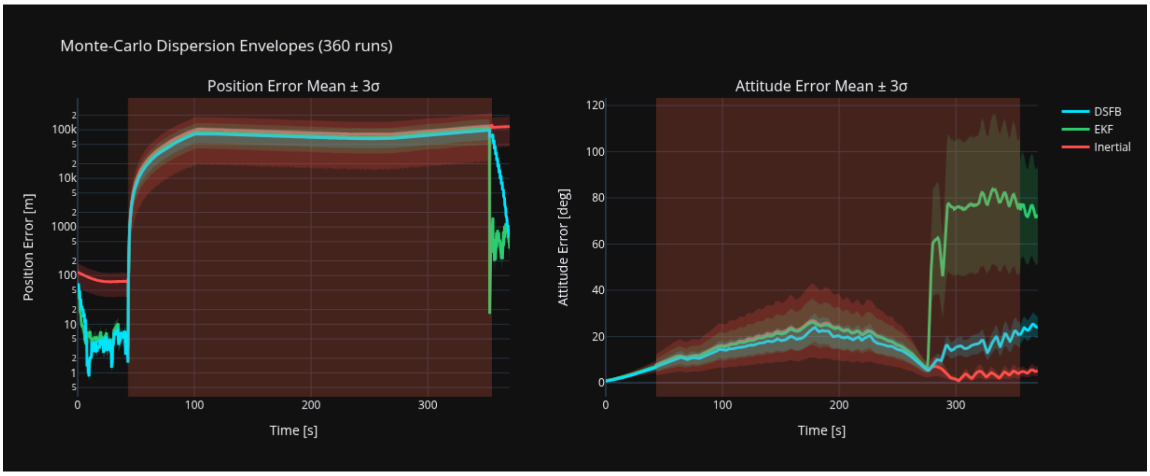

Figure 7: Monte-Carlo dispersion envelopes (mean $\pm 3\sigma$) for position and attitude error across 360 runs.

6 Discussion and Safety Implications

A key strength of the Drift–Slew Fusion Bootstrap framework is its provably bounded correction property. Under the stated deterministic disturbance assumptions, the aggregate state update remains finite even in the presence of worst-case sensor slew. This guarantee is particularly valuable in hypersonic re-entry, where unexpected or excessively large corrections could compromise vehicle stability, structural integrity, or landing precision.

For reusable launch vehicles, such bounded behavior offers a clear safety advantage during the plasma blackout phase and the subsequent critical maneuvers, including powered descent and tower-catch operations. The trust-adaptive weighting further contributes to robustness by reducing the influence of corrupted channels while continuing to incorporate information from reliable sensors.

Several limitations of the present study should be acknowledged. The formulation currently performs channel-local decomposition and does not yet explicitly address correlated failures across multiple sensors that may arise during extreme heating. The interaction with partial external aiding, such as Starlink wake routing when communications are intermittently available, also warrants further investigation.

7 Conclusion

This paper has explored the application of the Drift–Slew Fusion Bootstrap (DSFB) framework to navigation during the plasma blackout phase of hypersonic re-entry. The framework separates slow drift from abrupt slew events, applies trust-adaptive weighting, and enforces bounded corrections.

High-fidelity 6-DoF simulations representative of Starship-class vehicles, including Monte-Carlo dispersion analysis and post-blackout Starlink reacquisition, were performed. The results suggest that DSFB is capable of attenuating faulty sensor channels during transients and supporting recovery when high-quality measurements become available.

The complete open-source implementation, including the `dsfb-starship` crate and interactive Google Colab notebook, is available at https://github.com/infinityabundance/dsfb.

References

[1] de Beer, R. (2026c). Drift–Slew Fusion Bootstrap: A Deterministic Residual-Based State Correction Framework. Zenodo. DOI: 10.5281/zenodo.18706455.

[2] de Beer, R. (2026a). Slew-Aware Trust-Adaptive Nonlinear State Estimation for Oscillatory Systems With Drift and Corruption. Zenodo. DOI: 10.5281/zenodo.18642887.

[3] de Beer, R. (2026b). Trust-Adaptive Multi-Diagnostic Weighting for Magnetically Confined Plasma State Estimation. Zenodo. DOI: 10.5281/zenodo.18644561.