

Informing the Space Launch System Booster Separation Initial CFD Run Matrix with Observed Parametric Sensitivity

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It currently requires significant computational cost to simulate the flow physics of the booster separation event on the Space Launch System. This comes from the large parametric space in which the event occurs, as pre-separation flight conditions and separated booster core-relative trajectories can vary. Functionally removing the risk of core-booster collision mandates careful assessment of the fluid dynamics in terms of several trajectory parameters. However, simulating the entire trajectory envelope is computationally intractable given the high parametric dimension. In order to reduce the uncertainty in the resulting low-parametric-resolution aerodynamic booster separation database, a data-driven approach was developed to select which breakpoints should be studied by simulations and experiments and which should be relegated to a regression-based interpolation procedure. This technique works by simulating cases where the flow physics are most sensitive to changes in the parameters and leaving the less parametrically sensitive regions for interpolation. The result is a booster separation run matrix whose computational cost is comparable to that of previous database generations but has lower interpolation errors.

Nomenclature

C_T^{BSM}	=	thrust coefficient of booster separation motor, normalized with dynamic pressure q
CA	=	axial force coefficient (x-direction in vertical-plane axis system)
CLL	=	roll moment coefficient (z-direction in vertical-plane axis system)
CLM	=	pitch moment coefficient (z-direction in vertical-plane axis system)
CLN	=	yawing moment coefficient (z-direction in vertical-plane axis system)
CN	=	normal force coefficient (z-direction in vertical-plane axis system)
CY	=	side force coefficient (y-direction in vertical-plane axis system)
M_∞	=	freestream Mach number
q	=	dynamic pressure, computed with reference velocity, psf
α_c	=	core stage angle of attack in the vertical-plane axis system, deg
β_c	=	core stage angle of sideslip in the vertical-plane axis system, deg
Δx	=	booster-core relative x-position in vertical-plane axis system, ft
Δy	=	booster-core relative y-position in vertical-plane axis system, ft
Δz	=	booster-core relative z-position in vertical-plane axis system, ft
$\Delta\psi$	=	booster-core relative yaw angle, deg
$\Delta\theta$	=	booster-core relative pitch angle, deg
$\Delta\phi$	=	booster-core relative roll angle, deg

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I. Introduction

The solid rocket booster (SRB) separation event (Figure 1) is a common and complicated necessity in space launch system (SLS) missions. Solid rocket boosters employed in the liftoff and transition flight stages are jettisoned as the core stage proceeds through its ascent into orbit. However, on a given trajectory, the boosters are not guaranteed to always separate at the same airspeed, altitude, or rocket inclination. The duration of the booster separation motor firing, and the resulting unpowered departure from the core stage, can likewise vary significantly due to the nuanced aerodynamics of the flow regime [1]. Many of these booster trajectories lead them to impinge on the core engine plume, which is itself highly variable in shape. This plume impingement can lead to several modes, in one of which, the boosters are entrained in the core exhaust in such a way that they collide. Such an occurrence, naturally, must be avoided as much as possible.

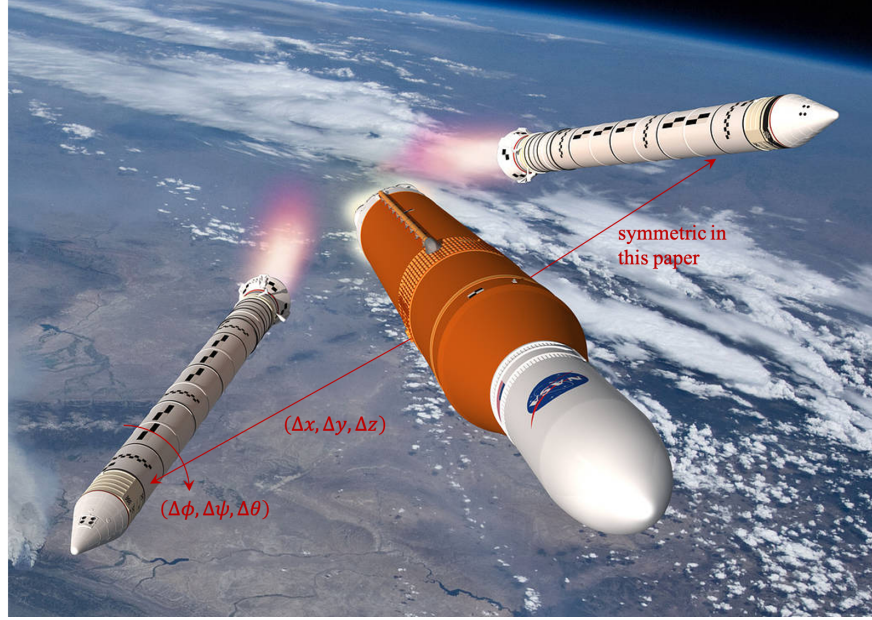


Fig. 1 Illustration of the SLS booster separation event. Core-relative booster coordinates are noted, as is the assumption that booster separation is symmetric in this paper.

A Monte Carlo approach is used to simulate the high-dimensional booster separation trajectory window. For a new SLS configuration, it is conventional to begin with a high-uncertainty trajectory window based on an existing, similar SLS configuration's aerodynamic forcing database and the new configuration's flight conditions [2]. An initial computational fluid dynamics (CFD) run matrix is then constructed to fill, relatively sparsely, the convex parameter space defined by this trajectory window. The resulting force and moment (F&M) database is then used to create a new trajectory ensemble, from which additional run points are identified iteratively until there is adequate confidence that the final database yields an accurate trajectory window [3].

In the case of symmetric booster separation, the parameters of interest are the boosters' core-relative position $(\Delta x, \Delta y, \Delta z)$, the boosters' core-relative rotation $(\Delta\psi, \Delta\theta)$,* the booster separation thrust coefficient C_T^{BSM} , and the core-stage parameters α_c , β_c , and q [3]. Each of these parameters is treated independently in the database, meaning the trajectory parameter space is eight-dimensional and populating the entire space is computationally intractable. In this work, all parameters are tracked on the right SRB (RSRB).

Existing database construction methods ensure that the nominal trajectory and the trajectory bounds are included in the CFD run matrix, but beyond that, the database's breakpoints are at least initially linearly distributed. The important exception is with Δx , which is used for organizing the other parameters; the result is a run matrix organized into several Δx slices with a relatively uniform distribution of breakpoints in the other parameters in each of these slices.

A limitation of this technique is that there is no guarantee that the flow physics behave predictably between these

*The third core-relative angle, $\Delta\phi$, is not aerodynamically significant due to the near-axisymmetric nature of the boosters.

breakpoints. The regression model employed by the trajectory simulator does not ensure its F&M interpolations are physically accurate. Therefore, if the breakpoints miss local extrema in the F&M values, these are smeared over in the trajectory simulations. This causes higher-than-desired uncertainty in the resulting trajectory simulations, which then requires more costs to account for in the rest of the system design cycle.

This paper outlines a data-driven approach by which parameter breakpoints can be identified to reduce the F&M database uncertainty. By selecting breakpoints based on the observed F&M sensitivity to each parameter, the resulting database will be less likely to have missed important flow physics within the parameter space. The regression model, which uses the database, then is less likely to interpolate incorrect flow physics amidst the breakpoints. This will be demonstrated for a booster separation run matrix slice that was constructed using both the old and the new methods.

II. Methodology and Results

In particular, it is known that the booster side force coefficient CY and the booster yawing moment CLN are centrally influential in bringing the boosters to problematic points in the parameter space, e.g., core recontact. A reasonable first step, then, is to study this force and moment in terms of each parameter of interest. The top half of Figure 2 shows the individual values of CY and CLN plotted versus $\Delta\psi$, for all the trajectories, plotted in black. The thick red line in each plot represents the nominal trajectory, and the thinner red line represents a random dispersed trajectory. The lower half of Figure 2 shows the range, or absolute value of the difference between the maximum and minimum CY or CLN value, at each booster yaw angle. While individual trajectories do not yield much insight, the trajectory collection as a whole presents a clear trend: there is a larger variation in the side force and yawing moment in the region of $\Delta\psi$ closer to the middle angles on the trajectory plots, apparent visually by the larger spread of coefficients at those values. For roughly the middle third of the $\Delta\psi$ range, these F&M coefficients tend to be less sensitive to $\Delta\psi$ and therefore, fewer breakpoints in these ranges will be necessary.

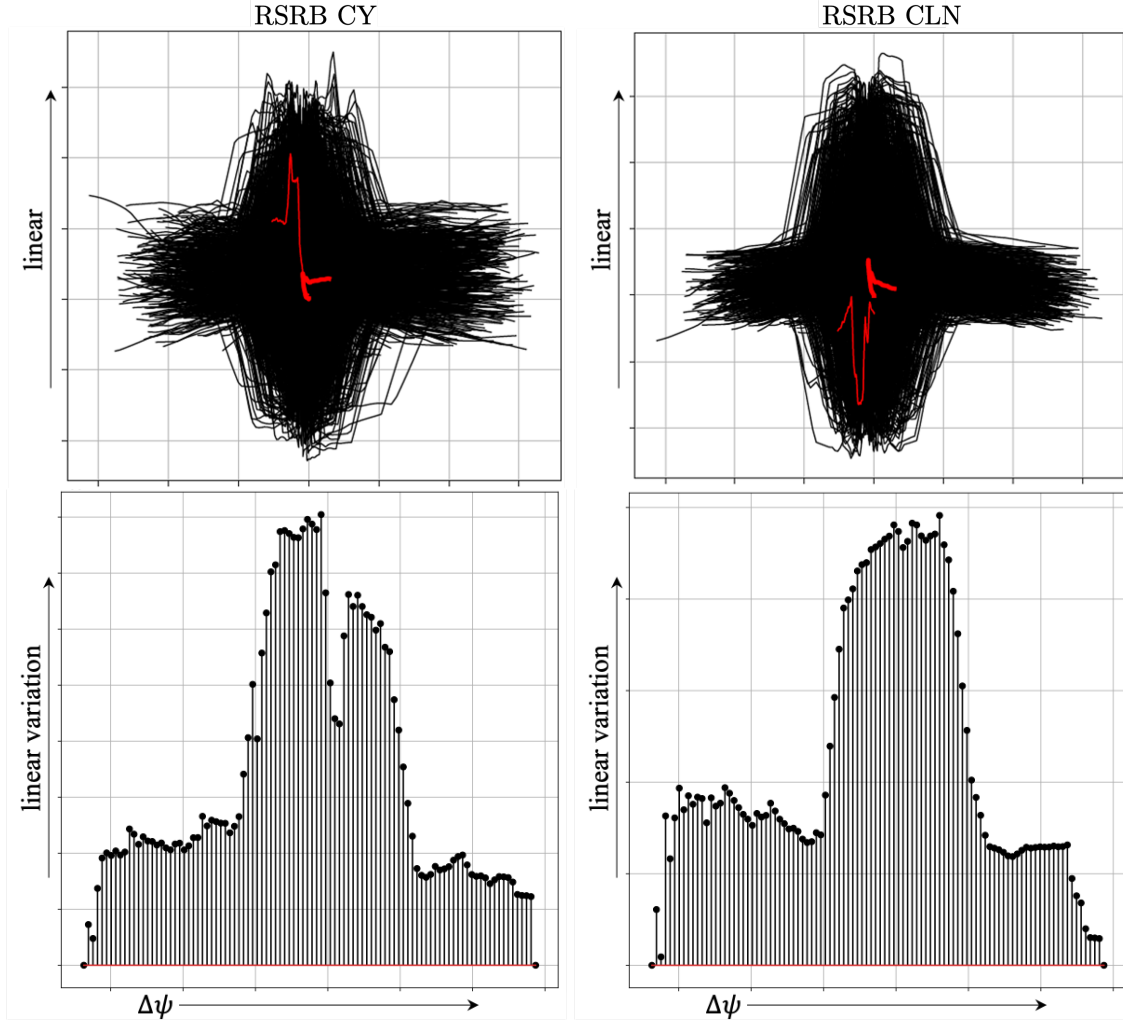


Fig. 2 Side force (left) and yawing moment (right) coefficients as functions of $\Delta\psi$ for all trajectories (top) and the histograms of the variations (bottom). The nominal trajectory is in thick-red and one dispersed trajectory is in thin-red.

While the variation in aero coefficients at a given $\Delta\psi$ is informative of the coefficients' sensitivity to that parameter, further insight into breakpoint selection can be elucidated from the coefficient gradients in terms of the parameter. Figure 3 presents such gradients and their ranges of variation. If a coefficient's parametric gradient is larger, it means that a small change in the parameter correlates to a more significant change in the coefficient. A higher variation within the coefficient gradient cloud indicates that at that parameter value, there is less certainty as to how the coefficient will change with small parameter changes, thereby likely yielding higher interpolation error within the regression model.

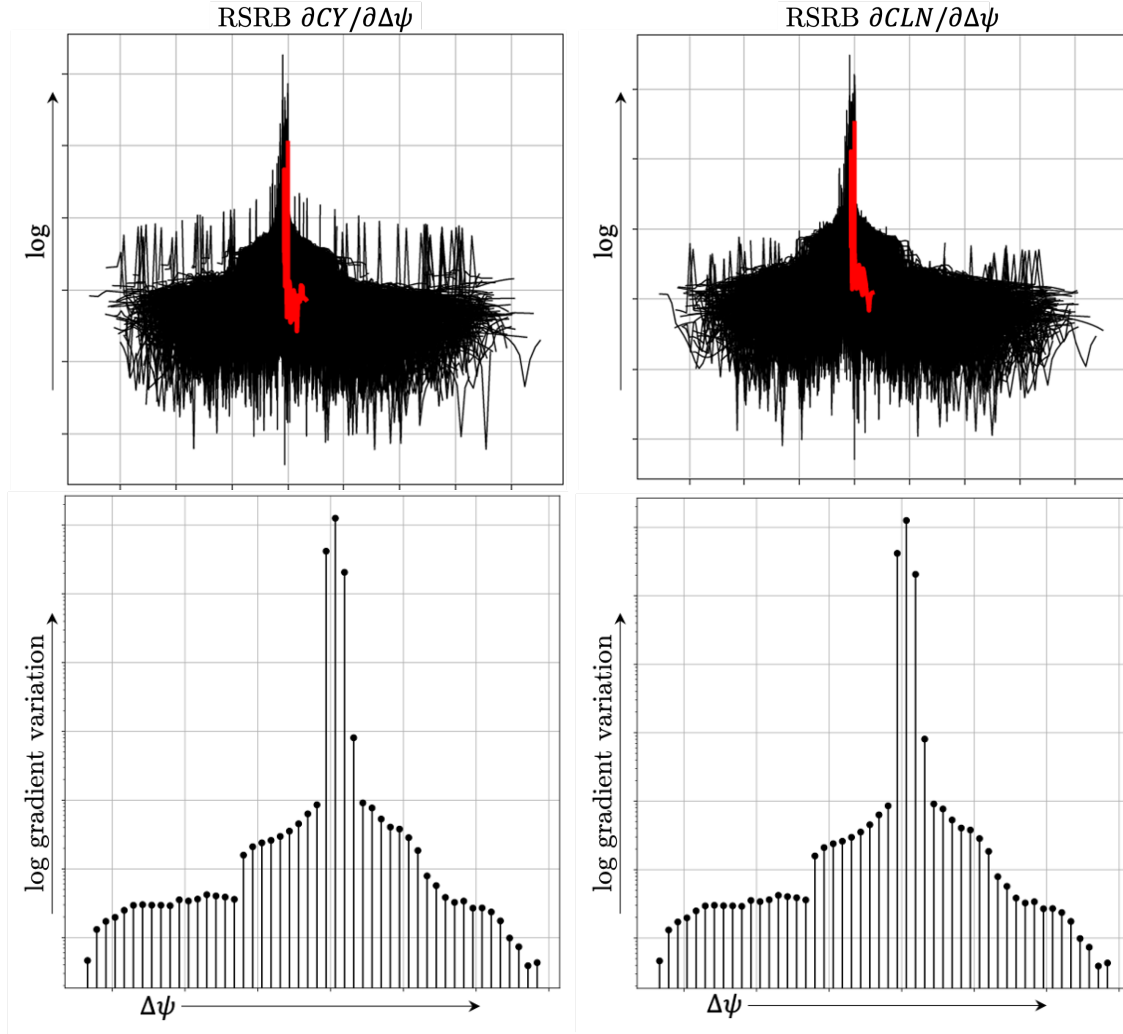


Fig. 3 Side force (left) and yawing moment (right) coefficient gradients (units of $lbf[*ft]/deg$) as functions of $\Delta \psi$ for all trajectories (top) and histograms of the variations (bottom). The nominal trajectory is in thick-red.

A shortcoming of these variation distributions is that they indicate trends only over the entire trajectory range. Current run matrix generation procedures, for good reason, parameterize the other parameters in terms of Δx such that different breakpoints are selected in, e.g., $\Delta \psi$, at different Δx breakpoints. From these variation histograms, it is not clear if a particular $\Delta \psi$ is an important breakpoint at all Δx breakpoints: just that within the entire trajectory window, it is important.

Figure 4 presents a contour of gradient variations for several values of Δx . Each column equates to a histogram like those in the bottom of Figure 2 but over only that small slice of Δx . To allow all columns to present trends within a single color scale, each Δx slice was normalized by its maximum value and that value was plotted on a second y-axis. For example, the maximum variation in the CY gradient based on $\Delta \psi$ in the blue-shaded band is orders of magnitude larger than its nearby Δx bands; it is apparent from this column presenting the highest blue dot in the dataset.

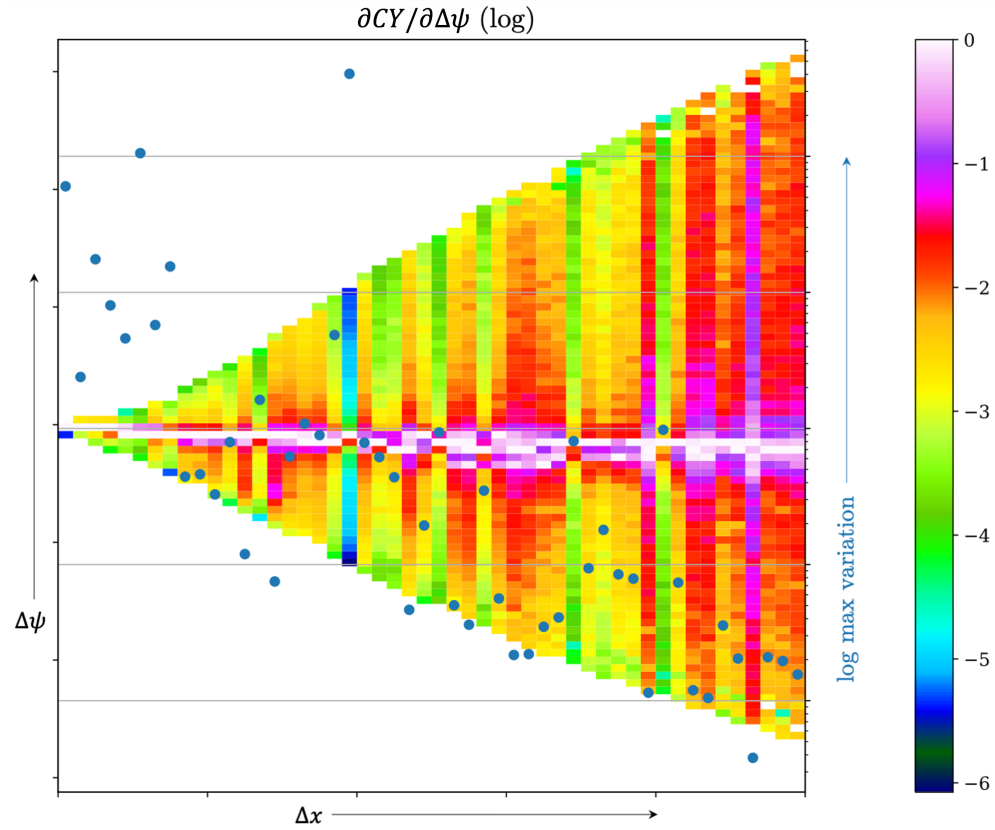


Fig. 4 Variation contours in the $\partial CY/\partial \Delta \psi$ gradient as a function of Δx , contoured on a log scale. Each column of distributions is independently normalized, with the column maximum variation noted on the second y-axis.

This contour plot presents trends similar to that of the trajectory distributions (Figure 5) but with additional insight into the statistics within the trajectory cloud. Breakpoints can be determined at a given Δx from the gradient variation trend. For example, the white band in Figure 4 indicates that the highest variation in the side force coefficient gradient does not stay centered in the trajectory data for all Δx but is also not in-line with either the nominal or the median trajectory in Figure 4.

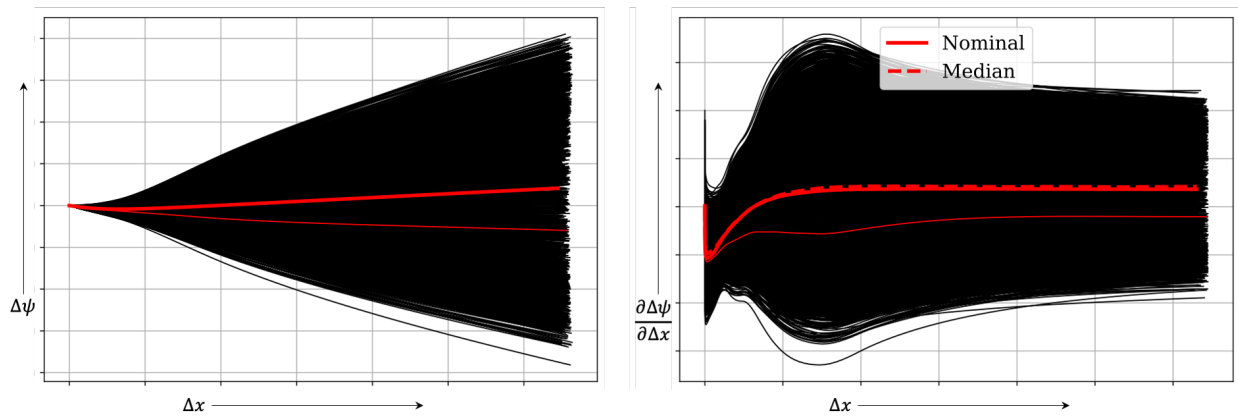


Fig. 5 Trajectories plotted as $\Delta \psi$ and its Δx derivative as functions of Δx .

Thus, at chosen Δx breakpoints, these contours present clear but qualitative recommendations for breakpoints in other

parameters like $\Delta\psi$. Exact breakpoints can be selected procedurally by minimizing a subsampling residual function of the histogram that comprises a particular Δx contour slice. Mathematically, one seeks a set of discrete points $\{\Delta\psi_d\}$ such that a residual function of the gradient variation $\mathcal{R}(g)$ is minimized, possibly with a constraint that the bounds in $\Delta\psi$ are included in the point set:

$$\{\Delta\psi_d\} \mid \min(\mathcal{R}(g)), \quad \{\min(\Delta\psi), \max(\Delta\psi)\} \in \{\Delta\psi_d\}. \quad (1)$$

One such residual function can be the absolute difference between the integrated gradient variation at all points and the integrated gradient variation at the few breakpoints. Because the trends in gradients span several orders of magnitude, the log of the variation is taken within the integrand.

$$\mathcal{R} \equiv \left| \int \log_{10} g(\Delta\psi) d\Delta\psi - \int \log_{10} g(\{\Delta\psi_d\}) d\Delta\psi \right| \quad (2)$$

To avoid $-\infty$ values where the gradient variation is zero (viz., where there was only one trajectory with information in a particular $\Delta\psi$ bin) the $\log_{10}$ function was defined to return a minimum of unity; for reference, the smallest substantial gradients observed were orders of magnitude larger than unity.

Thus, these objective and residual functions seek a subset of points in the parameter of interest, here $\Delta\psi$, which best capture the area under the gradient variation curve, on a log scale. A brute-force algorithm was used to test the utility of this approach on a small slice of Δx . Plots in Figure 6 show the resulting breakpoints if six total are sought including the bounds. It is clear that optimizing around the log integral, rather than the linear integral, better captures the variation distribution. Points seeming to float near the bottom of the y-axis are in fact at $-\infty$ on the log scale and are artificially brought up for plotting convenience.

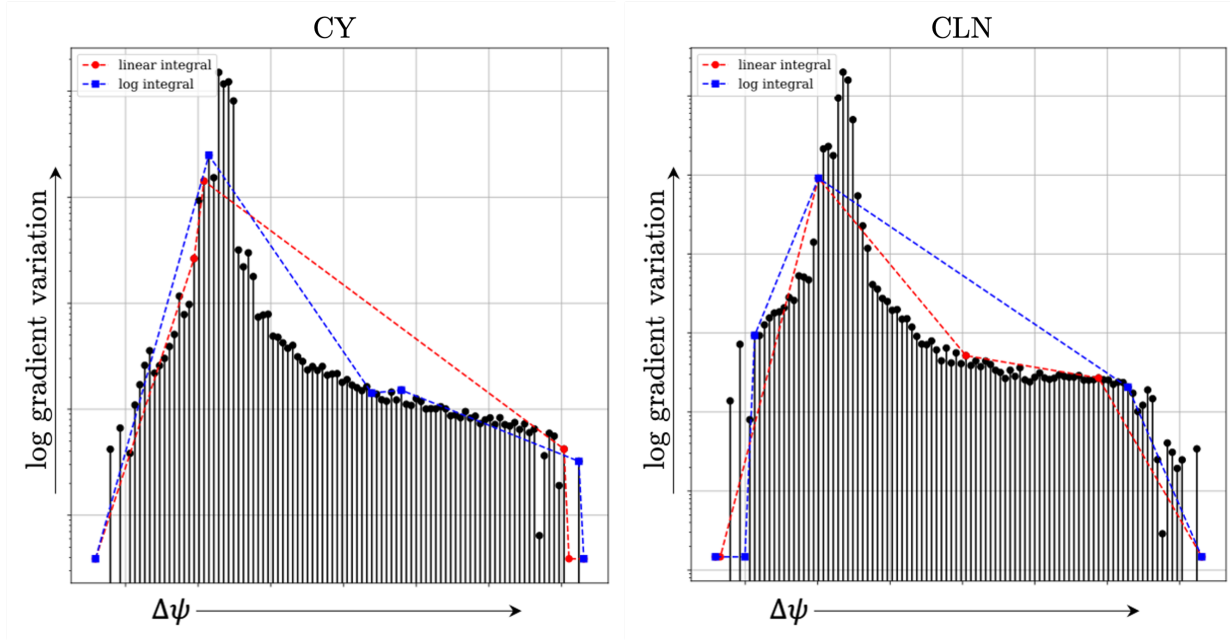


Fig. 6 Algorithm-selected breakpoints in $\Delta\psi$ in a small range of Δx given gradient variations in side force (left) and yawing moment (right) coefficients.

It is clear that the selected breakpoints differ notably based on which F&M coefficient is studied. As such, a reconciled residual function

$$\mathcal{R}_1 \equiv \left| \int \bar{g}(\Delta\psi) d\Delta\psi - \int \bar{g}(\{\Delta\psi_d\}) d\Delta\psi \right| \quad (3)$$

$$\bar{g} \equiv \frac{1}{N_{F\&M}} \sum_{n=1}^{N_{F\&M}} \frac{g_n}{\max(g_n)} \quad (4)$$

was introduced to yield a single breakpoint set given a relevant sequence of F&M coefficients. The gradient set may include just variations in CY and CLN, as is the case in these sample analyses. The variation magnitude in forces versus moments was significant; normalizing the force and moment variations by the max per-coefficient variations enables each to equally contribute to the resulting integrand. This normalization also removed the need to take the logarithm of the gradient variations before optimizing the integrals. A sample result is shown in Figure 7 where seven breakpoints were identified including the minimum and maximum values of $\Delta\Psi$. Thus, a run matrix can be constructed at a given Δx range for all parameters of interest and any F&M coefficient(s).

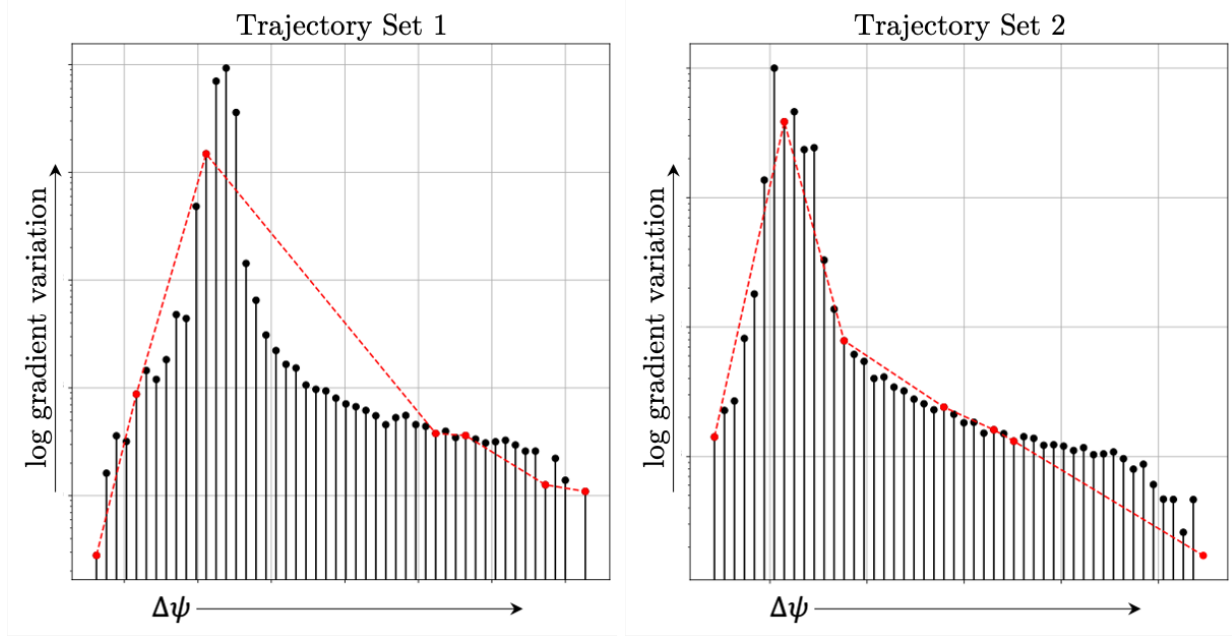


Fig. 7 Algorithm-selected breakpoints in $\Delta\psi$ in the same small range of Δx given gradient variations in side force and yawing moment coefficients. Left and right plots generated from two different trajectory sets.

Studying the plots of some parameters indicates that more or fewer points are necessary, e.g., the plots of C_T^{BSM} in Figure 8 demonstrate that fewer than seven breakpoints are likely adequate in that parameter. Regardless of final parametric resolution, this set of $7^7 = 823543$ run points can be downselected using a covariance analysis discussed below.

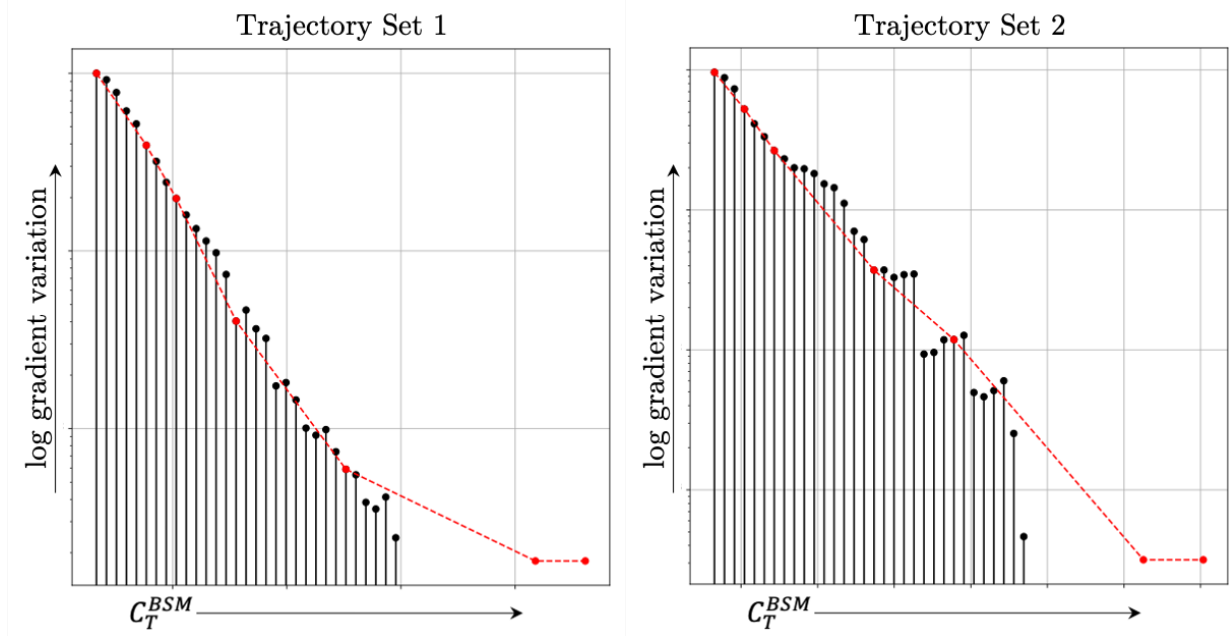


Fig. 8 Algorithm-selected breakpoints in C_T^{BSM} in a small range of Δx given gradient variations in side force and yawing moment coefficients. Left and right plots generated from two different trajectory sets.

A. Downselection of Breakpoints via Covariance Decomposition

A covariance-based run matrix attempts to take into account the covariance of booster position variables in order to more effectively allocate computational resources. It does this by restricting the run matrix points for highly correlated variables to remove points that are nonphysical. Specifically, it eliminates points where the combination of position variables cannot be reached even when the individual values are all reachable. The most important example of this is that the boosters cannot simultaneously have the minimum lateral translation (Δy) and maximum yaw ($\Delta \psi$).

The position variables of particular interest are Δy , Δz , $\Delta \theta$, and $\Delta \psi$ for the left and right boosters. The covariance matrices for these variables are first calculated from Monte Carlo booster trajectory data sets. To be precise, a 4×4 covariance matrix is calculated at each value of Δx (which for this limited study is fixed at one constant value).

Next, a matrix of points is found via Latin hypercube sampling (LHS). The $M \times N$ LHS matrix has M points valued between zero and one for each of the N variables of interest. The columns of the LHS matrix are then centered to have a mean of zero. This centered LHS matrix is multiplied by the lower triangular result of the Cholesky Decomposition of the covariance matrix. The resulting matrix is discretized to a fixed number of breakpoints and mapped to the desired value for each position variable. The process yields a matrix that has covariances similar to that of the covariance matrix used to generate it. A matrix of breakpoints can be generated in this way for each Δx .

III. Results at one Δx

Breakpoints were constructed via both the traditional and this new method to quantify how the new method can reduce the interpolation error in the usage of the resulting database. This was done only for one symmetric booster x-distance to save on the computational cost of the verification.

For the sake of comparing fairly the breakpoints of the two methods, the minima and maxima in each other parameter were set manually, consistent with the old method. Thus, the only differences between the two breakpoint sets were interior to the parametric convex space. A third breakpoint set was also created for validation, which included mostly points not in the other two sets. These were used to compare the interpolated sets to high-fidelity values.

For brevity, not all breakpoints from the three sets are listed here. Representative differences are visualized in Figure 9. It is clear that the difference in breakpoints affects the resulting force and moment coefficient values in interpolated

regions.

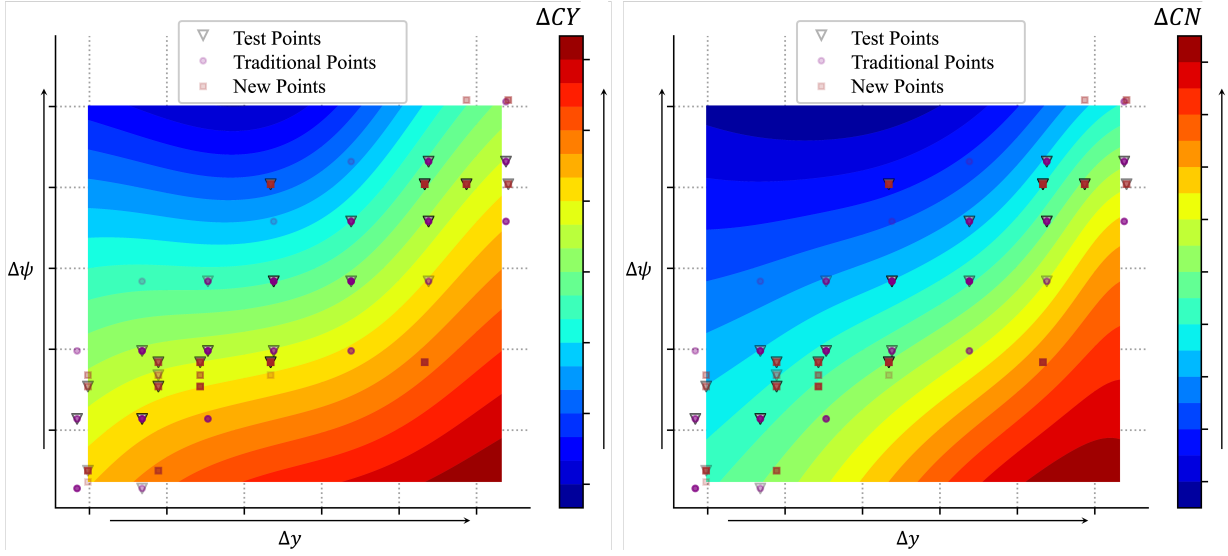


Fig. 9 Breakpoints in the three sets visualized as functions of only Δy and $\Delta \Psi$. The contours present the difference in interpolated CY (left) and CN (right) values between the new and old methods.

The two interpolated datasets were then compared to 82 validation points to quantify the quality of the new method. Error in the two methods is measured based on differences between the interpolated aerodynamic coefficients and these 82 validation CFD runs. Figure 10 presents histograms of these interpolation errors. A zero-error comparison would yield a histogram with zero mean and zero standard deviation. From these plots it is clear that the new method reduces both the standard deviation and the number of outliers in the coefficients for which it selected optimized breakpoints. In the other coefficients, the new breakpoints yield comparable or improved interpolation errors compared to the old method.

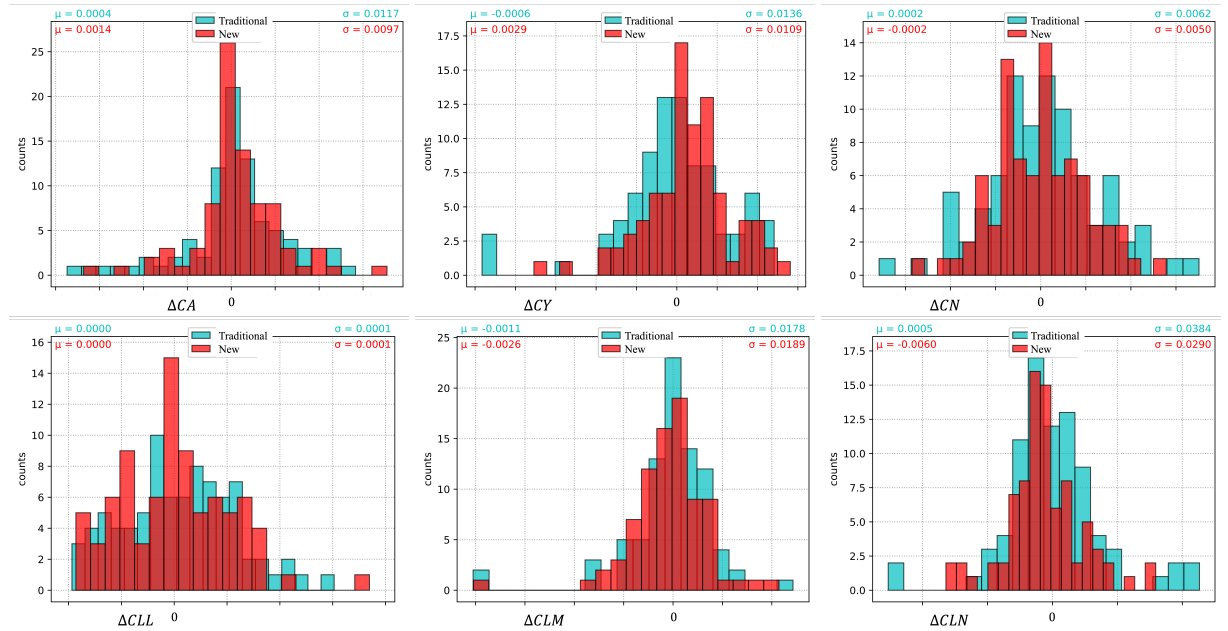


Fig. 10 Histograms of interpolation error in aerodynamic coefficients for the two methods. The new method was instructed to only optimize for CY (top center) and CLN (bottom right).

IV. Conclusions and Future Work

A new, more data-driven method of selecting breakpoints for aerodynamic databases was developed, which has been shown to reduce the resulting interpolation errors during database use. For complicated systems with a high number of independent parameters, like the booster separation phase of the Space Launch System's ascent trajectory, the necessarily parametrically coarse nature of these databases mandates both a reduction and understanding of this interpolation error. By ensuring that the trends in forces and moments are as smooth as can be expected between high-fidelity data points, database users can apply interpolation schemes with confidence that dangerous excursions in the aerodynamic forcing are not likely missed.

In addition to the reduction in interpolated database error, this data-driven method enables the number of breakpoints in a given parameter to be informed by anticipated trends in that parameter's particular sensitivity. Traditionally, all independent parameters were treated equally – with the highest affordable level of resolution – because there was not a reliable a priori metric to justify a coarsening of one parameter's breakpoints over another. With this method, the resolution of each parameter can be determined independently and the number of breakpoints can be selected by more than just engineering judgment. For example, with the arbitrary data used to test the method in this paper, it was clear that fewer than seven breakpoints would be necessary in C_T^{BSM} within the particular Δx range observed. This can both reduce the computational cost of database development and ensure that, for a given development cost, the parametric resolution is prioritized where it is most needed.

While this method is promising enough that it has been implemented by NASA in ongoing database development efforts, it does not rigorously address any possible coupling of the parameters, which are currently being treated as independent. The covariance analysis ensures that physically reasonable breakpoints are those actually studied in the resulting simulations and experiments, but whether the parameters identified as independent are both necessary and sufficient still remains an engineering challenge. Increasing this method into higher dimensions - creating high-dimensional histograms instead of those plotted here - is one possible way to further refine the breakpoint selection process while simultaneously quantifying the quality of the independent parameters selected for observation.

References

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