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Copula-based Method to Generate Consistent Surface Pressures Under Uncertainty

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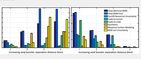
Motivation Background

- Aerodynamic databases are products used by other vehicle analysts (GNC, venting, etc...)
- Queried at a given trajectory condition and output processed aerodynamic data
  - Mach
  - Angle of attack/sideslip
- These databases are constructed from data pulled primarily from CFD simulations
- Two database types of interest here are integrated force and moment (FM), and surface pressure (SP) databases
- Databases include uncertainty models (output distributions)

Motivating Scenario

Uncertainty Background

- Numerical uncertainty tries to account for errors from:
  - Finite/non-converged/slightly-diverged
  - Numerical (mx convergence, discretization, etc.)
  - Database Modeling (interpolation, data assumptions, etc.)
- Full uncertainty build up also includes terms from wind tunnel:
  - Repeatability
  - Sensor calibration



Outline

- Motivation
- Aerodynamic Database Background
- Method
  - Data Set
  - Surface Pressure Generation Procedure
- Results
  - Validation
  - Simulated Uncertainty
- Concluding Remarks

Aerodynamic Database Details

- FM database
  - Outputs integrated force & moment coefficients
  - Constructed from CFD and time-averaged static experimental data
  - Uncertainty model provides a distribution
- SP database
  - Outputs surface pressures
  - Constructed from same CFD source data, no experimental data (yet?)
  - Uncertainty model uses high-level FM uncertainty
    - Assigns bias to high FM
    - Statistically similar to known surface pressures
- Aluminum Mean Discrepancy [1] sampler tool chosen to compare distributions

[1] Dalle, D.J., Aluminum, a Fun Unsupervised Learn Uncertainty to Surface Pressures, AIAA SciTech 2022
[2] Schmitt, et al., Antares2 Post-Sample, Feb 2019.

Generating the Uncertain Surface Pressures

- Assume some FM distribution at given trajectory point
- Sample FM and generate surface pressure
- Repeat to approx. equivalent uncertain surface pressure distribution
- Surface pressure sampling requirements:
  - Low bias to high FM
  - Statistically similar to known surface pressures

[1] Dalle, D.J., Aluminum, a Fun Unsupervised Learn Uncertainty to Surface Pressures, AIAA SciTech 2022
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Data Set

- The data for this study set was from 2019 AIAA CFD cases on a generic Hammerhead style vehicle

- Cases varied between -6 to 0 to 6 in angle of attack (α) and angle of sideslip (β)
- Cross-over Mach flow transition sequence surface was built from the raw data
  - Surface sampled at 1000 points within the CFD bounds

Generate Surface Pressure Basis Vectors

- Start by collecting surface pressure deltas into matrix C_P^*

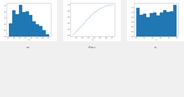
$$C_P^* = [C_{p_1}^*, C_{p_2}^*, ..., C_{p_n}^*]$$

- Perform Principal Component Analysis (PCA) on C_P^*

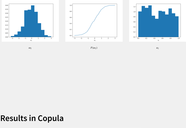
$$\begin{aligned} SVD(C_P^*) &= U_c \Sigma_c V_c^T \\ U_c w_c &= C_{p_c}^* \cdot q_{\infty(1,n)} \end{aligned}$$

Description of Copula

Apply marginal cdf in 1st dimension



Apply marginal cdf in 2nd dimension



Results in Copula

Sample from Copula

$F^{-1}(\omega_1)$

$F^{-1}(\omega_2)$

Surface Pressure Generation Method w/ Conditioning

- Use copula sampling procedure on ω to generate surface pressures
- Need modification in order to integrate to target forces & moments
- Sample from $C(u_1, u_2, \ldots, u_d | C_A, C_N, \ldots)$ (approx. $\mathcal{N}$)
- Apply conditioned inverse marginal cdfs $F_j^{-1}(\omega_j^* | C_A, C_N, \ldots)$
- Surface pressure draws will now be 'centered' around target FMs
- Chose surface pressure with largest probability density

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Validation of Method

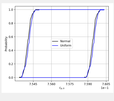
- Draw integrated force & moment coefficients randomly from known data
- Surface pressure generated corresponding to each of these drawn values
- MMD only ran on ω
- α=0.05 or 95% confidence level

Critical Value	MMD Score
0.0260077	0.0192575

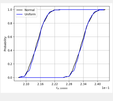
Performance Under Simulated Uncertainty

- Simulated aleatoric uncertainties in forces & moments according to: $C_{ij}^{unc} = C_i^{ref}(1 + \epsilon_{ij})$
  - C^{ref} is chosen reference case data
  - j is index of drawn uncertainty
  - $z \in (A, N, Y, LL, LM, LN)$
- Tested two uncertain distributions
  - $\epsilon_{ij} \approx \mathcal{N}(0, 0.0333)$
  - $\epsilon_{ij} \approx U(-0.1, 0.1)$
- 200 forces & moments were drawn and surface pressures generated for each
- Leave-one-out error of procedure is also included

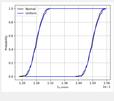
Simulated Uncertainty P-box Results



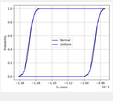
$\epsilon_{p,0}$



$\epsilon_{p,100000}$

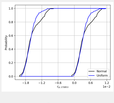


$\epsilon_{p,200000}$

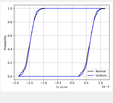


$\epsilon_{p,300000}$

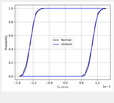
Simulated Uncertainty P-boxes Largest LOO error ratios



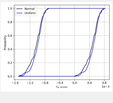
$\epsilon_{p,170853}$



$\epsilon_{p,291356}$



$\epsilon_{p,291355}$



$\epsilon_{p,343283}$

How realistic is this simulated uncertainty?

- Difficult to find any published uncertainty numbers in related work
- One reference has axial force coefficient code-to-code uncertainty at 10-20 percent [1]
- A full build up of uncertainty could also include terms for:
  - Wind tunnel (repeatability, balance calibration, etc.)
  - Database (interpolation, leave-one-out, etc.)
- Considering that, the simulated uncertainty showing near worst-case performance

Summary and Future Work

- Motive was develop surface pressure database with FM consistent uncertainty
- Method presented to generate surface pressures consistent with known data
- Validated with MMD two-sample test (coefficients)
- Performed decent in simulated uncertainty scenario, LOO relatively high
- Future work
  - Look into alt. approaches to approximating copula distribution
  - Test performance on larger database subset

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