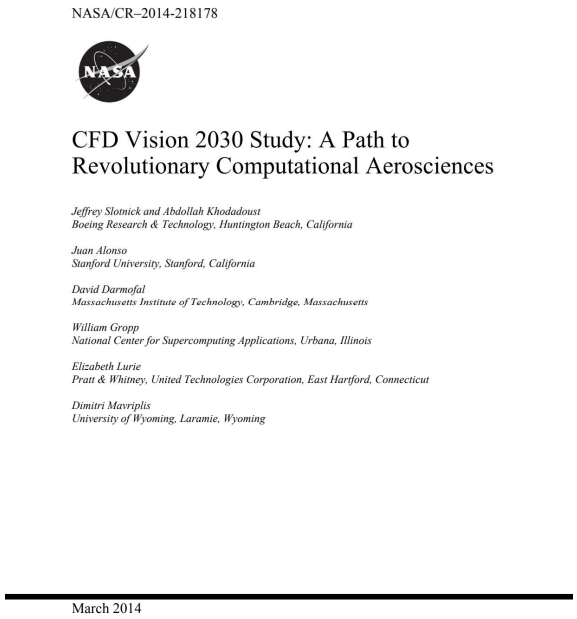
ICAS 2026 INVITED PRESENTATION

THE ROLE OF NEXT-GENERATION HPC AND MACHINE LEARNING IN ACHIEVING THE 2030 VISION GOALS

Nick Wyman, Cadence , Neil Ashton, NVIDIA

The engineering ambition of CFD Vision 2030



NASA/CR–2014-218178

CFD Vision 2030 Study: A Path to Revolutionary Computational Aerosciences

Jeffrey Slotnick and Abdollah Khodadoust
Boeing Research & Technology, Huntington Beach, California

Juan Alonso
Stanford University, Stanford, California

David Darmofal
Massachusetts Institute of Technology, Cambridge, Massachusetts

William Gropp
National Center for Supercomputing Applications, Urbana, Illinois

Elizabeth Lurie
Pratt & Whitney, United Technologies Corporation, East Hartford, Connecticut

Dimitri Mavriplis
University of Wyoming, Laramie, Wyoming

March 2014

Predictive CFD across the flight envelope

Separated and unsteady flows

Reliable error and uncertainty estimates

Less manual intervention

A capability goal for engineering design

NASA/CR-2014-218178

What the report anticipated about HPC

GPUs and heterogeneous computing were explicit

2014 roadmap priority	Software implication
Port codes to GPU / coprocessor systems	Keep data local and expose concurrency
Develop algorithms for deep memory hierarchies	Reduce movement and communication
Demonstrate exascale CFD capability	Measure useful application performance

The vision required investment in algorithms and software

Vision 2030, §5.1 and §6.2

What the report said about data and automation

2014	Reduced-order models, surrogates, data reuse and automated CFD processes
2020 roadmap	Machine learning enters explicitly, including turbulence modelling
2024 update	LLMs and engineering workflow orchestration (report published October 2025)

Agents offer a new way to pursue the original automation goal

CFD Vision 2030 roadmap reports

GPU acceleration depends on the solver

4.3×

FUN3D performance
SC18 benchmark

1 NVIDIA V100
vs 2 Xeon Gold 6148 CPUs
(40 CPU cores)

GPU residency

Keep solver kernels and data on the device

Concurrency

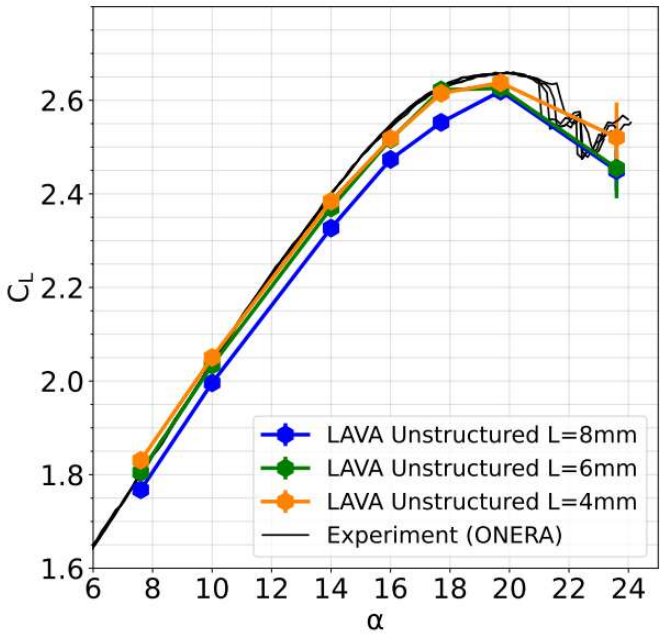
Expose enough parallel work

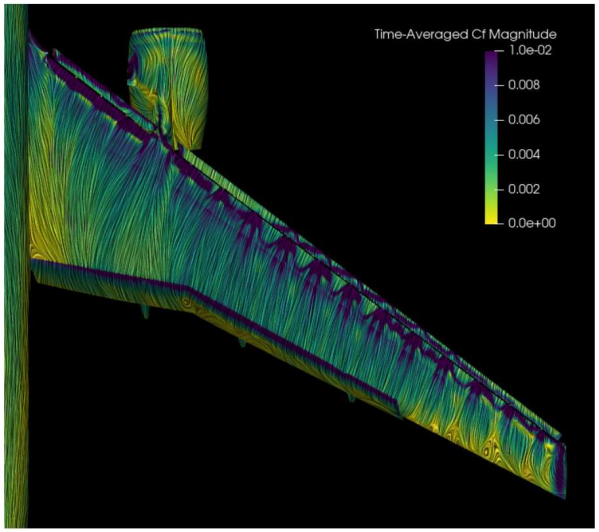
Communication

Reduce transfer and synchronisation costs

High-lift prediction shows the value of greater fidelity

CRM-HL, Case 2.4, wall-modelled LES





Near maximum lift

Resolved separation

Mesh and transition sensitivity remain

Higher fidelity expands what CFD can predict

Sozer et al., AIAA 2025-0887

The GPU economics of high-lift WMLES

LAVA WMLES, 325 million cells, FP64

Reported quantity	CPU	GPU	Ratio
Throughput MUPS per node	19.1	192	10.1× higher
Elapsed time hours per CTU	1.62	1.01	1.60× faster
Estimated energy MJ per CTU	467	46.4	10.1× lower

100 CPU nodes vs 16 GPU nodes (64 A100s)

CTU: convective time unit. Energy uses measured peak-power estimates.

Sozer et al., Table 3

Machine learning has several roles in CFD

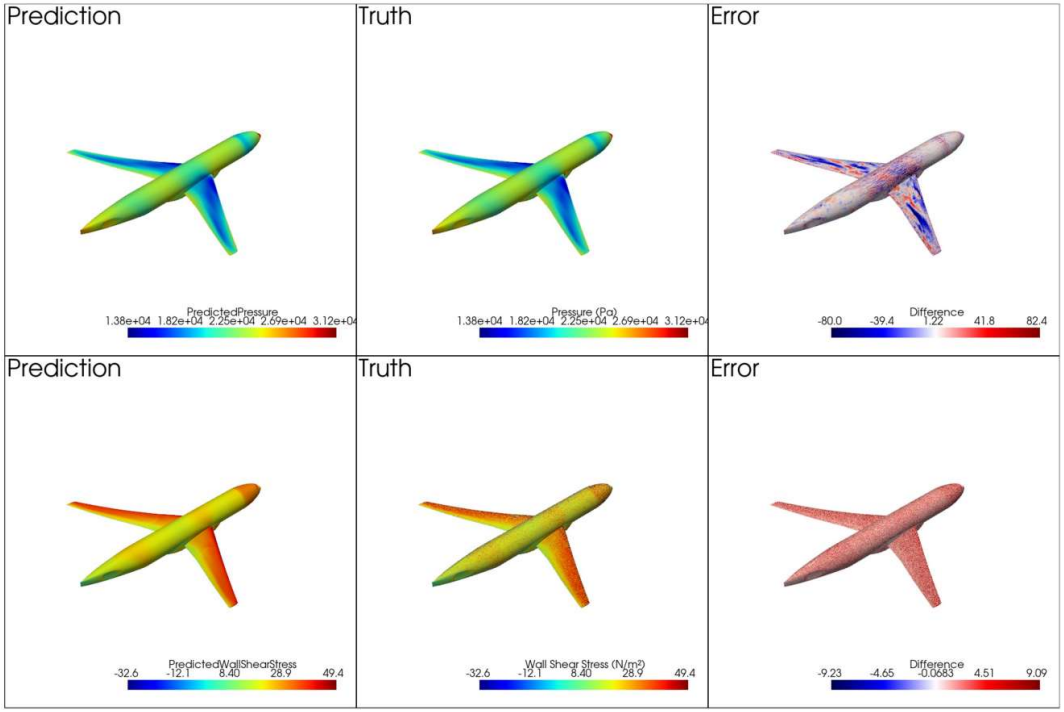
Where learning enters	CFD role
Around the solver	Field surrogates and design-space exploration
Inside the solver	Learned closures and numerical acceleration
Across the workflow	Case setup, tool use and evidence review

Example: the building-block-flow model learns subgrid and wall behaviour inside GPU WMLES

Ling et al., AIAA 2024-3686

Aerodynamic surrogates are becoming useful

SHIFT-Wing: subsonic and transonic configurations



Velocity relative L1 error

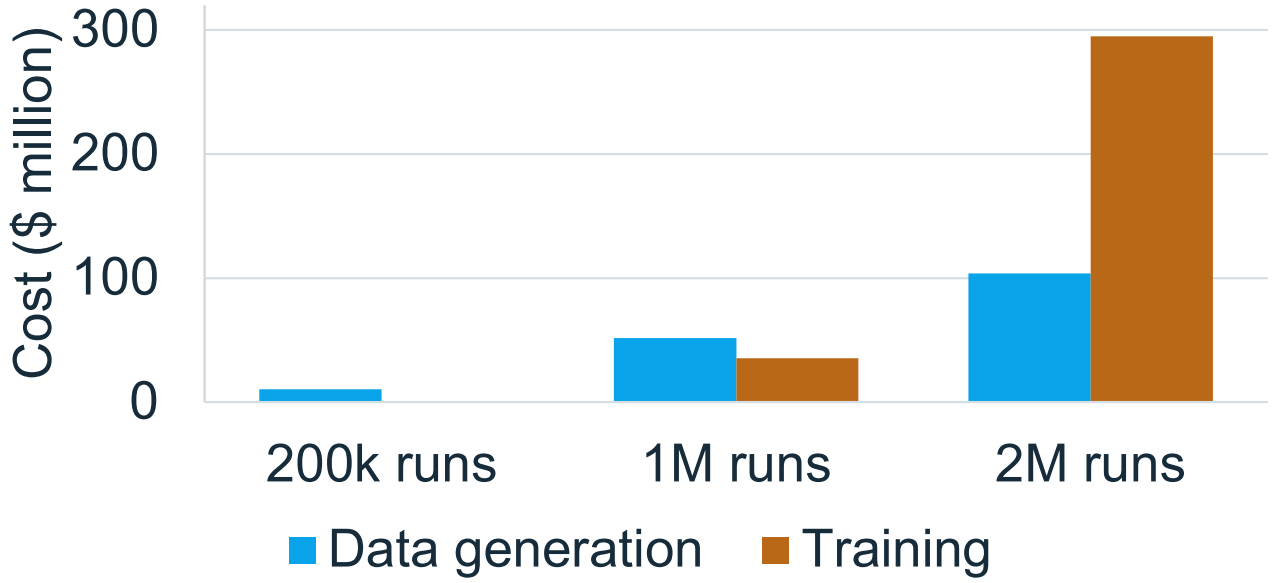
Mach	GeoTransolver
0.50	1.92%
0.85	2.00%

Defined geometry family
Held-out test designs

Adams et al., GeoTransolver v2

Cheap predictions still require expensive data

Illustrative foundation-model scenarios



200k-run scenario

$10.3M data
$0.397M training

Estimates only
See backup for assumptions

Efficient solvers determine the cost of learning from CFD

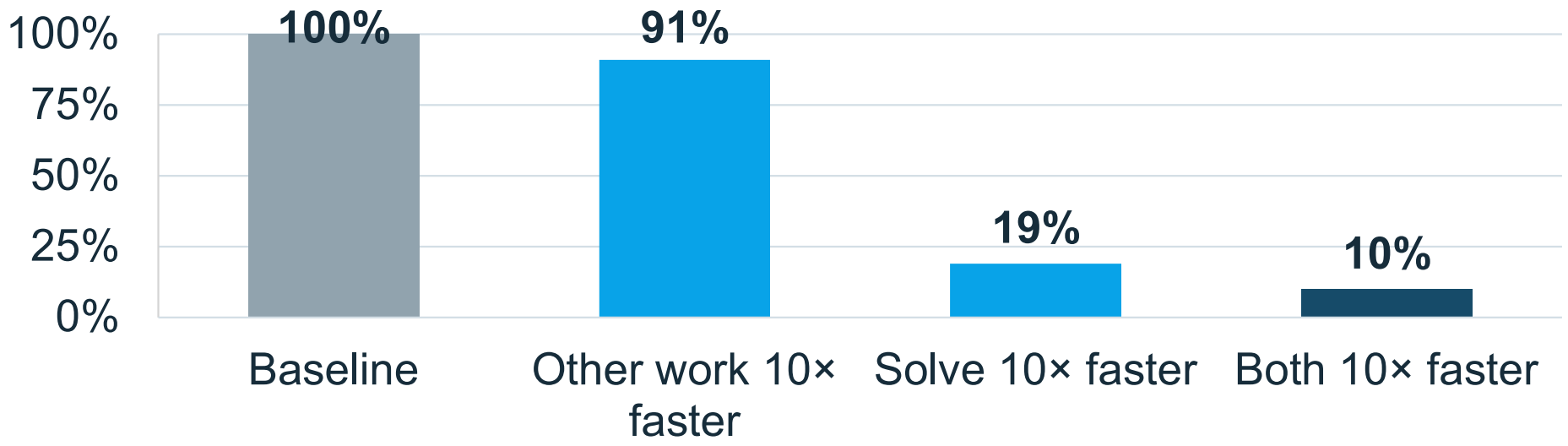
Ashton, Brandstetter & Mishra

The evidence engineering users need from ML

1 Unseen designs	Hold out entire geometries and operating regimes
2 Engineering quantities	Assess force, moment, separation and trends
3 Numerical behaviour	Check conservation, rollout stability and uncertainty
4 Experimental evidence	Quantify error beyond the CFD training labels

Slow tools limit the agent's learning loop

Illustrative serial cycle: 90% solve, 10% other work



Fast tools make agent iteration more valuable

Amdahl illustration, not measured data

Future HPC will require algorithmic choices

Data locality	Reuse on-device data and reduce global movement
Arithmetic intensity	Evaluate matrix-free and higher-order methods
Communication	Reduce synchronisation and overlap transfers
Useful performance	Compare time and energy at a target accuracy

Vision 2030 and Oxford HPC discussion

The route towards broader use of WRLES

Routine aircraft WRLES remains a demanding target

Approach	What determines useful accuracy
RANS	Closure behaviour in separated and off-design flows
WMLES / HRLES	Wall treatment, transition and resolved turbulence
WRLES	Near-wall resolution, time steps and sampling

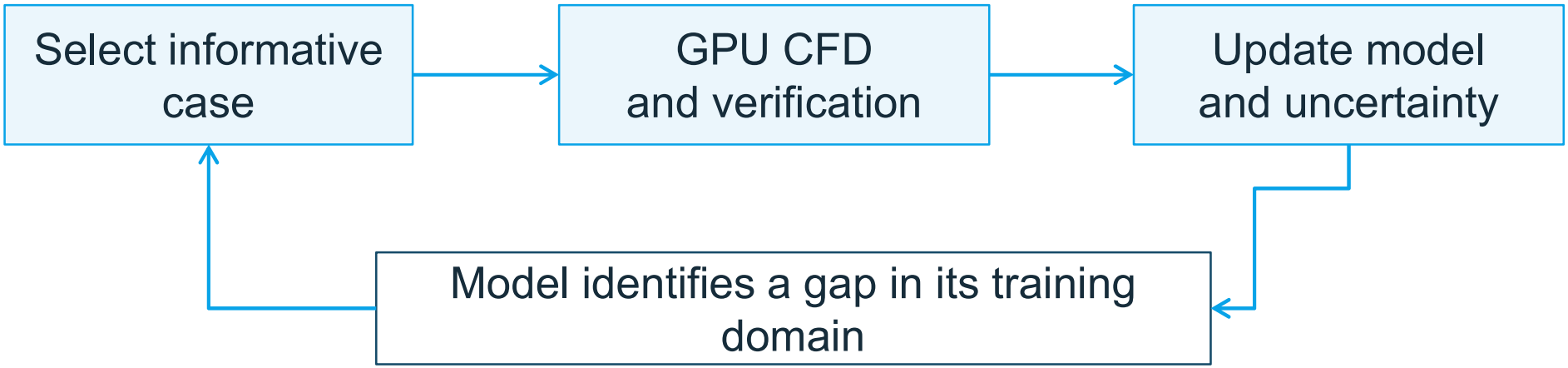
2014 cost model: WMLES $\propto Re^{1.3}$ WRLES $\propto Re^{2.5}$

Illustrative Reynolds-number scaling under the report's assumptions

Vision 2030, LES cost case study

Faster CFD and ML can improve each other

Proposed workflow for spending compute where it adds information

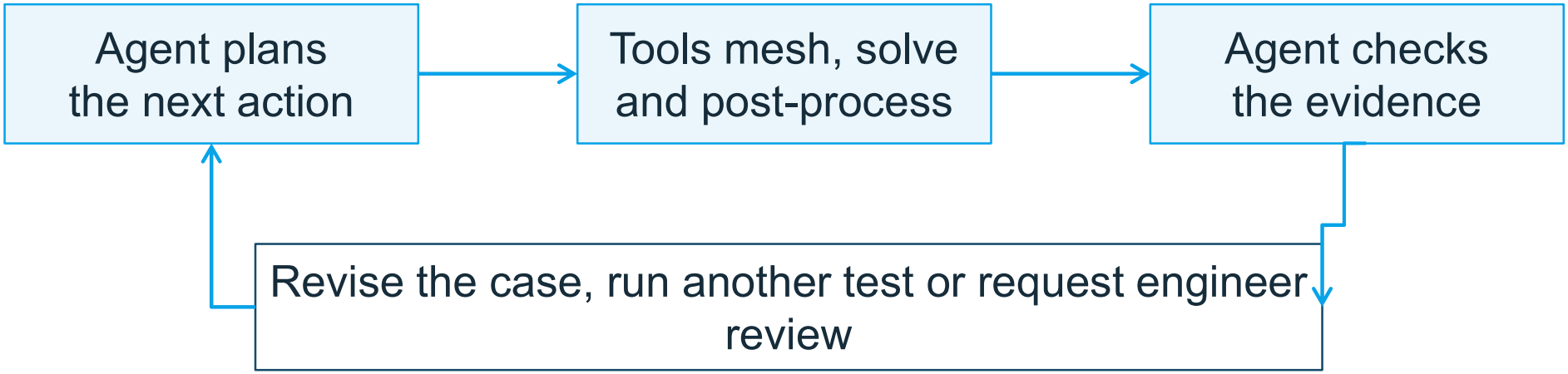


Multi-fidelity data and selective in-situ processing reduce waste

Proposed CFD–ML workflow

LLM agents offer a new route to CFD automation

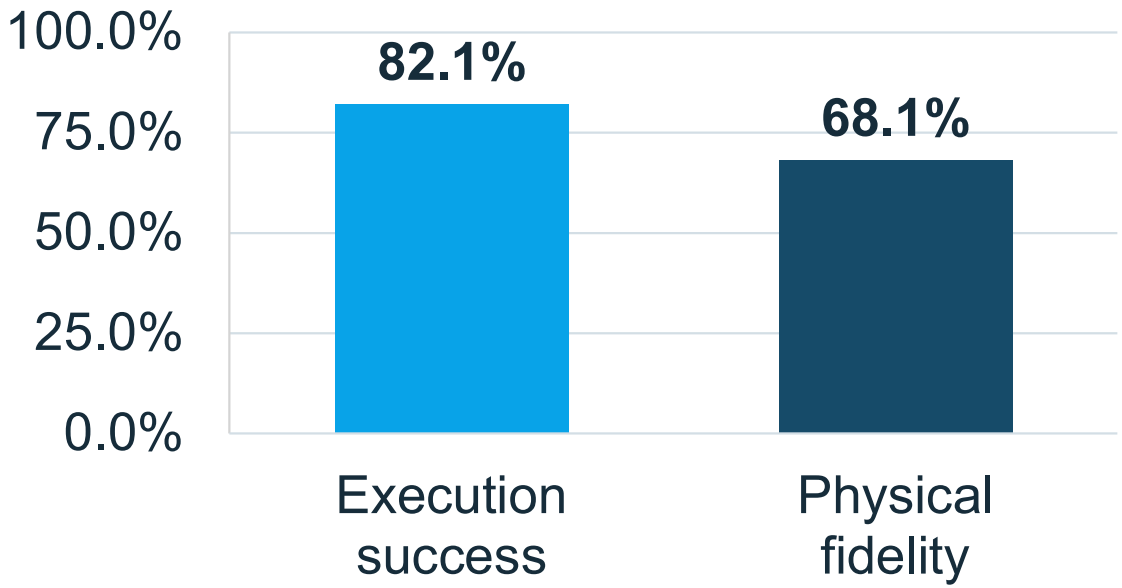
Engineer specifies an objective, constraints and acceptance criteria



Tool outputs determine progress through the workflow

Agent execution needs a physical check

ChatCFD: 315 tutorial and perturbed cases



The physical check

Requested boundary conditions
Appropriate physical models
Plausible flow features

Complex mesh generation excluded from this benchmark

ChatCFD, 2026

An outlook

HPC expands affordable fidelity → ML reuses simulation knowledge → Agents coordinate tools and evidence

Time and energy per validated design decision

Panel question: which bottleneck should we remove next?

Neil Ashton's outlook

CFD Vision 2045

The AIAA CFD2030 Integration Committee is pleased to announce the formation of a new multi-institution group tasked with defining where computational fluid dynamics and its allied fields should be by the year 2045 to meet the demands of future aerospace systems. These results will be compiled into a CFD 2045 Vision study that documents the capabilities required, the grand challenges that stand in the way, and a roadmap of research and technology milestones needed to reach those goals.

This effort builds on the legacy of the CFD Vision 2030 study, which shaped a decade of progress in CFD research and application.

We look forward to sharing more as the CFD2045 team begins its work and to engaging the community throughout the development of this next long-range vision for CFD.

For more information:
Contact: Prashant Khare (Prashant.Khare@uc.edu)
Website: https://www.cfd2030.com/

CFD Vision 2030 Grand Challenge Workshop

Chad Winkler

Boeing Engineering & Technology Innovation

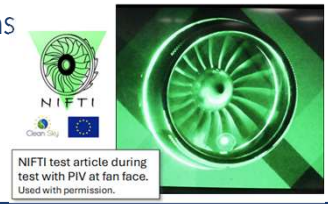
A CFD 2030 Grand Challenge Workshop Framework

Background

- The original 2014 CFD 2030 report proposed four grand challenges including three aircraft-centric problems:
  1. Powered, full-envelope LES
  2. Off-design turbofan transient simulation
  3. MDAO of highly flexible aircraft
- Follow-on discussions and work yielded the 2021 High Lift Grand Challenge Problem, a subset of the original (1) problem. Progress in high-lift prediction has been achieved; work remains.
- The international aerospace community is still far from achieving the 1st three original grand challenges. Would focus on a new combined grand challenge benefit the aerospace community?

Technology Gains from Joint Work on a New Grand Challenge

- Identification of industry needs to approach differently from previous methods:
  - Significant advancements are needed in experimental campaigns, computational tool development, and physics understanding
  - Likely will positively affect certification by analysis efforts, which can be highly proprietary
- One example: powered, aeroelastically-deformed commercial transport at high- and low-speed conditions
- More discussion is necessary



Recent Discussions

- Leads of several workshops have been meeting and have discussed partnering to solve the three original aircraft grand challenge problems
  - Propulsion Aerodynamics Workshop, Drag Prediction Workshop, Aeroelastic Prediction Workshop, High-Lift Prediction Workshop
  - Potential to expand to Ice Prediction Workshop and acoustics
- Conducted highly attended panel discussion (~70 attendees) at Aviation 2026 - demonstrating strong interest for such an effort
  - Expressed interest in a short white paper of effort by SciTech
  - Strategic intermediate building blocks must be carefully established
- Note: See AIAA 2021-0955 (Slotnick & Mavriplis). High-lift focus as per title, but also a lot of content related to this idea.

Next Steps

- Define key problems (will be a focus both today and tomorrow)
- Lay out building blocks to achieve such an effort
  - Goals will be a mix of detailed understanding within one community and multidisciplinary efforts
  - Path should be applicable to commercial and defense configurations
  - Existing workshops may continue for multiple more cycles independently or in joint partnerships
- Identify potential experimental campaigns to enable the effort
- Establish leadership, governance, ownership
- Mature concept and document in a white paper for SciTech '27

Representative Community Needs (Details)

Propulsion Needs (Chad Winkler)

- *Determine spillage impact of powered inlet on wing with control surfaces*
- *Determine jet effects increments on installed propulsion system*
- *Determine inlet response to gusts/throttle transients*

Drag Needs (Ben Rider)

- *Determine effect of a powered inlet upon wing at transonic conditions*
- *Measure high-Reynolds number unsteady buffet characteristics*
- *Capture high-quality deformation metrics across the envelope*

Aeroelastic Outlook (Kevin Jacobson)

- *Improved CFD-based aeroelastic prediction with control surfaces*
- *Determine structural flexibility's impact on transonic buffet*
- *Static aeroelastic effects for various flight conditions*

High-Lift Needs (Adam Clark)

- *Accurate CLmax prediction*
- *Boundary-Layer Transition Sensitivities*
- *Approach for handling multiple solutions in RANS*

Representative Community Needs (Details)

Propulsion Needs (Chad Winkler)

- ***Determine spillage impact of powered inlet on wing with control surfaces***
  Minimum data required: Wing section with turbine powered simulator (TPS) installed in a podded nacelle, with drag measurements as a function of inlet power setting.
  Outcome: Validated toolset for simulating rotating hardware with accurate drag predictions; Distortion maps as a function of Mach, alpha, beta, and power setting
- ***Determine jet effects increments on installed propulsion system***
  Minimum data required: Same config as above, with inclusion of accurate nozzle geometry, and core/bypass streams.
  Outcome: Validated toolset for simulating nozzle plumes and their impact on downstream surfaces, including surface temperatures.
- ***Determine inlet response to gusts/throttle transients***
  Minimum data required: Same config as above, but with time-varying freestream/fan conditions.
  Outcome: Tool validation with map of distortion vs gust/throttle transient type.

Drag Needs (Ben Rider)

- ***Determine effect of a powered inlet upon wing at transonic conditions***
  Minimum data required: Wing section with turbine powered simulator (TPS) installed in a podded nacelle, with drag measurements as a function of inlet power setting.
  Outcome: PAI effects upon integrated loads and sectional pressures
- ***Measure high-Reynolds number unsteady buffet characteristics***
  Minimum data required: Unsteady surface pressure data (preferably uPSP), F&M histories, and dynamic deformation metrics on either a wing or wing/body transport
  Outcome: Dataset for tool validation at the edge-of-the-envelope at flight scale
- ***Capture high-quality deformation metrics across the envelope***
  Minimum data required: Integrated F&M, sectional pressures, and static deformation metrics; appropriately validated FEM
  Outcome: Data set for tool validation across the envelope

Aeroelastic Outlook (Kevin Jacobson)

- ***Improved CFD-based aeroelastic prediction with control surfaces***
  Outcome: Ability to predict aeroservoelastic effects for high lift wind up stick force, control surface flutter
- ***Determine structural flexibility's impact on transonic buffet***
  Outcome: Ability to predict buffet for flight vehicles, not just rigid wind tunnel models
- ***Static aeroelastic effects for various flight conditions***
  Outcome: Accurate high lift and drag prediction of aircraft with flexible wings

High-Lift Needs (Adam Clark)

- ***Accurate CLmax prediction***
  Minimum data required: Lots of experimental data, none of it agrees. Need experimental consensus
  Outcome: Validated toolset(s) useful for leading edge design & corner of the envelope simulations.
- ***Boundary-Layer Transition Sensitivities***
  Minimum data required: State of boundary layer on relevant problem (transition data). Boundary layer characteristics post-transition (e.g. end of slat)
  Outcome: Confidence in SRS modeling approaches for transitional flows
- ***Approach for handling multiple solutions in RANS***
  Minimum data required: Detailed flow information (off-body) behind slat brackets
  Outcome: Expanded range of RANS calculations, enabling more affordable simulations

Points of Contact

- **CFD Vision 2030 Chair**
  - Nick Georgiadis (NASA Glenn); georgiadis@nasa.gov
- **Propulsion Aerodynamics Workshop Chair**
  - Chad Winkler (Boeing Engineering & Technology Innovation); chad.m.winkler@boeing.com
- **Drag Prediction Workshop Co-Chairs**
  - Ben Rider (Boeing Commercial Airplanes); ben.j.rider2@boeing.com
  - Brent Pomeroy (NASA Langley Emeritus); brent.w.pomeroy@nasa.gov
- **Aeroelastic Prediction Workshop Member and 2045 Coauthor**
  - Kevin Jacobson (NASA Langley); kevin.e.jacobson@nasa.gov
- **High-Lift Prediction Workshop Chair and 2045 Coauthor**
  - Adam Clark (Boeing Commercial Airplanes); adam.m.clark@boeing.com