Vision 2030 Roadmap Progress and Technology Highlights for 2021

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In 2021, the AIAA CFD Vision 2030 IC Roadmap subcommittee released a report [1] reviewing progress and challenges associated with the technology items identified on the Roadmap from its initial release through 2020. This document identified that while significant progress had been made on key technology demonstration items, many of the original milestones were behind schedule. With some of the findings since 2014, some of these milestones are less critical at present and new items of study have been identified. This report was followed by a companion paper [2] presented at AIAA Aviation that provided an updated Roadmap with shifted milestones and the addition of new technology milestones as well as enhanced Domain definitions. This paper also provided a TRL level scale to measure technology development appropriate for this type of community-level activity and performed an initial assessment of the tasks. More detailed descriptions were also provided to assist in quantifying progress.

This activity is continued by the roadmap subcommittee providing annual reviews of progress to assist in identifying critical technologies that need additional focus and to help promote successful progress on other tasks. Overall, the pandemic appears to have reduced the dissemination of information during this year, with seemingly less progress than typically expected. Many contacts have chosen to defer publications until 2022. The following sections outline key progress made toward the milestones in each Domain as identified by surveys of experts across the aerospace industry and literature reviews, particularly across AIAA publications. The authors acknowledge that this process is not complete and appreciate any feedback and assistance to improve these surveys going forward. We apologize for any omissions.

While not yet in an implementation phase, another CFD Vision 2030 IC activity highlighted three Grand Challenge problems at SciTech 2021. These activities provide another mechanism to rally progress toward achieving progress toward the Vision. These Grand Challenge problems outline a series of analyses and validation experiments to advance the state of the art in commercial high lift prediction [3], engine analysis [4], and space vehicle design [5]. These problems require community support to progress and offer the potential to demonstrate CFD capabilities at unprecedented levels and build confidence in the applications.

High Performance Computing

The aerospace CFD community has continued to see modest activity toward the HPC thrust of the roadmap, primarily aligned with more conventional, evolutionary hardware technologies. In addition to optimization efforts for CPU-based computing, development teams have continued to focus on porting strategies aimed at GPUs. These often include CUDA-based implementations targeting NVIDIA platforms, as well as portable abstractions such as the OpenACC approach based on the use of compiler directives. Examples include the work described in Refs. [6-16]. At leadership-class scale, the implementation demonstrated in Ref. [17] has enabled reacting-gas simulations on billions of mesh elements using 16,000 GPUs to achieve computational throughput equivalent to that of several million CPU cores. Finally, efforts associated with the revolutionary systems track of the roadmap continue to pursue low TRL research, which may take ten years or more to yield practical approaches for the aerospace CFD community.

There has been relatively little change amongst the upper tier of the Top500 rankings. Two new systems have appeared in the Top 10 over the past year, each relying on NVIDIA Tesla A100 GPUs. However, the next couple of years will likely see substantial shakeups in the rankings, with three exascale-class systems – Frontier, Aurora, and El Capitan – slated to arrive at the Department of Energy, and several new European systems targeted to achieve several hundred petaflops each. These new systems will generally leverage AMD and NVIDIA GPUs, with Aurora based on Intel GPUs.

Physical Modeling

Assessment and improvement of smooth body separation prediction capability is a current focus of RANS modeling. A workshop is planned for SciTech 2022 to address this key roadmap issue [18]. Significant effort is currently focused on a Gaussian speed bump configuration. Experimental investigations, LES and DNS are in progress [19,20]. While there is significant effort to assess the accuracy of RANS models for a wide range of applications, there is limited evidence of major advances in RANS modeling capability [21].

Improvements in wall modeled large eddy simulation (WMLES) and demonstrations of WMLES capabilities on complex configurations were reported in 2021. Loazano-Duran, Moin and Park [22] evaluate WMLES accuracy in 3-D boundary layers. This work shows that WMLES can be applied to flows with highly 3-D boundary layers, but some error is introduced with a 2-D-based wall model. Yu, Yan and Milani [23] evaluate the matching point requirements for WMLES and advocate a method that allows the first mesh cell as a matching point. Macdonald and Candler [24] apply WMLES to a hypersonic flow and assess its performance. Gross, Castillo and Lee evaluate WMLES for supersonic boundary layers [25]. The expanded applications and evaluations of WMLES for complex geometries indicate expanded use and maturation of this modeling approach.

The use of DNS and LES methods for obtaining high fidelity turbulence data for use as benchmark data for RANS method evaluation continues to expand. In addition to the analyses of the speed bump [19,20,26,27], Nicholson, Huang, Duan, Choudhari and Bowersox [28] used DNS to study streamline curvature in a Mach 5 flow. They evaluated RANS model predictions of turbulence quantities, solving turbulence model equations for the DNS based velocity field. Gaskin, Poggie and Blaisdel [29] evaluated roughness patterns in the low end of the fully rough regime in a Mach 2 boundary layer. Bowyer, Cantwell, Onn and West [30] evaluated wingtip vortex flowfields with LES and compared several RANS models to the simulation results. Bhagwandin and Martin [31] simulated the shock boundary layer interaction for a hollow cylinder with a flared cone at Mach 10 with LES and compared to test data. This configuration is frequently used as a RANS method benchmark.

The investigation of machine learning for the improvement of physical models is growing and the range of applications is expanding. This is an emerging area that was not mentioned in the original CFD 2030 report. While this is an area with a high level of activity, these methods have mostly been demonstrated on simple, canonical flows, mostly 2-D or axisymmetric. Pochampalli, Ozkaya, Zhou, Suarez and Gauger [32] used machine learning to modify the production term in the Spalart Almaras turbulence model. They demonstrated their method on NACA 0012 and NACA 0021 airfoils. They also used Machine learning to modify the S-A turbulence model to improve predictions of the separated flow over the NASA hump model [33]. A team of researchers from New Mexico State University and the University of Arizona applied machine learning to estimate the amplification factor for transition prediction. The machine learning estimates were integrated into Coder's transport-based transition model and tested on an airfoil and a low pressure turbine cascade [34]. Machine learning was also applied to the modeling of chemical kinetics [35].

Recently a five-year assessment of CFD 2030 milestones in the Physical Modeling area was completed. Progress in transition prediction was highlighted as an area lagging the original roadmap milestone. The recent expansion in efforts to develop robust and accurate transport equation-based transition prediction models continued in 2021. Groot, Patel, Saiyasak, Coder, Stefanski and Reed [36] assessed the Amplification Transport Model of Coder et al. [37] for transition prediction in hypersonic flow. While the method showed promising results, significant discrepancies between model predictions and parabolized stability equation predictions are evident for some flows. Interest in this area is also exemplified by the work of Lee and Baeder [38] who calibrate a one equation transition model for the S-A RANS model. Efforts to simulate transitional flow with DNS continue. The study by Hartman, Hader and Fasel [39] of transition on a blunt cone at Mach 6 with LES is an example of ongoing efforts in this area.

It is hard at the present time to see any breakthroughs in physical model development in 2021. However, it is clear that there has been evolutionary progress and maturation of methods over the past year. The upcoming NASA sponsored symposium, "Turbulence Modeling: Roadblocks, and the Potential for Machine Learning" [40], will provide an opportunity to assess progress and highlight promising research directions with potential to advance turbulence and transition prediction capabilities.

Algorithms

Making improvements to the robustness and efficiency of higher order schemes, particularly for time-dependent simulations is a continuing theme in the Algorithms Domain. Fidkowski [41] performed a rigorous stability analysis of the discontinuous Galerkin (DG), hybridized discontinuous Galerkin (HDG), and embedded discontinuous Galerkin (EDG) to demonstrate that while the degree of freedom count decreases significantly with HDG and EDG, so do their stability properties with Jacobi solvers, particularly for advection dominated problems. Franciolini et al. [42] showed that more advanced preconditioning methods including multigrid can result in significantly improved convergence properties for higher order systems. Yoon and Maviplis [43] compared the performance of space time DG formulations with fully implicit Runge Kutta time integration methods and illustrated the equivalence between these schemes as previously discussed in Huynh et al. [44] Using enstrophy histories for multiple unsteady LES benchmark problems, Wang [45] was able to provide evidence of significant performance improvements of higher order methods at comparable accuracy levels. Improvements were also reported for traditional second-order scheme performance by fine tuning the nonlinear solver algorithm HANIM [46] as well as through discretization adjustments for viscous terms [47].

Motivated by scatter in the second aeroelastic prediction workshop, an NIPC analysis of a 2D transonic aeroelastic problem [48] suggests that plausible uncertainties in flow parameters and geometry imperfections can lead to large scatter in flutter speed. This step highlights the benefits of including UQ analysis even in deterministic analysis scenarios such as computational workshops. Taylor and Rumsey [49] proposed a more general perspective for validation experiments that has larger synergy between the physical test and the numerical simulation with an intended end result of identifying the predictive capabilities of CFD.

Geometry Modeling and Mesh Generation

Geometry Modeling

The rectangular nature of the parameterization underlying the B-spline techniques that form the backbone of contemporary MCAD modelling systems is the source of many of the challenges faced in incorporating BREP models into computational simulation workflows. (The rectangular topology necessitates the frequent use of surface-to-surface intersections that, for reasons of robustness and convenience, are approximated, rendering the regions of the BREP in the immediate vicinity of such intersections geometrically ambiguous and nongeometrically-watertight.) To address this well-known limitation, researchers at the University of Groningen have developed a generalized B-spline construction that extends uniform, bicubic B-splines to multisided regions spanned over extraordinary vertices in quadrilateral meshes [50]. The resulting multisided surfaces are C2 continuous internally and connect with G2 continuity to adjacent regular and other multisided B-spline patches.

The lack of geometric watertightness exhibited by most MCAD geometry models in the immediate vicinity of surface-to-surface intersections creates challenges for mesh generation, especially adaptive mesh refinement where, in regions of high flow gradients, the edge lengths of cells can be comparable (or even smaller) than the local lack of geometric watertightness in the BREP. In recent years, much effort has been expended toward reducing the manual effort required to address the attendant challenges. Park et al. [51] review some of the techniques that have recently been embedded in mesh generation software. These include (i) using scaffolds built from a combination of the topological and geometrical entities in the BREP to provide a watertight basis for meshing; (ii) bridging the geometric gaps between topological and parametric geometric BREP entities with local facetted geometric entities; (iii) using an existing linear mesh to building a cubic surrogate quilt; (iv) superimposing a displacement field computed at the intersections, but smoothed over the remainder of the boundary, onto the original BREP to reduce the lack of geometric watertightness. None of the techniques rely on a priori knowledge of the tolerancing scheme used to build the source BREP, using displacements between the (transmitted) edges and (in situ computed) p-curves to guide their mitigation schemes. In each case, as far as possible, links between the mesh and the underlying BREP running parameters are maintained, thereby facilitating standard queries pertaining to surface properties (e.g., curvature) that may be used to guide the mesh generation (and/or refinement) process.

Untraditional techniques continue to demonstrate improved capabilities for CFD applications especially in terms of eliminating preprocessing steps like geometry model repair preparation. Immersogeometric analysis (IMGA) [52], inspired by isogeometric analysis (IGA), make direct use of the BREP of a complex model by immersing it in a non-body-fitted discretization of the fluid region. Geometry model cleanup is not required and the meshing burden is vastly reduced. As demonstrated by Hsu [53], a mesh in excess of 11 million cells can be generated in "seconds" and the resulting mean flow computed about a complex geometry model (a tractor) is reported as comparing favorably with that derived using a body-fitted mesh.

Mesh Generation

Recent work demonstrated important steps toward improved robustness and automation of geometry processing and mesh generation methods on complex geometries. These methods often rely on field calculations (e.g., cross fields, sizing fields, deformation) that in turn require their own meshing step, which can lack robustness. Work by Sawhney & Crane [54] demonstrates how to create certain classes of these fields robustly on poor-quality geometry without any background mesh.

An example of a framework for more closely coupling the mesh and the geometry is MeshLink, an open-source project described by Wyman et al. [55]. MeshLink consists of two components. First, a schema has been defined for describing the one-to-many associativity of a surface mesh to curves and surfaces in the geometry model. Second, a high-level library provides a kernel-agnostic wrapper for simplifying the necessary geometry queries to a downstream consumer (e.g., flow solver).

The Exascale Computing Project [56] and the Center for Efficient Exascale Discretizations [57] have produced a paper to summarize recent research efforts and accomplishments [58]. The paper's 30 authors, representing two national labs and five universities, state that they use high-order elements and "traditional" refinement of unstructured meshes to increase the degrees of freedom in the finite element domain versus "brute force" refinement of a linear mesh. This general trend is observed throughout applied CFD; instead of simply using meshes with more and more mesh points, AMR is used to efficiently resolve the mesh only where needed.

That is not to say that work on exploiting HPC resources to improve meshing performance has ceased. The software Gmsh has reported increased performance with the addition of multithreading [59]. On 2x AMD EPYC 64-Core (127 cores), Gmsh generated 663 million tetrahedra in less than five minutes around an aircraft and 721 million tetrahedra in just over two minutes for another geometry model.

The application of mesh adaptation in production workflows has been used to evaluate CFD as a surrogate for Mach 2.4 to 4.6 wind-tunnel testing [60]. The evaluation included expert-crafted meshes and multiple flow solvers. Simulations of the high-speed leg of the wind tunnel with an empty test section [61,62] and models installed with support hardware [63-65] created an extreme range of geometric scales. Simulations of vortices generated by structures upstream of the wind tunnel throat and the corners of the throat were propagated through the sonic throat to the supersonic test section. These simulated vortices impacted the model and support hardware to provide context for previously unexplained measurement anomalies. The Space Launch System (SLS) model and support hardware had high-fidelity geometric detail [65], which indicates progress in accommodating complex geometry sources in production CFD environments with mesh adaptation.

Generating high-quality quad meshes is still an area where robustness is currently lacking in current pipelines. Work by Pietroni et al. [66] appears to show a step forward in this area.

Knowledge Extraction

In 2021, there has been considerable effort in the use of Machine Learning (ML) methods and Data Analytics (DA) to aid the engineer in extracting knowledge from large scale CFD simulations. Brunton et.al. [67] described in a review article how machine learning methods will influence Aerospace Engineering. One of the opportunities for machine learning is in "human–machine interactions (advanced design interfaces, interactive visualizations,…" where ML is used to inform uncertainty quantification (UQ), feature extraction and knowledge extraction from large scale CFD simulations. Duraisamy [68] gave a review paper where he presented his "Perspectives on machine learning and its use to augment RANS and LES modeling of turbulence." As computer systems have grown and with the availability of ML software such as TensorFlow [69], there has been a growth in the use of these methods. Duraisamy and his colleagues [70] have been developing turbulence models informed from ML methods. Fukami, Fukagata and Taira [71] used a data reconstruction method with supervised learning to recover high-resolution turbulent flows from coarse flow data in space and time. Blonigan et al. [72] use a DA method, Conservative Manifold Least-Squares Petrov-Galerkin Projection, to form a reduced order model.

Uncertainty Quantification (UQ) is one of the drivers for the development of the ML and DA methods. Model input uncertainty propagation is required; however, it is presently intractable to assess on the high fidelity CFD representative of the CFD 2030 Grand Challenges and in vehicle design studies. Surrogate/Reduced Order Models using DA and ML may make this type of analysis tractable. Good user interfaces are needed to enable engineers to easily manage and extract knowledge from the large amount of information that will be generated (1000s of 10B cell unsteady runs by 2030). Pullan et al. continue development of DBslice as a step toward this. In 2019, he presented the use of a web-based UI using open source software and developed a UI based upon ML and augmented reality [73]. In 2022, he presented how ML methods can be used to guide and inform the engineer in a CFD study of high-fidelity turbomachinery simulations [74].

In 2022, we anticipate continued progress in the development and application of DA and ML methods to further enhance our ability to extract large scale CFD simulations. It has been recently announced that Wang (University of Kansas) in partnership with NVIDIA and CADENCE was awarded an INCITE computer allocation on Summit [75] to perform high fidelity high order simulations. To this date, they have executed a 73 billion degree of freedom simulation on 5^{th}-order elements. DA and ML methods and improved visualization and computational environments will be needed to extract knowledge from these large datasets.

MDAO

There have been many efforts towards increased discipline coupling for air vehicle design, a selection of which include aeropropulsion, aerothermoelasticity, thermal management, and control. Yildirim et al. [76] developed two approaches for fully-coupled aeropropulsion modeling. The first utilizes source terms in an actuator zone and the second facilitates coupling through boundary conditions. Both approaches couple tightly with a 1D thermodynamic cycle (in this case pyCycle) in order to account for the propulsion coupling on the aerodynamic model. Smith et al. [77] extended the FUNtoFEM and MELD aeroelasticity frameworks to include heat transfer for aerothermoelastic coupling and adjoint-based gradient evaluation. A simple gradient-based aerothermoelastic design optimization of a flexible, thermally-conducting panel in supersonic flow was demonstrated. Shi et al. [78] demonstrated a methodology for automatically populating aircraft thermal management system architectures. They demonstrated automatic generation of conventional architectures given conventional requirements, but also demonstrated unintuitive and novel thermal management layouts for a novel vehicle concept. Repolho Cagliari et al. [79] present a method for simultaneous plant and control optimization of chaotic dynamical systems utilizing the least-squares shadowing adjoint. Falck et al. [80] published dymos, a tool built on OpenMDAO for optimal control of multidisciplinary systems. dymos could be used in a broader context of codesign, where control is one piece of a broader (multidisciplinary) design optimization. Finally, two summaries were presented on large-scale collaborative programs in the area of multidisciplinary design optimization. Méheut [81] gave a summary on the main results of the EU MADELEINE project focused on strengthening capabilities and use of multiphysics adjoint solvers for design of aircraft systems and subsystems. Görtz et al. [82] gave an overview of results from the DLR project VicToria (Virtual Aircraft Technology Integration Platform) working toward multifidelity, multidisciplinary design optimization of long-range passenger aircraft.

Recent work in the area of uncertainty quantification (UQ) for air vehicle design optimization demonstrated improvements in multidisciplinary frameworks accounting for UQ as well as improved scalability for UQ-enabled design optimization. Ghosh and Mavris [83] present a framework for uncertainty-based multidisciplinary analysis (UMDA) that admits concurrent disciplinary uncertainty propagation while accounting for the dependence of coupling variables. This contrasts with UMDA processes that decouple uncertainty propagation, which may cause loss of statistical dependencies between coupling variables. In order to alleviate the computational expense of many random parameters in reliability-based design optimization (RBDO), Clark et al. [84] treated normally distributed and non-normally distributed random parameters and stochastic design variables in separate manners. Specifically, normally distributed random parameters were characterized via nondeterministic kriging nonstationary variation estimation, while non-normal parameters were propagated utilizing a surrogate-based method. Utilizing the developed approach, an RBDO solution for a 10-dimensional nonlinear thermoelastic aircraft panel was obtained in a tractable manner without gradient information.

Assessment

Based on the assessments described above and consultation with subject matter experts across the aerospace industry, the Roadmap Subcommittee assigned approximate Technology Readiness Level (TRL) rankings for each of the milestones. Both the assessment and the scale used for this assessment are included in the Appendix. Overall, these assessments reflect minimal changes from 2020. It is not clear if this apparent lack of progress is due to near-term perception bias, incomplete information, or actual minimal progress in the technology areas associated with the milestones since the last assessment. It is also important to recognize that these TRL levels primarily address the availability of a particular technology and not necessarily its appropriateness for particular classes of simulations.

One of the objectives of this report is to identify overall progress toward the CFD Vision 2030 as has been described in the preceding sections. It is also necessary to identify potential risks that may prevent the Vision from being realized because of insufficient observed progress toward the objectives and milestones. It is recognized that both the technology development required and available time to achieve the milestone are key considerations, as well as the degree to which the technology is critical to the overall Vision. As an example, advances in high performance computing are an important foundation to the Vision, but there continues to be steady progress on this front in both traditional and revolutionary concepts such that this technology is not seen as a risk item at present. It is also recognized that some technologies (Reynolds stress modeling, for example) may be behind expectations on the Roadmap, but are not presently considered to be key to the overall Vision as alternatives exist. Finally, there are several milestones requiring an extremely large scope of activity and/or computing such as a 100B cell mesh and 10B point unsteady visualization. These milestones are believed to be within reach by an expert with extreme effort on leadership-class computing but have not yet been met and are not practical for routine application.

Multiple approaches have been utilized to identify the technology risks including projection of TRL progress toward achieving the milestone and assessment/review by the subject matter experts involved in this report. An initial list of 14 items were identified by assuming a TRL increase of 1 per year and assessing if the technology had reached a TRL level of 6 (demonstrating the practicality of the technology) by the milestone date. The items were then assessed to determine if steady progress was being made or if technology development toward objectives had stagnated. Finally, the stagnated technology items were prioritized based on their identification as being on the critical path toward reaching the primary objectives of the Vision. Based on this approach, the following items are currently deemed to be at risk:

- Inclusion of more detailed chemical kinetics in computations and advanced turbulence-combustion interaction models, particularly LES simulations where the flamelet model is not sufficient, is believed to be a critical step toward achieving the enhanced combustion modeling expected by the Vision.
- Robust and distributed geometry modeling and interpretation is required across all meshing thrusts and is a common thread that could slow development if outstanding issues are not resolved. Adaptive meshes may drive mesh cell sizes below the level of tolerances used to assemble the geometry model. High-order mesh curving will encounter geometry model trimming issues. Meshing on HPC platforms will require distributed geometry and lightweight geometry access across thousands of compute cores.
- Defining and accepting standards for facilitating coupling among discipline analyses is a critical step for reaching MDAO milestones. The coupling standards need to include API definitions and data requirements for both high-fidelity simulation and other model forms for effective interfacing not only of values, but also sensitivities for both optimization and robustness assessment.
- Uncertainty quantification and propagation methods through CFD are important to establish confidence in the simulation results, especially when the results are being used in advance of configuration testing to make decisions.

While increasing the development rate of these items is important to achieving the Vision, there may be other technology risks that the selection process has inadvertently omitted. The present milestones identified on the Roadmap tend to reflect specific technical approaches rather than the underlying technical requirement. It may be that the identified approach will not sufficiently address the requirement, even when the associated milestone is met. With this in mind, there are two considerations as we move forward. First, it may be important to also measure trust or confidence levels for existing roadmap technologies since the TRL measurements are primarily limited to development and adoption. Second, as new approaches are developed and published, an emphasis should be placed on meeting the underlying needs of the Vision and avoiding a positive-selection bias because of a subset of results that may not be appropriate for the entire class of targeted objectives. Ultimately, developed models should be validated and predictive with relevance to the broader vision objectives. Furthermore, technology development requires experimental confirmation and established community confidence to reach the objectives of the Vision. Future Roadmap updates should assess approaches for measuring progress toward key needs of the Vision in addition to development of specific potential technology enablers. It may also be necessary to add intermediate milestones for some of the larger technology advances scheduled near the year 2030 to enable a more accurate assessment of progress at that time.

References

[1] A. Cary, J. Chawner, E. Duque, W. Gropp, W. Kleb, R. Kolanay, E. Nielsen and B. Smith, "CFD Vision 2030 - Roadmap Updates," 2021.

[2] A. Cary, J. Chawner, E. Duque, W. Gropp, W. Kleb, R. Kolanay, E. Nielsen and B. Smith, "CFD Vision 2030 Road Map: Progress and Perspectives," AIAA 2021-2726. 2021.

[3] J. Slotnick and D. Mavriplis, "A Grand challenge for the Advancement of Numerical Prediction of High Lift Aerodynamics," in *AIAA SciTech Forum*, AIAA 2021-0955. 2021.

[4] M. Anand, G. Medic, U. Paliath, K. Suder, M. Malik and G. Laskowski, "Vision 2030 Aircraft Propulsion Grand Challenge Problem: Full-engine CFD Simulations with High Geometric Fidelity and Physics Accuracy," in *AIAA Scitech Forum*, AIAA 2021-0956. 2021.

[5] D. Schuster, "CFD 2030 Grand Challenge: CFD-in-the-Loop Monte Carlo Flight Simulation for Space Vehicle Design," in *AIAA Scitech Forum*, AIAA 2021-0957. 2021.

[6] M. Acton, M. Wolff and M. List, "Computational Inlet Swirl Distortion Investigation of a High-Speed Compressor," in *AIAA Scitech Forum*, AIAA 2021-0387. 2021.

[7] J. Appa, M. Turner and N. Ashton, "Performance of CPU and GPU HPC Architectures for Off-Design Aircraft Simulations," in *AIAA Scitech Forum*, AIAA 2021-0141. 2021.

[8] M. Bernardini, M. Cimini, F. Stella, E. Cavillini, A. Di Mascio, A. Neri, F. Salvadore and E. Martelli, "Implicit Large-Eddy Simulation of Solid Rocket Motors using the Immersed Boundary Method," in *AIAA Scitech Forum*, AIAA 2021-3696. 2021.

[9] E. De Araujo, J. Filho and Z. J. Wang, "A Matrix-free GMRES Algorithm on GPU Clusters for Implicit Large Eddy Simulation," in *AIAA Scitech Forum*, AIAA 2021-1837. 2021.

[10] A. Figueroa and R. Lohner, "Experiences Porting a High Order Cartesian Finite Difference Solver to GPUs Using OpenACC," in *AIAA Scitech Forum*, AIAA 2021-1208. 2021.

[11] D. Jude, J. Sitaraman and A. Wissink, "An Octree-based, Cartesian CFD Solver for Helios on CPU and GPU Architectures," in *AIAA Scitech Forum*, AIAA 2021-0841. 2021.

[12] L. Kedward and C. Allen, "Optimisation of a Dinite-Volume Test-bench Code for Highly Parallel Architectures," in *AIAA Scitech Forum*, AIAA 2021-0143. 2021.

[13] D. Kessler, R. Johnson, K. Obenschain, E. D., A. Koniges, G. Candler, H. Johnson, J. Bretheim, H. Thornburg, G. Patnaik, K. Roe, D. McDaniel, R. Bond, E. Nielsen, A. Walden, G. Nastac and R. Campbell, "The Influence of Computer Architecture on Performance and Scaling for Hypersonic Flow Simulations," in *AIAA Scitech Forum*, AIAA 2021-0144. 2021.

[14] A. Markesteijn, H. Jawahar, S. Karabasov and M. Azarpeyvand, "Large Eddy Simulation for Airfoil with Serrated Trailing-edges at High Angle of Attack," in *AIAA Scitech Forum*, AIAA 2021-2200. 2021.

[15] R. Vandenhoeck and A. Lani, "Development of a GPU-Enabled High-Order Flux Reconstruction Solver for High-Speed Flows," in *AIAA Scitech Forum*, AIAA 2021-0055. 2021.

[16] X. Zhai, D. Gutzwiller, K. Puri and C. Hirsh, "GPU Acceleration of the FINE/FR CFD Solver in a Heterogeneous Environment with OpenACC Directives," in *Proceedings of the 7th International WACCPD Workshop, Springer Lecture Notes in Computer Science*, 2021.

[17] G. Nastac, A. Walden, E. Nielsen and K. Frendi, "Implicit Thermochemical Nonequilibrium Flow Simulations on Unstructured Grids using GPUs," in *AIAA Scitech Forum*, AIAA 2021-0159. 2021.

[18] M. C. Adler, L. P. Riley, D. R. Gonzalez and S. K. Lele, "Wall-Modeled Large-Eddy Simulation and RANS for Pre-Workshop on Smooth-Body Separation," in *AIAA Scitech Forum*, AIAA 2021-1553. 2021.

[19] J. R. Wright, R. Balin, J. A. Evans and K. E. Jansen, "Unstructured LES-DNS of a Turbulent Boundary Layer over a Gaussian Bump," in *AIAA Aviation Forum*, AIAA 2021-2992. 2021.

[20] M. L. Shur, P. R. Spalart, M. K. Strelets and A. K. Traviin, "Direct Numerical Simulation of the two-dimensional speed bump flow at increasing Reynolds numbers," *International Journal of Heat and Fluid Flow,* vol. 90, August 2021.

[21] A. S. Ghate, G. K. Kenway, G. D. Stich, O. M. F. Browne, J. A. Housman and C. C. Kiris, "Transonic Lift and Drag Predictions using Wall Modelled Large Eddy Simulations," in *AIAA Scitech Forum*, AIAA 2021-1439. 2021.

[22] M. Cho, A. Lozano-Duran and P. Moin, "Wall-Modeled Large-Eddy Simulation of Turbulent Boundary Layers with Mean-Flow Three-Dimensionality," *AIAA Journal,* vol. 59, no. 5, May 2021.

[23] H. H. A. Xu, X. I. A. Yang and P. M. Milani, "Assessing Wall-Modeled Large-Eddy Simulation for Low-Speed Flows with Heat Transfer," *AIAA Journal,* vol. 59, no. 6, June 2021.

[24] R. L. Macdonald and G. V. Candler, "Evaluation of Wall Modeled Large Eddy Simulation of Cold Wall Hypersonic Boundary Layer," in *AIAA Scitech Forum*, AIAA 2021-1844. 2021.

[25] A. Gross, P. Castillo and S. Lee, "Wall-Modeled Large-Eddy Simulations of Turbulent Shockwave Boundary Layer Interaction and Boundary Layer Flows," in *AIAA Aviation Forum*, AIAA 2021-2749. 2021.

[26] A. Uzun and M. R. Malik, "High Fidelity Simulation of Turbulent Flow Past Gaussian Bump," *AIAA Journal,* vol. 60, no. 4, pp. 2130-2149, 2022.

[27] A. Uzun and M. R. Malik, "Simulation of a Turbulent Flow Subjected to Favorable and Adverse Pressure Gradients," *Theoretical and Computational Fluid Dynamics,* vol. 35, no. 3, pp. 293-329, 2021.

[28] G. L. Nicholson, J. Huang, L. Duan, M. M. Choudhari and R. D. W. Bowersox, "Simulation and Modeling of Hypersonic Turbulent Boundary Layers Subject to Favorable Pressure Gradients due to Streamline Curvature," in *AIAA Scitech Forum*, AIAA 2021-1672. 2021.

[29] E. J. W. Bowyer, C. D. Cantwell, J. H. M. Onn and A. West, "Large Eddy Simulation of Wingtip Vortex Evolution in an Adverse Pressure Gradient," in *AIAA Scitech Forum*, AIAA 2021-1940. 2021.

[30] J. J. Gaskins, J. Roggie and G. Blaisdell, "A Preliminary Study of Roughness Effects on a Compressible Turbulent Boundary Layer," in *AIAA Scitech Forum*, AIAA 2021-1445. 2021.

[31] V. Bhagwandin and M. P. Martin, "LES of Shock-Turbulent Boundary Layer Interaction over a Mach 10 Hollow Cylinder with Flare," in *AIAA Scitech Forum*, AIAA 2021-1820. 2021.

[32] R. Pochampalli, E. Ozkaya, B. Y. Zhou, G. Suarez and N. R. Gauger, "Machine Learning Enhancement of the Spalart-Allmaras Turbulence Model using Convolutional Neural Network," in *AIAA Scitech Forum*, AIAA 2021-1445. 2021.

[33] G. Suarez, E. Ozkaya, R. Pochampalli, N. R. Gauger and B. Y. Zhou, "Towards Turbulence Modeling Enhancement via the Correction of Boussinesq's Hypothesis - A Data-Driven Approach," in *AIAA Aviation Forum*, AIAA 2021-3088. 2021.

[34] P. Barraza, P. Castillo, A. Tena, A. L. M. Gross, V. Tsakagiannis and H. F. Fasel, "Machine-Learning Based Amplification Factor Transport Equation for Transition Modeling," in *AIAA Aviation Forum*, AIAA 2021-2706. 2021.

[35] A. Sharma, A. Moses and R. Johnson, "Toward Compact, Numerically Stable Machine Learning Functions for Chemical Kinetics," in *AIAA Scitech Forum*, AIAA 2021-1785. 2021.

[36] K. J. Groot, J. M. Patel, A. Saiyasak, J. G. Coder, D. L. Stefanski and H. L. Reed, "Assessment of the Amplification Factor Transport Transition Model for High-Mach Number Flows," in *AIAA Aviation Forum*, AIAA 2021-2830. 2021.

[37] J. G. Coder and M. D. Maughmer, "Computational Fluid Dynamics Compatible Transition Modeling Using an Amplification Factor Transport Equation," *AIAA Journal,* vol. 52, no. 11, November 2014.

[38] B. Lee and J. D. Baeder, "Prediction and validation of laminar-turbulent transition using SA-γ transition model," in *AIAA Scitech Forum*, AIAA 2021-1532. 2021.

[39] A. B. Hartman, C. Hader and H. F. Fasel, "Direct Numerical Simulations of laminar-turbulent boundary-layer transition for a blunt cone at Mach 6," in *AIAA Scitech Forum*, AIAA 2021-0744. 2021.

[40] NASA, "2022 Symposium on Turbulence Modeling: Roadblocks and the Potential for Machine Learning," [Online]. Available: https://turbmodels.larc.nasa.gov/turb-prs2022.html.

[41] K. Fidkowski, "Analysis of Iterative Solvers for Hybridized Discontinuous Galerkin Methods," in *AIAA Aviation Forum*, AIAA 2021-2718. 2021.

[42] M. Franiolini, A. Garai and S. Murman, "Efficient preconditioning of a high-order solver for multiple physics," in *AIAA Aviation Forum*, AIAA 2021-2719. 2021.

[43] S.-H. Yoon and D. Mavriplis, "High-Order Space-Time Discontinuous Galerkin Discretization Using Tensor-Product Formulations," in *AIAA Scitech Forum*, AIAA 2021-0156. 2021.

[44] H. T. Huynh, Z. J. Wang and P. E. Vincent, "High-order methods for computational fluid dynamics: A brief review of compact differential formulations on unstructured grids," *Computers and Fluids,* vol. 98, pp. 209-220, 2014.

[45] Z. J. Wang, "Relative performance of high-order to 2nd order schemes for benchmark LES problems," in *AIAA Aviation Forum*, AIAA 2021-2738. 2021.

[46] L. Wang, B. Diskin, E. Nielsen and Y. Liu, "Improvements in Iterative Convergence of FUN3D Solutions," in *AIAA Scitech Forum*, AIAA 2021-0857. 2021.

[47] Y. Liu, B. Diskin, W. K. Anderson, E. Nielsen and L. Wang, "Edge Based Viscous Method for Node-Centered Formulations," in *AIAA Aviation Forum*, AIAA 2021-2728. 2021.

[48] M. Righi, P. Greco and A. Da Ronch, "Uncertainties Quantification of CFD-Based Flutter Prediction," in *AIAA Scitech Forum*, AIAA 2021-1038. 2021.

[49] N. J. Taylor and C. L. Rumsey, "CFD Validation Experiments: Toward a Broader Perspective," in *AIAA Scitech Forum*, AIAA 2021-1933. 2021.

[50] G. J. Hettinga and J. Kosinka, "A multisided C2 B-spline patch over extraordinary vertices in quadrilateral meshes," *Computer-Aided Design,* vol. 127, 2020.

[51] M. Park, R. Haimes, N. Wyman, P. Baker and A. Loseille, "Boundary Representation Tolerance Impacts on Mesh Generation and Adaptation," in *AIAA Aviation Forum*, AIAA 2021-2992. 2021.

[52] K. Saurabh, B. Gao, M. Fernando, S. Xu, M. A. K. B. Khanwale, M.-C. Hsu, A. Krishnamurthy, H. Sundar and B. Ganapathusubramanian, "Industrial Scale Large Eddy Simulations with Adaptive Octree Meshes Using Immersogeometric Analysis," *Computers & Mathematics with Applications,* vol. 97, pp. 28-44, 2021.

[53] M.-C. Hsu, "Recent Advances in Immersogeometric Analysis," in *Symposium on INdustrial applications of IGA at the 16th U.S. National Congress on Computational Mechanics*, 2021.

[54] R. Sawhney and K. Crane, "Monte Carlo Geometry Processing: A Grid-Free Approach to PDE-Based Methods on Volumetric Domains," *ACM Trans. Graph,* vol. 38, no. 4, July 2020.

[55] N. Wyman, M. Park and J. Chawner, "A Framework for Mesh-Geometry Associativity during Mesh Adaptation," in *AIAA Scitech Forum*, AIAA 2021-1900. 2021.

[56] Exascale Computing Project, [Online]. Available: http://www.exascaleproject.org.

[57] Center for Efficient Exascale Discretizations (CEED), [Online]. Available: http://ceed.exascaleproject.org.

[58] T. kolev, P. Fischer, M. Misun, J. Dongarra, J. Brown, D. Veselin, T. Warburton, S. Tomov, M. Shephard, A. Abdelfattah, V. Barra, N. Beams, J.-S. Camier, N. Chalmers, Y. Dudouit, A. Karakus, I. Karlin, S. Kerkemeier, Y.-H. Lan, D. Medina, A. Merzari, A. Obabko, W. Pazner, T. Rathnayake, C. Smith, L. Spies, K. Swirydowicz, J. Thompson, A. Tombouldides and V. Tomov, "Efficient Exascale Discretizations: High-Order Finite Element Methods," 2021.

[59] C. Geuzaine, "Towards (very) large scale finite element mesh generation with Gmsh," in *2nd ELEMENT Workshop*, 2021.

[60] J. C. Ross, M. N. Rhode, B. E. F. K. T. Edquist, M. Schoenenberger, G. J. Brauckmann, W. Kleb, T. K. West, S. J. ALter and D. W. Witte, "Evaluation of CFD as a Surrogate for Mach 2.4 to 4.6 Wind-Tunnel Testing – Project Overview," in *AIAA Aviation Forum*, AIAA 2021-2961. 2021.

[61] E. P. Hubbard and H. P. Hulden, "Evaluation of CFD as a Surrogate for Wind-Tunnel Testing: Experimental Uncertainty Quantification for the UPWT Flow Survey Test," in *AIAA Aviation Forum*, AIAA 2021-2962. 2021.

[62] R. E. Childs, P. M. Stremel, V. M. Hawke, J. A. Garcia, S. J. Alter, C. Hunter, W. Kleb, P. Parikh, M. N. Patel and K. Salari, "Flow Characterization of the NASA Langley Unitary Plan Wind Tunnel, Test Section 2: Computational Results," in *AIAA Aviation Forum*, AIAA 2021-2963. 2021.

[63] J. C. Ross, M. Dennison, R. Childs, J. Garcia, S. P., V. Hawke, H. Spooner, P. Robinson, M. Reed, W. Kleb, N. Watkins, P. M. Danehy, R. Burns and T. Fahringer, "Evaluation of CFD for Simulation of High-Supersonic Control-Surface Effectiveness," in *AIAA Aviation Forum*, AIAA 2021-2964. 2021.

[64] M. Denison, J. Garcia, B. Nikaido, S. Murman, J. Ross, R. Childs, P. Stremel, W. Kleb, S. J. Alter, T. K. West and P. Robinson, "Evaluation of CFD Predictions of Cobra-MRV Control Surface Effectiveness at the NASA Langley Unitary Plan Wind Tunnel," in *AIAA Aviation Forum*, AIAA 2021-2965. 2021.

[65] J. R. L. Koch, E. Dumlupinar, J. A. Housman, C. C. Kiris, M. M. Patel, W. Kleb, G. J. Brauckmann and S. J. Alter, "CFD Analysis of Space Launch System Solid Rocket Booster Separation within the Langley Unitary Plan Wind Tunnel," in *AIAA Aviation Forum*, AIAA 2021-2966. 2021.

[66] N. Pietroni, S. Nuvoli, T. Alderighi, P. Cignoni and M. Tarini, "Reliable Feature-Line Driven Quad-Remeshing," 2021.

[67] S. L. Brunton, N. J. Kutz, K. Manohar, A. Y. Aravkin, K. Morgansen, J. Klemisch, N. Goebel, J. Buttrick, j. Poskin, A. W. Blom-Schieber and T. Hogan, "Data-driven aerospace engineering: reframing the industry with machine learning," *AIAA Journal,* vol. 59, no. 8, pp. 2820-2847, 2021.

[68] K. Duraisamy, "Perspectives on machine learning-augmented Reynolds-averaged and large eddy simulation models of turbulence," *Physical Review Fluids,* vol. 6, no. 5, 2021.

[69] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard and M. Kudlur, "Tensorflow: A system for large-scale machine learning," in *12th USENIX symposium on operating systems design anf implementation (OSDI 16)*, 265-283. 2016.

[70] V. Srivastava and K. Duraisamy, "Generalizable Physics-constrained Modeling using Learning and Inference assisted by Feature Space Engineering," *arXiv,* 2021.

[71] K. Fukami, K. Fukagata and K. Taira, "Machine-learning-based spatio-temporal super resolution reconstruction of turbulent flows," *Journal of Fluid Mechanics,* vol. 909, 2021.

[72] P. Blonigan, T. Chuan, D. Wong and F. Jasik, "Grid Tailored Reduced-Order Models for Steady Hypersonic Aerodynamics," *Bulletin of the American Physical Society,* vol. 66, 2021.

[73] G. Pullan, T. Chuan, D. Wong and F. Jasik, "Enhancing Web-Based CFD Post-Processing using Machine Learning and Augmented Reality," in *AIAA Scitech Forum*, AIAA 2019-2223. 2019.

[74] A. Kotnik and G. Pullan, "A Spatial Arrangement Visualisation Strategy for Learning from Large Ensembles of Unsteady Flow-field Data," in *AIAA Scitech Forum*, AIAA 2022-0810. 2022.

[75] [Online]. Available: https://www.doeleadershipcomputing.org.

[76] A. Yildirim, J. S. Gray, C. A. Mader and J. R. R. A. Martins, "Coupled Aeropropulsive Design Optimization of a Podded Electric Propulsor," in *AIAA Aviation forum*, AIAA 2021-3032. 2021.

[77] L. J. Smith, L. J. Halim, G. J. Kennedy and M. J. Smith, "A high-fidelity coupling framework for aerothermoelastic analysis and adjoint-based gradient evaluation," in *AIAA Scitech Forum*, AIAA 2021-0407. 2021.

[78] M. Shi, J. Gladin and D. N. Mavris, "A Systematic Methodology for Populating the Aircraft Thermal Management System Architecture Space," in *AIAA Scitech Forum*, AIAA 2021-1295. 2021.

[79] L. V. Repolho Cagliari, J. Hicken and S. Mishra, "Using the LSS adjoint for simultaneous plant and control optimization of chaotic dynamical systems," *Structural and Multidisciplinary Optimization,* vol. 64, pp. 2361-2376, 2021.

[80] R. Falck, J. S. Gray, K. Ponnapalli and T. Wright, "dymos: A Python package for optimal control of multidisciplinary systems," *Journal of Open Source Software,* vol. 6, no. 59, 2021.

[81] M. Meheut, "Multidisciplinary Adjoint-based Optimizations in the MADELEINE Project: Overview and Main Results," in *AIAA Aviation Forum*, AIAA 2021-3052. 2021.

[82] S. Görtz, M. Abu-Zurayk, Č. Ilić, T. Wunderlich, S. Keye, M. Schulze, K. T., C. Kaiser, Ö. Süelözgen, T. Kier, A. Schuster, S. Dähne, M. Petsc, D. Kohlgrüber, J. Häßy, R. Mischke, A. Weinert, P. Knechtges, S. Gottfried and J. Hartmann, "Overview of Collaborative Multi-Fidelity Multidisciplinary Design Optimization Activities in the DLR Project VicToria," in *AIAA Aviation Forum*, AIAA 2020-3167. 2020.

[83] S. Ghosh and D. N. Mavris, "Methodology for Probabilistic Analysis of Distributed Multidisciplinary Architecture," *Journal of Aircraft,* vol. 58, no. 3, May-June 2021.

[84] D. L. Clark, H. Bae and E. E. Forster, "Gaussian Surrogate Dimension Reduction for Efficient Reliability-Based Design Optimization," *AIA Journal,* vol. 58, no. 11, 202.

Appendix: Milestones and TRL rating history

Table 1. Technology Readiness Level assessment of milestones.

Domain/ Timeline / Milestone	Milestone year	2020 TRL	2021 TRL
HPC			
CFD on massively parallel systems			
Demonstrate implementation of CFD algorithms for extreme parallelism in CFD codes (e.g., FUN3D)	2019	6	6
Demonstrate efficiently scaled CFD simulation capability on an exascale system	2024	0	0
30 exaFLOPS, unsteady, maneuvering flight, full engine simulation (with combustion)	2030	0	0
CFD on Revolutionary Systems (Quantum, Bio, etc.)			
Demonstrate solution of a representative model problem	2023	2	2
Demonstrate solution of a representative model problem	2027	0	0
Physical Modeling			
RANS			
Improved RST models in CFD codes	2016	7	7
Integrated transition prediction (Tollmein-Schlichting modeling)	2017	6	6
Integrated transition prediction (non-TS)	2027	3	3
Highly accurate RST models for flow separation	2025	2	2
Demonstration of machine learning to simulation of complex flow regime	2025	1	3
Hybrid RANS/LES			
Integrated transition prediction	2025	2	2
Unsteady, complex geometry, separated flow at flight Reynolds number (e.g., high lift)	2023	4	4
LES			
Integrated transition prediction	2025	2	2
WMLES/WRLES for complex 3D flows at appropriate Re	2023	5	5
Unsteady, 3D geometry, separated flow (e.g., rotating turbomachinery with reactions)	2027	3	3
Combustion			
Chemical kinetics calculation speedup	2017	3	3
Chemical kinetics in LES	2021	4	4
Multiregime turbulence-chemistry interaction model	2025	3	3
Unsteady, 3D geometry, separated flow (e.g., rotating turbomachinery with reactions)	2027	3	3

Algorithms			
Convergence/Robustness			
Automated robust solvers	2022	7	7
Unsteady, complex geometry, separated flow at flight Reynolds number (e.g., high lift)	2023	7	7
Scalable optimal solvers	2021	6	6
Improved discretizations for scale-resolving methods (low-dissipation, HO,…)	2024	5	5
Accurate and robust methods for long time integration	2026	2	2
Production scalable entropy-stable solvers	2029	3	3
Uncertainty Quantification (UQ)			
Characterization of UQ in aerospace	2023	4	4
Reliable error estimates in CFD codes	2025	5	5
Uncertainty propagation capabilities in CFD	2022	4	4
Identification of tail events/probabilities from CFD codes	2027	3	3
Large scale stochastic capabilities in CFD	2030	0	0
Geometry Modeling and Mesh Generation			
Geometry Modeling			
Quantified, reversible data transfer demonstrated between opaque and open geometry model representations.	2023	5	5
Associative equivalence demonstrated for OML manipulation schemes.	2025	0	3
Distributed, open geometry representation platform established	2027	0	2
Robust, quantifiable multidisciplinary data exchange supported by open data standard.	2029	0	2
HPC Meshing			
Large-scale parallel mesh generation	2020	5	5
Generate a 100 billion cell, fit-for-purpose volume mesh.	2025	1	1
Generate a 1 trillion cell, fit-for-purpose volume mesh.	2030	1	1
Fixed Meshing			
Tighter CAD coupling	2015	9	9
CAD coupling available in commercial grid generation	2023	5	5
Automatic generation of suitable mesh on complex geometry on 1st attempt.	2021	4	4
Automatic generation of a family of meshes about a complex configuration.	2023	4	4
Adaptive Grid			
Production AMR in CFD codes	2016	5	5
Adaptive meshing techniques will accept typical assembly tolerance levels and unfavorable B-Rep topologies to accept a pragmatic interpretation of geometry.	2023	0	4
Adaptive curved meshing to support higher-order solvers will be available from multiple implementations.	2026	0	3

Accurate CFD solutions are verified by asymptotic convergence rate demonstration or low variation between independent implementations.	2028	0	3
Adaptive mesh computations displace fixed meshes as the default and practitioners will rarely visualize the mesh directly.	2030	0	2
Knowledge Extraction			
Integrated Databases			
Simplified data representation	2017	3	3
Accepted data fusion techniques	2026	3	3
Creation of real-time multifidelity database: 1000 unsteady CFD simulations plus test data with complete UQ of all data sources	2025	2	3
Visualization			
On demand analysis/visualization of a 10B point unsteady CFD simulation	2022	4	4
On demand analysis/visualization of a 100B point unsteady CFD simulation	2025	2	2
MDAO			
Define standard for coupling to other disciplines	2016	4	4
High fidelity coupling techniques/frameworks	2017	4	4
Robust CFD for complex MDAs	2019	4	4
Incorporation of UQ for MDAO	2025	2	2
MDAO simulation of an entire aircraft (e.g., aeroacoustics)	2027	3	3
UQ-enabled MDAO	2030	1	1
Full vehicle coupled analytic sensitivities, including geometric and subsystems	2025	4	4
Full Vehicle coupled analytic sensitivites for chaotic systems	2030	0	0

Table 2. Technology Readiness Level (TRL) assessment scale.

TRL	Definition	DOD DAG Description	Present Purpose
1	Basic Principles observed and reported	Lowest level of technology readiness. Scientific research begins to be translated into applied research and development. Examples might include paper studies of a technology's basic properties.	High quality conference article describing concept/underlying principles
2	Technology concept and/or application formulated	Invention begins. Once basic principles are observed, practical applications can be invented. Applications are speculative and there may be no proof or detailed analysis to support the assumptions. Examples are limited to analytic studies.	High quality journal article results from feasibility study.
3	Analytical and experimental critical function and/or characteristic proof of concept	Active research and development is initiated. This includes analytical studies and laboratory studies to physically validate analytical predictions of separate elements of the technology. Examples include components that are not yet integrated or representative.	Article or high-quality paper demonstrating prototype of capability (limited scope)
4	Component and/or breadboard validation in laboratory experiment	Basic technological components are integrated to establish that they will work together. This is relatively "low fidelity" compared to the eventual system. Examples include integration of "ad hoc" hardware in the laboratory.	Capability evaluated/implemented by a CFD team; basic demo
5	Component and/or breadboard validation in relevant environment	Fidelity of breadboard technology increases significantly. The basic technological components are integrated with reasonably realistic supporting elements so it can be tested in a simulated environment.	Successful demonstration of capability on a production-level case
6	System/subsystem model or prototype demonstration in a relevant environment	Representative model or prototype system, which is well beyond that of TRL 5, is tested in a relevant environment. Represents a major step up in a technology's demonstrated readiness.	Capability used multiple times by a single CFD team for purposes beyond demonstration (application)
7	System prototype demonstration in an operational environment	Prototype near, or at, planned operational system. Represents a major step up from TRL 6, requiring demonstration of an actual system prototype in an operational environment such as an aircraft, vehicle, or space.	Use/Evaluation of capability by independent organizations (perhaps in different implementations). This is typically inspired by the successful demonstration of some significant milestone in terms of efficiency, ease of use/robustness, or accuracy.
8	Actual system completed and qualified through test and demonstration	Technology has been proven to work in its final form and under expected conditions. In almost all cases, this TRL represents the end of true system development. Examples include developmental test and evaluation of the system in its intended weapon system to determine if it meets design specifications.	Application of capability (beyond demonstration) by independent organizations. This implies sufficient robustness for use (value achieved exceeds investment required)
9	Actual system proven through successful mission operations	Actual application of the technology in its final form and under mission conditions, such as those encountered in operational test and evaluation. Examples include using the system under operational mission conditions.	Routine/expected use of capability by multiple organizations. OR Acceptance of results by multiple teams