SOL ENGINEERING SERVICES

Engineering Design Under Sparse Data

Prototype economics, CFD error in impingement flows, coupon-to-assembly domain shift and the Army sparse-data research agenda

Prepared for DEVCOM Army Research Laboratory, the Ground Vehicle Systems Center, and university and industry partners of the CF-JET effort

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Executive Summary

Hardware programs for liquid cold plates produce a handful of physical test articles per funding cycle, and the design space of a jet-impingement plate is larger than that handful by four to six orders of magnitude. A National Renewable Energy Laboratory (NREL) program on jet-impingement heat exchangers received $1.6 million over fiscal years 2011 to 2013 and had characterized one prototype by March 2013, when it approved the second and third.[1] Nine design variables at three levels each give 19,683 combinations, which is 6,561 times the three prototypes of that program (derived, Table 2). The CF-JET concept is an additively manufactured, jet-impingement cold plate with a carbon fiber target plate, a 1.5 kW design point and a case-to-coolant target of 0.02 K/W, which converts to 72 mm²·K/W on a 60 mm by 60 mm footprint (derived).[2] A design effort at that level of ambition rests on simulation and on small amounts of test data, and the accuracy of both determines whether the target is met.

Six findings support that conclusion.

- **Prototype economics.** The public program records reviewed show one to three prototype configurations per funding cycle and program funding of $0.7 million to $1.6 million per NREL project (Table 1). Four of the printed and jet cold plate studies reviewed report simulation results without hardware, so the published corpus is dominated by solver output.[3456]
- **Solver error in impingement flows.** A review of turbulence models for jet impingement does not recommend the standard k-ε model and reports stagnation-region errors of 21.5 to 27.8 percent and local errors of 15 to 30 percent for the better variants.[7] A 2023 benchmark in air finds the k-ω SST model within about 2 to 6 percent at the stagnation point at H/D = 2, and area-averaged differences of 10 percent (median) to 15 percent (maximum) for the best-performing settings (Table 3).[8]
- **Effect on the target.** A predicted margin of 15 percent against the 72 mm²·K/W target tolerates a 25 percent overprediction of the convective coefficient when conduction uses 18 mm²·K/W, and a 43 percent overprediction when conduction uses 36 mm²·K/W (derived, Table 4).
- **Domain shift.** A single-jet rig observes no crossflow. An in-line array after seven upstream rows retains 71 percent of its crossflow-free Nusselt number, and a staggered array retains 65 percent, in the air-based correlation (derived).[9] Annealing raised the conductivity of printed AlSi10Mg by 18 to 41 percent with no measurable change in porosity.[10] In the NREL program, the pressure drop error of the CFD model rose from at most 7.6 percent for the baseline channel to 14.8 percent for the jet configuration.[11]
- **Army sparse-data research agenda.** ARL-BAA-0038 states that the Army has limited data to train or adapt AI and ML systems, expects domain-expert rules to ease the need for data, and expects uncertainty-aware processing over neuro-symbolic architectures to clarify the limits of data-driven inference.[12] Of its five potential research goals, three correspond to elements of the CF-JET design process (Table 6).
- **Evidence on SOL's approach.** SOL describes codified engineering steps, uncertainty-aware neuro-symbolic inference and a data flywheel that recalibrates models from coupon, single-jet and prototype data.[1314] SOL Aquifer is documented in SOL's 2026 HVAC poster, from work with Alabama A&M University students through Georgia Tech funded internships, and the Forest-to-Desert Framework is defined in SOL's topic development report for ARL-BAA-0107. Hardware validation has not yet been published, so the evidence for the approach on hardware is the CF-JET program itself.

The implications for CF-JET are specific. The predicted margin should exceed the documented solver error, which calls for 10 to 17 percent at the error levels in the literature. Validation should include an array-level

article with the return-port arrangement of the full plate. Material properties should come from coupons built and post-processed like the plate. Each surrogate prediction should include a statement of whether it interpolates or extrapolates the test data.

1. Introduction and Scope

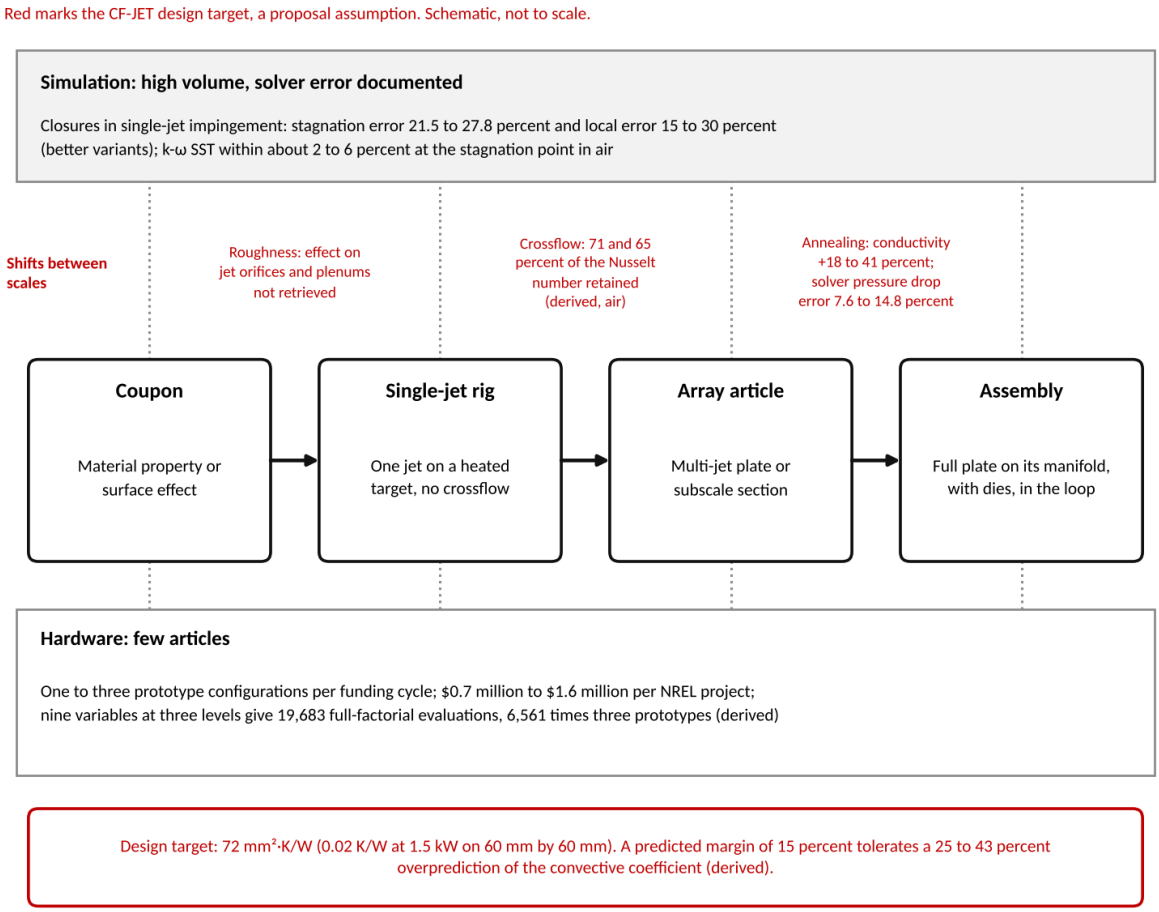
Design programs for thermal hardware begin with little data. Each physical article takes months to build and test, the geometry changes between articles, and the measurements cover a small number of operating points. The data that exist in volume come from simulation. This paper examines that condition for a jet-impingement cold plate, using four questions: how many prototypes comparable programs build and at what cost, how large the documented errors of CFD are in impingement flows, how the literature characterizes the gap between coupon-scale and full-scale behavior, and what Department of Defense and Army Research Laboratory (ARL) documents state about AI and ML with extremely sparse data.

The reference design is the CF-JET concept: a 3D-printed jet-impingement cold plate with interleaved return ports and a carbon fiber target plate containing perpendicular pitch-based fiber inserts under each die, sealed by a thin electroplated metal coolant face. The design point of 1.5 kW on a 60 mm by 60 mm footprint, 50/50 water-glycol at 65 °C inlet, 4 to 8 L/min and a pressure drop of 30 kPa or less are SOL proposal assumptions, and the target of 0.02 K/W is the case-to-coolant resistance the proposal sets.[15] The concept description gives ranges for jet diameter (0.5 to 2 mm), jet grid pitch (3 to 8 mm), impingement gap (1 to 3 mm) and jet count (about 100 to 150).[16]

Three terms recur. A coupon is a small specimen that measures a material property or a surface effect. A single-jet rig is a test of one jet on a heated target, and an array article is a test of a multi-jet plate or a subscale section with the return-port arrangement of the full plate. The assembly is the full plate on its manifold, with dies, in the coolant loop.

The paper covers single-phase liquid cooling. It does not review the thermal performance of cold plates in general, which the literature on conventional plates and jet crossflow treats, and it does not evaluate individual surrogate algorithms. Figure 1 relates the four scales to the simulation and hardware evidence.

Figure 1. Scales of evidence for a jet-impingement cold plate and the shifts between them



Values are those reported in the cited sources or derived in this paper. The design target is a proposal assumption.[17] *The diagram is schematic and not to scale.*

2. Hardware Programs Build Few Prototypes

2.1 Public program records show one to three prototype configurations per funding cycle

The most complete public record of a comparable program is the NREL project on advanced liquid cooling, which developed jet-impingement heat exchangers for automotive inverters. The presentation reports total project funding of $1.6 million, all from the Department of Energy, for fiscal years 2011 to 2013.[18] Finite element and CFD modeling of the first prototype finished in September 2011. The first plastic jet-based prototype was fabricated in February 2012, and pressure drop and thermal testing began. Experimental and CFD characterization of that prototype finished in March 2013, when the team designed a second prototype and approved fabrication of the second and third. Testing of those two was planned for September 2013.[19]

The same laboratory tested three cooling configurations on a traction drive inverter at full power: a baseline channel-flow heat exchanger, jets on a plain surface and jets on a microfinned surface. The tests were conducted at 40 to 100 kW output on a dynamometer with 50/50 water-ethylene glycol.[20] Those three configurations correspond to the second and third prototypes of the program record, which indicates that a three-configuration comparison was the program's full scope of hardware testing. The inference is an interpretation of the two records, which do not state the link directly.

Table 1. **Public records of comparable thermal hardware programs**

Program	Period and funding	Test articles reported	Reported result	Evidence type
NREL advanced liquid cooling, project APE039[21]	FY2011 to FY2013; $1.6 million, all DOE	One plastic jet prototype fabricated February 2012 and characterized by March 2013; second and third approved March 2013	CFD within about 1.5% of measured thermal resistance for baseline cases; pressure drop within 0.5% to 7.6% for baseline and 14.8% for jets; measured resistance 12.1% lower with jets	Government presentation
NREL traction inverter cooling[22]	Not stated	Three configurations tested at full inverter power, 40 to 100 kW output, on a dynamometer	Higher thermal performance with jets than with the channel baseline	Peer-reviewed conference preprint
NREL power electronics thermal management, project ELT211[23]	FY2019 to FY2023; $700,000 DOE share	Not stated in the slides read	Not applicable	Government presentation
ARPA-E COOLERCHIPS[2425]	Announced September 2022; $40 million for 15 projects	Not stated	Program director expects 90% of projects to miss their objectives	Trade press

Accuracy values for project APE039 are read from the comparison table of the presentation and are not independently recomputed (requires independent verification). The ELT211 slides read state funding and dates only. The COOLERCHIPS items are trade press reports of a government program and are used for scale only.

2.2 Program funding per prototype configuration is in the hundreds of thousands of dollars

Funding of $1.6 million divided by the three prototypes of the NREL program gives $0.53 million per prototype configuration (derived). That figure is an upper bound on fabrication cost, because the funding also covered modeling, reliability studies and testing. The ELT211 project received a DOE share of $700,000 over fiscal years 2019 to 2023.[26] At the scale of an ARPA-E program, trade press reports $40 million across 15 projects, an average of $2.7 million per project (derived), and reports a program director's expectation that 90 percent of the projects will fail to meet their objectives.[2728] The 90 percent expectation is a program-level statement of risk for advanced cooling hardware and is not evidence about any single design.

2.3 The design space is larger than the number of tests by orders of magnitude

A jet-impingement plate with a carbon fiber target plate has many design variables. Nine illustrative ones are jet diameter, jet pitch, impingement gap, jet count and layout, return-port spacing, target plate thickness, fiber insert pitch, plated layer thickness and flow rate. A full-factorial sweep at three levels per variable requires 19,683 evaluations, at four levels 262,144, and at five levels 1,953,125 (Table 2). Three prototypes cover 0.015 percent of the three-level grid. Physical testing cannot sample such a space, and the arithmetic explains why a program that builds a few articles relies on a model to select and interpret them. Figure 2 plots the count against three prototypes.

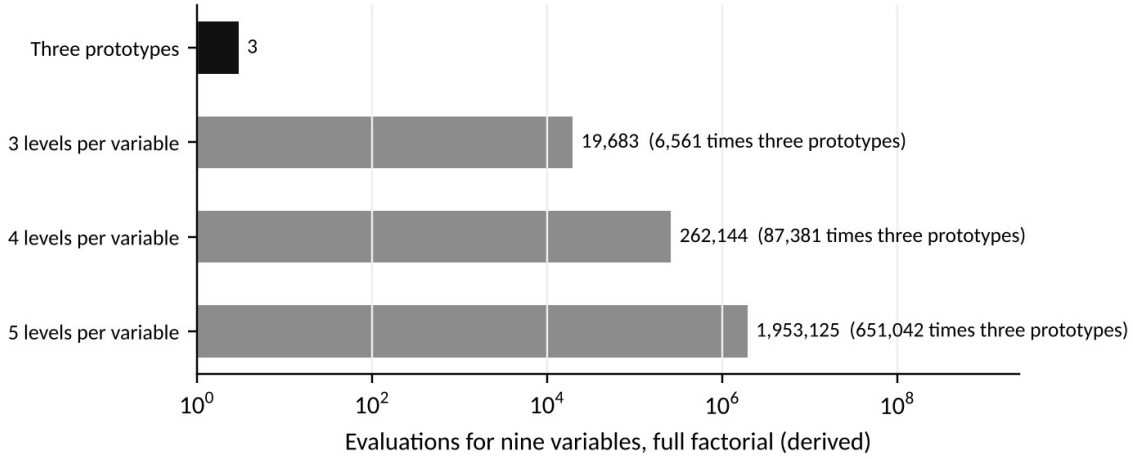
Table 2. **Full-factorial design space for nine illustrative variables against three prototypes**

Levels per variable	Full-factorial evaluations (derived)	Multiple of three prototypes (derived)
3	19,683	6,561

Levels per variable	Full-factorial evaluations (derived)	Multiple of three prototypes (derived)
4	262,144	87,381
5	1,953,125	651,042

The nine variables are an illustrative list drawn from the elements of the CF-JET concept. The count is the number of levels raised to the ninth power. Fractional designs and sequential sampling reduce the count and are discussed in Table 7.

Figure 2. Full-factorial evaluations for nine variables against three prototypes (derived)



The count is the number of levels raised to the ninth power, as in Table 2.

2.4 Much of the published literature reports simulation only

Several of the printed and jet cold plate studies in the literature report numerical results without hardware. Hoang et al. report copper and aluminum plate comparisons from simulation, Fallahtafti et al. optimize micro pin fins numerically, Pahinkar et al. study jet-array heat sinks numerically, and Barua et al. compare direct and indirect cooling of power modules in a draft conference paper that reports simulation.[29303132] A designer or a learning algorithm that draws on this literature receives mostly outputs of RANS solvers, and those outputs contain the solver bias documented in Table 3. A surrogate trained on published numerical results learns the solver as well as the physics.

2.5 No source reviewed reports prototype counts or fabrication cost per article

No survey, dataset or government report retrieved for this paper gives the distribution of prototype counts or per-article cost for single-phase cold plate programs. These statements rest on two NREL records and on funding totals that include work other than fabrication. Fabrication cost per printed cold plate appears only in vendor quotations, which are not citable as independent evidence. The evidence gap limits the paper to the conclusion that programs of this type build a small number of articles, and a count for the average program cannot be stated.

3. CFD Error in Impingement Flows

3.1 Standard k-ε overpredicts stagnation heat transfer by 21 to 28 percent

The most detailed review of turbulence models for impinging jets is the chapter by Zuckerman and Lior,

which compares the k-ε, k-ω, Reynolds stress, algebraic stress, shear stress transport and v²-f families.[33] For k-ε, Heyerichs and Pollard reported Nusselt number errors of 21.5 to 27.8 percent in the stagnation region and +32 to +38.4 percent at the secondary peak, and Craft et al. reported overprediction of up to 40 percent at the center of the impingement region.[34] The review states that the standard k-ε model is not recommended for impinging jets and that even the best k-ε variants show local errors of 15 to 30 percent. Gurgul and Fornalik-Wajs found overprediction of 40 to 200 percent for low-Reynolds-number k-ε models at H/D = 2 and Re = 23,000 in air, and excluded them from further analysis.[35]

3.2 k-ω SST gives the smallest stagnation errors among two-equation models in air, with limits at the secondary peak

In the same benchmark, the k-ω family overpredicted the stagnation-region Nusselt number by 6 to 30 percent, and SST was closest at about 2 to 6 percent.[36] The Kato-Launder production limiter reduced the stagnation Nusselt number by about 10 percent for SST and about 8 percent for k-ε RNG. The area-averaged measure favored k-ε RNG with the limiter, with a median difference below 5 percent. SST with the limiter and the intermittency transition model showed medians below 10 percent and maxima near 15 percent. The best model changed with spacing: SST with the limiter and the intermittency transition model were recommended for H/D of 1 and 2, and k-ε RNG with the limiter for H/D of 4 and 6, where the latter still differed by about 18 percent on average in the far field at H/D = 6.[37]

The review by Zuckerman and Lior reports k-ω errors up to 30 percent locally, up to 18 percent in the study by Heyerichs and Pollard, which outperformed nine k-ε implementations, up to 40 percent in the wall jet with wall functions, and up to 100 percent locally where the secondary peak was misplaced.[38] A separate study of a single jet at Re = 23,000 and H/d = 2 found SST to give the best balance of accuracy and cost against v²-f and a Reynolds stress model. It captured the profile of the primary and secondary peaks and misplaced the secondary peak. The low-Reynolds-number damping in the SST implementation controlled the location and intensity of that peak. Coarsening the mesh to a 2 mm base size changed the stagnation-point value by 11.12 percent on average, and the grid convergence index was 0.26 percent on the fine grid and 0.63 percent on the intermediate grid.[39]

The Reynolds stress model produced velocity errors of up to 40 percent and Reynolds stress errors of more than 100 percent in the cited work, and the review does not recommend it as an alternative.[40] The v²-f model was about 8 percent above data in the 2023 benchmark and is described in the review as giving some of the best predictions, with values within the spread of experimental data.[41][42] Most reported errors in the review are local or stagnation values, and area-averaged errors are rarely given.

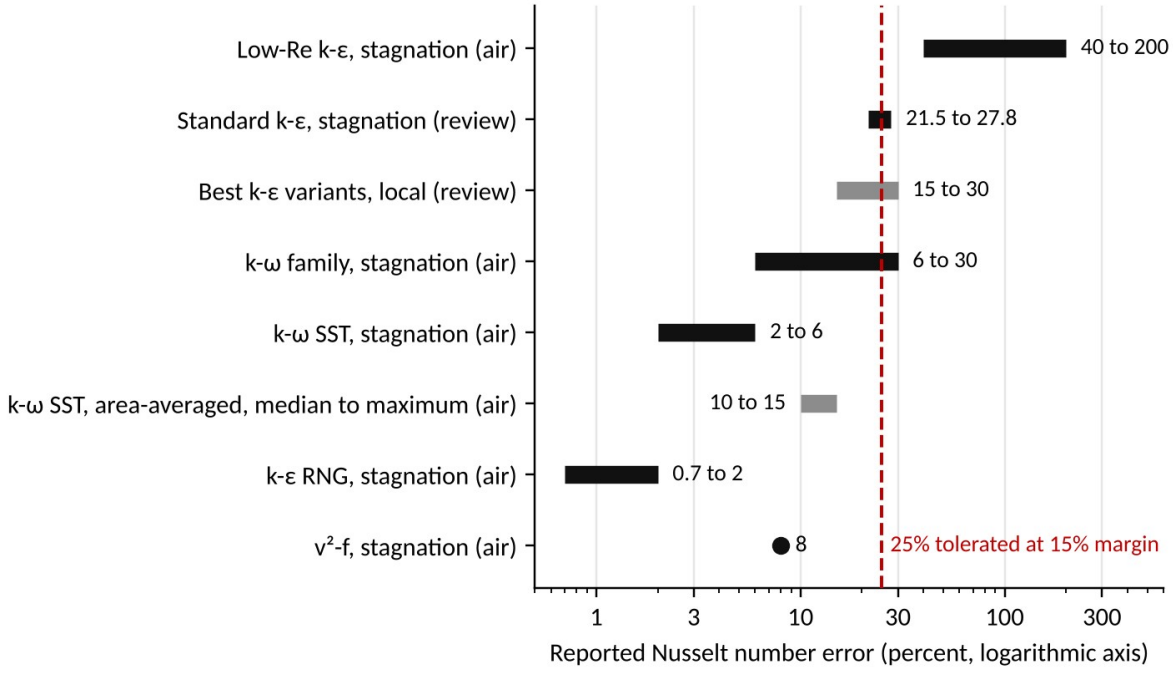
Table 3. Reported Nusselt number errors of RANS closures for single-jet impingement

Closure	Conditions	Reported error	Source
Standard and high-Re k-ε variants	Various single-jet studies	Not recommended. Stagnation errors of 21.5% to 27.8% and +32% to +38.4% at the secondary peak; up to 40% at the center; best variants 15% to 30% locally	Zuckerman and Lior review[43]
Low-Re k-ε	Air, H/D = 2, Re = 23,000	Overprediction of 40% to 200% at the stagnation region	Gurgul and Fornalik-Wajs[44]
k-ε RNG, enhanced wall treatment	Same	0.7% to 2% at the stagnation region; median average difference below 5% with the Kato-Launder limiter	Gurgul and Fornalik-Wajs[45]

Closure	Conditions	Reported error	Source
k-ω family	Review; air benchmark	Up to 30% locally; up to 18% in one comparison; 6% to 30% at stagnation in the benchmark; up to 100% locally when the secondary peak is misplaced	Zuckerman and Lior review; Gurgul and Fornalik-Wajs[46]
k-ω SST	Air, H/D = 2, Re = 23,000	About 2% to 6% at stagnation; about 10% lower stagnation value with the limiter; median average difference below 10% and maximum near 15%; secondary peak position mismatched; 11.12% stagnation change on a 2 mm mesh	Gurgul and Fornalik-Wajs; Chitsazan et al.[47]
v^2-f	Same	About 8% above data in the benchmark; among the best predictions in the review	Gurgul and Fornalik-Wajs[48]
Reynolds stress model	Review	Velocity errors of up to 40% and Reynolds stress errors above 100%; not recommended	Zuckerman and Lior review[49]

All results are for single jets, mostly in air. Error signs and test conditions follow the cited sources, and the abstract-level summaries of the review sections were read from the chapter text without the original page numbers, so section numbers are given. Gurgul and Fornalik-Wajs vary Re from 10,000 to 30,000 and H/D from 1 to 6 with a constant wall heat flux.

Figure 3. Reported Nusselt number errors of RANS closures in single-jet impingement



Ranges are the errors stated in the cited sources, plotted on a logarithmic axis. Black bars are stagnation-region errors, and grey bars are local or area-averaged errors. The red dashed line marks the 25 percent overprediction that a 15 percent predicted margin tolerates when conduction uses 18 mm²·K/W (derived, Table 4).

3.3 Conjugate and liquid cases have less published accuracy data

The NREL program compared CFD with measurement for a baseline channel heat exchanger and a jet configuration. In the comparison table of the presentation, the thermal resistance agreed within about 1.5 percent for the baseline cases and matched for the jet case at 1.67×10^{-4} m³/s (0.116 °C/W). The pressure drop differed by 0.5, 1.8 and 7.6 percent for the baseline at the three flow rates and by 14.8 percent for the jet configuration at 1.67×10^{-4} m³/s.[50] The pressure drop error was therefore largest for the configuration

that was new to the solver, which is a small example of the shift described in Table 5. The values were read from the presentation table (requires independent verification).

A conjugate simulation of high-Prandtl-number oil jets (Pr between 77 and 161, Re between 226 and 2,850) reports that the surface-averaged heat transfer compares very well with an earlier experiment, and the record gives no error figure.[51] No source retrieved for this paper reports the error of SST or a comparable closure for a water-glycol jet array with conduction through a composite target plate. The benchmark errors in Table 3 are single-jet results, mostly in air, and the CF-JET design point operates in a liquid with a Prandtl number far above that of air, in an array, over a layered target. The accuracy of the solver for that case has to be measured, and Table 3 gives the starting range.

3.4 A predicted margin of 15 percent tolerates a 25 percent overprediction of the convective coefficient

The target of 72 mm²·K/W divides between conduction through the plate and convection at the cooled face. Suppose conduction and spreading use 18 mm²·K/W, which is 25 percent of the budget, and convection uses the remaining 54 mm²·K/W. If a CFD model overpredicts the convective coefficient by a fraction e, the true convective resistance is (1 + e) times the predicted value. A design that the model predicts to meet the target with margin m has a predicted total of 72(1 − m) mm²·K/W, and it meets the target in hardware when the corrected total remains at or below 72 mm²·K/W.[52]

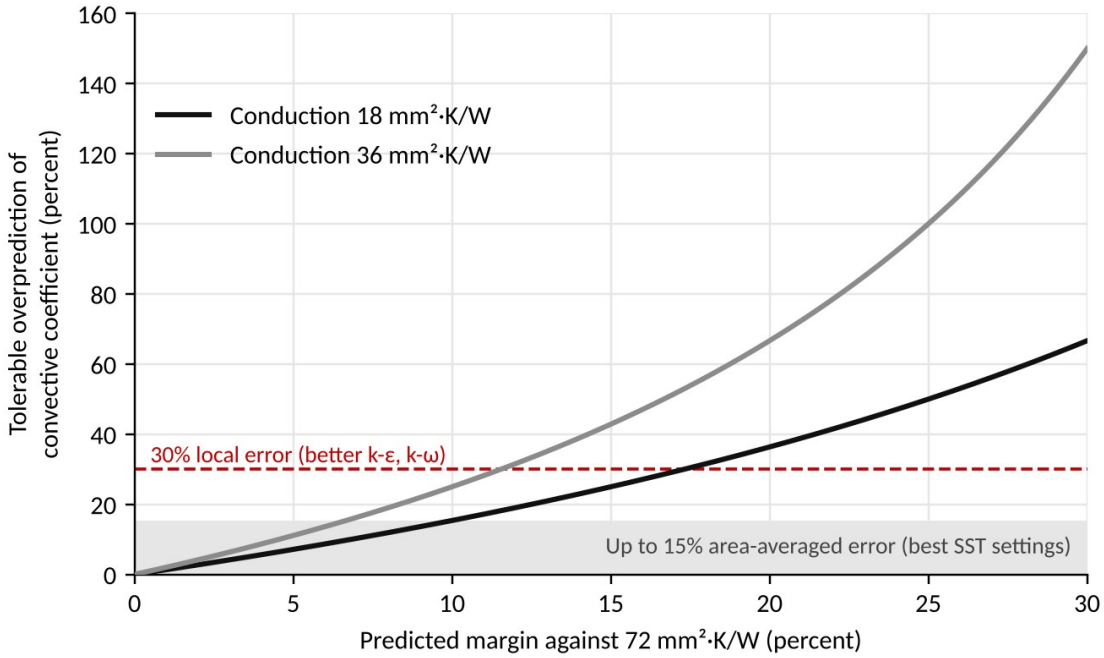
Table 4 gives the tolerable overprediction at six predicted margins for two conduction shares. A design that the model predicts to just meet the target has no tolerance. A 10 percent margin tolerates a 15 percent overprediction when conduction uses 18 mm²·K/W and 25 percent when it uses 36 mm²·K/W. Read against the documented errors, a 15 percent area-averaged error needs a predicted margin of 9.8 percent (conduction 18) or 6.5 percent (conduction 36), a 30 percent error needs 17.3 or 11.5 percent, and a 40 percent error needs 21.4 or 14.3 percent (all derived). Overprediction of the coefficient is the non-conservative direction. The k-ε results in Table 3 overpredict, and one study in the review reports underprediction of up to 25 percent in the normalized Nusselt number, so the sign depends on the closure and the region.[53]

Table 4. Tolerable overprediction of the convective coefficient by predicted margin against 72 mm²·K/W (derived)

Predicted margin	Tolerable overprediction, conduction 18 mm²·K/W	Tolerable overprediction, conduction 36 mm²·K/W
0%	0.0%	0.0%
5%	7.1%	11.1%
10%	15.4%	25.0%
15%	25.0%	42.9%
20%	36.4%	66.7%
30%	66.7%	150.0%

Derived in this paper from the target of 72 mm²·K/W. Tolerable overprediction is the largest fractional overprediction of the convective coefficient for which the hardware total still meets the target. The calculation assumes that the error acts on the convective term alone.

Figure 4. Tolerable overprediction of the convective coefficient against predicted margin



Derived in this paper from the target of 72 mm²·K/W. The shaded band marks the area-averaged differences of up to 15 percent reported for the best settings in the 2023 benchmark, and the dashed line marks 30 percent, the upper local error of the better k-ε and k-ω variants in the review.

3.5 Validation standards quantify error at validation points and leave extrapolation to judgment

The ASME standard for verification and validation in CFD and heat transfer specifies how to quantify the accuracy of a solution at a specified validation point, using the uncertainties of both the solution and the experiment. The standard places the accuracy at other points of the domain, including interpolation and extrapolation inside the validation domain, in the area of engineering judgment specific to each family of problems, and outside its scope.[54] A later paper on the interpretation of the standard states that validation under it is an assessment of model error without a pass or fail criterion.[55] Roy and Oberkampf describe a framework in which model-form uncertainty is quantified by comparison with data at validation points and then extrapolated to points in the application domain where experimental data do not exist.[56]

Kennedy and O'Hagan propose a Bayesian calibration in which the predictions allow for all sources of uncertainty, and in which a discrepancy term corrects for the inadequacy of the model that remains after the best-fitting parameters are chosen.[57] That framework is the standard statistical statement of the sparse-data problem for a simulator: a few field observations calibrate the parameters and estimate the discrepancy. For a program with three prototypes, each validation point is one sample of the error across a design space with thousands of combinations, and the extrapolation of the error structure to untested designs is the largest contributor to uncertainty in the predicted margin.

4. Domain Shift from Coupon to Assembly

Domain shift is the difference between the conditions of a test and the conditions of the application. For a cold plate, a coupon measures a material or a surface, a single-jet rig measures local heat transfer with no neighbors, and the assembly combines many jets, return flow, layered materials and printed surfaces.

Each step from the coupon to the assembly adds an effect that the smaller test did not contain. The literature documents several of these effects in numbers, and Table 5 lists them with the evidence available for each.

4.1 Crossflow removes a documented share of single-jet heat transfer in arrays

In an array, the spent flow from upstream jets moves across the target and deflects downstream jets. The Florschuetz correlation, developed for arrays of round jets in air with crossflow, expresses the array-average Nusselt number as a function of the ratio of crossflow to jet mass velocity.[58] Evaluated for the in-line and staggered cases at a crossflow ratio built up by seven upstream rows, the correlation retains 71 percent of the crossflow-free Nusselt number for the in-line array and 65 percent for the staggered array (derived).[59] A single-jet rig observes none of that loss, so a heat transfer coefficient measured on one jet overstates the array average by 41 to 54 percent when the array has that much crossflow (derived as the reciprocal of the retained fractions).

The CF-JET concept includes interleaved return ports whose purpose is to limit crossflow, and the concept calls for 100 to 150 jets.[60] The correlation applies to air and to a return arrangement that exits the array at its edges, so it does not predict the performance of the interleaved layout in water-glycol. It identifies the quantity that an array-level test has to measure, which is the retained fraction of the single-jet coefficient at the full jet count.

4.2 Properties of printed material depend on the build and its post-processing

Thermal conduction through the plate depends on properties that a handbook value does not capture for printed material. Butler et al. measured the thermal conductivity of AlSi10Mg made by selective laser melting and found that annealing raised it by 18 to 41 percent, depending on the processing parameters, with no measurable change in porosity.[61] The result matters for the conduction share of the budget in Table 4, because a conductivity that differs by tens of percent between as-built and annealed material moves the conduction resistance by the same fraction. The CF-JET target plate is carbon fiber with electroplated faces, and the plated and printed layers have their own property distributions. No source retrieved for this paper reports the conductivity of an electroplated layer on a printed substrate, and a coupon test of the same stack-up would supply it.

4.3 Surface roughness of printed channels changes friction and heat transfer

As-built surfaces from additive processes are rougher than machined surfaces, and the literature includes studies of the effect of internal channel roughness on friction factor and heat transfer in printed heat exchangers and microchannel heat sinks.[62][63][64] The studies address channels, and the CF-JET plate has jet orifices and a plenum. The magnitude of the effect on an orifice discharge coefficient and on the pressure drop of a jet array was not available from the sources retrieved, and the abstract-level information read for this paper does not support a numerical statement. The effect belongs in the catalogue as a known direction of shift with an unquantified size for this geometry.

4.4 The solver was least accurate on the configuration that was new to it

In the NREL program, the CFD pressure drop error was at most 7.6 percent for the baseline channel and 14.8 percent for the jet configuration.[65] The thermal resistance of the jet case matched the measurement. The two metrics diverged in the new configuration, which indicates that a model validated for one geometry predicts some outputs of the next geometry well and others poorly, and that the output with

the larger error is not known before the test. The pressure drop budget of CF-JET is 30 kPa, and the pump limits the flow at the design point, so the pressure drop error has the same consequence for the design as the thermal error has.

4.5 Learned models inherit the shift

Mandler and Weigand tested a data-augmented SST model that was trained on a single two-dimensional periodic hills flow. They applied it to other Reynolds numbers, other hill geometries, a three-dimensional ribbed case, a channel, an impinging jet and an industrial ribbed two-pass cooling channel.[66] On the training case the model reduced the mean absolute error of skin friction by about 7 percent relative to SST. Across the other cases, the accuracy gained where the model was calibrated was smaller than the accuracy lost elsewhere, and in the two-pass channel the model lost accuracy globally while it gained locally where the flow resembled the training case.[67] The rank correlation between the local density of training samples and local accuracy was about 14 percent, and the authors attribute the errors to similar model inputs that require different outputs, not to extrapolation alone.[68] Duraisamy, Iaccarino and Xiao review the use of data in turbulence modeling and place the question of generalization beyond the training flows among the open problems of the field.[69]

A study of deep learning under dataset shift, reported through its authors' blog summary, found that accuracy fell as the shift grew, that calibration worsened, and that models became confidently wrong while their stated uncertainty stayed low. Temperature scaling, which improves calibration on in-distribution data, often made calibration worse on shifted data, and an ensemble of about five models degraded most gradually.[70] The study used image classification benchmarks, so the numbers do not transfer to thermal problems, and the direction of the result applies to any learned surrogate: a model reports the same confidence at a design that lies outside its training data as at one inside it unless the method estimates that difference.

Table 5. Catalogue of coupon-to-assembly shifts with documented effects

Shift	Smaller-scale condition	Assembly condition	Documented effect	Evidence
Crossflow	Single jet with no neighbors	100 to 150 jets with interleaved return ports	In-line and staggered arrays retain 71% and 65% of the crossflow-free Nusselt number after seven upstream rows (derived, air)[71]	Correlation, air
Printed material conductivity	As-built coupon	Annealed or plated plate	Annealing raised conductivity by 18% to 41% with no measured porosity change[72]	Peer-reviewed
Surface roughness	Machined or polished coupon	As-built printed surfaces	Direction known for channels; size for jet orifices and plenums not retrieved[737475]	Peer-reviewed and dissertation
Configuration change in the solver	Baseline channel	Jet configuration	CFD pressure drop error of at most 7.6% for the baseline and 14.8% for jets[76]	Government slides
Flow regime for learned closures	Training flow	Other geometries and regimes	Gain on the training case of about 7%; global loss in a cooling channel[77]	Peer-reviewed

Shift	Smaller-scale condition	Assembly condition	Documented effect	Evidence
Dataset shift for learned models	In-distribution test data	Shifted data	Accuracy and calibration fall; models become overconfident[78]	Blog summary of a conference paper

The crossflow values are derived in this paper from the Florschuetz correlation for air and are not measurements for water-glycol. The roughness row lists the direction of the effect; the magnitude for jet arrays is an evidence gap.

4.6 Scaling studies address the same question for other equipment

The question of how a test of a small sample or a reduced-scale facility predicts a full system has a long record in other thermal fields. A 1989 SAE paper addresses the prediction of heat exchanger performance from a test of a small sample.[79] The Committee on the Safety of Nuclear Installations of the OECD Nuclear Energy Agency issued a state-of-the-art report on scaling in system thermal-hydraulics for reactor safety and design.[80] Neither document addresses jet-impingement cold plates, and the abstract-level information retrieved does not support quantitative statements about their methods. They show that scaling analysis is an established discipline with its own methods, and that a coupon program without a scaling argument leaves the extrapolation unexamined.

5. Army Research on AI and ML with Extremely Sparse Data

5.1 ARL-BAA-0038 states the problem as limited data and extreme epistemic uncertainty

The ARL research topic on artificial intelligence and machine learning with extremely sparse data begins from the observation that the Army has limited data to train or adapt AI and ML systems for dynamic and diverse operating environments. It seeks learning and inference that give useful predictions under extreme epistemic uncertainty. The topic expects that combining data-driven learning with rules elicited from experts will reduce the need for data, and that uncertainty-aware processing over neuro-symbolic architectures will clarify the limits of data-driven inference.[81] The topic is a foundational research topic, and it does not mention thermal hardware. Its statement of the problem corresponds closely to the situation in Table 1 and Table 2, where each prototype is a costly sample and the design space is large.

5.2 Three of the five research goals correspond to elements of a hardware design process

The topic lists five potential research goals. The first is a theory of optimal learning and inference when supervised training data is limited. The second is computationally efficient approximation of that processing. The third is a set of criteria for when conventional AI and ML models are sufficient, given the difficulty of the task and the availability of data, and when they are not. The fourth is efficient processing on edge computing devices, and the fifth is distributed learning and inference with graph neural networks.[82] Table 6 maps these goals to the CF-JET design process.

Table 6. ARL-BAA-0038 research goals mapped to the CF-JET design process

Research goal	Corresponding element in a jet-impingement design effort	Status of the correspondence
1. Optimal learning and inference with limited supervised data	Calibration of a surrogate to a few coupon, single-jet and prototype measurements	Direct. The CF-JET approach describes surrogates with uncertainty quantification recalibrated from test data[8384]

Research goal	Corresponding element in a jet-impingement design effort	Status of the correspondence
2. Computationally efficient approximations	Surrogates that replace repeated conjugate CFD runs in a design sweep	Direct. Evidence of speed or accuracy on thermal hardware is not independently published
3. Criteria for sufficiency of conventional AI and ML	A rule for when a surrogate prediction interpolates the test data and when it extrapolates	Direct. Table 4 and Table 5 supply the quantities such a rule has to bound
4. Edge computing	None in the program description	No matching element
5. Distributed learning with graph neural networks	None in the program description	No matching element

The goals are paraphrased from the topic text. The mapping is an interpretation by the author of this paper. The program description available for this paper contains no element that corresponds to goals 4 and 5.

5.3 The evidence for SOL-specific methods is limited to SOL documents

SOL describes its approach in the CF-JET proposal and in the SOL Aquifer pipeline diagram. The Forest-to-Desert Framework™ and SOL Aquifer™ codify engineering steps as software, which includes scripted condition sweeps, physics solvers in code, a SQL database with provenance, and surrogate training with uncertainty quantification. The approach combines codified physics and rules with learned surrogates in uncertainty-aware neuro-symbolic inference, and a data flywheel recalibrates the models from coupon, single-jet and prototype test data.[8586] SOL Aquifer originated in a project on modeling HVAC system performance that SOL performed with Alabama A&M University students.[87] These are SOL's proposed or demonstrated capabilities as stated in SOL documents. The HVAC work, carried out through Georgia Tech funded internships, is documented in SOL's 2026 poster, Modeling HVAC System Performance: Code as Architecture Approach to AI, and the Forest-to-Desert Framework, with its name, three parts and seven-phase protocol, is defined in SOL's topic development report for ARL-BAA-0107. No hardware validation of either has yet been published; the CF-JET program is meant to supply it. The architecture corresponds to the combination that ARL-BAA-0038 names as its expectation, with domain-expert rules, learned components and uncertainty-aware inference in one pipeline, and the match describes the design intent and says nothing yet about measured performance.

6. Methods for Learning from Few Samples

6.1 Each method answers a different part of the sparse-data problem

A design effort with a few prototypes can allocate its samples in more than one way, and the methods in the literature differ in what they assume. Table 7 compares five. Full-factorial and one-factor-at-a-time designs are the baseline: the first covers the space at a cost that grows as a power of the variable count (Table 2), and the second varies a single parameter and misses interactions among jet pitch, gap and flow rate that govern an array. Space-filling designs with a statistical surrogate sample the space with far fewer evaluations, at the price of a model whose accuracy has to be assessed.

Bayesian calibration with a discrepancy term, as proposed by Kennedy and O'Hagan, treats the solver as an imperfect model of the hardware. A few measurements calibrate the solver's parameters and estimate how far the solver departs from reality, and the prediction includes both uncertainties.[88] Applied to a cold plate, the discrepancy term would capture the convective overprediction of Table 4 as a quantity with a posterior distribution, in place of a single assumed percentage. The method needs measurements that cover the region of the design space where predictions are wanted, which returns the problem to the

sampling of prototypes.

Data-driven augmentation of turbulence closures uses high-fidelity data to correct a RANS model. The evidence in Table 5 shows that such a model gains on the training flow and can lose elsewhere, so its use calls for a stated domain of validity.[8990] Ensembles give a practical estimate of when a learned model has left its training domain, and the reported result is that an ensemble of about five members degraded most gradually under shift.[91] The neuro-symbolic, uncertainty-aware approach that ARL-BAA-0038 names combines codified physics, which does not need data, with learned components that do, and it reports uncertainty with each prediction.[92]

Table 7. Comparison of methods for allocating few samples in a design effort

Method	What it assumes	Failure condition	Output	Evidence
Full-factorial sweep	Evaluation is cheap enough to cover the grid	Count grows as levels to the power of variables (Table 2)	Complete map of the sampled grid	Arithmetic
One-factor-at-a-time	Variables act independently	Interactions among pitch, gap and flow	Local sensitivities	Arithmetic
Space-filling design with a surrogate	Smooth response between sample points	Response with sharp features, such as secondary peaks	Fast prediction with a fitted error estimate	General practice, no source retrieved
Bayesian calibration with discrepancy[93]	The solver is correct up to a modeled discrepancy	Measurements do not cover the application region	Posterior for parameters and discrepancy	Peer-reviewed
Data-driven turbulence closures[9495]	Training flows resemble the application	Mismatch between similar inputs and different responses	Corrected RANS predictions	Peer-reviewed
Neuro-symbolic inference with uncertainty[9697]	Codified physics holds in the application domain	Rules that fail outside their validity range	Prediction with stated uncertainty	Army topic text and SOL documents

The space-filling row describes general practice and cites no source because none was retrieved for this paper. The last row combines the Army topic statement with SOL's proposed approach, and no independent hardware validation is available.

6.2 The data flywheel adds samples at the rate of testing

A data flywheel recalibrates models as test data arrive from coupons, single jets and prototypes.[98] The rate of that process is set by the testing. If the program tests three configurations, the recalibration has three array-level samples, plus whatever coupon and single-jet tests are cheaper to repeat. The method gains most from the inexpensive tests, so the order of testing matters: coupon and single-jet tests are numerous and cheap, and they calibrate the parts of the model that those tests can reach. The array-level samples are few, and they calibrate the terms that only an array exhibits, which are crossflow and return-port effects in Table 5.

7. Implications for the CF-JET Effort

7.1 Risks

- **Solver bias against a tight margin.** If the predicted margin is below the tolerance in Table 4 for the documented error, the hardware misses the 72 mm²·K/W target even when the simulation meets it. The documented errors reach 15 to 30 percent for the better closures in air, and no source retrieved

quantifies the error for a water-glycol array.

- **Single-jet data applied to the array.** A coefficient measured on one jet overstates the array average by the crossflow loss in Table 5. The air-based correlation implies 41 to 54 percent in the stated case, and the interleaved return ports are intended to reduce it by an amount that has not been measured.
- **Property assumptions for printed and plated layers.** A conductivity that changes by 18 to 41 percent with heat treatment changes the conduction budget by a similar fraction, and no source retrieved reports the conductivity of an electroplated coolant face on a printed substrate.
- **Surrogate confidence outside the data.** A learned surrogate can report the same confidence in an extrapolation as in an interpolation, and the Army topic identifies the limits of data-driven inference as an open question.
- **Pressure drop as a second target.** In the NREL record, the pressure drop error was the larger of the two errors for the new configuration. The 30 kPa limit gives the plate little room for a similar error.

7.2 Design implications

- **Set the predicted margin from the error budget.** At 18 mm²·K/W of conduction, a 15 percent convective error calls for a predicted margin of 9.8 percent, and a 30 percent error calls for 17.3 percent (Table 4). The margin is a design input that follows from the validated solver error.
- **Validate the solver at the application conditions.** The ASME V&V 20 standard quantifies accuracy at a validation point and places other points in the domain outside its scope, so the validation point should be an array-level article with water-glycol and the return-port layout of the full plate.
- **Build coupons like the plate.** Conductivity and surface condition should come from coupons that are built, heat treated and plated like the target plate, and the test record should state the build and processing history.
- **Report each surrogate prediction with its position in the data.** A prediction inside the convex hull of the test data is an interpolation, and a prediction outside it is an extrapolation with a wider interval.
- **Sequence the tests by cost.** Coupon and single-jet tests calibrate material and local heat transfer terms. The array-level tests calibrate crossflow and return-port terms and should be planned around the quantities in Table 5.

7.3 Open research questions

- What is the area-averaged error of SST and of the better alternatives for a water-glycol jet array with conduction through a layered target?
- What fraction of the single-jet coefficient does the interleaved return-port layout retain at 100 to 150 jets in a liquid?
- How do the conductivity and interface resistance of a plated layer on a printed substrate depend on build orientation and post-processing?
- What criterion separates interpolation from extrapolation for a design space with nine variables and a few array-level samples (ARL-BAA-0038 goal 3)?
- What is the number and cost of prototypes in comparable programs, and can a public dataset of that record be assembled?

8. Conclusion

A jet-impingement cold plate program reaches its target through a model that few tests calibrate. The public records reviewed show one to three prototype configurations per funding cycle against a design space of tens of thousands of combinations at three levels per variable. The documented CFD error in impingement flows is 2 to 6 percent at the stagnation point for the best closure in air and 10 to 15 percent for area-averaged values, with 15 to 30 percent local errors for the better variants in the review. Measured against a 72 mm^2·K/W target, those errors call for predicted margins of about 10 to 17 percent when conduction uses 18 mm^2·K/W.

The shift from coupon to assembly adds crossflow, property changes from processing and surface effects, and learned models lose accuracy outside their training data. ARL-BAA-0038 states the same problem as limited data and extreme epistemic uncertainty and expects domain rules and uncertainty-aware inference to help. Three of its five goals correspond to elements of the CF-JET design process. The evidence for SOL's own method is its proposal and pipeline documents, and an independent hardware validation has yet to be published. The CF-JET program can supply that validation if its test plan measures the solver error and the array-level crossflow loss at the design point, and reports each surrogate prediction with its position in the test data.

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