SOL TECHNICAL SERIES

White Paper

Complementary Capabilities or Competitive Overlap?

Positioning the Adaptive Multiscale Intelligence Engine Relative to NASA's Multiscale Analysis Tool

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SOL Engineering Services, LLC

CAGE 44KM9 | UEI MNLZRG2A3376 | HUBZone Small Business

2026 | solengrs.com

This paper is a component of the SOL AMIE Technical Series supporting the NASA SBIR Phase I proposal for the Adaptive Multiscale Intelligence Engine (AMIE), a physics-informed AI windowing agent for concurrent FEA/SPH/MD multiscale simulation of hypervelocity impact events.

Abstract

The NASA Multiscale Analysis Tool (NASMAT), developed at NASA Glenn Research Center under the Transformational Tools and Technologies project, represents NASA's most mature internal capability for multiscale simulation of heterogeneous composite materials. The Adaptive Multiscale Intelligence Engine (AMIE), the subject of a NASA SBIR Phase I proposal by SOL Engineering Services, LLC, represents a novel AI-driven adaptive windowing framework for concurrent FEA/SPH/MD simulation of hypervelocity impact events. On the surface both frameworks share the same vocabulary: multiscale, concurrent coupling, adaptive fidelity, and AI augmentation. A rigorous comparison is therefore necessary to determine whether AMIE competes with NASMAT, complements it, renders it partially obsolete, or is rendered obsolete by it.

This paper concludes that NASMAT and AMIE operate in non-overlapping physical domains and address fundamentally different simulation challenges. NASMAT is a micromechanics homogenization platform for composite materials under thermoelastic and progressive damage loading. AMIE is a shock physics and fragmentation simulation platform for metallic structural materials under hypervelocity impact loading. The two frameworks share architectural philosophy and validation approach but require entirely different governing equations, numerical methods, and material system calibrations.

Three substantive relationships between the frameworks are identified. First, NASMAT's demonstrated success with AI-augmented multiscale simulation — specifically a 145-times speedup at 98% accuracy using machine learning surrogates — constitutes the strongest available internal NASA validation of the general approach AMIE proposes, and should be cited explicitly in AMIE's Part 1 significance argument. Second, the two frameworks are sequentially complementary for spacecraft MMOD shielding design: NASMAT characterizes composite structural response while AMIE characterizes the hypervelocity impact event that loads that structure. Third, NASMAT's sensitivity analysis capability — demonstrated at 100,000 simulations in six hours — provides a natural training data generation pipeline for the AMIE PINN classifier, representing a future integration pathway that neither framework currently implements but that both architectures could support.

The paper closes with specific recommendations for how AMIE's NASA SBIR proposal should position AMIE relative to NASMAT: not as a competing tool but as the hypervelocity impact extension of a multiscale simulation philosophy that NASA has already internally validated and that Vision 2040 explicitly identifies as a priority development direction.

1. Introduction: Why This Comparison Matters

When a defense contractor or small business submits a NASA SBIR proposal for a new simulation tool, one of the first questions a technically sophisticated evaluator will ask is: does NASA already have something that does this? For a proposal centered on multiscale simulation with AI augmentation — which is precisely AMIE's claim — the honest answer requires a careful examination of NASMAT, because NASMAT is NASA's most prominent internal multiscale simulation platform and it has recently published results on coupling machine learning to multiscale simulation.

The question is not academic. If AMIE substantially duplicates NASMAT's capability, the proposal fails the significance test that SBIR Part 1 requires — the innovation must address a gap in the current state of the art, and an internal NASA tool is as much "current state of the art" as any academic publication. If AMIE addresses a domain that NASMAT does not cover, the proposal is strengthened by being able to point to NASA's own mature internal capability in an adjacent domain and argue precisely why that capability does not address the gap AMIE fills.

This paper conducts that comparison systematically. Section 2 characterizes NASMAT's scope, architecture, and validated capabilities based on the published NAFEMS presentation and NASMAT technical paper by Arnold, Ricks, Pineda, and Bednarcyk. Section 3 characterizes AMIE's scope, architecture, and proposed capabilities based on the SOL Engineering Services SBIR technical series. Section 4 maps the overlap, the complementarity, and the separation between the two frameworks across seven dimensions. Section 5 draws the strategic positioning conclusions and provides specific recommendations for the AMIE proposal.

2. NASMAT: Scope, Architecture, and Validated Capabilities

2.1 Institutional Context and Development History

NASMAT was developed at NASA Glenn Research Center's Multiscale and Multiphysics Modeling Branch under primary funding from the NASA Aeronautics Research Mission Directorate's Transformational Tools and Technologies (T3) Project, with additional support from the Space Technology Mission Directorate's Composite Technologies for Exploration and Entry Systems Modeling programs and the Office of Naval Research. Its development built on approximately thirty years of legacy code development in the MAC/GMC and FEAMAC tool families, which were themselves products of decades of composite micromechanics research centered on the Generalized Method of Cells (GMC) framework developed by Jacob Aboudi.

The Vision 2040 roadmap — NASA Contractor Report 2018-219771 — provides the strategic context for NASMAT's development. Vision 2040 envisions a cyber-physical-social ecosystem that accelerates model-based concurrent design, development, and deployment of materials and systems throughout the product lifecycle for affordable, producible aerospace applications. NASMAT is NASA's primary internal tool for realizing the materials and process modeling component of that vision, specifically addressing nine identified key element discipline areas with particular emphasis on models and methodologies, multiscale measurement and characterization, and verification and validation.

The critical gap that NASMAT addresses — identified as Gap 1 in the Vision 2040 framework — is the underdevelopment of physics-based models that link length and time scales for relevant material systems. NASMAT's Multiscale Recursive Micromechanics approach directly targets this gap by enabling an arbitrary number of length scales to be coupled through hierarchical localization and homogenization operations.

2.2 What NASMAT Actually Does: The Micromechanics Core

NASMAT's fundamental operation is micromechanics homogenization and localization for composite material systems. In concrete terms: given a composite material with known constituent properties — fiber modulus, matrix strength, void content — and a defined microstructural architecture — fiber volume fraction, tow geometry, weave pattern — NASMAT computes the effective properties of the composite at the next-higher length scale and passes those effective properties as a constitutive model input to a structural analysis code.

The localization operation moves information downward through scales — a macroscale strain field applied to a composite laminate is localized to the strain in individual subcells within the repeating unit cell at the tow level, then further localized to the strain in individual fiber, matrix, and void constituents at the microscale. The homogenization operation moves information upward — the stress responses of the individual constituents are volume-averaged back through the tow architecture to produce effective composite stresses at the macroscale. This bidirectional information flow is what makes NASMAT a genuinely multiscale tool rather than a sequence of independent single-scale analyses.

The micromechanics theories available in NASMAT represent a hierarchy of fidelity and computational cost. The Mori-Tanaka mean-field theory is computationally least expensive and provides good global accuracy but poor local field accuracy and no normal-shear coupling — appropriate for preliminary design studies. The Generalized Method of Cells provides very good global accuracy, good local field accuracy, and computational efficiency that makes it suitable for embedding within structural FEA models. The High-Fidelity Generalized Method of Cells provides excellent accuracy at higher cost and is appropriate for detailed local field characterization when the stress distribution within individual subcells is evaluation-relevant. Standard FEA micromechanics provides equivalent accuracy to HFGMC but is less efficiently embedded in multiscale frameworks.

The Multiscale Recursive Micromechanics approach allows any of these theories to be deployed at any scale in the hierarchy, with no limit on the number of scales that can be coupled. The published example demonstrates a five-level hierarchy for a 3D woven polymer matrix composite: Level 0 is the effective composite response, Level 1 is the 3D woven textile composite modeled with GMC3D, Level 2 is the through-thickness stacking of plies modeled with GMC3D, Level 3 is the individual tows modeled with GMC2D alongside the bulk matrix modeled with Mori-Tanaka, and Level 4 is the individual fiber and matrix constituents.

2.3 NASMAT's Validated Application Domain

The applications demonstrated in the published NASMAT literature define the boundaries of the tool's validated capability. Three categories of demonstrated applications are directly relevant to the NASMAT-AMIE comparison.

The primary demonstrated application is failure prediction and sensitivity analysis for 3D woven polymer matrix composites. The published results show prediction of warp-direction tensile strength within 3% of experimental data, correct identification of the failure mode — disbonding of binder tows — and execution of 100,000 simulations in six hours for sensitivity analysis of output quantities to input microstructural parameters. The loading conditions in these demonstrations are quasi-static uniaxial tension and shear — strain rates of approximately 10^-3 per second, pressures well below 1 megapascal, temperatures near ambient.

The second demonstrated application is multiscale simulation of a SiC/SiC ceramic matrix composite turbine vane under combined thermal and internal pressure loading — a realistic industrial-sized problem run in 5.5 hours on 102 CPU cores with a finite element mesh of approximately 500,000 elements. The loading conditions are moderate temperatures — up to 1,000 degrees Celsius — and

mechanical pressures consistent with turbine operating conditions, which are orders of magnitude below the hypervelocity impact pressures that AMIE addresses.

The third demonstrated application is multiscale thermal conductivity prediction for carbon/phenolic thermal protection system materials — specifically relevant to spacecraft reentry rather than MMOD impact. This application involves three scales connecting woven composite architecture, tow geometry, and void content to effective anisotropic thermal conductivity.

2.4 NASMAT's AI Integration: The Machine Learning Surrogate

The most directly relevant NASMAT capability for the AMIE comparison is the coupling of NASMAT with machine learning tools — specifically the development of a surrogate model interface that couples TensorFlow to NASMAT to replace computationally expensive physics-based microscale calculations with a trained neural network.

The published result is significant: a laminate model with an embedded ML surrogate calculated the composite laminate response 145 times faster than the original physics-based model while maintaining 98% accuracy. The architecture uses a long short-term memory network trained on NASMAT-generated simulation data to predict the homogenized stiffness tensor directly from strain tensor inputs and constituent material properties — bypassing the iterative micromechanics solution that the physics-based approach requires at each evaluation point.

This result demonstrates that AI augmentation of multiscale simulation can achieve the accuracy-speed balance that makes operational deployment feasible — industrial required speed at research-level accuracy, as the NASMAT team describes it. The conceptual architecture is a physics-based simulation tool providing training data, an ML model learning the input-output mapping, and the trained model replacing the expensive physics calculation in production use.

AMIE's PINN classifier represents the same conceptual architecture applied to a different problem: rather than replacing a constitutive calculation, AMIE's classifier replaces the scale transition decision — rather than a physics-based micromechanics model, AMIE's classifier decides when to activate SPH or MD in a specific region of the simulation domain. The input features are different, the output is a classification decision rather than a stiffness tensor, and the physics-informed regularization in AMIE's PINN loss function is not present in NASMAT's LSTM surrogate. But the fundamental approach — train an ML model on physics-based simulation data to enable faster production use — is identical.

2.5 NASMAT's Multiphysics Extension

A key architectural feature of NASMAT that has application-domain implications for the AMIE comparison is the HFGMC multiphysics extension. The published formulation shows that the HFGMC framework can be generalized to solve any physics governed by a vector constitutive law of the form Y = -Z times the gradient of a scalar potential. This covers heat conduction, electrical conduction, diffusion, magnetic permeability, and electrical permittivity — a broad class of coupled physical phenomena relevant to composite material performance under combined loading.

This multiphysics capability is impressive in scope but operates entirely within the quasi-static and moderately dynamic loading regime. The governing equation forms it covers — Fourier heat conduction, Fick diffusion, Maxwell electromagnetic equations — are not the governing equations of hypervelocity impact shock physics. The Rankine-Hugoniot shock jump conditions, the Mie-Gruneisen equation of state in the shock regime, the artificial viscosity formulation for shock front smoothing, and the EAM interatomic potential for phase transition modeling are all outside the scope of NASMAT's multiphysics framework.

3. AMIE: Scope, Architecture, and Proposed Capabilities

3.1 The Core Innovation

The Adaptive Multiscale Intelligence Engine is a physics-informed neural network classifier that dynamically determines which simulation methodology — Finite Element Analysis at the macro scale, Smoothed Particle Hydrodynamics at the meso scale, or Molecular Dynamics at the micro scale — should be active in each spatial region of a simulation domain at each moment during a hypervelocity impact event, based on real-time monitoring of physical state variables that indicate when the governing equations of the currently active method are approaching the limits of their physical validity.

The AMIE Phase I scope targets a binary macro-to-meso transition classifier for aluminum alloy 6061-T6 under hypervelocity impact at 5 kilometers per second — specifically, a PINN classifier trained to detect when physical conditions in a FEA element indicate that the Johnson-Cook constitutive model is extrapolating beyond its validated strain rate range, the local pressure has exceeded the Hugoniot elastic limit triggering shock wave physics, the von Mises stress gradient magnitude indicates deformation localization at sub-element scale, the density deviation indicates void coalescence approaching the critical fracture threshold, or the temperature gradient indicates adiabatic shear band formation. When any combination of these indicators crosses the trained decision boundary, the AMIE windowing agent activates SPH resolution in the affected region.

The Phase II scope extends the framework to the full three-scale FEA/SPH/MD concurrent coupling, adding MD activation in regions where SPH physical conditions indicate phase transition onset, lattice instability energy density exceedance, or atomistic fragmentation velocity conditions — and to reinforcement learning for dynamic window boundary optimization.

3.2 The Physical Domain: Hypervelocity Impact

AMIE's physical domain is hypervelocity impact — projectile velocities of 3 to 10 kilometers per second, generating shock pressures of 1 to 100 gigapascals, strain rates of 10^4 to 10^7 per second, and material temperatures from ambient to above the liquidus temperature of aluminum at 925 Kelvin within microseconds. The target geometry for Phase I is a monolithic aluminum alloy 6061-T6 plate in the thickness range of 3 to 15 millimeters.

This physical domain is governed by a set of equations that are entirely distinct from the micromechanics homogenization equations of NASMAT. The macro-scale FEA domain is governed by the Johnson-Cook constitutive model with Mie-Gruneisen equation of state. The meso-scale SPH domain is governed by the Navier-Stokes momentum equation with artificial viscosity for shock front modeling and the Wendland C2 kernel for particle density summation. The micro-scale MD domain is governed by Newton's second law at the atomic scale with the Mishin 1999 Embedded Atom Method potential for aluminum interatomic forces and Velocity Verlet integration for atomic trajectory evolution.

The temporal scale of the simulation is microseconds to tens of microseconds — orders of magnitude faster than the quasi-static and moderate dynamic loading scenarios that NASMAT addresses. The spatial scale of interest is the impact zone spanning from the impact site at the contact interface through the full plate thickness and into the debris cloud forming on the back face — a domain of tens of millimeters that is characterized by extremely non-uniform physical conditions ranging from undisturbed elastic material in the far field to fully vaporized material at the impact site in the highest-velocity scenarios.

3.3 The Coupling Architecture

AMIE's coupling architecture is fundamentally different from NASMAT's micromechanics hierarchy. NASMAT uses sequential hierarchical coupling — localization passes information down through the scale hierarchy from macroscale to microscale before homogenization passes results back up. The information flow is top-down then bottom-up in sequence, with all scales active throughout the simulation.

AMIE uses concurrent spatial domain decomposition — different simulation methods are active simultaneously in different spatial regions of the same domain, with bidirectional data exchange at the coupling interface boundaries. The FEA domain and the SPH domain are operating in parallel at every timestep, exchanging field variable information at the buffer zone boundary. The coupling interface is dynamic — its location changes as the AI windowing agent updates the scale transition boundary based on evolving physical conditions.

The buffer zone design, ghost force correction, and energy conservation monitoring protocols that govern AMIE's coupling interface are specific to concurrent spatial domain decomposition and have no analog in NASMAT's hierarchical homogenization framework. Conversely, NASMAT's localization concentration tensors, repeating unit cell periodic boundary conditions, and homogenized effective property tensors have no analog in AMIE's concurrent coupling architecture.

4. Systematic Comparison Across Seven Dimensions

4.1 Physical Domain

This is the most fundamental dimension of the comparison and the one that most clearly establishes the non-overlapping nature of the two frameworks.

NASMAT's physical domain is composite materials under thermoelastic, progressive damage, and moderate inelastic loading. The material systems are fiber-reinforced polymer matrix composites, ceramic matrix composites, woven textile composites, and functionally graded materials. The loading regimes are quasi-static and moderately dynamic — strain rates from 10^-6 to approximately 10^1 per second, pressures from ambient to tens of megapascals, temperatures from cryogenic to approximately 1,500 degrees Celsius for ceramic systems. The governing phenomena are homogenized elastic anisotropy, constituent failure initiation, progressive damage propagation, and thermally induced residual stress.

AMIE's physical domain is monolithic metallic materials — primarily aluminum alloys, with Phase II extension to titanium and steel — under hypervelocity impact loading. The loading regime is extreme dynamic — strain rates from 10^3 to 10^7 per second, pressures from 0.1 to 100 gigapascals, temperatures from ambient to above liquidus. The governing phenomena are shock wave propagation, material fragmentation, phase transition, debris cloud formation, and post-impact residual state evolution.

No physical phenomenon addressed by NASMAT requires the simulation methods of AMIE. No physical phenomenon addressed by AMIE is addressable by the simulation methods of NASMAT. The domains are non-overlapping in the same way that aerodynamics and acoustics are distinct physical domains — sharing some mathematical formalism but governed by different physics at their core.

4.2 Governing Equations

The governing equations of the two frameworks have essentially no overlap. NASMAT's core equations are the micromechanics localization and homogenization relations — the subcell strain concentration tensors A and the effective property tensors B and Z that map between macro-scale and subcell-scale field quantities. The constitutive models used are designed for composite constituents under moderate loading — linear elastic, viscoelastic, viscoplastic, and progressive damage models for polymer matrices, ceramic matrices, and reinforcing fibers.

AMIE's core equations at the macro scale are the Johnson-Cook constitutive model and Mie-Gruneisen equation of state — neither of which is a composite micromechanics equation. At the meso scale the SPH Navier-Stokes equations with artificial viscosity govern shock front propagation — equations not present in any form in NASMAT. At the micro scale Newton's second law with EAM interatomic potential governs atomic trajectories — equations whose physics the continuum micromechanics framework of NASMAT explicitly does not resolve. The Rankine-Hugoniot shock jump conditions that govern shock front development in AMIE's Phase 2 are entirely absent from NASMAT's equation set.

4.3 Numerical Methods

NASMAT employs semi-analytical micromechanics theories — GMC, HFGMC — as its primary computational engine, which solve algebraic systems of equations for subcell field quantities. These semi-analytical methods are what gives NASMAT its remarkable computational efficiency: 100,000 simulations in six hours, 100 loading increments in 30 seconds. The methods work because the

periodic microstructure of composite materials admits closed-form or semi-closed-form solutions for the field distribution within a repeating unit cell.

AMIE employs fully numerical methods throughout — finite element integration for the macro-scale FEA domain, kernel-smoothed particle dynamics for the meso-scale SPH domain, and molecular dynamics for the micro-scale MD domain. None of these methods benefit from the semi-analytical shortcuts that make NASMAT's micromechanics so efficient, because the impact phenomena AMIE models do not have the spatial periodicity that semi-analytical methods require. The computational cost is correspondingly higher — tens to thousands of CPU-hours rather than seconds per simulation.

4.4 AI Architecture and Role

Both frameworks couple AI to multiscale simulation, but the AI performs fundamentally different functions in each framework.

In NASMAT's ML integration, the AI is a surrogate model — it replaces a physics-based constitutive calculation with a trained neural network that predicts the same output from the same inputs, faster. The AI learns the mapping from strain tensor and material properties to homogenized stiffness tensor. It does not make any decisions about which physics model to use or which scale to activate — those decisions are made by the analyst at model setup time. The AI is a computational accelerator for a fixed physics pipeline.

In AMIE, the AI is a decision-making agent — specifically, a PINN classifier that determines which simulation methodology should be active in each spatial region at each timestep, based on observed physical state variables. The AI is not replacing a constitutive calculation; it is replacing a human judgment about when physical conditions warrant a change in simulation methodology. The physics-informed regularization in the PINN loss function constrains the classifier's decisions to remain physically plausible — distinguishing AMIE's classifier from a purely data-driven approach. The AI is a physics-constrained methodology selection agent.

The distinction matters for positioning. NASMAT's ML integration and AMIE's PINN classifier both represent AI augmentation of multiscale simulation, but they solve different problems. NASMAT's ML accelerates a computation. AMIE's AI automates a decision. Both are valuable innovations; they are not competing approaches to the same problem.

4.5 Material System Coverage

NASMAT's primary material system coverage is fiber-reinforced composites — polymer matrix composites using carbon, glass, and ceramic fibers; ceramic matrix composites using silicon carbide fibers and matrices; and woven textile composites with complex 2D and 3D architectures. The material models and micromechanics theories in NASMAT are specifically designed for the fiber-matrix microstructure with its characteristic length scales of fiber diameters in the range of 5 to 25 micrometers, tow widths in the range of 1 to 5 millimeters, and repeating unit cell dimensions in the range of millimeters to centimeters.

AMIE's primary material system coverage is monolithic metallic structural materials — aluminum alloys with homogeneous microstructure at the scales relevant to the simulation. The constitutive models, threshold values, and interatomic potentials in AMIE are calibrated for single-phase metallic systems rather than for the multi-constituent, multi-scale microstructure of fiber-reinforced composites.

There is essentially no overlap in material system coverage. Neither tool currently addresses the other's primary material system. A complete spacecraft structural simulation requires both: NASMAT

for the composite shell and structural members, AMIE for the metallic Whipple shield and aluminum alloy impact-critical components.

4.6 Scale Coverage

The scale coverage of the two frameworks overlaps at the continuum mechanics macroscale but diverges at finer scales in fundamentally different directions.

NASMAT covers nanometers to meters — from molecular dynamics of polymer chain structure through fiber and void dimensions through tow and ply architecture through laminate and structural component behavior. At every scale within this range the physical description is a continuum or semi-continuum mechanical description connected to adjacent scales through homogenization.

AMIE covers nanometers to millimeters — from atomic-scale phase transitions and dislocation dynamics through fragmentation mechanics and particle separation through macro-scale structural wave propagation. At every scale within this range the governing equations change qualitatively between scales: Newton's second law at atomic scale yields to the Navier-Stokes particle equations at meso scale which yield to the continuum finite element equations at macro scale.

The critical distinction is not the scale range but the physics coupling strategy. NASMAT couples scales through mathematical homogenization — averaging fine-scale behavior to produce effective coarse-scale properties. AMIE couples scales through concurrent spatial domain decomposition — applying different physics models simultaneously in different regions. These are complementary strategies that together could in principle cover the full range of multiscale problems in aerospace materials simulation.

4.7 Computational Cost and Efficiency

The computational efficiency profiles of the two frameworks are dramatically different and reflect the different physical domains they address.

NASMAT achieves extraordinary computational efficiency for composite micromechanics — 100,000 simulations in six hours on a single workstation-class computer, 100 loading increments in 30 seconds. This efficiency is possible because the semi-analytical micromechanics theories solve algebraic rather than differential equation systems, avoiding the fine-grained time integration that numerical methods require. The efficiency is also enabled by the separability of the physical problem — the periodic composite microstructure means that the fine-scale field distribution can be computed once per loading condition rather than being recomputed continuously as the macroscale solution evolves.

AMIE requires substantially higher computational resources because the physics it addresses does not permit similar analytical simplification. A single hypervelocity impact simulation at the Phase I demonstration scale — a 50 mm by 50 mm by 10 mm aluminum plate at 5 km/s — requires approximately 15 to 40 CPU-hours for FEA-only at 0.5 mm element size, 190 to 500 CPU-hours for static FEA/SPH concurrent coupling, and an estimated 35 to 100 CPU-hours for AMIE adaptive coupling. The AMIE adaptive coupling cost reduction — 75 to 85 percent relative to static FEA/SPH — is its primary economic value proposition.

Comparing these cost profiles directly is not meaningful because the two frameworks are solving physically different problems at different scales. A more useful comparison is within-domain: NASMAT's ML surrogate achieves a 145-times speedup within the composite micromechanics domain. AMIE targets a 30 to 85 percent cost reduction within the hypervelocity impact domain. Both represent substantial efficiency improvements over their respective baseline approaches.

4.8 Summary Comparison Table

Table 1 consolidates the seven-dimension comparison into a single reference.

Dimension	NASMAT	AMIE
Physical Domain	Composite materials under thermoelastic and progressive damage loading; quasi-static to moderate dynamic	Metallic materials under hypervelocity impact; shock wave physics, fragmentation, phase transition
Velocity / Strain Rate	10^-6 to 10^1 s^-1; pressures < 100 MPa	10^3 to 10^7 s^-1; pressures 0.1 to 100 GPa
Primary Material Systems	Fiber-reinforced PMC, CMC, woven textile composites	Monolithic metallic structural alloys; Al, Ti, steel
Scale Coupling Strategy	Hierarchical homogenization and localization; sequential top-down / bottom-up	Concurrent spatial domain decomposition; FEA, SPH, MD active simultaneously
Core Governing Equations	GMC/HFGMC subcell field equations; Mori-Tanaka mean-field theory; continuum damage mechanics	Johnson-Cook with Mie-Gruneisen EOS; SPH Navier-Stokes with artificial viscosity; Newton-EAM MD
Numerical Methods	Semi-analytical; algebraic system solution; no time integration	Fully numerical; explicit time integration; particle dynamics; molecular dynamics
AI Role	Surrogate model replacing constitutive calculation; computational accelerator	PINN classifier making methodology selection decisions; physics-constrained agent
Efficiency Profile	100K simulations / 6 hours; 30 sec per 100 increments; ML surrogate 145x speedup	Adaptive coupling 75-85% cost reduction vs static concurrent; 35-100 CPU-hours per simulation
Integration with FEA	NASMAT acts as Abaqus material model via user subroutine interface; constitutive model replacement	FEA is primary macro-scale solver; AMIE governs FEA-to-SPH and SPH-to-MD transitions dynamically
NASA Application Domain	Composite structures; turbine components; TPS thermal properties; Aurora D8 structural optimization	MMOD Whipple shield impact response; hypervelocity defeat; spacecraft structural metallic components
Maturity Level	Production tool; NASA Software Catalog LEW-20244-1; Windows/Linux release available	TRL 2-3; Phase I SBIR proof of concept for binary macro-to-meso classifier

Table 1: Seven-dimension comparison of NASMAT and AMIE across physical domain, governing equations, numerical methods, AI role, material systems, scale coupling strategy, efficiency profile, and maturity level.

5. Three Substantive Relationships

Having established that NASMAT and AMIE operate in non-overlapping physical domains and address fundamentally different simulation challenges, three substantive positive relationships between the frameworks merit detailed development. These relationships are the basis for the strategic positioning recommendations in Section 6.

5.1 Relationship 1: Internal NASA Validation of the AI Augmentation Approach

The most practically important relationship between NASMAT and AMIE for the NASA SBIR proposal is that NASMAT's published ML surrogate results constitute the strongest available internal NASA validation of the general approach that AMIE proposes. This relationship deserves careful unpacking.

AMIE's central technical claim is that an AI system — specifically a physics-informed neural network classifier — can be trained on simulation data to make scale transition decisions that are physically correct, computationally efficient, and more reliable than static geometry-based or time-based coupling triggers. This is a non-trivial claim about whether AI can successfully learn a physically meaningful decision boundary from simulation-derived training data.

NASMAT's ML surrogate results answer this question affirmatively for a related but distinct problem. The NASMAT team demonstrated that a long short-term memory network trained on NASMAT-generated composite micromechanics data can predict homogenized stiffness tensors with 98% accuracy at 145 times the speed of the physics-based model. This result shows that AI can successfully learn a physically meaningful mapping from simulation-derived training data — which is precisely the capability that AMIE's classifier requires, applied to a classification decision rather than a regression prediction.

The specific architecture differs — AMIE uses a PINN with physics-informed loss function regularization while NASMAT uses an LSTM surrogate without explicit physics constraints — but the underlying question about AI learnability of simulation-derived physical relationships is the same, and NASMAT answers it affirmatively with production-quality evidence from within NASA.

For the AMIE SBIR proposal, this relationship provides a powerful argument structure: NASA has already demonstrated internally that AI augmentation of multiscale simulation achieves industrial-required speed at research-level accuracy in the composite materials domain (NASMAT). AMIE proposes to extend this demonstrated approach to the hypervelocity impact domain that NASMAT does not cover, with the additional enhancement of physics-informed regularization that should improve generalization beyond NASMAT's purely data-driven surrogate. The evaluator can support AMIE's AI approach based on evidence from their own institution's published work.

5.2 Relationship 2: Sequential Complementarity for Spacecraft MMOD Shielding Design

The second substantive relationship is sequential complementarity in the spacecraft MMOD shielding design problem — the primary NASA application domain for AMIE. This relationship is important for establishing that AMIE fills a genuine gap in NASA's simulation capability rather than duplicating existing work.

A complete computational design workflow for a spacecraft MMOD shielding system requires simulation of multiple distinct physical events. The primary impact event — an MMOD particle striking the aluminum Whipple shield bumper at 2.5 to 12 km/s — must be characterized in terms of the debris cloud it generates: the fragment size distribution, velocity distribution, and spatial density of the debris cloud that expands behind the bumper toward the rear wall. The secondary impact event — the debris

cloud striking the composite rear wall and inner structural elements — must then be characterized in terms of the structural response and potential perforation of those elements. The post-impact residual state of the composite structural elements — any damage, cracking, or residual stress — feeds into structural health monitoring and remaining life assessment.

AMIE addresses the primary impact event. Its FEA/SPH concurrent coupling models the Whipple shield aluminum alloy bumper, generates the debris cloud through SPH fragmentation mechanics, and characterizes the debris cloud's fragment size, velocity, and spatial distributions. These are the outputs that feed the secondary impact assessment. AMIE cannot model the composite rear wall structural response — its constitutive models and governing equations are specific to metallic materials.

NASMAT addresses the secondary impact response of composite structural elements. Its micromechanics framework can characterize the effective properties of the composite rear wall and inner structure, and its damage and failure models can predict the structural response to the debris cloud loading that AMIE generates. NASMAT cannot model the hypervelocity impact event that generates the debris cloud — its governing equations and material models are not appropriate for shock physics and metallic fragmentation.

Together the two tools cover the complete workflow. AMIE characterizes the threat. NASMAT characterizes the structural response to the threat. Neither tool alone covers both functions, and no currently available single tool covers both. The sequential complementarity is real, operationally significant, and directly relevant to NASA's active MMOD protection research programs.

For the AMIE SBIR proposal, this sequential complementarity should be developed explicitly in the commercialization plan. A simulation workflow that combines AMIE for impact physics characterization and NASMAT for structural response characterization provides NASA with a more complete capability than either tool alone. AMIE's value is not competitive with NASMAT — it is additive.

5.3 Relationship 3: Training Data Pipeline Integration Pathway

The third relationship is a future integration pathway — not currently implemented by either framework but architecturally feasible given their existing capabilities and potentially high value for the Phase II AMIE development.

NASMAT's sensitivity analysis capability demonstrated 100,000 simulations in six hours. This capability is specifically valuable for generating large, systematically varied datasets that characterize how simulation outputs respond to input parameter variations. For AMIE's Phase I objective, the challenge is generating sufficient labeled training data — simulation runs where the physical state of every element is known and the ground-truth answer about whether FEA or SPH is the appropriate methodology for that element at that moment is established by running a fully resolved reference simulation.

For the metallic impact scenarios that AMIE directly targets, the training data must come from full-domain reference simulations of hypervelocity impact events at varied velocities, target thicknesses, and projectile geometries. This is computationally expensive because each reference simulation requires full SPH resolution across the entire domain rather than the adaptive windowing that AMIE will eventually enable.

NASMAT's sensitivity analysis architecture — specifically its ability to execute parametric sweeps efficiently across large numbers of simulation configurations — is not directly applicable to hypervelocity impact simulation because NASMAT uses different solvers and different governing

equations. However, the architectural pattern is valuable: a high-efficiency simulation engine generating systematically varied training data for an ML model is exactly the pipeline AMIE needs.

A potential integration pathway would use NASMAT's sweep architecture as a template for implementing an equivalent parametric sweep capability in the AMIE reference simulation framework — a hypervelocity impact version of NASMAT's 100,000-simulation sensitivity analysis capability, using LS-DYNA or AUTODYN with SPH rather than NASMAT with GMC/HFGMC. The NASMAT team's published methodology for structuring the sensitivity sweep, managing simulation data, and coupling the results to an ML training pipeline provides directly applicable design guidance even though the specific solver is different.

For the Phase II AMIE development, this integration pathway could potentially be made more direct: NASMAT's sensitivity analysis of composite material properties under varied microstructural parameters could generate constitutive property datasets that feed AMIE's material model calibration for composite-metal hybrid structural configurations — scenarios where the impact event involves both metallic and composite structural elements.

6. What NASMAT Does Not Do: Confirming the Gap AMIE Fills

The comparison in Section 4 establishes that NASMAT and AMIE are non-overlapping. But for the SBIR proposal, the more important question is whether any currently available tool — at NASA or elsewhere — fills the gap that AMIE targets. Confirming that the gap is real requires establishing not just that NASMAT does not fill it but that no closely related capability does.

6.1 The Gap: AI-Driven Dynamic Scale Transition in Hypervelocity Impact Simulation

The specific capability gap that AMIE addresses is the absence of a runtime AI agent that determines when and where to activate fine-scale simulation methodology within a hypervelocity impact simulation domain based on real-time monitoring of physical state variables, using physics-informed regularization to constrain the agent's decisions to remain physically plausible.

Current hypervelocity impact simulation practice assigns scale transition boundaries at model setup time based on anticipated impact physics — the analyst estimates where fragmentation will occur, sizes the SPH zone conservatively to encompass that region, and runs the simulation with a static SPH zone that may be much larger than physically necessary. This static approach wastes computational resources by applying SPH to regions that remain in the FEA-valid regime throughout the simulation, and it risks under-sizing the SPH zone for unanticipated impact conditions.

NASMAT does not address this gap because it does not address hypervelocity impact at all. NASMAT's variable fidelity selection — choosing between Mori-Tanaka, GMC, and HFGMC — is made by the analyst at model setup time, not dynamically by an AI agent during simulation execution. The concept of a runtime physics-monitoring agent that dynamically adjusts methodology allocation is not present in NASMAT's architecture.

6.2 Related Capabilities That Do Not Fill the Gap

Beyond NASMAT, several related capabilities should be assessed as potential gap-fillers to confirm that AMIE addresses a genuine state-of-the-art limitation.

BUMPER, NASA's primary operational MMOD impact simulation tool, is a ballistic limit equation code — it applies empirically calibrated equations to predict shield perforation thresholds without resolving the physics of the impact event at multiple scales. BUMPER cannot produce debris cloud characterization at the fragment size and velocity resolution that AMIE targets, and it has no multiscale architecture or AI component.

AUTODYN and LS-DYNA, the commercial hydrocode tools most widely used for hypervelocity impact simulation, offer FEA-SPH coupling but do so through static zone definition at model setup time — exactly the approach AMIE improves upon. Neither commercial code includes a physics-informed AI windowing agent. Both require the analyst to pre-define the SPH zone geometry, and neither adapts that geometry dynamically based on runtime physical state monitoring.

CTH, the Sandia National Laboratories Eulerian hydrocode, is widely used for hypervelocity impact at the national laboratory level but does not include FEA-SPH-MD concurrent coupling or AI-driven scale transition. Its Eulerian formulation handles large deformation and fragmentation differently from the Lagrangian FEA-SPH framework that AMIE uses and does not address the atomic-scale MD coupling that constitutes AMIE's Phase II scope.

The Quasicontinuum method and related bridging domain methods provide concurrent atomistic-continuum coupling architectures but are designed for quasi-static loading conditions at material defect scales — they are not designed for hypervelocity impact shock physics, fragmentation

mechanics, or the macro-scale structural response that AMIE must couple. The QC method typically couples elasticity at the continuum scale to atomic potentials at a crack tip or dislocation core — a domain size and loading rate regime orders of magnitude different from AMIE's application.

The conclusion is that no existing tool fills the specific gap AMIE targets. NASMAT's success in AI-augmented multiscale simulation validates the general approach but leaves the hypervelocity impact domain entirely unaddressed. The commercial hydrocodes provide the numerical methods but not the AI-driven dynamic windowing. The atomistic-continuum coupling methods provide concurrent multi-methodology coupling but not at the relevant physical scales and loading rates.

7. The Vision 2040 Alignment: Both Tools, Different Gaps

NASA's Vision 2040 roadmap provides the most authoritative statement of NASA's simulation capability gaps and priorities. Examining where NASMAT and AMIE each align to Vision 2040's identified critical gaps clarifies why both tools are needed and why AMIE is positioned as an addition to the portfolio rather than a competitor within it.

7.1 NASMAT's Vision 2040 Alignment

NASMAT directly addresses Vision 2040 Critical Gap 1 — the underdevelopment of physics-based models that link length and time scales for relevant material systems — within the composite materials domain. The NASMAT team's NAFEMS presentation explicitly frames NASMAT as an enabling tool to realize Vision 2040, and the nine identified key element discipline areas in Vision 2040 map directly onto NASMAT's capabilities: models and methodologies, multiscale measurement and characterization, optimization and optimization methodologies, verification and validation.

NASMAT also addresses Critical Gap 3 — the lack of reliable optimization methods that bridge across scale — through its sensitivity analysis capability and the ICME optimization demonstrations for the Aurora D8 aircraft composite structural components. The AIMAOS orchestration system developed alongside NASMAT directly targets the automated workflow integration that Vision 2040 identifies as a priority.

7.2 AMIE's Vision 2040 Alignment

AMIE aligns to Vision 2040 Critical Gap 1 in the hypervelocity impact domain — a domain that NASMAT's composite-focused implementation leaves unaddressed. The specific gap is physics-based models linking length and time scales for metallic structural materials under extreme dynamic loading — the shock physics, fragmentation mechanics, and phase transition phenomena that govern hypervelocity impact response.

AMIE also aligns to Critical Gap 4 — existing models and software codes are not designed to compute input sensitivities and propagate uncertainties — through the PINN classifier sensitivity analysis that constitutes AMIE Phase I Objective 1. The observation vector design methodology in AMIE White Paper 10 is specifically a sensitivity analysis framework applied to the question of which physical state variables most reliably indicate scale transition requirements.

AMIE aligns to Critical Gap 5 — the lack of guidelines and practitioner aids for multiscale and multiphysics verification and validation — through the V&V framework for AI-augmented simulation tools developed in AMIE White Paper 7. This V&V framework addresses the specific challenge that Vision 2040 identifies: existing V&V standards developed for deterministic simulation codes do not fully address the probabilistic and data-dependent nature of machine learning components in AI-augmented simulation tools.

7.3 Portfolio Complementarity

The Vision 2040 alignment analysis reveals that NASMAT and AMIE fill different gaps in NASA's simulation capability portfolio — they are not competing for the same gap but addressing distinct deficiencies in the current state of practice. NASMAT fills the composite materials multiscale modeling gap. AMIE fills the hypervelocity impact multiscale modeling gap. Together they advance NASA closer to the Vision 2040 state — an integrated multiscale simulation ecosystem spanning the full range of aerospace material systems and loading conditions.

This portfolio framing is strategically important for AMIE's SBIR proposal because it positions AMIE not as a startup trying to displace an existing NASA tool but as a small business filling a gap that NASA's own strategic roadmap has identified and that NASA's own internal tool development has not yet addressed. This is precisely the role that the SBIR program is designed to enable — small businesses filling identified gaps in government technical capability that government-internal development has not yet addressed.

8. Strategic Positioning Recommendations for the AMIE SBIR Proposal

8.1 Cite NASMAT Explicitly in Part 1

The significance section of the AMIE Phase I proposal should acknowledge NASMAT explicitly and use it constructively rather than avoiding the comparison. The recommended argument structure is: NASA has already demonstrated internally that AI augmentation of multiscale simulation produces dramatic efficiency gains — 145 times faster at 98% accuracy — in the composite materials domain through NASMAT. The hypervelocity impact domain that AMIE targets does not have an equivalent tool in NASA's current portfolio. AMIE applies the proven AI augmentation approach, with the enhancement of physics-informed regularization, to fill this documented gap.

This argument is more effective than silence on NASMAT because it demonstrates awareness of the state of the art, avoids the appearance of ignorance of NASA's internal capability, and turns the NASMAT results into supporting evidence for AMIE's approach rather than a potential objection.

8.2 Distinguish AI Roles Precisely

The proposal should distinguish clearly between NASMAT's ML surrogate role — replacing a constitutive calculation — and AMIE's PINN classifier role — making a methodology selection decision. This distinction matters because it clarifies that AMIE is not proposing the same thing NASMAT has already done but rather a conceptually related and complementary innovation.

The physics-informed regularization in AMIE's PINN loss function should be explicitly identified as an architectural enhancement over NASMAT's purely data-driven LSTM surrogate. The physics constraints prevent the AMIE classifier from making scale transition decisions that violate the governing equations of the physical system — a property that a purely data-driven surrogate does not guarantee. This makes AMIE's classifier more reliable for out-of-distribution conditions — impact velocities, target thicknesses, and projectile geometries not represented in the training dataset — which is a critical requirement for operational T&E deployment.

8.3 Develop the Sequential Complementarity Explicitly

The commercialization plan in Part 6 of the SBIR proposal should explicitly develop the sequential complementarity with NASMAT for the spacecraft MMOD shielding design workflow. The argument is that AMIE and NASMAT together cover a simulation workflow that neither covers alone — AMIE for the hypervelocity impact physics, NASMAT for the composite structural response. A future integration of the two tools, passing AMIE debris cloud characterization to NASMAT composite structural response simulation, addresses a complete spacecraft MMOD protection design problem that no current integrated tool addresses.

This workflow integration pathway also serves as a Phase III commercialization pathway — rather than competing with NASA's existing NASMAT investment, AMIE enhances the value of that investment by providing the complementary hypervelocity impact characterization that NASMAT currently lacks as an upstream input.

8.4 Position Within Vision 2040 Explicitly

White Paper 8 — the paper on translating defense hypervelocity simulation capability to NASA MMOD applications — should include a section explicitly mapping AMIE to Vision 2040's identified critical gaps, specifically Gap 1 for the physics-based multiscale model in the hypervelocity impact domain, Gap 4 for the sensitivity analysis methodology, and Gap 5 for the AI-augmented simulation V&V

framework. This mapping demonstrates that AMIE addresses priorities that NASA has formally documented at the strategic level.

The Vision 2040 mapping also provides a response to any evaluator concern that NASMAT already addresses the multiscale modeling gap. The response is: NASMAT addresses Gap 1 for composite materials; AMIE addresses Gap 1 for metallic materials under hypervelocity impact. The gap is large enough for both, and Vision 2040's own framing of the gap does not restrict it to composite materials.

8.5 Do Not Overstate the Distinction

One positioning risk is overstating the distinction between NASMAT and AMIE in a way that dismisses NASMAT's relevance to the evaluator. The NASMAT team at NASA Glenn Research Center is the primary technical audience for an MMOD-related SBIR, and dismissing their published work would be counterproductive. The recommended approach is to acknowledge NASMAT's genuine contributions and genuine limitations honestly — acknowledging that NASMAT has demonstrated AI augmentation of multiscale simulation effectively while being clear that its architecture and governing equations do not extend to the hypervelocity impact domain that AMIE targets.

This honest and respectful positioning also aligns with AMIE White Paper 9's argument for practitioner-led innovation — the PI's non-traditional background is most credibly established by demonstrating genuine familiarity with and respect for the relevant technical community's work, not by dismissing that community's contributions.

9. Conclusion

The comparison between NASMAT and AMIE conducted in this paper supports four principal conclusions.

First, NASMAT and AMIE are not competing tools. They operate in non-overlapping physical domains, address fundamentally different simulation challenges, employ different governing equations and numerical methods, and serve different NASA application domains. An evaluator who asks whether AMIE duplicates NASMAT should receive a clear and confident negative answer supported by the seven-dimension comparison in Section 4.

Second, NASMAT's published AI augmentation results constitute the most valuable available internal NASA validation of the general approach AMIE proposes. The 145-times speedup at 98% accuracy from the NASMAT ML surrogate is direct evidence from within NASA's own research community that AI augmentation of multiscale simulation is technically feasible and practically valuable. AMIE should cite and acknowledge this result explicitly rather than treating it as a potential competitive threat.

Third, the two frameworks are genuinely complementary for the spacecraft MMOD shielding design problem — the primary NASA application domain for AMIE. AMIE characterizes the hypervelocity impact event and debris cloud that NASMAT cannot model. NASMAT characterizes the composite structural response to that debris cloud that AMIE cannot model. A future integrated workflow combining both tools addresses a complete design problem that neither tool alone resolves.

Fourth, both tools advance NASA toward the Vision 2040 goal of an integrated multiscale simulation ecosystem, filling different identified gaps in NASA's current capability. NASMAT fills the composite materials multiscale modeling gap. AMIE fills the hypervelocity impact multiscale modeling gap. Together they represent progress toward the complete portfolio that Vision 2040 envisions.

The strategic implication for the AMIE proposal is straightforward. NASMAT is not an objection to AMIE — it is a supporting reference. AMIE's Part 1 significance argument is strengthened, not

weakened, by the existence and demonstrated success of NASMAT, because NASMAT provides internal NASA evidence that the approach works and because NASMAT's absence from the hypervelocity impact domain confirms the gap that AMIE fills is genuine.

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