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Development of scalable design optimization parameters for bi-component protective systems

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Changing the World's Energy Future

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Advanced Materials & Manufacturing for Extreme Environments: Multi-role and Integrated Material Systems

Development of scalable design optimization parameters for bi-component protective systems

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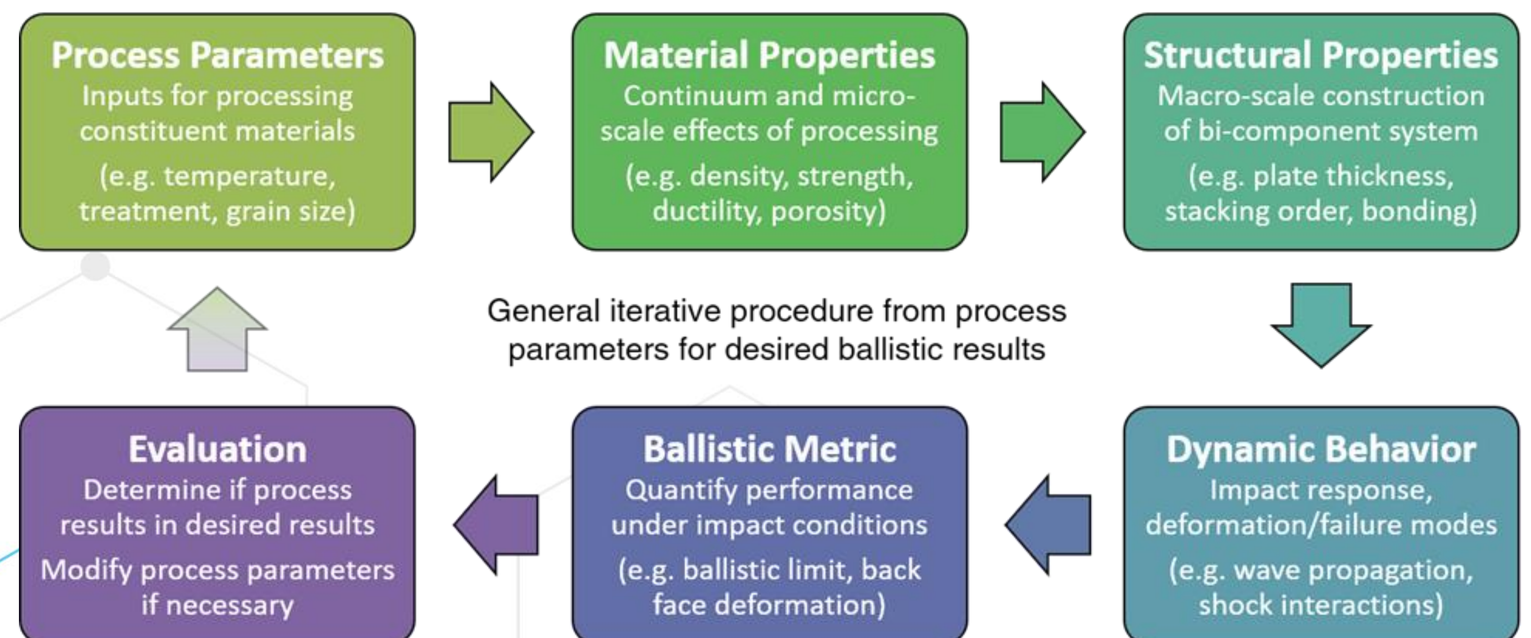
Objectives

- To develop and extend current scaling laws to predict and optimize the impact performance of bonded bi-component protection-systems
- To obtain dimensionless parameters at each step of the system design cycle to streamline and optimize the rapid deployment of bi-component protection systems



- Large sample space → Near infinite combinations + continuous variables (e.g. thickness)
- Short-circuit via machine learning → Functional relationships not established

Challenges compared to prior efforts

- Metallic alloys → rate-independent, isotropic
- Single component → analytically simple, no inter-component bonding
- Ductile failure of metals → energy-based failure vs. brittle fracture
- Consideration of structural effects of bi-component system e.g. flexural stiffness

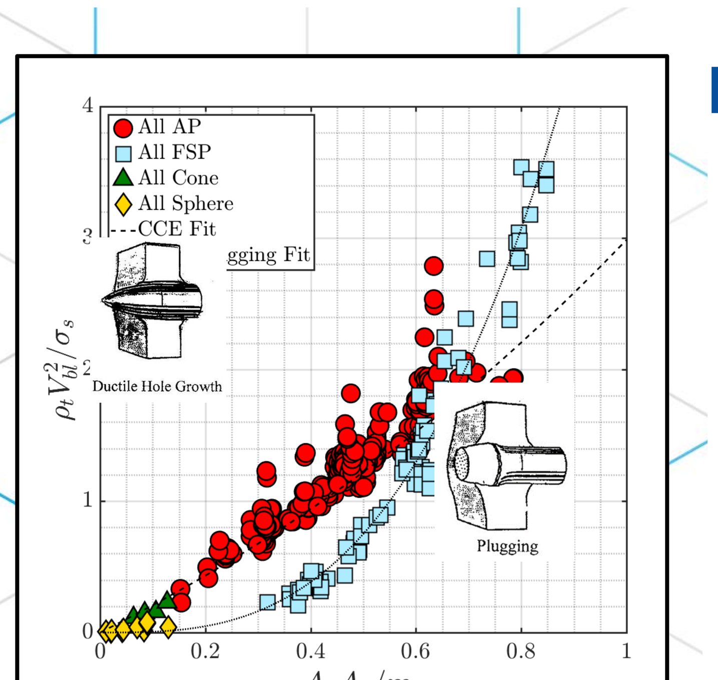


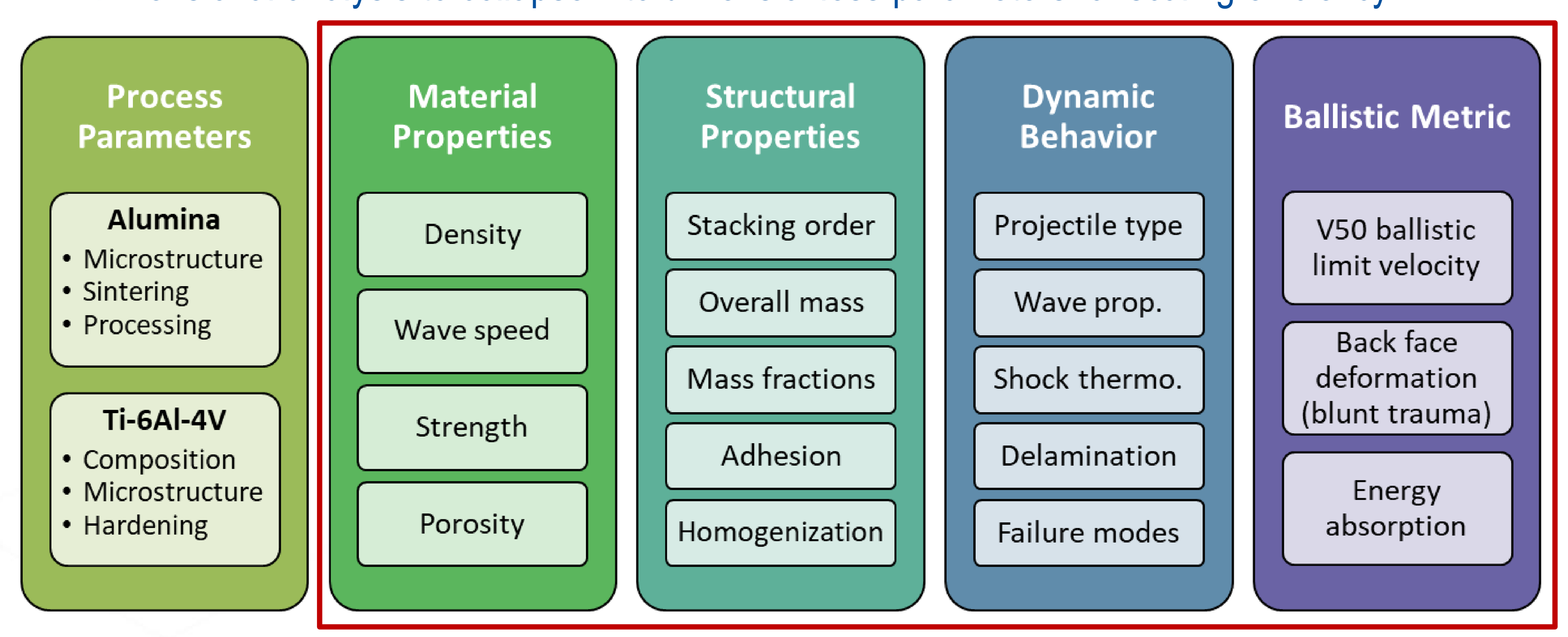
Fig. 1: Non-dimensional parametrization of ballistic resistance of aluminum alloys used in armor systems against different armor-piercing (AP) calibers.

Novelty of current research

- Ceramic-faced bi-component systems
- Parametrization of inter-component bonding strength and effects
- High-dimensionality input data condensed to functional dimensionless parameters
- Algorithmic and analytical verification of dimensionless parameters

Approach

- Collate relevant parameters for each step
- Dimensional analysis to collapse into dimensionless parameters for scaling efficiency



Phase 1: Ballistic experiments

- Alumina/Ti-6Al-4V, different bonding levels
- .50-cal fragment simulating projectile (FSP)
- Saboted launch with 30-mm gun at National Security Test Range
- Post-mortem imaging and analysis by fixing fractured alumina plates with resin

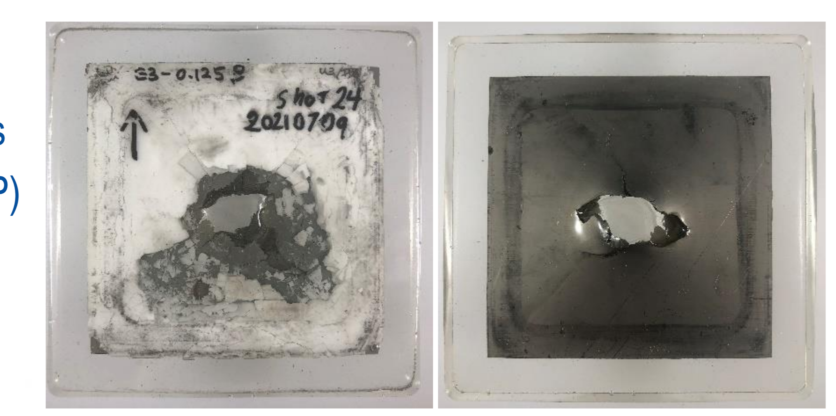
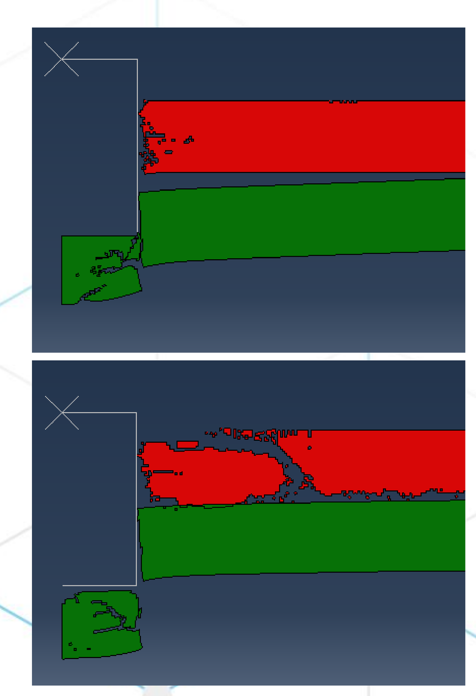


Fig. 2: Perforated bicomponent plate bonded with epoxy, front alumina ceramic (left) and rear Ti-6Al-4V plate (right).



Phase 2: Computational simulations

- Abaqus/Explicit with custom Fortran VUMAT
- Alumina ceramic: Johnson-Holmquist 2 material model
- Ti-6Al-4V alloy: Johnson-Cook plasticity and damage
- Bonding parametrization
  - Ideal with no delamination ('1')
  - Stacked ('0')
  - Epoxy → to be parametrized between 0 and 1

Fig. 3: Simulation of .50-cal FSP impacting alumina (red)/Ti-6Al-4V (green) plate using Abaqus/Explicit, stacked (top) and idealized bonding (bottom).

Phase 3: Non-dimensional parametrization of relevant input parameters

- Inter-component bonding → bending stiffness, energy dissipation
- Machine learning methods based on Buckingham Pi theorem e.g. SLAW, PyDimension

Results

- Basic functional form $\frac{\rho V_{bl}^2}{\sigma_c} = f\left(\frac{A_d A_p}{m_p}\right)$

ρ	target effective density	A_d	target areal density
V_{bl}	target ballistic limit velocity	A_p	projectile presented area
σ_c	**target characteristic strength**	m_p	projectile mass

- Previously derived for sharp- and flat-nosed projectiles impacting monolithic ductile plates

$$\frac{\rho_k V_{bl}^2}{\sigma_{HEL}} = f\left(\frac{A_{d,0} A_p}{m_p}, \frac{D_1}{D_{1+2}}\right)$$

$$\rho_k(h_1 + h_2) = \rho_1 h_1 + \rho_2 h_2 = A_{d,0} \qquad k = \rho_1 h_1 / A_{d,0} \qquad D_i = E_i h_i^3 / 12$$

- Hugoniot Elastic Limit (HEL): effective ceramic strength (from elastic to elastic-plastic state)

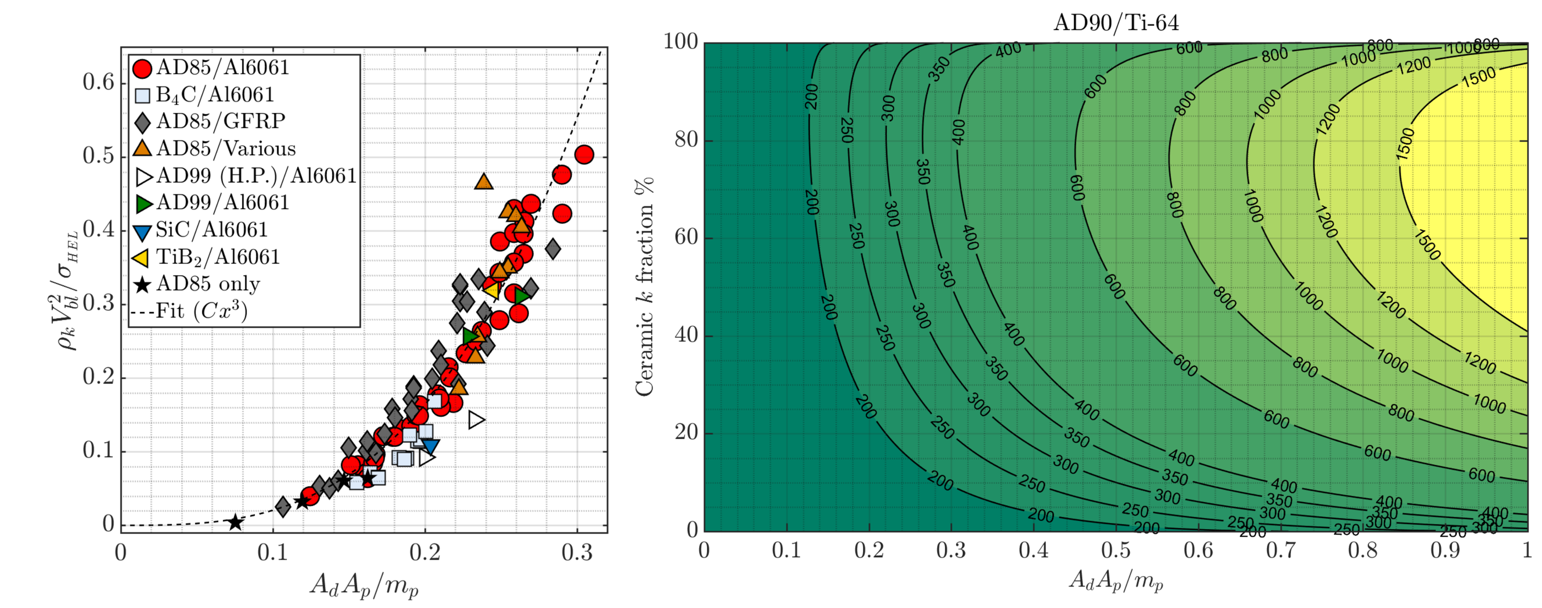
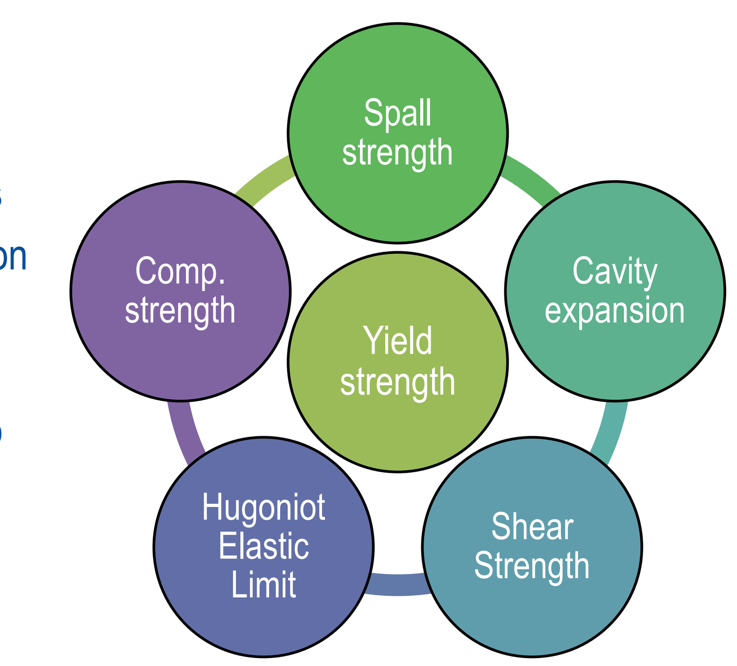


Fig. 4: Collapsed historical ballistic data [1] for ceramic-faced light armor systems (left). Prediction map for alumina AD90/Ti-6Al-4V bi-component armor (right).

Significance & Future Work

- Rapid deployment of protective armor systems
- Reduced dimensionality data for implementation in machine learning models
- Functional characteristic strength allows link to crystal plasticity or microstructural strength models e.g. Hall-Petch



References

1. Wilkins, M. L. (1978). Mechanics of penetration and perforation. Int. J of Eng Sci, 16(11), 793-807.

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