

A Multiscale Terrain Model for Off-Road Mobility Simulation

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Motivation

NextGen NATO Reference Mobility Model (NRMM) needs physics-based models for mobility Go/NoGo map

Thrust Area 3: Complex Terramechanics is to establish a vision for the long term terramechanics approaches that overcome the limitations of existing models.

| | Quantum Mechanics | Molecular Dynamics | Micro-scale Model | Macro-Scale Model | Height Field Model | Height Model | Empirical Steady-State model |
|--|--|--|--|--|---|--|------------------------------|
| Fidelity | Very high | | | | | | Very low |
| Description | Sub-atomic to atomic scale models | Molecular scale model | Soil particles individually modeled | Soil particles lumped to form a virtual particle or a finite element (e.g. DEM or FEM) | Terrain is divided into vertical cells. For each cell height and state of stress is stored. A Bekker-Wong-Janosi type pressure-sinkage-traction-slip model is used for each cell. | Normal stress and slip are used to calculate sinkage and tractive force using a Bekker-Wong-Janosi type model. | NRMM / NRMM-II |
| Number of Soil DOFs for vehicle mobility applications | $>10^{20}$ | 10^{18} | $10^{14} - 10^{11}$ | $10^7 - 10^6$ | $10^4 - 10^3$ | 1 | 0 |
| Current Computational Cost | Prohibitive | Prohibitive | Years of HPC time. | 6 hours to 1 week | Minutes/real time | Faster than real time | Faster than real time |
| Our current state of knowledge | Unknown how to take the model to the macro-scale | Taking the model to the macro-scale requires more research because the soil consists of many materials | More research is needed to understand the micro-mechanical soil interaction forces | More research is needed to improve, calibrate, and validate the soil models | More research is needed to improve, calibrate, and validate the soil models | More research is needed to improve, calibrate, and validate the soil models | Implemented in NRMM/NRMM-II |



NextGen NATO Reference Mobility Model Cooperative Demonstration of Technology (CDT)



From STO Technical Report: "AVT-248 Next-Generation NATO Reference Mobility Model (NRMM) Development"

❑ Mesh-Based Finite Element Soil Models

- Eulerian FE Method
- Lagrangian ALE Method

❑ Mesh-Free Particle-Based Soil Models

- SPH Method
- Discrete Element Method
- Material Point Method

Finite Element (FE) soil model

- Macro-scale soil method
- Phenomenological constitutive model
- Suited for cohesive soil
- Limitation in constitutive model

Discrete Element (DE) soil model

- Grain-scale soil model
- Physical inter-particle contact & sliding
- Suited for cohesionless soil
- High computational cost

To eliminate limitations of existing models, **develop a new method for off-road mobility simulations**



Hierarchical multiscale FE-DE method

| Measure | Lagrangian/ALE FEM | Eulerian FEM | DEM | SPH | MPM |
|---|--------------------|--------------|-----------|-----|-----|
| Accuracy/generalizability of soil material models | 5 | 3 | 8 | 6 | 6 |
| Range of soil deformation | 4 | 9 | 9 | 9 | 9 |
| Ability to include embedded obstacles | 3 | 7 | 9 | 9 | 9 |
| Fidelity of the soil-vehicle interface | 5 | 7 | 8 | 8 | 8 |
| Computational speed | 5 | 7 | 6 | 5 | 6 |
| Experimental Validation | 4 | 4 | 6 | 5 | 4 |
| Current use in vehicle mobility | 5 | 4 | 8 | 6 | 5 |
| Total | 31 | 41 | 54 | 48 | 47 |

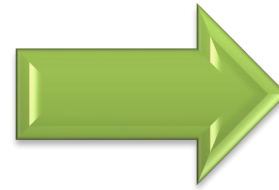
From STO Technical Report: "AVT-248 Next-Generation NATO Reference Mobility Model (NRMM) Development"

ARC Project (Univ of Iowa)

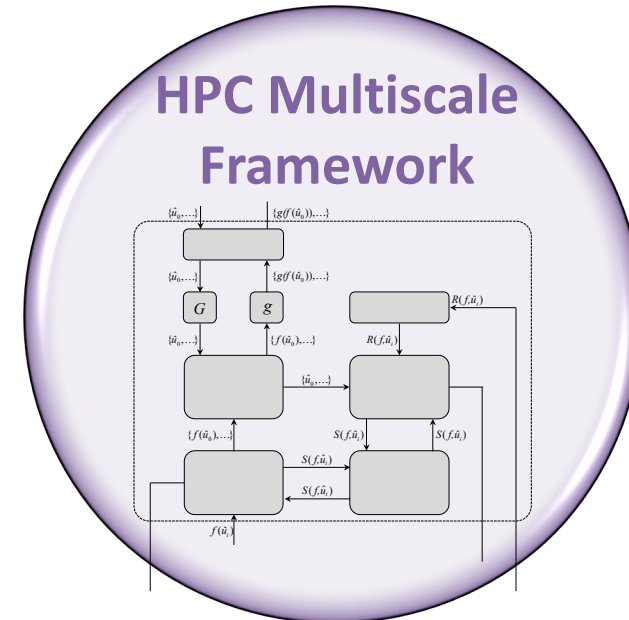


University of Iowa:

- Develop an HPC FE-DE multiscale off-road mobility simulation capability
- Conduct the performance evaluation and validation
- Develop neural network surrogate models for the lower-scale RVEs for computational speedup



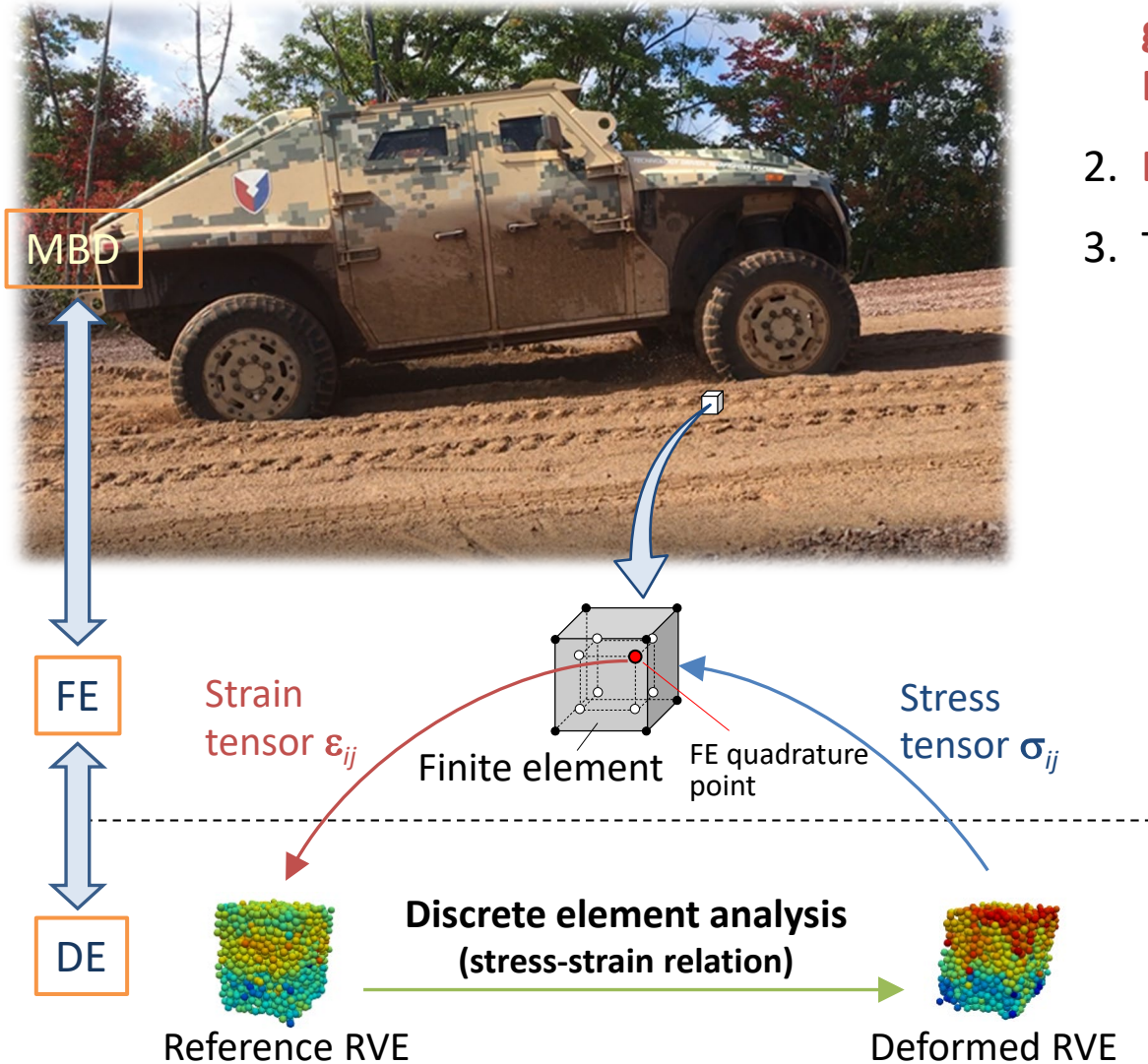
GVSC ILIR Project w/ ARL



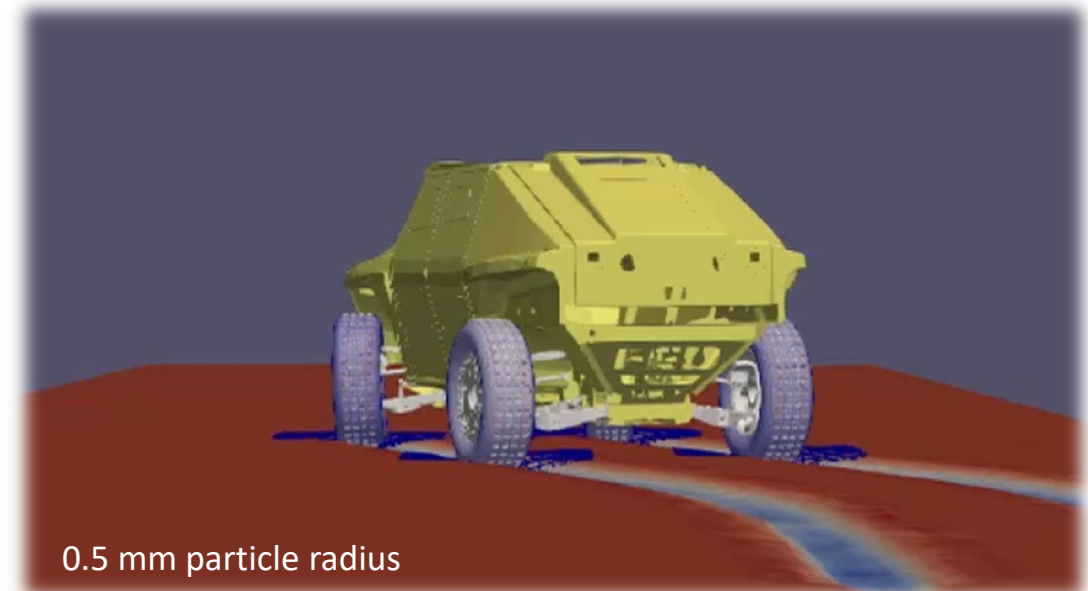
CCDC GVSC/ARL:

- Integrate the multiscale off-road mobility solver into the scale-bridging framework on DSRC HPC
- Optimize the computational complexity of the scale-bridging process

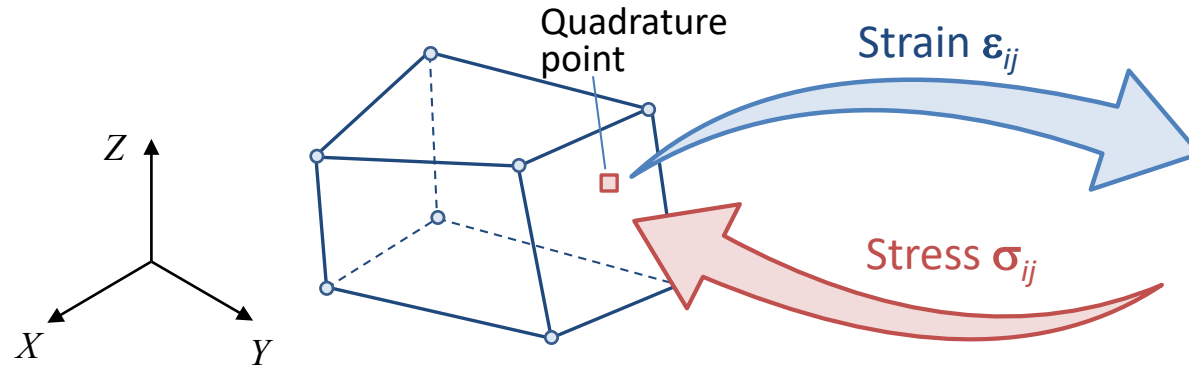
Hierarchical FE-DE Multiscale Off-Road Mobility Model



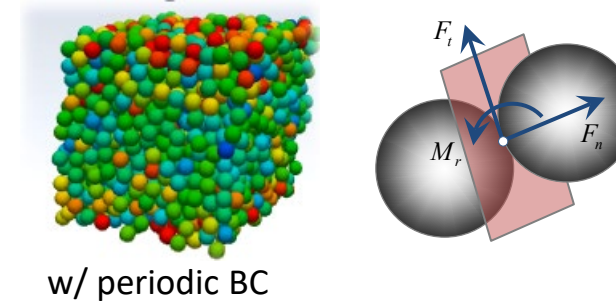
1. Macro-scale soil deformation is modeled by FE mesh, while **grain-scale material behavior of granular soil is modeled by DE representative volume element (RVE)**
2. **Eliminates constitutive assumptions** of FE soil models
3. The **scale separation** allows for
 - (a) decreasing the number of DE particles as compared to single-scale DE models
 - (b) massively parallelizing DE calculations
 - (c) facilitating cross-scale understanding of terrain behavior



UPPER-SCALE MODEL



LOWER-SCALE MODEL



w/ periodic BC

Finite Element

Representative Volume Element (RVE)

- Position vector: $\mathbf{r} = \mathbf{S}(\xi, \eta, \zeta)\mathbf{e}$


- Incremental strain tensor:
$$\Delta \boldsymbol{\varepsilon} = \begin{bmatrix} \Delta \varepsilon_{11} & \Delta \varepsilon_{12} & \Delta \varepsilon_{13} \\ & \Delta \varepsilon_{22} & \Delta \varepsilon_{23} \\ \text{sym.} & & \Delta \varepsilon_{33} \end{bmatrix}$$


- Second PK stress tensor:
$$\mathbf{S} = J \mathbf{F}^{-1} \boldsymbol{\sigma} \mathbf{F}^{-T}$$

- Generalized internal forces:
$$\mathbf{Q}_s = \int_{V_0} \left(\frac{\partial \mathbf{E}}{\partial \mathbf{e}} \right)^T \mathbf{S} dV_0$$

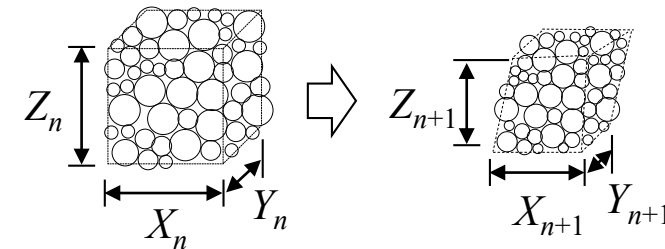
- Eqs. of motion:
$$\mathbf{M}\ddot{\mathbf{e}} = \mathbf{Q}_s + \mathbf{Q}_e$$

Scale bridging


(Upper to lower)


(Lower to upper)

- Strain BC for RVE:
$$\mathbf{X}_{n+1}^{RVE} = \mathbf{X}_n^{RVE} + \Delta \mathbf{X}_n^{RVE}$$

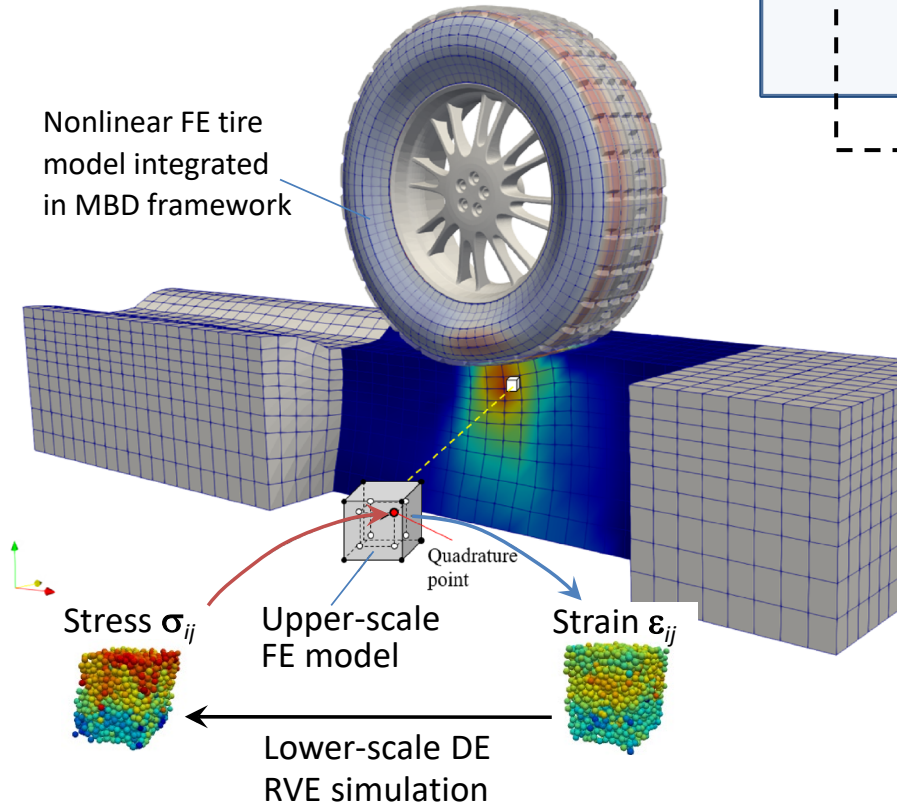


- Homogenized Cauchy stress tensor:
$$\boldsymbol{\sigma} = \frac{1}{V} \sum_{N_c} \mathbf{d}^c \otimes \mathbf{f}^c$$
- Homogenized Tangent moduli:
$$\frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} = \frac{1}{V} \sum_{N_c} (k_n \mathbf{n}^c \otimes \mathbf{d}^c \otimes \mathbf{n}^c \otimes \mathbf{d}^c + k_t \mathbf{t}^c \otimes \mathbf{d}^c \otimes \mathbf{t}^c \otimes \mathbf{d}^c)$$

Guo and Zhao, *IJNME*. 2014

Parallel Computing Scheme for Multiscale Mobility Solver

Hybrid shared- & distributed-memory parallel computing algorithm

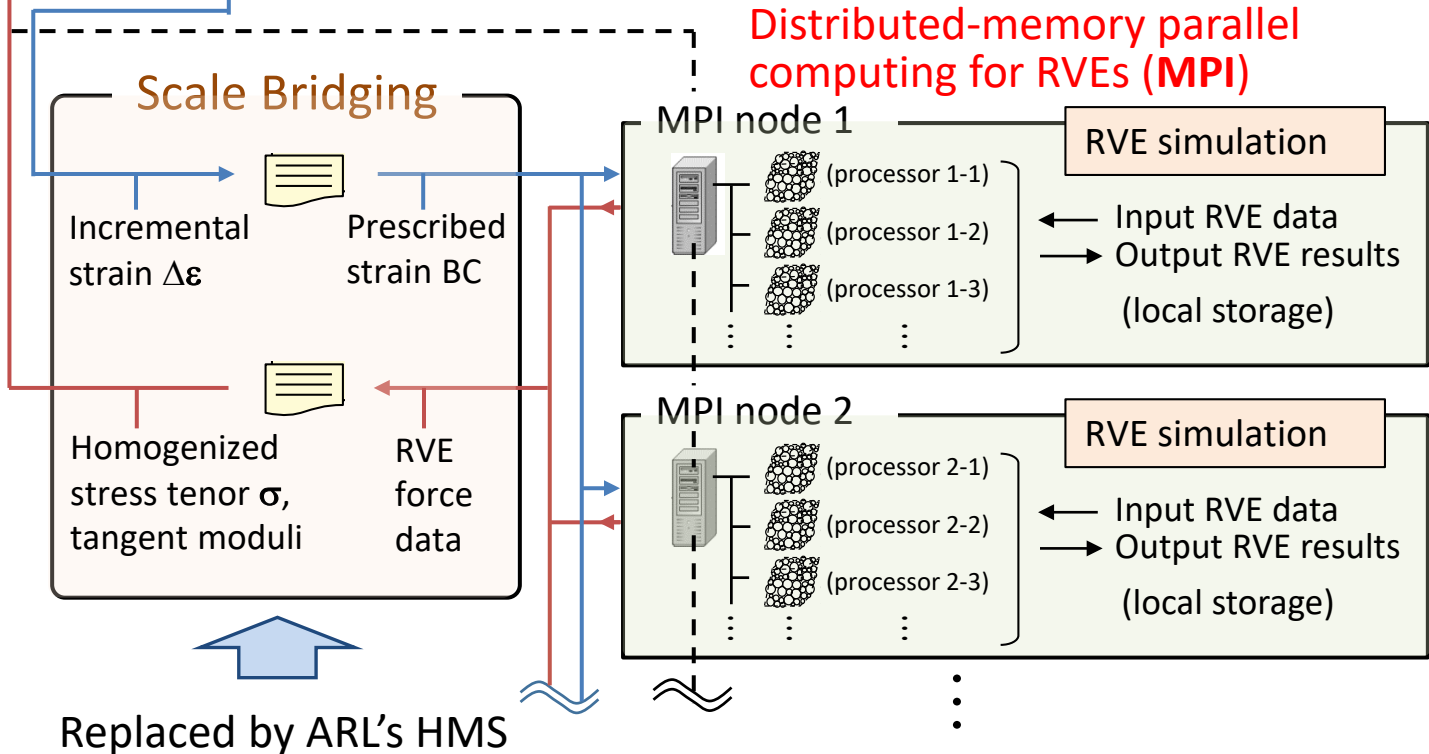


MPI node 0 (**OpenMP**) – master node

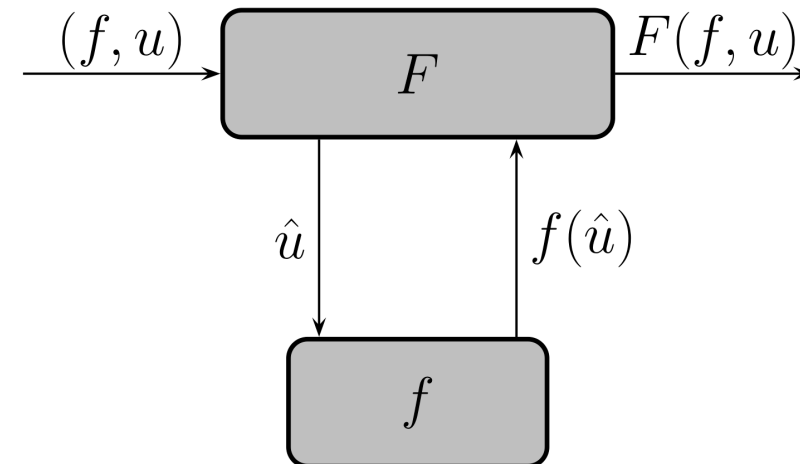
$$\mathbf{M}_r \ddot{\mathbf{q}}_r + \mathbf{C}_{q_r} \boldsymbol{\lambda} = \mathbf{Q}_r(\mathbf{q}_r, \mathbf{e}_t, \dot{\mathbf{q}}_r, \dot{\mathbf{e}}_t) \dots \dots \dots (1) \text{ Rigid vehicle components}$$

$$\mathbf{M}_t \ddot{\mathbf{e}}_t + \mathbf{C}_{e_t} \boldsymbol{\lambda} = \mathbf{Q}_t(\mathbf{q}_r, \mathbf{e}_t, \mathbf{e}_s, \dot{\mathbf{q}}_r, \dot{\mathbf{e}}_t, \dot{\mathbf{e}}_s, \boldsymbol{\alpha}) \dots \dots \dots (2) \text{ Nonlinear FE tires}$$

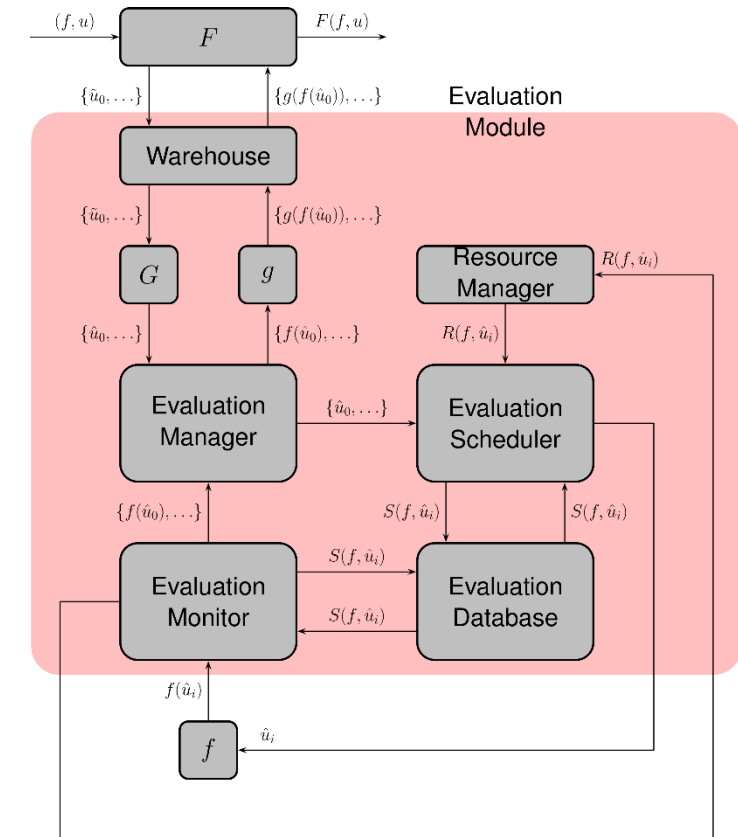
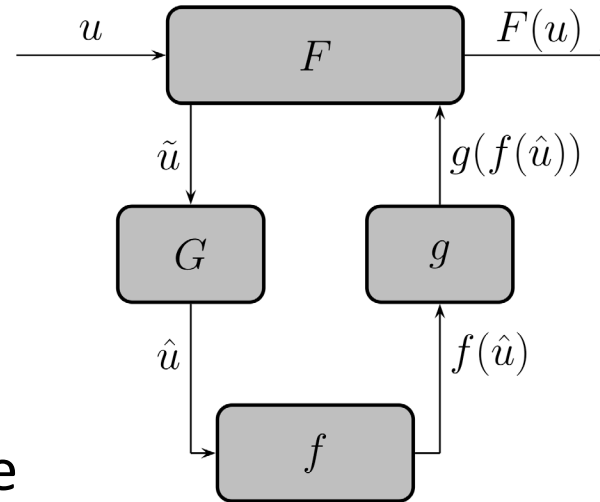
$$\mathbf{C}(\mathbf{q}_r, \mathbf{e}_t, t) = \mathbf{0} \dots \dots \dots (3) \text{ Joint constraints}$$

$$\mathbf{M}_s \ddot{\mathbf{e}}_s = \mathbf{Q}_s(\mathbf{e}_t, \mathbf{e}_s, \dot{\mathbf{e}}_t, \dot{\mathbf{e}}_s) \dots \dots \dots (4) \text{ Multiscale soil model}$$


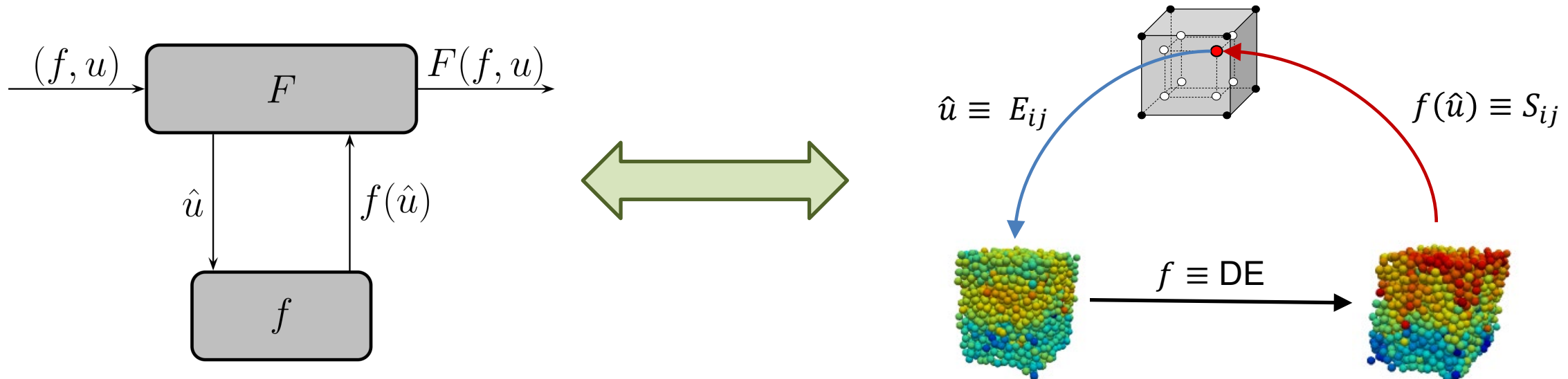
- Multiscale modeling: a systematic approach to construct high-fidelity material models
- Identify relevant physics at individual scales (spatial and temporal)
- Combine physics associated with individual scales into a multiscale model
- Fundamental building block: a two-scale model
 - F acquires missing data (closure relation) from f
 - Communicate \hat{u} to f
 - Assimilate $f(\hat{u})$ into F
- Divide-and-conquer strategy: easily incorporate disparate physics



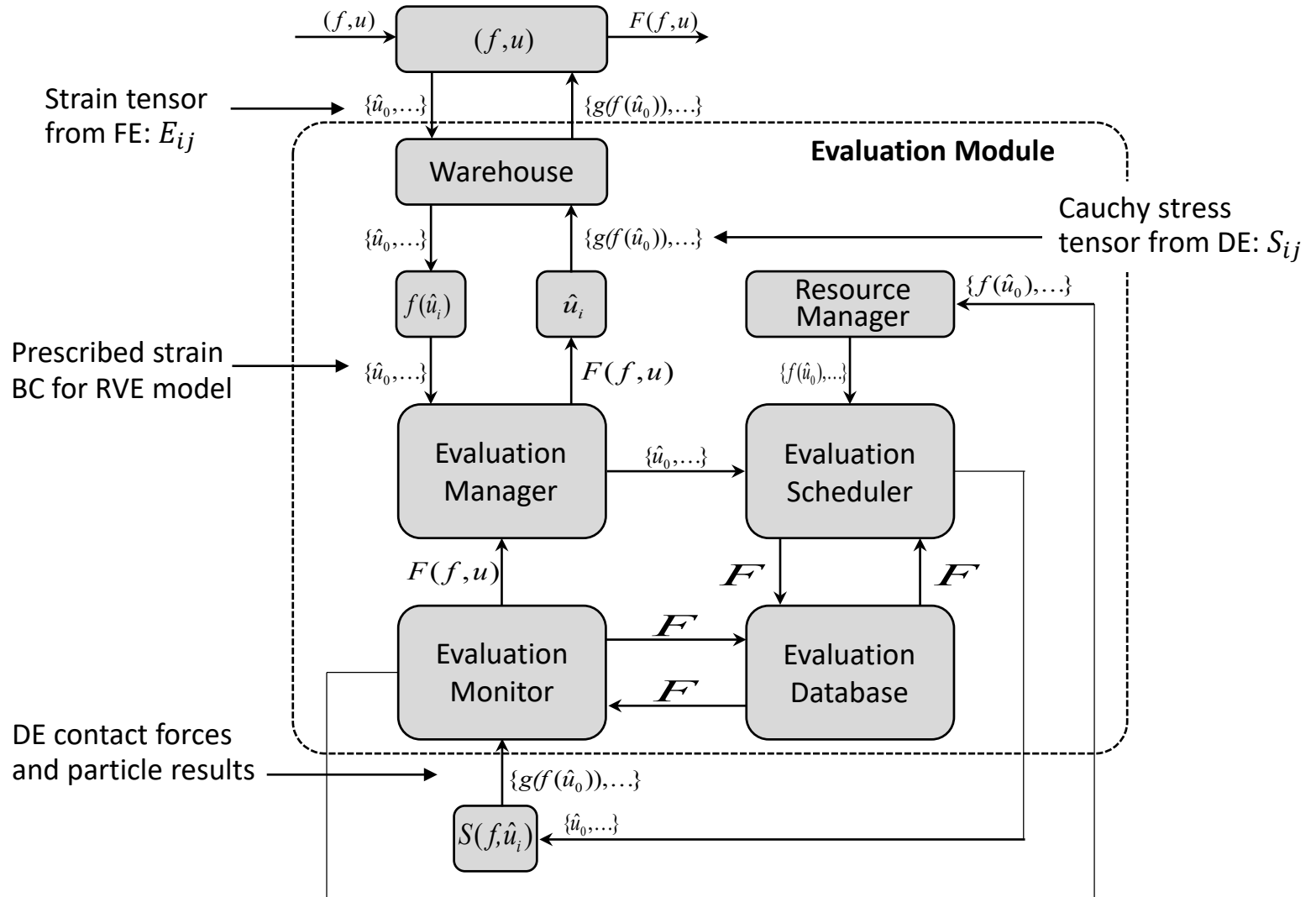
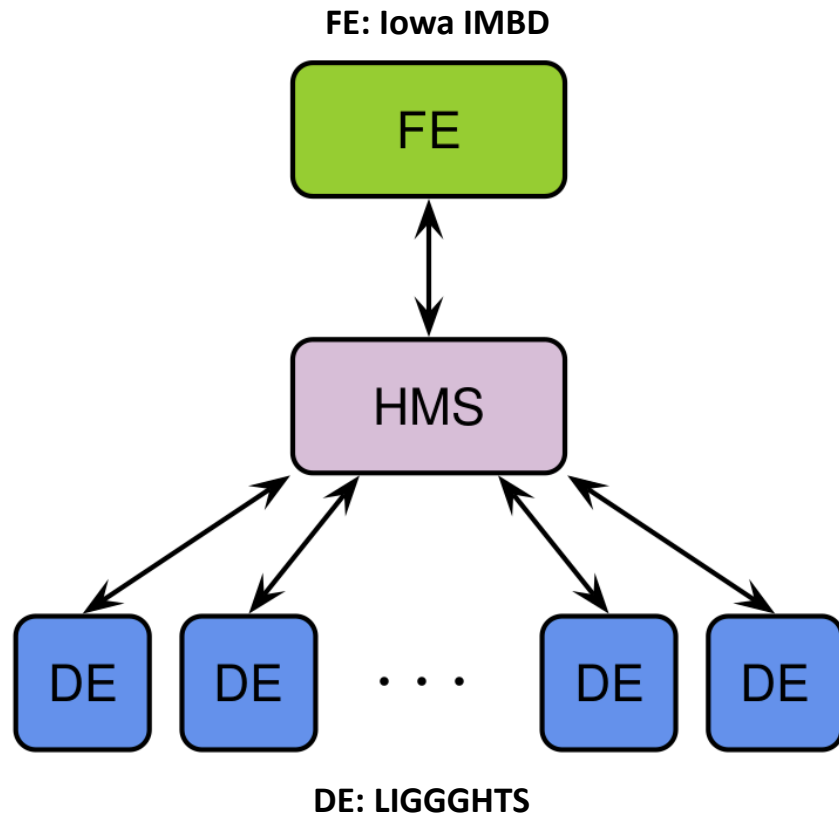
- Multiscale modeling is a computational endeavor
- High-fidelity computational at-scale models often available
- Scale bridging:
 - Communicate \tilde{u}
 - Evaluate $f(\hat{u})$
 - Calculate $g(f(\hat{u}))$
 - Communicate $g(f(\hat{u}))$
- Scale bridging crucial for multiscale
- But can be hard and computationally challenging



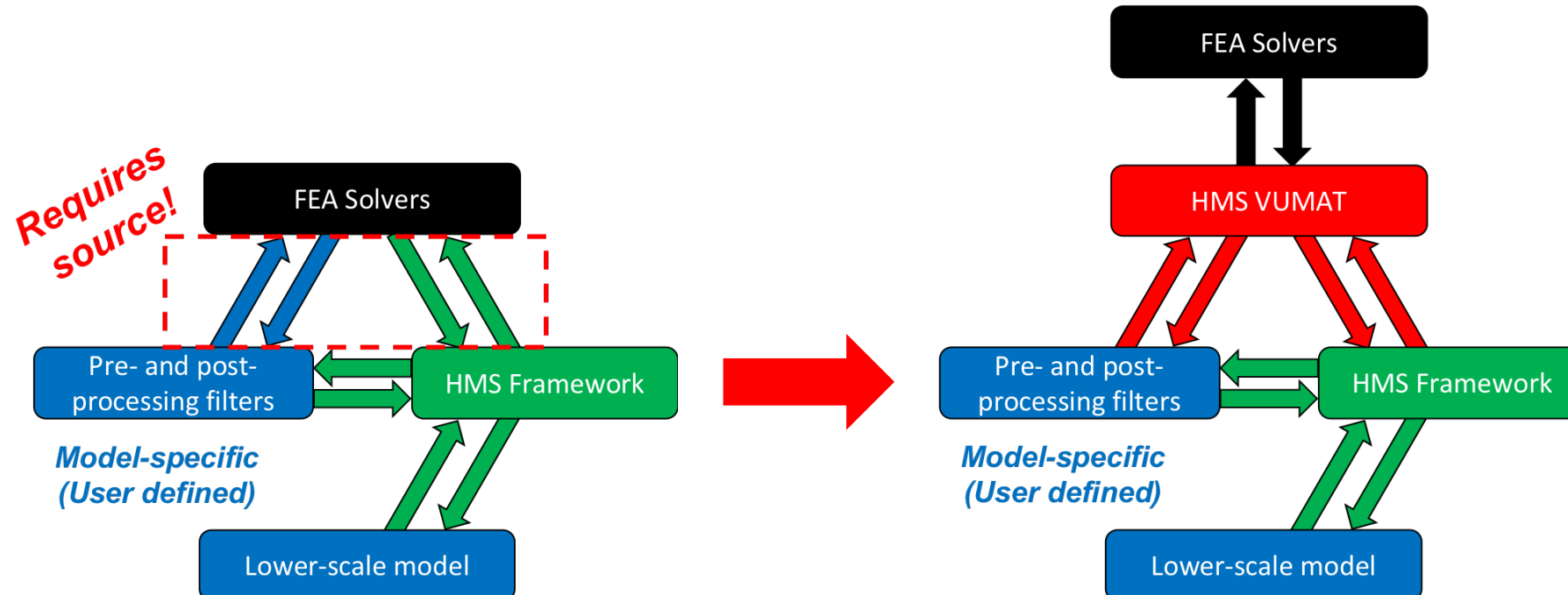
- Goal: construct a two-scale soil model
- Macroscale model: finite-element (FE) model of soil deformation
- Microscale (grain-scale) model: discrete-element (DE) model of soil
- Closure relation: constitutive relation ($S_{ij}(E_{ij})$) for the macroscale model
- Constitutive relation obtained through direct evaluation of the microscale model



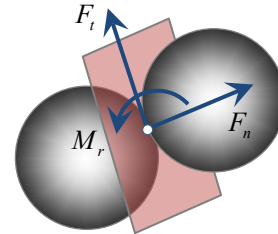
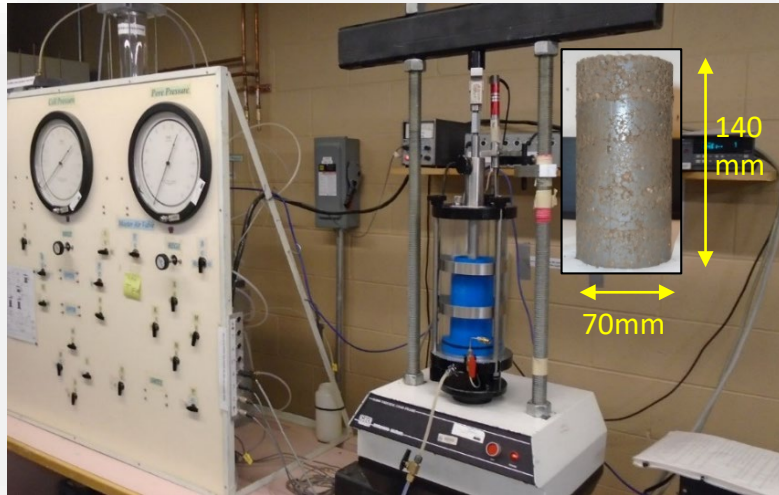
Multiscale Model of Soil Deformation: Scale-Bridging



- We are also developing a generic scale-bridging VUMAT—a standard user subroutine to define material behavior
- VUMAT allows to incorporate any lower-scale material model
- Greatly simplifies development and integration of lower-scale models
- Scale-bridging VUMAT remains unchanged when adding new lower-scale models
- Currently tested in ALE3D, ABAQUS, and EPIC



Laboratory Soil Test Simulation and Validation

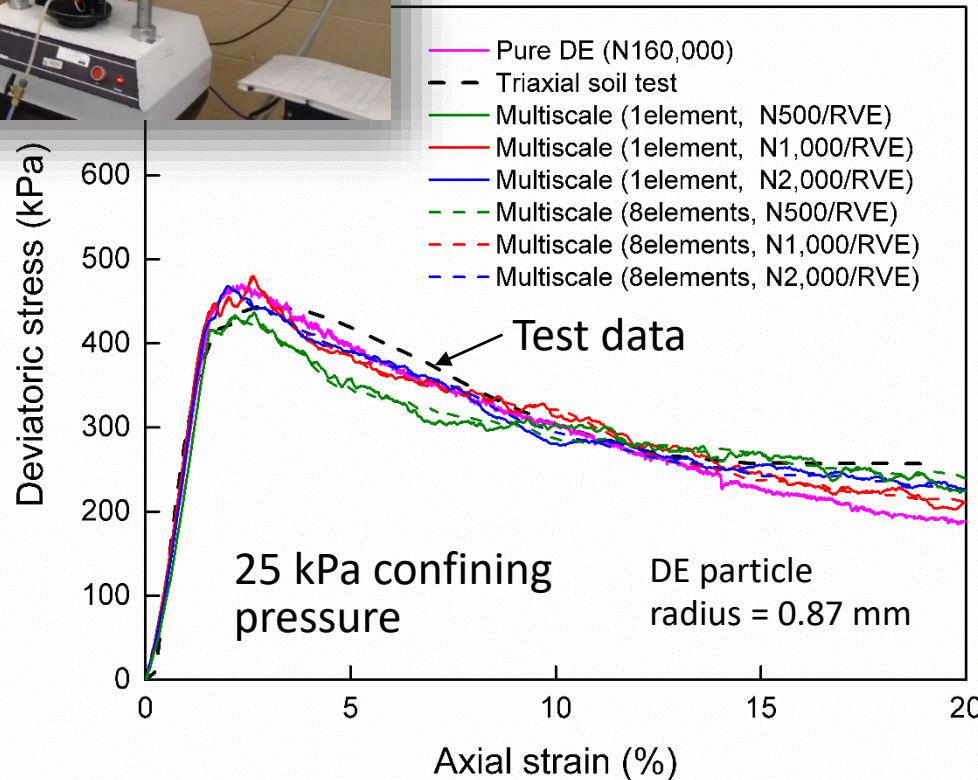


Stress-strain curve

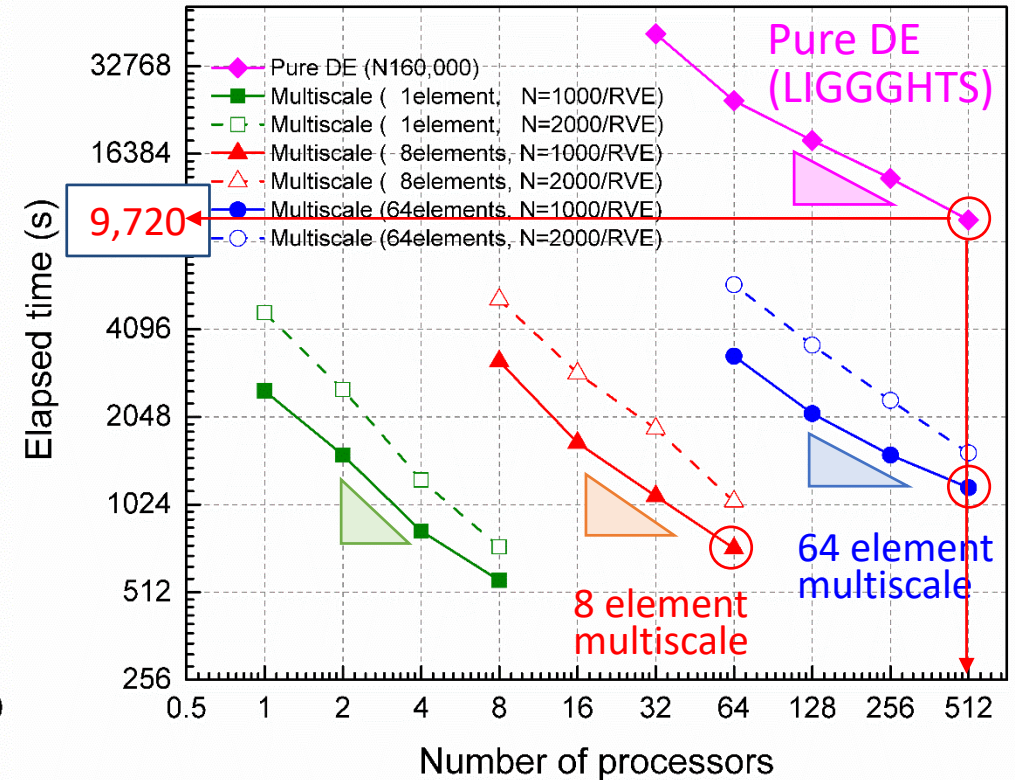
- Normal force: $F_n = 2E\sqrt{r_e \delta_n} \cdot \delta_n / 3(1-\nu^2)$
- Tangential force: $F_t = \begin{cases} 4G\sqrt{r_e \delta_n} \cdot \delta_t / (2-\nu) & \dots \text{sticking} \\ \mu F_n & \dots \text{sliding} \end{cases}$
- Rolling resistance moment: $M_r = \begin{cases} \beta K_n r_e^2 \eta^2 \cdot \theta_r & \dots \text{sticking} \\ \eta F_n r_e & \dots \text{sliding} \end{cases}$

DE parameters

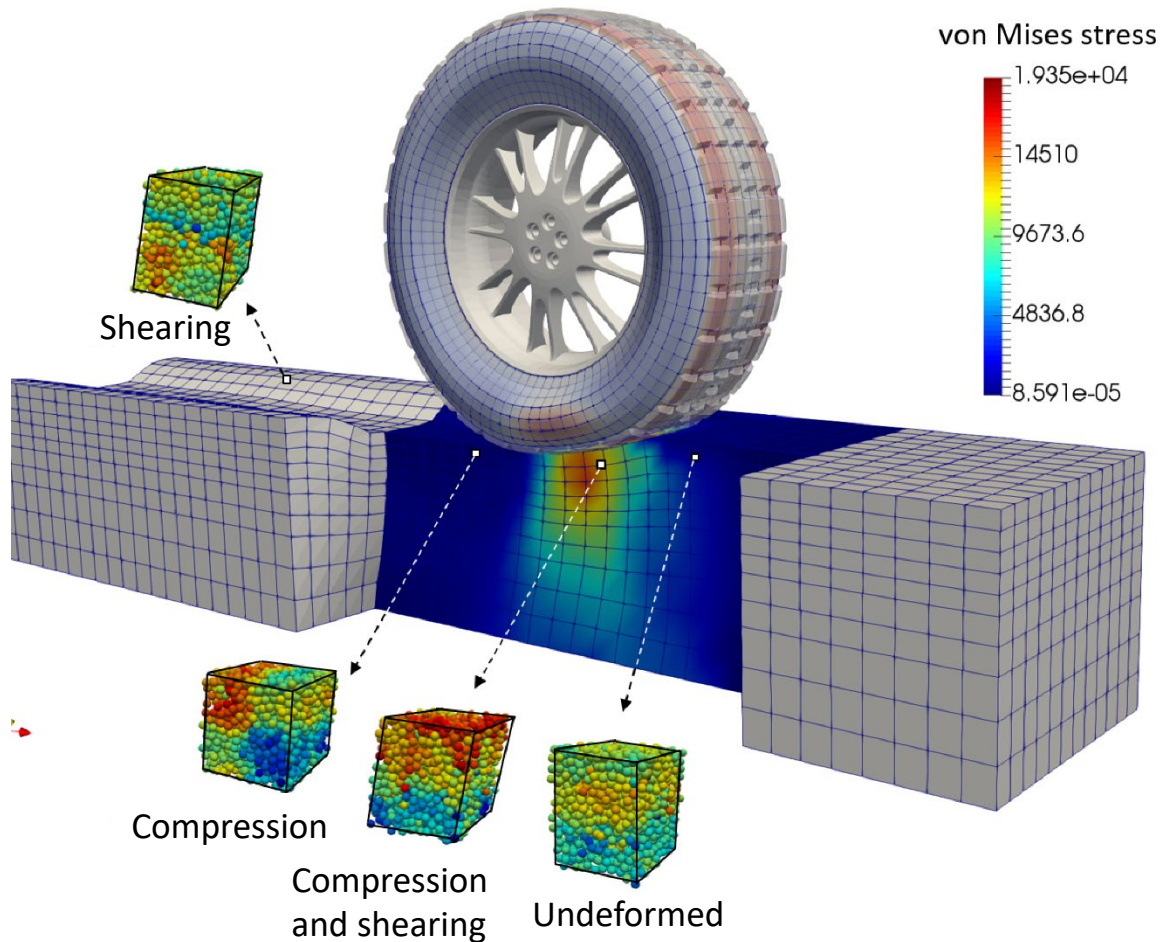
$E = 1.5 \text{ GPa}$
 $\nu = 0.293$
 $\mu = 0.452$
 $\beta = 2.25$
 $\eta = 0.99$



Parallel computing scalability

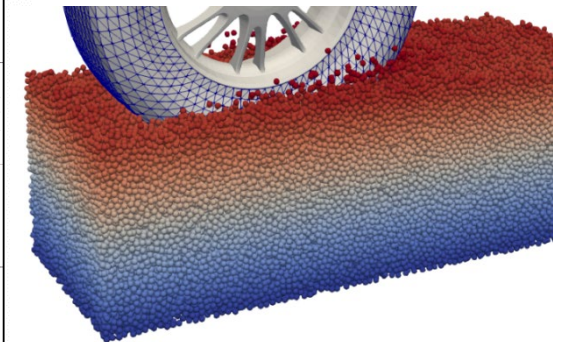
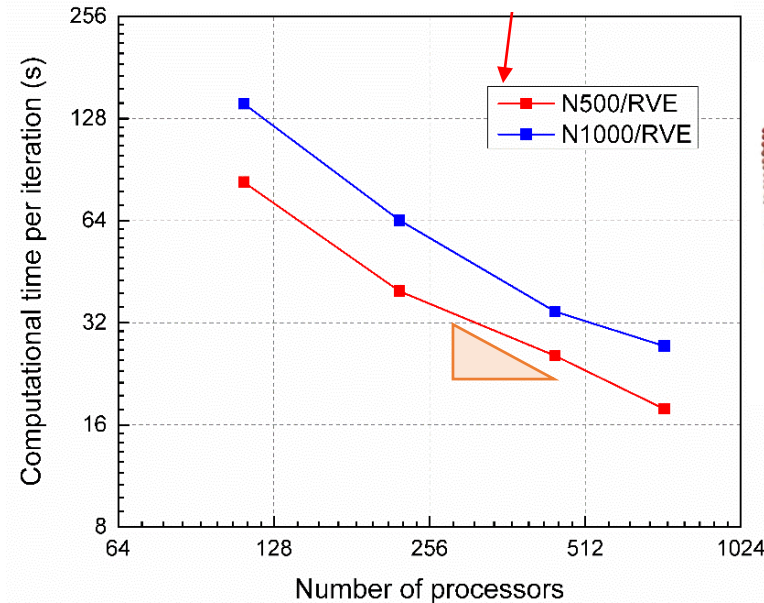


Soil Bin Mobility Test Simulation and Validation



| | Multiscale | Pure DE (LIGGGHTS) | |
|---------------------|-----------------------------------|------------------------------------|----------------------------|
| Particle radius | 0.87 mm | 6.5 mm | 0.87 mm |
| Number of particles | 9.6 million (500/RVE) | 83,453 | 35 million |
| Computational time | 3 hrs ($\Delta t=5E-4$ s) | 60 hrs ($\Delta t=1E-5$ s) | Prohibitively high! |

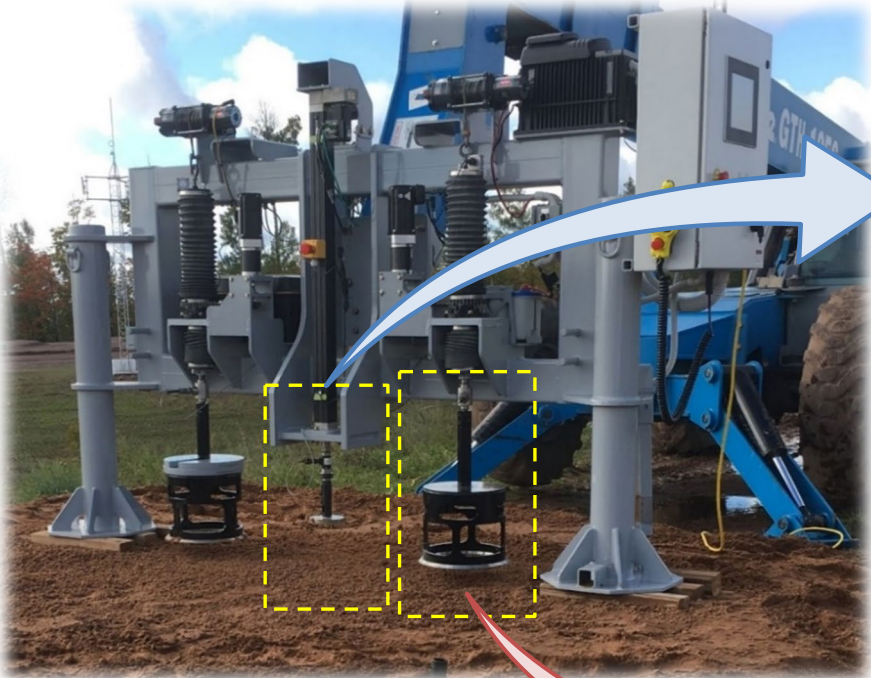
Parallel computing scalability



Pure DE soil patch model
6.5-mm particle radius

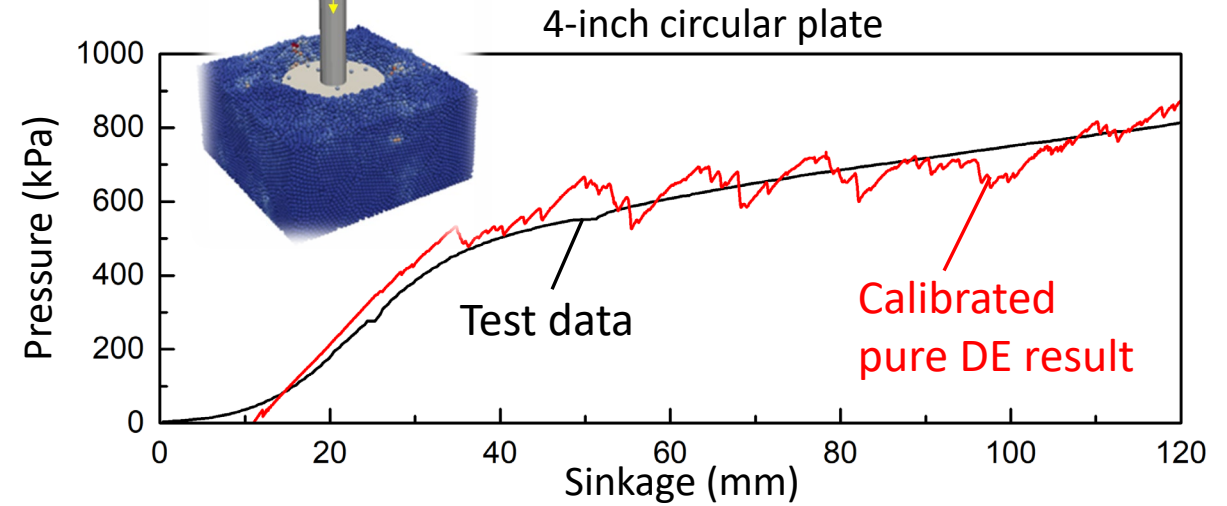
In-situ Bevameter Test and DE Parameter Calibration

Bevameter Soil Test



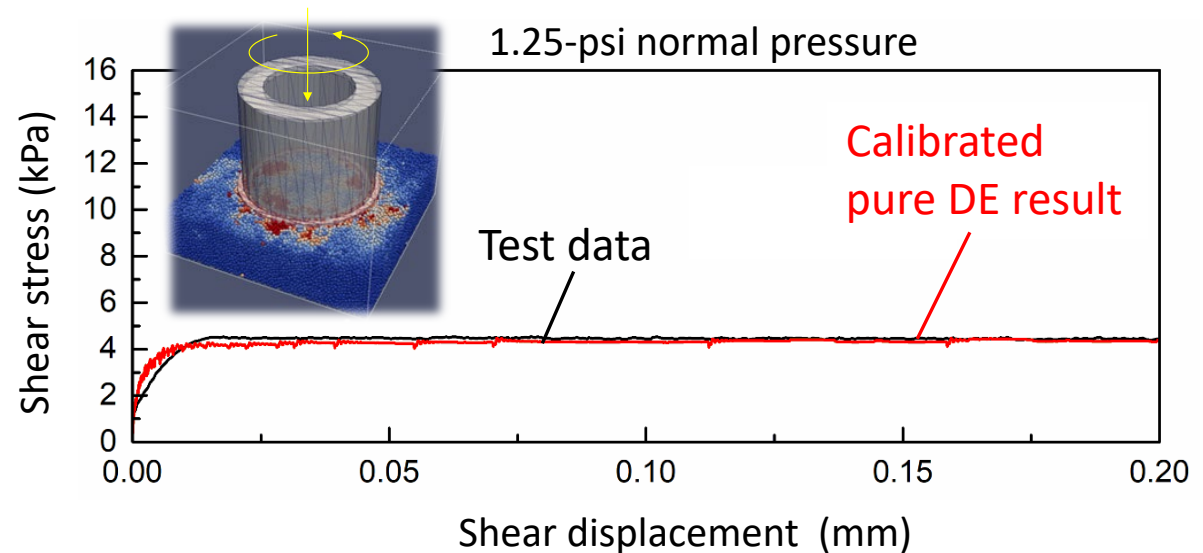
NextGen NATO Reference Mobility Model
Cooperative Demonstration of Technology (CDT)

□ Pressure-sinkage test



□ Shear ring test

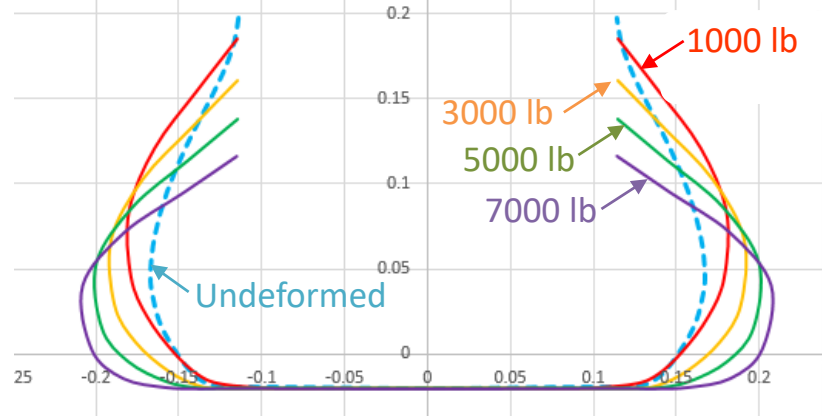
Rubberized surface w/o grousers



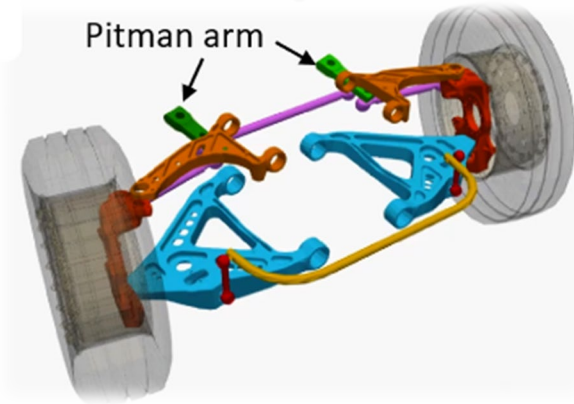
MBD Modeling of FED- α Vehicle with Flex Tires



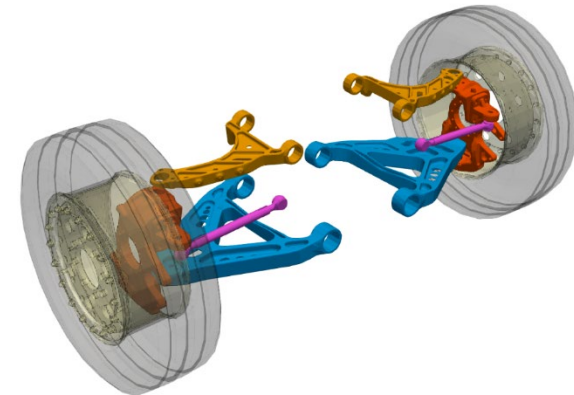
Tire deformed shapes (35 psi)



MBD suspension model

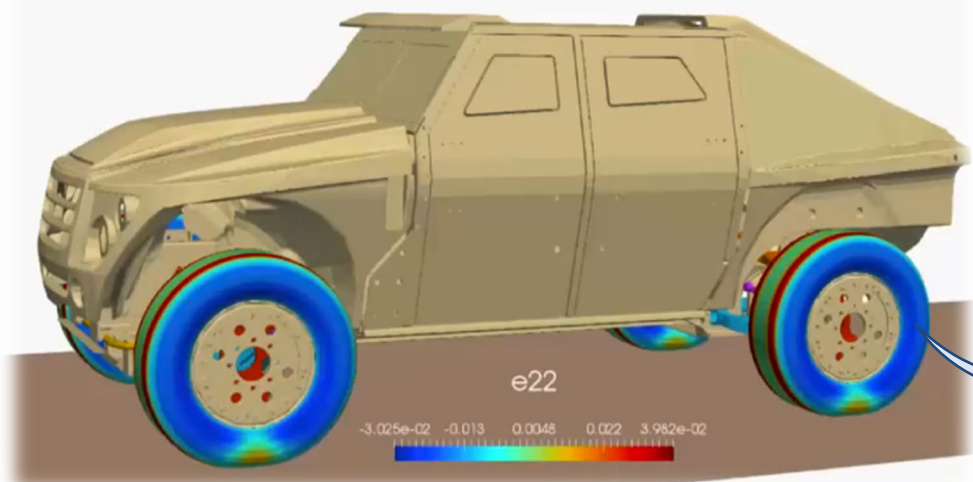
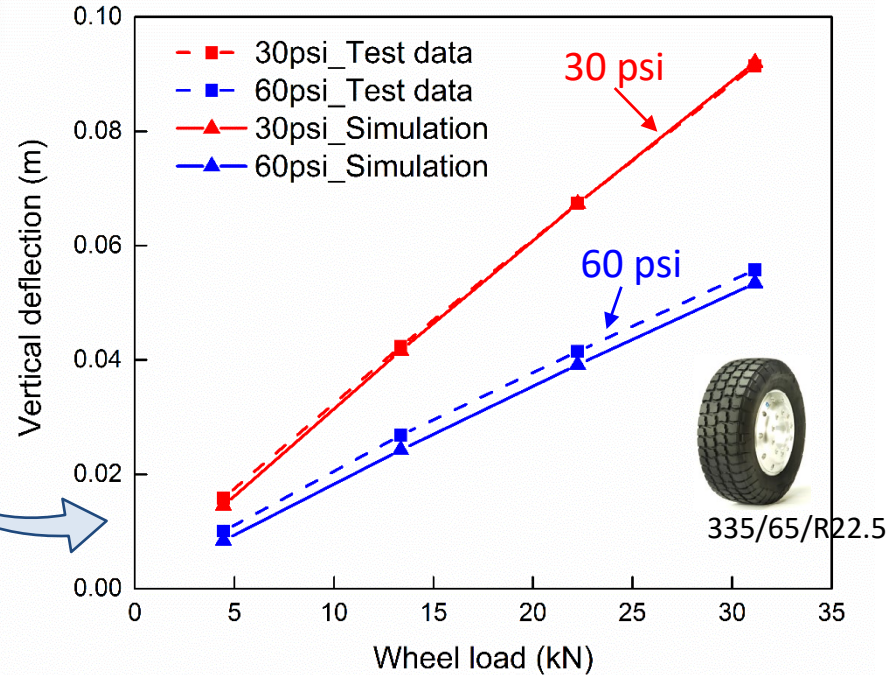


(Front suspension)



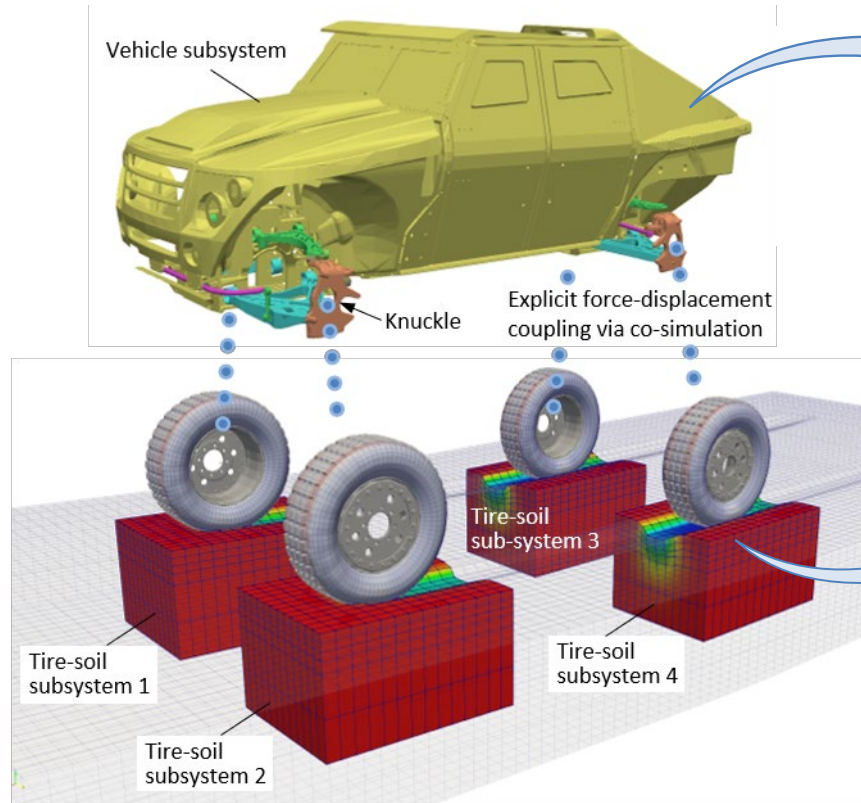
(Rear suspension)

Tire load-deflection curve



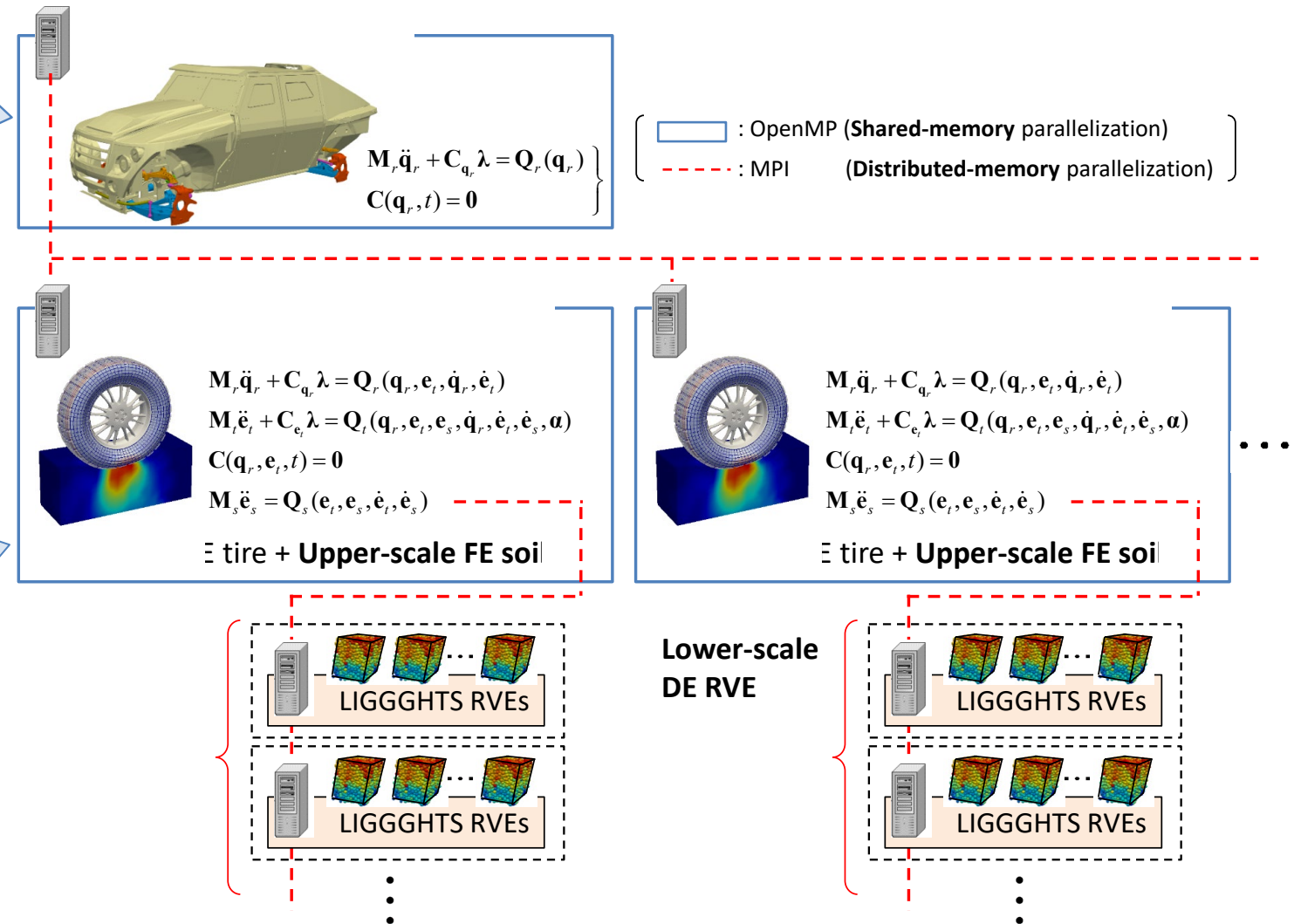
Parallel Computing Framework for Full Vehicle Simulations

Co-simulation Vehicle-Terrain Interaction Model (domain decomposition)

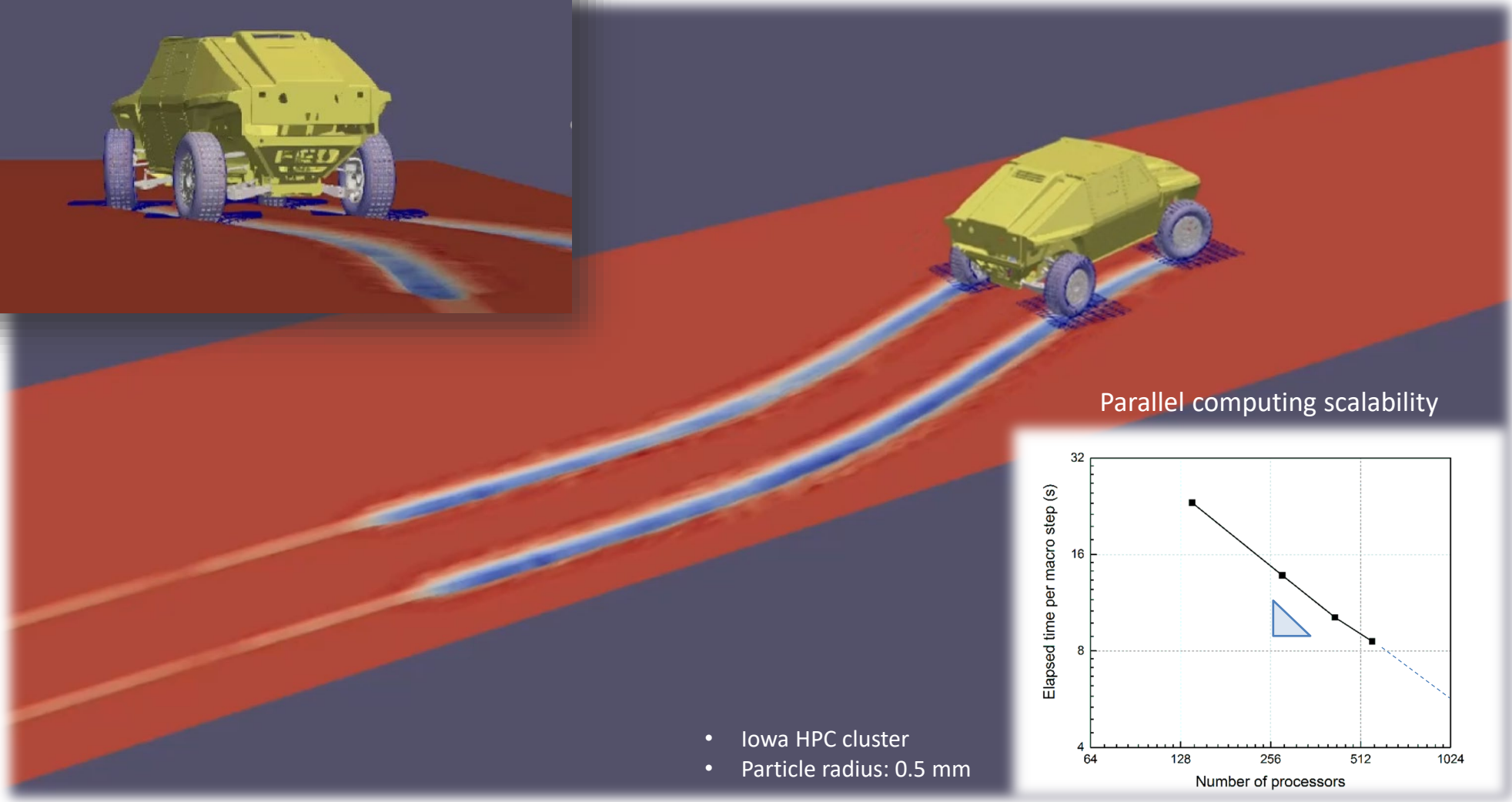
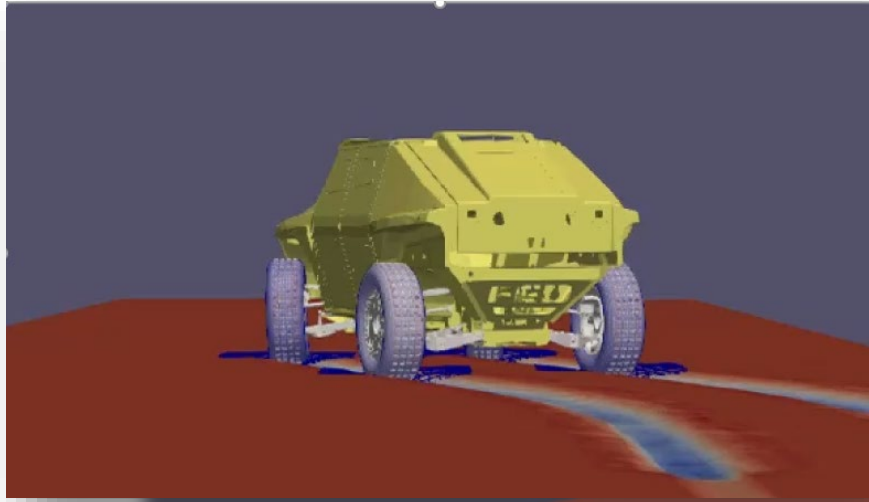


Four tire-soil subsystems are run in parallel and coupled with the vehicle subsystem by co-simulation algorithm

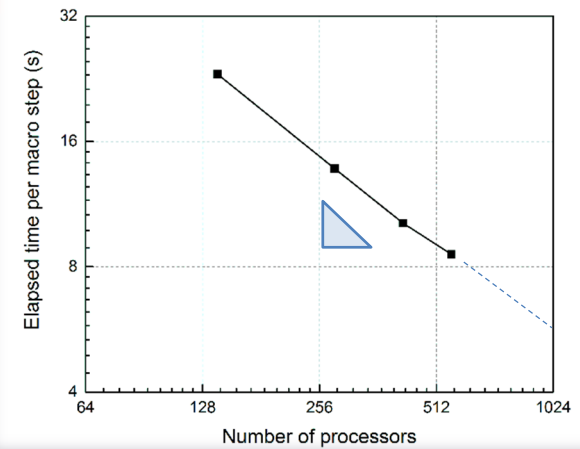
Hybrid OpenMP-MPI Parallel Computing Framework



Lane Change Maneuver Simulation on Multiscale Soil Model

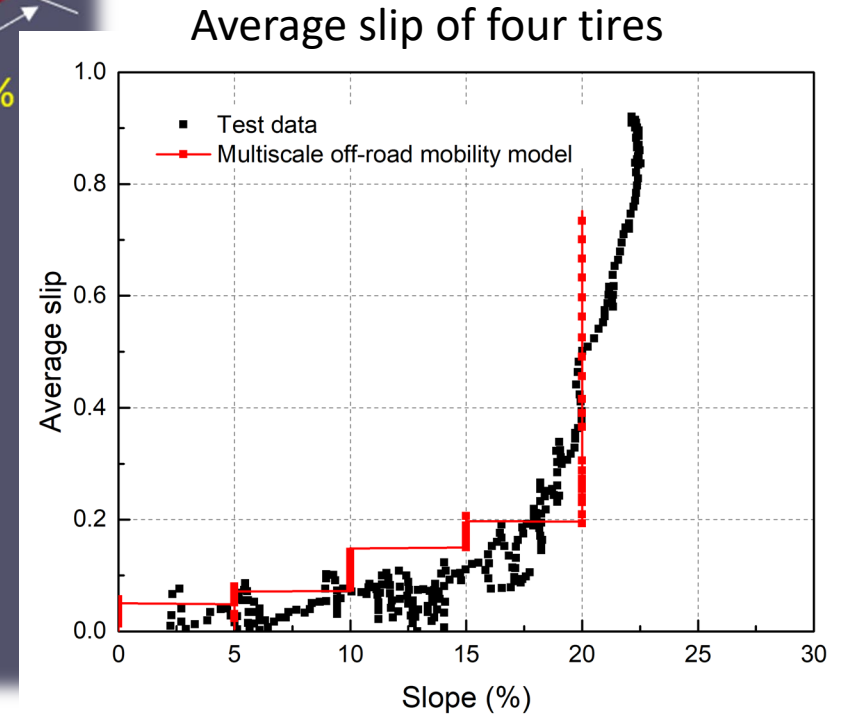
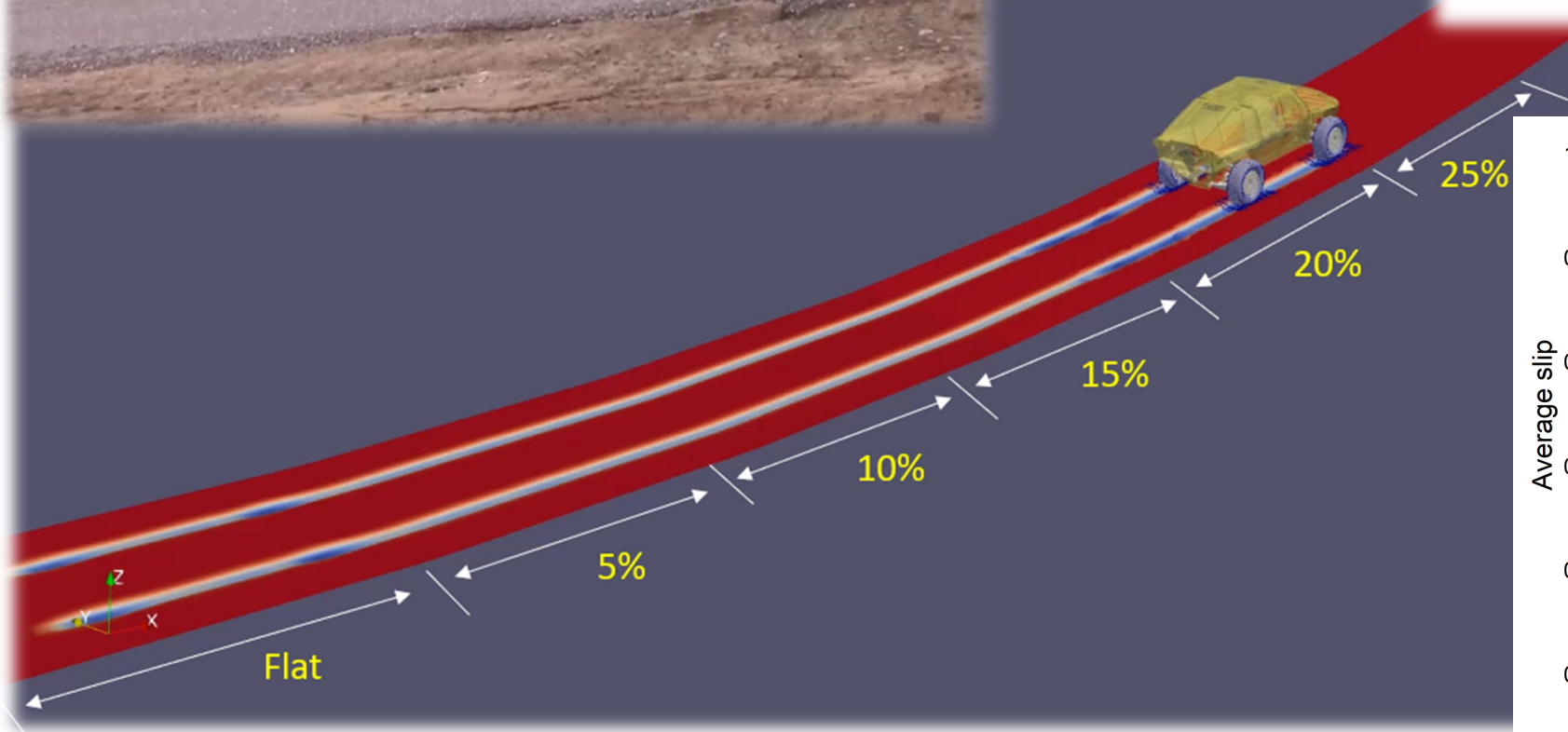
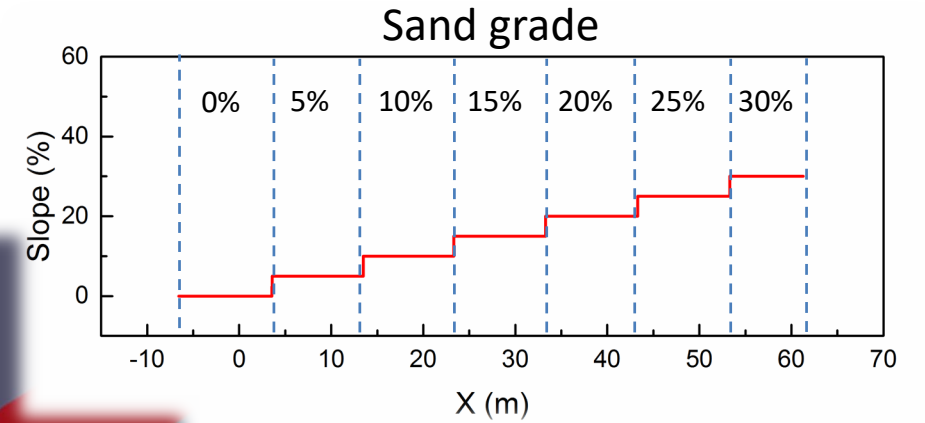


Parallel computing scalability



- Iowa HPC cluster
- Particle radius: 0.5 mm

Variable Hill Climb Simulation and Validation

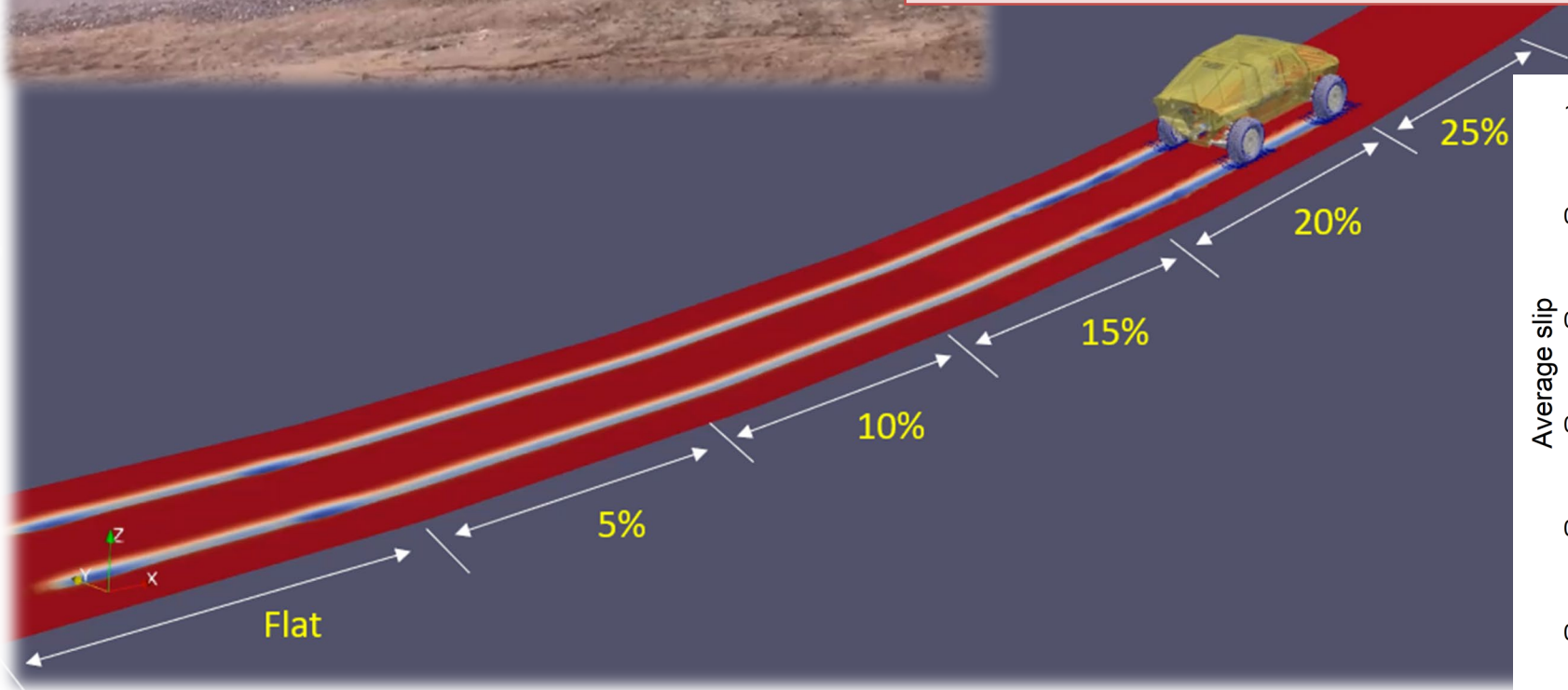


Variable Hill Climb Simulation and Validation

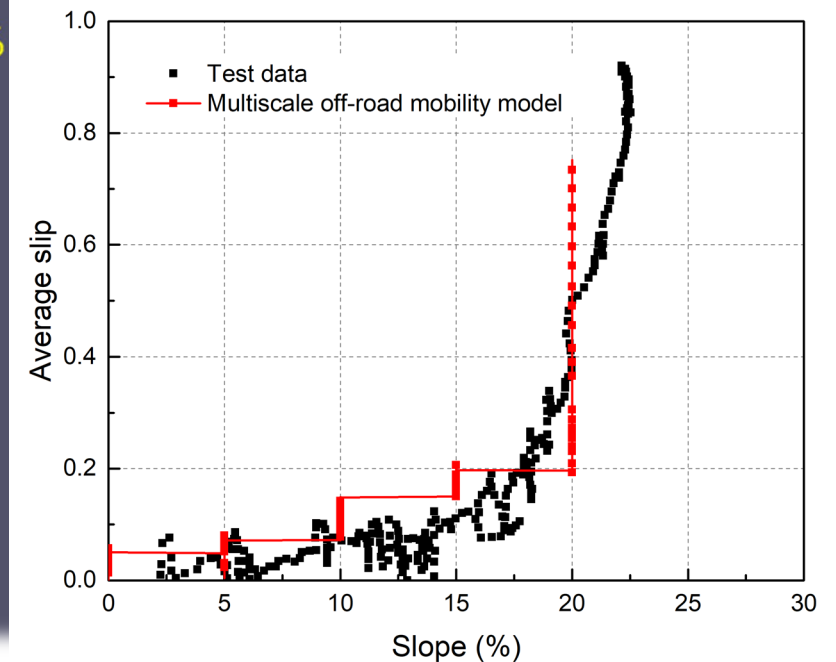


Open Question:

- The lower-scale DE RVE calculations account for roughly 80 % of the overall computational time and **speedup of RVE computations** is critical for quick prediction of off-road mobility.
- Can machine learning (ML) technique be leveraged to speed up high-fidelity off-road mobility simulations?

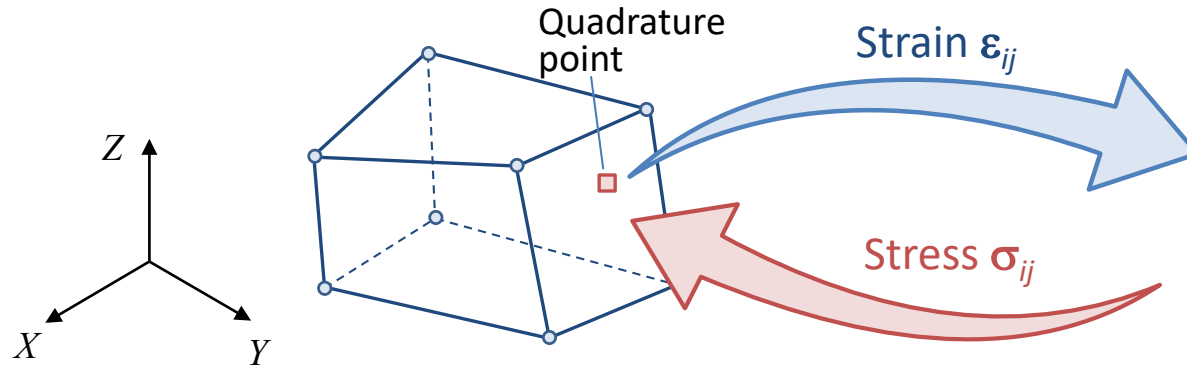


Average slip of four tires

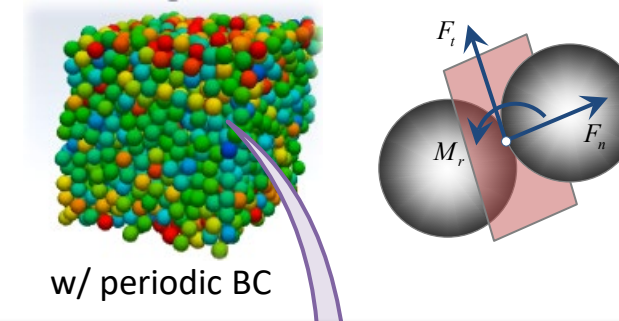


FE-ANN Hierarchical Multiscale Modeling

UPPER-SCALE MODEL



LOWER-SCALE MODEL



Finite Element

Neural Network Surrogate RVE

- Position vector: $\mathbf{r} = \mathbf{S}(\xi, \eta, \zeta)\mathbf{e}$

- Incremental strain tensor:
$$\Delta\boldsymbol{\varepsilon} = \begin{bmatrix} \Delta\varepsilon_{11} & \Delta\varepsilon_{12} & \Delta\varepsilon_{13} \\ & \Delta\varepsilon_{22} & \Delta\varepsilon_{23} \\ \text{sym.} & & \Delta\varepsilon_{33} \end{bmatrix}$$

- Second PK stress tensor:
$$\mathbf{S} = J\mathbf{F}^{-1}\boldsymbol{\sigma}\mathbf{F}^{-T}$$

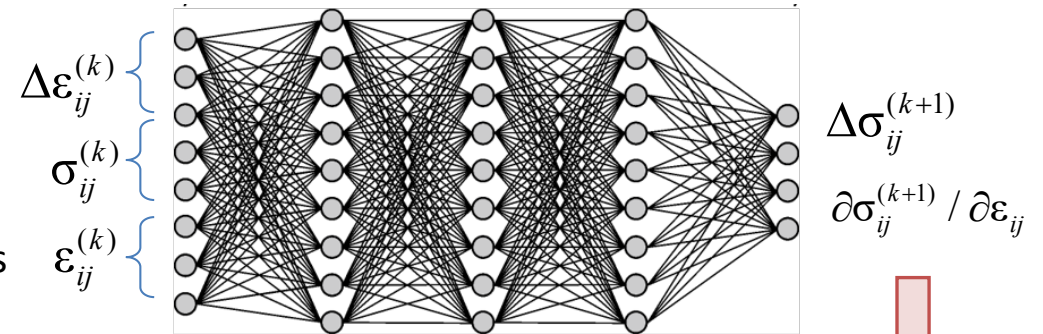
- Generalized internal forces:
$$\mathbf{Q}_s = \int_{V_0} \left(\frac{\partial \mathbf{E}}{\partial \mathbf{e}} \right)^T \mathbf{S} dV_0$$

- Eqs. of motion:
$$\mathbf{M}\ddot{\mathbf{e}} = \mathbf{Q}_s + \mathbf{Q}_e$$

Scale bridging

(Upper to lower)

More inputs as needed

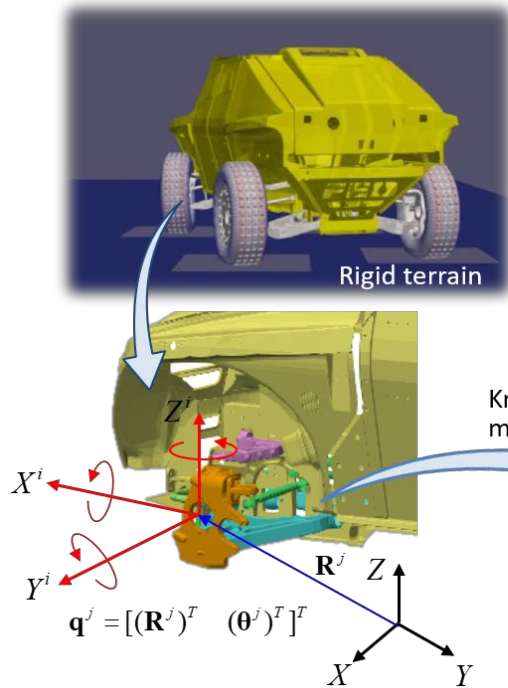


Cauchy stress tensor and tangent moduli
 (Lower to upper)

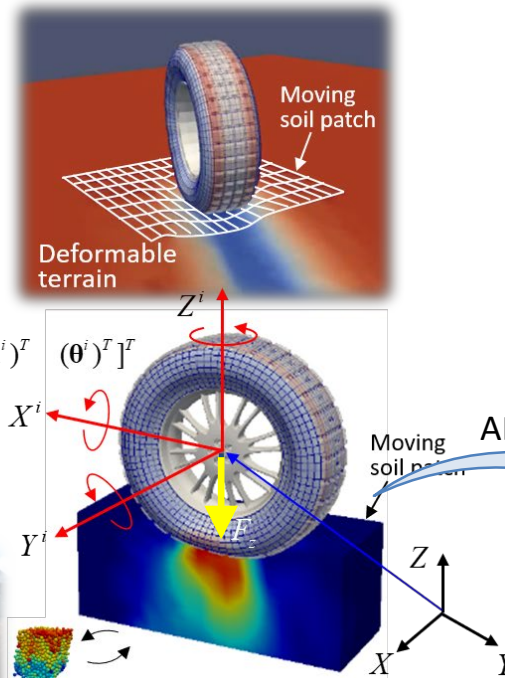
Training Procedure for Full Vehicle Simulations

- Producing appropriate training data, retaining a **sufficient range of stress variation of deformable terrain in mobility prediction scenarios**, is of critical importance to ensure the accuracy and robustness of ANN surrogate model.
- However, **conducting multiple FE-DE multiscale off-road mobility simulations would require extensive computational efforts prior to the mobility prediction** and ultimately reduces the overall computational speedup that can be attained by the FE-ANN multiscale off-road mobility model.

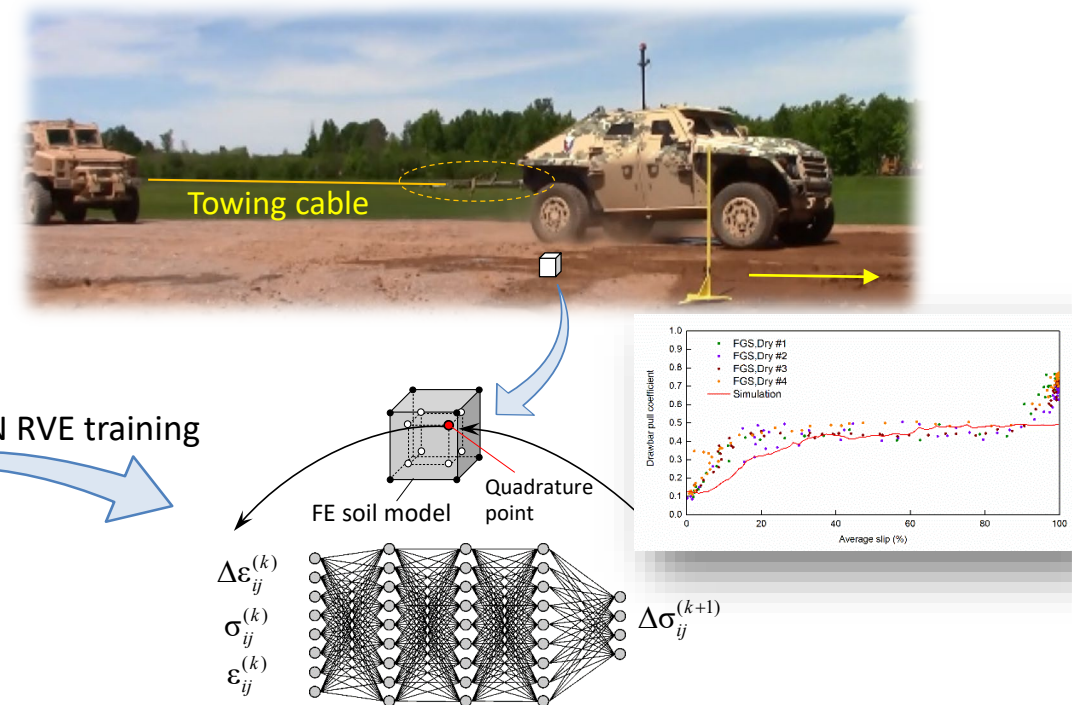
Step 1: Vehicle cornering simulation on rigid ground



Step 2: Virtual single tire test rig simulation with FE-DE terrain

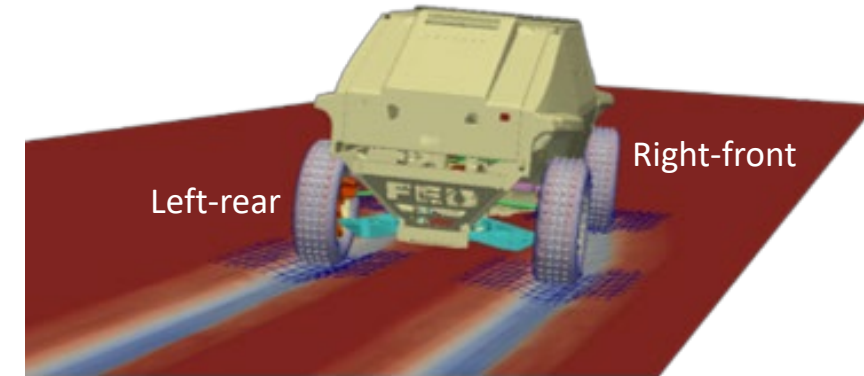


Step 3: Mobility prediction with FE-ANN multiscale model

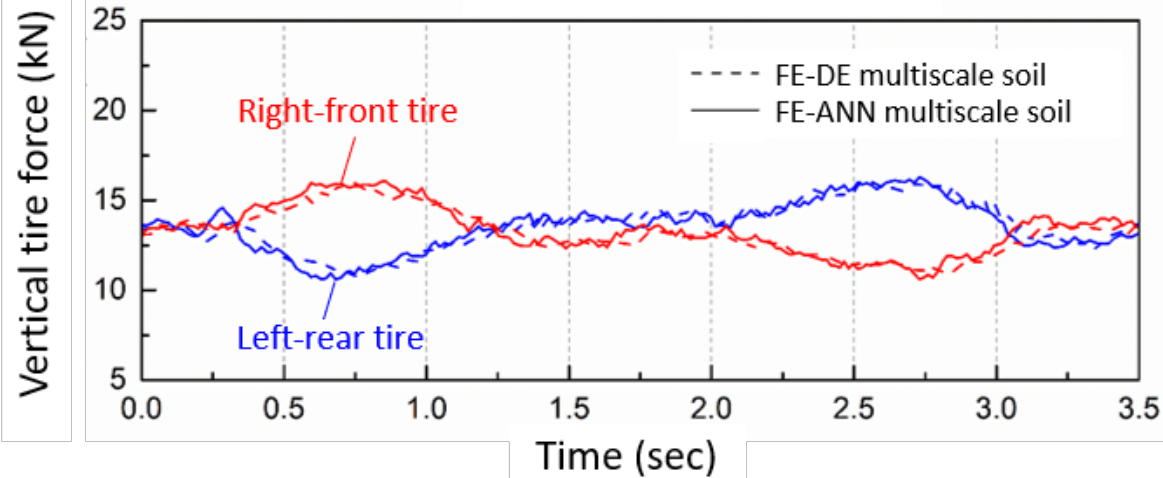


FE-ANN Multiscale Terrain for Lane Change Maneuver Simulation

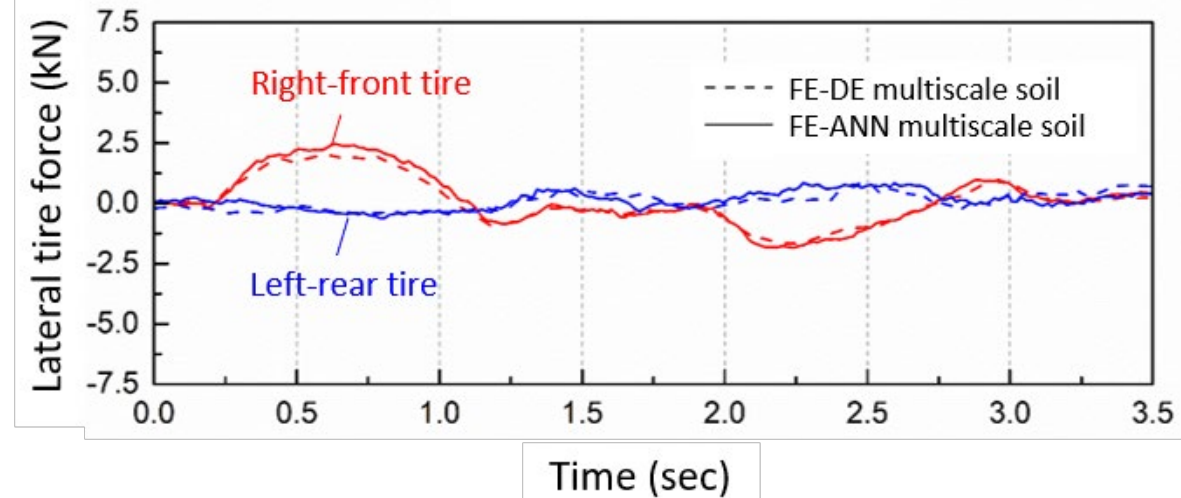
- As steering motion of the front tires induces complex soil deformation modes, an **ANN RVE** is developed with only the right-front soil patch data with single tire test rig model (~1.15 sec).
- The ANN RVE is composed of seven hidden layers, each of which has 600 neurons (7 x 600), and it is **used for all four soil patches in the simulation**.
- Each soil patch has 360 elements, within which 2,880 RVEs are defined. 10,752 ANN RVEs in total.



Vertical tire forces



Lateral tire forces



FE-ANN terrain: 27 hours (1 day & 3 hours)
FE-DE terrain: 140 hours (5 days & 20 hours)

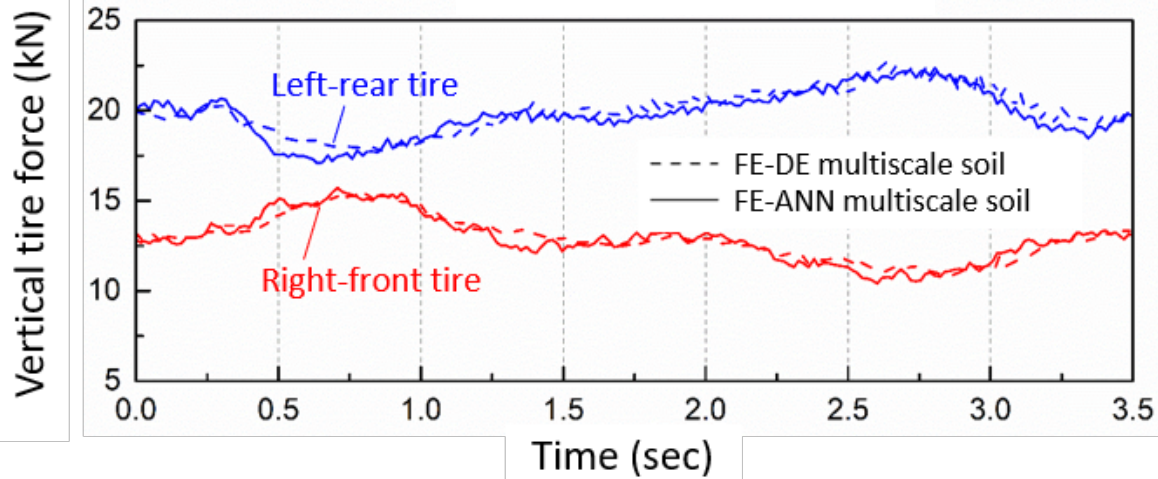
71% reduction in comp. time

Robustness of ANN RVE: Increased Vehicle Weight

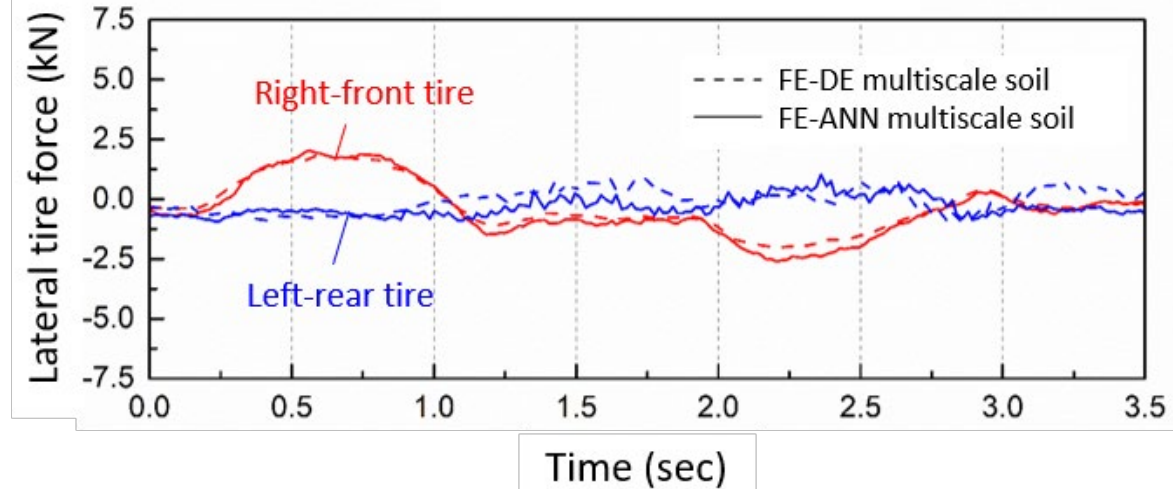
| | FED Vehicle (reference) | | FED Vehicle w/ payload |
|----------------------|-------------------------|---|------------------------|
| Vehicle weight (kg) | 5,481 | → | 6,736 |
| Weight distribution | 54% (F) , 46% (R) | → | 42 % (F) , 58% (R) |
| Longitudinal CG (mm) | 1,710 | → | 1,927 |
| Vertical CG (mm) | 1,001 | → | 823 |



Vertical tire forces



Lateral tire forces

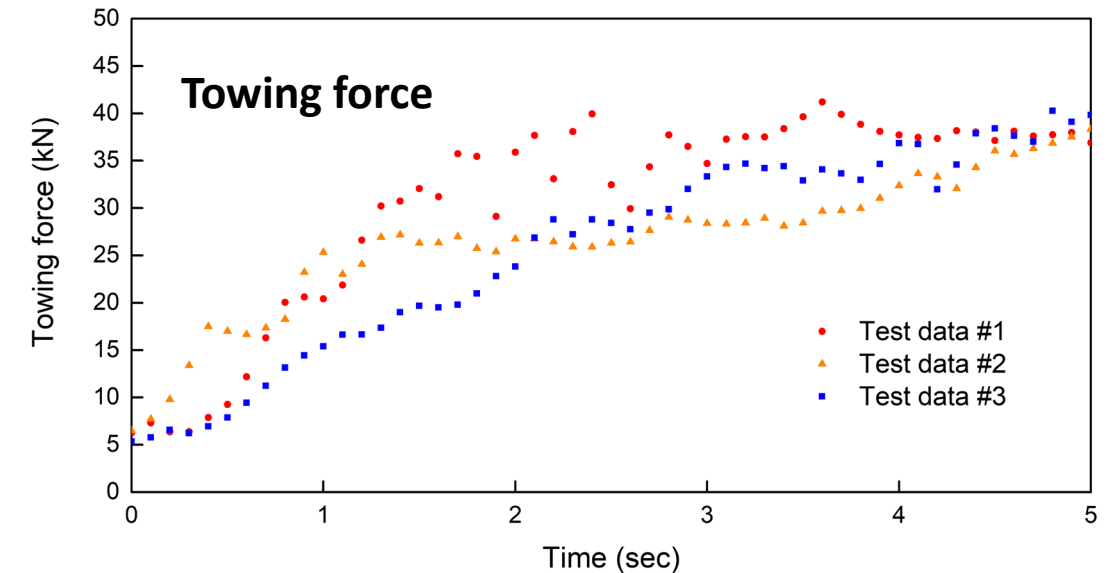
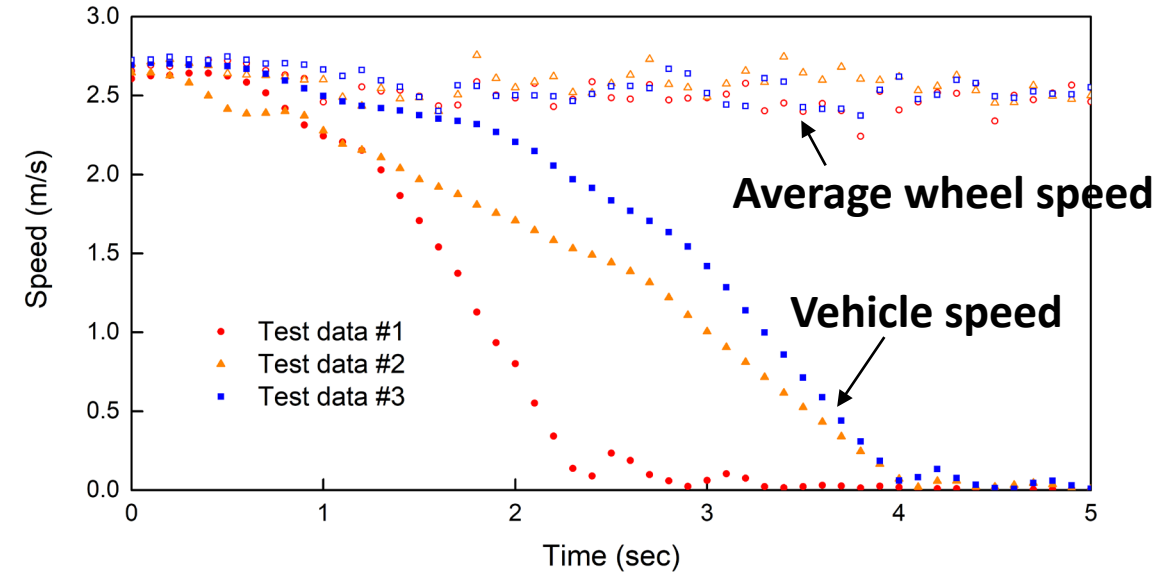


FE-ANN terrain: 27 hours (1 day & 3 hours)
FE-DE terrain: 140 hours (5 days & 20 hours)

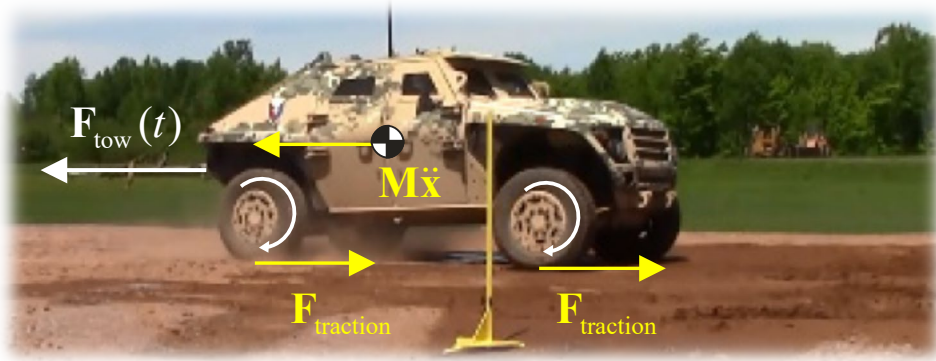
71% reduction in comp. time

Drawbar Pull Test on Fine Grain Sand (FGS)

- It is crucial to **examine whether the vehicle and terrain behavior in scenarios not considered in the training data can be predicted accurately.**
- To address this issue, a drawbar pull simulation on the FGS terrain is considered using the ANN RVE model trained with the cornering scenario.
- In the drawbar pull test, the **driver maintained constant wheel speeds** by keeping the gas pedal position constant (**differential being locked**).



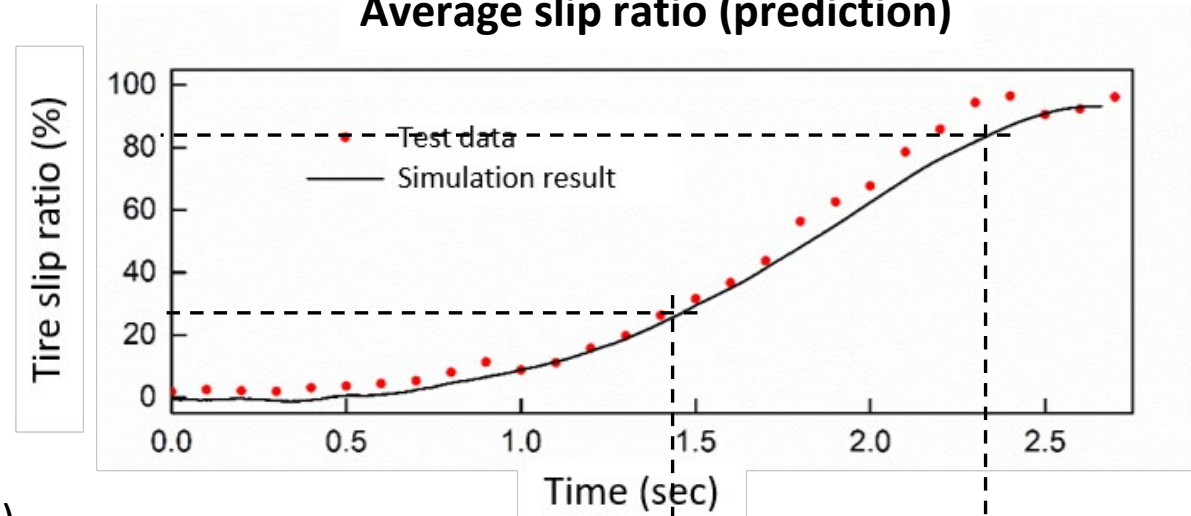
FE-ANN Drawbar Pull Simulation and Comparison with Test Data



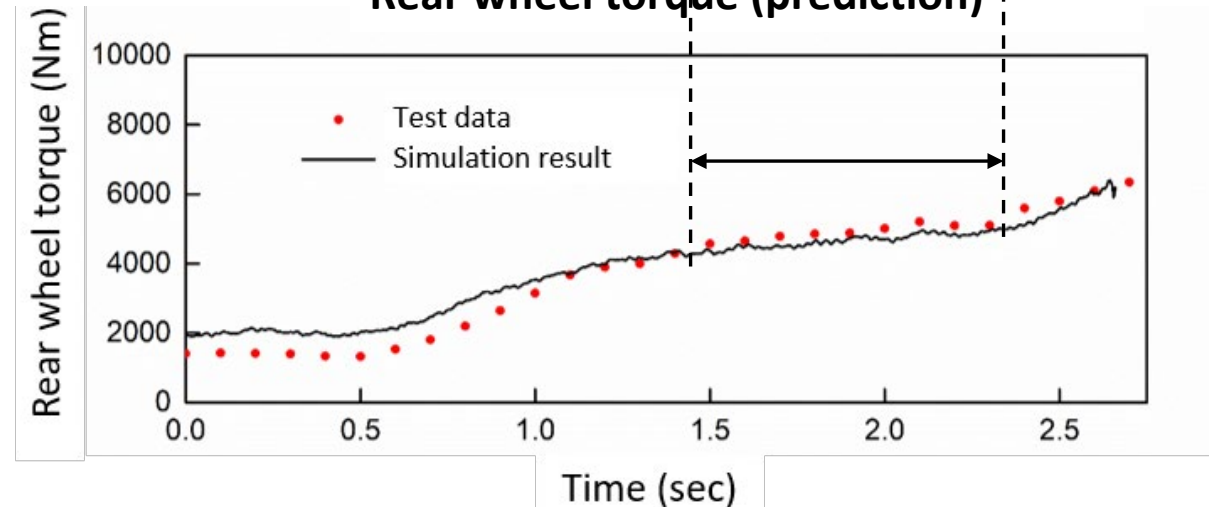
$$\underbrace{\mathbf{M}\ddot{\mathbf{x}}}_{\text{Predict}} = \underbrace{\sum \mathbf{F}_{\text{traction}}}_{\text{Predict (tire-soil)}} - \underbrace{\mathbf{F}_{\text{tow}}(t)}_{\text{Input}}$$

- Tire slip
 - Tire forces (wheel torques)
 - Vehicle deceleration $\ddot{\mathbf{x}}$
- The wheel rotational speeds as well as the towing force from the test data are prescribed to mimic the vehicle test condition.
 - As the towing force increases, tire slip increases. The vehicle is finally immobilized at a 100 % slip.
 - The wheel torque increases gradually to oppose the increase in the longitudinal tire force.

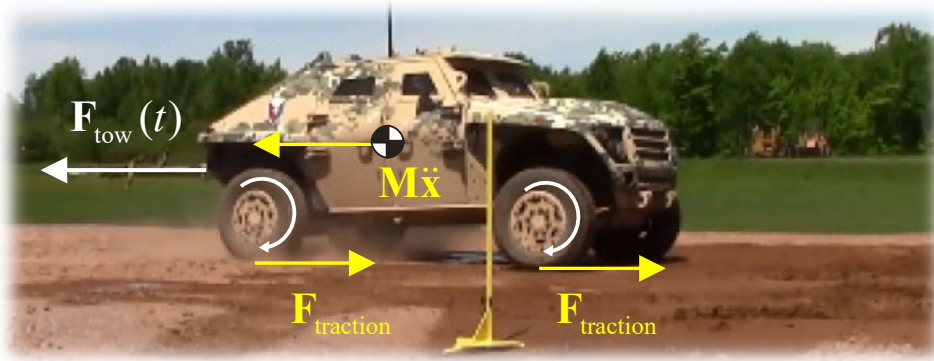
Average slip ratio (prediction)



Rear wheel torque (prediction)

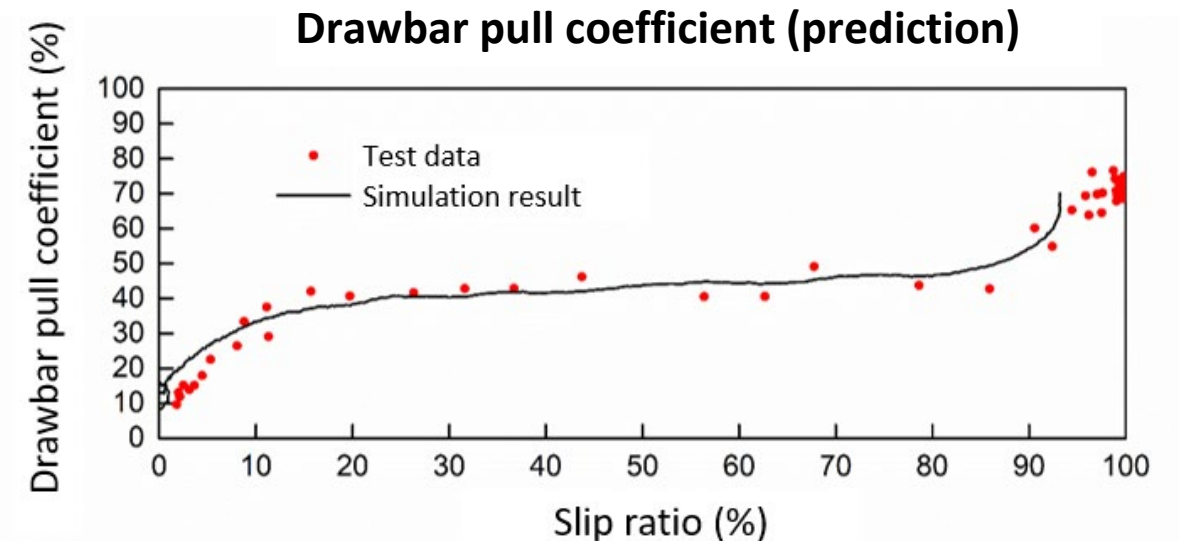
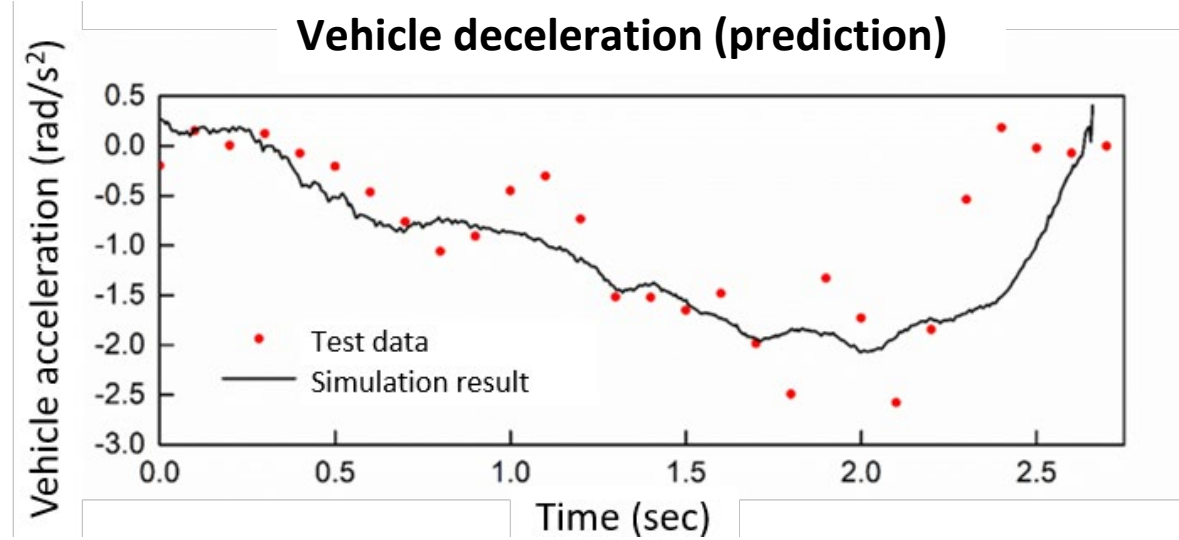


FE-ANN Drawbar Pull Simulation and Comparison with Test Data



$$\underbrace{\mathbf{M}\ddot{\mathbf{x}}}_{\text{Predict}} = \underbrace{\sum \mathbf{F}_{\text{traction}}}_{\text{Predict (tire-soil)}} - \underbrace{\mathbf{F}_{\text{tow}}(t)}_{\text{Input}} \Rightarrow \begin{cases} \bullet \text{ Tire slip} \\ \bullet \text{ Tire forces (wheel torques)} \\ \bullet \text{ Vehicle deceleration } \ddot{\mathbf{x}} \end{cases}$$

- While the test data exhibit higher variation in deceleration, the increasing trend of the vehicle deceleration is well captured by the FE-ANN model.
- With the ANN RVE trained with the data from the single tire test rig model in the cornering scenario, the vehicle drawbar pull performance is predicted successfully without adjustment and retraining of the neural network.



Summary and Conclusions

- ❑ Multiscale modeling provides a **powerful tool for predicting complex granular terrain behavior in off-road vehicle mobility simulations.**
- ❑ Developed a **hierarchical FE-DE multiscale off-road mobility model**, allowing for eliminating limitations of existing single-scale deformable terrain models.
- ❑ ARL-developed **HMS** multiscale framework improves the computational time, and exhibits good scalability.
- ❑ Substantial computational speedup by a **data-driven neural network surrogate model** for the lower-scale DE RVE while ensuring the predictive accuracy and robustness under various vehicle maneuvering scenarios.

❑ Future work

- Creating ANN RVE for different types of soil with **Transfer Learning**
- Considering more soil parameters in neural networks
- Explore replacing upper-scale FE model with commercial software or open-source codes through **HMS VUMAT** interface.
- Integrate the multiscale terrain models into **CREATE-GV** software

