

Advanced material modeling in FEniCSx

Jérémie Bleyer

coll.: Andrey Latyshev, Corrado Maurini, Filippo Masi

Laboratoire Navier, ENPC, Univ Gustave Eiffel, CNRS



FEniCS 2023
June 14th-16th 2023

Nonlinear solid mechanics and nonlinear constitutive behavior

FEniCS archetypal example: **hyperelasticity**, e.g. compressible neo-Hookean

$$\psi(\boldsymbol{F}) = \frac{\lambda}{2}(J - 1)^2 + \frac{\mu}{2} (I_1 - 3 - 2 \ln J)$$

where $I_1 = \text{tr}(\boldsymbol{C}) = \text{tr}(\boldsymbol{F}^T \boldsymbol{F})$ and $J = \det \boldsymbol{F}$.

Easy definition and derivation with **UFL operators**

Nonlinear solid mechanics and nonlinear constitutive behavior

FEniCS archetypal example: **hyperelasticity**, e.g. compressible neo-Hookean

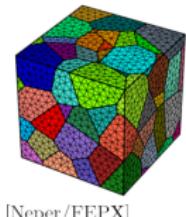
$$\psi(\boldsymbol{F}) = \frac{\lambda}{2}(J - 1)^2 + \frac{\mu}{2} (I_1 - 3 - 2 \ln J)$$

where $I_1 = \text{tr}(\boldsymbol{C}) = \text{tr}(\boldsymbol{F}^T \boldsymbol{F})$ and $J = \det \boldsymbol{F}$.

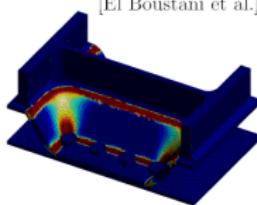
Easy definition and derivation with **UFL operators**

What about ?

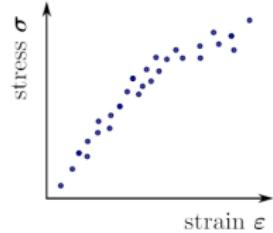
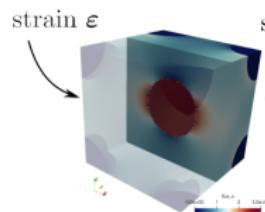
- damage, viscoelasticity, (visco)plasticity, etc.
- multiscale models
- data-driven models



[Helfer et al.]



[El Boustani et al.]



Non-linear mechanics setting

Generic (small strain) setting: Find $\mathbf{u} \in V$ such that:

$$\int_{\Omega} \boldsymbol{\sigma}(\nabla^s \mathbf{u}) : \nabla^s \mathbf{v} \, d\Omega = \int_{\Omega} \mathbf{f} \cdot \mathbf{v} \, d\Omega + \int_{\partial\Omega_N} \boldsymbol{\tau} \cdot \mathbf{v} \, dS \quad \forall \mathbf{v} \in V \quad (1)$$

Local non-linear mapping, **not expressible** using UFL

$$\boldsymbol{\epsilon} = \nabla^s \mathbf{u} \longrightarrow \boxed{\text{CONSTITUTIVE RELATION}} \longrightarrow \boldsymbol{\sigma}$$

Non-linear mechanics setting

Generic (small strain) setting: Find $\mathbf{u} \in V$ such that:

$$\int_{\Omega} \boldsymbol{\sigma}(\nabla^s \mathbf{u}) : \nabla^s \mathbf{v} \, d\Omega = \int_{\Omega} \mathbf{f} \cdot \mathbf{v} \, d\Omega + \int_{\partial\Omega_N} \boldsymbol{\tau} \cdot \mathbf{v} \, dS \quad \forall \mathbf{v} \in V \quad (1)$$

Local non-linear mapping, **not expressible** using UFL

$$\boldsymbol{\epsilon} = \nabla^s \mathbf{u}, \mathcal{S}_n \longrightarrow \boxed{\text{CONSTITUTIVE RELATION}} \longrightarrow \boldsymbol{\sigma}, \mathcal{S}_{n+1}$$

- implicit non-linear equation
- implicit non-linear equations with state variables \mathcal{S}_n
- non-linear FE computation on a RVE
- Neural-Network inference
- closest-point projection onto a data manifold

Non-linear mechanics setting

Generic (small strain) setting: Find $\mathbf{u} \in V$ such that:

$$\int_{\Omega} \boldsymbol{\sigma}(\nabla^s \mathbf{u}) : \nabla^s \mathbf{v} d\Omega = \int_{\Omega} \mathbf{f} \cdot \mathbf{v} d\Omega + \int_{\partial\Omega_N} \boldsymbol{\tau} \cdot \mathbf{v} dS \quad \forall \mathbf{v} \in V \quad (1)$$

Local non-linear mapping, **not expressible** using UFL

$$\boldsymbol{\epsilon} = \nabla^s \mathbf{u}, \mathcal{S}_n \longrightarrow \boxed{\text{CONSTITUTIVE RELATION}} \longrightarrow \boldsymbol{\sigma}, \mathcal{S}_{n+1}$$

- implicit non-linear equation
- implicit non-linear equations with state variables \mathcal{S}_n
- non-linear FE computation on a RVE
- Neural-Network inference
- closest-point projection onto a data manifold

Material modeling

a science in its own right, sometimes with dedicated tools

Additional challenges

- **Derivatives:** Newton method for solving (1) requires the **Jacobian**, at least:

$$\delta\sigma(\nabla^s \boldsymbol{u}) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \boldsymbol{u}$$

Additional challenges

- **Derivatives:** Newton method for solving (1) requires the **Jacobian**, at least:

$$\delta\sigma(\nabla^s \boldsymbol{u}) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \boldsymbol{u}$$

sometimes:

$$\delta\sigma(\nabla^s \boldsymbol{u}, T) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \boldsymbol{u} + \frac{\partial \boldsymbol{\sigma}}{\partial T} \delta T$$

$$\delta S_{n+1}(\nabla^s \boldsymbol{u}, T) = \frac{\partial S_{n+1}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \boldsymbol{u} + \frac{\partial S_{n+1}}{\partial T} \delta T$$

Additional challenges

- **Derivatives:** Newton method for solving (1) requires the **Jacobian**, at least:

$$\delta\sigma(\nabla^s \mathbf{u}) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u}$$

sometimes:

$$\delta\sigma(\nabla^s \mathbf{u}, T) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u} + \frac{\partial \boldsymbol{\sigma}}{\partial T} \delta T$$

$$\delta S_{n+1}(\nabla^s \mathbf{u}, T) = \frac{\partial S_{n+1}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u} + \frac{\partial S_{n+1}}{\partial T} \delta T$$

- **Generalized stresses:** $\boldsymbol{\sigma}$ (solids), (N, M, Q) (beams), (N, M, Q) (plates/shells), Cosserat, strain gradient, etc.

Additional challenges

- **Derivatives:** Newton method for solving (1) requires the **Jacobian**, at least:

$$\delta\sigma(\nabla^s \mathbf{u}) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u}$$

sometimes:

$$\delta\sigma(\nabla^s \mathbf{u}, T) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u} + \frac{\partial \boldsymbol{\sigma}}{\partial T} \delta T$$

$$\delta S_{n+1}(\nabla^s \mathbf{u}, T) = \frac{\partial S_{n+1}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u} + \frac{\partial S_{n+1}}{\partial T} \delta T$$

- **Generalized stresses:** $\boldsymbol{\sigma}$ (solids), (N, M, Q) (beams), (N, M, Q) (plates/shells), Cosserat, strain gradient, etc.
- **Coupled physics:** THM

Additional challenges

- **Derivatives:** Newton method for solving (1) requires the **Jacobian**, at least:

$$\delta\sigma(\nabla^s \mathbf{u}) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u}$$

sometimes:

$$\delta\sigma(\nabla^s \mathbf{u}, T) = \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u} + \frac{\partial \boldsymbol{\sigma}}{\partial T} \delta T$$

$$\delta S_{n+1}(\nabla^s \mathbf{u}, T) = \frac{\partial S_{n+1}}{\partial \boldsymbol{\varepsilon}} : \nabla^s \delta \mathbf{u} + \frac{\partial S_{n+1}}{\partial T} \delta T$$

- **Generalized stresses:** $\boldsymbol{\sigma}$ (solids), (N, M, Q) (beams), (N, M, Q) (plates/shells), Cosserat, strain gradient, etc.
- **Coupled physics:** THM
- **Finite strains**

dolfinx_materials: Python package for material behaviors

Objective: provide simple way of defining and handling complex material constitutive behaviors **within dolfinx**

dolfinx_materials: Python package for material behaviors

Objective: provide simple way of defining and handling complex material constitutive behaviors within dolfinx

Concept: see the constitutive relation as a *black-box function* mapping **gradients** (e.g. strain $\boldsymbol{\varepsilon} = \nabla^s \mathbf{u}$) to **fluxes** (e.g. stresses $\boldsymbol{\sigma}$) at the level of **quadrature points**

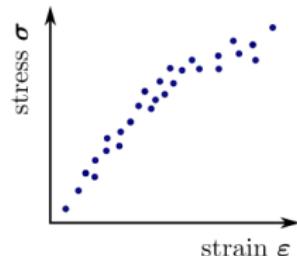
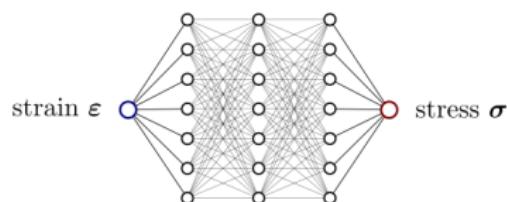
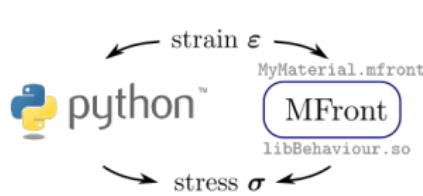
dolfinx_materials: Python package for material behaviors

Objective: provide simple way of defining and handling complex material constitutive behaviors within dolfinx

Concept: see the constitutive relation as a *black-box function* mapping **gradients** (e.g. strain $\epsilon = \nabla^s u$) to **fluxes** (e.g. stresses σ) at the level of **quadrature points**

Concrete implementation of the constitutive relation

- a user-defined Python function
- provided by an external library (e.g. behaviors compiled with MFront)
- a neural network inference
- solution to a FE computation on a RVE, etc.



A Python elasto-plastic behaviour

Material: provides info at the quadrature point level e.g. dimension of gradient inputs/stress outputs, stored internal state variables, required external state variables

```
class ElastoPlasticIsotropicHardening(Material):
    @property
    def internal_state_variables(self):
        return {"p": 1} # cumulated plastic strain

    def constitutive_update(self, eps, state):
        eps_old = state["Strain"]
        deps = eps - eps_old
        p_old = state["p"]

        C = self.elastic_model.compute_C()
        sig_el = state["Stress"] + C @ deps      # elastic predictor
        s_el = K() @ sig_el
        sig_Y_old = self.yield_stress(state["p"])
        sig_eq_el = np.sqrt(3 / 2.0) * np.linalg.norm(s_el)
        if sig_eq_el - sig_Y_old >= 0:
            dp = fsolve(lambda dp: sig_eq_el - 3*mu*dp - self.yield_stress(p_old + dp), 0.0)
        else:
            dp = 0
        state["Strain"] = eps_old + deps
        state["p"] += dp
        return sig_el - 3 * mu * s_el / sig_eq_el * dp
```

Pseudo-code on the dolfinx side

QuadratureMap: storage of different quantities as Quadrature functions, evaluates UFL expression at quadrature points and material behavior for a set of cells

```
u = fem.Function(V)
qmap = QuadratureMap(u, deg_quad, material) # material = ["Strain"] --> ["Stress"]
qmap.register_gradient("Strain", eps(u))

sig = qmap.fluxes["Stress"]    # a function defined on "Quadrature" space

Res = ufl.inner(sig, eps(v)) * qmap.dx - ufl.inner(f, u) * dx
Jac = ...

for i in Newton_loop:          # custom Newton solver
    qmap.update()              # update current stress estimate
    b = assemble_vector(Res)
    A = assemble_matrix(Jac)
    solve(A, b, du.vector)   # compute displacement correction
    u.vector[:] += du.vector[:]

qmap.advance()                 # updates previous state with current one for next time step
```

Above code **independent from** the material, provided that gradients = ["Strain"] and fluxes = ["Stress"]

About the Jacobian and non-linear solvers

Material should provide a "tangent" operator

```
def constitutive_update(self, eps, state):
    [...]
    return sig, Ct
```

can be the algorithmic consistent operator, the secant, the elastic operator, etc...

```
Res = ufl.inner(sig, eps(v)) * qmap.dx - ufl.inner(f, u) * dx
Jac = qmap.derivative(Res, u, du)
```

About the Jacobian and non-linear solvers

Material should provide a "tangent" operator

```
def constitutive_update(self, eps, state):
    [...]
    return sig, Ct
```

can be the algorithmic consistent operator, the secant, the elastic operator, etc...

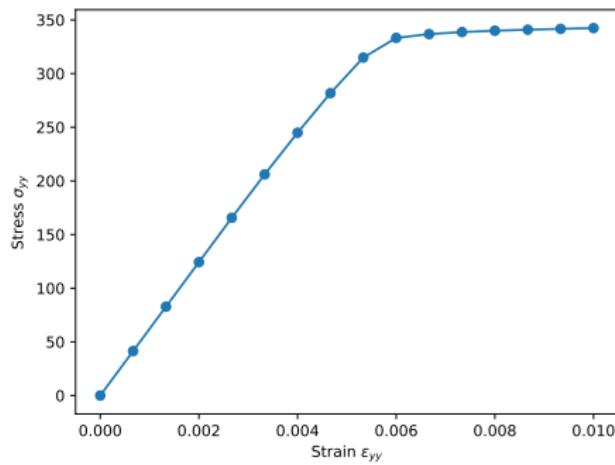
```
Res = ufl.inner(sig, eps(v)) * qmap.dx - ufl.inner(f, u) * dx
Jac = qmap.derivative(Res, u, du)
```

Here: `qmap.derivative(Res, u, du) = ufl.derivative(Res, u, du) + ufl.inner(Ct * eps(du), eps(v)) * qmap.dx + ... where Ct is a Quadrature function storing the values of $\frac{d\text{"Stress"}}{d\text{"Strain"}}$.`

Available solvers: NewtonSolver, PETSc.SNES

Example

2D plane strain perforated plate in tension



Plane stress version

3D constitutive behaviour, 2D displacement \mathbf{u} :

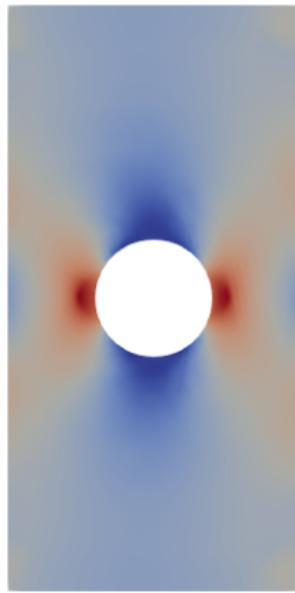
$$\boldsymbol{\varepsilon} = \begin{bmatrix} \nabla^s \mathbf{u} & 0 \\ 0 & \epsilon_{zz} \end{bmatrix}$$
$$\boldsymbol{\sigma} = \begin{bmatrix} \boldsymbol{\sigma}_{2D} & 0 \\ 0 & 0 \end{bmatrix}$$

Mixed approach : Find $(\mathbf{u}, \epsilon_{zz}) \in V$ s.t.:

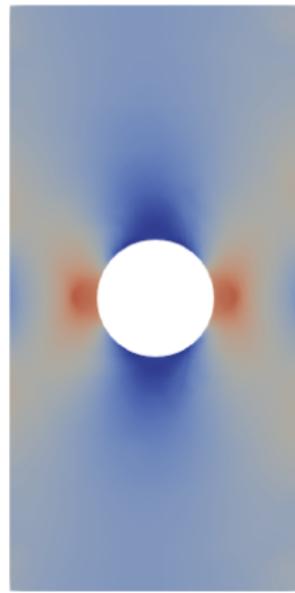
$$\int_{\Omega} (\boldsymbol{\sigma}_{2D}(\nabla^s \mathbf{u}, \epsilon_{zz}) : \nabla^s \mathbf{v} + \sigma_{zz}(\nabla^s \mathbf{u}, \epsilon_{zz}) \hat{\epsilon}_{zz}) \, d\Omega = \int_{\Omega} \mathbf{f} \cdot \mathbf{v} \, d\Omega + \int_{\partial\Omega_N} \boldsymbol{\mathcal{T}} \cdot \mathbf{v} \, dS \quad \forall (\mathbf{v}, \hat{\epsilon}_{zz}) \in V$$

here $V = ("CG", 2) \times ("DG", 1)$

Plane stress version



(a) plane strain

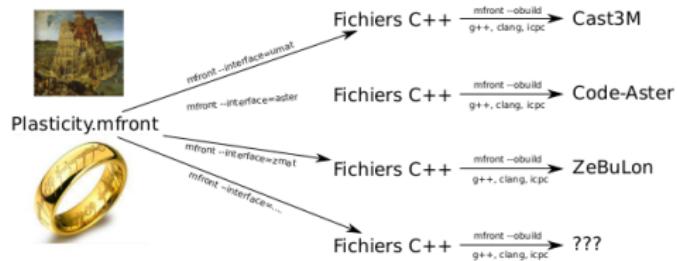


(b) plane stress

Figure: Vertical stress σ_{yy}

MFront: a code-generator tool for complex constitutive laws

developed at CEA, mainly by Thomas Helfer



Philosophy

efficient, reliable, sustainable material library
independent of any FE solver:

- dedicated optimized interfaces (Abaqus, Castem, Code Aster)
- generic interfaces (C, Python, Fortran, Julia) : MGIS¹

reduce code burden and source of errors (different conventions/code)
syntax close to the mathematical constitutive equations

¹ MFrontGenericInterfaceSupport project

A simple example: Norton viscoplasticity

```
@DSL Implicit;
@Behaviour Norton;
@Brick StandardElasticity;

@MaterialProperty stress E;
E.setGlossaryName("YoungModulus");
@MaterialProperty real v, A, nn;
v.setGlossaryName("PoissonRatio");
A.setEntryName("NortonCoefficient");
nn.setEntryName("NortonExponent");

@StateVariable real p;
p.setGlossaryName("EquivalentViscoplasticStrain");

@Integrator{
    constexpr const auto Me = Stensor4::M();
    const auto μ = computeMu(E, v);
    const auto σe = sigmaeq(σ);
    const auto iσe = 1 / (max(σe, real(1.e-12) + E));
    const auto vP = A · pow(σe, nn);
    const auto ∂vP/∂σe = nn · vP · iσe;
    const auto n = 3 · deviator(σ) · (iσe / 2);
    // Implicit system
    fεel += Δp · n;
    fp -= vP · Δt;
    // jacobian
    ∂fεel/∂Δεel += 2 · μ · θ · dp · iσe · (Me - (n ⊗ n));
    ∂fεel/∂Δp = n;
    ∂fp/∂Δεel = -2 · μ · θ · ∂vP/∂σe · Δt · n;
} // end of @Integrator
```

Implicit system:

$$f_{\epsilon^e} = \Delta\epsilon^e - \Delta\epsilon + \Delta p n = 0$$

$$f_p = \Delta p - A(\sigma_{eq})^n = 0$$

Jacobian:

$$\frac{\partial f_{\epsilon^e}}{\partial \Delta\epsilon^e} = \mathbb{I} + \frac{2\mu\theta\Delta p}{\sigma_{eq}} (\mathbb{M} - \mathbf{n} \otimes \mathbf{n})$$

$$\frac{\partial f_{\epsilon^e}}{\partial \Delta p} = \mathbf{n}$$

$$\frac{\partial f_p}{\partial \Delta\epsilon^e} = -2\mu\theta\Delta t A n(\sigma_{eq})^{n-1} \mathbf{n}$$

tangent operator $\mathbb{C}_t = (J^{-1})_{11} \mathbb{C}$ using the inverse jacobian

Unicode support

Inside dolfinx_materials

MFrontMaterial class for loading a MFront library, calling the behaviour integration and giving access to fluxes, state variables and tangent operators

The **only** metadata not provided by MGIS is how the gradients (e.g. strain) are expressed as functions of the unknown fields \mathbf{u} (e.g. displacement)

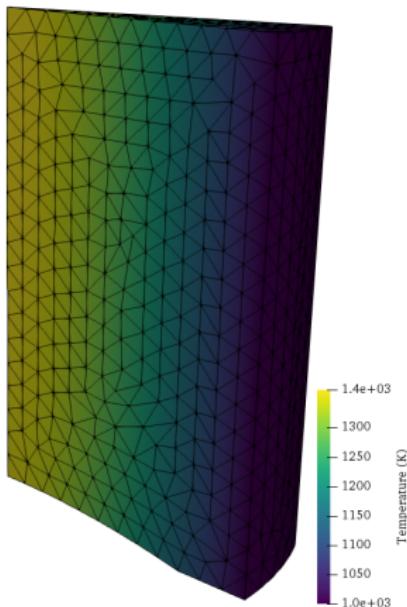
The user is required to provide this link with UFL expressions (**registration**):

```
mat_prop = {"YoungModulus": E, "PoissonRatio": nu,
            "HardeningSlope": H, "YieldStrength": sig0}
material = MFrontMaterial("src/libBehaviour.so",
                          "IsotropicLinearHardeningPlasticity",
                          hypothesis="plane_strain",
                          material_properties=mat_prop)

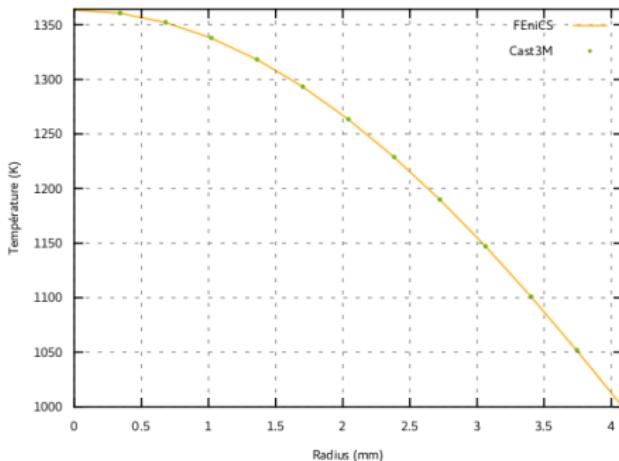
qmap = QuadratureMap(domain, deg_quad, material)
qmap.register_gradient("Strain", strain(u))
sig = qmap.fluxes["Stress"]

Res = ufl.dot(sig, strain(v)) * qmap.dx
Jac = qmap.derivative(Res, u, du)
```

Examples - Stationary non-linear heat transfer



| quad_deg | dolfinx/MFront | dolfinx |
|----------|----------------|---------|
| 2 | 15.76 s | 15.22 s |
| 5 | 16.53 s | 15.56 s |



Extension to large strains

Quite simple using for instance $\mathbf{F} = \mathbf{I} + \nabla \mathbf{u}$ and \mathbf{P} (PK1 stress):

Residual is:

$$\int_{\Omega} \mathbf{P}(\mathbf{F}) : \nabla \mathbf{v} \, d\Omega - W_{\text{ext}}(\mathbf{v}) = 0 \quad \forall \mathbf{v} \in V$$

```
material = MFrontMaterial("src/libBehaviour.so", "Ogden")

qmap = QuadratureMap(domain, deg_quad, material)
qmap.register_gradient("DeformationGradient", F(u))
P = qmap.fluxes["FirstPiolaKirchhoffStress"]
Res = ufl.dot(P, dF(v)) * qmap.dx - ufl.inner(f, v) * dx
```

Extension to large strains

Quite simple using for instance $\mathbf{F} = \mathbf{I} + \nabla \mathbf{u}$ and \mathbf{P} (PK1 stress):

Residual is:

$$\int_{\Omega} \mathbf{P}(\mathbf{F}) : \nabla \mathbf{v} \, d\Omega - W_{\text{ext}}(\mathbf{v}) = 0 \quad \forall \mathbf{v} \in V$$

```
material = MFrontMaterial("src/libBehaviour.so", "Ogden")

qmap = QuadratureMap(domain, deg_quad, material)
qmap.register_gradient("DeformationGradient", F(u))
P = qmap.fluxes["FirstPiolaKirchhoffStress"]
Res = ufl.dot(P, dF(v)) * qmap.dx - ufl.inner(f, v) * dx
```

Consistent tangent bilinear form is:

$$a(\mathbf{u}, \mathbf{v}) = \int_{\Omega} \nabla \mathbf{u} : \frac{\partial \mathbf{P}}{\partial \mathbf{F}} : \nabla \mathbf{v} \, d\Omega$$

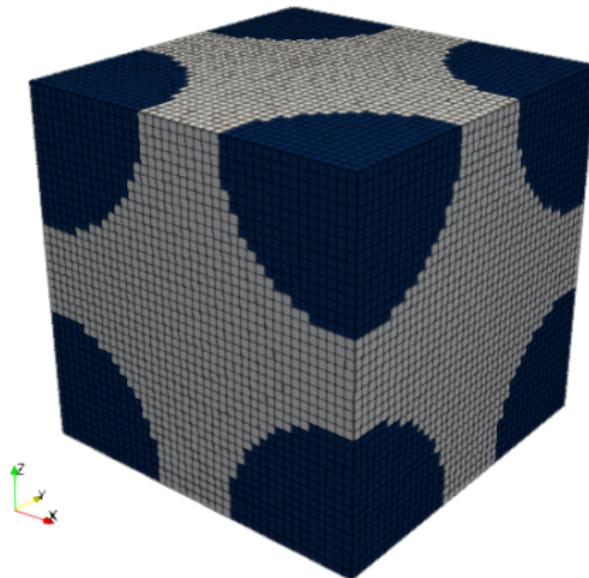
a MFront behaviour usually returns $\mathbb{C}_t = \partial \sigma / \partial \mathbf{F}$, MGIS provides conversion methods (extremely useful!):

```
bopts = mgis_bv.FiniteStrainBehaviourOptions()
bopts.stress_measure = mgis_bv.FiniteStrainBehaviourOptionsStressMeasure.PK1
bopts.tangent_operator = mgis_bv.FiniteStrainBehaviourOptionsTangentOperator.DPK1_DF
```

Ogden hyperelasticity

$$\psi(\mathbf{F}) = \frac{1}{2}K(J-1)^2 + \sum_{i=1}^N \frac{\mu_i}{\alpha_i} \left(\bar{\lambda}_1^{\alpha_i} + \bar{\lambda}_2^{\alpha_i} + \bar{\lambda}_3^{\alpha_i} \right)$$

where $\bar{\lambda}_j$ are eigenvalues of $\bar{\mathbf{C}} = J^{-2/3} \mathbf{F}^T \mathbf{F}$



Ogden hyperelasticity

16 CPUs: **Linear solves** ($\times 77$) = 283.6 s, **Constitutive update** ($\times 98$): 20.93 s

Return mapping using convex optimization

For elasto-plastic problems, constitutive update is equivalent to projection of elastic predictor onto the yield surface:

$$\begin{aligned} \min_{\sigma} \quad & \frac{1}{2}(\sigma - \sigma_{\text{el}}) : \mathbb{C}^{-1} : (\sigma - \sigma_{\text{el}}) \\ \text{s.t.} \quad & f(\sigma) \leq 0 \end{aligned}$$

local Newton methods may fail for **highly non-smooth surfaces** (Mohr-Coulomb, Rankine, multi-surface)

can use **convex optimization solvers** in such cases (e.g. cvxpy)

Return mapping using convex optimization

For elasto-plastic problems, constitutive update is equivalent to projection of elastic predictor onto the yield surface:

$$\begin{aligned} \min_{\sigma} \quad & \frac{1}{2}(\sigma - \sigma_{el}) : \mathbb{C}^{-1} : (\sigma - \sigma_{el}) \\ \text{s.t.} \quad & f(\sigma) \leq 0 \end{aligned}$$

local Newton methods may fail for **highly non-smooth surfaces** (Mohr-Coulomb, Rankine, multi-surface)

can use **convex optimization solvers** in such cases (e.g. cvxpy)

e.g. **Rankine**: $f(\sigma) \leq 0 \Leftrightarrow \begin{cases} \max \sigma_I \leq f_t \\ \min \sigma_I \geq -f_c \end{cases}$

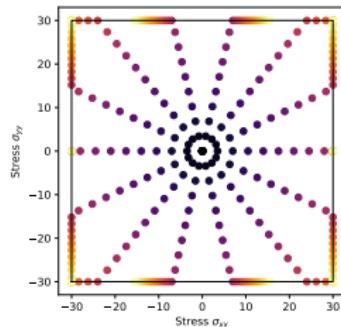
```
import cvxpy as cp
...
def set_cvxpy_model(self):
    self.sig = cp.Variable((3,))
    self.sig_el = cp.Parameter((3,))
    obj = 0.5 * cp.quad_form(self.sig - self.sig_el, np.linalg.inv(C))
    Sig = cp.bmat([[self.sig[0], self.sig[2] / np.sqrt(2)],
                   [self.sig[2] / np.sqrt(2), self.sig[1]]])
    cons = [cp.lambda_max(Sig) <= self.ft,
            cp.lambda_min(Sig) >= -self.fc]
    self.prob = cp.Problem(cp.Minimize(obj), cons)
```

Rankine yield surface

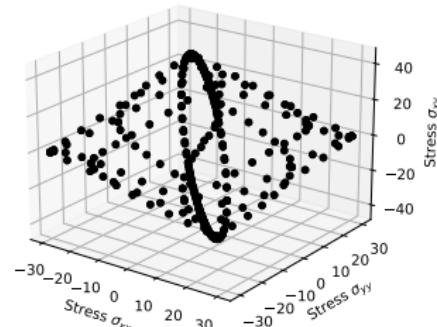
```
def constitutive_update(self, eps, state):
    eps_old = state["Strain"]
    deps = eps - eps_old
    sig_old = state["Stress"]

    self.sig_el.value = sig_old + self.elastic_model.C @ deps
    self.prob.solve(solver=cp.MOSEK, verbose=False)

    state["Strain"] = eps
    state["Stress"] = self.sig.value
    return sig, self.elastic_model.C
```



(a) In-plane load cases

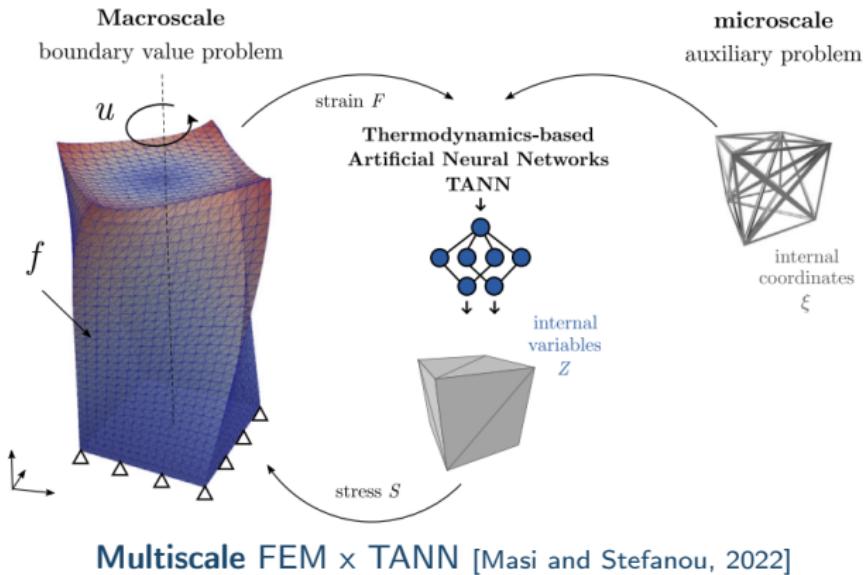


(b) 3D yield surface

Thermodynamics-based Artificial Neural Networks (TANN)

[Masi et al., 2019; Masi and Stefanou, 2022]

NN for the constitutive modeling of materials with **inelastic** and **complex microstructure**, complying with **thermodynamics requirements**



constitutive relation of RVE is **trained** on various load paths at the **microlevel**
constitutive relation at the **macrolevel** is **inferred** from the trained model

FEM x TANN in dolfinx_materials

```
import tensorflow as tf
import numpy as np

class TannMaterial(Material):
    def __init__(self, ANN_filename, nb_isv):
        self.model = tf.saved_model.load(ANN_filename)
        self.nb_isv = nb_isv

    @property
    def internal_state_variables(self):
        return {"ivars": self.nb_isv, "free_energy": 1, "dissipation": 1}

    def constitutive_update(self, eps, state):
        state_vars = np.concatenate((state["Strain"], state["Stress"], state["ivars"]))
        deps = eps - state["Strain"]
        inputs = np.concatenate((state_vars, deps))
        stress, svars, Ctang = self.model(inputs, training=False)
```

tangent operator is computed via NN automatic differentiation

FEM x TANN in dolfinx_materials

Underlying microstructure = 3D truss

Conclusions and Outlook

Project available at:

https://gitlab.enpc.fr/navier-fenics/dolfinx_materials

Applications

- **Multiscale** computations: full-field (FE/FFT) or mean-field (micromechanics) models
- **Data-driven** models: projection onto a data manifold
- **Micromorphic regularizations** of softening plasticity models

Technical aspects

- similar to `ExternalOperator` in UFL (current discussions with Jack Hale)
- JAX/autograd for automatic differentiation of Python implementations
- cvxpy derivatives currently limited to a specific solver and of weak accuracy (Quasi-Newton methods ?)
- constitutive relation to be evaluated **inside the assembly loop**

Conclusions and Outlook

Project available at:

https://gitlab.enpc.fr/navier-fenics/dolfinx_materials

Applications

- **Multiscale** computations: full-field (FE/FFT) or mean-field (micromechanics) models
- **Data-driven** models: projection onto a data manifold
- **Micromorphic regularizations** of softening plasticity models

Technical aspects

- similar to `ExternalOperator` in UFL (current discussions with Jack Hale)
- JAX/autograd for automatic differentiation of Python implementations
- cvxpy derivatives currently limited to a specific solver and of weak accuracy (Quasi-Newton methods ?)
- constitutive relation to be evaluated **inside the assembly loop**

Thank you for your attention !