

Stochastic formulation of generalized standard materials

Jérémy Bleyer

Laboratoire Navier, ENPC, Univ Gustave Eiffel, CNRS

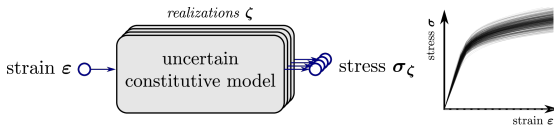


CSMA 2024
Giens, 13-17 Mai 2024

Objectives

Material constitutive law: $\sigma = F(\varepsilon)$

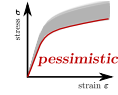
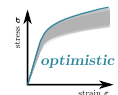
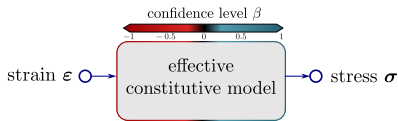
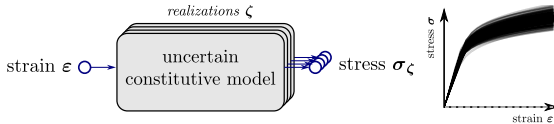
uncertain material properties \Rightarrow need for an **effective behavior**



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uncertain material properties \Rightarrow need for an **effective behavior**



must account for **history-dependent** behaviors and **thermodynamic consistency**

Generalized standard materials

Dissipative materials can be modeled using the GSM framework [Halphen & Nguyen, 1983]

- state variables: $\boldsymbol{\varepsilon}, \boldsymbol{\alpha}$ with $\boldsymbol{\alpha} = p, \boldsymbol{\varepsilon}^p, d, f$, etc.
- free energy: $\psi(\boldsymbol{\varepsilon}, \boldsymbol{\alpha})$
- pseudo-dissipation potential: $\phi(\dot{\boldsymbol{\varepsilon}}, \dot{\boldsymbol{\alpha}})$

ψ and ϕ are **convex, non-negative and zero at the origin**

Evolution equations

$$\boldsymbol{\sigma} = \boldsymbol{\sigma}^{\text{nd}} + \boldsymbol{\sigma}^{\text{d}}$$

$$0 = \boldsymbol{Y}^{\text{nd}} + \boldsymbol{Y}^{\text{d}}$$

$$(\boldsymbol{\sigma}^{\text{nd}}, \boldsymbol{Y}^{\text{nd}}) \in \partial_{(\boldsymbol{\varepsilon}, \boldsymbol{\alpha})} \psi(\boldsymbol{\varepsilon}, \boldsymbol{\alpha})$$

$$(\boldsymbol{\sigma}^{\text{d}}, \boldsymbol{Y}^{\text{d}}) \in \partial_{(\dot{\boldsymbol{\varepsilon}}, \dot{\boldsymbol{\alpha}})} \phi(\dot{\boldsymbol{\varepsilon}}, \dot{\boldsymbol{\alpha}})$$

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Advantages

- satisfies thermodynamic requirements such as **positive dissipation, stability**
- handles **rate-dependent** and **rate-independent** behaviors (for $\phi(\boldsymbol{x})$ homogeneous of degree 1)
- $\phi(\boldsymbol{x})$ usually **non-smooth** (plasticity)

Evolution equations

After time discretization, evolution equations are obtained from the incremental potential [Ortiz & Stainier, Mielke, etc.]

$$\psi(\boldsymbol{\varepsilon}, \boldsymbol{\alpha}) + \Delta t \phi \left(\frac{\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_n}{\Delta t}, \frac{\boldsymbol{\alpha} - \boldsymbol{\alpha}_n}{\Delta t} \right)$$

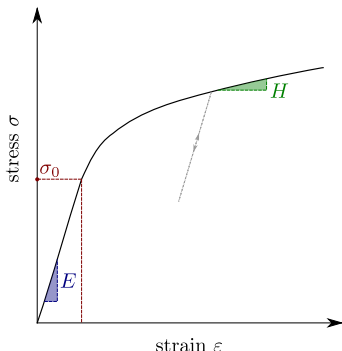
Simplifying assumptions: $\boldsymbol{\varepsilon}$ is non-dissipative, ϕ is 1-homogeneous, single-step $\boldsymbol{\alpha}_n = 0$

$$j(\boldsymbol{\varepsilon}) := \inf_{\boldsymbol{\alpha}} \psi(\boldsymbol{\varepsilon}, \boldsymbol{\alpha}) + \phi(\boldsymbol{\alpha})$$

$$\Rightarrow \boldsymbol{\sigma} \in \partial_{\boldsymbol{\varepsilon}} j$$

Example: 1D linear elasticity + isotropic power-law hardening

$$\begin{aligned} \psi(\boldsymbol{\varepsilon}, \boldsymbol{\alpha}) &= \psi_{\text{el}}(\boldsymbol{\varepsilon} - \boldsymbol{\alpha}) + \psi_{\text{h}}(\boldsymbol{\alpha}) \\ &= \frac{1}{2} E (\boldsymbol{\varepsilon} - \boldsymbol{\alpha})^2 + \frac{1}{m} H \boldsymbol{\alpha}^m \\ \phi(\dot{\boldsymbol{\alpha}}) &= \sigma_0 |\dot{\boldsymbol{\alpha}}| \end{aligned}$$



Uncertain case

Now j depends upon **stochastic parameters** ζ with known probability distribution

Goal: formulate an **effective potential** to describe the effective behavior

$$j^{\text{eff}}(\varepsilon) = \mathcal{R} [j(\varepsilon; \zeta)]$$

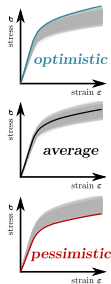
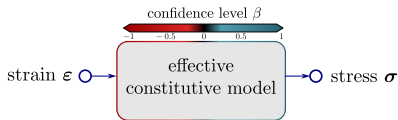
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$$\psi(\varepsilon, \alpha) = \frac{1}{2} E_{\zeta} (\varepsilon - \alpha)^2 + \frac{1}{m} H_{\zeta} \alpha^m \quad ; \quad \phi(\dot{\alpha}) = \sigma_0 \zeta |\dot{\alpha}|$$



Outline

- 1 Average effective behavior
- 2 Risk-averse estimates
- 3 Optimisitic and pessimistic structural response

Average behavior

Uncertain convex potential: $j(\varepsilon; \zeta)$, conjugate potential $j^*(\sigma; \zeta)$

Stochastic programming framework

Two possibilities:

1 ε is a **first-stage** variable: $j^{\text{eff}}(\varepsilon) = \mathbb{E}[j](\varepsilon)$

2 σ is a **first-stage** variable $j^{*,\text{eff}}(\sigma) = \mathbb{E}[j^*](\sigma)$

(internal state variables α are always **second-stage** variables)

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(internal state variables α are always **second-stage** variables)

e.g. **Elasticity**: $j(\boldsymbol{\varepsilon}_{\boldsymbol{\zeta}}; \boldsymbol{\zeta}) = \frac{1}{2} \boldsymbol{\varepsilon}_{\boldsymbol{\zeta}} : \mathbb{C}_{\boldsymbol{\zeta}} : \boldsymbol{\varepsilon}_{\boldsymbol{\zeta}}$

$$j^{\text{eff}}(\boldsymbol{\varepsilon}) = \mathbb{E} \left[\frac{1}{2} \boldsymbol{\varepsilon} : \mathbb{C}_{\boldsymbol{\zeta}} : \boldsymbol{\varepsilon} \right] = \frac{1}{2} \boldsymbol{\varepsilon} : \mathbb{E}[\mathbb{C}_{\boldsymbol{\zeta}}] : \boldsymbol{\varepsilon}$$

$$\text{or } j^{\text{eff}}(\boldsymbol{\varepsilon}) = \inf_{\boldsymbol{\varepsilon}_{\boldsymbol{\zeta}}} \mathbb{E} \left[\frac{1}{2} \boldsymbol{\varepsilon}_{\boldsymbol{\zeta}} : \mathbb{C}_{\boldsymbol{\zeta}} : \boldsymbol{\varepsilon}_{\boldsymbol{\zeta}} \right] = \frac{1}{2} \boldsymbol{\varepsilon} : \mathbb{E}[\mathbb{C}_{\boldsymbol{\zeta}}^{-1}]^{-1} : \boldsymbol{\varepsilon}$$

s.t. $\mathbb{E}[\boldsymbol{\varepsilon}_{\boldsymbol{\zeta}}] = \boldsymbol{\varepsilon}$

Uncertain elastoplasticity with non-linear hardening

$$j(\varepsilon_\zeta, \alpha_\zeta) = \frac{1}{2} E_\zeta (\varepsilon_\zeta - \alpha_\zeta)^2 + \frac{1}{m} H_\zeta (\alpha_\zeta)^m + \sigma_{0\zeta} |\alpha_\zeta|$$

Primal formulation: ε as first-stage

$$j^{\text{eff}}(\varepsilon) = \inf_{\alpha_\zeta} \frac{1}{2} \mathbb{E} [E_\zeta (\varepsilon - \alpha_\zeta)^2] + \frac{1}{m} \mathbb{E} [H_\zeta (\alpha_\zeta)^m] + \mathbb{E} [\sigma_{0\zeta} |\alpha_\zeta|]$$

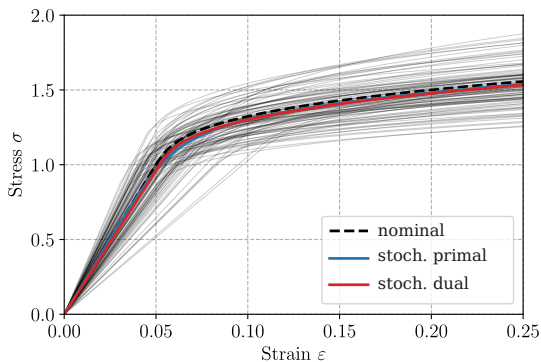
Dual formulation: σ as first-stage

$$j^{\text{eff}}(\varepsilon) = \inf_{e_\zeta, \alpha_\zeta} \frac{1}{2} \mathbb{E} [E_\zeta (\varepsilon + e_\zeta - \alpha_\zeta)^2] + \frac{1}{m} \mathbb{E} [H_\zeta (\alpha_\zeta)^m] \\ + \sup_{\zeta} [\sigma_0(\zeta) |\alpha_\zeta|] \\ \text{s.t. } \mathbb{E}[e_\zeta] = 0$$

⇒ note how free energy and dissipation are **treated differently!** \mathbb{E} vs \sup

Numerical results

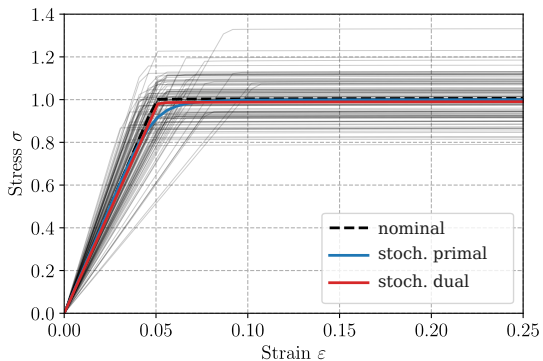
Monte-Carlo sampling approximation: GSM with N internal variables solved using `cvxpy`, 30 load steps



Hardening case $\bar{H} = \bar{E}/20$

Numerical results

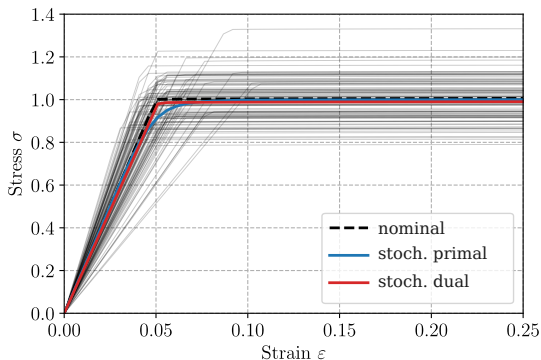
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Nearly perfectly plastic case $\bar{H} = \bar{E}/2000$

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Monte-Carlo sampling approximation: GSM with N internal variables solved using `cvxpy`, 30 load steps



Nearly perfectly plastic case $\bar{H} = \bar{E}/2000$

some differences: **progressive plasticity** onset ("structural hardening"), **almost similar yield strength** $\mathbb{E}[X] \approx \mathbb{E}[X^{-1}]^{-1}$ for lognormal variables with small variance

Outline

- ① Average effective behavior
- ② Risk-averse estimates
- ③ Optimisitic and pessimistic structural response

Risk-averse measures

Risk-measure \mathcal{R} : assume X be a **random cost**: $\mathbb{E}[X] = \text{OK}$ whereas $\mathcal{R}[X] = \text{BAD}$ e.g.:

- the safety margin $\mathcal{R}[X] = \mathbb{E}[X] + k \text{std}[X]$, for $k > 0$
- the worst-case value: $\mathcal{R}[X] = \sup X$
- the *Value-at-Risk* (VaR) for a level $\beta \in [0; 1]$ (or the β -quantile):

$$\mathcal{R}[X] = \text{VaR}_\beta(X) = \inf\{Z \text{ s.t. } \mathbb{P}[Z \geq X] \geq \beta\}$$

- and many more...

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 \Rightarrow **coherent risk measures** [Artzner, 1999]

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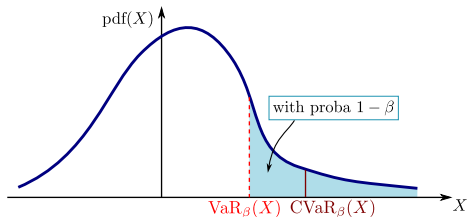
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- **safety margin** and **VaR** are **not coherent**
- **worst-case value** is coherent but **too conservative**
- **expected value** is coherent but **risk-neutral**

Conditional Value-at-Risk (CVaR)

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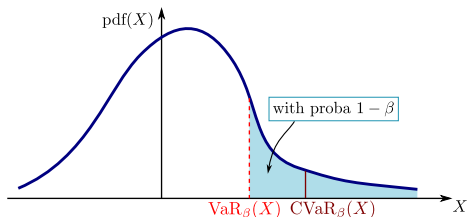
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Key result: convex optimization characterization

$$\text{CVaR}_\beta(X) = \inf_{\lambda} \lambda + \frac{1}{1-\beta} \mathbb{E}[\langle X - \lambda \rangle_+]$$

Extends to **random convex functions**:

$$\boxed{\text{CVaR}_\beta(f)(x) = \inf_{\lambda} \lambda + \frac{1}{1-\beta} \mathbb{E}[\langle f(x; \zeta) - \lambda \rangle_+]} \text{ is convex}$$

Examples

1D elasticity: $j(\varepsilon_\zeta; \zeta) = \frac{1}{2} E_\zeta \varepsilon_\zeta^2$

$$j^{\text{eff}}(\varepsilon) = \text{CVaR}_\beta(\psi)(\varepsilon) = \frac{1}{2} \text{CVaR}_\beta(E) \varepsilon^2$$

replaces uncertain Young modulus E_ζ with an **optimistic estimate** $\text{CVaR}_\beta(E)$

General case

take **CVaR** on **free-energy** and **dissipation potential** + ε first-stage

$$j^{\text{eff}}(\varepsilon) = \inf_{\alpha_\zeta} \text{CVaR}_\beta(\psi(\varepsilon, \alpha_\zeta; \zeta)) + \text{CVaR}_\beta(\phi(\alpha_\zeta; \zeta))$$

if $\beta = 0$, $\text{CVaR} = \mathbb{E}$ and we recover the **primal formulation** for the average behavior \Rightarrow results in **optimistic** stiffness, strength and hardening

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what about **pessimistic estimates** ?

Dual CVaR

need for a "left-tail" CVaR which still yields a **convex potential**
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$$j^{\text{eff}}(\varepsilon) = \text{dCVaR}_\beta(j)(\varepsilon) = \frac{1}{2} \text{CVaR}_\beta(E^{-1})^{-1} \varepsilon^2$$

seems OK: $\text{dCVaR}_0(E) = \mathbb{E}[E^{-1}]^{-1}$ and $\text{dCVaR}_1(E) = \sup\{E^{-1}\}^{-1}$

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But... not coherent, lacks **homogeneity**

⇒ for a plastic potential $\phi(\dot{\alpha}) = \sigma_{0\zeta} \dot{\alpha}$, we show that

$$\text{dCVaR}_\beta(\phi) = \inf_\zeta \sigma_{0\zeta} \dot{\alpha}$$

too pessimistic, irrespective of the confidence level β .

Correct dual CVaR

$$\boxed{\text{dCVaR}_\beta(j) = \text{CVaR}_\beta(j^\circ)^\circ}$$

where $f^\circ(\mathbf{x}) = \inf\{\mu \geq 0 \text{ s.t. } \mu f^*(\mathbf{x}/\mu) \leq 1\}$ is the **polar** of f [Rockafellar, 1970]

Properties:

- $f^\circ \geq g^\circ$ if $f \leq g$
- $j^\circ = j^*$ if j quadratic
- $\text{dCVaR}_\beta(\phi)(\dot{\alpha}) = \text{CVaR}_\beta(\sigma_0^{-1})^{-1} |\dot{\alpha}|$ for the plastic potential
- $\mathcal{R}[j] = \text{dCVaR}_\beta(j)$ is a **coherent risk measure**

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Convex representation

$$\text{dCVaR}_\beta(f)(\mathbf{x}) = \inf_{v \geq 0, \hat{\mathbf{x}}} \max \left\{ \mathbb{E}[vf(\hat{\mathbf{x}}/v; \zeta)]; (1 - \beta) \sup_{\zeta} \{vf(\hat{\mathbf{x}}/v; \zeta)\} \right\}$$

$$\text{s.t. } \mathbb{E}[\hat{\mathbf{x}}] = \mathbf{x}$$

$$\mathbb{E}[v] = 1$$

Risk-averse behavior of stochastic GSM

Optimistic estimate: take **CVaR** of **free-energy** and **dissipation potential** + ε as first-stage

$$j^{\text{eff}}(\varepsilon) = \inf_{\alpha_\zeta} \text{CVaR}_\beta(\psi(\varepsilon, \alpha_\zeta)) + \text{CVaR}_\beta(\phi(\alpha_\zeta))$$

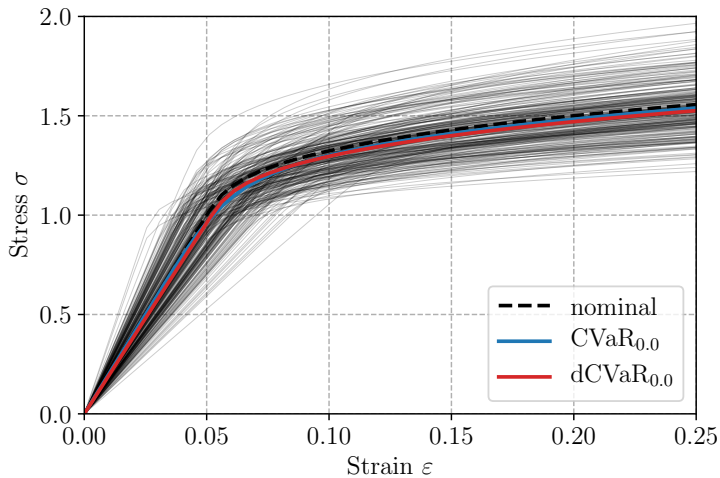
Pessimistic estimate: take **dCVaR** of **free-energy** and **dissipation potential** + σ as first-stage variable

$$j^{\text{eff}}(\varepsilon) = \inf_{\alpha_\zeta, \varepsilon_\zeta} \text{dCVaR}_\beta(\psi(\varepsilon_\zeta, \alpha_\zeta)) + \text{dCVaR}_\beta(\phi(\alpha_\zeta))$$

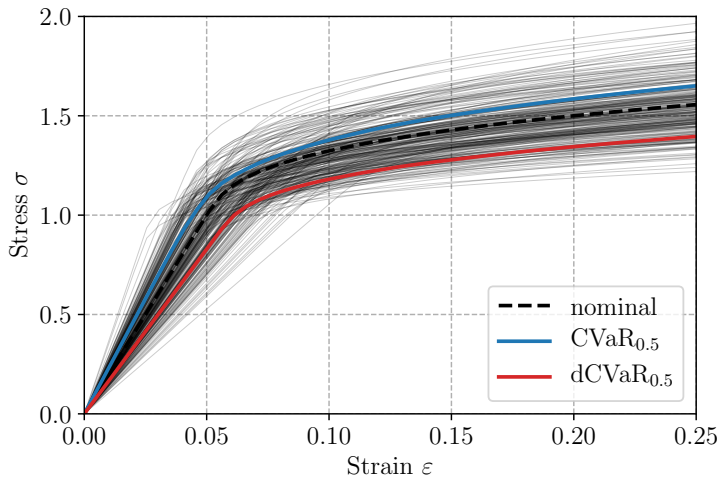
$$\mathbb{E}[\varepsilon_\zeta] = \varepsilon$$

we essentially recover the previous primal/dual **risk-neutral** formulations when $\beta = 0$

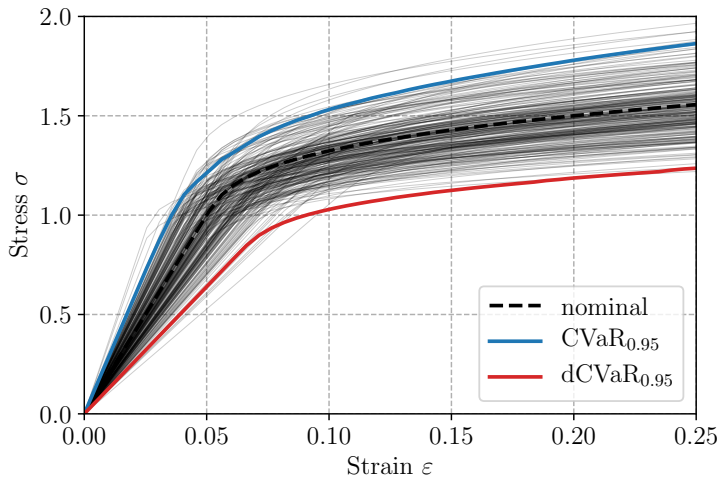
Numerical results

risk-neutral case $\beta = 0$

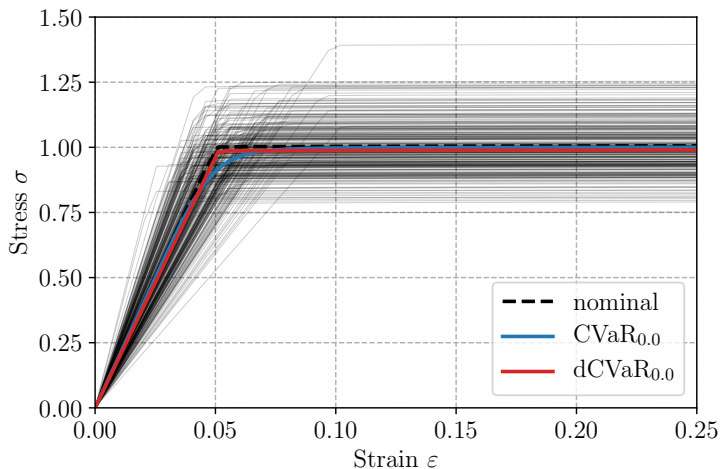
Numerical results

moderate risk-aversion $\beta = 0.5$

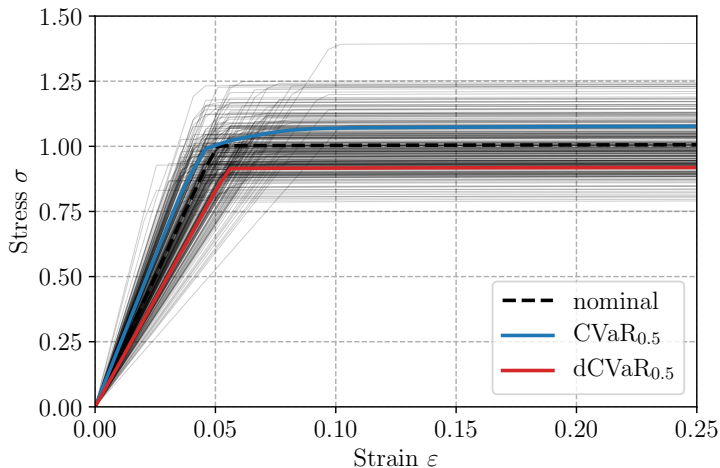
Numerical results

strong risk-aversion $\beta = 0.95$

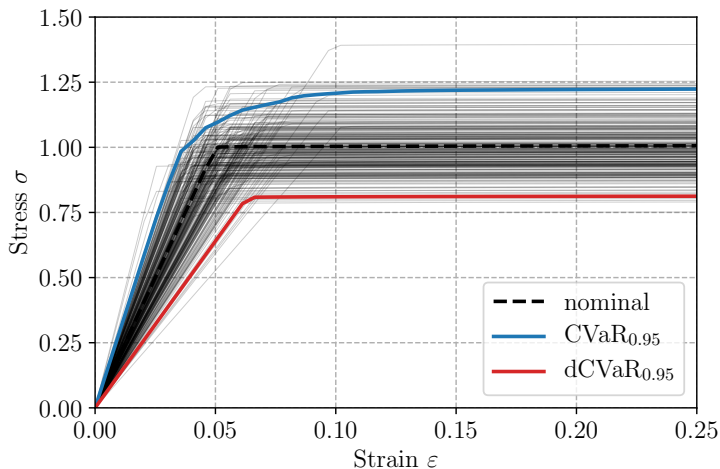
Numerical results

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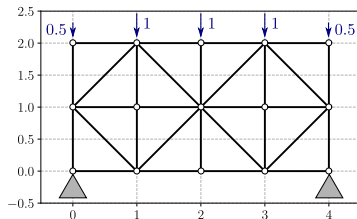
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- ① Average effective behavior
- ② Risk-averse estimates
- ③ **Optimistic and pessimistic structural response**

A truss example

Truss structure with members obeying stochastic elastoplastic hardening behaviour



Global nominal variational principle:

$$\mathbf{u}_{n+1}, \alpha_{n+1} = \arg \inf_{\mathbf{u} \in \mathcal{U}_{\mathbf{ad}}, \alpha} \int_{\Omega} \psi(\boldsymbol{\varepsilon}, \boldsymbol{\alpha}) \, d\Omega + \int_{\Omega} \phi(\boldsymbol{\alpha}) \, d\Omega - \langle \mathbf{F}, \mathbf{u} \rangle$$

Risk-neutral case: effective global potential obtained from local effective properties

$$\mathcal{R}[J](\boldsymbol{\varepsilon}) = \mathbb{E} \left[\int_{\Omega} j(\boldsymbol{\varepsilon}; \boldsymbol{\zeta}) \, d\Omega \right] = \int_{\Omega} \mathbb{E} [j](\boldsymbol{\varepsilon}) \, d\Omega = \int_{\Omega} \mathcal{R}[j](\boldsymbol{\varepsilon}) \, d\Omega$$

Risk-averse case: **does not work**, $\mathcal{R} = \text{CVaR}/\text{dCVaR}$ not additive

Risk-averse stochastic programming formulation

Work directly on the **global** free-energy and dissipation potentials:

Optimistic formulation:

$$\mathbf{u}_{n+1}, \alpha_{\zeta, n+1} = \arg \inf_{\mathbf{u} \in \mathcal{U}_{\mathbf{ad}}, \alpha_{\zeta}} \text{CVaR}_{\beta}(\Psi)(\varepsilon, \alpha_{\zeta}) + \text{CVaR}_{\beta}(\Phi)(\alpha_{\zeta}) - \langle \mathbf{F}, \mathbf{u} \rangle$$

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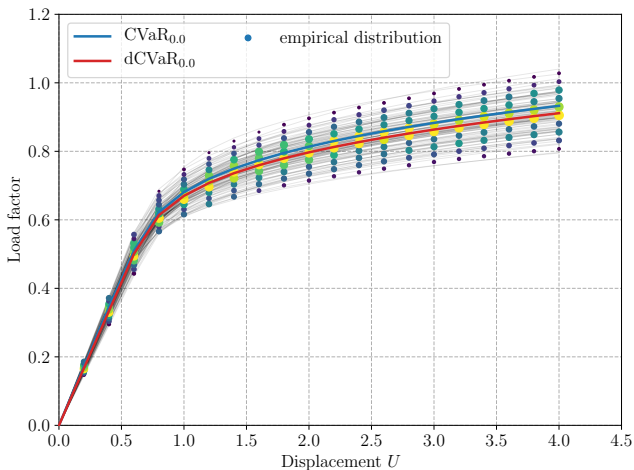
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$$\mathbf{u}_{n+1}, \alpha_{\zeta, n+1} = \arg \inf_{\mathbf{u} \in \mathcal{U}_{\mathbf{ad}}, \alpha_{\zeta}} \text{dCVaR}_{\beta}(\Psi)(\varepsilon, \alpha_{\zeta}) + \text{dCVaR}_{\beta}(\Phi)(\alpha_{\zeta}) - \langle \mathbf{F}, \mathbf{u} \rangle$$

Both of them are **2-stage convex stochastic programming** problems which can be solved using Monte-Carlo sampling approximation

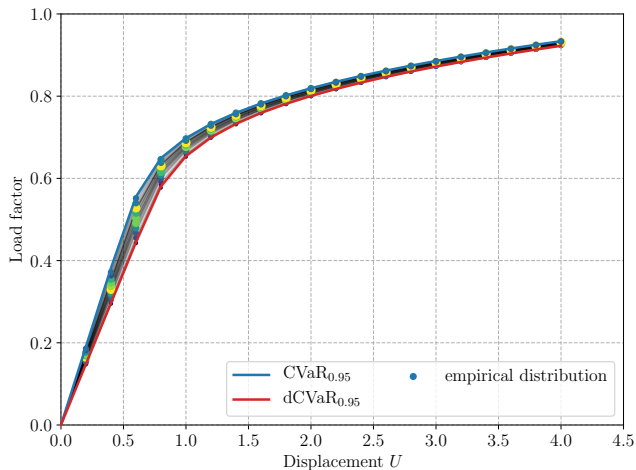
Illustrative application

Risk-neutral case



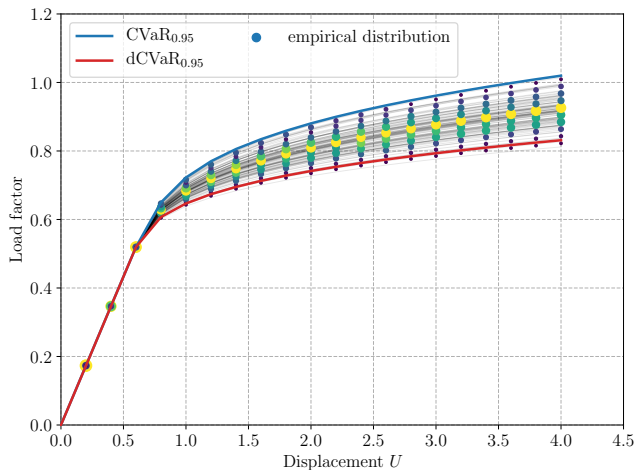
Illustrative application

Risk-averse case: uncertainty on Young modulus only



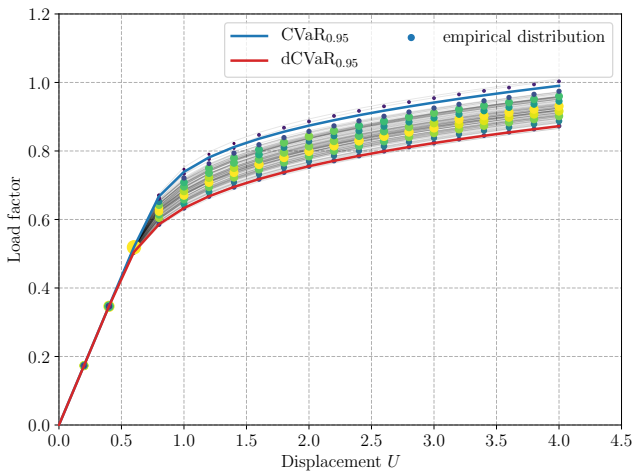
Illustrative application

Risk-averse case: uncertainty on **hardening modulus** only



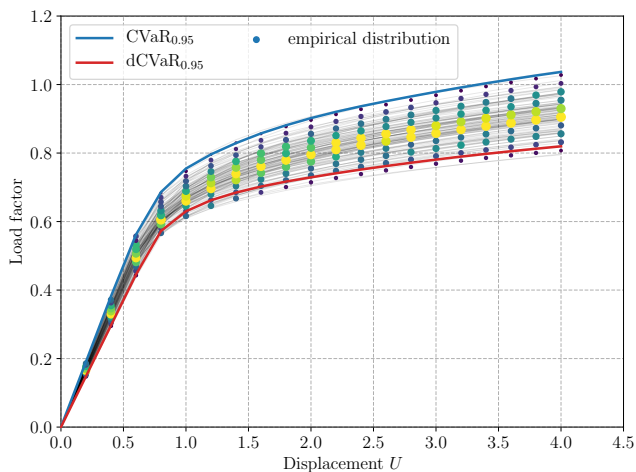
Illustrative application

Risk-averse case: uncertainty on yield stress only

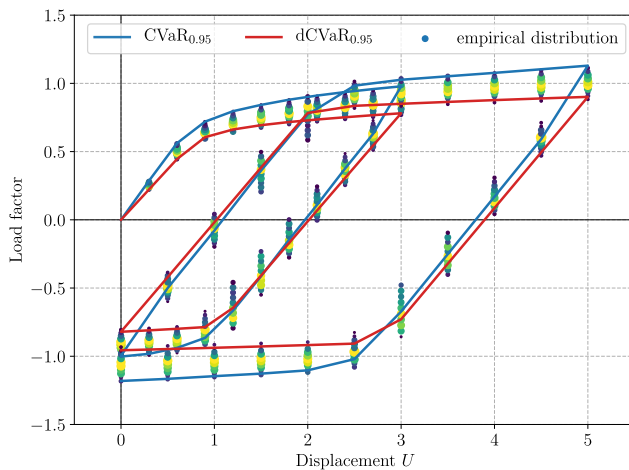


Illustrative application

Risk-averse case: combined uncertainty



Cyclic loading



Conclusions and Outlook

Conclusions

- **consistent formulation** of **effective stochastic** behaviour in the GSM setting
- introduce the concepts of **risk measures** to characterize tail distribution behaviors
- dCVaR as a **novel coherent risk measure**
- extension of risk-neutral and risk-averse formulations to **global structural scale**

<https://hal.science/hal-04076581>

Outlook

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- **active scenarios strategies** in Newton-Raphson loop
- **non-linear decision rules, Polynomial Chaos expansions**, etc.

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Thank you for your attention !