

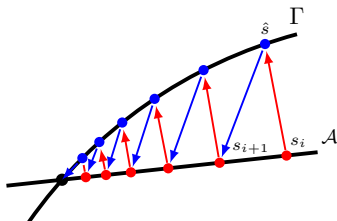
# Model order reduction for fatigue analysis

S. Alameddine<sup>†</sup>, A. Fau<sup>†</sup>,  
U. Nackenhorst<sup>†</sup>, D. Néron<sup>‡</sup>, P. Ladevèze<sup>‡</sup>

<sup>†</sup> IBNM, Leibniz Universität Hannover

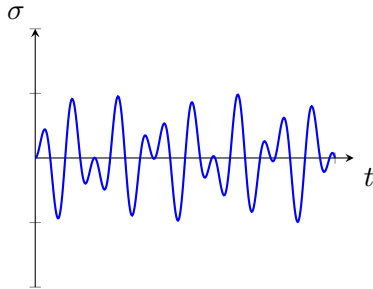
<sup>‡</sup> LMT, ENS Cachan, CNRS, Université Paris Saclay

29. August 2018



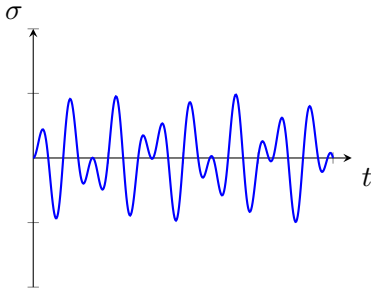
# Fatigue damage

## ■ Fluctuating loads



# Fatigue damage

## ■ Fluctuating loads



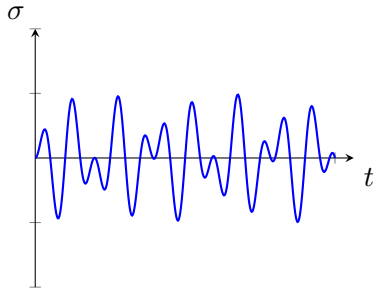
## ■ Material degradation



Image by alegri / 4freephotos.com

# Fatigue damage

■ Fluctuating loads



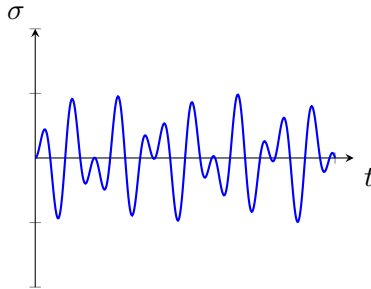
■ Material degradation



Image by alegri / 4freephotos.com

# Fatigue damage

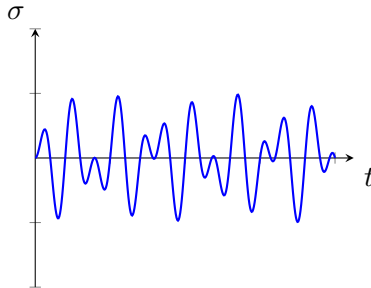
## ■ Fluctuating loads



- Virtual experiments
- Continuum damage model
- Millions of cycles
- Macro crack initiation
- Computationally expensive

# Fatigue damage

## ■ Fluctuating loads



## ■ Virtual experiments

## ■ Continuum damage model

## ■ Millions of cycles

## ■ Macro crack initiation

## ■ Computationally expensive

Model order reduction (MOR) techniques

# Outline

- 1 State of art
- 2 Reduced order model for cyclic loading
- 3 Numerical examples
- 4 Conclusions and future research

# Outline

- 1 State of art
- 2 Reduced order model for cyclic loading
- 3 Numerical examples
- 4 Conclusions and future research



# ROM for non-linear problems

- Short-term damage computations
  - Proper orthogonal decomposition (POD)
 

[Kerfriden et al, 2011-2012, Ryckelynck, 2005-2011].
  - Proper generalised decomposition (PGD)
 

[Bhattacharyya et al, 2017].
- Long-term fatigue computations
  - Temporal homogenisation
 

[Fish and Yu, 2002; Devulder et al, 2010]
  - Space-time finite element method
 

[Oden, 1969; Bhamare, 2014; Fritzen and Hassani, 2018]
  - Modified jump cycle approach
 

[Bhattacharyya et al, 2018]

# Previous works with LATIN

- An approach to include damage in a LATIN-PGD framework 😊
- Modified jump cycle approach to tackle large number of cycles 😊
- Limited to specific models and constant amplitude loads ☹
- No two-time scale, no time savings and many modes are generated ☹
- Generalised formulation for different nonlinear material models
- Efficient variable amplitude simulations

# Outline

- 1 State of art
- 2 Reduced order model for cyclic loading
- 3 Numerical examples
- 4 Conclusions and future research

# Mechanical problem

## Admissibility equations

### ■ Static admissibility

$$\nabla \cdot \boldsymbol{\sigma} + \mathbf{b} = \mathbf{0} \quad \text{in } \Omega$$

$$\boldsymbol{\sigma} \cdot \mathbf{n} = \bar{\mathbf{t}} \quad \text{on } \partial\Omega_N$$

### ■ Kinematic admissibility

$$\boldsymbol{\varepsilon} = \nabla^s \mathbf{u} \quad \text{in } \Omega$$

$$\mathbf{u} = \bar{\mathbf{u}} \quad \text{on } \partial\Omega_D$$

## Nonlinear material model

### ■ State equations

$$\boldsymbol{\sigma} = \mathbf{f}(\boldsymbol{\psi}, \boldsymbol{\varepsilon}^e)$$

$$\boldsymbol{\beta} = \mathbf{g}(\boldsymbol{\psi}, \boldsymbol{\alpha})$$

$$Y = \mathbf{q}(\boldsymbol{\psi}, D)$$

### ■ Evolution equations

$$\dot{\boldsymbol{\varepsilon}}^p = \hat{\mathbf{f}}(\boldsymbol{\phi}, \boldsymbol{\sigma})$$

$$\dot{\boldsymbol{\alpha}} = \hat{\mathbf{g}}(\boldsymbol{\phi}, \boldsymbol{\beta})$$

$$\dot{D} = \hat{\mathbf{q}}(\boldsymbol{\phi}, D)$$

# Solution algorithm

- Many LATIN algorithms for different non-linear problems
- A combination with some modifications

- Local stage, given initial conditions

Solve the state and evolution equations to get  $\hat{s}$

- Global stage

Solve the admissibility equations to get  $s_{i+1}$

- Data flow between these stages

$$(\hat{\sigma} - \sigma_i) + \mathbb{H}^+ (\hat{\varepsilon} - \varepsilon_i) = 0$$

$$(\sigma_{i+1} - \hat{\sigma}) - \mathbb{H}^- (\varepsilon_{i+1} - \hat{\varepsilon}) = 0$$

- Iterate until convergence with an energy error indicator

$$\xi = \frac{\|s_{i+1} - \hat{s}\|}{\frac{1}{2} \|s_{i+1} + \hat{s}\|}, \quad \|s\|^2 = \int_{[0,T] \times \Omega} (\sigma : \mathbb{C}^{-1} \sigma + \varepsilon : \mathbb{C} \varepsilon) \, d\Omega \, dt$$

# The global stage

## ■ Weak form at iteration $i + 1$

$$\int_{[0,T] \times \Omega} \boldsymbol{\sigma}_{i+1} : \boldsymbol{\varepsilon}(u^*) \, d\Omega \, dt = \int_{[0,T] \times \Omega} \mathbf{b} \cdot u^* \, d\Omega \, dt + \int_{[0,T] \times \partial\Omega_N} \bar{\mathbf{t}} \cdot u^* \, dS \, dt, \quad \forall u^* \in \mathcal{U}_0$$

## ■ Correction $\Delta \bullet_{i+1} = \bullet_{i+1} - \bullet_i$

$$\Delta \boldsymbol{\sigma}_{i+1} - \mathbb{H}^- \Delta \boldsymbol{\varepsilon}_{i+1} - \hat{\mathbf{f}} = \mathbf{0}, \quad \hat{\mathbf{f}} = \underbrace{(\hat{\boldsymbol{\sigma}} - \boldsymbol{\sigma}_i) - \mathbb{H}^-(\hat{\boldsymbol{\varepsilon}} - \boldsymbol{\varepsilon}_i)}_{\text{known}}$$

$$\int_{[0,T] \times \Omega} \Delta \boldsymbol{\sigma}_{i+1} : \boldsymbol{\varepsilon}(\Delta u^*) \, d\Omega \, dt = 0$$

# Proper Generalised Decomposition

- Low-rank approximation of the solution

$$u(\mathbf{x}, t) = \sum_{i=1}^N \lambda_i(t) v_i(\mathbf{x})$$

- Enriching with one mode

$$\Delta u = \lambda(t) v(\mathbf{x}) \quad \Delta u^* = \lambda^* v + \lambda v^*$$

- Updating ( $\mu$ ) previously generated time modes

$$\Delta u = \sum_{i=1}^{\mu} \Delta \lambda_i(t) \underbrace{v_i(\mathbf{x})}_{known}$$

# Static admissibility

- Static admissibility and global search direction

$$\int_{[0,T] \times \Omega} \mathbb{H}^- \Delta \epsilon_{i+1} : \epsilon(\Delta u^*) \, d\Omega \, dt = - \int_{[0,T] \times \Omega} \hat{f} : \epsilon(\Delta u^*) \, d\Omega \, dt$$

- Space problem:  $\langle \bullet \rangle = \int_{[0,T]} \bullet \, dt$ , given  $\lambda_j$

$$\langle \lambda_j \lambda_j \rangle \int_{\Omega} \nabla v^* : \mathbb{H}^- \nabla v_{j+1} \, d\Omega = - \langle \lambda_j \rangle \int_{\Omega} \nabla v^* : \hat{f} \, d\Omega$$

- Time problem, given  $v_{j+1}$ :

$$\int_{[0,T]} \lambda^* \left[ \int_{\Omega} \nabla v_{j+1} : \mathbb{H}^- \nabla v_{j+1} \, d\Omega \right] \lambda_{j+1} \, dt = - \langle \lambda^* \rangle \int_{\Omega} \nabla v_{j+1} : \hat{f} \, d\Omega$$



# Algorithmic point of view

- Choosing the search directions as

$$\mathbb{H}^+ = 0, \quad \mathbb{H}^- = \alpha \mathbb{C} \quad \alpha \in ]0, 1]$$

- Enrichment

$$\begin{aligned} \gamma \underline{\underline{K}} \underline{v}_{i+1} &= \underline{F} & \gamma \in \mathbb{R} & \quad \underline{\underline{K}} \in \mathbb{R}^{n \times n} & \quad \underline{F} \in \mathbb{R}^n \\ a \underline{\lambda}_{i+1} &= \underline{b} & a \in \mathbb{R} & \quad \quad b \in \mathbb{R}^{n_t} \end{aligned}$$

- Update

$$\underline{\underline{A}} \{ \Delta \underline{\lambda}_i \} = \underline{b} \quad \underline{\underline{A}} \in \mathbb{R}^{N \times N} \quad \underline{b} \in \mathbb{R}^{N \times n_t}$$

# Multiple cycles with variable load amplitudes

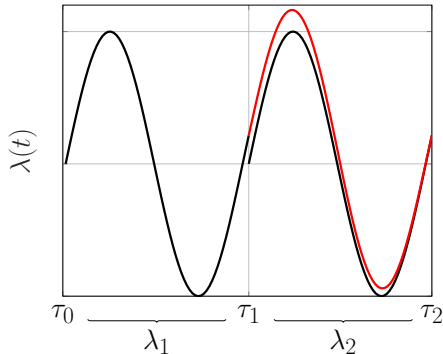
- The stiffness
- The elastic solution
- An initial guess

# Multiple cycles with variable load amplitudes

- The stiffness  
Computed only once
- The elastic solution  
Only once and parametrised over the load amplitude
- An initial guess  
From the previous cycle

# The initial guess

- Time modes are shifted and scaled to ensure continuity



$$\lambda_2(t) = \lambda_1(t) + a t + b$$

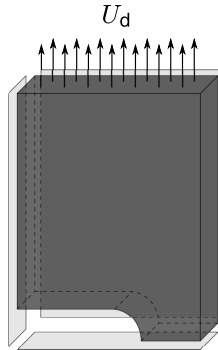
$$\lambda_2(\tau_1) = \lambda_1(\tau_1) \quad \lambda_2(\tau_2) = \lambda_1(\tau_2)$$

# Outline

- 1 State of art
- 2 Reduced order model for cyclic loading
- 3 Numerical examples
- 4 Conclusions and future research

# Numerical results

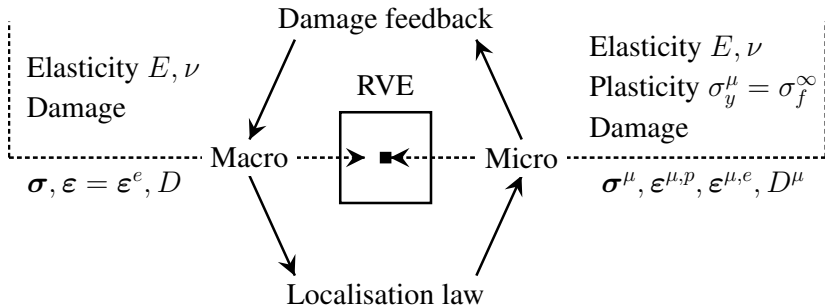
- A plate with a central groove subjected to cyclic loading (Cr-Mo steel at 20°C and 580°C)



# Quasi-brittle material model

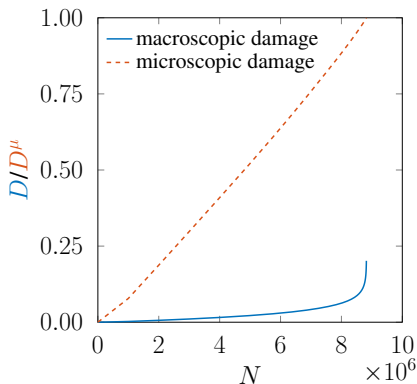
In collaboration with Bhattacharyya and Desmorat

## ■ Two-scale damage model



## ■ With an adaptive jump cycle algorithm

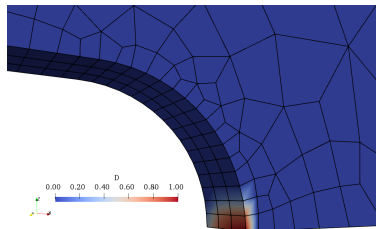
# Damage evolution



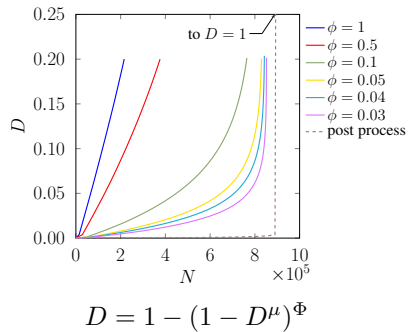
Damage evolution at the weakest Gauss point



# Damage behaviour



Damage distribution  
at the micro-scale



# Visco-plastic material model

## ■ State equations

$$\sigma = \mathbb{C} \varepsilon^e (1 - D)$$

$$\beta = C \alpha$$

$$Y = \frac{1}{2} \varepsilon^e : \mathbb{C} \varepsilon^e$$

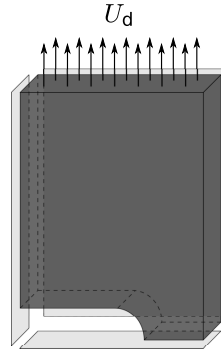
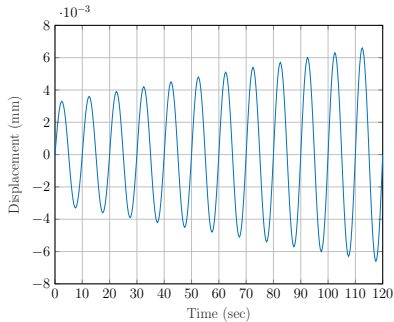
## ■ Evolution equations

$$\dot{\varepsilon}^p = k \langle f^p \rangle_+^n \left[ \frac{3}{2} \frac{\tau}{J_2(\tau)} \right] \frac{1}{1 - D}$$

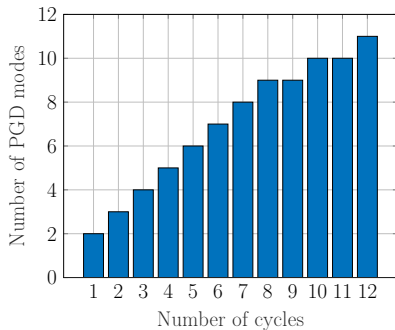
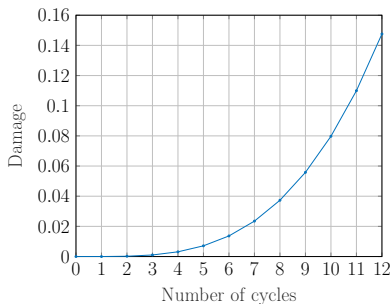
$$\dot{\alpha} = k \langle f^p \rangle_+^n \left[ \frac{3}{2} \frac{\tau}{J_2(\tau)} - \frac{a}{C} \beta \right]$$

$$\dot{D} = k_d \langle f^d \rangle_+^{n_d}$$

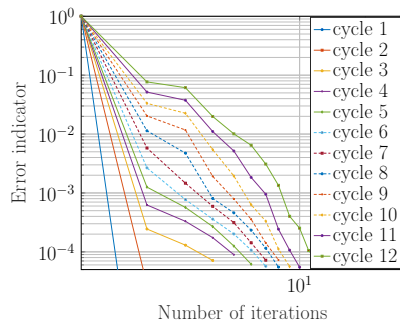
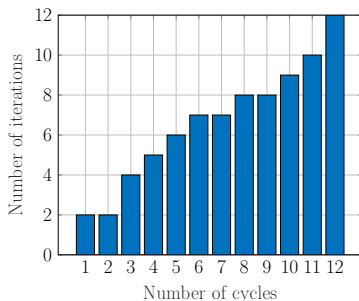
# Variable amplitude



# Variable amplitude

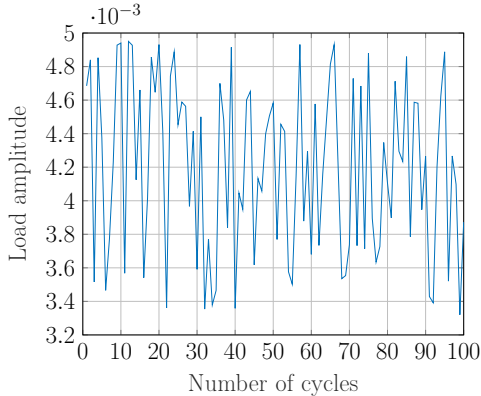


# Variable amplitude



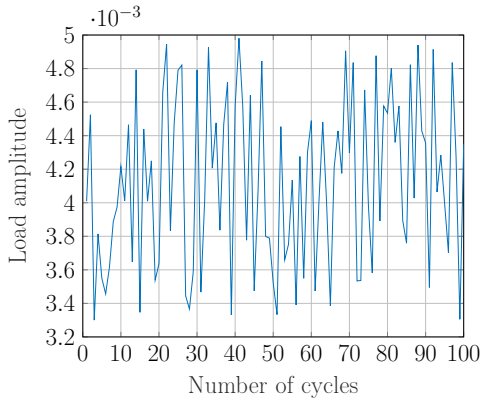
# Random amplitudes

## Cyclic load with the random amplitudes



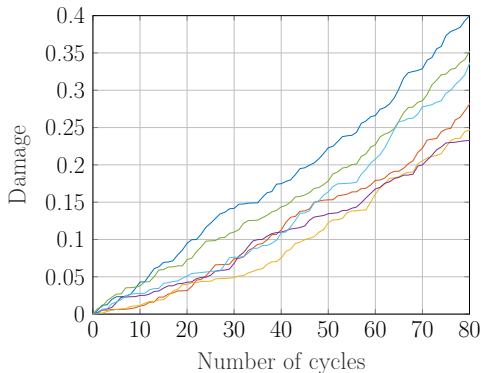
# Random amplitudes

## Cyclic load with the random amplitudes



# Random amplitudes

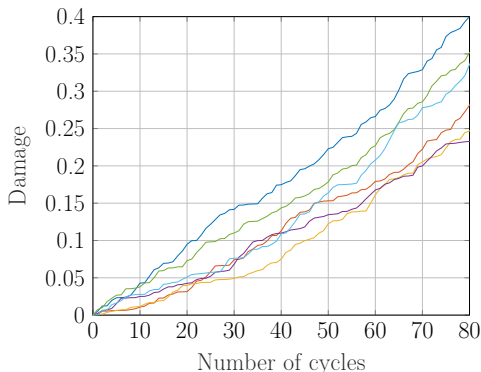
Cyclic load with the random amplitudes





# Random amplitudes

Cyclic load with the random amplitudes



Number of modes is less than 20

# Outline

- 1 State of art
- 2 Reduced order model for cyclic loading
- 3 Numerical examples
- 4 Conclusions and future research**

## Conclusion and future research

- Efficient cycle by cycle simulation for damage problems.
- Works for low and high cycle fatigue.

# Conclusion and future research

- Efficient cycle by cycle simulation for damage problems.
- Works for low and high cycle fatigue.

## Challenges

- The computation of the local stage.
- The integration of the error indicator and the time update.

# Conclusion and future research

- Efficient cycle by cycle simulation for damage problems.
- Works for low and high cycle fatigue.

## Challenges

- The computation of the local stage.
- The integration of the error indicator and the time update.

## Future development

- Machine learning in the local stage.
- Reduced integration scheme.

## Conclusion and future research

- Efficient cycle by cycle simulation for damage problems.
- Works for low and high cycle fatigue.

### Challenges

- The computation of the local stage.
- The integration of the error indicator and the time update.

### Future development

- Machine learning in the local stage.
- Reduced integration scheme.

Thank you for your attention

# Github repository

<https://github.com/dbeurle/neon>

# Quasi-brittle material model

Eshelby-Kröner localisation law

$$(\epsilon^\mu - \epsilon) = \gamma (\epsilon^{\mu,p} - \epsilon^p),$$

where  $\gamma$  is the Eshelby coefficient given by

$$\gamma = \frac{2}{15} \frac{4 - 5\nu}{1 - \nu}.$$



# Quasi-brittle material model

## ■ State equations

$$\tilde{\sigma}^{\mu} = \mathbf{C} \varepsilon^{\mu, e}$$

$$Y^{\mu} = R_v \frac{(\tilde{\sigma}_{eq}^{\mu})^2}{2E}$$

$$\beta^{\mu} = \mathbf{Q} \alpha^{\mu}$$

## ■ Evolution equations

$$\dot{\varepsilon}^{\mu, p} = \frac{3}{2} \frac{\tilde{\sigma}^{\mu} - \beta^{\mu}}{(\tilde{\sigma}^{\mu} - \beta^{\mu})_{eq}} \frac{\dot{\lambda}_p}{1 - D^{\mu}}$$

$$\dot{\alpha}^{\mu} = \frac{3}{2} \frac{\tilde{\sigma}^{\mu} - \beta^{\mu}}{(\tilde{\sigma}^{\mu} - \beta^{\mu})_{eq}} \dot{\lambda}_p$$

$$\dot{D}^{\mu} = \left( \frac{Y^{\mu}}{S} \dot{p}^{\mu} \right)^s$$

# Crack closure effect

The effective stress

$$\tilde{\sigma} = \frac{\sigma_D}{1-D} + \left[ \frac{\langle \sigma_H \rangle}{1-D} + \langle -\sigma_H \rangle \right] \mathbb{I}$$

The triaxiality function

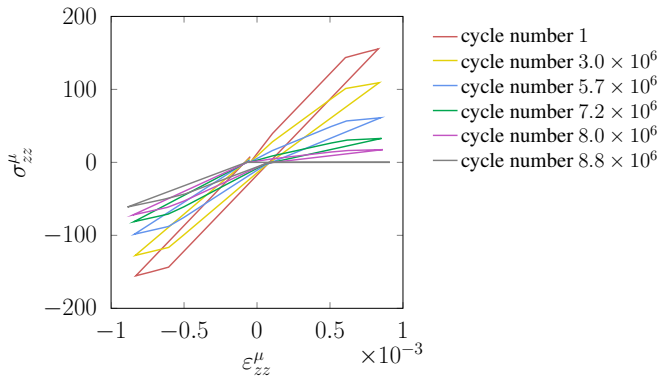
$$R_v = \frac{2}{3} (1 + \nu) + 3 (1 - 2\nu) \left\langle \frac{\sigma_H^\mu}{\sigma_{eq}^\mu} \right\rangle^2$$

$$\sigma_{eq}^\mu = \sqrt{\frac{3}{2} \sigma_{D_{ij}}^\mu \sigma_{D_{ij}}^\mu} \quad \tilde{\sigma}_{eq}^\mu = \sqrt{\frac{3}{2} \tilde{\sigma}_{D_{ij}}^\mu \tilde{\sigma}_{D_{ij}}^\mu}$$

The micro-scale yield function  $f^\mu$  is given as

$$f^\mu = (\tilde{\sigma}_D^\mu - \beta^\mu)_{eq} - \sigma_f^\infty,$$

# Stress-strain response



Stress-strain diagram at certain cycles at the micro-scale

# Visco-plastic material model

## ■ Free energy function

$$\psi(\epsilon^e, \alpha, D) = \frac{1}{2} \epsilon^e : \mathbb{C}(1 - D) \epsilon^e + \frac{1}{2} C \alpha : \alpha$$

## ■ Dissipation potential

$$\phi = \phi^p + \phi^d$$

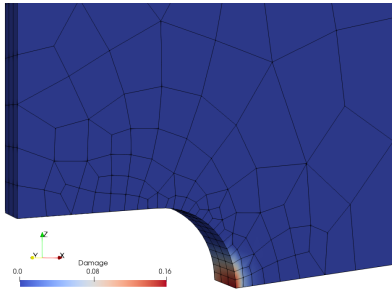
$$\phi^p = \frac{k_p}{n_p + 1} \langle f^p \rangle_+^{n_p + 1}, \quad f^p = J_2(\tau) + \frac{a}{2C} \beta : \beta - \sigma_y$$

$$\phi^d = \frac{k_d}{n_d + 1} \langle f^d \rangle_+^{n_d + 1}, \quad f^d = Y - Y_0$$

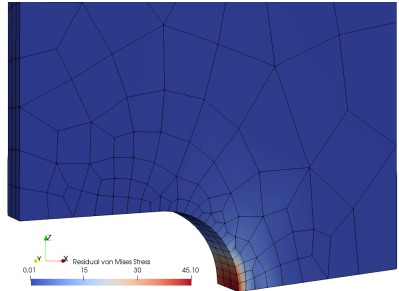
$$\sqrt{3}$$

$$\sigma^{\text{dev}}$$

# Variable amplitude

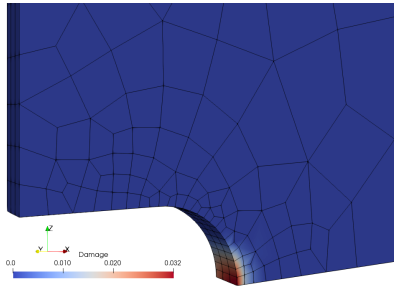


Damage distribution

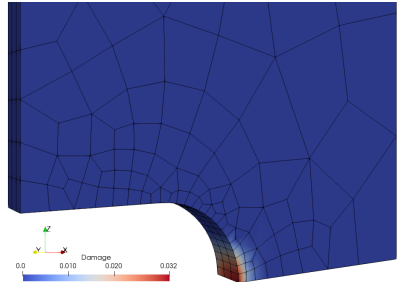


Von Mises stress distribution

# Numerical results



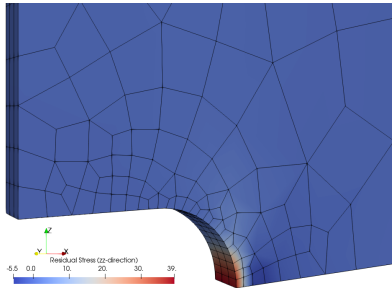
Newton-Raphson



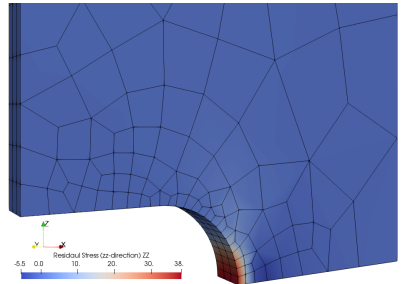
LATIN-PGD

Damage contour at the last time step

# Numerical results



Newton-Raphson



LATIN-PGD

Residual stress distribution after removing the load

# Differences

- State equations in the local stage
- PGD for the strain instead of the plastic one
- Cycle by cycle
- Modes rescaling



