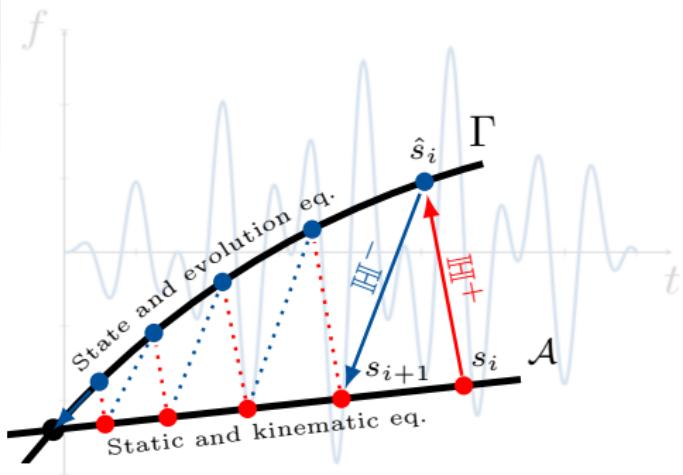


# A Semi-incremental Model Order Reduction Approach for Fatigue Damage Computations

Shadi Alameddin

IBNM, Leibniz Universität Hannover  
06. February 2020



IRTG-1627



Deutsche  
Forschungsgemeinschaft

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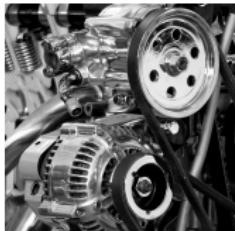
IRTG-1627

**DFG**

Deutsche  
Forschungsgemeinschaft

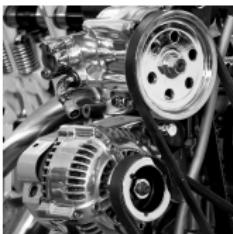
# Fatigue damage

## ■ Fluctuating loads



# Fatigue damage

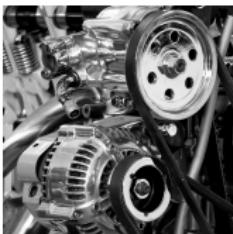
- Fluctuating loads



- Large number of load cycles  
thousands or millions
- Material degradation  
lower load carrying capacity
- Continuum damage model  
damage evolution in rate form
- Computational expense  
memory and time

# Fatigue damage

- Fluctuating loads



- Large number of load cycles  
thousands or millions
- Material degradation  
lower load carrying capacity
- Continuum damage model  
damage evolution in rate form
- Computational expense  
memory and time

## Model order reduction (MOR) techniques

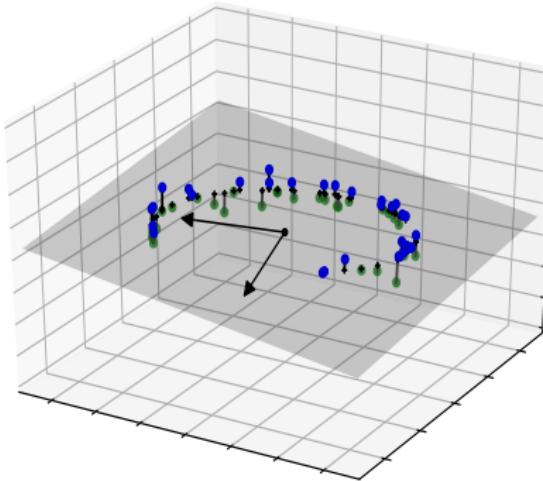
- 1** Reduced order model for cyclic loading
- 2** Challenges and workarounds
- 3** Numerical examples
- 4** Conclusions and current research

- 1 Reduced order model for cyclic loading**
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- 3 Numerical examples**
- 4 Conclusions and current research**

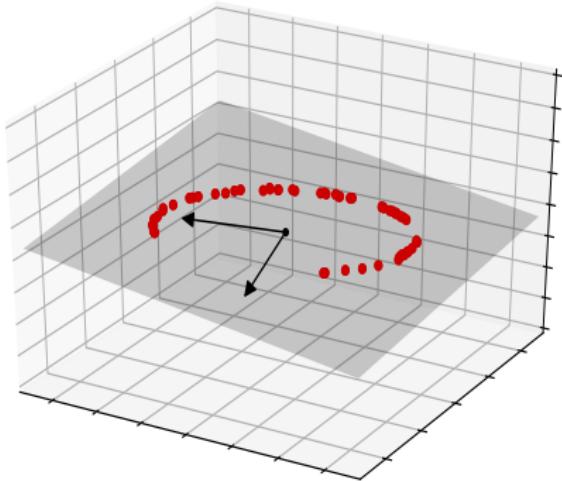
# Dimensionality Reduction

Projection-based approach

Solutions lie close to a low-dimensional subspace



High-dimensional space



2D subspace

# Mechanical problem

Infinitesimal strain and isothermal quasi-static settings

## Admissibility equations (**AD**)

Static admissibility

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

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

$$\boldsymbol{\sigma} = \boldsymbol{\sigma}^T$$

Kinematic admissibility

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

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

## Nonlinear constitutive model (**CM**)

State equations

$$\mathcal{F} = f(\psi(\boldsymbol{\varepsilon}, \mathcal{I}))$$

Evolution equations

$$\dot{\mathcal{I}} = g(\phi^*(\boldsymbol{\sigma}, \mathcal{F}))$$

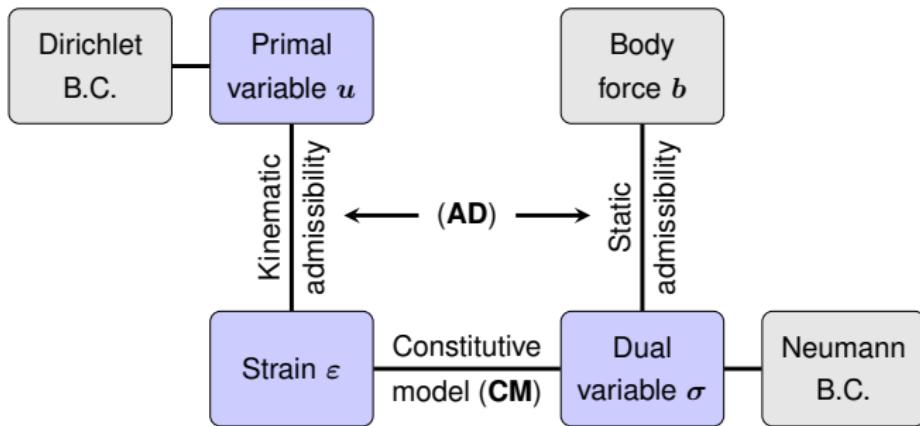
[GSM by Halphen & Nguyen 1975]

# LATIN vs. incremental schemes

LATIN: large time increment

An **incremental** scheme:

Solve



for each time step **consecutively**.

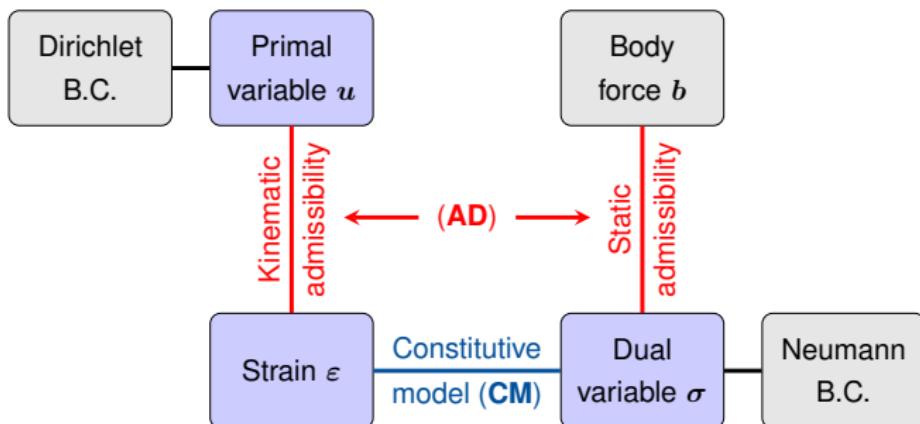
[de Souza Neto 2008]

# LATIN vs. incremental schemes

LATIN: large time increment

A **LATIN** scheme:

Solve iteratively (**AD**) and (**CM**)



for all time steps **simultaneously**.

[Ladevèze 1989, 1999; Néron et al 2012]

# What does simultaneously mean?

école  
normale  
supérieure  
paris-saclay

l i l  
i o 2  
l o d 4

Leibniz  
Universität  
Hannover

# What does simultaneously mean?

école  
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# LATIN solution algorithm

- Elastic initialisation  $\{(\boldsymbol{\varepsilon}_i, \mathcal{I}_i), (\boldsymbol{\sigma}_i, \mathcal{F}_i) \mid i = 0\}$

- Evaluate **(CM)** at the local stage

given( $\boldsymbol{\sigma}_i, \mathcal{F}_i$ )      seek( $\boldsymbol{\varepsilon}_{\text{local}}, \mathcal{I}_{\text{local}}, \mathcal{F}_{\text{local}}$ )

- Transfer data using affine relation (search direction eq.)

$$(\boldsymbol{\sigma}_{\text{global}} - \boldsymbol{\sigma}_{\text{local}}) - \alpha \mathbb{C} : (\boldsymbol{\varepsilon}_{\text{global}} - \boldsymbol{\varepsilon}_{\text{local}}) = \mathbf{0} \quad \alpha \in ]0, 1]$$

- Solve **(AD)** to get  $(\boldsymbol{\sigma}_{\text{global}}, \boldsymbol{\varepsilon}_{\text{global}})$  at the global stage

- Iterate until convergence with an energy error indicator

$$\xi^2 = \frac{1 + \alpha^2}{2T} \int_{\Omega \times \mathcal{T}} (\boldsymbol{\varepsilon}_{\text{global}} - \boldsymbol{\varepsilon}_{\text{local}}) : \mathbb{C} : (\boldsymbol{\varepsilon}_{\text{global}} - \boldsymbol{\varepsilon}_{\text{local}}) \, d\Omega \, dt$$

# LATIN solution algorithm

- Elastic initialisation  $\{(\boldsymbol{\varepsilon}_i, \mathcal{I}_i), (\boldsymbol{\sigma}_i, \mathcal{F}_i) \mid i = 0\}$

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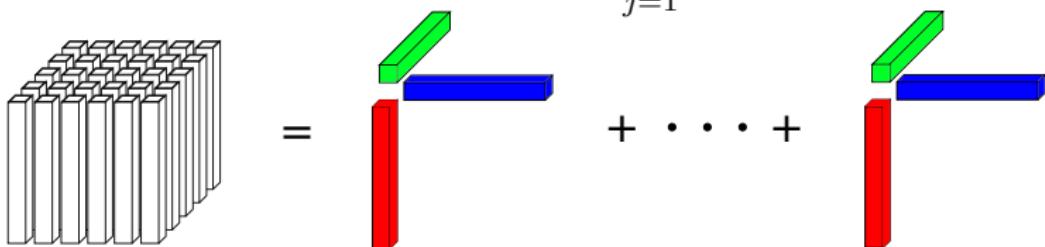
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# Proper Generalised Decomposition

as set of linear subspaces

- Low-rank approximation  $u(x, t, \bullet) = \sum_{j=1}^N \mathbf{v}_j(\mathbf{x}) \circ \boldsymbol{\lambda}_j(t) \circ \boldsymbol{\gamma}(\bullet)$



[Chinesta and Ladevèze 2014]

# Proper Generalised Decomposition

as set of linear subspaces

- Update of  $\mu$  previously generated modes

$$\Delta \mathbf{u}_{i+1}(\mathbf{x}, t, \bullet) = \sum_{j=1}^{\mu} \underbrace{\mathbf{v}_j(\mathbf{x})}_{\text{const.}} \circ \boxed{\Delta \boldsymbol{\lambda}_j(t)} \circ \underbrace{\boldsymbol{\gamma}_j(\bullet)}_{\text{const.}}$$

- Enrichment to  $\mu$  previously generated modes

$$\Delta \mathbf{u}_{i+1}(\mathbf{x}, t, \bullet) = \mathbf{v}_{\mu+1}(\mathbf{x}) \circ \boldsymbol{\lambda}_{\mu+1}(t) \circ \boldsymbol{\gamma}_{\mu+1}(\bullet)$$

$$\Delta \mathbf{u}_{i+1}(\mathbf{x}, t, \bullet) = \sum_{j=1}^{\mu} \underbrace{\mathbf{v}_j(\mathbf{x})}_{\text{const.}} \circ \boxed{\Delta \boldsymbol{\lambda}_j(t)} \circ \underbrace{\boldsymbol{\gamma}_j(\bullet)}_{\text{const.}} + \text{new term}$$

# Alternated directions algorithm

Galerkin finite element discretisation

## ■ Temporal update step

$$\underline{\tilde{A}} \underline{\tilde{\Lambda}}^T = \underline{\tilde{B}} \quad \underline{\tilde{A}} \in \mathbb{R}^{\mu \times \mu} \quad \underline{\tilde{B}} \in \mathbb{R}^{\mu \times n_t}$$
$$\underline{\tilde{\Lambda}} = [\Delta \lambda_1, \dots, \Delta \lambda_\mu]$$

## ■ Spatial problem, with homogeneous boundary conditions

$$\underline{\underline{K}} \underline{v} = \underline{f} \quad \underline{\underline{K}} \in \mathbb{R}^{n \times n} \quad \underline{v}, \underline{f} \in \mathbb{R}^n$$

Temporal problem, with zero initial conditions

$$a \underline{\lambda} = \underline{b} \quad a \in \mathbb{R} \quad \underline{\lambda}, \underline{b} \in \mathbb{R}^{n_t}$$

1 Reduced order model for cyclic loading

2 Challenges and workarounds

3 Numerical examples

4 Conclusions and current research

# Challenges in a PGD framework

- Efficient variable amplitude and frequency scenarios

$$\int_{\Omega} \bullet \, d\Omega \quad \int_{\mathcal{T}} \bullet \, dt$$

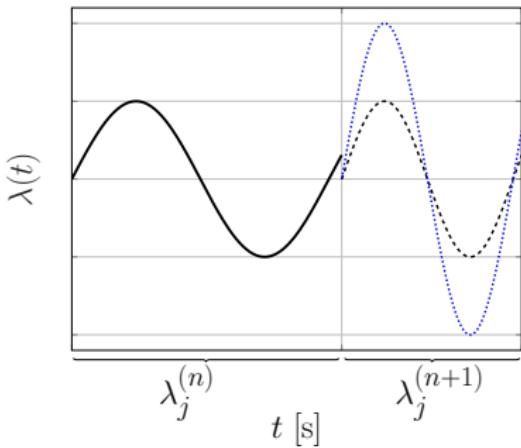
- The fast increase in the number of modes

$$\boldsymbol{u}(\boldsymbol{x}, t) = \sum_{j=1}^{\mu} \boldsymbol{v}_j(\boldsymbol{x}) \circ \boldsymbol{\lambda}_j(t) \text{ with large } \mu$$

- The evaluation of the error indicator and the local stage

# Semi-incremental extension

- The temporal domain is divided into cycles
- Cycles are simulated consecutively



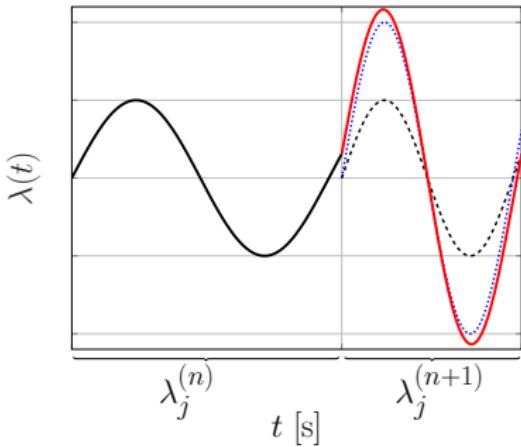
- Already generated  $\{\lambda_j(t)\}_{j=1}^{\mu}$  are scaled to  $\tilde{t} \in [0, 1]$
- Scaled back to the temporal coordinate of the current cycle

[Bhattacharyya et al 2018; Fritzen et al 2018]

# Semi-incremental extension

- Continuity of the temporal modes is an issue
- Temporal modes are vertically scaled and shifted via

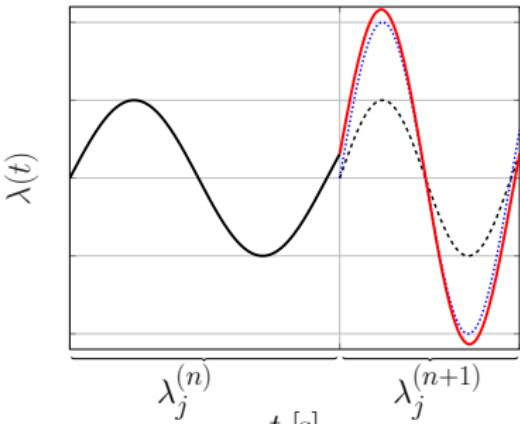
$$\tilde{\lambda}_j^{(n+1)}(\tilde{t}) = m \tilde{\lambda}_j^{(n)}(\tilde{t}) + g \tilde{t} + h \quad \text{with I.C. and B.C.}$$



# Semi-incremental extension

- Continuity of the temporal modes is an issue
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$$\tilde{\lambda}_j^{(n+1)}(\tilde{t}) = m \tilde{\lambda}_j^{(n)}(\tilde{t}) + g \tilde{t} + h \quad \text{with I.C. and B.C.}$$



Variable loading / integration over confined domains 😊

# SVD Compression of PGD

- Large number of modes
- Slow temporal update step

$$\underline{\tilde{A}} \underline{\tilde{\Lambda}}^T = \underline{\tilde{B}}$$

$$\underline{\tilde{A}} \in \mathbb{R}^{\mu \times \mu} \quad \underline{\tilde{\Lambda}} = [\Delta \underline{\lambda}_1, \dots, \Delta \underline{\lambda}_{\mu}] \quad \underline{\tilde{B}} \in \mathbb{R}^{\mu \times n_t}$$

- Enrichment with a Gram-Schmidt scheme is not optimal
- SVD is optimal but expensive to compute

# SVD Compression of PGD

- Given a solution  $\underline{\underline{U}} = \underline{\underline{V}} \underline{\underline{\Lambda}}^T \in \mathbb{R}^{n \times n_t}$  with

$$\underline{\underline{V}} = [\underline{v}_1, \dots, \underline{v}_\mu] \in \mathbb{R}^{n \times \mu} \quad \underline{\underline{\Lambda}} = [\underline{\lambda}_1, \dots, \underline{\lambda}_\mu] \in \mathbb{R}^{n_t \times \mu}$$

- Exploit the outer product format of PGD

$$\underline{\underline{V}} = \underline{\underline{Q}}_v \underline{\underline{R}}_v \quad \underline{\underline{\Lambda}} = \underline{\underline{Q}}_\lambda \underline{\underline{R}}_\lambda$$

- Compute SVD of a small matrix

$$\underline{\underline{T}} = \underline{\underline{R}}_v \underline{\underline{R}}_\lambda^T \in \mathbb{R}^{\mu \times \mu} \quad \underline{\underline{T}} \approx \underline{\underline{\Theta}} \underline{\underline{S}} \underline{\underline{W}}^T$$

- Solution with a compressed basis

$$\underline{\underline{U}} \approx \underline{\underline{Q}}_v \underline{\underline{\Theta}} \quad \underline{\underline{S}} \quad \underline{\underline{W}}^T \underline{\underline{Q}}_\lambda^T$$

[Bebendorf 2008]

# SVD Compression of PGD

- Given a solution  $\underline{\underline{U}} = \underline{\underline{V}} \underline{\underline{\Lambda}}^T \in \mathbb{R}^{n \times n_t}$  with

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- Solution with a compressed basis

$$\underline{\underline{U}} \approx \underline{\underline{\Theta}} \underline{\underline{S}} \underline{\underline{W}}^T \underline{\underline{\Theta}}^T$$

Non-demanding optimal decomposition 😊

[Bebendorf 2008]

# What is left?

- $\varepsilon_{\text{global}}$  is approximated using PGD

- $\varepsilon_{\text{local}}$  is NOT!

$$(\sigma_{\text{global}} - \sigma_{\text{local}}) - \alpha \mathbb{C} : (\varepsilon_{\text{global}} - \varepsilon_{\text{local}}) = \mathbf{0}$$

- Low-rank approximation of  $\varepsilon_{\text{local}}$
- Randomised SVD (RSVD) algorithm
- Dedicated arithmetic toolbox to handle operations on PGD

# Stress decomposition

## Algebra on Low-rank Matrices

$$\underline{\underline{A}} = \underline{\underline{V}}_A \underline{\underline{S}}_A \underline{\underline{\Lambda}}_A^\top \quad \underline{\underline{B}} = \underline{\underline{V}}_B \underline{\underline{S}}_B \underline{\underline{\Lambda}}_B^\top$$

### ■ Addition

$$\underline{\underline{C}} = \underline{\underline{A}} + \underline{\underline{B}} = [\underline{\underline{V}}_A \quad \underline{\underline{V}}_B] \begin{bmatrix} \underline{\underline{S}}_A & 0 \\ 0 & \underline{\underline{S}}_B \end{bmatrix} [\underline{\underline{\Lambda}}_A \quad \underline{\underline{\Lambda}}_B]^\top = \underline{\underline{V}}_C \underline{\underline{S}}_C \underline{\underline{\Lambda}}_C^\top$$

### ■ Multiplication

$$\underline{\underline{A}} \underline{x} = \underline{\underline{V}}_A \underline{\underline{S}}_A \left( \underline{\underline{\Lambda}}_A^\top \underline{x} \right)$$

### ■ Deviatoric Operation

$$\underline{\underline{A}}_{\text{dev}} = \underline{\underline{P}}_{\text{dev}} \underline{\underline{V}}_A \underline{\underline{S}}_A \underline{\underline{\Lambda}}_A^\top = \left( \underline{\underline{P}}_{\text{dev}} \underline{\underline{V}}_A \right) \underline{\underline{S}}_A \underline{\underline{\Lambda}}_A^\top$$

# Stress decomposition

## Algebra on Low-rank Matrices

$$\underline{\underline{A}} = \underline{\underline{V}}_A \underline{\underline{S}}_A \underline{\underline{\Lambda}}_A^\top \quad \underline{\underline{B}} = \underline{\underline{V}}_B \underline{\underline{S}}_B \underline{\underline{\Lambda}}_B^\top$$

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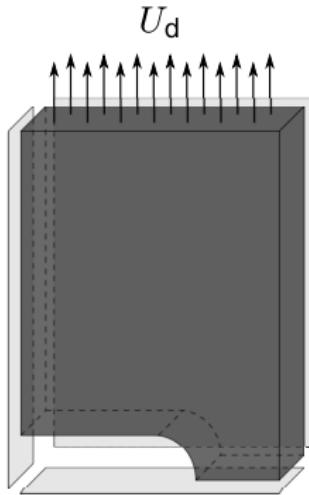
$$\underline{\underline{A}}_{\perp A} = \underline{\underline{P}}_{\perp A} \underline{\underline{V}}_A \underline{\underline{S}}_A \underline{\underline{\Lambda}}_A^\top = \left( \underline{\underline{P}}_{\perp A} \underline{\underline{V}}_A \right) \underline{\underline{S}}_A \underline{\underline{\Lambda}}_A^\top$$

Most operations exploit the PGD decomposition 😊

- 1** Reduced order model for cyclic loading
- 2** Challenges and workarounds
- 3** Numerical examples
- 4** Conclusions and current research

# Numerical results

- A plate subjected to cyclic loading (Cr-Mo steel at 580°C)



# Viscoplastic viscodamage material

## ■ Stress-strain

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

$$\dot{\boldsymbol{\varepsilon}}^p = \dot{\lambda} \ \mathbf{N}$$

## ■ Kinematic hardening

$$\beta = \frac{2}{3} c \alpha$$

$$\dot{\alpha} = \dot{\lambda} \left( \tilde{\mathbf{N}} - \frac{3}{2} \frac{a}{c} \beta \right)$$

## ■ Isotropic hardening

$$R = R_\infty (1 - e^{-b r})$$

$$\dot{r} = \dot{\lambda}$$

## ■ Damage

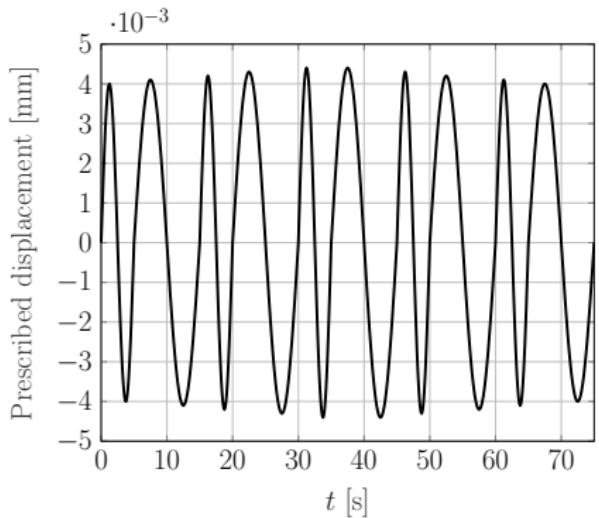
$$Y = \frac{1}{2} \boldsymbol{\varepsilon}^e : \mathbb{C} : \boldsymbol{\varepsilon}^e$$

$$\dot{D} = \frac{\dot{\lambda}}{1 - D} \left( \frac{Y}{S} \right)^s$$

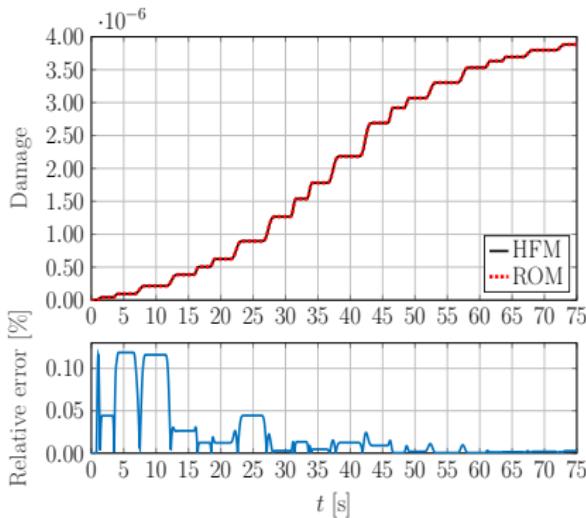
# Model verification

$1884 \cdot 200 \cdot 10$  DOF

With respect to a modified Newton-Raphson scheme



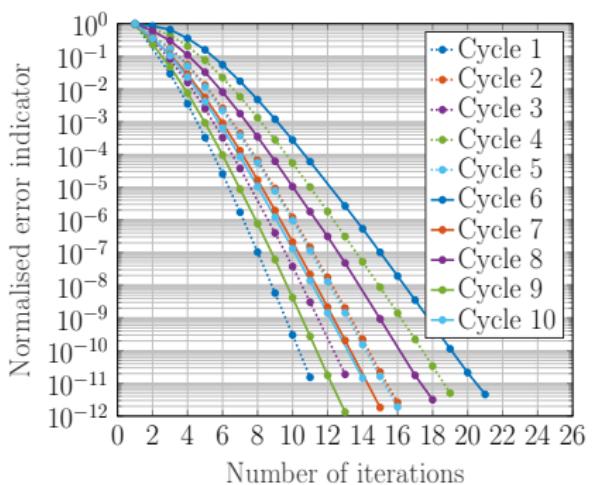
Prescribed displacement



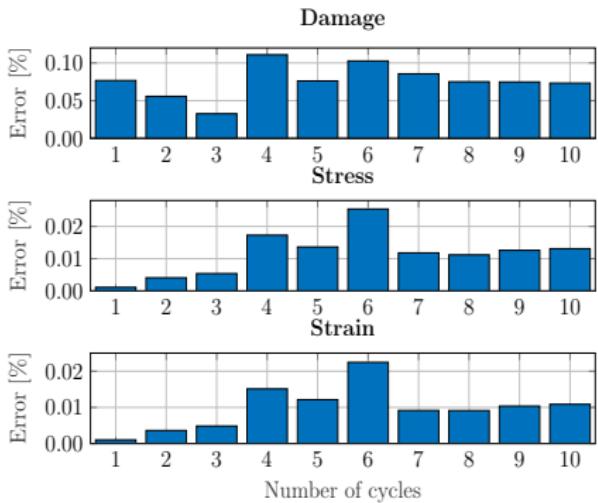
Damage evolution

# Model verification

$$\|e\|_{\Omega \times \mathcal{T}}^2 = \frac{1}{T |\Omega|} \int_{\mathcal{T}} \int_{\Omega} e : e \, d\Omega \, dt \quad (\text{norm in Bochner space})$$



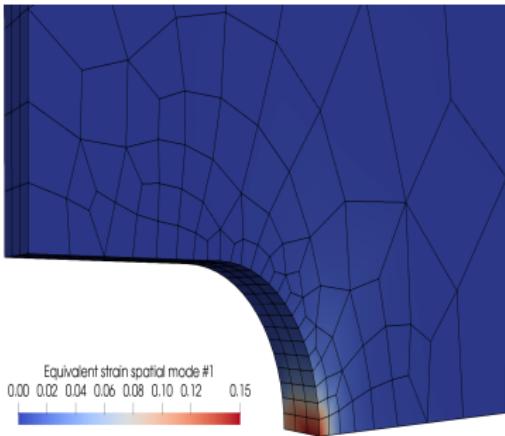
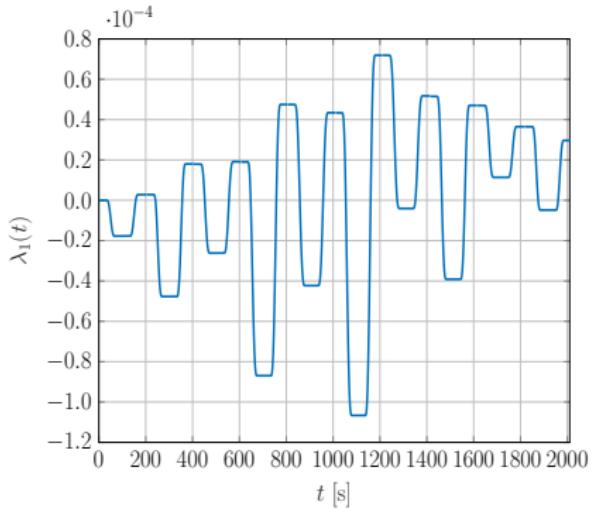
Error indicator



Space-time average relative error

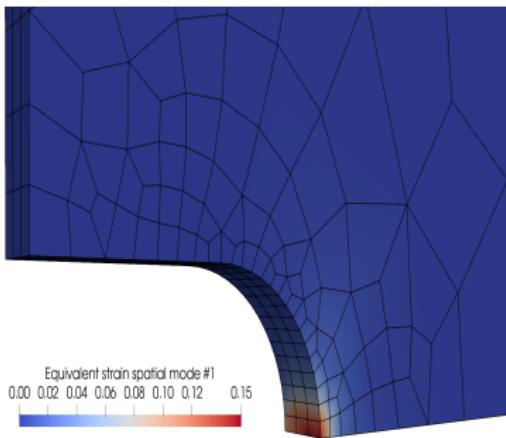
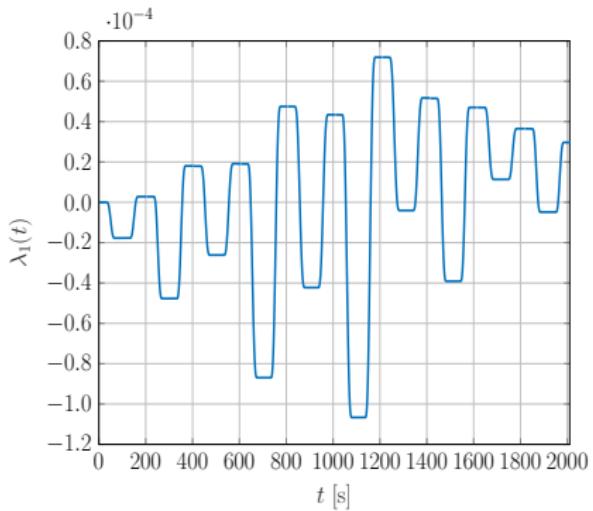
# Model verification

## The first temporal and spatial modes



# Model verification

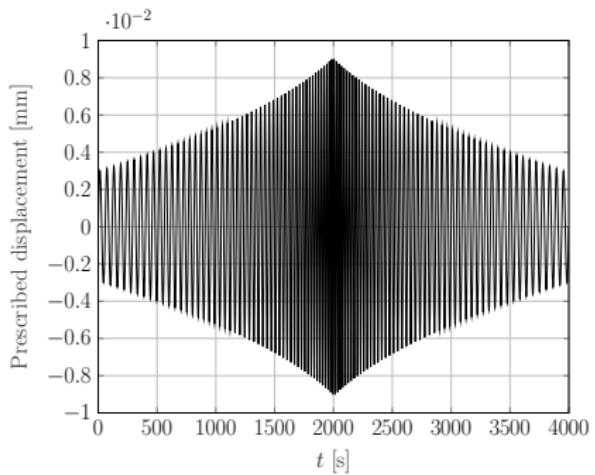
The first temporal and spatial modes



12 modes / Speedup factor  $\sim 25$

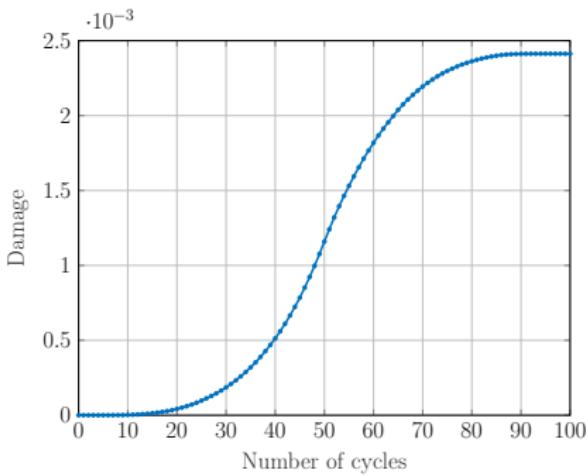
# Variable amplitudes & frequencies

Amplitudes:  $[30, 90] \cdot 10^{-4}$  mm



Prescribed displacement

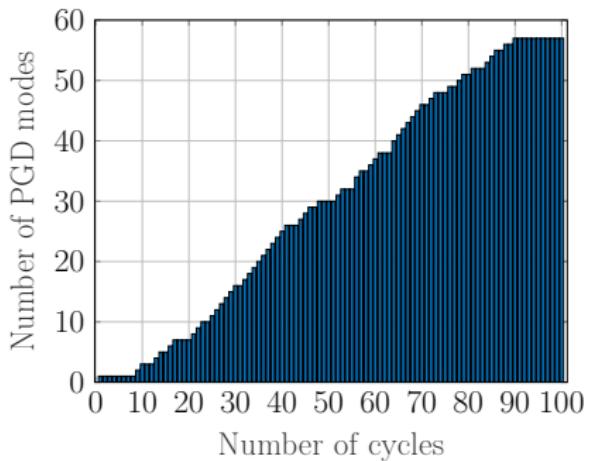
Time periods: [20, 60] sec



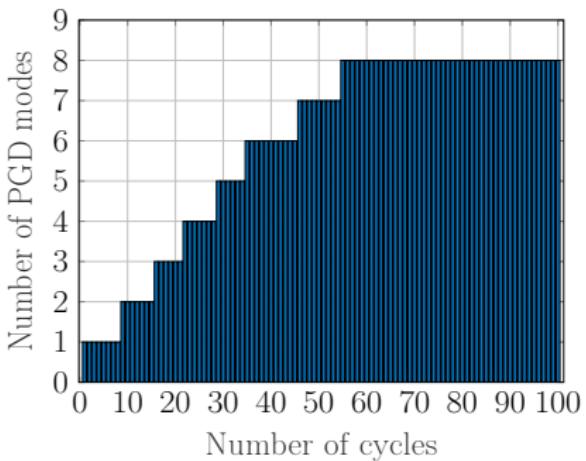
Damage evolution

# Variable amplitudes & frequencies

The growth of the ROB using an SVD scheme



Gram-Schmidt

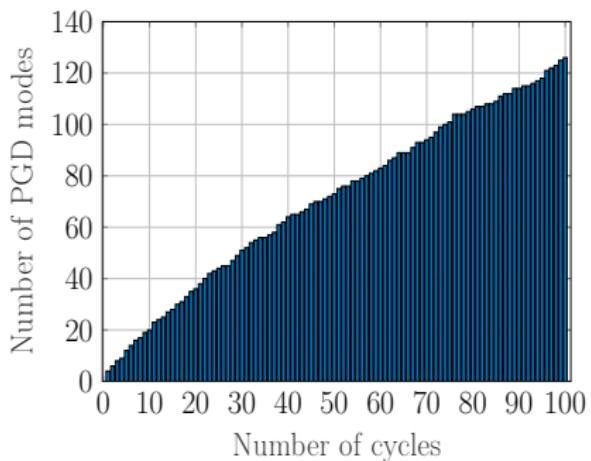


SVD scheme

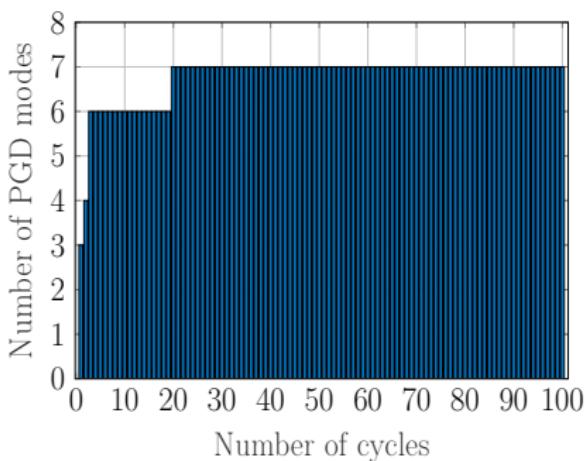
# Different ortho. schemes

$50,547 \cdot 33 \cdot 100$  DOF

In case of random loading and fine discretisation



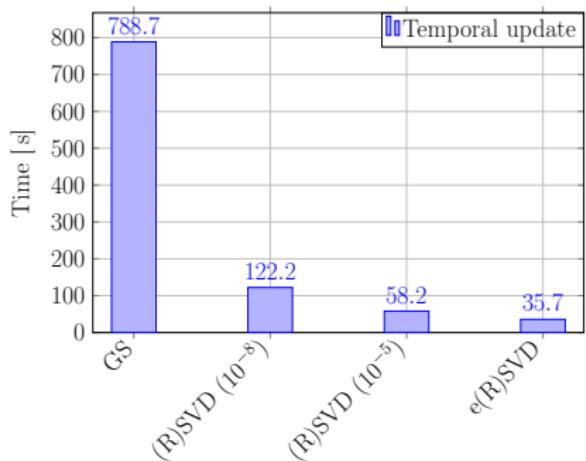
Gram-Schmidt



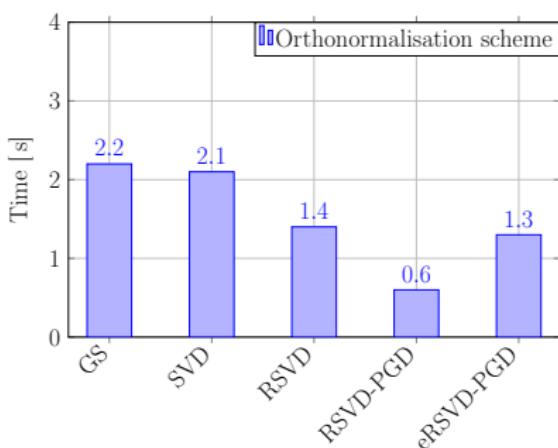
SVD scheme

# Different ortho. schemes

The required time to update and orthonormalise the modes



Temporal update

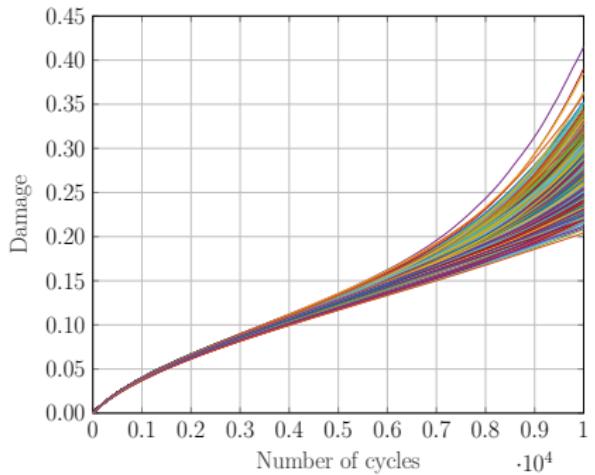


Orthonormalisation step

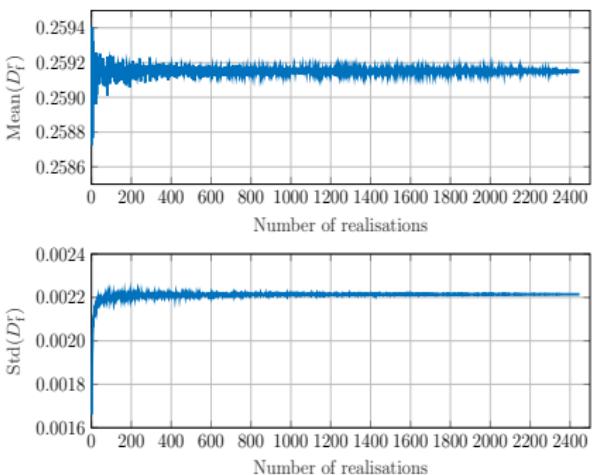
# Random amplitude loading

$1884 \cdot 41 \cdot 10^4$  DOF

■  $10^4$  cycles, uniform distribution in  $[53, 56] \cdot 10^{-2}$  mm



Different damage realisations

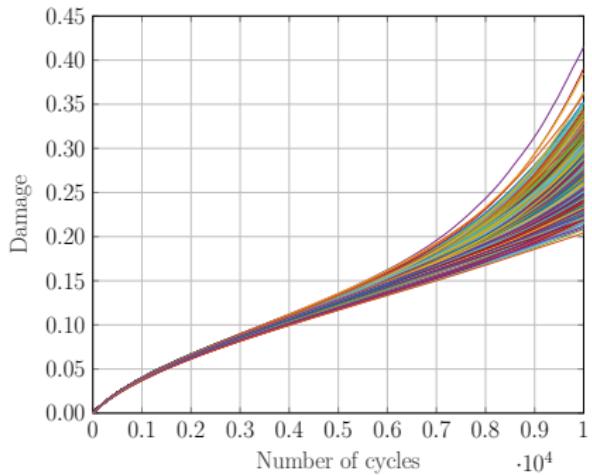


The mean and SD of  $D_f$

# Random amplitude loading

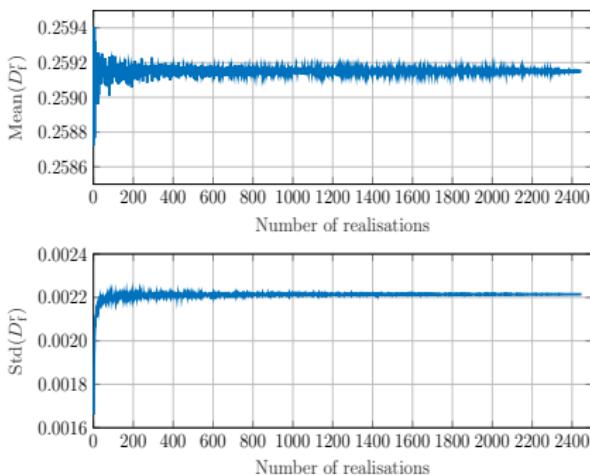
$1884 \cdot 41 \cdot 10^4$  DOF

■  $10^4$  cycles, uniform distribution in  $[53, 56] \cdot 10^{-2}$  mm



Critical damage value  $D_c = 0.3$

Probability of failure  $P_f = 5.4\%$

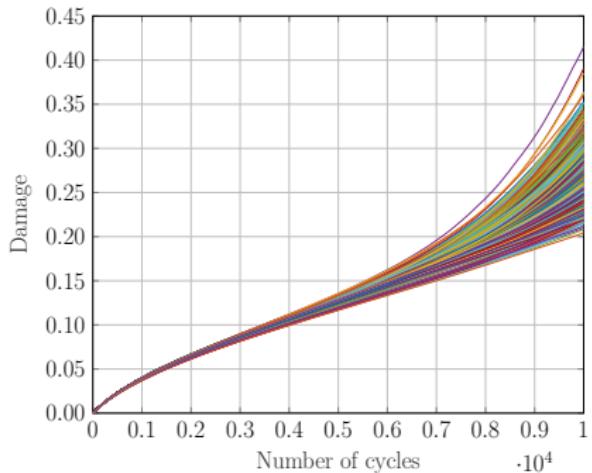


Requirements:  
[15 – 35] min and [1 – 1.5] GB

# Random amplitude loading

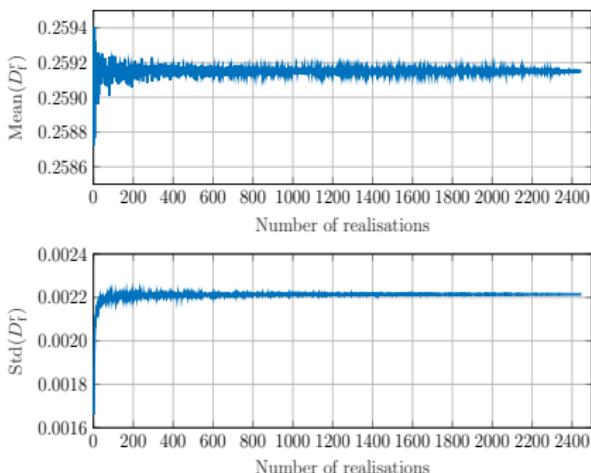
$1884 \cdot 41 \cdot 10^4$  DOF

■  $10^4$  cycles, uniform distribution in  $[53, 56] \cdot 10^{-2}$  mm



Critical damage value  $D_c = 0.3$

Probability of failure  $P_f = 5.4\%$



Requirements:

[15 – 35] min and [1 – 1.5] GB

Approx. 10 modes / Time-saving factors 50 ~ 100

# Outline

- 1** Reduced order model for cyclic loading
- 2** Challenges and workarounds
- 3** Numerical examples
- 4** Conclusions and current research

# Conclusion and future research

- Efficient semi-incremental scheme for damage problems
- Can handle variable amplitude and frequency loadings
- Provides a minimal expansion of PGD
- Most operations are done over decomposed QoI
- Open-source code: [gitlab.com/shadialameddin/romfem](https://gitlab.com/shadialameddin/romfem)

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## Current tasks

- Improve the documentation of the code
- Reducing the cost of evaluating the constitutive model

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Thank you for your attention

# Alternated directions algorithm

■ Spatial problem, with homogeneous boundary conditions:

$$\int_{\Omega} \nabla^s \mathbf{v}^* : \left( \int_{\mathcal{T}} \lambda \mathbb{H}^- \lambda dt \right) : \nabla^s \mathbf{v} d\Omega = - \int_{\Omega} \nabla^s \mathbf{v}^* : \left( \int_{\mathcal{T}} \lambda \hat{\mathbf{f}} dt \right) d\Omega$$
$$\underline{\underline{K}} \underline{\underline{v}} = \underline{\underline{f}} \quad \underline{\underline{K}} \in \mathbb{R}^{n \times n} \quad \underline{\underline{v}}, \underline{\underline{f}} \in \mathbb{R}^n$$

Temporal problem, with zero initial conditions:

$$\int_{\mathcal{T}} \lambda^* \left( \int_{\Omega} \nabla^s \mathbf{v} : \mathbb{H}^- : \nabla^s \mathbf{v} d\Omega \right) \lambda dt = - \int_{\mathcal{T}} \lambda^* \left( \int_{\Omega} \nabla^s \mathbf{v} : \hat{\mathbf{f}} d\Omega \right) dt$$
$$a \underline{\lambda} = \underline{b} \quad a \in \mathbb{R} \quad \lambda, b \in \mathbb{R}^{nt}$$

# Alternated directions algorithm

## ■ Temporal update step

$$\begin{aligned}\underline{\tilde{A}} \underline{\tilde{\Lambda}}^\top &= \underline{\tilde{B}} & \underline{\tilde{A}} \in \mathbb{R}^{\mu \times \mu} & \underline{\tilde{B}} \in \mathbb{R}^{\mu \times n_t} \\ \underline{\tilde{\Lambda}} &= [\Delta \underline{\lambda}_1, \dots, \Delta \underline{\lambda}_\mu]\end{aligned}$$

$$\tilde{A}_{kl} = \alpha \int_{\Omega} (\underline{\underline{B}} \underline{v}_k)^\top \underline{\underline{C}} (\underline{\underline{B}} \underline{v}_l) \, d\Omega$$

$$\tilde{B}_{kl} = - \int_{\Omega} (\underline{\underline{B}} \underline{v}_k)^\top \hat{\underline{f}}|_{t=t_l} \, d\Omega$$

$$\psi(\boldsymbol{\varepsilon}^e, \boldsymbol{\alpha}, r, D) = \psi^{eD}(\boldsymbol{\varepsilon}^e, D) + \psi^p(\boldsymbol{\alpha}, r)$$

$$\psi = \frac{1}{2} \, \boldsymbol{\varepsilon}^e : (1 - D) \, \mathbb{C} : \boldsymbol{\varepsilon}^e + \frac{1}{3} \, c \, \boldsymbol{\alpha} : \boldsymbol{\alpha} + R_\infty \, \left( r + \frac{e^{-b \, r}}{b} \right)$$

$$\phi^*(\boldsymbol{\sigma}, \boldsymbol{\beta}, R) = \phi^p + \phi^\beta$$

$$\phi^p = \frac{k_p}{1+n_p} \left\langle \frac{f^p}{k_p} \right\rangle^{n_p+1} \qquad \qquad f^p = \sqrt{3J_2(\boldsymbol{\tau})} - R - \sigma_y$$

$$\phi^\beta = \frac{3}{4} \frac{a}{c} \, \boldsymbol{\beta} : \boldsymbol{\beta}$$

$$\phi^d = \frac{S}{(s+1)(1-D)} \left( \frac{Y}{S} \right)^{s+1}$$

- Start with an elastic initialisation  $s_0 = \{\sigma_0, Q_0, \varepsilon_0, q_0\}$
- Evaluate **(CM)** to get  $s_{\text{local}}$  (local stage)
- Solve **(AD)** to get  $s_{\text{global}}$  (global stage)
- Transfer data using affine relations (search direction eq.)

$$(\boldsymbol{\sigma}_{\text{global}} - \boldsymbol{\sigma}_{\text{local}}) - \mathbb{H}^\top : (\boldsymbol{\varepsilon}_{\text{global}} - \boldsymbol{\varepsilon}_{\text{local}}) = \mathbf{0}$$

- Iterate until convergence with an energy error indicator

$$\xi = \frac{\|s_{\text{global}} - s_{\text{local}}\|}{\frac{1}{2} \|s_{\text{global}} + s_{\text{local}}\|}, \quad \|s\|^2 = \frac{1}{2T} \int_{\Omega \times \mathcal{T}} (\boldsymbol{\sigma} : \mathbb{C}^{-1} : \boldsymbol{\sigma} + \boldsymbol{\varepsilon} : \mathbb{C} : \boldsymbol{\varepsilon}) \, d\Omega \, dt.$$