

Plastic Strain Computation

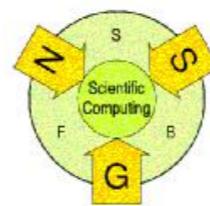
Project F1306

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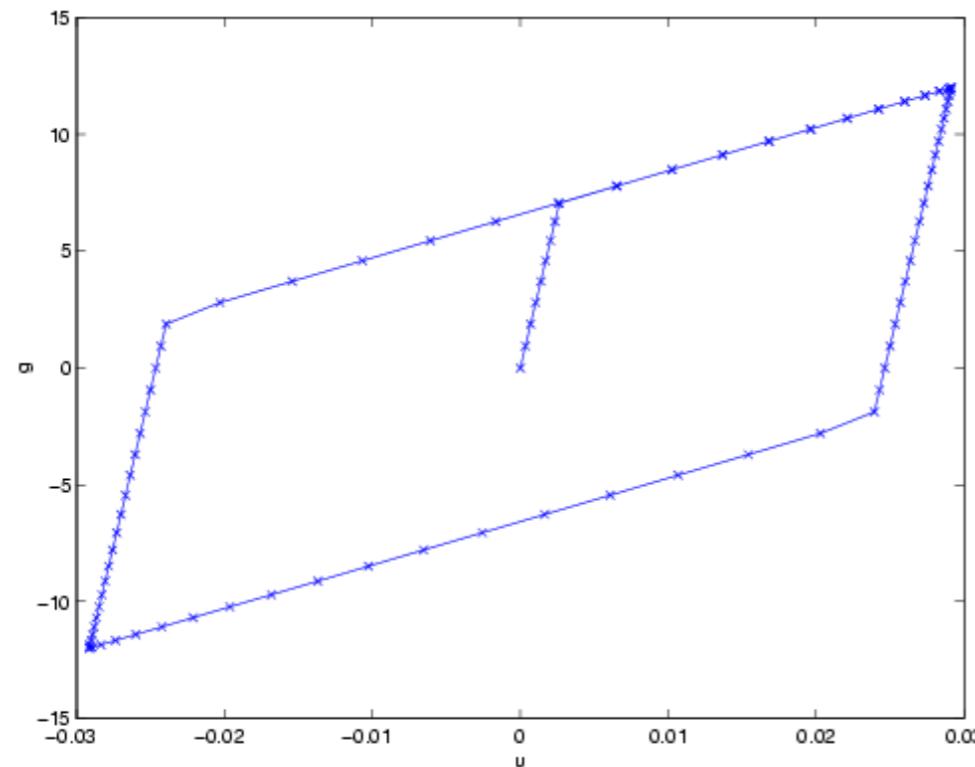


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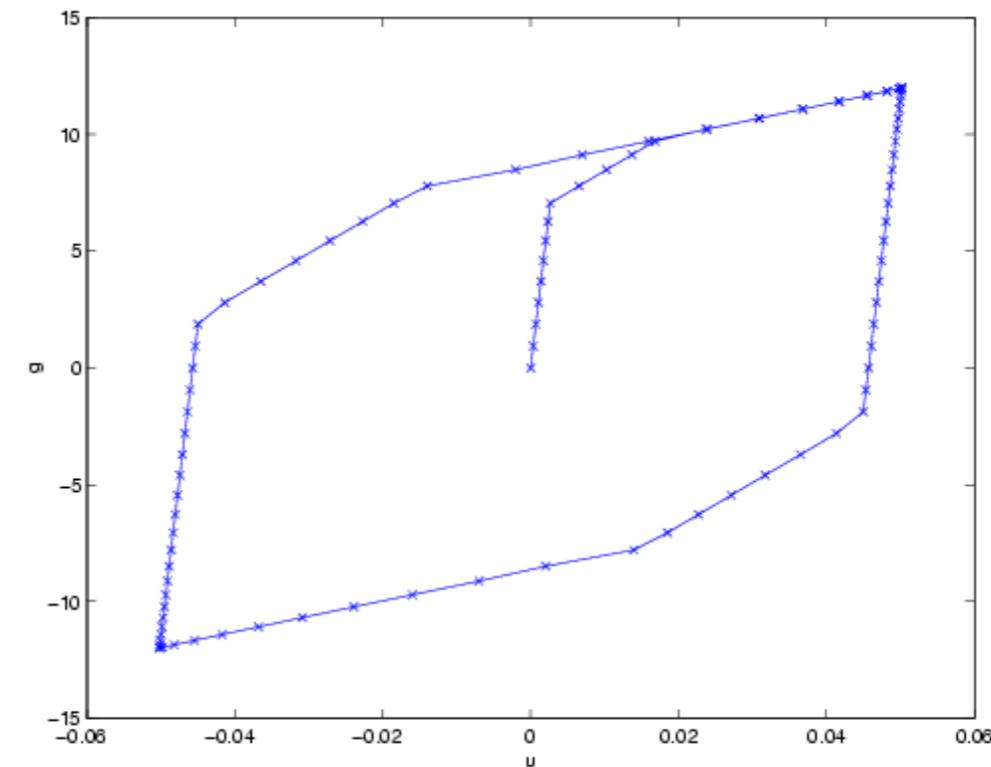


Why Multi-yield (Two-yield) model?

- More realistic hysteresis stress-strain relation in materials!



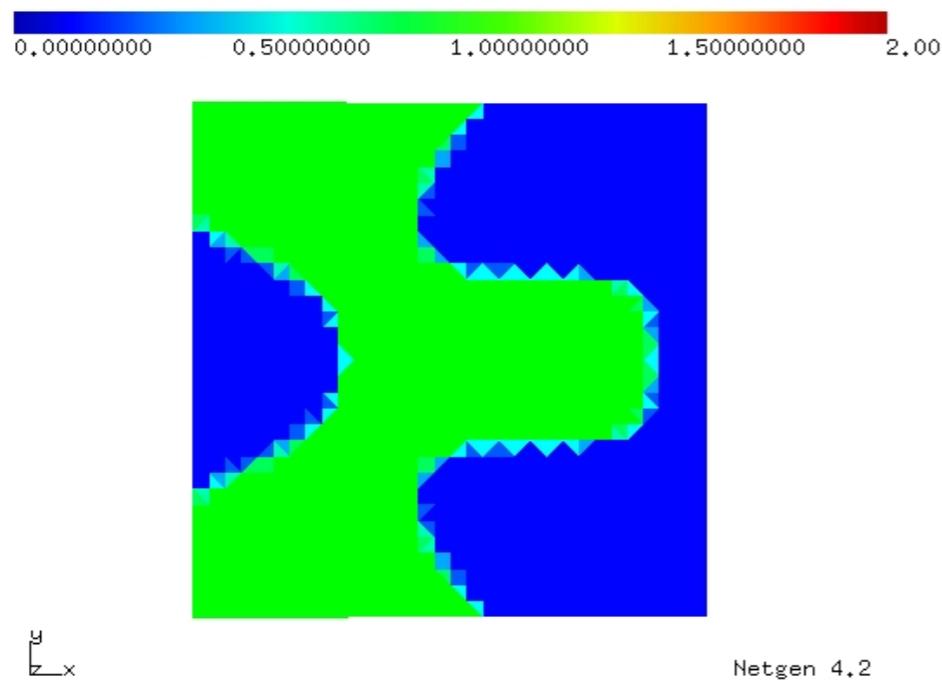
Kinematic hardening model.



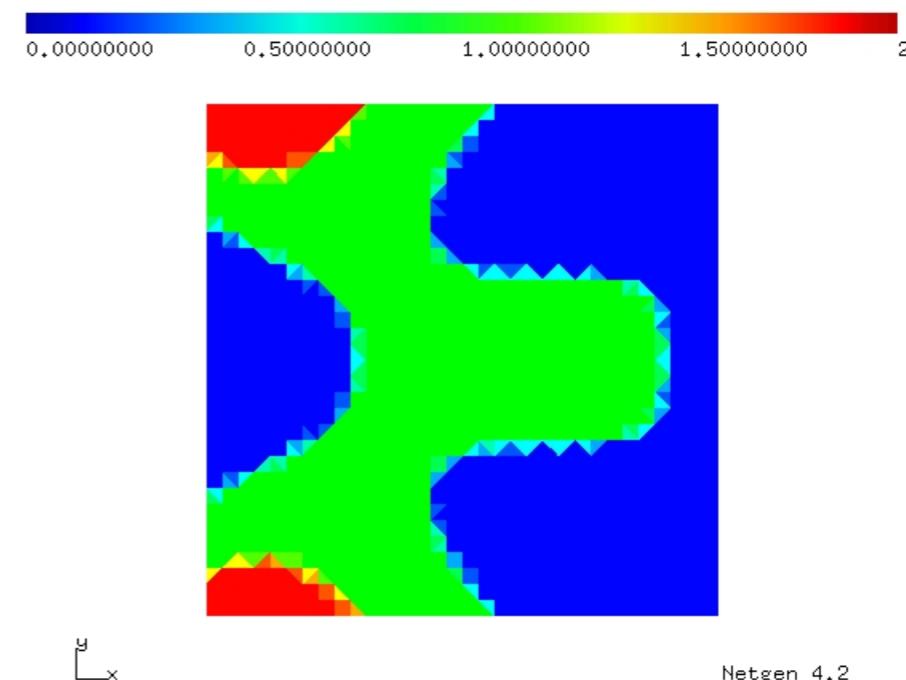
Two-yield hardening model.

NETGEN/NGSOLVE calculations

Elastoplastic domains (blue - elastic, green - first plastic, red - second plastic)



Kinematic hardening model.



Two-yield hardening model.

Direct minimization problem in \tilde{p}

Kinematic hardening model:

$$f(Q) = \frac{1}{2}(\mathbb{C} + \mathbb{H})Q : Q - Q : A + \sigma^y ||Q|| \rightarrow \min$$

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$$f\begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} = \frac{1}{2} \begin{pmatrix} \mathbb{C} + \mathbb{H}_1 & \mathbb{C} \\ \mathbb{C} & \mathbb{C} + \mathbb{H}_2 \end{pmatrix} \begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} : \begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} - \begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} : \begin{pmatrix} A_1 \\ A_2 \end{pmatrix} + \sigma_1^y ||Q_1|| + \sigma_2^y ||Q_2|| \rightarrow \min$$

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$$\text{minimizer } (\tilde{p}_1, \tilde{p}_2) = ?$$

Direct minimization problem: Two-yield model - analytical approach

Lemma: Let $f(P) = \min_Q f(Q)$, $P = (P_1, P_2)$, If $P_1 \neq 0, P_2 \neq 0 \Rightarrow \|P_2\|$ is a root of a 8-th degree polynomial.

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Proof: f has a subdifferential, i.e., $\partial f(P) = (\hat{\mathbb{C}} + \hat{\mathbb{H}})P - A + \partial||\cdot||_{\sigma^y}(P)$

Minimum condition on P : $0 \in \partial f(P) \Leftrightarrow A - (\hat{\mathbb{C}} + \hat{\mathbb{H}})P \in \partial||\cdot||_{\sigma^y}(P)$

In case $P_1 \neq 0, P_2 \neq 0$ is $\partial||\cdot||_{\sigma^y}(P) = \{\sigma_1^y \frac{P_1}{\|P_1\|}, \sigma_2^y \frac{P_2}{\|P_2\|}\}$

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Nonlinear system in $P_1, P_2 \in \text{dev } \mathbb{R}_{sym}^{d \times d}$ with $\mu, h_1, h_2, \sigma_1^y, \sigma_2^y > 0$, $\text{dev } A_1, \text{dev } A_2 \in \text{dev } \mathbb{R}_{sym}^{d \times d}$

$$\begin{pmatrix} \text{dev } A_1 \\ \text{dev } A_2 \end{pmatrix} - \begin{pmatrix} (2\mu + h_1)\mathbb{I} & 2\mu\mathbb{I} \\ 2\mu\mathbb{I} & (2\mu + h_2)\mathbb{I} \end{pmatrix} \begin{pmatrix} P_1 \\ P_2 \end{pmatrix} = \begin{pmatrix} \sigma_1^y \frac{P_1}{\|P_1\|} \\ \sigma_2^y \frac{P_2}{\|P_2\|} \end{pmatrix}$$

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Subst. $\xi_1 = \|P_1\|, \xi_2 = \|P_2\|$ with $A, B, C, D, E, F, G, H, I, J \in \mathbb{R}$

$$A + B\xi_1 + C\xi_1^2 - (G + H\xi_1 + I\xi_2 + J\xi_1\xi_2)^2 = 0$$

$$D + E\xi_2 + F\xi_2^2 - (G + H\xi_1 + I\xi_2 + J\xi_1\xi_2)^2 = 0$$

MAPLE 5 \Rightarrow 8-th degree polynomial in ξ_2 (\Rightarrow no analytical formula!):

$$\begin{aligned}
 & \left(J^4 F^2 \right) \xi_2^8 + \left(2\%4 J^2 F \right) \xi_2^7 + \left(2\%3 J^2 F + \%4^2 \right) \xi_2^6 + \left(2\%2 J^2 F + 2\%3\%4 \right) \xi_2^5 \\
 & + \left(2\%1 J^2 F + 2\%2\%4 + \%3^2 - F(BJ+2IC)^2 \right) \xi_2^4 \\
 & + \left(-E(BJ+2IC)^2 - 2F(2CG+BH)(BJ+2IC) + 2\%1\%4 + 2\%2\%3 \right) \xi_2^3 \\
 & + \left(-D(BJ+2IC)^2 - 2E(2CG+BH)(BJ+2IC) - F(2CG+BH)^2 + 2\%1\%3 + \%2^2 \right) \xi_2^2 \\
 & + \left(-2D(2CG+BH)(BJ+2IC) - E(2CG+BH)^2 + 2\%1\%2 \right) \xi_2 \\
 & + \left(\%1^2 - D(2CG+BH)^2 \right) = 0,
 \end{aligned}$$

where $\%1 := H^2 D - C G^2 - A H^2 - B G H - C D$,

$\%2 := -B G J - 2 H J A - C E - 2 I C G + H^2 E - I B H + 2 H J D$,

$\%3 := -C F - J^2 A + 2 H J E - I B J + C + J^2 D + H^2 F$,

$\%4 := 2 H J F + J^2 E$.

Analytical Approach: example

Given $\mu = 1, \sigma_1^y = 1, \sigma_2^y = 2, h_1 = 1, h_2 = 1$ and $A_1 = A_2 = \begin{pmatrix} 20 & 0 \\ 0 & 0 \end{pmatrix}$.

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The direct calculation shows

$$l_1 = \begin{pmatrix} 10 + 10\xi_1 & 0 \\ 0 & -10 - 10\xi_1 \end{pmatrix},$$

$$l_2 = \begin{pmatrix} 20 - 10\xi_2 & 0 \\ 0 & -20 - 10\xi_2 \end{pmatrix},$$

$$r = 5\xi_1\xi_2 + 6\xi_1 + 3\xi_2 + 2.$$

The nonlinear system of equation for $\xi_1, \xi_2 > 0$:

$$200 + 400\xi_1 + 200\xi_1^2 - (2 + 3\xi_2 + 6\xi_1 + 5\xi_1\xi_2)^2 = 0,$$

$$800 + 800\xi_2 + 200\xi_2^2 - (2 + 3\xi_2 + 6\xi_1 + 5\xi_1\xi_2)^2 = 0.$$

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ξ_1 solved from the second equation

$$\xi_1 = \frac{-3\xi_2 - 2 \pm 10\sqrt{10}(2 + \xi_2)}{5\xi_2 + 6}$$

Subst. (**— term only!**) in the first eq. gives

$$\frac{(5\xi_2 + 8 - 10\sqrt{2})(5\xi_2 + 4 - 10\sqrt{2})(\xi_2 + 2)}{(6 + 5\xi_2)} = 0.$$

Roots

$$\xi_2 = \left\{ -\frac{4}{5} + 2\sqrt{2}, -\frac{8}{5} - 2\sqrt{2}, -2, -2 \right\}$$

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$$\xi_1 = \left\{ -\frac{1 - 1 + 40\sqrt{2}}{5(1 + 10\sqrt{2})}, \frac{1201 + 2\sqrt{2}}{5(1 + 10\sqrt{2})} \right\},$$

Positive solution

$$\xi_1 = -\frac{1 - 1 + 40\sqrt{2}}{5(1 + 10\sqrt{2})} \approx 3.028427125$$

Symbolic techniques

- Resolvent in Maple: original 8-th degree polynomial contains a second degree polynomial factor with complex solutions only
⇒ 6-th degree polynomial in ξ_2 (longer expression)

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New perspectives/cooperations:

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New perspectives/cooperations:

- Homotopy method for numerical approximation of polynomials (with F1303 - J. Schicho, T. Beck)
- Lagrange inversion formula leading to Melin's serie in polynomial coefficients (with F1305 - P. Paule)

Direct minimization problem: Two-yield model - iterative approach

Algorithm (*): Given $\mu, h_1, h_2, \sigma_1^y, \sigma_2^y$, dev A_1 , dev A_2 and tolerance ≥ 0 .

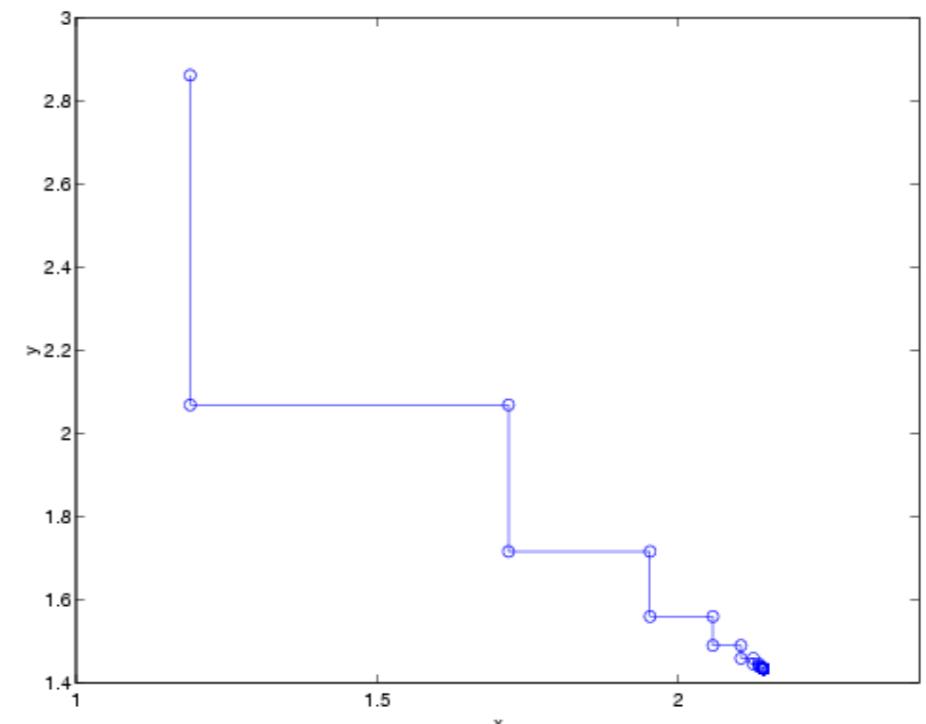
- (a) Choose $(P_1^0, P_2^0) \in \text{dev } \mathbb{R}_{\text{sym}}^{d \times d} \times \text{dev } \mathbb{R}_{\text{sym}}^{d \times \min!d}$, set $i := 0$.
- (b) Find $P_2^{i+1} \in \text{dev } \mathbb{R}_{\text{sym}}^{d \times d}$ s. t.

$$f(P_1^i, P_2^{i+1}) = \min_{Q_2 \in \text{dev } \mathbb{R}_{\text{sym}}^{d \times d}} f(P_1^i, Q_2).$$

- (c) Find $P_1^{i+1} \in \text{dev } \mathbb{R}_{\text{sym}}^{d \times d}$ s. t.

$$f(P_1^{i+1}, P_2^{i+1}) = \min_{Q_1 \in \text{dev } \mathbb{R}_{\text{sym}}^{d \times d}} f(Q_1, P_2^{i+1}).$$

- (d) If $\frac{\|P_1^{i+1} - P_1^i\| + \|P_2^{i+1} - P_2^i\|}{\|P_1^{i+1}\| + \|P_1^i\| + \|P_2^{i+1}\| + \|P_2^i\|} > \text{tolerance}$ set $i := i + 1$ and goto (b), otherwise output (P_1^{i+1}, P_2^{i+1}) .



The approximations $P_1^i = (x^i, 0; 0, -x^i)$, $P_2^i = (y^i, 0; 0, -y^i)$, $i = 0, 1, \dots$ of Algorithm (*) in the $x - y$ coordinate system.

- global convergence with the rate $1/2$:

$$\|P_1^i - P_1\|^2 + \|P_2^i - P_2\|^2 \leq C_0 \cdot q^i$$