

- Geometrical optimization of a reactor's core of gen IV using FreeFem++



joint-work<sup>1</sup> between SINETICS department at EDF R&D, Clamart and CMAP, Ecole Polytechnique

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1. PEPS agreement

# Introduction

## Goals of the internship

### Aims and context

- Apply a shape optimization method to the conception of a nuclear reactor of generation IV having a reduced sodium void effect
- Implement the method with the finite element software FreeFem++
- Show to what extent the method could be applied in this context

- 1 I. Setting of the problem
- 2 II. Shape optimization equations
- 3 III. Numerical results

## Modeling of the reactor

### Description of the core

- We assume the reactor can be simplified to a cylinder and that we have an axisymmetric geometry  $\Omega = [0, R] \times [0, h]$
- $\Omega = \cup_{i=1}^4 \Omega_i$  is defined as the reunion of 4 regions having some averaged physical properties, each of them being characterized by a set of homogenized coefficients  $(D, \Sigma_a, \Sigma_f)$
- The active core is composed by 3 different materials : we denote by  $\Omega_f$  the fissile material
- The last region is the reflector surrounding the active core : absorbing region made of steel material

## 1-group energy diffusion model

### State equation

- Using the notations :  $\partial\Omega_D = \{(r, z) \in \partial\Omega; r \neq 0\}$ ,  $\partial\Omega_N = \{(r, z) \in \partial\Omega; r = 0\}$  and  $u$  the neutrons flux
- We consider the simplified 1 group energy diffusion equation formulated on the space  $X = \{\phi \in H^1(\Omega); \phi|_{\partial\Omega_D} = 0\}$  on a bounded domain  $\Omega = \cup_i \Omega_i$  :

$$\begin{cases} -D \Delta u + \Sigma_a u = \lambda \nu \Sigma_f u & \text{in } \Omega_i \\ \text{transmissions conditions} & \text{on } \partial\Omega_i \cap \partial\Omega_j \\ u = 0 & \text{on } \partial\Omega_D \cap \partial\Omega_i \\ \frac{\partial u}{\partial n} = 0 & \text{on } \partial\Omega_N \cap \partial\Omega_i \end{cases} \quad (1)$$

**Remark :** With this convention for  $\lambda$ , we have  $\lambda = \frac{1}{k_{eff}}$

$k_{eff}$  is a key parameter linked to the neutronic equilibrium of the core (generally close to 1)

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## Variational form

The state equation represents an equilibrium between the reactions describing the behaviour of neutrons at steady states :

$$\underbrace{-D \Delta u}_{\text{leakage rate}} + \underbrace{\sum_a u}_{\text{absorption rate}} = \underbrace{\nu \sum_f u}_{\text{production rate}} \quad (2)$$

### Variational form

We are looking for weak solutions of the variational form :

Find  $u \in X$  such that :

$$\int_{\Omega} Dr \nabla u \cdot \nabla v + r \sum_a u v \, dx = \lambda \int_{\Omega} r \nu \sum_f u v \, dx \quad \forall v \in X$$

In the following we write :

$$a(u, v) = \int_{\Omega} Dr \nabla u \cdot \nabla v + r \sum_a u v \, dx$$

$$b(u, v) = \int_{\Omega} r \nu \sum_f u v \, dx. \quad (3)$$

## Cost function

### Estimation of the sodium void effect

We want to determine the first eigenvalue of this problem, which is simple, since this is the only to have a physical meaning (eigenvector keep the same sign over  $\Omega$ )

- By considering two set of homogenized coefficients for this equation in a nominal state (with index " $n$ ") and a perturbed one (index " $v$ "), we calculate the sodium void effect as  $\delta\rho_{Na} = \lambda_n - \lambda_v$

Our cost function is :

$$J(\Omega_f) = + + \quad (4)$$

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The last term is not differentiable so we approximate it by the following quantity :

$$V(\Omega_f)^{1-\frac{1}{s}} \left( \int_{\Omega_f} r \sum_{fn} u_n dr dz \right)^{-1} \left| \int_{\Omega_f} r (\sum_{fn} u_n)^s dr dz \right|^{1/s} \quad (5)$$

## What the algorithm does

volume courant enroulé = -0.00679709 valeur du multiplicateur = 1 tension: 0 hauteur interne = 1effet viscoélastique = 12.1707 valeur total scalaire = 14.1291

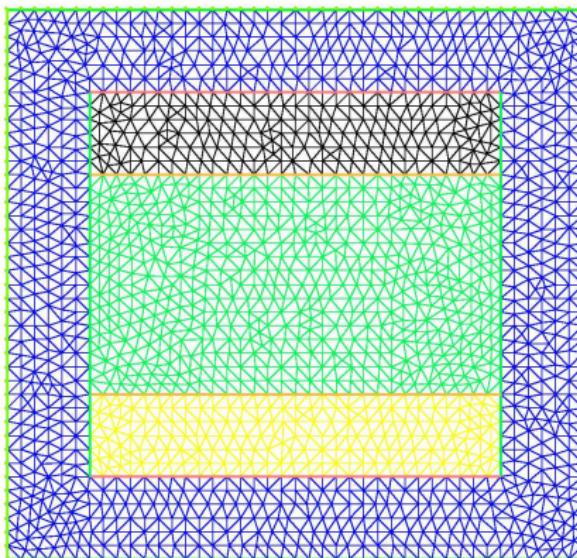


Figure: Initial shape

volume courant enroulé = 0.0070201 valeur du multiplicateur = 0.789954 tension: 499 hauteur interne = 1effet viscoélastique = 0.286718 valeur total scalaire = 8.71508

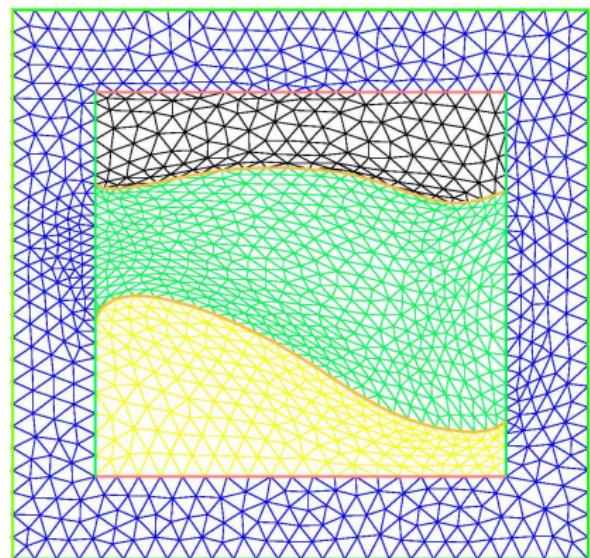


Figure: Shape after 500 iterations

## Admissible shape transformation of the bounded set $\Omega$

- We move the shape during a time  $t$  with a lipschitzian velocity field satisfying  $\|t\theta_n\|_\infty \leq 1$  moving the points with the following equation :

$$x \rightarrow x + t \theta_n(x)$$

Thus, we have  $\Omega_{n+1} = (I_d + t \theta_n)(\Omega_n)$

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Thus, we have  $\Omega_{n+1} = (I_d + t \theta_n)(\Omega_n)$

- We impose  $\theta \cdot n = 0$  on  $\partial\Omega$  and on the external boundary of the active core
- The volume constraint expresses as  $\text{vol}(T(\Omega_f)) = \text{vol}(\Omega_f)$

$$T = Id + t \theta$$

## Gradient method

- The optimization variable is the velocity field  $\theta_n$
- We characterize the optimal shape by first order optimality conditions
- We define the shape derivative in  $\Omega$  of the function  $J(\Omega)$  as the derivative at the point 0 of the application :

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- That is also the linear form on  $W^{1,\infty}(\Omega_f, \mathbb{R}^2)$  such that :

$$J((Id + t \theta)(\Omega_f)) = J(\Omega_f) + \langle J'(\Omega_f), \theta \rangle + o(\theta) \quad (6)$$

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- Once we know the shape derivative  $J'(\Omega_f)(\theta)$ , we apply a gradient descent algorithm by solving the following problem :

$$\forall \theta \in H^1(\Omega_f, \mathbb{R}^2) : J'(\Omega_f)(\theta) + \langle \theta_n, \theta \rangle = 0 \quad (7)$$

for the scalar product on  $X \times X$ , it gives  $J'(\Omega_f)(\theta_n) = -\|\theta_n\|^2$

## Lagrangian associated to the minimization problem

- $J$  does not depend explicitly on the shape  $\Omega$
- Use of the adjoint method
- We introduce the Lagrangian  $\mathcal{L}$  that transforms the initial problem into a new one without constraints on the variables :

$$\begin{aligned} \mathcal{L}(\Omega, \hat{u}_n, \hat{u}_v, \hat{p}_n, \hat{p}_v, \hat{\lambda}_n, \hat{\lambda}_v) = & \underbrace{\hat{\lambda}_n - \hat{\lambda}_v}_{\text{sodium void effect}} + \underbrace{(\hat{\lambda}_n - \lambda_0)^2}_{\text{target reactivity}} \\ & + vol(\Omega_f)^{1-\frac{1}{s}} \underbrace{\frac{\left( \int_{\Omega_f} r (\Sigma_{fn} \hat{u}_n)^s dr dz \right)^{\frac{1}{s}}}{\int_{\Omega_f} r \Sigma_{fn} \hat{u}_n dr dz}}_{\text{shape factor}} \\ & + \underbrace{\sum_{k=n,v} a_k(\Omega, \hat{u}_k, \hat{p}_k) - \hat{\lambda}_k b_k(\Omega, \hat{u}_k, \hat{p}_k)}_{\text{states equations}} \end{aligned}$$

## Adjoint method

- Let  $(u_k, \lambda_k)$  be the solution of the state equation in the state  $k$
- We have the relation :

$$J(\Omega) = \mathcal{L}(\Omega, u_n, u_v, \lambda_n, \lambda_v, p, q) \quad \forall (p, q) \in X^2 \quad (8)$$

- By composed derivation, we get :

$$\langle \frac{\partial J}{\partial \Omega}, \theta \rangle = \sum_k (\langle \frac{\partial \mathcal{L}}{\partial \hat{p}_k}, \hat{p}'_k(\theta) \rangle + \langle \frac{\partial \mathcal{L}}{\partial \hat{u}_k}, \hat{u}'_k(\theta) \rangle + \langle \frac{\partial \mathcal{L}}{\partial \hat{\lambda}_k}, \hat{\lambda}'_k(\theta) \rangle) + \langle \frac{\partial \mathcal{L}}{\partial \Omega}, \theta \rangle$$

- The adjoint state is defined in the following manner :

$$\begin{cases} \frac{\partial \mathcal{L}}{\partial \hat{\lambda}_k}(u_k, p_k, \lambda_k) = 0 \\ \langle \frac{\partial \mathcal{L}}{\partial \hat{u}_k}, \phi \rangle(u_k, p_k, \lambda_k) = 0 \quad \forall \phi \in X \end{cases} \iff p_k := \text{adjoint state of } u_k \quad (9)$$

Finally, we obtain :

$$\langle \frac{\partial J}{\partial \Omega}, \theta \rangle = \langle \frac{\partial \mathcal{L}}{\partial \Omega}, \theta \rangle \quad (10)$$

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## The two studied configurations

$$J(\Omega, e) = \alpha_1 J_1 + \alpha_2 J_2 + \alpha_3 J_3 \quad (11)$$

- We consider two cases : one with the same weights for the parametric and geometric optimization, another one with distinct weights taking into account the physical dependency of each criterium  $J_i$  to  $e$  and  $\Omega$
- With an admissible error on the volume of 10% and an initial value of  $e_{Pu} = 20\%$  on  $\Omega_f$
- Thanks to a program given by O. PANTZ we apply a change of topology of the mesh when needed.

We look at the following quantities to asses the convergence :

$$\text{For } e : \|e^n - e^{n-1}\| = \int_{\Omega_f} r(e^n(r, z) - e^{n-1}(r, z))^2 dr dz$$

$$\text{For } \Omega : \frac{J'(\Omega_n)(\theta_n)}{J'(\Omega_0)(\theta_0)}$$

# The behaviour of our algorithm in images

(Loading video.mpg)

# After a first step (1)

maillage initial

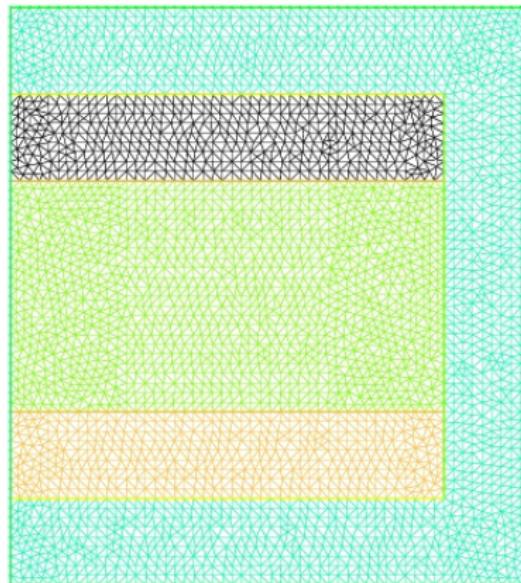


Figure: Initial condition

## After a first step (2)

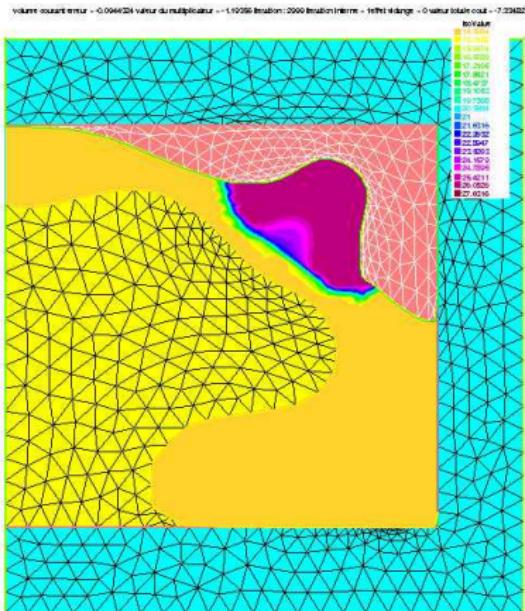


Figure: Case 1 :  $\delta\rho_{Na} = -29,06 \text{ pcm}$

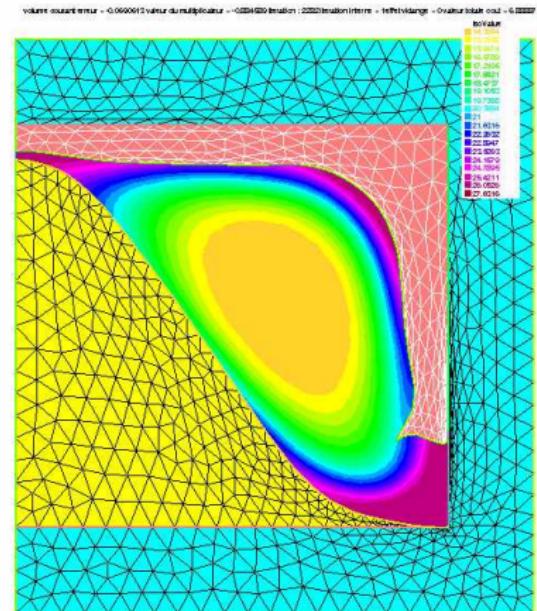


Figure: Case 2 :  $\delta\rho_{Na} = 5,88 \text{ pcm}$

# Cost function

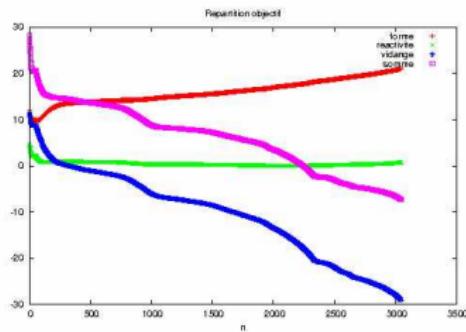


Figure:  $J = \alpha_i J_i$

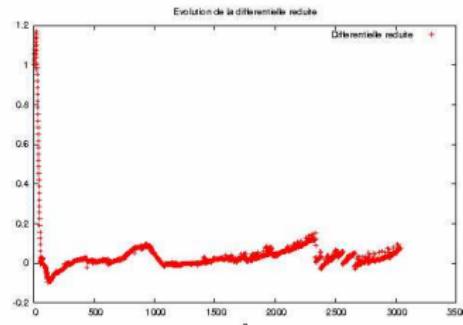
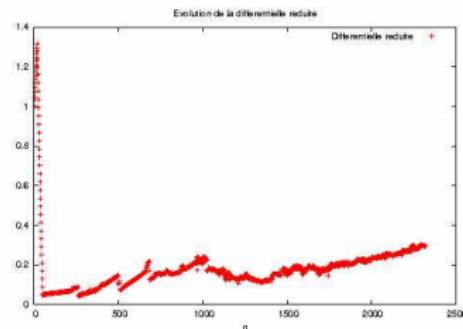
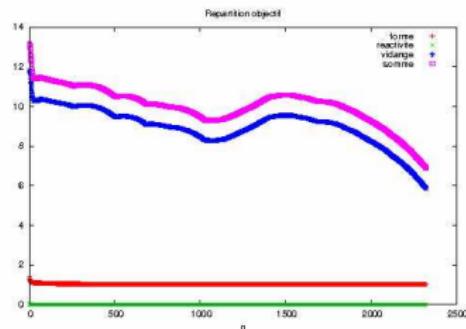


Figure:  $\frac{J'(\Omega_n)(\theta_n)}{J'(\Omega_0)(\theta_0)}$



## After having changed the topology

maillage initial

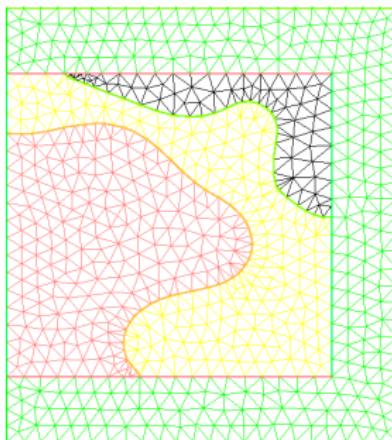


Figure: Case 1

maillage initial

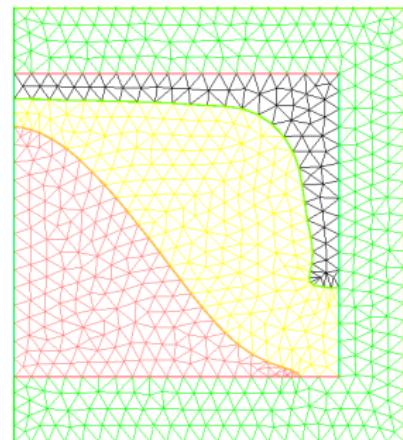


Figure: Case 2

## After a second step (1)

volume courant erreur = -0.0679336 valeur du multiplicateur = -1.34366 itération : 199 itération interne = 1 effet visuel

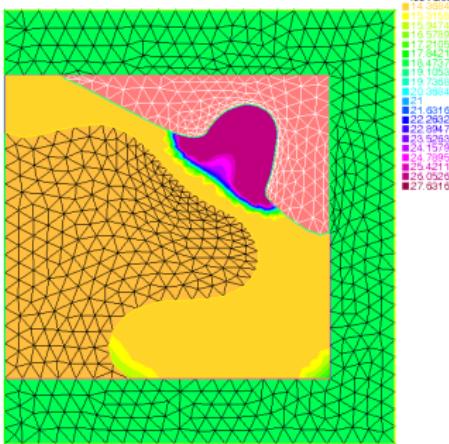


Figure: Case 1 :  $\delta\rho_{Na} = -35\text{pcm}$

volume courant erreur = -0.0893419 valeur du multiplicateur = -0.986507 itération : 199 itération interne = 1 effet visuel

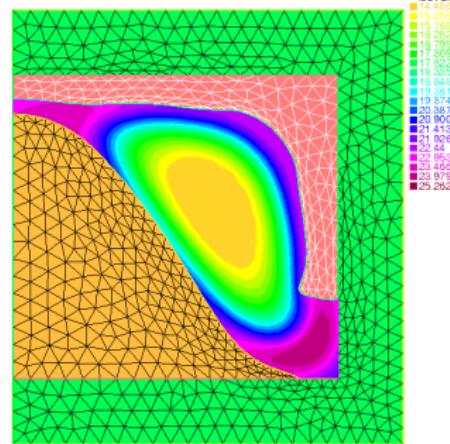


Figure: Case 2 :  $\delta\rho_{Na} = 4\text{pcm}$

# Convergence indexes

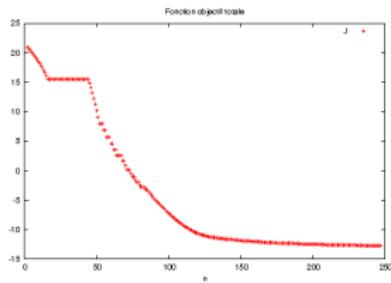


Figure:  $J = \alpha_i J_i$

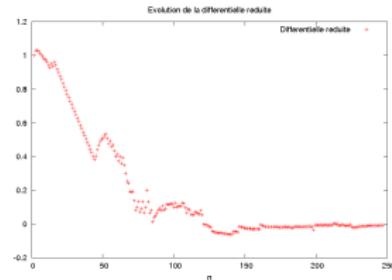
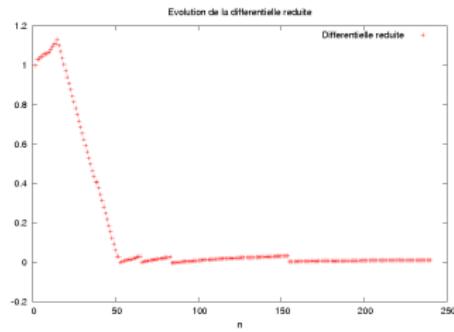
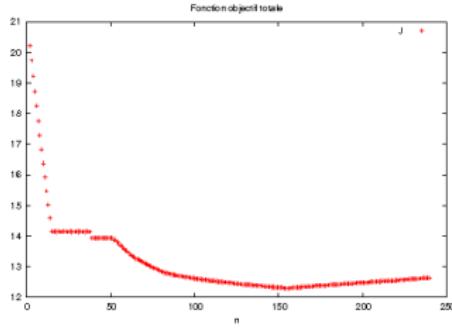


Figure:  $\frac{J'(\Omega_n)(\theta_n)}{J'(\Omega_0)(\theta_0)}$



## Conclusion and perspectives

- Simulation must still be done with the 2 groups energy diffusion model
- Initialize with different shape to check the robustness of the algorithm
- Generalize the remeshing with Level-Set to much more complex situations
- Apply a penalization step to obtain feasible design

Thank you for your attention