

Structure-preserving reduced basis method for cross-diffusion systems

JAD DABAGHI, Virginie Ehrlacher

École des Ponts ParisTech (CERMICS) & INRIA Paris (MATHERIALS)

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École des Ponts
ParisTech



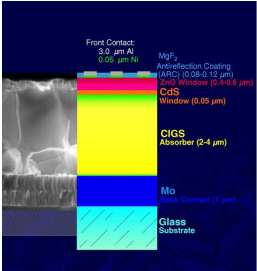
Outline

- 1 Introduction
- 2 Model problem and discretization
- 3 A first POD reduced model
- 4 A structure preserving POD reduced model
- 5 Numerical experiments
- 6 Conclusion

Motivation

Numerical simulation of the PVD process for the fabrication of CIGS (Copper-Indium-Galium-Selenium) solar panels

- 1 The chemical species are injected under gaseous form in a hot chamber.
- 2 A cross-diffusion process occurs and the local volumic fraction of the species evolve with respect to time
- 3 **goal** : optimize the injected flux to obtain high performance solar cells



The numerical simulation of the cross-diffusion system is highly expensive

Need to construct robust schemes to reduce the computational time

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Model Problem

$\Omega \subset \mathbb{R}^2$: polygonal domain, $T > 0$: final simulation time, N_s : number of chemical species.

Cross-diffusion model

$$\begin{aligned}
 \partial_t u_i - \nabla \cdot \left(\sum_{j=1}^{N_s} a_{i,j} (u_j \nabla u_i - u_i \nabla u_j) \right) &= 0 \quad \text{in } \Omega \times [0, T], \text{ for } i \in [1, N_s], \\
 \left(\sum_{j=1}^{N_s} a_{i,j} (u_j \nabla u_i - u_i \nabla u_j) \right) \cdot \mathbf{n} &= 0 \quad \text{on } \partial\Omega \times [0, T], \text{ for } i \in [1, N_s], \\
 u_i(\mathbf{x}, 0) &= u_i^0(\mathbf{x}) \quad \text{in } \Omega, \text{ for } i \in [1, N_s].
 \end{aligned}$$

- Assume $\mathbb{A} \in \mathbb{R}^{N_s, N_s}$, $\mathbb{A} = (a_{i,j})_{1 \leq i,j \leq N_s}$ is symmetric with nonnegative coefficients and that its diagonal terms vanish.

Gradient flow structure

Entropy functional:

$$E(\mathbf{u}) := \int_{\Omega} \sum_{i=1}^{N_s} u_i(\mathbf{x}) \ln(u_i(\mathbf{x})) \, d\mathbf{x} \quad \mathbf{u} = (u_i)_{i \in [1, N_s]}$$

The cross-diffusion system has a gradient flow structure and can be rewritten as

$$\partial_t \mathbf{u} - \nabla \cdot (\mathbb{C}(\mathbf{u}) \nabla dE(\mathbf{u}))$$

$$(\mathbb{C}(\mathbf{u}) \nabla dE(\mathbf{u})) \cdot \mathbf{n} = 0$$

$$\mathbf{u}(\mathbf{x}, 0) = \mathbf{u}^0(\mathbf{x}) \quad \text{in } \Omega.$$

- $\mathbb{C}(\mathbf{u}) \in \mathbb{R}^{N_s, N_s}$: mobility matrix
- dE : Entropy differential defined by

$$(dE(\mathbf{u}))_i := \frac{\partial E(\mathbf{u})}{\partial u_i} = 1 + \ln(u_i).$$

Theorem

There exists a weak solution \mathbf{u} satisfying

$$\mathbf{u} \in \left[L^2_{\text{loc}}(\mathbb{R}^+, H^1(\Omega, \mathbb{R}^{N_s})) \right]^{N_s} \quad \text{and} \quad \partial_t \mathbf{u} \in \left[L^2_{\text{loc}}(\mathbb{R}^+, \left[H^1(\Omega, \mathbb{R}^{N_s}) \right]') \right]^{N_s}.$$

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① mass conservation: $\int_{\Omega} u_i(x, t) \, dx = \int_{\Omega} u_i^0(x) \, dx \quad \forall t \in [0, T], \quad \forall i \in [1, N_s].$

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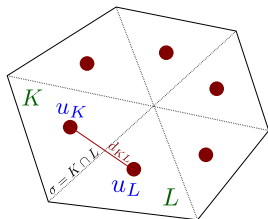
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- ④ entropy-entropy dissipation relation

$$\frac{d}{dt} E(\mathbf{u}) + \int_{\Omega} \sum_{1 \leq i < j \leq N} a_{i,j} \mathbf{u}_i(x) \mathbf{u}_j(x) |\nabla \ln(\mathbf{u}_i(x)) - \nabla \ln(\mathbf{u}_j(x))|^2 \, dx = 0.$$

The cell-centered finite Volume method



$$D_{K\sigma} \mathbf{u}_i^n = u_{i,L}^n - u_{i,K}^n$$

- N_s unknowns per cell $\mathbf{U}^n := (u_{i,K}^n)_{K \in \mathcal{T}_h, i \in \llbracket 1, N_s \rrbracket} \in \mathbb{R}^{N_e \times N_s}$

- $\mathbf{U}^0 \in \mathbb{R}^{N_s \times N_e}$ where $u_{i,K}^0 = \frac{1}{|K|} \int_K u_i^0(x) dx$

- FV scheme : find $\mathbf{U}^n \in \mathbb{R}^{N_e \times N_s}$ satisfying

$$|K| \frac{u_{i,K}^n - u_{i,K}^{n-1}}{\Delta t_n} + \sum_{\sigma \in \mathcal{E}_K} \mathcal{F}_{i,K\sigma}^n(\mathbf{U}^n) = 0$$

Flux: $\mathcal{F}_{i,K\sigma}^n(\mathbf{U}^n) := -a^* \tau_\sigma D_{K\sigma} \mathbf{u}_i^n - \tau_\sigma \left(\sum_{j=1}^N (a_{i,j} - a^*) (u_{j,\sigma}^n D_{K\sigma} \mathbf{u}_i^n - u_{i,\sigma}^n D_{K\sigma} \mathbf{u}_j^n) \right).$

$$\text{edge unknown } u_{i,\sigma}^n := \begin{cases} 0 & \text{if } \min(u_{i,K}^n, u_{i,K\sigma}^n) < 0, \\ u_{i,K}^n & \text{if } u_{i,K}^n = u_{i,K\sigma}^n \geq 0, \\ \frac{u_{i,K}^n - u_{i,K\sigma}^n}{\ln(u_{i,K}^n) - \ln(u_{i,K\sigma}^n)} & \text{if } u_{i,K}^n \neq u_{i,K\sigma}^n \geq 0. \end{cases}$$

Remark

- The main idea of the introduction of the parameter $a^* > 0$ is to avoid unphysical solutions *Cancès, Gaudoul 2020*.
- The numerical flux is conservative in the sense that for $\sigma \in \mathcal{E}_h^{\text{int}}$, $\sigma = K|L$,

$$F_{i,L\sigma}^n = -F_{i,K\sigma}^n.$$

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Structural properties of the discrete solution:

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Structural properties of the discrete solution:

Theorem (Cancès, Gaudoul 2020)

- ① mass conservation $\sum_{K \in \mathcal{T}_h} |K| u_{i,K}^n = \int_{\Omega} u_i^0(x) \, dx \quad \forall i \in [1, N_s], \quad \forall n \in [0, N_t].$
- ② positivity $u_{i,K}^n > 0 \quad \forall K \in \mathcal{T}_h, \quad \forall i \in [1, N_s], \quad \forall n \in [0, N_t].$
- ③ Volume filling constraints: $\sum_{i=1}^{N_s} u_{i,K}^n = 1 \quad \forall K \in \mathcal{T}_h, \quad \forall n \in [0, N_t].$
- ④ Decays of the discrete entropy $E_{\mathcal{T}_h}(\mathbf{U}^n) \leq E_{\mathcal{T}_h}(\mathbf{U}^{n-1}) \quad \forall n \in [1, N_t]$ where

$$E_{\mathcal{T}_h}(\mathbf{U}) := \sum_{K \in \mathcal{T}_h} \sum_{i=1}^{N_s} |K| u_{i,K} \ln(u_{i,K}).$$

Newton linearization

The finite volume procedure defines a nonlinear system of algebraic equations

$$G^n(\mathbf{U}^n) = 0 \quad \text{where} \quad G^n : \mathbb{R}^{N_e \times N_s} \rightarrow \mathbb{R}^{N_e \times N_s}.$$

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Initialization of Newton solver: Let $n \in \llbracket 1, N_t \rrbracket$ and $\mathbf{U}^{n,0} \in \mathbb{R}^{N_e \times N_s}$ be fixed (typically $\mathbf{U}^{n,0} = \mathbf{U}^{n-1}$).

Linear system : the Newton algorithm generates a sequence $(\mathbf{U}^{n,k})_{k \geq 1}$, with $\mathbf{U}^{n,k} \in \mathbb{R}^{N_e \times N_s}$ solution of

$$\mathbb{A}^{n,k-1} \mathbf{U}^{n,k} = \mathbf{B}^{n,k-1}.$$

The jacobian matrix $\mathbb{A}^{n,k-1} \in \mathbb{R}^{N_e \times N_s, N_e \times N_s}$ and the right-hand side vector $\mathbf{B}^{n,k-1} \in \mathbb{R}^{N_e \times N_s}$ are defined by

$$\mathbb{A}^{n,k-1} := \mathbb{J}_{G^n}(\mathbf{U}^{n,k-1}) \quad \text{and} \quad \mathbf{B}^{n,k-1} := \mathbb{J}_{G^n}(\mathbf{U}^{n,k-1}) \mathbf{U}^{n,k-1} - G^n(\mathbf{U}^{n,k-1})$$

Summary

- ① We proposed the cell-centered finite volume method to solve the cross-diffusion system.
- ② This discrete system preserves the structural properties of the solution.

We want to solve the cross-diffusion problem for a wide variety of cross-diffusion matrices \mathbb{A} . It involves high computational cost.

We construct a reduced model to save computational time that preserves the structural properties of the solution.

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The offline stage

Some notation: To each cross-diffusion matrix $\mathbb{A} = (a_{i,j})$ is associated a parameter $\mu \in \mathcal{P}$.

$$\forall \mu \in \mathcal{P} \longleftrightarrow \text{a solution } \mathbf{U}_{\mu}^n \in \mathbb{R}^{N_s \times N_e}.$$

The offline stage:

- 1 We compute snapshots of solution $\mathbf{U}_{\mu}^n \in \mathbb{R}^{N_s \times N_e}$ for $\mu \in \mathcal{P}^{\text{off}} \subset \mathcal{P}$ (a certain number of so-called high-fidelity trajectories). Next, compute the corresponding snapshots matrix

$$\mathbb{M} = [\mathbb{M}_{\mu_1} \quad \mathbb{M}_{\mu_2} \quad \dots \quad \mathbb{M}_{\mu_{p^*}}] \in \mathbb{R}^{N_s \times N_e, N_t \times p^*}.$$

- 2 SVD decomposition : $\mathbb{M} = \underbrace{\mathbb{V}}_{\in \mathbb{R}^{N_s \times N_e, N_s \times N_e}} \times \underbrace{\mathbb{S}}_{\in \mathbb{R}^{N_s \times N_e, N_t \times p^*}} \times \underbrace{\mathbb{W}^T}_{\in \mathbb{R}^{N_t \times p^*, N_t \times p^*}}.$

Here, $\mathbb{S}_{ii} = \sqrt{\sigma_i}$ for $1 \leq i \leq \min(N_s \times N_e, N_t \times p^*)$ and σ_i are the eigenvalues of $\mathbb{M}\mathbb{M}^T$.

- 3 Select r columns from the matrice \mathbb{V} as follows : $\sum_{k \geq r+1} \sigma_k^2 \leq \varepsilon$ for $\varepsilon \geq 0$ a fixed tolerance. \Rightarrow We obtain a reduced basis $\mathbb{V}^r = (\mathbf{V}_1, \dots, \mathbf{V}_r).$

The online stage

For each $\mu \in \mathcal{P}$, at each time step $n = 1 \dots N_t$, the solution of the reduced model denoted by $\tilde{\mathbf{U}}_\mu^n \in \mathbb{R}^{N_s \times N_e}$ is expressed in the basis $(\mathbf{V}^1, \dots, \mathbf{V}^r)$ as

$$\tilde{\mathbf{U}}_\mu^n := \sum_{k=1}^r c_\mu^{k,n} \mathbf{V}^k, \quad \tilde{\mathbf{U}}_\mu^0 := \Pi_{\text{span}(\mathbf{V}^1, \dots, \mathbf{V}^r)} \mathbf{U}^0.$$

How to derive the expression of the coefficients $c_\mu^{k,n}$?

We define the function $H : \mathbb{R}^r \rightarrow \mathbb{R}^r$ by $H_l(\mathbf{c}_\mu^n) := \langle \mathbf{V}^l, G^n(\tilde{\mathbf{U}}_\mu^n) \rangle \quad \forall 1 \leq l \leq r$.
The vector $\mathbf{c}_\mu^n \in \mathbb{R}^r$ is solution to the nonlinear problem

$$H(\mathbf{c}_\mu^n) = 0.$$

Remark
This reduced model does not necessarily preserve the structural properties of the numerical solution.

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The offline stage

- 1 Compute snapshots of solutions.
- 2 Compute the matrix $\overline{\mathbf{M}} \in \mathbb{R}^{N_s \times N_e, N_t \times p^*}$ defined by

$$\overline{\mathbf{M}} = [\overline{\mathbf{M}}_{\mu_1} \quad \overline{\mathbf{M}}_{\mu_2} \quad \dots \quad \overline{\mathbf{M}}_{\mu_{p^*}}] \in \mathbb{R}^{N_s \times N_e, N_t \times p^*}.$$

where each matrix $\overline{\mathbf{M}}_{\mu_\alpha} \in \mathbb{R}^{N_s \times N_e, N_t}$ are defined by $[\overline{\mathbf{M}}_{\mu_\alpha}]_{i,K} = z_{\mu_\alpha, i, K}^n = \ln(u_{\mu_\alpha, i, K}^n)$.

- 3 SVD decomposition

$$\overline{\mathbf{M}} = \underbrace{\overline{\mathbf{V}}}_{\in \mathbb{R}^{N_s \times N_e, N_s \times N_e}} \times \underbrace{\overline{\mathbf{S}}}_{\in \mathbb{R}^{N_s \times N_e, N_t \times p^*}} \times \underbrace{\overline{\mathbf{W}}^T}_{\in \mathbb{R}^{N_t \times p^*, N_t \times p^*}}.$$

- 4 Select r basis functions. Add to the matrix $\overline{\mathbf{V}}^r$ N_s identity bloc matrices as follows

Example: $N_s = 3$

$$\bar{\bar{V}}^{r^*} = \begin{bmatrix} \bar{V}_{1,K1}^1 & \bar{V}_{1,K1}^2 & \cdots & \bar{V}_{1,K1}^r & 1 & 0 & 0 \\ \bar{V}_{1,K2}^1 & \bar{V}_{1,K2}^2 & \cdots & \bar{V}_{1,K2}^r & 1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \bar{V}_{1,K_{N_e}}^1 & \bar{V}_{1,K_{N_e}}^2 & \cdots & \bar{V}_{1,K_{N_e}}^r & 1 & 0 & 0 \\ \bar{V}_{2,K1}^1 & \bar{V}_{2,K1}^2 & \cdots & \bar{V}_{2,K1}^r & 0 & 1 & 0 \\ \bar{V}_{2,K2}^1 & \bar{V}_{2,K2}^2 & \cdots & \bar{V}_{2,K2}^r & 0 & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \bar{V}_{2,K_{N_e}}^1 & \bar{V}_{2,K_{N_e}}^2 & \cdots & \bar{V}_{2,K_{N_e}}^r & 0 & 1 & 0 \\ \bar{V}_{3,K1}^1 & \bar{V}_{3,K1}^2 & \cdots & \bar{V}_{3,K1}^r & 0 & 0 & 1 \\ \bar{V}_{3,K2}^1 & \bar{V}_{3,K2}^2 & \cdots & \bar{V}_{3,K2}^r & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \bar{V}_{3,K_{N_e}}^1 & \bar{V}_{3,K_{N_e}}^2 & \cdots & \bar{V}_{3,K_{N_e}}^r & 0 & 0 & 1 \end{bmatrix}$$

Remark

The matrix $\bar{\mathbf{V}}^{r^}$ is not orthogonal. We employ a QR factorization on the matrix $\bar{\mathbf{V}}^{r^*}$ so that $\bar{\mathbf{V}}^{r^*} = \mathbf{Q} \times \tilde{\mathbf{R}}$ where $\mathbf{Q} \in \mathbb{R}^{N_s \times N_e, r^*}$ is orthogonal, and $\tilde{\mathbf{R}} \in \mathbb{R}^{r^*, r^*}$ is upper triangular.*

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For each $\mu \in \mathcal{P}$, at each time step $n = 1 \dots N_t$, we define a “temporary reduced solution” denoted by $\bar{\mathbf{z}}_{\mu}^n \in \mathbb{R}^{N_s \times N_e}$. It is expressed in the basis $(\mathbf{Q}^1, \dots, \mathbf{Q}^{r^*})$ as

$$\bar{\mathbf{z}}_{\mu}^n := \sum_{k=1}^{r^*} \bar{c}_{\mu}^{k,n} \mathbf{Q}^k \quad \text{and} \quad \bar{\mathbf{z}}_{\mu}^0 := \Pi_{\text{Span}(\mathbf{Q}^1, \dots, \mathbf{Q}^{r^*})} \mathbf{z}_{\mu}^0 \quad \text{where} \quad z_{\mu,i,K}^0 := \ln(u_{\mu,i,K}^0).$$

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Definition of the coefficient $\bar{c}_\mu^{k,n}$

Solve the nonlinear problem $\bar{H}_l(\bar{\mathbf{c}}_\mu^n) = 0$ with $\bar{H}_l(\bar{\mathbf{c}}_\mu^n) := \langle \mathbf{Q}^l, G^n(\bar{\mathbf{U}}_\mu^n) \rangle \quad \forall 1 \leq l \leq r^*.$

How can we construct a structure preserving reduced model ?

Safe reduced solution

$$\overline{\mathbf{U}}_{\mu}^n := (\overline{u}_{\mu,i,K}^n)_{i \in [1, N_s], K \in \mathcal{T}_h} \quad \text{with} \quad \overline{u}_{\mu,i,K}^n := \exp(\overline{z}_{\mu,i,K}^n) / \sum_{j=1}^{N_s} \exp(\overline{z}_{\mu,j,K}^n).$$

Structural properties of the reduced solution

- 1 Positivity $\overline{u}_{\mu,i,K}^n > 0 \quad \forall \mu \in \mathcal{P} \quad \forall K \in \mathcal{T}_h \quad \forall i \in [1, N_s] \quad \forall n \in [0, N_t].$
- 2 Volume filling constraint: $\sum_{i=1}^{N_s} \overline{u}_{\mu,i,K}^n = 1 \quad \forall \mu \in \mathcal{P} \quad \forall K \in \mathcal{T}_h, \quad \forall n \in [1, N_t].$
- 3 mass conservation

$$\sum_{K \in \mathcal{T}_h} |K| \overline{u}_{\mu,i,K}^n = \sum_{K \in \mathcal{T}_h} |K| \overline{u}_{\mu,i,K}^{n-1} = \int_{\Omega} \overline{u}_i^0(x) \, dx \quad \forall i \in [1, N_s] \quad \forall n \in [1, N_t].$$

- 4 The discrete counterpart of the entropy decays along time

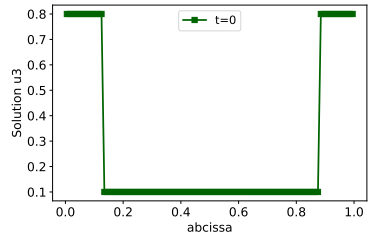
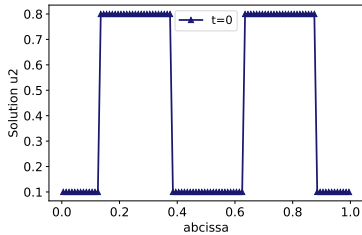
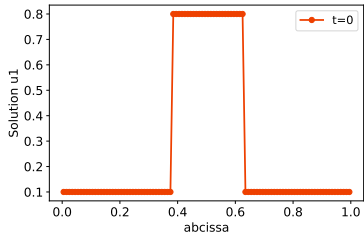
$$E_{\mathcal{T}_h}(\overline{\mathbf{U}}_{\mu}^n) - E_{\mathcal{T}_h}(\overline{\mathbf{U}}_{\mu}^{n-1}) + \Delta t_n \min_{i,j} a_{i,j} \sum_{\sigma \in \mathcal{E}_h^{\text{int}}} \sum_{i=1}^{N_s} \tau_{\sigma} \overline{u}_{\mu,i,\sigma}^n (D_{K\sigma}(\ln(\overline{u}_{\mu,i}^n)))^2 \leq 0 \quad \forall n \in [1, N_t].$$

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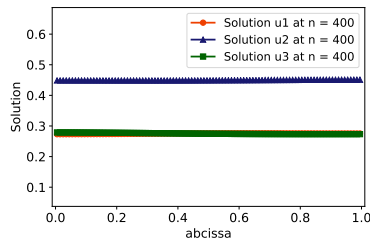
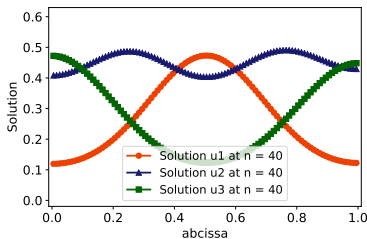
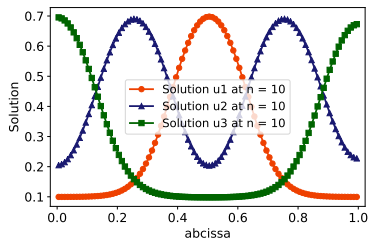
Initial condition

● discontinuous solution



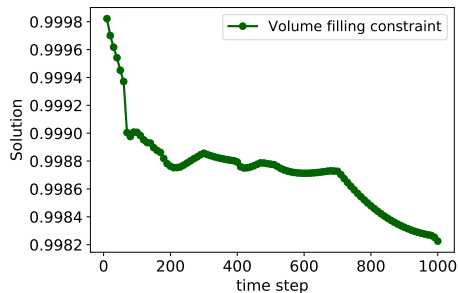
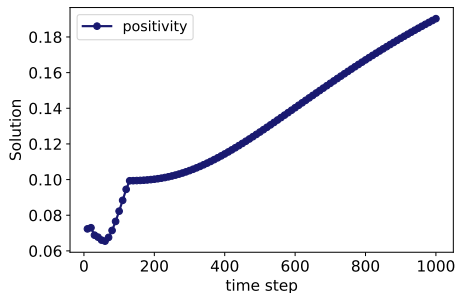
Shape of the solution

$$\mathbb{A}_{\mu} := \begin{pmatrix} 0 & 0.75 & 0.73 \\ 0.75 & 0 & 0.84 \\ 0.73 & 0.84 & 0 \end{pmatrix}$$



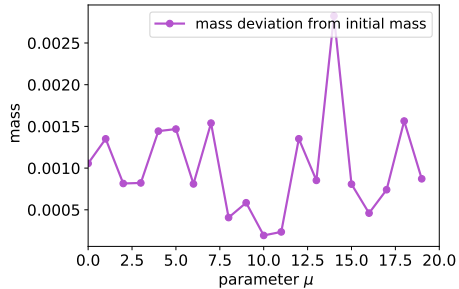
Typical behavior of a cross-diffusion system

Structural properties of the solution



$$\mathcal{P}_U(t_n) := \inf_{\mu \in \mathcal{P}^{\text{off}}} \inf_{K \in \mathcal{T}_h} U_{\mu, K}^n$$

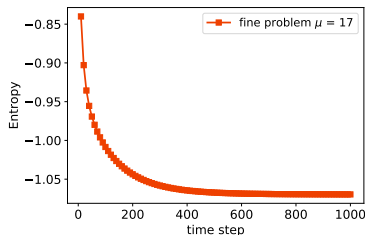
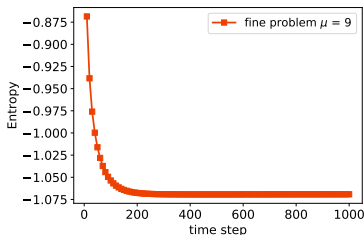
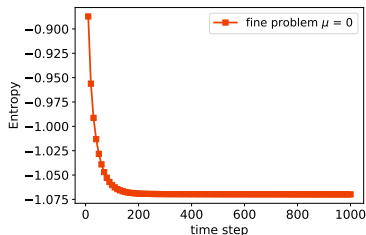
$$\mathcal{S}_U(t_n) := \inf_{\mu \in \mathcal{P}^{\text{off}}} \inf_{K \in \mathcal{T}_h} \sum_{i=1}^{N_s} U_{\mu, i, K}^n$$



$$\mathcal{E}_U(\mu) := \max_{i \in \llbracket 1, N_s \rrbracket} \max_{n \in \llbracket 1, N_t \rrbracket} \left| \sum_{K \in \mathcal{T}_h} |K| U_{\mu, i, K}^n - \int_{\Omega} u_i^0(x) dx \right|$$

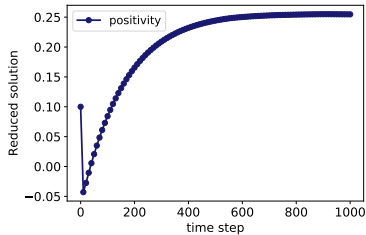
Structural properties of the Solution

$$\mathbb{A}_{\mu_0} := \begin{pmatrix} 0 & 0.75 & 0.73 \\ 0.75 & 0 & 0.84 \\ 0.73 & 0.84 & 0 \end{pmatrix} \quad
 \mathbb{A}_{\mu_9} = \begin{pmatrix} 0 & 0.93 & 0.71 \\ 0.93 & 0 & 0.44 \\ 0.71 & 0.44 & 0 \end{pmatrix} \quad
 \mathbb{A}_{\mu_{17}} = \begin{pmatrix} 0 & 0.37 & 0.004 \\ 0.37 & 0 & 0.72 \\ 0.004 & 0.72 & 0 \end{pmatrix}$$

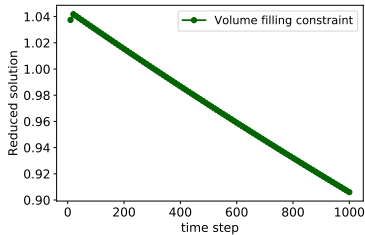


First POD reduced model

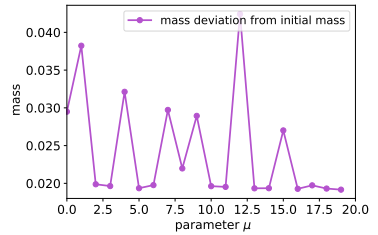
Violation of the structural properties of the solution



$r = 2$



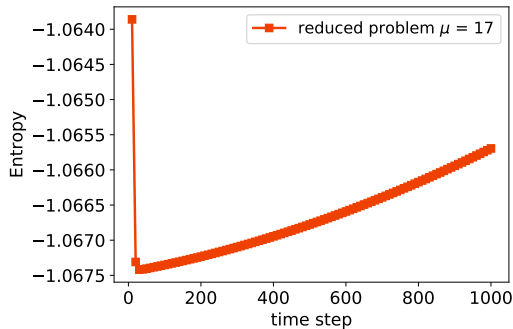
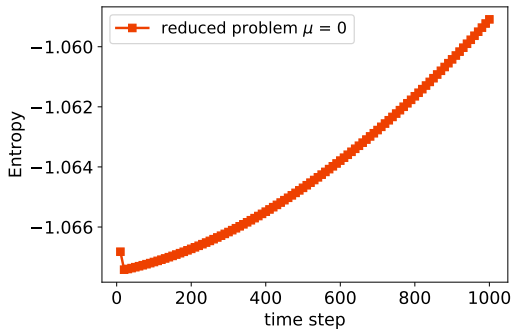
$r = 1$



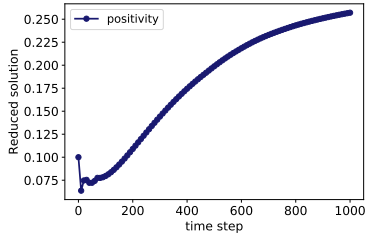
$r = 1$

$$\mathbb{A}_0 = \begin{pmatrix} 0 & 0.93 & 0.71 \\ 0.93 & 0 & 0.44 \\ 0.71 & 0.44 & 0 \end{pmatrix}$$

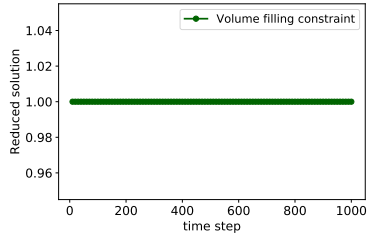
$$\mathbb{A}_{17} = \begin{pmatrix} 0 & 0.37 & 0.004 \\ 0.37 & 0 & 0.72 \\ 0.004 & 0.72 & 0 \end{pmatrix}$$



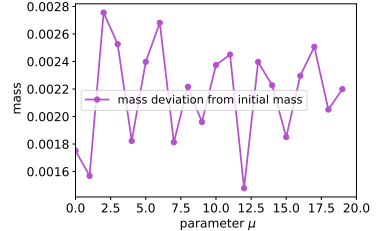
Second POD reduced model



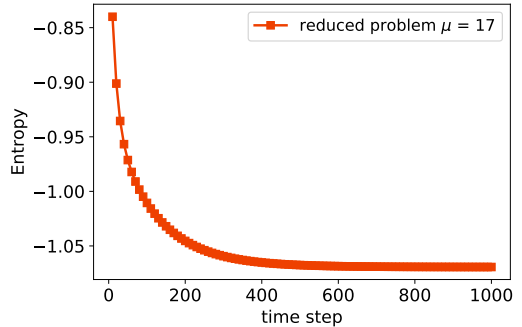
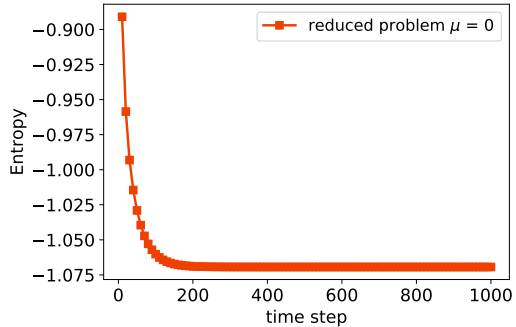
$r = 2$



$r = 1$



$r = 1$



The entropy decreases with respect to time.

Second test case

- We consider the PVD process : 4 species.
- Ω is a one dimensional domain consisting in a segment of length $L = 1 m$.
- $\Delta x = 10^{-2}$.
- Final simulation time $T = 0.5$ s and $\Delta t = 2.5 \times 10^{-4}$ s.
- Compute $\mu = 20$ snapshots of solutions.

Initial guess

We take

$$w_1^0(x) = e^{-25(x-0.5)^2}, \quad w_2^0(x) = x^2 + \varepsilon, \quad w_3(x) = 1 - e^{-25(x-0.5)^2}, \quad w_4(x) = |\sin(\pi x)|$$

where $\varepsilon = 10^{-6}$.

To satisfy the volume filling constraint property we use a renormalization

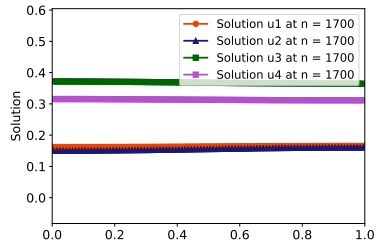
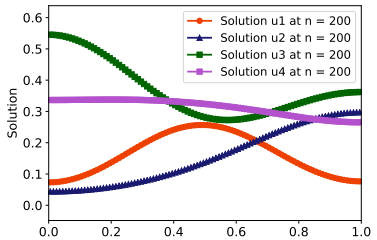
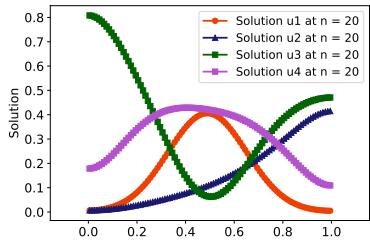
$$u_i^0(x_j) = \frac{w_i^0(x_j)}{\sum_{l=1}^{N_s} w_l^0(x_j)}$$

where $x_j, j \in [1, N_e]$ are the cell centers of the mesh.

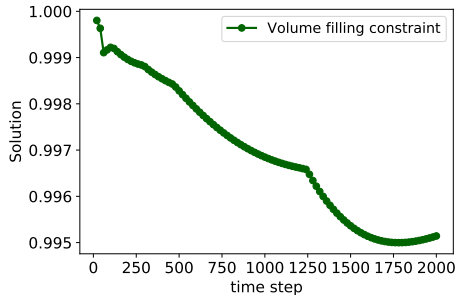
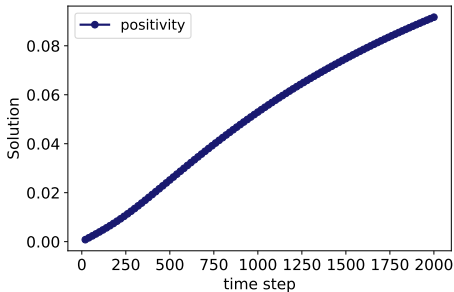
Fine solution

Cross-diffusion matrix

$$\mathbb{A}_{17} = \begin{pmatrix} 0 & 0.64 & 0.31 & 0.53 \\ 0.64 & 0 & 0.99 & 0.84 \\ 0.32 & 0.99 & 0 & 0.99 \\ 0.53 & 0.84 & 0.99 & 0 \end{pmatrix}$$

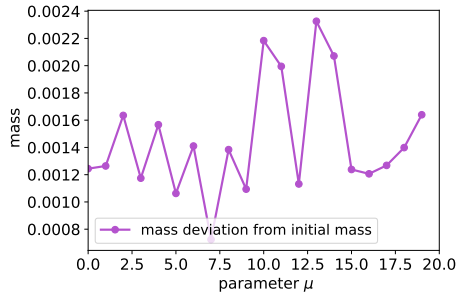


Properties of the solution



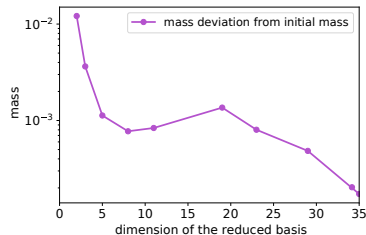
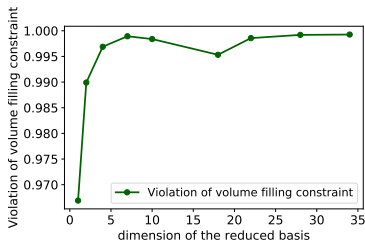
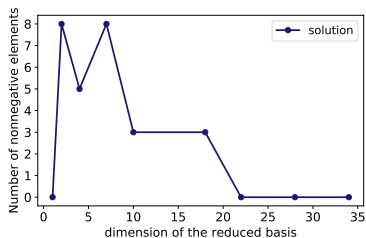
$$\mathcal{P}_{\bar{U}}(t_n) := \inf_{\mu \in \mathcal{P}^{\text{off}}} \inf_{K \in \mathcal{T}_h} \bar{U}_{\mu, K}^n$$

$$\mathcal{S}_{\bar{U}}(t_n) := \inf_{\mu \in \mathcal{P}^{\text{off}}} \inf_{K \in \mathcal{T}_h} \sum_{i=1}^{N_s} \bar{U}_{\mu, i, K}^n$$



$$\mathcal{E}_{\overline{U}}(\mu) := \max_{i \in \llbracket 1, N_s \rrbracket} \max_{n \in \llbracket 1, N_t \rrbracket} \left| \sum_{K \in \mathcal{T}_h} |K| \overline{U}_{\mu, i, K}^n - \int_{\Omega} \overline{u}_i^0(x) \, dx \right|$$

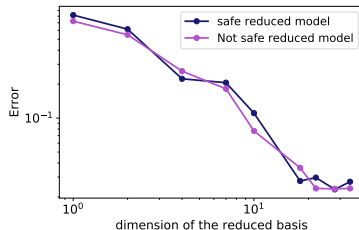
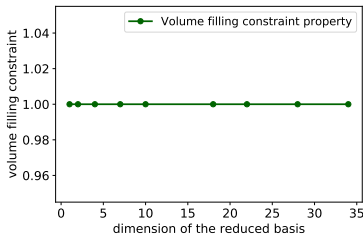
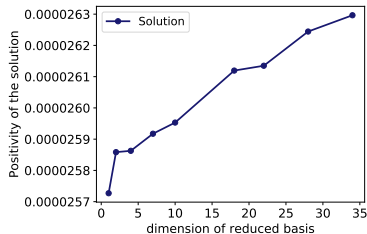
First POD reduced model



$$\inf_{n \in \llbracket 1, N_t \rrbracket} \inf_{\mu \in \mathcal{P}^{\text{off}}} \inf_{K \in \mathcal{T}_h} \sum_{i=1}^{N_s} \tilde{U}_{\mu, i, K}^n \quad \max_{\mu \in \mathcal{P}^{\text{off}}} \max_{i \in \llbracket 1, N_s \rrbracket} \max_{n \in \llbracket 1, N_t \rrbracket} \left| \sum_{K \in \mathcal{T}_h} |K| \bar{U}_{\mu, i, K}^n - \int_{\Omega} \bar{u}_i^0(x) dx \right|$$

Violation of the physical properties.

Safe POD reduced model



$$\inf_{n \in \llbracket 1, N_t \rrbracket} \inf_{\mu \in \mathcal{P}^{\text{off}}} \inf_{K \in \mathcal{T}_h} \bar{U}_{\mu, K}^n \quad \inf_{n \in \llbracket 1, N_t \rrbracket} \inf_{\mu \in \mathcal{P}^{\text{off}}} \inf_{K \in \mathcal{T}_h} \sum_{i=1}^{N_s} \bar{U}_{\mu, i, K}^n$$

$$\max_{i \in \llbracket 1, N_s \rrbracket} \left\| u_{\mu}^i - u_{\mu}^{i, \text{red}} \right\|_{L^\infty(\mathcal{P}^{\text{off}}, L^2(\Omega), L^\infty([0, T]))} := \max_{\mu \in \mathcal{P}^{\text{off}}} \max_{n \in \llbracket 1, N_t \rrbracket} \left(\sum_{K \in \mathcal{T}_h} \left| u_{\mu, i, K}^n - u_{\mu, i, K}^{n, \text{red}} \right|^2 \right)^{\frac{1}{2}}$$

Outline

- 1 Introduction
- 2 Model problem and discretization
- 3 A first POD reduced model
- 4 A structure preserving POD reduced model
- 5 Numerical experiments
- 6 Conclusion**

Conclusion and perspectives

Conclusion

- We constructed an efficient reduced model preserving the physical properties of the cross-diffusion system.

Perspectives

- Construct a reduced basis method with a posteriori estimators for high accuracy.
- EIM algorithm to reduce the computational time.