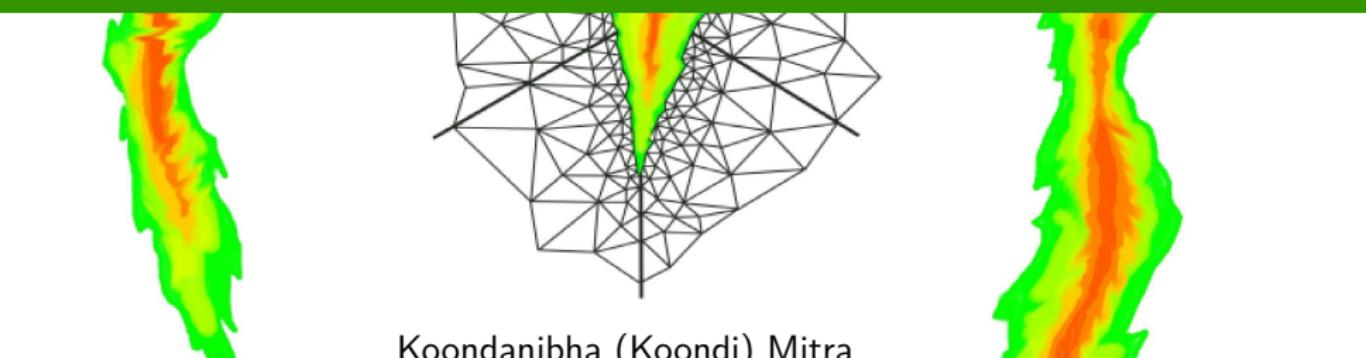


Reliable, Robust, & Efficient A Posteriori Estimates for Nonlinear Elliptic Problems using Linearization



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joint work with Martin Vohralík

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- ① Introduction
- ② Main analytical results
- ③ Scope of the results
- ④ Numerical results

① Introduction

② Main analytical results

③ Scope of the results

④ Numerical results

Nonlinear elliptic problems

For $d \in \mathbb{N}$, let $\Omega \subset \mathbb{R}^d$ be an open and bounded polytope. Let $u \in H_0^1(\Omega)$ solve the elliptic operator equation: for $\mathcal{R} : H_0^1(\Omega) \rightarrow H^{-1}(\Omega)$,

$$\langle \mathcal{R}(u), \varphi \rangle = 0, \quad \forall \varphi \in H_0^1(\Omega).$$

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Assumption 1 \mathcal{R} is monotone & Lipschitz in some sense*

For an arbitrary $\tilde{u} \in H_0^1(\Omega)$, and constants $\lambda_M > \lambda_m > 0$

$$\lambda_m \operatorname{dist}(\tilde{u}, u) \leq \sup_{\varphi \in H_0^1(\Omega)} \frac{\langle \mathcal{R}(\tilde{u}), \varphi \rangle}{\|\nabla \varphi\|} \leq \lambda_M \operatorname{dist}(\tilde{u}, u)$$

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This implies that the error of $\tilde{u} \in H_0^1(\Omega)$ can simply be measured by

$$\|\mathcal{R}(\tilde{u})\|_{H^{-1}(\Omega)} := \sup_{\varphi \in H_0^1(\Omega)} \frac{\langle \mathcal{R}(\tilde{u}), \varphi \rangle}{\|\nabla \varphi\|}$$

- To have **reliable, locally efficient** a posteriori error estimates **robust with respect to nonlinearities**

$$C_m \eta(\tilde{u}) \leq \|\mathcal{R}(\tilde{u})\|_{H^{-1}(\Omega)} \leq C_M \eta(\tilde{u})$$

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$$C_m \eta(\tilde{u}) \leq \|\mathcal{R}(\tilde{u})\|_{H^{-1}(\Omega)} \leq C_M \eta(\tilde{u})$$

However, generally C_M/C_m depends on λ_M/λ_m which can be large, and thus the estimate is not robust with respect to nonlinearities

1 A linear example

| 4

Consider the diffusion eq: $\langle \mathcal{R}(u), \varphi \rangle := (A(x)\nabla u, \nabla \varphi) - (f, \varphi) = 0.$

Let $\lambda_m^2 \leq A(x) \leq \lambda_M^2$.

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Let $\lambda_m^2 \leq A(x) \leq \lambda_M^2$. If $u_h \in V_h \subset H_0^1(\Omega)$ is the f.e. solution of the problem then Cea's lemma gives

$$\|\nabla(u - u_h)\| \leq \frac{\lambda_M}{\lambda_m} \|\nabla(u_h - \varphi_h)\|, \quad \forall \varphi_h \in V_h.$$

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However, defining the energy norm $\|\varphi\|_{1,A} = \|A(x)^{\frac{1}{2}}\nabla\varphi\|$ one has

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Similarly, if we use the error measure

$$\|\mathcal{R}(\tilde{u})\|_{-1,A} := \sup_{\varphi \in H_0^1(\Omega)} \frac{\langle \mathcal{R}(\tilde{u}), \varphi \rangle}{\|\varphi\|_{1,A}}$$

then we have robust estimates [Repin (2000)]

1 Moving to the nonlinear case

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Then $\|\mathcal{R}(\cdot)\|_{-1, A(\cdot, u)}$ cannot be defined since $u \in H_0^1(\Omega)$ is unknown.

Consider the nonlinear eq: $\langle \mathcal{R}(u), \varphi \rangle = (A(\mathbf{x}, u) \nabla u, \nabla \varphi) - (f, \varphi) = 0$.

Linearization iterations

We generally solve nonlinear equations by linearization iterations, i.e., by finding a sequence $\{u_h^i\}_{i \in \mathbb{N}} \subset V_h \subset H_0^1(\Omega)$.

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Example (Fixed point iteration) For each $i \in \mathbb{N}$ and $u_h^i \in V_h$, let $u_h^{i+1} \in V_h$ be the finite element solution of

$$\langle \mathcal{R}_{\text{lin}}^{u_h^i}(u), \varphi \rangle := (A(\mathbf{x}, u_h^i) \nabla u, \nabla \varphi) - (f, \varphi) = 0$$

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Then defining the energy norms generated at iteration i as

$$\begin{cases} |\!|\!| \varphi |\!|\!|_{1, u_h^i} := \|A(\mathbf{x}, u_h^i)^{\frac{1}{2}} \nabla \varphi\| & \text{for } \varphi \in H_0^1(\Omega), \\ |\!|\!| \varsigma |\!|\!|_{-1, u_h^i} := \sup_{\varphi \in H_0^1(\Omega)} \langle \varsigma, \varphi \rangle / |\!|\!| \varphi |\!|\!|_{1, u_h^i} & \text{for } \varsigma \in H^{-1}(\Omega), \end{cases}$$

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we have robust estimates of $\left\| \mathcal{R}_{\text{lin}}^{u_h^i}(u_h^{i+1}) \right\|_{-1, u_h^i}$ (discretization error)

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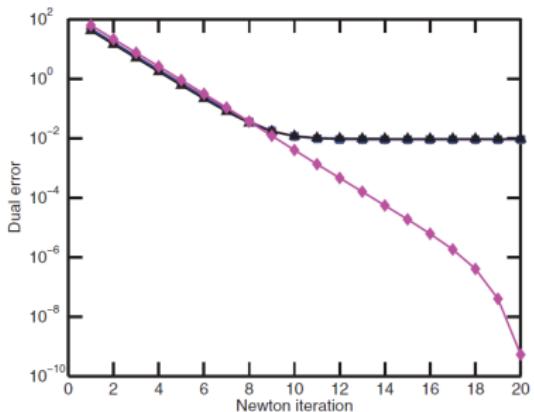
we have robust estimates of $\left\| \mathcal{R}_{\text{lin}}^{u_h^i}(u_h^{i+1}) \right\|_{-1,u_h^i}$ (discretization error)

but not of $\left\| \mathcal{R}(u_h^{i+1}) \right\|_{-1,u_h^i}$

- Can we get a robust estimate of $\|\mathcal{R}(u_h^i)\|_{-1, u_h^i}$ using the linearization iterations?

- ▶ Can we get a robust estimate of $\|\mathcal{R}(u_h^i)\|_{-1, u_h^i}$ using the linearization iterations?
- ▶ If yes, then can this be used to stop the iterations adaptively?

[Ern & Vohralík (2013)]



See also: [El Alaoui *et al* (2011)], [Blechta *et al* (2018)], [Heid & Wihler (2020)]

① Introduction

② Main analytical results

Decomposition of error

A posteriori error estimates

③ Scope of the results

④ Numerical results

2 An orthogonal decomposition result

| 7

Theorem 1 Decomposition of the total error using linearization

Under Assumption 1, and provided that the linearization iterations $\{u_h^i\}_{i \in \mathbb{N}} \subset V_h \subset H_0^1(\Omega)$ are generated by linear problems

$$\langle \mathcal{R}_{\text{lin}}^{u_h^i}(u), \varphi \rangle = \mathfrak{L}(u_h^i; u - u_h^i, \varphi) + \langle \mathcal{R}(u_h^i), \varphi \rangle = 0, \quad \forall \varphi \in H_0^1(\Omega),$$

for a symmetric, bounded, coercive, bilinear form $\mathfrak{L}(u_h^i, \cdot, \cdot)$, and

$$\|\varphi\|_{1,u_h^i} = \mathfrak{L}(u_h^i; \varphi, \varphi)^{\frac{1}{2}}, \quad \|\varsigma\|_{-1,u_h^i} = \sup_{\varphi \in H_0^1(\Omega)} \frac{\langle \varsigma, \varphi \rangle}{\|\varphi\|_{1,u_h^i}},$$

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we have

$$\underbrace{\|\mathcal{R}(u_h^i)\|_{-1,u_h^i}^2}_{\text{total error}} = \underbrace{\|\mathcal{R}_{\text{lin}}^{u_h^i}(u_h^{i+1})\|_{-1,u_h^i}^2}_{\text{discretization error of the linearization step}} + \underbrace{\|u_h^{i+1} - u_h^i\|_{1,u_h^i}^2}_{\text{linearization error}}.$$

- The linearization error is computed directly, we define

$$\eta_{\text{lin}, \Omega}^i := \| \|u_h^{i+1} - u_h^i\| \|_{1, u_h^i}^2.$$

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$$\eta_{\text{lin}, \Omega}^i := \|u_h^{i+1} - u_h^i\|_{1, u_h^i}^2.$$

- For estimating $\|\mathcal{R}_{\text{lin}}^{u_h^i}(u_h^{i+1})\|_{-1, u_h^i}^2$ we introduce $\eta_{\text{disc}, \Omega}^i$, following the analysis on robust estimates of singularly perturbed reaction-diffusion problems in [Smears & Vohralík (2020)], [Verfürth (1998), (2005)]

Theorem 2 Reliable, efficient, and robust a posteriori estimates

Global reliability

$$\|\mathcal{R}(u_T^i)\|_{-1, u_h^i}^2 \leq [\eta_\Omega^i]^2 = \sum_{K \in \mathcal{T}} ([\eta_{\text{disc}, K}^i]^2 + [\eta_{\text{lin}, K}^i]^2).$$

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Global efficiency

$$[\eta_\Omega^i]^2 \lesssim \|\mathcal{R}(u_h^i)\|_{-1, u_h^i}^2 + (\text{data oscillation terms}).$$

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Global efficiency

$$[\eta_\Omega^i]^2 \lesssim \|\mathcal{R}(u_h^i)\|_{-1, u_h^i}^2 + (\text{data oscillation terms}).$$

Local efficiency

For $\omega \subset \Omega$, there exists a neighbourhood $\mathfrak{T}_\omega \subseteq \Omega$ such that

$$[\eta_\omega^i]^2 \lesssim \|\mathcal{R}(u_h^{i+1})\|_{-1, u_h^i, \mathfrak{T}_\omega}^2 + [\eta_{\text{lin}, \mathfrak{T}_\omega}^i]^2 + (\text{data oscillation terms}).$$

- ① Introduction
- ② Main analytical results
- ③ Scope of the results
 - Class of problems
 - Linearization schemes
- ④ Numerical results

Class 1: gradient independent diffusivity problems

For all $\varphi \in H_0^1(\Omega)$, $\mathcal{R} : H_0^1(\Omega) \rightarrow H^{-1}(\Omega)$ is defined as

$$\langle \mathcal{R}(u), \varphi \rangle := \langle f(x, u), \varphi \rangle + \tau(\bar{\mathbf{K}}(x)(\mathcal{D}(x, u)\nabla u + \mathbf{q}(x, u)), \nabla \varphi)$$

3 Class of problems

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Semilinear equations $\Delta u = f(x, u)$

Such equations pop up in quantum mechanics (special solutions to nonlinear Klein-Gordon equations), gravitation influences on stars, membrane buckling problems etc.

Time-discrete nonlinear advection-reaction-diffusion equations

with time-step $\tau > 0$ following evolutions equations reduce to this case

Poro-Fischer equations: $\partial_t u = \Delta u^m + \lambda u(1-u)$

Richards equation: $\partial_t S(u) = \nabla \cdot [\bar{\mathbf{K}}(x)\kappa(S(u))(\nabla u + \mathbf{g})] + f(x, u)$

Biofilm equations: $\partial_t u_k = \mu_k \Delta \Phi_k(u_k) + f_k((u_k)_{k=1}^n)$

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Assumption 1 is satisfied if $\tau > 0$ is small, and

- ▶ $\mathcal{D} : \Omega \times \mathbb{R} \rightarrow \mathbb{R}^+$ is bounded and Lipschitz
- ▶ $\bar{\mathbf{K}} : \Omega \rightarrow \mathbb{R}^{d \times d}$ is symmetric positive definite
- ▶ $f : \Omega \times \mathbb{R} \rightarrow \mathbb{R}$ is monotone and Lipschitz upto the boundary
- ▶ $\mathbf{q} : \Omega \times \mathbb{R} \rightarrow \mathbb{R}^d$ is bounded, and satisfies a Lipschitz condition*

with

$$\text{dist}(u, v) = \left\| \bar{\mathbf{K}}^{\frac{1}{2}} \nabla \int_u^v \mathcal{D} \right\|$$

Class 2: gradient dependent diffusivity problems

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For $a(\cdot)$ satisfying the ellipticity condition, and $b(\cdot) > 0$

Mean curvature flow: $\sigma(\mathbf{x}, \mathbf{y}) = \left(a(\mathbf{x}) + \frac{b(\mathbf{x})}{\sqrt{1+|\mathbf{y}|^2}} \right) \mathbf{y}$

p -Laplacian problems*: $\sigma(\mathbf{x}, \mathbf{y}) = (a(\mathbf{x}) + b(\mathbf{x})|\mathbf{y}|^{p-2})\mathbf{y}$

Compressive flow*: $\sigma(\mathbf{x}, \mathbf{y}) = b(\mathbf{x}) \left(1 - \frac{r-1}{2} |\mathbf{y}|^2 \right)^{\frac{1}{r-1}} \mathbf{y}$

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Assumption 1 is satisfied if $f(\mathbf{x}, \cdot)$, $\sigma(\mathbf{x}, \cdot)$ is monotone and Lipschitz

$$(\sigma(\mathbf{x}, \mathbf{y}) - \sigma(\mathbf{x}, \mathbf{z})) \cdot (\mathbf{y} - \mathbf{z}) \geq \lambda_m |\mathbf{y} - \mathbf{z}|^2 \quad \text{for } \mathbf{x} \in \Omega \text{ and } \mathbf{y}, \mathbf{z} \in \mathbb{R}^d,$$

$$|\sigma(\mathbf{x}, \mathbf{y}) - \sigma(\mathbf{x}, \mathbf{z})| \leq \lambda_M |\mathbf{y} - \mathbf{z}| \quad \text{for } \mathbf{x} \in \Omega \text{ and } \mathbf{y}, \mathbf{z} \in \mathbb{R}^d.$$

with

$$\text{dist}(u, v) = \|\nabla(u - v)\|$$

Abstract linearization

For all $u_h^i \in V_h$, define the symmetric, coercive, and bounded bilinear form

$$\mathcal{L}(u_h^i; v, w) := (L(\mathbf{x}, u_h^i) v, w) + (\mathbf{a}(\mathbf{x}, u_h^i) \nabla v, \nabla w).$$

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Then we compute $u_h^{i+1} \in V_h$ as the f.e. solution of the equation

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With respect to \mathcal{L} , the linearized energy norms are defined as

$$\|\varphi\|_{1,u_h^i} = \mathcal{L}(u_h^i; \varphi, \varphi)^{\frac{1}{2}} = \left(\int_{\Omega} L(\mathbf{x}, u_h^i) \varphi^2 + |\mathfrak{a}(\mathbf{x}, u_h^i)^{\frac{1}{2}} \nabla \varphi|^2 \right)^{\frac{1}{2}},$$

$$\|\varsigma\|_{-1,u_h^i} = \sup_{\varphi \in H_0^1(\Omega)} \frac{\langle \varsigma, \varphi \rangle}{\|\varphi\|_{1,u_h^i}}.$$

3 Linearization schemes: practical examples

| 12

Abstract linearization

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Scheme	$L(\mathbf{x}, v)$	$\mathfrak{a}(\mathbf{x}, v)/\tau$
Picard	$\partial_\xi f(\mathbf{x}, v)$	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$
Jäger–Kačur	$\max_{\xi \in \mathbb{R}} \left(\frac{f(\mathbf{x}, \xi) - f(\mathbf{x}, v)}{\xi - v} \right)$	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$
L -scheme	L (constant) $\geq \frac{1}{2} \sup \partial_\xi f$	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$
M -scheme	$\partial_\xi f(\mathbf{x}, v) + M\tau$ (constant)	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$

Examples in gradient independent diffusivity case

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Scheme	$L(\mathbf{x}, v)$	$\mathbf{a}(\mathbf{x}, v)/\tau$
Picard	$\partial_\xi f(\mathbf{x}, v)$	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$
Jäger–Kačur	$\max_{\xi \in \mathbb{R}} \left(\frac{f(\mathbf{x}, \xi) - f(\mathbf{x}, v)}{\xi - v} \right)$	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$
L -scheme	L (constant) $\geq \frac{1}{2} \sup \partial_\xi f$	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$
M -scheme	$\partial_\xi f(\mathbf{x}, v) + M\tau$ (constant)	$\bar{\mathbf{K}}(\mathbf{x}) \mathcal{D}(\mathbf{x}, v)$

Examples in gradient independent diffusivity case

- ▶ Newton scheme leads to a non-symmetric \mathcal{L} and is treated separately

Abstract linearization

For $\mathcal{L}(u_h^i; v, w) := (L(\mathbf{x}, u_h^i)v, w) + (\mathbf{a}(\mathbf{x}, u_h^i)\nabla v, \nabla w)$,

compute $u_h^{i+1} \in V_h$ as the f.e. solution of the equation

$$\mathcal{L}(u_h^i; u_h^{i+1} - u_h^i, \varphi) = -\langle \mathcal{R}(u_h^i), \varphi \rangle, \quad \forall \varphi \in H_0^1(\Omega).$$

Scheme	$L(\mathbf{x}, v)$	$\mathbf{a}(\mathbf{x}, v)/\tau$
Kačanov	$\partial_\xi f(\mathbf{x}, v)$	$A(\mathbf{x}, \nabla v)$
Zarantonello	0	\wedge (constant) > 0

Examples in gradient dependent diffusivity case

① Introduction

② Main analytical results

③ Scope of the results

④ Numerical results

Gradient independent diffusivity

Gradient independent diffusivity case

The Newton scheme

Algorithm 1 Adaptive linearization

For a fixed $0 < \mu \ll 1$, we iterate until for some $i = \bar{i} \in N$,

$$\eta_{\text{lin}, \Omega}^{\bar{i}} \leq \mu [\eta_{\Omega}^{\bar{i}}].$$

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Effectivity indices

Global effectivity index: Eff. Ind. := $\eta_{\Omega}^i / \| \mathcal{R}(u_h^i) \|_{-1, u_h^i}$

Local effectivity index: (Eff. Ind.) $_K$:= $\eta_K^i / \| \mathcal{R}(u_h^i) \|_{-1, u_h^i, K}$, $\forall K \in \mathcal{T}$,

Algorithm 1 Adaptive linearization

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Mesh

Three mesh-levels used: $h = \frac{0.1}{\ell}$ where $\ell \in \{1, 2, 4\}$

4 Gradient independent diffusivity case: Richards equation

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For $\Omega = (0, 1) \times (0, 1)$ we study

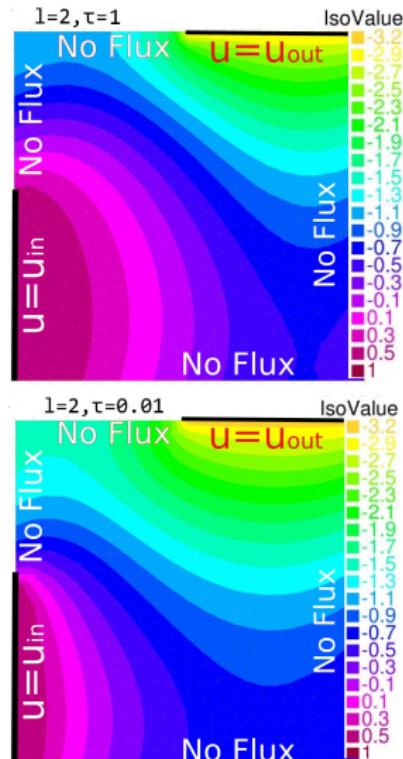
$$\begin{aligned} \langle \mathcal{R}(\tilde{u}), \varphi \rangle &= (S(\tilde{u}) - S(\bar{u}), \varphi) \\ &+ \tau(\bar{\mathbf{K}}\kappa(S(\tilde{u}))[\nabla \tilde{u} - \mathbf{g}], \nabla \varphi) \end{aligned}$$

where the van Genuchten parametrization for S , κ is used:

$$\begin{cases} S(\xi) := \left(1 + (2 - \xi)^{\frac{1}{1-\lambda}}\right)^{-\lambda}, \\ \kappa(s) := \sqrt{s} \left(1 - (1 - s^{\frac{1}{\lambda}})^\lambda\right)^2, \end{cases}$$

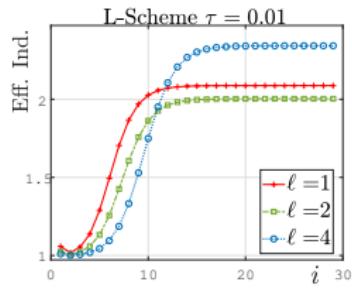
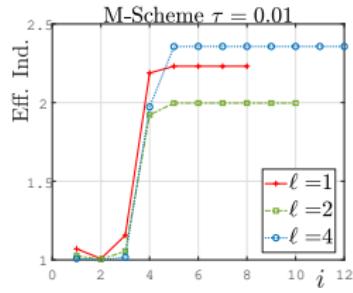
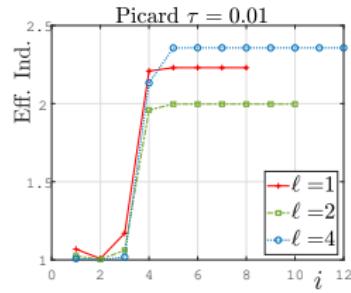
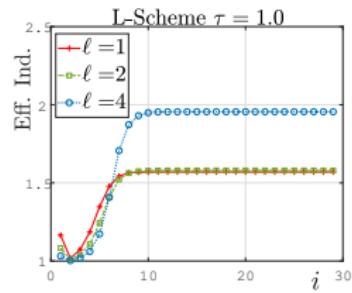
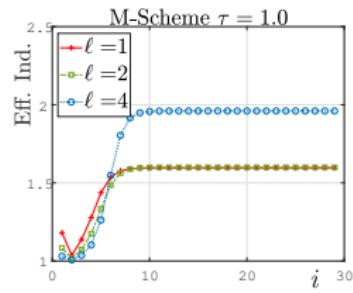
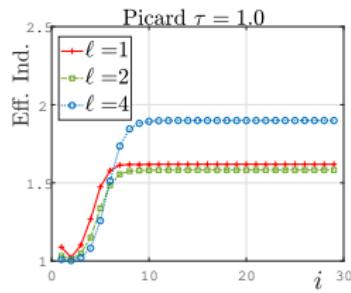
with $\lambda = 0.5$, $u_h^0 = 0$,

$$\bar{\mathbf{K}} = \begin{bmatrix} 1 & 0.2 \\ 0.2 & 1 \end{bmatrix}, \text{ and } \mathbf{g} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$



4 Global effectivity

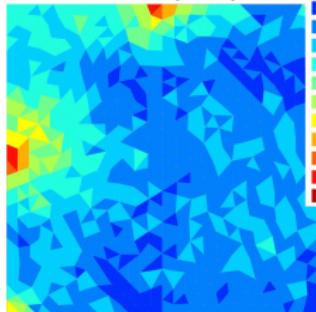
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4 Distribution of error vs. estimates

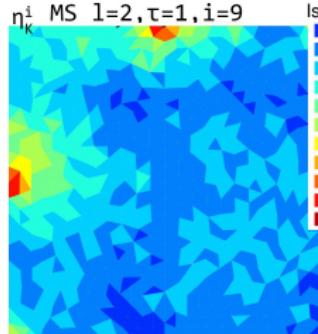
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Error MS $l=2, \tau=1, i=9$



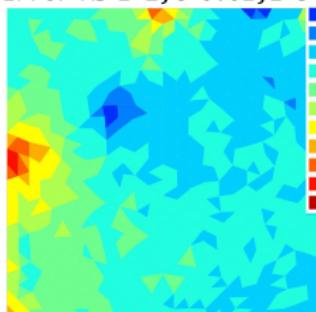
Error

η_K^i MS $l=2, \tau=1, i=9$

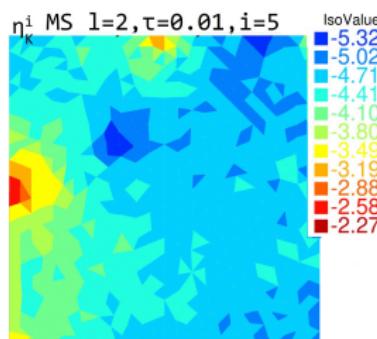


Estimate

Error MS $l=2, \tau=0.01, i=5$

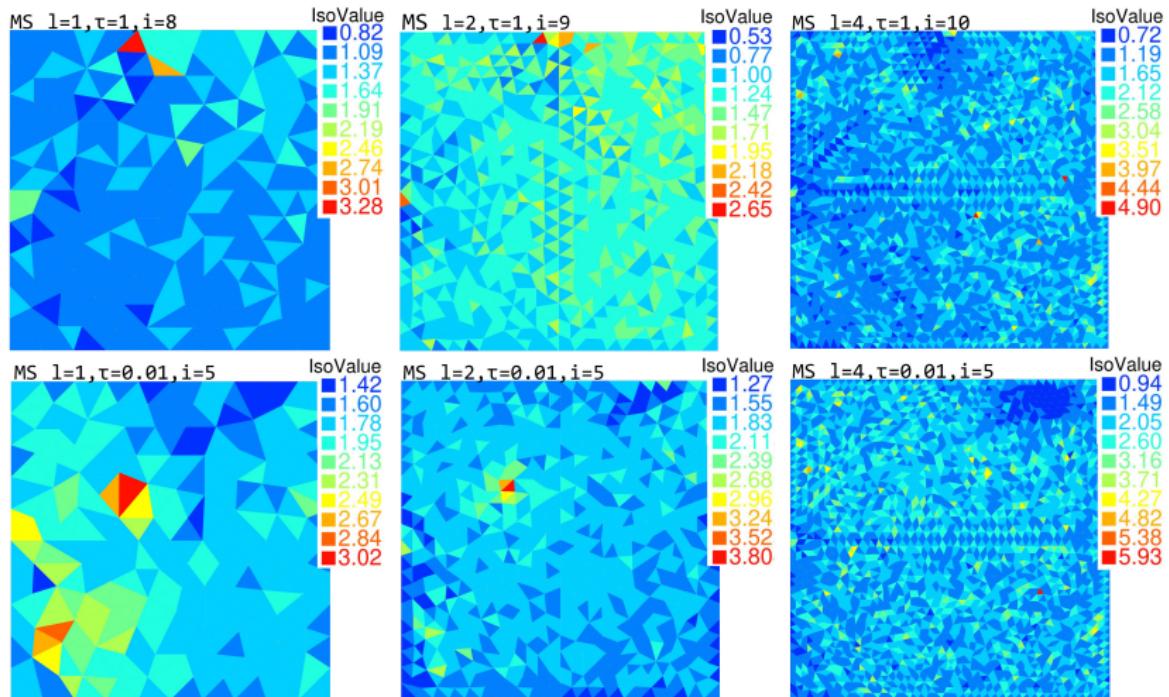


η_K^i MS $l=2, \tau=0.01, i=5$



4 Local effectivity

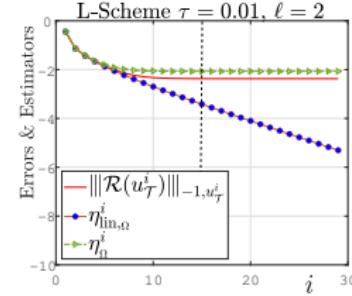
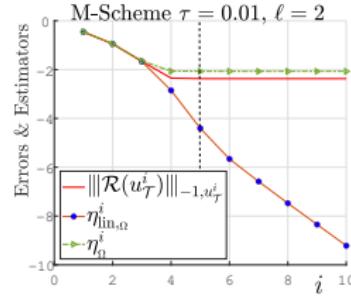
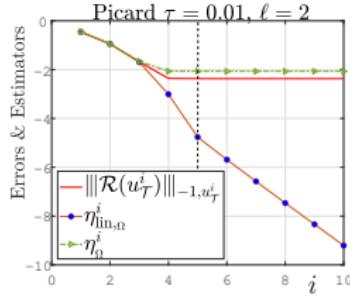
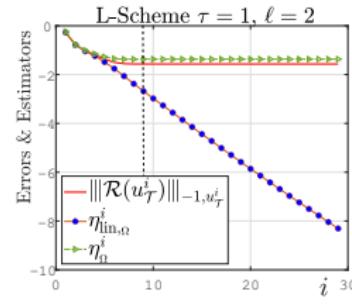
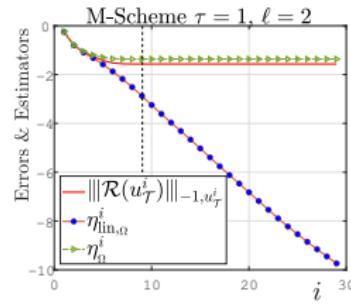
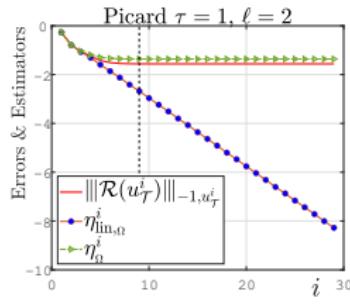
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4 Error with linearization iterations

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For the adaptive stopping criteria $\mu = 0.05$ is chosen



4 Gradient independent diffusivity case

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We consider in Ω the equation

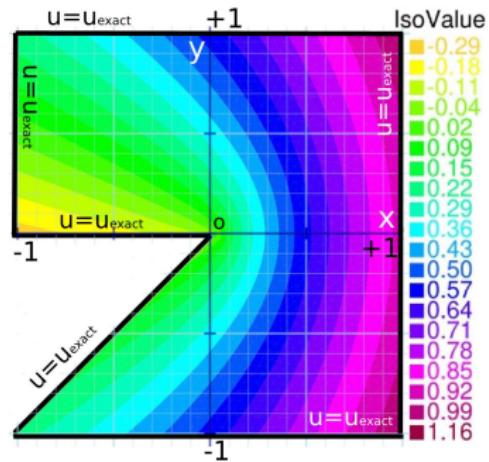
$$\varepsilon u - \nabla \cdot [A(|\nabla u|) \nabla u] = f$$

where

$$A(\mathbf{y}) = 2 + \frac{\mathbf{y}}{(1 + |\mathbf{y}|^2)},$$

$\varepsilon = 10^{-2}$, and a singular $f \in H^{-1}(\Omega)$ is chosen such that the solution becomes

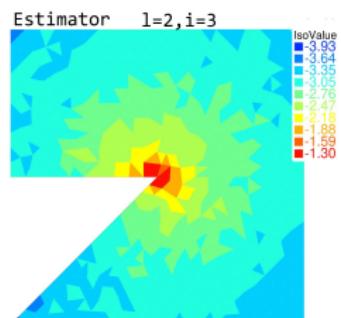
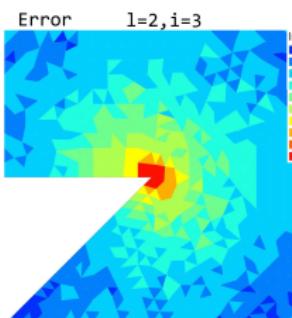
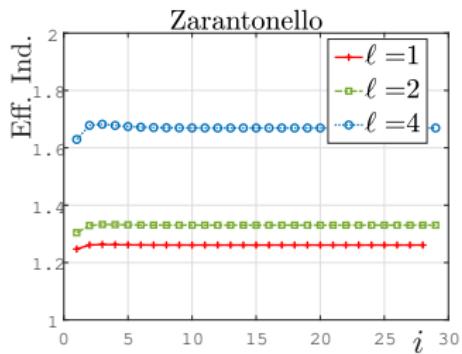
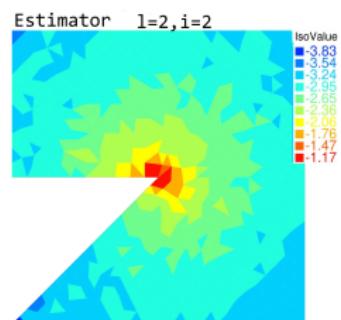
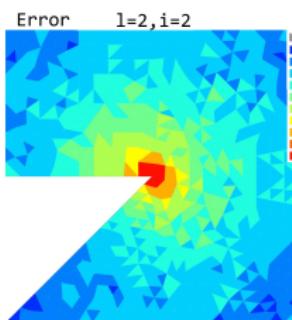
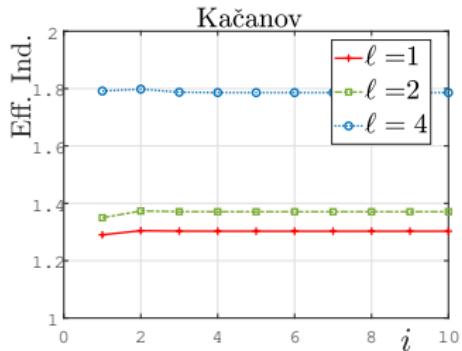
$$u_{\text{exact}} = r^{\frac{4}{7}} \cos\left(\frac{4}{7}\theta\right).$$



Ω

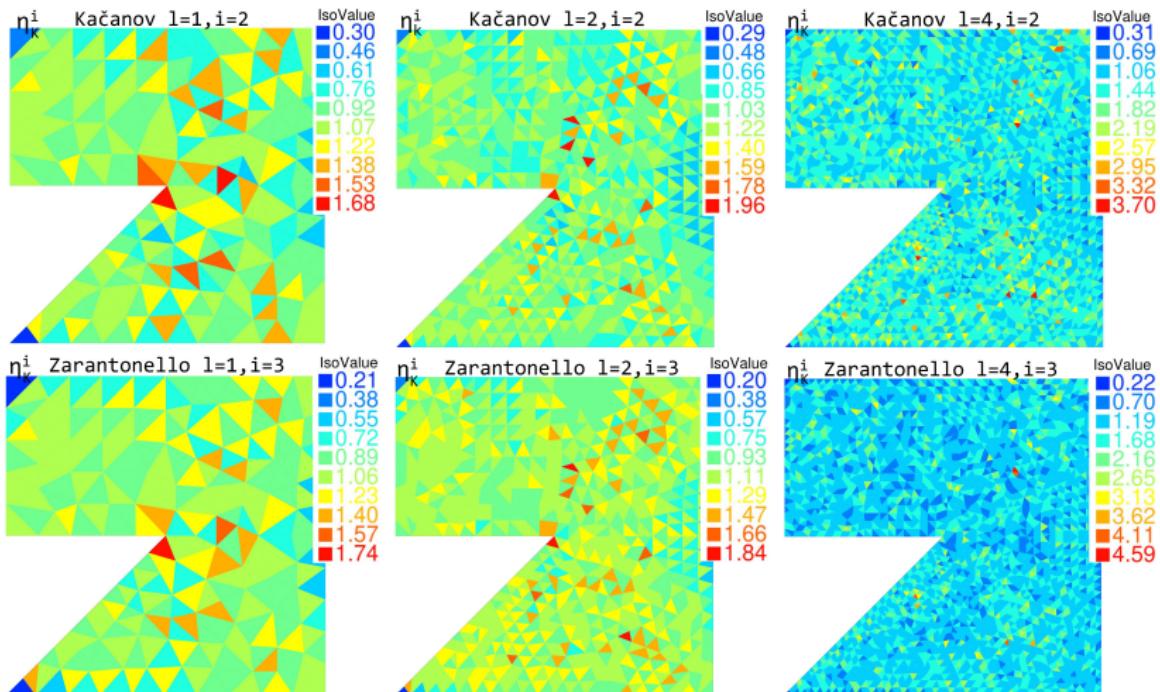
4 Global effectivity and distribution of error

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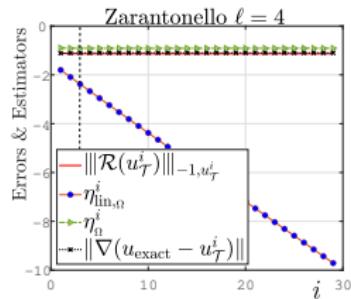
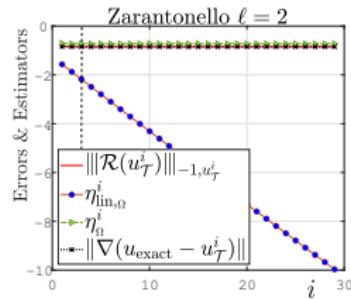
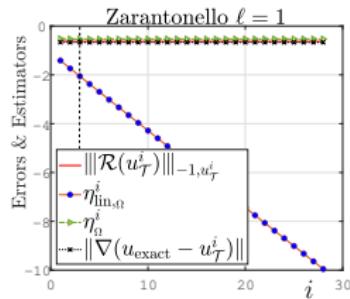
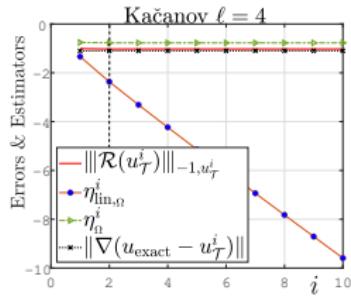
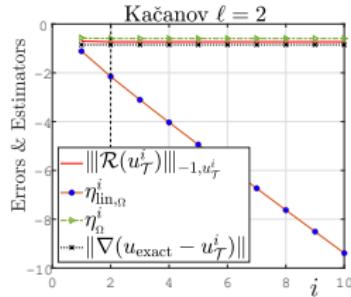
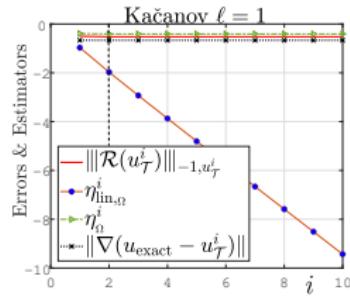
4 Local effectivity

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4 Error with linearization iterations

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For the Newton scheme, the linearization operator

$$\mathfrak{L}(u_h^i; v, w) := (L(\mathbf{x}, u_h^i) v, w) + (\mathfrak{a}(\mathbf{x}, u_h^i) \nabla v, \nabla w) + (\mathbf{w}(\mathbf{x}, u_h^i) v, \nabla w),$$

is **non-symmetric**.

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is **non-symmetric**. However, if for some $C_N \in [0, 2)$ we have

$$\mathbf{w}(\mathbf{x}, u_T^i) \mathfrak{a}^{-1}(\mathbf{x}, u_T^i) \mathbf{w}(\mathbf{x}, u_T^i) \leq C_N^2 L(\mathbf{x}, u_T^i), \quad \forall \mathbf{x} \in \Omega, \text{ and } i \in \mathbb{N},$$

4 The Newton scheme

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then,

$$C_m(C_N) \left[\left\| \mathcal{R}_{\text{lin}}^{u_h^i}(u_{\mathcal{T}}^{i+1}) \right\|_{-1, u_h^i}^2 + \|u_{\mathcal{T}}^{i+1} - u_h^i\|_{1, u_h^i}^2 \right] \leq \|\mathcal{R}(u_h^i)\|_{-1, u_h^i}^2$$

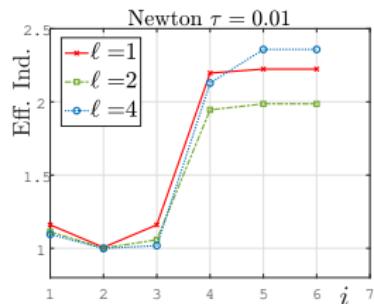
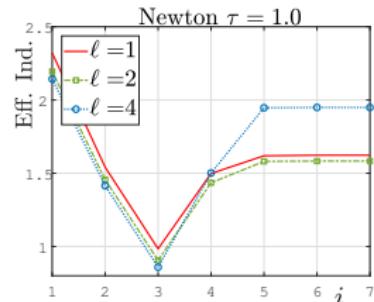
$$\leq C_M(C_N) \left[\left\| \mathcal{R}_{\text{lin}}^{u_h^i}(u_{\mathcal{T}}^{i+1}) \right\|_{-1, u_h^i}^2 + \|u_{\mathcal{T}}^{i+1} - u_h^i\|_{1, u_h^i}^2 \right]$$

with $C_m(C_N), C_M(C_N) \rightarrow 1$ if $C_N \searrow 0$.

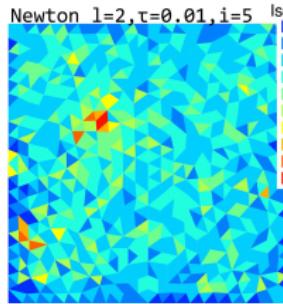
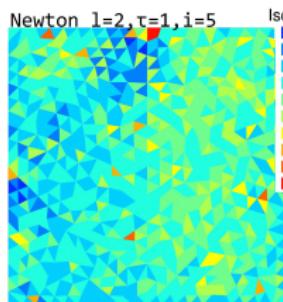
4 The Newton scheme: numerical results

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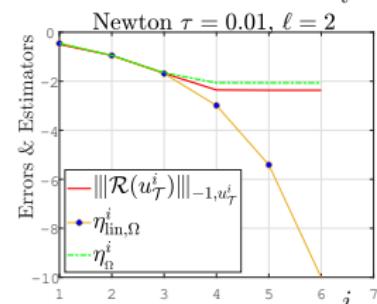
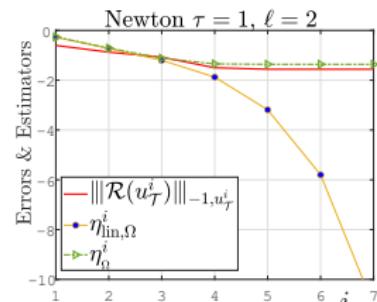
For gradient independent diffusivity case, we have



Global Effectivity



Local Effectivity



Error with iterations

4 Thank you for your time

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A collage of various languages expressing 'thank you' in different scripts and colors. The languages include: d'akujem (Croatian), Tak (Korean), Dankie (Afrikaans), kiitos (Finnish), Спасибо (Russian), הָאֵת (Hebrew), ଧନ୍ୟବାଦ (Bengali), terima kasih (Indonesian), Asante (Swahili), Gracias (Spanish), شُكْرًا (Arabic), mulțumesc (Romanian), hvala (Croatian), salamat (Filipino), 謝謝 (Chinese), Thank you (English), Danke (German), Hvala (Croatian), ありがとう (Japanese), Obrigado (Portuguese), Merci (French), Grazie (Italian), 谢谢 (Chinese), dank u (Dutch), ευχαριστώ (Greek), Благодаря (Bulgarian), Děkuji (Czech), ačiū (Lithuanian), Tack (Swedish), xvala (Georgian), Sağol (Turkish), تشكّر از شما (Persian), Dziękuję (Polish), Спасибі (Belarusian), падзякуй (Belarusian), 감사합니다 (Korean), dziękuję (Polish), teşekkür ederim (Turkish), paldies (Latvian), and তোমাকে ধন্যবাদ (Bengali).