

# POD-deflation method for highly heterogeneous porous media

Gabriela B. Diaz Cortes <sup>1</sup>, Kees Vuik <sup>1</sup>, Jan Dirk Jansen <sup>2</sup>.

<sup>1</sup>EWI

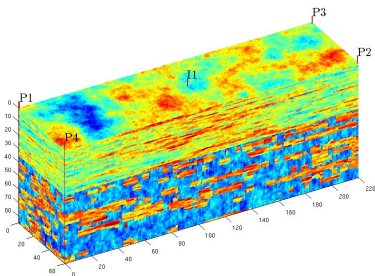
Delft University of Technology

<sup>2</sup>CiTG

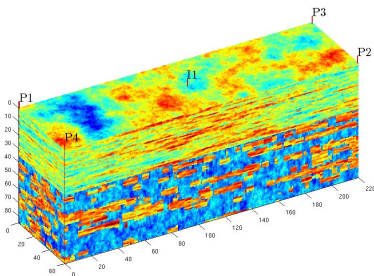
Delft University of Technology

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Geosciences, 2017

Single-phase flow, grid size  $60 \times 220 \times 85$  grid cells, contrast in permeability  $10^7$ .

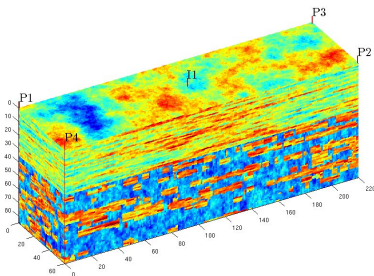


Single-phase flow, grid size  $60 \times 220 \times 85$  grid cells, contrast in permeability  $10^7$ .



Method	Number of iterations
ICCG	1029

Single-phase flow, grid size  $60 \times 220 \times 85$  grid cells, contrast in permeability  $10^7$ .



Method	Number of iterations
ICCG	1029
DICCG	1

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## Flow through a porous medium

Darcy's law + mass balance equation. [1]

$$\frac{\partial(\phi\rho_{\alpha}S_{\alpha})}{\partial t} - \nabla \cdot (\rho_{\alpha}\lambda_{\alpha}(\nabla p_{\alpha} - \rho_{\alpha}g\nabla z)) = q_{\alpha}\rho_{\alpha}.$$

$\alpha$  Fluid Phase (oil (o) / water (w))

$S_{\alpha}$  Phase Saturation

$\phi$  Rock Porosity

$\rho_{\alpha}$  Fluid Density

$p_{\alpha}$  Phase Pressure

$K$  Rock Permeability

$k_{r\alpha}$  Relative Permeabilities

$\lambda_{\alpha}(S_{\alpha}) = \frac{Kk_{r\alpha}(S_{\alpha})}{\mu_{\alpha}}$  Phase Mobilities

$\mu_{\alpha}$  Fluid viscosity

$g$  Gravity

$z$  Reservoir Depth

$q$  Sources

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Single phase incompressible

$$\mathcal{T} \mathbf{p}_w = \mathbf{q}$$

$$\mathcal{T}_{i-\frac{1}{2},j,l} = \frac{\Delta y}{\Delta x} h \lambda_{i-\frac{1}{2},j,l}$$



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Single phase compressible

$$\mathbf{J}(\mathbf{p}_w^k) \delta \mathbf{p}_w^{k+1} = -\mathbf{F}(\mathbf{p}_w^k; \mathbf{p}_w^n)$$

# Problem Definition, Reservoir Simulation

## Flow through a porous medium

Darcy's law + mass balance equation. [1]

$$\frac{\partial(\phi\rho_\alpha S_\alpha)}{\partial t} - \nabla \cdot (\rho_\alpha \lambda_\alpha (\nabla p_\alpha - \rho_\alpha g \nabla z)) = q_\alpha \rho_\alpha.$$

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Single phase compressible

$$\mathbf{J}(\mathbf{p}_w^k) \delta \mathbf{p}_w^{k+1} = -\mathbf{F}(\mathbf{p}_w^k; \mathbf{p}_w^n)$$

Two phases Incompressible

$$-\nabla \cdot (\mathbf{f}_w(\mathbf{S}_w) \lambda_T \nabla \mathbf{p}_o) = \mathbf{q}$$

MRST ( Lie 2013) [2]

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# Conjugate Gradient Method (CG)

Single phase		Two phases
Incompressible	Compressible	Incompressible
$\mathcal{T} \mathbf{p}_w = \mathbf{q}$	$\mathbf{J}(\mathbf{p}_w^k) \delta \mathbf{p}_w^{k+1} = -\mathbf{F}(\mathbf{p}_w^k; \mathbf{p}_w^n)$	$-\nabla \cdot (\mathbf{f}_w(\mathbf{S}_w) \lambda_T \nabla \mathbf{p}_o) = \mathbf{q}$

Successive approximations to obtain a more accurate solution  $\mathbf{x}$  [3]

$$\mathcal{A} \mathbf{x} = \mathbf{b},$$

$$\mathbf{x}^0, \quad \text{initial guess}$$

$$\vdots$$

$$\mathbf{x}^k = \mathbf{x}^{k-1} + \mathcal{M}^{-1} \mathbf{r}^{k-1}, \quad \mathbf{r}^k = \mathbf{b} - \mathcal{A} \mathbf{x}^{k-1}.$$

$$\min_{\mathbf{x}^k \in \kappa_k(\mathcal{A}, \mathbf{r}^0)} \|\mathbf{x} - \mathbf{x}^k\|_{\mathcal{A}}, \quad \|\mathbf{x}\|_{\mathcal{A}} = \sqrt{\mathbf{x}^T \mathcal{A} \mathbf{x}}.$$

Convergence

$$\|\mathbf{x} - \mathbf{x}^k\|_{\mathcal{A}} \leq 2 \|\mathbf{x} - \mathbf{x}^0\|_{\mathcal{A}} \left( \frac{\sqrt{\kappa(\mathcal{A})} - 1}{\sqrt{\kappa(\mathcal{A})} + 1} \right)^{k+1}.$$

*Preconditioning*

Improve the spectrum of  $\mathcal{A}$ .

$$\mathcal{M}^{-1}\mathcal{A}\mathbf{x} = \mathcal{M}^{-1}\mathbf{b}.$$

Convergence

$$\|\mathbf{x} - \mathbf{x}^k\|_{\mathcal{A}} \leq 2\|\mathbf{x} - \mathbf{x}^0\|_{\mathcal{A}} \left( \frac{\sqrt{\kappa(\mathcal{M}^{-1}\mathcal{A})} - 1}{\sqrt{\kappa(\mathcal{M}^{-1}\mathcal{A})} + 1} \right)^{k+1},$$

$$\kappa(\mathcal{M}^{-1}\mathcal{A}) \leq \kappa(\mathcal{A}).$$

*IC(0)*

Let  $a_{i,j} \in \mathcal{A}$  and  $\ell_{i,j} \in \mathcal{L}^*$ ,  $\mathcal{L}^*$  the matrix from the Cholesky decomposition, such that  $\ell_{i,j} = 0$  if  $a_{i,j} = 0$ . *Cholesky Decomposition*  
If  $\mathcal{A} \in \mathcal{R}^{n \times n}$  is *SPD*,

$$\mathcal{A} = \mathcal{L}\mathcal{L}^T$$

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## Deflation

$$\begin{aligned} \mathcal{P} &= \mathcal{I} - \mathcal{A}\mathcal{Q}, & \mathcal{P} &\in \mathbb{R}^{n \times n}, & \mathcal{Q} &\in \mathbb{R}^{n \times n}, \\ \mathcal{Q} &= \mathcal{Z}\mathcal{E}^{-1}\mathcal{Z}^T, & \mathcal{Z} &\in \mathbb{R}^{n \times k}, & \mathcal{E} &\in \mathbb{R}^{k \times k}, \\ & & \mathcal{E} &= \mathcal{Z}^T \mathcal{A} \mathcal{Z} \text{ (Tang 2008, [4]).} \end{aligned}$$

## Convergence

## Deflated system

$$\|\mathbf{x} - \mathbf{x}^k\|_{\mathcal{A}} \leq 2\|\mathbf{x} - \mathbf{x}^0\|_{\mathcal{A}} \left( \frac{\sqrt{\kappa_{\text{eff}}(\mathcal{P}\mathcal{A})} - 1}{\sqrt{\kappa_{\text{eff}}(\mathcal{P}\mathcal{A})} + 1} \right)^{k+1}.$$

## Deflated and preconditioned system

$$\|\mathbf{x} - \mathbf{x}^k\|_{\mathcal{A}} \leq 2\|\mathbf{x} - \mathbf{x}^0\|_{\mathcal{A}} \left( \frac{\sqrt{\kappa_{\text{eff}}(\mathcal{M}^{-1}\mathcal{P}\mathcal{A})} - 1}{\sqrt{\kappa_{\text{eff}}(\mathcal{M}^{-1}\mathcal{P}\mathcal{A})} + 1} \right)^{k+1}.$$

$$\kappa_{\text{eff}}(\mathcal{M}^{-1}\mathcal{P}\mathcal{A}) \leq \kappa_{\text{eff}}(\mathcal{P}\mathcal{A}) \leq \kappa(\mathcal{A}).$$

*Recycling deflation* (Clemens 2004, [5]).

$$\mathcal{Z} = [\mathbf{x}^1, \mathbf{x}^2, \mathbf{x}^{q-1}],$$

$\mathbf{x}^i$ 's are solutions of the system.

*Multigrid and multilevel* (Tang 2009, [6]).

The matrices  $\mathcal{Z}$  and  $\mathcal{Z}^T$  are the restriction and prolongation matrices of multigrid methods.

*Subdomain deflation* (Vuik 1999,[7]).

## Proposal

Use solution of the system with diverse well configurations as deflation vectors (Recycling deflation).

Use as deflation vectors the basis obtained from Proper Orthogonal Decomposition (POD).



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# Proper Orthogonal Decomposition (POD)

POD: find an 'optimal' basis for a given data set (Markovinović 2009 [8], Astrid 2011 [9])

$$\Phi = [\phi_1, \phi_2, \dots, \phi_l] \in \mathbb{R}^{n \times l}$$

$\phi_i$ , basis functions.

- Get the snapshots

$$\mathcal{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m].$$

- $l$  eigenvectors of  $\mathcal{R}$  satisfying:

$$\frac{\sum_{j=1}^l \lambda_j}{\sum_{j=1}^m \lambda_j} \leq \alpha, \quad 0 < \alpha \leq 1.$$

$$\mathcal{R} := \frac{1}{m} \mathcal{X} \mathcal{X}^T \equiv \frac{1}{m} \sum_{i=1}^m \mathbf{x}_i \mathbf{x}_i^T.$$

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# Numerical experiments

## Heterogeneous permeability (Neumann boundary conditions).

Single-phase flow

$nx = ny = 64$  grid cells.

Neumann boundary conditions.

15 snapshots, 4 linearly independent.

$W1 = W2 = W3 = W4 = -1$  bars,

$W5 = +4$  bars.

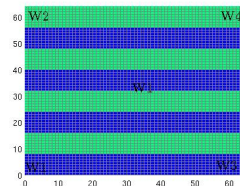


Figure: Heterogeneous permeability layers.

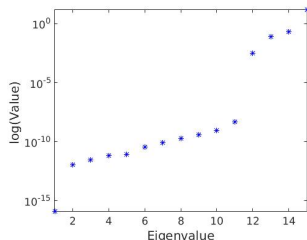


Figure: Eigenvalues of  $\mathcal{R} = \frac{1}{m} \mathcal{X} \mathcal{X}^T$ .

$\sigma_2$ (mD)	$10^{-1}$	$10^{-3}$	$10^{-5}$	$10^{-7}$
ICCG	90	131	65*	64*
DICCG <sub>15</sub>	500*	500*	500*	500*
DICCG <sub>4</sub>	1	1	1*	1*
DICCG <sub>POD4</sub>	1	1	1*	1*

Table: Iterations, tol  $10^{-7}$

# Numerical experiments (Heterogeneous permeability)

Condition number of a SPD matrix.

$$\kappa_2(\mathcal{A}) = \frac{\lambda_{\max}(\mathcal{A})}{\lambda_{\min}(\mathcal{A})}$$

$\sigma_2$ (mD)	$10^{-1}$	$10^{-3}$	$10^{-5}$	$10^{-7}$
$\kappa(\mathcal{A})$	$2.6 \times 10^3$	$2.4 \times 10^5$	$2.4 \times 10^7$	$2.4 \times 10^9$
$\kappa(M^{-1}\mathcal{A})$	206.7	$8.3 \times 10^3$	$8.3 \times 10^5$	$8.3 \times 10^7$
$\kappa_{\text{eff}}(M^{-1}PA)$	83.27	$6 \times 10^3$	$1 \times 10^6$	$6 \times 10^7$

Table: Condition number for various permeability contrasts between the layers, grid size of  $32 \times 32$ ,  $\sigma_1 = 1\text{mD}$ .

Relative error

$$e = \frac{\|\mathbf{x} - \mathbf{x}^k\|_2}{\|\mathbf{x}\|_2} \leq \kappa_2(\mathcal{A})\epsilon, \quad \text{with } \mathbf{x} \text{ the true solution and } \mathbf{x}^k \text{ the approximation.}$$

Taking  $e = 10^{-7}$ ,

$\sigma_2$ (mD)	$10^{-1}$	$10^{-3}$	$10^{-5}$	$10^{-7}$
$\text{tol} = \frac{e}{\kappa_2(M^{-1}\mathcal{A})} = \frac{10^{-7}}{\kappa_2(M^{-1}\mathcal{A})}$	$5 \times 10^{-9}$	$1 \times 10^{-10}$	$1 \times 10^{-12}$	$1 \times 10^{-14}$
$\text{tol} = \frac{e}{\kappa_{\text{eff}}(M^{-1}PA)} = \frac{10^{-7}}{\kappa_{\text{eff}}(M^{-1}PA)}$	$1 \times 10^{-8}$	$2 \times 10^{-10}$	$1 \times 10^{-12}$	$2 \times 10^{-14}$

Table: Tolerance needed for various permeability contrast between the layers, grid size of  $32 \times 32$ ,  $\sigma_1 = 1\text{mD}$ , for an error of  $e = 10^{-7}$ .

# Numerical experiments (SPE 10)

## SPE 10 model, 2nd layer

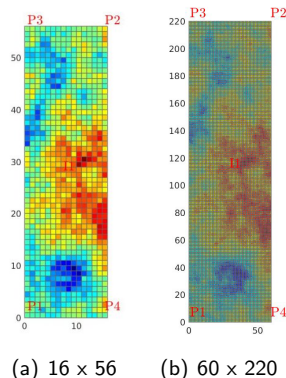


Figure: Permeability field,  $16 \times 56$  and  $60 \times 220$  grid cells (upscaled with MRST [2]).

Grid size	$16 \times 56$	$30 \times 110$	$46 \times 166$	$60 \times 220$
Contrast ( $\times 10^7$ )	1.04	2.52	2.6	2.8

Table: Contrast in permeability for different grid sizes ( $\sigma_{max}/\sigma_{min}$ ).

Condition number	
$\kappa(A)$	$2.2 \times 10^6$
$\kappa(M^{-1}A)$	377
$\kappa_{eff}(M^{-1}PA)$	82.7

Table: Table with the condition number of the SPE10 model, grid size of  $16 \times 56$ .

# Numerical experiments(SPE 10)

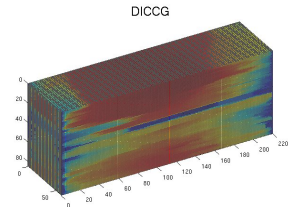
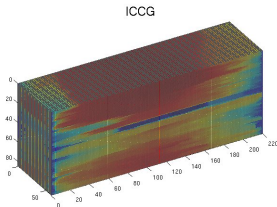
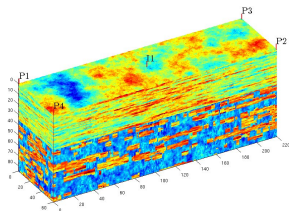
## *SPE 10 model, 2nd layer*

Tol (snapshots)	Method	16 x 56	30 x 110	46 x 166	60 x 220
	ICCG	34	73	126	159
$10^{-1}$	DICCG <sub>4</sub>	33	72	125	158
$10^{-3}$	DICCG <sub>4</sub>	18	38	123	151
$10^{-5}$	DICCG <sub>4</sub>	11	21	27	55
$10^{-7}$	DICCG <sub>4</sub>	1	1	1	1

**Table:** Number of iterations for ICCG and DICCG, diverse tolerance for the snapshots, different grid sizes. DICCG<sub>4</sub> is computed with 4 deflation vectors.

# Numerical experiments

## *SPE 10 model, 85 layers*



Method	Number of iterations
ICCG	1029
DICCG	1

**Table:** Number of iterations for the SPE10 benchmark (85 layers) for the ICCG and DICCG methods, relative tolerance  $10^{-7}$ .



# Numerical experiments

## *Compressible SPE 10 problem*

60x220x85 grid cells.

Neumann boundary conditions.

$W_1 = W_2 = W_3 = W_4 = 100$  bars,  $W_5 = 600$  bars.

Initial pressure 200 bars.

Contrast in permeability of  $3 \times 10^7$ .

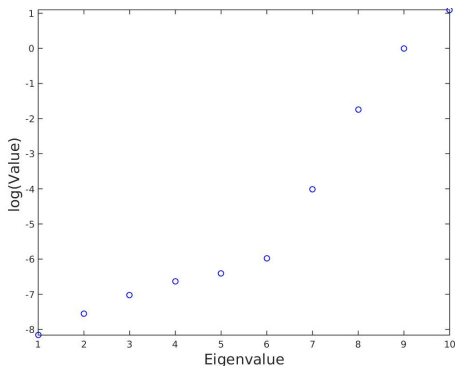


Figure: Eigenvalues of the data snapshot correlation matrix.

# Numerical experiments

## Compressible SPE 10 problem

1 <sup>st</sup> NR Iteration					
Total ICCG (only)	Method	ICCG Snapshots	DICCG	Total ICCG+DICCG	% of total ICCG
10173	DICCG <sub>10</sub>	1770	1134	2904	28
10173	DICCG <sub>POD<sub>4</sub></sub>	1770	1554	3324	32

Table: Average number of linear iterations for the first NR iteration, full SPE 10 benchmark.

2 <sup>nd</sup> NR Iteration					
Total ICCG (only)	Method	ICCG Snapshots	DICCG	Total ICCG+DICCG	% of total ICCG
10231	DICCG <sub>10</sub>	1830	200	2030	20
10231	DICCG <sub>POD<sub>4</sub></sub>	1830	200	2030	20

Table: Average number of linear iterations for the second NR iteration, full SPE 10 benchmark.

# Numerical experiments

Layered problem, two phases, water injection through wells, 35 x 35 cells

Well	Water Sat	Oil Sat	Pressure
$P_1$	0	1	50 bars
$P_2$	0	1	50 bars
$P_3$	0	1	50 bars
$P_4$	0	1	50 bars
$I$	1	0	200 bars

Table: Wells properties.

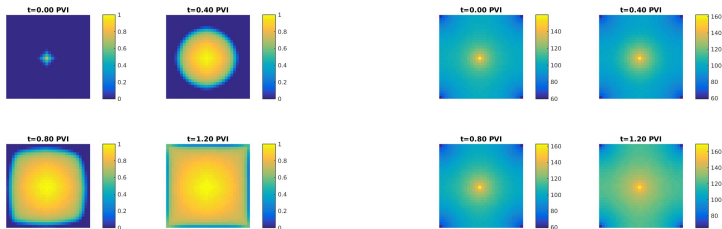


Figure: Pressure fields.

Figure: Water Saturation.

# Numerical experiments

Layered problem, two phases, water injection through wells, 35 x 35 cells

$\frac{\sigma_2}{\sigma_1}$	Total ICCG	Method	ICCG Snapshots	DICCG	Total ICCG + DICCG	% of total ICCG
$10^1$	24394	DICCG <sub>POD<sub>10</sub></sub>	502	1869	2371	10
$10^1$	24394	DICCG <sub>POD<sub>5</sub></sub>	502	2477	2979	12
$10^2$	27364	DICCG <sub>POD<sub>10</sub></sub>	551	1906	2457	9
$10^2$	27364	DICCG <sub>POD<sub>5</sub></sub>	551	2583	3134	11
$10^3$	27092	DICCG <sub>POD<sub>10</sub></sub>	529	2033	2562	9
$10^3$	27092	DICCG <sub>POD<sub>5</sub></sub>	529	2430	2959	11

Table: No capillary pressure included.

$\frac{\sigma_2}{\sigma_1}$	Total ICCG	Method	ICCG Snapshots	DICCG	Total ICCG + DICCG	% of total ICCG
$10^1$	23810	DICCG <sub>POD<sub>10</sub></sub>	502	2641	3143	13
$10^1$	23810	DICCG <sub>POD<sub>5</sub></sub>	502	2683	3185	13
$10^2$	27629	DICCG <sub>POD<sub>10</sub></sub>	551	2719	3270	12
$10^2$	27629	DICCG <sub>POD<sub>5</sub></sub>	551	2793	3344	12
$10^3$	23962	DICCG <sub>POD<sub>10</sub></sub>	517	2872	3389	14
$10^3$	23962	DICCG <sub>POD<sub>5</sub></sub>	517	2744	3261	14

Table: Capillary pressure included.

# Numerical experiments

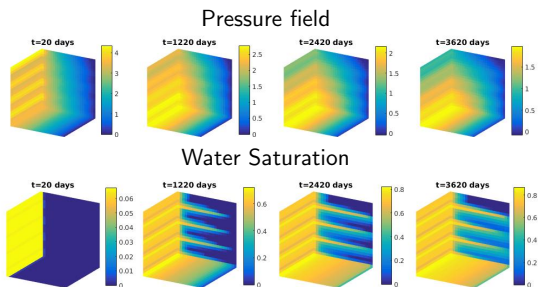
Layered problem, two phases, water injection through the boundary,  $24 \times 24 \times 24$  cells.

	Water	Oil
$S_{0,x \neq 0, L_x}$	0	1
$S_{x=0}$	1	0
$S_{x=L_x}$	0	1

Table: Saturations.

Property	Value	Units
$Q_{x=0}$	0.4	$m^3/day$
$P_{0,x \neq 0, L_x}$	100	bars
$P_{x=L_x}$	0	bars

Table: Control.



# Numerical experiments

Layered problem, two phases, water injection through the boundary,  $24 \times 24 \times 24$  cells.

$\frac{\sigma_2}{\sigma_1}$	Total ICCG	Method	ICCG Snapshots	DICCG	Total ICCG +DICCG	% of total ICCG
$10^1$	19426	DICCG <sub>POD<sub>10</sub></sub>	654	1969	2623	14
$10^1$	19426	DICCG <sub>POD<sub>5</sub></sub>	654	2258	2912	15
$10^2$	22577	DICCG <sub>POD<sub>10</sub></sub>	762	2340	3102	14
$10^2$	22577	DICCG <sub>POD<sub>5</sub></sub>	762	2714	3476	15
$10^3$	21832	DICCG <sub>POD<sub>10</sub></sub>	594	2086	2680	12
$10^4$	18483	DICCG <sub>POD<sub>10</sub></sub>	529	1868	2397	13

Table: Gravity included.

$\frac{\sigma_2}{\sigma_1}$	Total ICCG	Method	ICCG Snapshots	DICCG	Total ICCG +DICCG	% of total ICCG
$10^1$	17224	DICCG <sub>POD<sub>10</sub></sub>	660	3431	4091	24
$10^1$	17224	DICCG <sub>POD<sub>5</sub></sub>	660	3658	4318	25
$10^2$	20562	DICCG <sub>POD<sub>10</sub></sub>	763	3468	4231	21
$10^2$	20562	DICCG <sub>POD<sub>5</sub></sub>	763	3596	4359	21
$10^3$	18514	DICCG <sub>POD<sub>10</sub></sub>	605	2894	3499	19
$10^3$	18514	DICCG <sub>POD<sub>5</sub></sub>	605	2943	3548	19

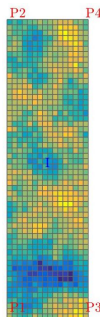
Table: Capillary pressure ( $C = 10 * (1 - S)$ ) and gravity included

# Numerical experiments

*SPE 10, first layer, 16 x 56 grid cells*

Well	Water Sat	Oil Sat	Pressure
$P_1$	0	1	275 bars
$P_2$	0	1	275 bars
$P_3$	0	1	275 bars
$P_4$	0	1	275 bars
$I$	1	0	1100 bars

Table: Wells properties.



Total ICGG	Method	ICCG Snapshots	DICCG	Total ICGG + DICCG	% of total ICGG
11313	$DICCG_{POD_{10}}$	567	1615	2182	19
11313	$DICCG_{POD_5}$	567	2235	2802	25

Table: Comparison between the ICCG and DICCG methods of the average number of linear iterations for the SPE 10 problem, 16 x 56 grid cells (upscaled with MRST[2]).

# Numerical experiments

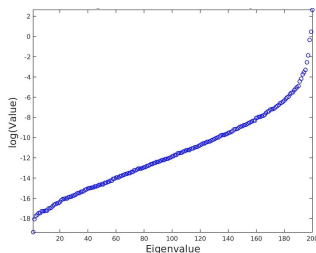
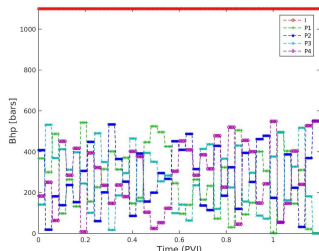
SPE 10, first layer, 16 x 56 grid cells, training example

Well	Water Sat	Oil Sat	Pressure
$P_1$	0	1	$rand(0 - 275)$ bars
$P_2$	0	1	$rand(0 - 275)$ bars
$P_3$	0	1	$275 - P_1$ bars
$P_4$	0	1	$275 - P_2$ bars
$I$	1	0	1100 bars

Table: Wells properties.

Total	Method	DICCG	% of total
11362	DICCG <sub>POD<sub>30</sub></sub>	1734	16
11362	DICCG <sub>POD<sub>10</sub></sub>	2498	23

Table: Comparison between the ICCG and DICCG methods of the average number of linear iterations for the SPE 10 problem, 16 x 56 grid cells.





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- Solution is reached in 1 iteration for DICCG method for the single phase incompressible problem.  
TU Delft Report: [\[10\]](#).
- A reduction of  $\approx 80\%$  of the ICCG number of iterations is achieved with DICCG method for the solution of the pressure equation, for the two phase layered and SPE 10 problems and for the full SPE 10 compressible problem ( $\approx 10^6$  grid cells).  
JCAM paper: [G.B. Diaz Cortes, C. Vuik and J.D. Jansen, 2017 \[11\]](#)
- Number of iterations for the DICCG method does not depend on the contrast between the coefficients or the grid size.  
TU Delft Report: [\[12\]](#).

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**Lemma 1.** Let  $\mathbf{A} \in \mathbb{R}^{n \times n}$  be a non-singular matrix, and  $\mathbf{x}$  is the solution of:

$$\mathbf{Ax} = \mathbf{b}.$$

Let  $\mathbf{x}_i, \mathbf{b}_i \in \mathbb{R}^n$ ,  $i = 1, \dots, m$ , be vectors linearly independent (*l.i.*) and

$$\mathbf{Ax}_i = \mathbf{b}_i.$$

The following equivalence holds

$$\mathbf{x} = \sum_{i=1}^m c_i \mathbf{x}_i \quad \Leftrightarrow \quad \mathbf{b} = \sum_{i=1}^m c_i \mathbf{b}_i.$$

Proof  $\Rightarrow$   $\mathbf{x} = \sum_{i=1}^m c_i \mathbf{x}_i \Rightarrow \mathbf{b} = \sum_{i=1}^m c_i \mathbf{b}_i.$

$$\begin{aligned} \mathbf{Ax} &= \sum_{i=1}^m \mathbf{A}c_i \mathbf{x}_i = \mathbf{A}(c_1 \mathbf{x}_1 + \dots + c_m \mathbf{x}_m) = \\ &= \mathbf{A}c_1 \mathbf{x}_1 + \dots + \mathbf{A}c_m \mathbf{x}_m = c_1 \mathbf{b}_1 + \dots + c_m \mathbf{b}_m = \sum_{i=1}^m c_i \mathbf{b}_i = \mathbf{b}. \end{aligned}$$

**Lemma 2.** If the the deflation matrix  $\mathbf{Z}$  is constructed with a set of  $m$  vectors

$$\mathbf{Z} = [\mathbf{x}_1 \quad \dots \quad \dots \quad \mathbf{x}_m],$$

such that  $\mathbf{x} = \sum_{i=1}^m c_i \mathbf{x}_i$ , with  $\mathbf{x}_i$  l.i., then the solution of system (34) is obtained with one iteration of DCG.

$$\mathbf{x} = \mathbf{Q}\mathbf{b} + \mathbf{P}^T \hat{\mathbf{x}}.$$

$$\begin{aligned} \mathbf{Q}\mathbf{b} &= \mathbf{Z}\mathbf{E}^{-1}\mathbf{Z}^T \left( \sum_{i=1}^m c_i \mathbf{b}_i \right) = \mathbf{Z}(\mathbf{Z}^T \mathbf{A}\mathbf{Z})^{-1} \mathbf{Z}^T \left( \sum_{i=1}^m c_i \mathbf{A}\mathbf{x}_i \right) \\ &= \mathbf{Z}(\mathbf{Z}^T \mathbf{A}\mathbf{Z})^{-1} \mathbf{Z}^T (\mathbf{A}\mathbf{Z}\mathbf{c}) = \mathbf{Z}\mathbf{c} \\ &= c_1 \mathbf{x}_1 + c_2 \mathbf{x}_2 + c_3 \mathbf{x}_3 + c_4 \mathbf{x}_4 + c_5 \mathbf{x}_5 = \sum_{i=1}^m c_i \mathbf{x}_i = \mathbf{x}. \end{aligned}$$

$$\mathbf{P}\mathbf{A}\hat{\mathbf{x}} = \mathbf{P}\mathbf{b} = (\mathbf{I} - \mathbf{A}\mathbf{Q})\mathbf{b} = \mathbf{b} - \mathbf{A}\mathbf{Q}\mathbf{b} = \mathbf{b} - \mathbf{A}\mathbf{x} = \mathbf{0}$$

$$\mathbf{P}\mathbf{A}\hat{\mathbf{x}} = \mathbf{A}\mathbf{P}^T \hat{\mathbf{x}} = \mathbf{0} \quad \Rightarrow \quad \mathbf{P}^T \hat{\mathbf{x}} = \mathbf{0}$$

$$\mathbf{x} = \mathbf{Q}\mathbf{b} + \mathbf{P}^T \hat{\mathbf{x}} = \mathbf{Q}\mathbf{b} = \mathbf{x}.$$