

# Iterative Solvers for Large Linear Systems

## Part Vb: Variants of BiCG

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- Basics of Iterative Methods
- Splitting-schemes
  - Jacobi- u. Gauß-Seidel-scheme
  - Relaxation methods
- Methods for symmetric, positive definite Matrices
  - Method of steepest descent
  - Method of conjugate directions
  - CG-scheme

- Multigrid Method
  - Smoother, Prolongation, Restriction
  - Twogrid Method and Extension
- **Methods for non-singular Matrices**
  - **GMRES**
  - **BiCG, CGS and BiCGSTAB**
- Preconditioning
  - ILU, IC, GS, SGS, ...

# Methods for non-singular Matrices

Method of conjugate gradients (CG)

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graph TD; A[Method of conjugate gradients (CG)] --> B[Bi-conjugate gradients method (BiCG)]; A --> C[Generalized Minimal Residual method (GMRES)]; D[BiCG-Method] --> E[CG-Squared method (CGS)]; D --> F[Bi-CG Stabilized method (BiCGSTAB)];
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Bi-conjugate gradients  
method (BiCG)

Generalized Minimal Residual  
method (GMRES)

BiCG-Method

CG-Squared method  
(CGS)

Bi-CG Stabilized method  
(BiCGSTAB)

# CGS-Algorithm

## Aim:

- Accelerate the BiCG-method
- Avoid multiplications with  $A^T$

## Monitoring:

- Polynomial representation

$$r_j = \varphi_j(A)r_0, \quad p_j = \psi_j(A)r_0 \implies r_j^* = \varphi_j(A^T)r_0, \quad p_j^* = \psi_j(A^T)r_0$$

- Occurrence of  $r_j^*$  and  $p_j^*$

Solely to calculate the scalar values  $\alpha_j$  and  $\beta_j$

$$(r_j, r_j^*) \text{ and } (Ap_j, p_j^*)$$

## Basic Idea:

$$(x, A^T y) = x^T A^T y = (Ax)^T y = (Ax, y) \implies (Ax, A^T y) = (A^2 x, y)$$

# CGS-Algorithm

## Reformulation:

Using

$$r_j = \varphi_j(\mathbf{A})r_0, \quad p_j = \psi_j(\mathbf{A})r_0 \quad \text{and} \quad r_j^* = \varphi_j(\mathbf{A}^T)r_0, \quad p_j^* = \psi_j(\mathbf{A}^T)r_0$$

yields

$$(r_j, r_j^*) = (\varphi_j(\mathbf{A})r_0, \varphi_j(\mathbf{A}^T)r_0) = \underbrace{(\varphi_j^2(\mathbf{A})r_0, r_0)}_{=: \hat{r}_j} = (\hat{r}_j, r_0)$$

as well as

$$(A p_j, p_j^*) = (A \psi_j(\mathbf{A})r_0, \psi_j(\mathbf{A}^T)r_0) = (A \underbrace{\psi_j^2(\mathbf{A})r_0}_{=: \hat{p}_j}, r_0) = (A \hat{p}_j, r_0)$$

## Technical Exercise:

Express the scalar values  $\alpha_j$  and  $\beta_j$  by means of  $\hat{r}_j$  and  $\hat{p}_j$

## CGS-Algorithm

CGS-Algorithmus —

Wähle  $\mathbf{x}_0 \in \mathbb{R}^n$  und  $\varepsilon > 0$

$\mathbf{u}_0 = \mathbf{r}_0 = \mathbf{p}_0 := \mathbf{b} - \mathbf{A}\mathbf{x}_0$ ,  $j := 0$

Solange  $\|\mathbf{r}_j\|_2 > \varepsilon$

$$\mathbf{v}_j := \mathbf{A}\mathbf{p}_j, \alpha_j := \frac{(\mathbf{r}_j, \mathbf{r}_0)_2}{(\mathbf{v}_j, \mathbf{r}_0)_2}$$

$$\mathbf{q}_j := \mathbf{u}_j - \alpha_j \mathbf{v}_j$$

$$\mathbf{x}_{j+1} := \mathbf{x}_j + \alpha_j (\mathbf{u}_j + \mathbf{q}_j)$$

$$\mathbf{r}_{j+1} := \mathbf{r}_j - \alpha_j \mathbf{A}(\mathbf{u}_j + \mathbf{q}_j)$$

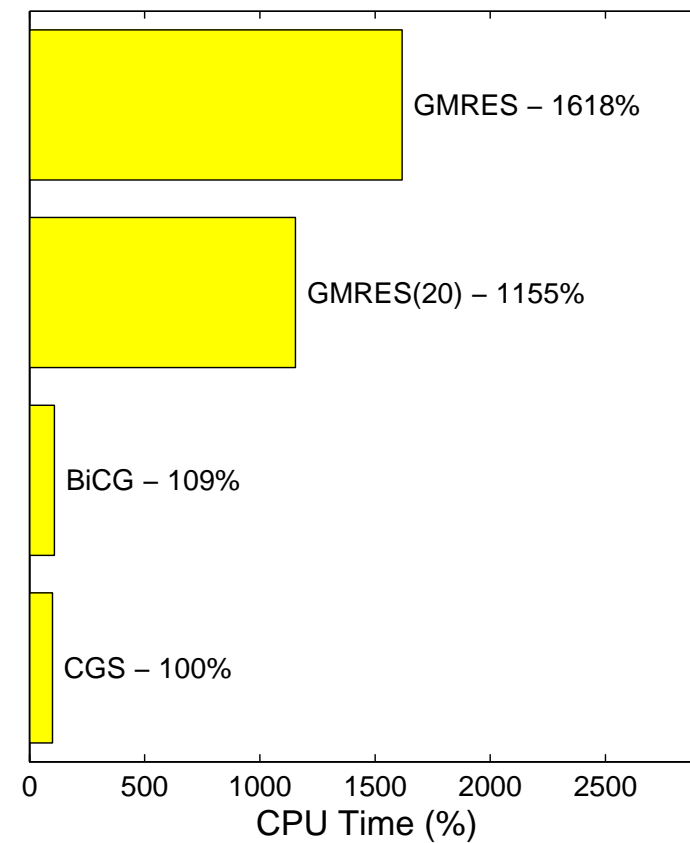
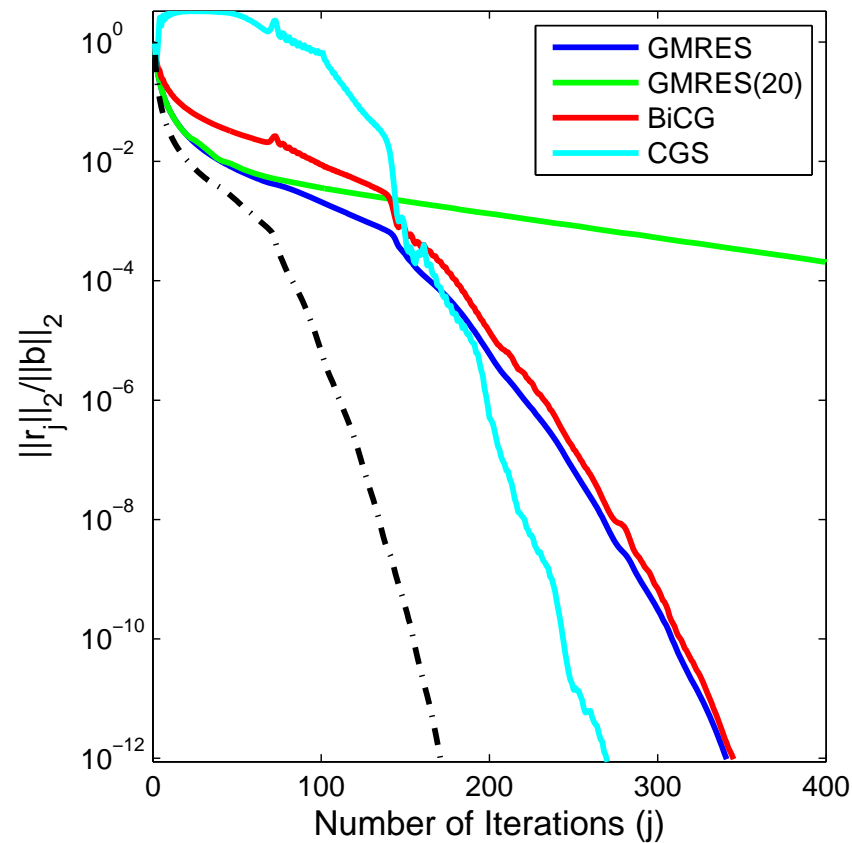
$$\beta_j := \frac{(\mathbf{r}_{j+1}, \mathbf{r}_0)_2}{(\mathbf{r}_j, \mathbf{r}_0)_2}$$

$$\mathbf{u}_{j+1} := \mathbf{r}_{j+1} + \beta_j \mathbf{q}_j$$

$$\mathbf{p}_{j+1} := \mathbf{u}_{j+1} + \beta_j (\mathbf{q}_j + \beta_j \mathbf{p}_j), j := j + 1$$

# Comparison of GMRES, GMRES(m), BiCG and CGS

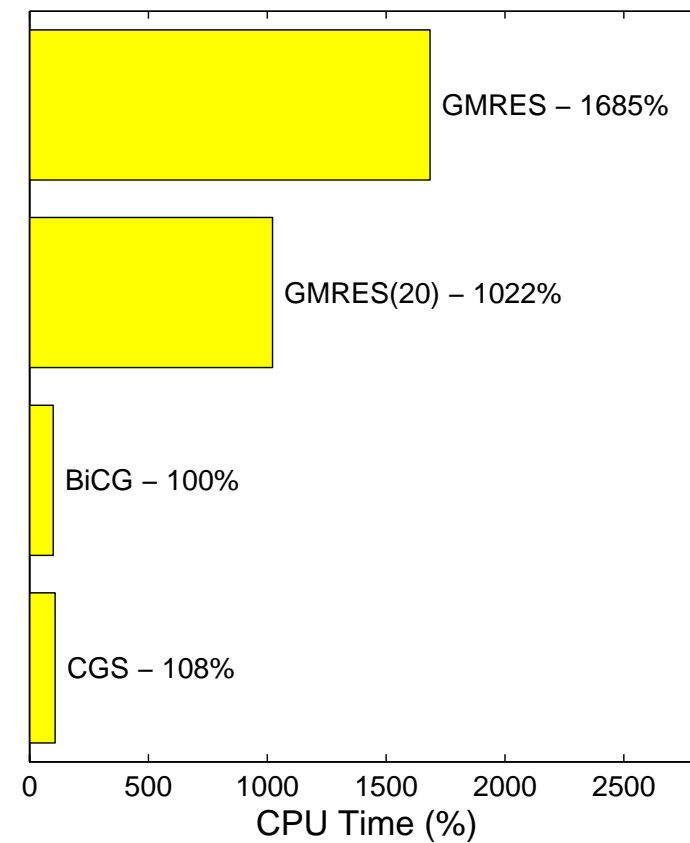
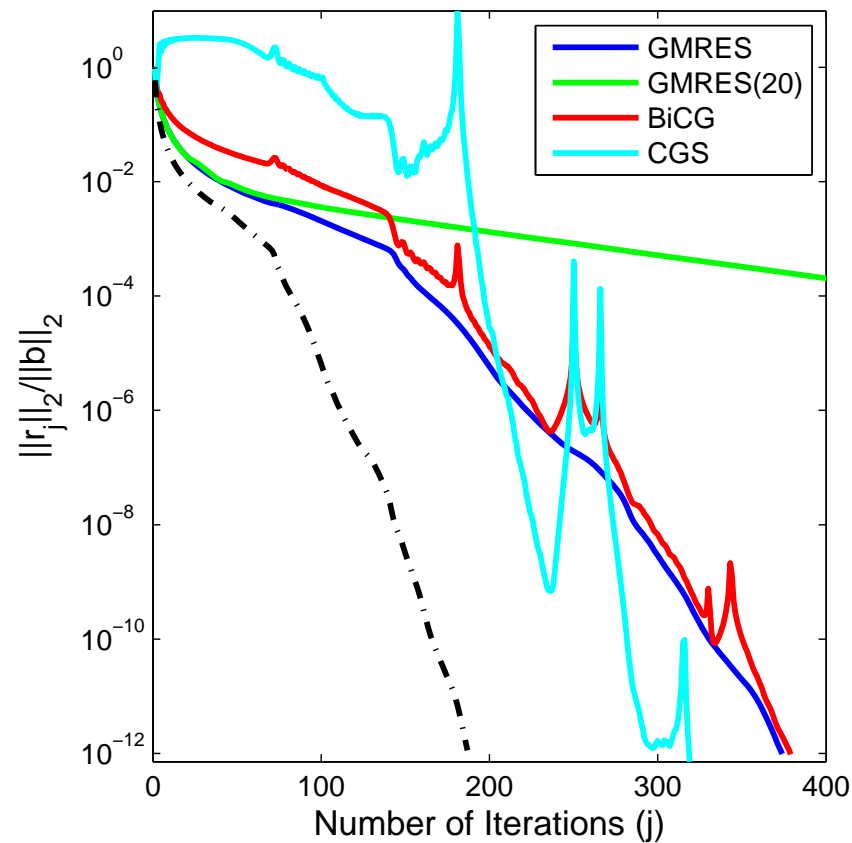
Test 1: Pure Diffusion ( $\alpha = 0, \epsilon = 1$ )





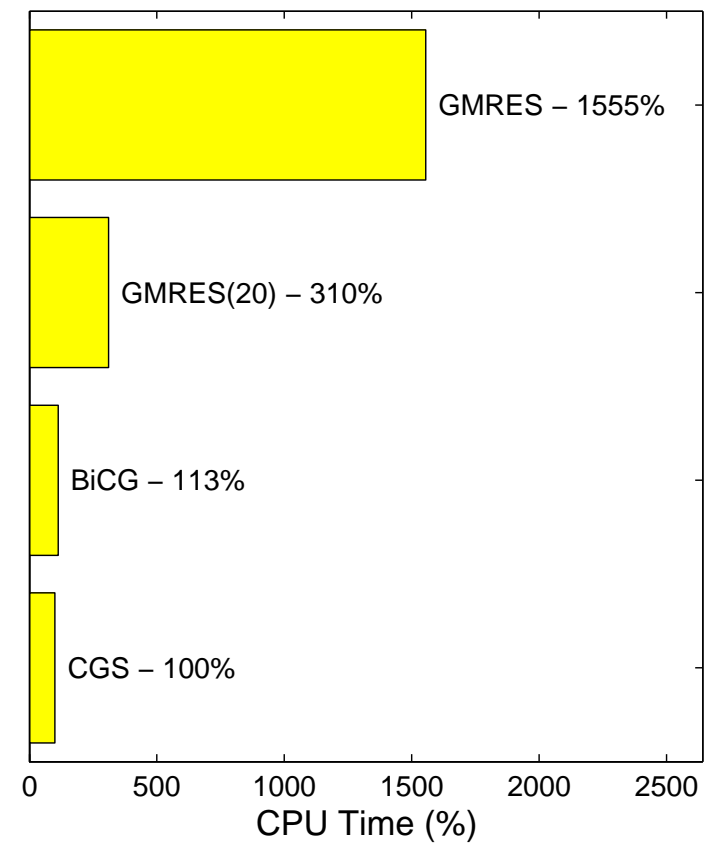
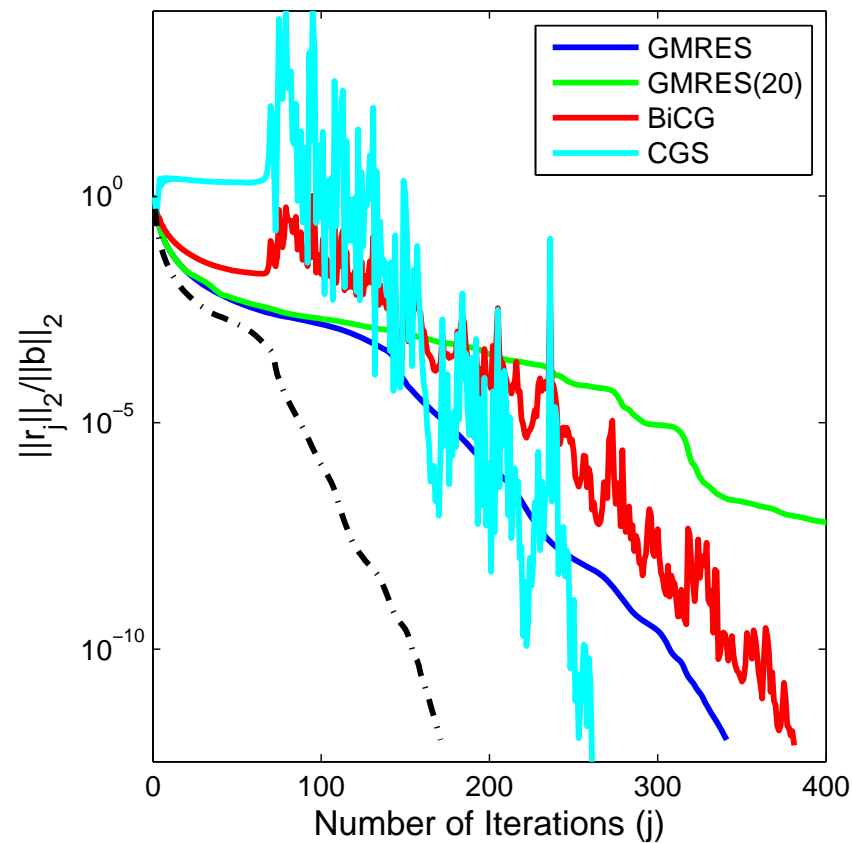
# Comparison of GMRES, GMRES(m), BiCG and CGS

Test 2: Weak Convection-Diffusion ( $\alpha = 0.1, \epsilon = 1$ )



# Comparison of GMRES, GMRES(m), BiCG and CGS

Test 3: Convection-Diffusion ( $\alpha = 1, \epsilon = 0.1$ )



# CGS-Algorithm - Summary

## Derivation:

- Based on BiCG-Algorithm
- Squaring the polynomial representation

## Advantages:

- Keenly less storage requirements (compared to GMRES)
- No symmetry constraint on  $A$  (compared to CG)
- Requires no multiplications with  $A^T$  (compared to BiCG)

## Disadvantages:

- No minimization of an underlying functional  
→ Oszillations in the convergence history
- Possible break down due to division by  $(Ap_j, r_0)$

# Methods for non-singular Matrices

Method of conjugate gradients (CG)

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Bi-conjugate gradients  
method (BiCG)

Generalized Minimal Residual  
method (GMRES)

BiCG-Method

CG-Squared method  
(CGS)

Bi-CG Stabilized method  
(BiCGSTAB)

# BiCGSTAB-Algorithm

## Aim:

- Improving the BiCG- and CGS-method
- Avoid multiplications with  $A^T$
- Introducing a minimization of the residual

## Procedure:

- Polynomial representation

$$r_j = \varphi_j(A)r_0, \quad p_j = \psi_j(A)r_0$$

- Employ

$$\tilde{r}_j^* = \Phi_j(A^T)r_0, \quad \tilde{p}_j^* = \Phi_j(A^T)r_0$$

with

$$\Phi_0(A^T) = I, \quad \Phi_{j+1}(A^T) = (I - \omega_j A^T)\Phi_j(A^T)$$

# BiCGSTAB-Algorithm

## Reformulation:

Introducing  $\tilde{r}_j^* = \phi_j(A^T)r_0$  and  $\tilde{p}_j^* = \phi_j(A^T)r_0$  into BiCG yields

$$(r_j, \tilde{r}_j^*) = (\varphi_j(A)r_0, \phi_j(A^T)r_0) = (\phi_j(A)\varphi_j(A)r_0, r_0)$$

and

$$(Ap_j, \tilde{p}_j^*) = (A\psi_j(A)r_0, \phi_j(A^T)r_0) = (\phi_j(A)A\psi_j(A)r_0, r_0)$$

## Minimization of the residual:

- $r_{j+1} = (I - \omega_j A)s_j$
- Define  $f_j(\omega) = \|(I - \omega A)s_j\|_2^2$

$$\Rightarrow f_j'(\omega) = -2(As_j, s_j) + 2\omega(As_j, As_j)$$

$$f_j''(\omega) = 2(As_j, As_j) \geq 0$$

$$\Rightarrow \omega_j = \arg \min_{\omega \in \mathbb{R}} f_j(\omega) = \frac{(As_j, s_j)}{(As_j, As_j)}$$

## BiCGSTAB-Algorithm

BiCGSTAB-Algorithmus —

Wähle  $\mathbf{x}_0 \in \mathbb{R}^n$  und  $\varepsilon > 0$

$\mathbf{r}_0 := \mathbf{p}_0 := \mathbf{b} - \mathbf{A} \mathbf{x}_0$ ,  $\rho_0 := (\mathbf{r}_0, \mathbf{r}_0)_2$ ,  $j := 0$

Solange  $\|\mathbf{r}_j\|_2 > \varepsilon$

$\mathbf{v}_j := \mathbf{A} \mathbf{p}_j$ ,  $\alpha_j := \frac{\rho_j}{(\mathbf{v}_j, \mathbf{r}_0)_2}$

$\mathbf{s}_j := \mathbf{r}_j - \alpha_j \mathbf{v}_j$ ,  $\mathbf{t}_j := \mathbf{A} \mathbf{s}_j$

$\omega_j := \frac{(\mathbf{t}_j, \mathbf{s}_j)_2}{(\mathbf{t}_j, \mathbf{t}_j)_2}$

$\mathbf{x}_{j+1} := \mathbf{x}_j + \alpha_j \mathbf{p}_j + \omega_j \mathbf{s}_j$

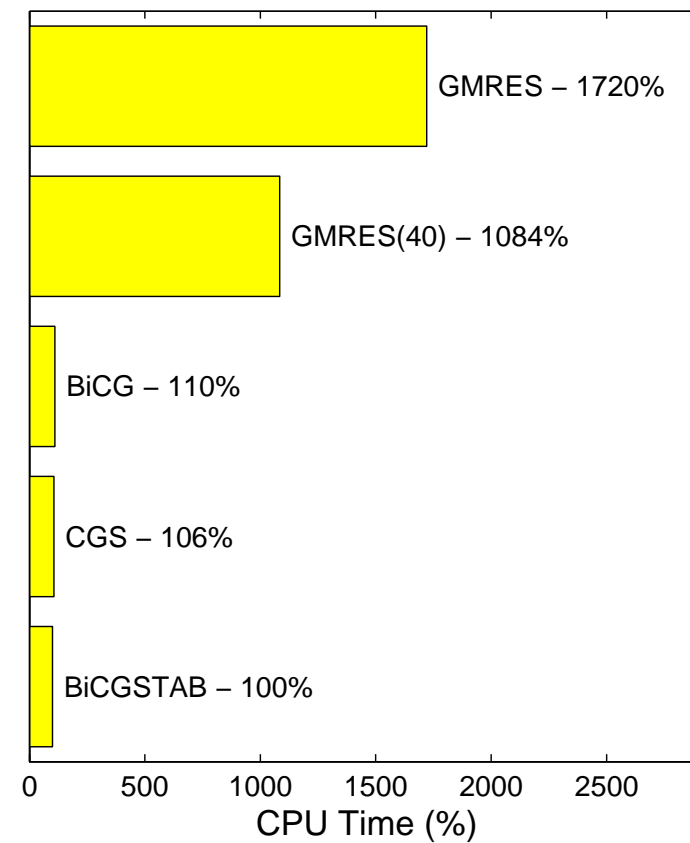
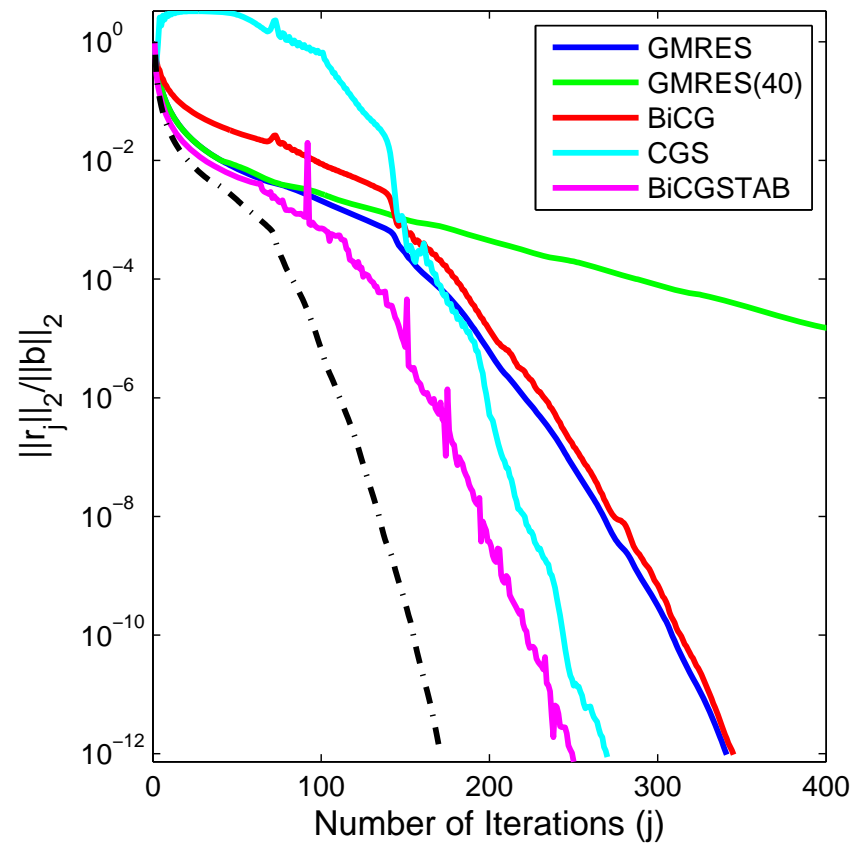
$\mathbf{r}_{j+1} := \mathbf{s}_j - \omega_j \mathbf{t}_j$

$\rho_{j+1} := (\mathbf{r}_{j+1}, \mathbf{r}_0)_2$ ,  $\beta_j := \frac{\alpha_j \rho_{j+1}}{\omega_j \rho_j}$

$\mathbf{p}_{j+1} := \mathbf{r}_{j+1} + \beta_j (\mathbf{p}_j - \omega_j \mathbf{v}_j)$ ,  $j := j + 1$

# Comparison of GMRES, BiCG, CGS and BiCGSTAB

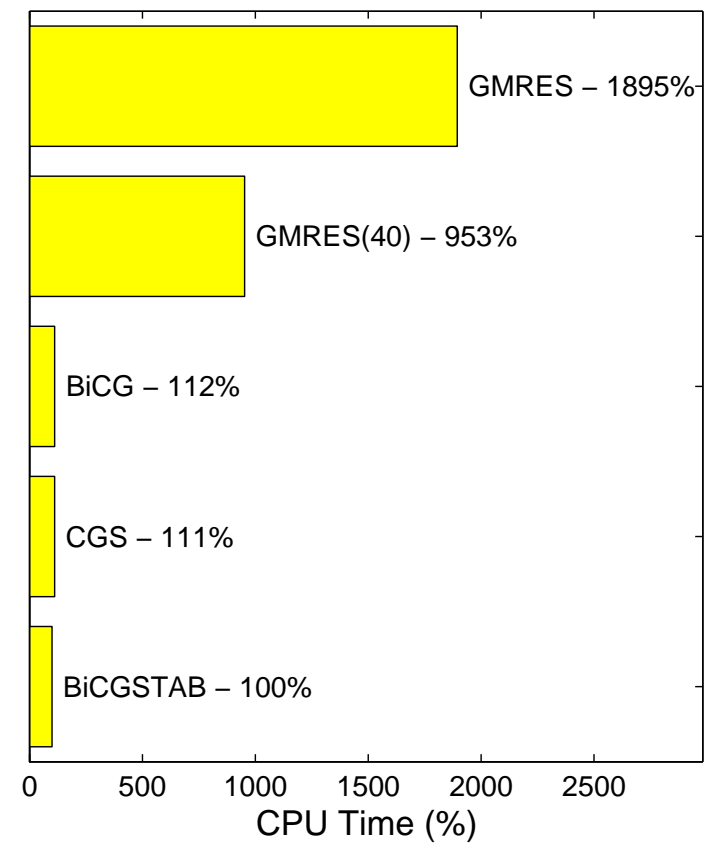
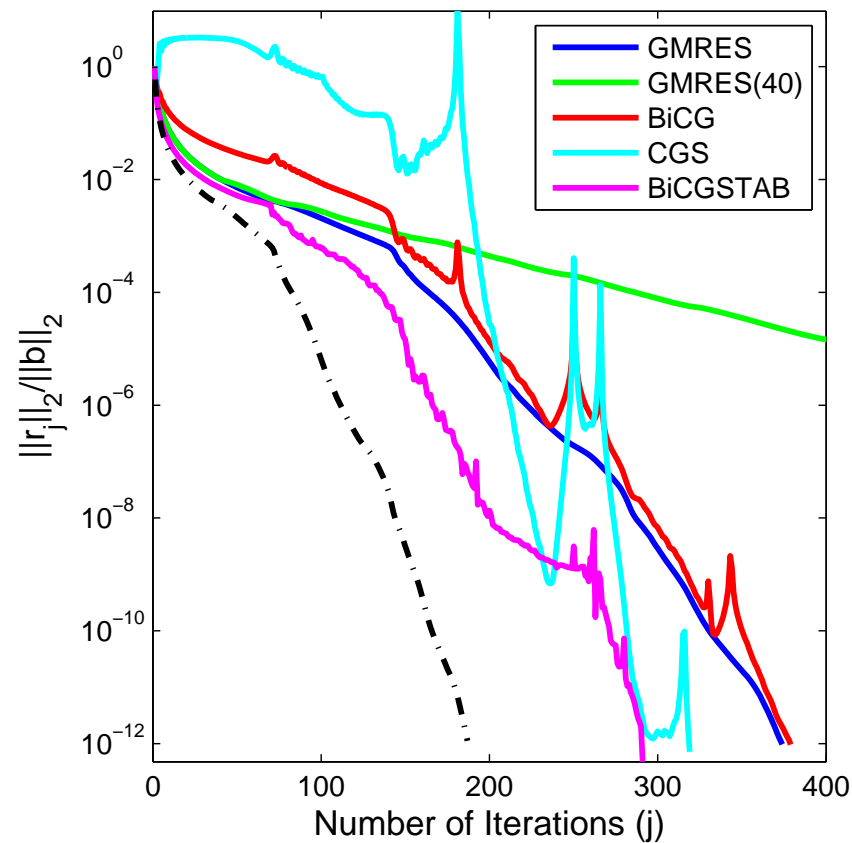
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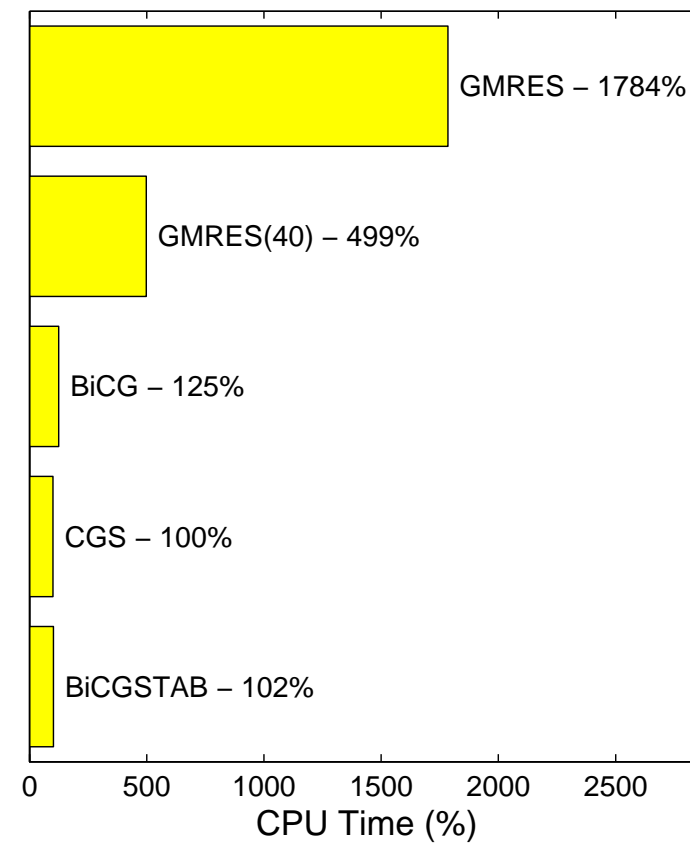
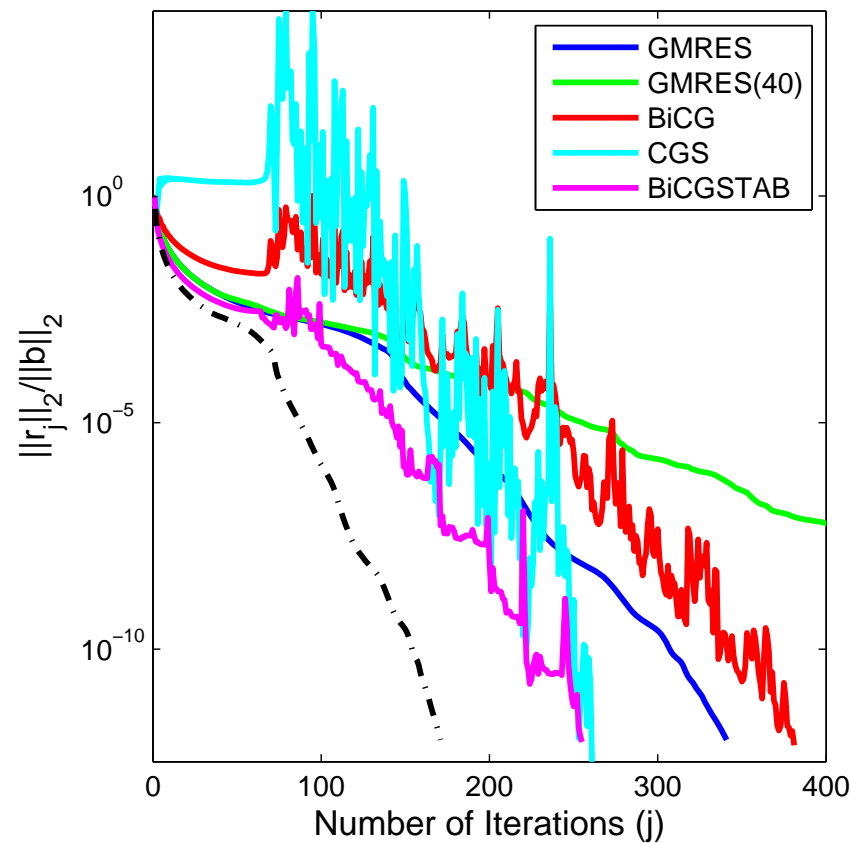
# Comparison of GMRES, BiCG, CGS and BiCGSTAB

Test 2: Weak Convection-Diffusion ( $\alpha = 0.1, \epsilon = 1$ )



# Comparison of GMRES, BiCG, CGS and BiCGSTAB

Test 3: Convection-Diffusion ( $\alpha = 1, \epsilon = 0.1$ )



# BiCGSTAB-Algorithm - Summary

## Derivation:

- Based on BiCG-Algorithm
- Squaring the polynomial representation
- Residual minimization

## Advantages:

- Keenly less storage requirements (compared to GMRES)
- No symmetry constraint on  $A$  (compared to CG)
- Requires no multiplications with  $A^T$  (compared to BiCG)
- Additional minimization technique (compared to CGS)  
→ Smooth convergence history

## Disadvantages:

- Possible break down due to division by  $(Ap_j, r_0)$