

# A note on GMRES preconditioned by a perturbed $LDL^T$ decomposition with static pivoting

M. Arioli, I. S. Duff, S. Gratton, and S. Pralet

- Multifrontal
- Static pivoting
- GMRES and Flexible GMRES
- Flexible GMRES: a roundoff error analysis
- GMRES right preconditioned: a roundoff error analysis
- Test problems
- Numerical experiments

# Linear system

We wish to solve large sparse systems

$$Ax = b$$

where  $A \in \mathbf{R}^{N \times N}$  is symmetric indefinite

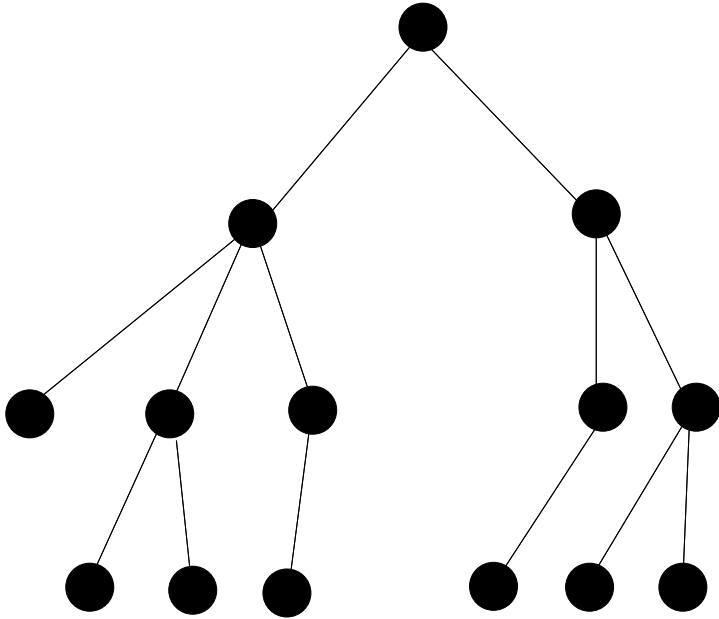
## Linear system

A particular and important case arises in saddle-point problems where the coefficient matrix is of the form

$$\begin{bmatrix} H & A \\ A^T & 0 \end{bmatrix}$$

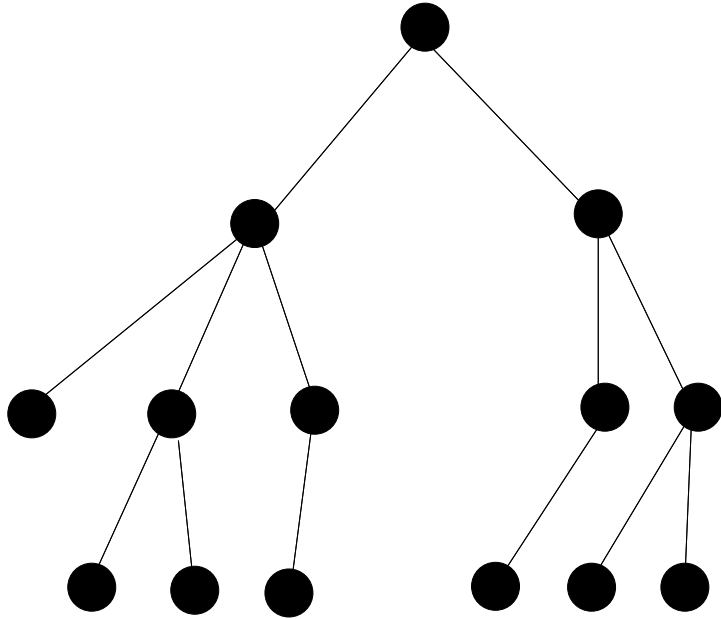
Since we want accurate solutions, we would prefer to use a direct method of solution and our method of choice uses a multifrontal approach.

## ASSEMBLY TREE



# Multifrontal method

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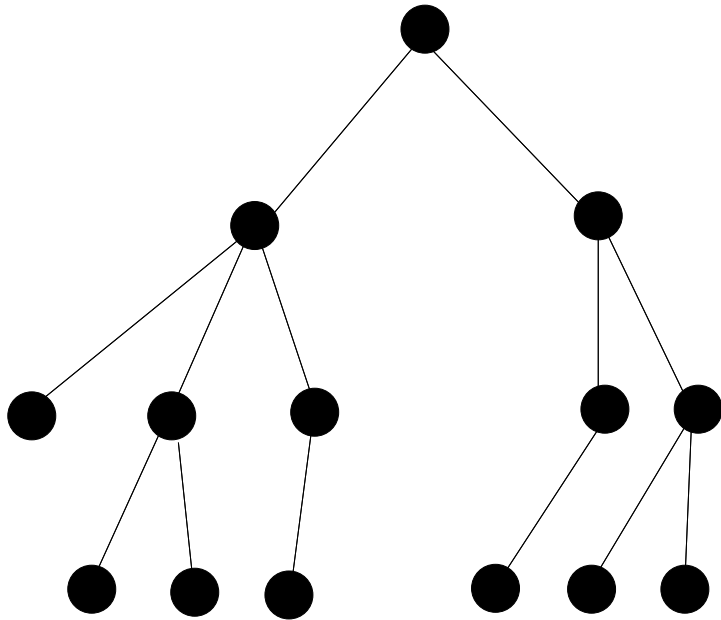


## AT EACH NODE

$F_{11}$	$F_{12}$
$F_{12}^T$	$F_{22}$

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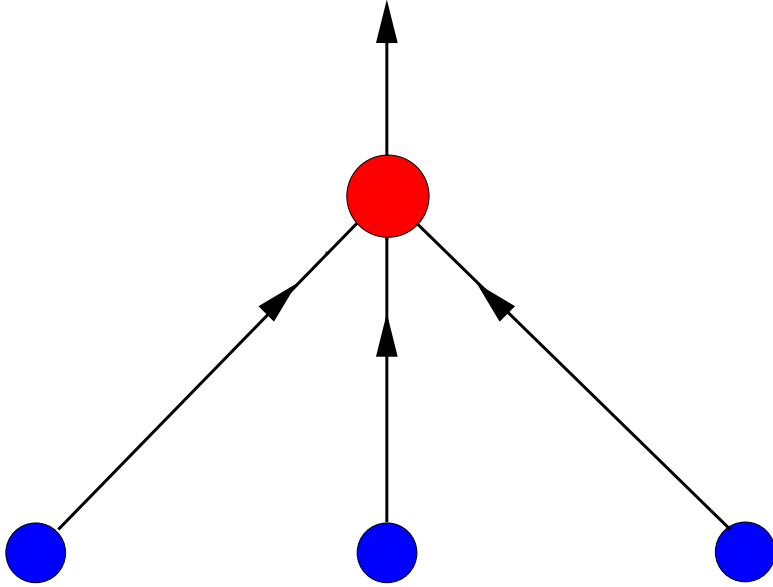


## AT EACH NODE

$F_{11}$	$F_{12}$
$F_{12}^T$	$F_{22}$

$$F_{22} \leftarrow F_{22} - F_{12}^T F_{11}^{-1} F_{12}$$

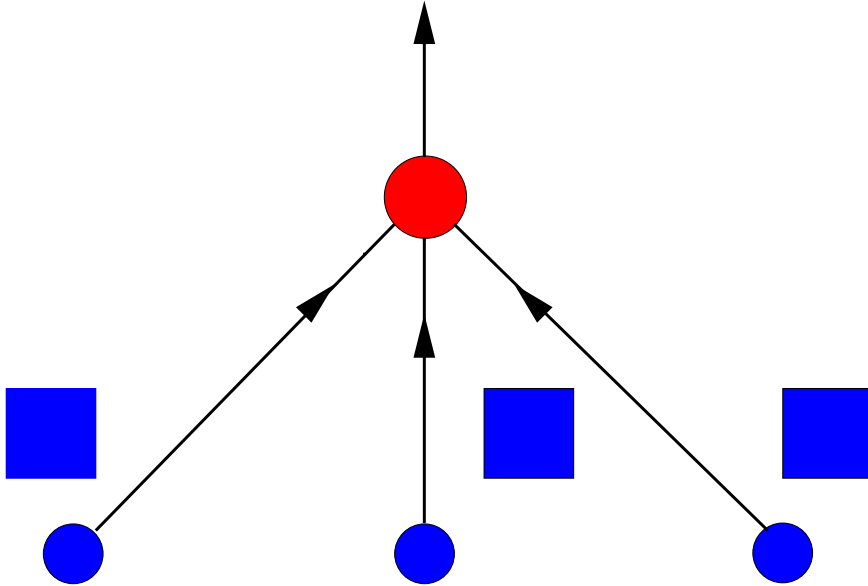
# Multifrontal method



■ From children to parent



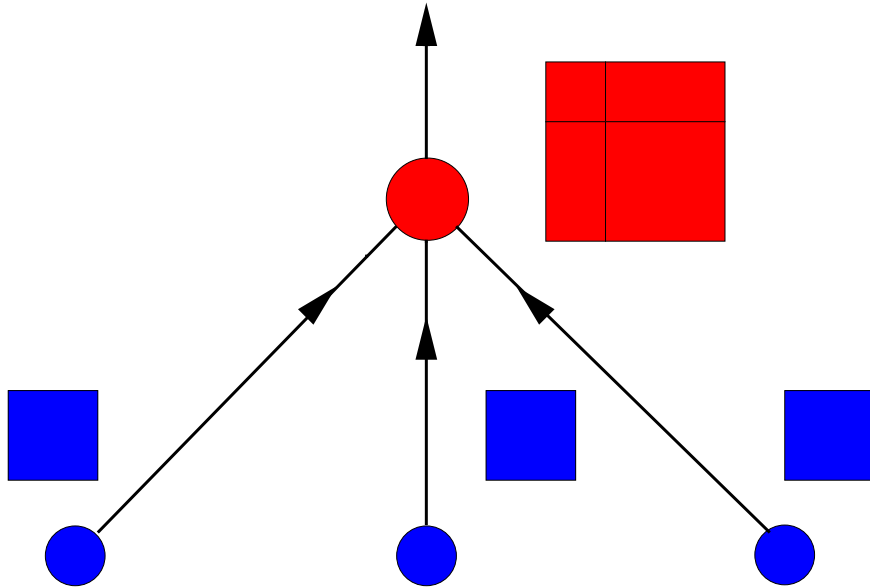
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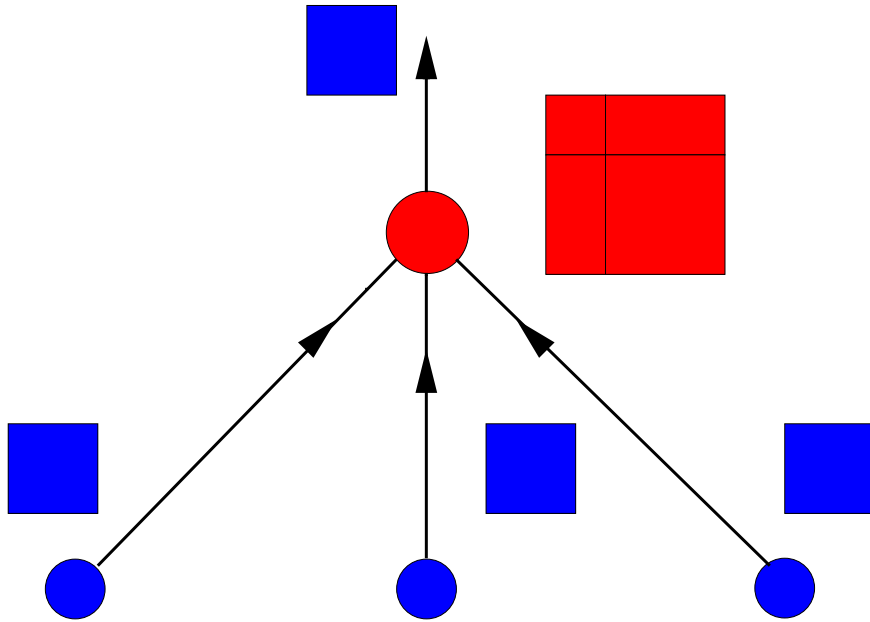
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- **ELIMINATION** Full Gaussian elimination, Level 3 BLAS (TRSM, GEMM)

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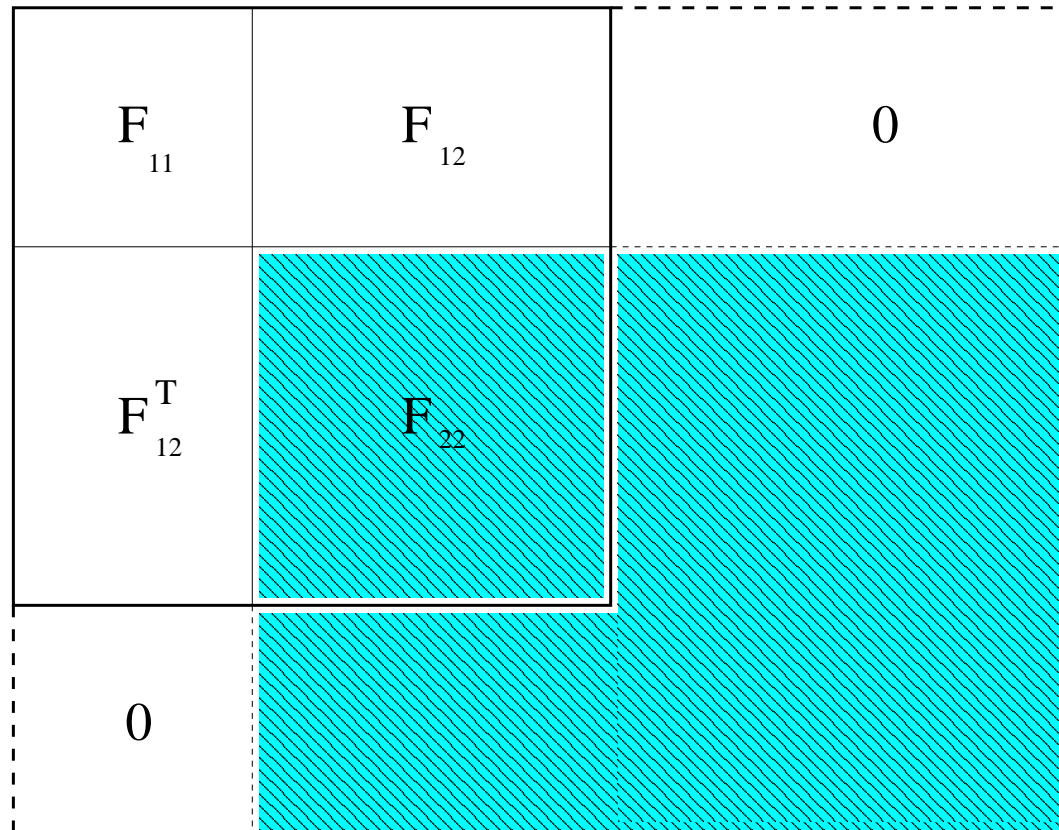
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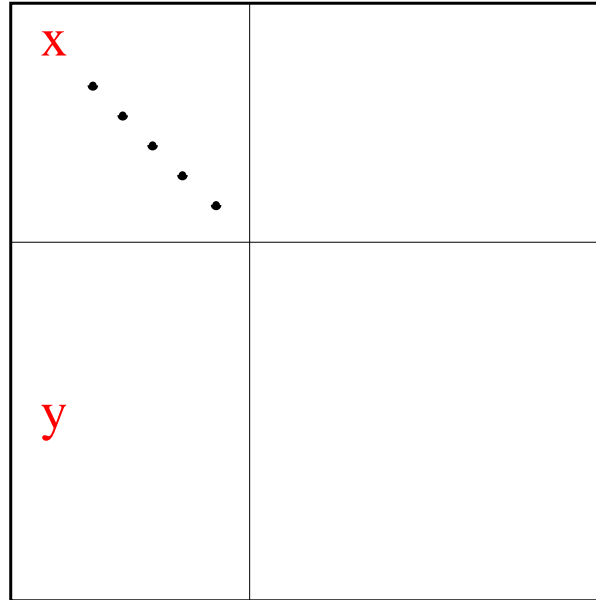
Pivot can only be chosen from  $F_{11}$  block since  $F_{22}$  is **NOT** fully summed.

# Multifrontal method



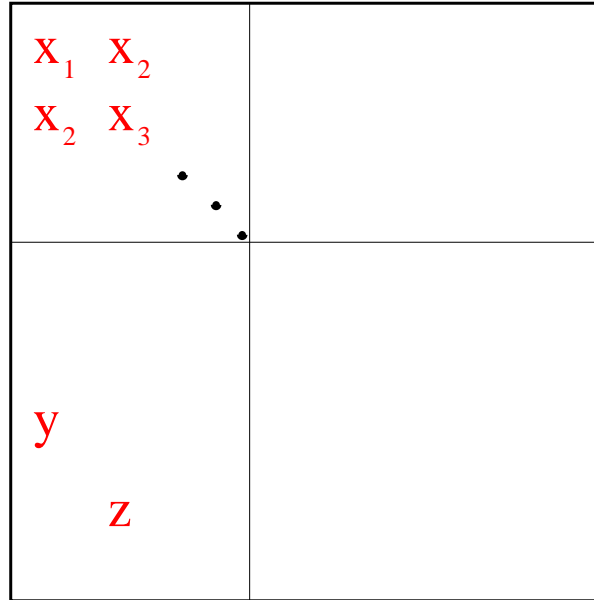
Situation wrt rest of matrix

# Pivoting ( $1 \times 1$ )



Choose  $x$  as  $1 \times 1$  **pivot** if  $|x| > u|y|$   
where  $|y|$  is the largest in column.

## Pivoting ( $2 \times 2$ )

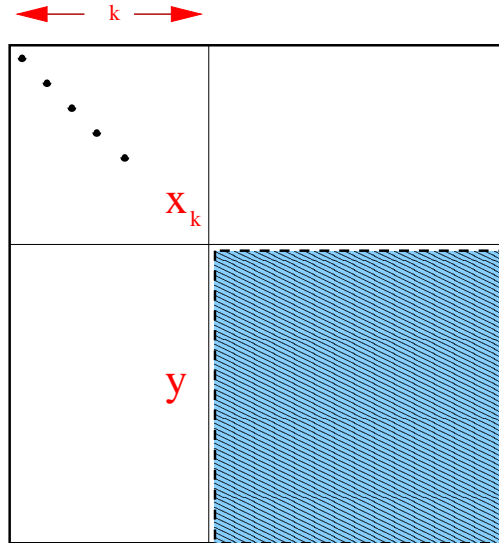


For the indefinite case, we can choose  $2 \times 2$  **pivot** where we require

$$\left| \begin{bmatrix} x_1 & x_2 \\ x_2 & x_3 \end{bmatrix}^{-1} \right| \begin{bmatrix} |y| \\ |z| \end{bmatrix} \leq \begin{bmatrix} \frac{1}{u} \\ \frac{1}{u} \end{bmatrix}$$

where again  $|y|$  and  $|z|$  are the largest in their columns.

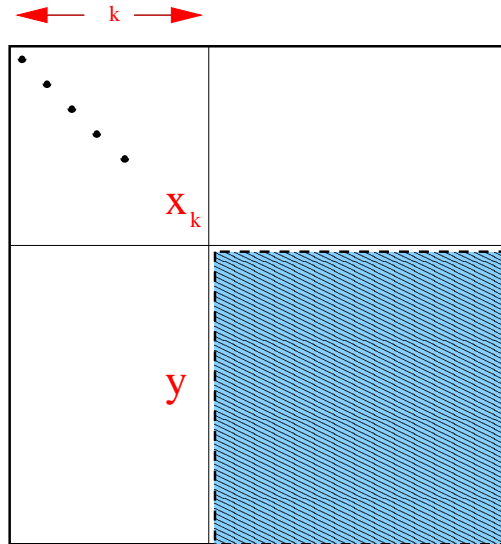
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If we assume that  $k - 1$  pivots are chosen but  $|x_k| < u|y|$  :



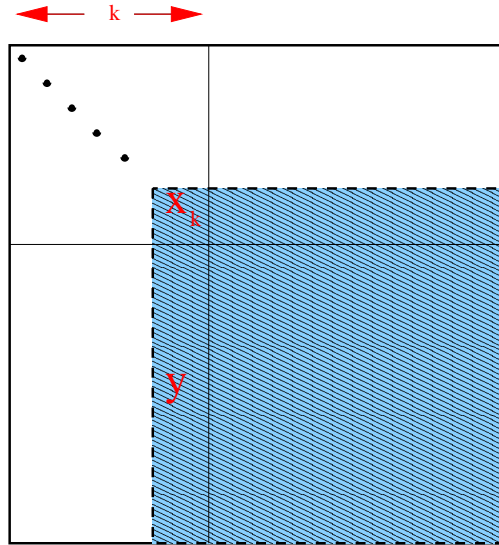
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- we can either take the **RISK** and use it or

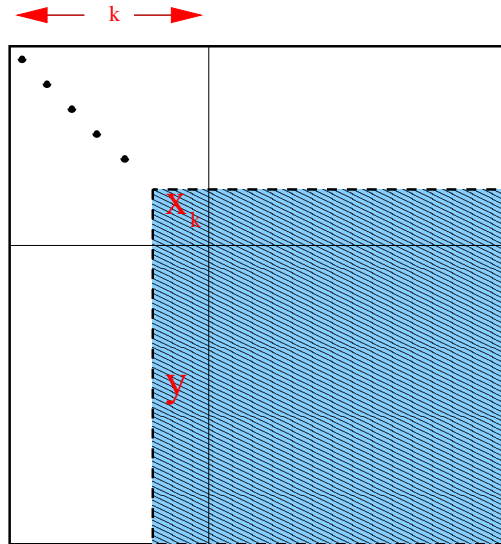
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- **DELAY** the pivot and then send to the parent a larger Schur complement.

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This can cause more work and storage

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An **ALTERNATIVE** is to use **Static Pivoting**, by replacing  $x_k$  by

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and CONTINUE.

This is even more important in the case of parallel implementation where static data structures are often preferred

Several codes use (or have an option for) this device:

- SuperLU (Demmel and Li)
- PARDISO (Gärtner and Schenk)
- MA57 (Duff and Pralet)

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The three codes then have an **Iterative Refinement** option.  
IR will converge if  $\rho(M^{-1}E) < 1$



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■  $\approx \varepsilon \implies$  big growth in preconditioning matrix  $M$

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In real life  $\rho(M^{-1}E) > 1$

# Right preconditioned GMRES and Flexible GMRES

```

procedure [x] = right_Prec_GMRES(A,M,b)
     $x_0 = M^{-1}b$ ,  $r_0 = b - Ax_0$  and  $\beta = ||r_0||$ 
     $v_1 = r_0 / \beta$ ;  $k=0$ ;
    while  $||r_k|| > \mu(||b|| + ||A|| ||x_k||)$ 
         $k = k + 1$ ;
         $z_k = M^{-1}v_k$ ;  $w = Az_k$ ;
        for  $i = 1, \dots, k$  do
             $h_{i,k} = v_i^T w$ ;
             $w = w - h_{i,k}v_i$ ;
        end for;
         $h_{k+1,k} = ||w||$ ;
         $v_{k+1} = w / h_{k+1,k}$ ;
         $V_k = [v_1, \dots, v_k]$ ;
         $H_k = \{h_{i,j}\}_{1 \leq i \leq j+1; 1 \leq j \leq k}$ ;
         $y_k = \arg \min_y ||\beta e_1 - H_k y||$ ;
         $x_k = x_0 + M^{-1}V_k y_k$  and  $r_k = b - Ax_k$ ;
    end while ;
end procedure.

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```

procedure [x] =FGMRES(A,M,b)
     $x_0 = M^{-1}b$ ,  $r_0 = b - Ax_0$  and  $\beta = ||r_0||$ 
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## Roundoff error 1

The computed  $\hat{L}$  and  $\hat{D}$  in floating-point arithmetic satisfy

$$\left\{ \begin{array}{l} A + \delta A + \tau E = M \\ \|\delta A\| \leq c(n)\varepsilon \|\hat{L}\| \|\hat{D}\| \|\hat{L}^T\| \\ \|E\| \leq 1. \end{array} \right.$$

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Moreover, we assume that

$$\max\{||M^{-1}||, ||\bar{Z}_k||\} \leq \frac{\tilde{c}}{\tau}.$$

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The first two stages of the roundoff error analysis are the same for both FGMRES and GMRES. the last two stages are specific to each one of the two algorithms.

## Roundoff error FGMRES

We can prove that Flexible GMRES computes a  $\bar{x}_k$  s.t.

$$\|b - A\bar{x}_k\| \leq c(n, k)\varepsilon(\|b\| + \|A\| \|\bar{x}_0\| + \|A\| \|\bar{Z}_k\| \|M(\bar{x}_k - \bar{x}_0)\|) + \mathcal{O}(\varepsilon^2)$$

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If  $\boxed{c(n, k)\varepsilon\|A\| \|\bar{Z}_k\| < 1 \quad \forall k}$

$$\|b - A\bar{x}_k\| \leq 2\mu\varepsilon(\|b\| + \|A\| (\|\bar{x}_0\| + \|\bar{x}_k\|)) + \mathcal{O}(\varepsilon^2).$$

$$\mu = \frac{c(n, k)}{1 - c(n, k)\varepsilon\|A\| \|\bar{Z}_k\|}$$

As we did for FGMRES, we can prove that right preconditioned GMRES computes a  $\bar{x}_k$  s.t.

$$\|b - A\bar{x}_k\| \leq c_1(n, k)\chi\varepsilon \left\{ \|b\| + \|A\| \|\bar{\mathbf{x}}_0\| + \|AM^{-1}\| \|M\| \|\bar{x}_k - \bar{\mathbf{x}}_0\| + \right. \\ \left[ \|A\| \|\bar{Z}_k\| + \|AM^{-1}\| \|M^{-1}\| \|\hat{L}\| \|\hat{D}\| \|\hat{L}^T\| \right] \times \\ \left. \left[ \|M(\bar{x}_k - \bar{\mathbf{x}}_0)\| + n\varepsilon \|M\| (\|\bar{x}_k - \bar{\mathbf{x}}_0\| + \|\bar{\mathbf{x}}_0\|) \right] \right\} + \mathcal{O}(\varepsilon^2).$$

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If  $\boxed{\zeta = c_2(n, k) \varepsilon \left[ \|A\| \|\bar{Z}_k\| + \|M^{-1}\| \|\hat{L}\| \|\hat{D}\| \|\hat{L}^T\| \right] < 1 \quad \forall k}$

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$$\|b - A\bar{x}_k\| \leq \xi \varepsilon \left[ \|b\| + (\|A\| + \|M^{-1}\|) (\|\bar{x}_k\| + \|\bar{\mathbf{x}}_0\|) \right] + \mathcal{O}(\varepsilon^2).$$

$$\xi = \frac{c_2(n, k)}{1 - \zeta}$$

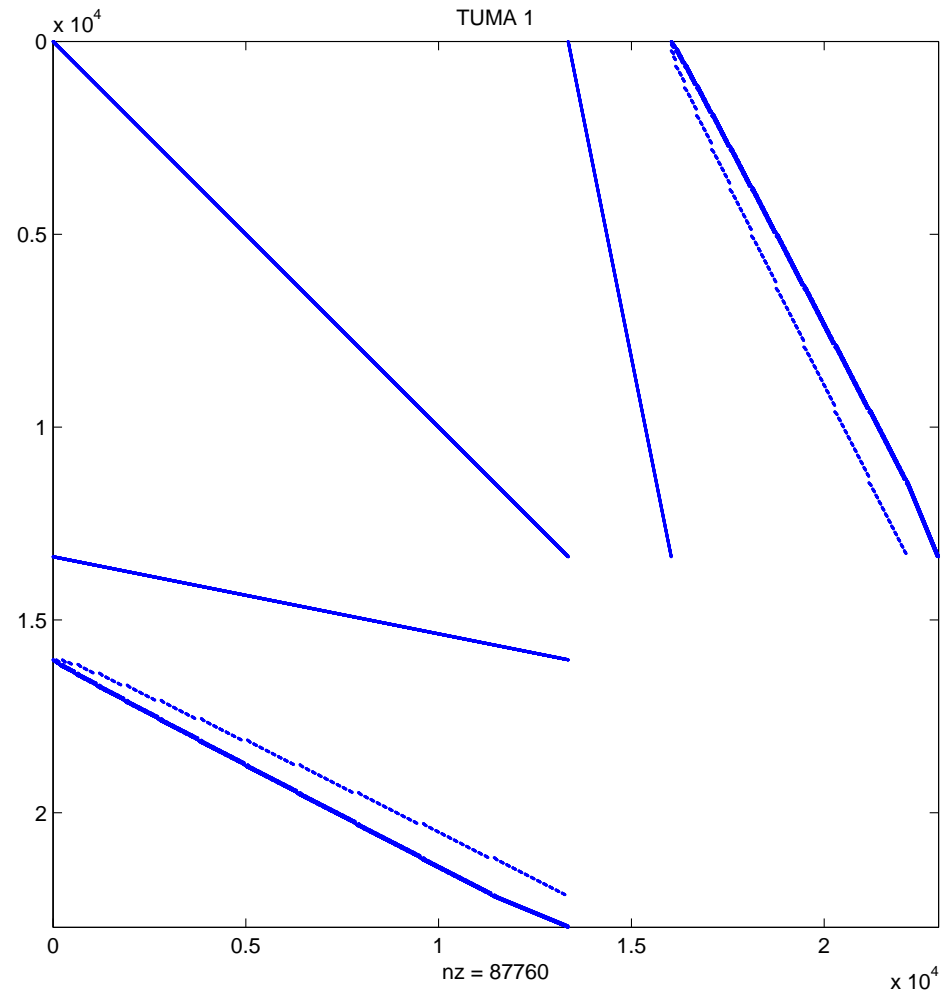
# Test Problems

	n	nnz	Description
CONT_201	80595	239596	KKT matrix Convex QP (M2)
CONT_300	180895	562496	KKT matrix Convex QP (M2)
TUMA_1	22967	76199	Mixed-Hybrid finite-element

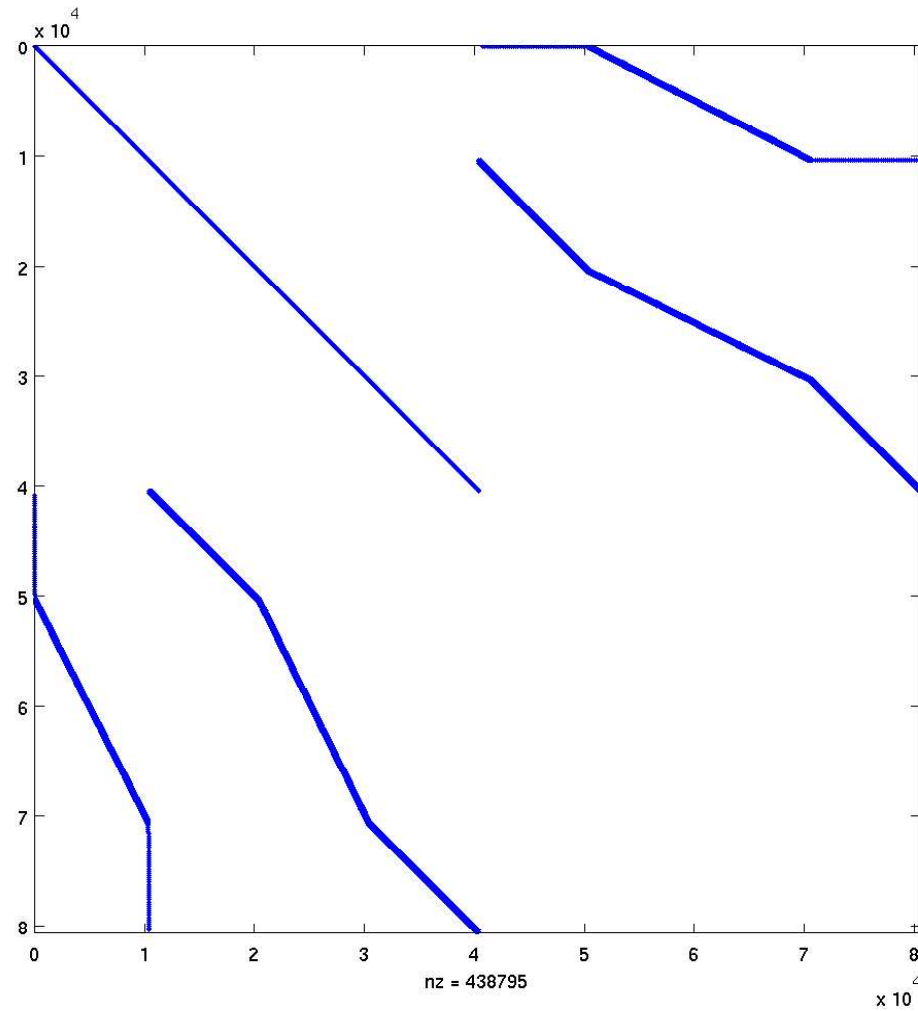
Test problems



# Test Problems: TUMA 1



# Test Problems: CONT-201



# Numerical experiments: TUMA 1

	$\frac{  b - A\bar{x}_k  }{  b   +   A     \bar{x}_k  }$							
$\tau$	FGMRES	GMRES	$  M  $	$  M^{-1}  $	$  x_0  $	$  \hat{L}  \hat{D}  \hat{L}^T  $	$  \bar{Z}_k  $	$  \bar{x}_k - \bar{x}_0  _2$
1e-02	9.3e-17	5.7e-15	4.89	623.57	336.4	3.9e+04	186.14	315.6
1e-04	2.8e-17	9.4e-17	4.89	625.34	89.01	1.5e+05	53.69	2.8
1e-06	2.8e-17	2.0e-16	4.89	625.36	87.70	1.5e+07	42.97	2.6e-02
1e-08	2.8e-17	7.7e-17	4.89	625.76	87.69	1.5e+09	42.95	2.6e-04
1e-10	2.8e-17	3.7e-14	4.89	625.03	87.69	1.5e+11	4.44	1.6e-04
1e-12	2.8e-17	9.0e-10	4.89	626.55	87.69	1.5e+13	26.54	1.4e-02
1e-14	5.7e-17	4.7e-06	4.89	621.60	87.68	1.5e+15	232.13	1.3
1e-15	4.3e-12	9.0e-04	22.98	931.62	91.99	2.2e+17	443.34	19.8

TUMA 1 results

# Numerical experiments: CONT\_201

	$\frac{  b - A\bar{x}_k  }{  b   +   A     \bar{x}_k  }$							
$\tau$	FGMRES	GMRES	$  M  $	$  M^{-1}  $	$  x_0  $	$   \hat{L}  \hat{D}  \hat{L}^T  $	$  \bar{Z}_k  $	$  \bar{x}_k - \bar{x}_0  _2$
1e-02	1.1e-03	1.1e-03	8.11	1.9e+04	296.5	5.4e+06	1.7e+04	267.6
1e-04	5.7e-07	5.7e-07	8.08	5.4e+05	394.9	1.9e+08	5.3e+05	372.7
1e-06	7.0e-17	4.6e-13	8.08	4.4e+06	159.2	1.4e+10	4.9e+06	137.0
1e-08	4.5e-17	1.1e-11	8.08	3.6e+07	241.8	2.5e+12	3.5e+07	113.4
1e-10	3.5e-17	7.5e-10	8.08	1.5e+07	163.0	8.7e+14	1.0e+06	1.4
1e-12	3.7e-17	1.8e-08	8.08	1.5e+07	199.6	1.7e+16	5.4e+02	58.5
1e-14	2.6e-15	5.0e-04	197.6	1.2e+07	16504	3.4e+18	1.7e+03	16585
1e-15	1.4e-12	6.8e-02	421.1	4.9e+06	36941	2.5e+19	5.1e+02	37022

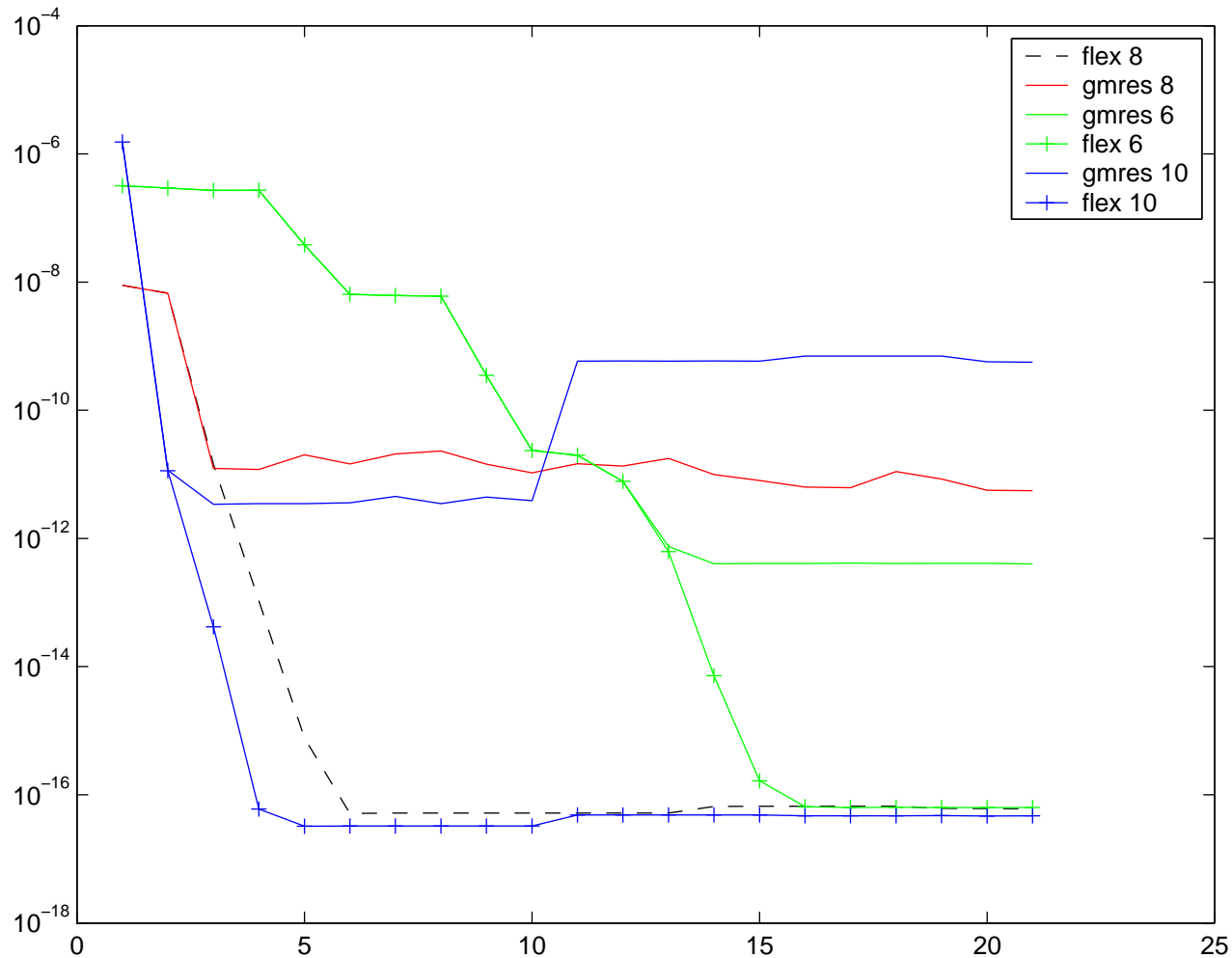
CONT\_201 results

# Numerical experiments: CONT\_300

	$\frac{  b - A\bar{x}_k  }{  b   +   A     \bar{x}_k  }$							
$\tau$	FGMRES	GMRES	$  M  $	$  M^{-1}  $	$  x_0  $	$   \hat{L}   \hat{D}   \hat{L}^T   $	$  \bar{Z}_k  $	$  \bar{x}_k - \bar{x}_0  _2$
1e-02	1.2e-03	1.2e-03	8.1	1.7e+04	345.9	4.2e+07	1.2e+04	286.4
1e-04	1.2e-06	1.2e-06	8.1	3.1e+05	357.0	2.3e+09	2.3e+05	300.2
1e-06	7.9e-15	1.1e-12	8.1	2.5e+06	309.0	2.3e+11	2.1e+06	252.2
1e-08	4.4e-17	4.4e-12	8.1	9.1e+07	266.8	4.0e+13	7.1e+07	284.0
1e-10	3.5e-17	3.4e-08	8.0	7.7e+07	246.0	2.5e+15	6.1e+05	1.8
1e-12	4.1e-17	1.4e-06	16.3	7.6e+07	372.9	3.9e+17	7.3e+02	181.6
1e-14	2.0e-15	9.2e-04	3031.6	7.4e+07	20176	3.5e+19	5.1e+02	20159
1e-15	7.9e-15	2.0e-02	25391	6.1e+07	70577	2.6e+20	5.5e+02	70670

CONT\_300 results

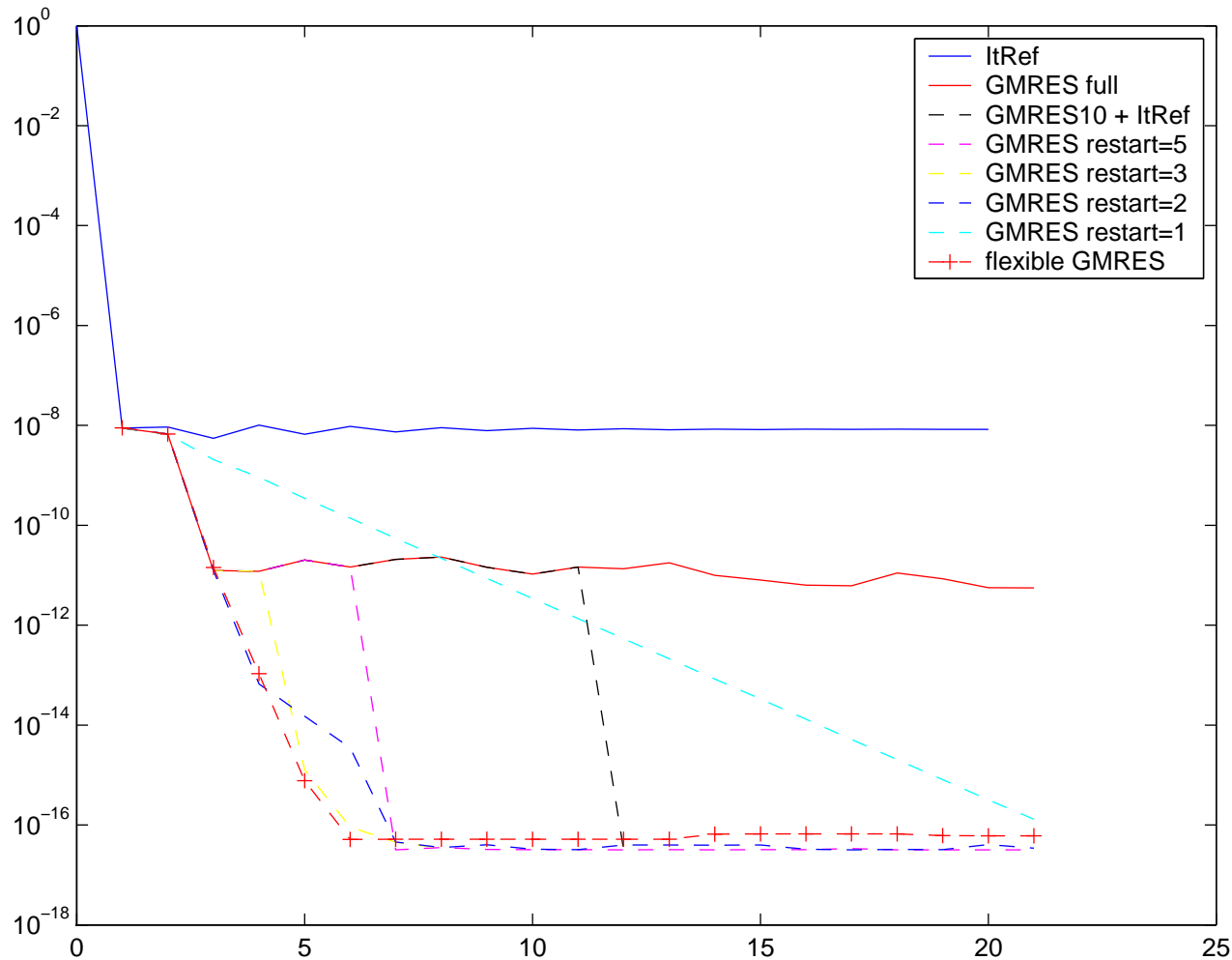
# Numerical experiments



GMRES vs. FGMRES on CONT-201 test example:

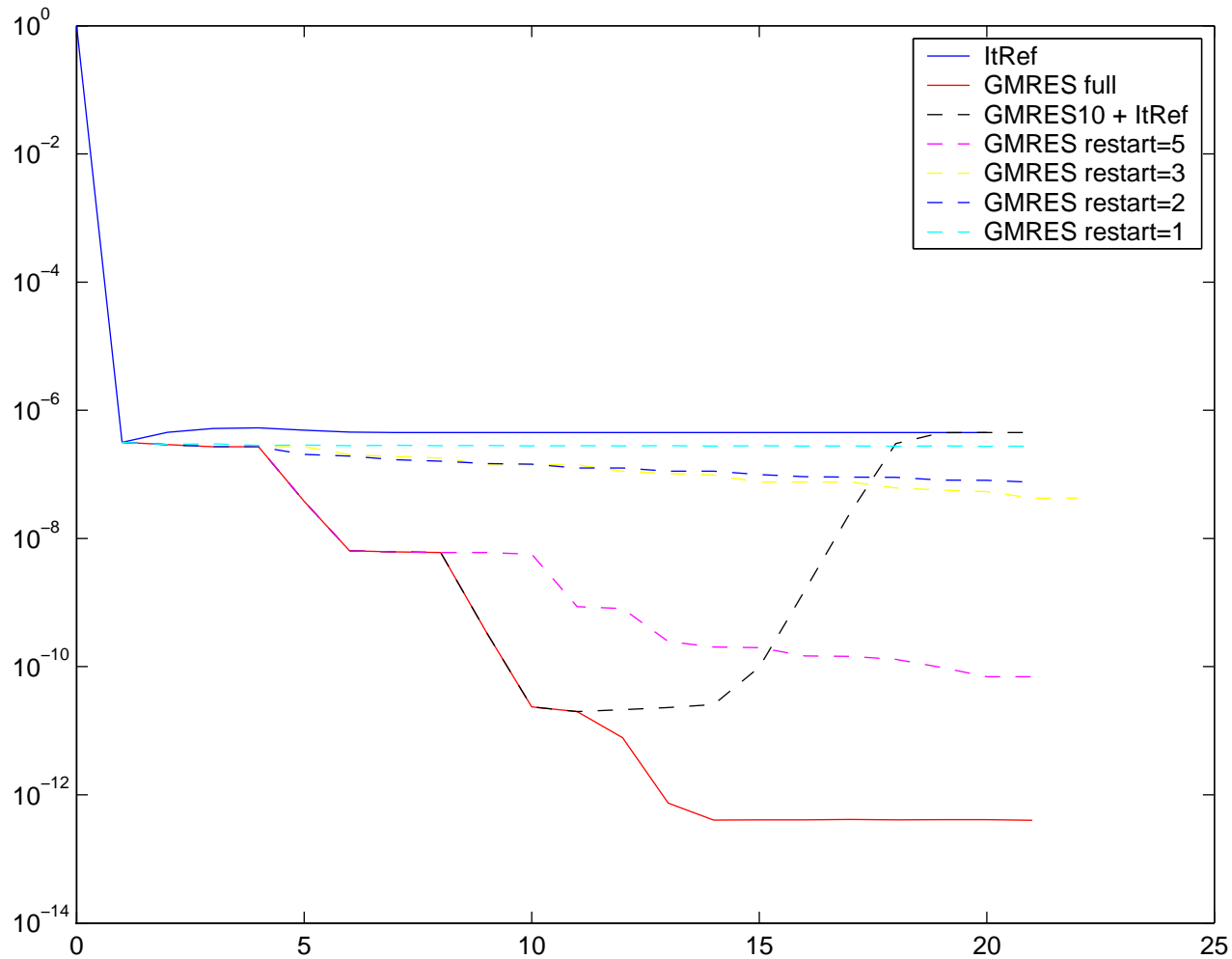
$$\tau = 10^{-6}, 10^{-8}, 10^{-10}$$

# Numerical experiments



Restarted GMRES vs. FGMRES on CONT-201 test example:  $\tau = 10^{-8}$

# Numerical experiments



Restarted GMRES on CONT-201 test example:  $\tau = 10^{-6}$



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- Understanding of why  $\tau \approx \sqrt{\varepsilon}$  is best.