



GMRES preconditioned by a perturbed LDL^T decomposition with static pivoting

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<http://www.numerical.rl.ac.uk/people/marioli/marioli.html>



Outline

- Multifrontal
- Static pivoting
- GMRES and Flexible GMRES: a roundoff error analysis
- 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

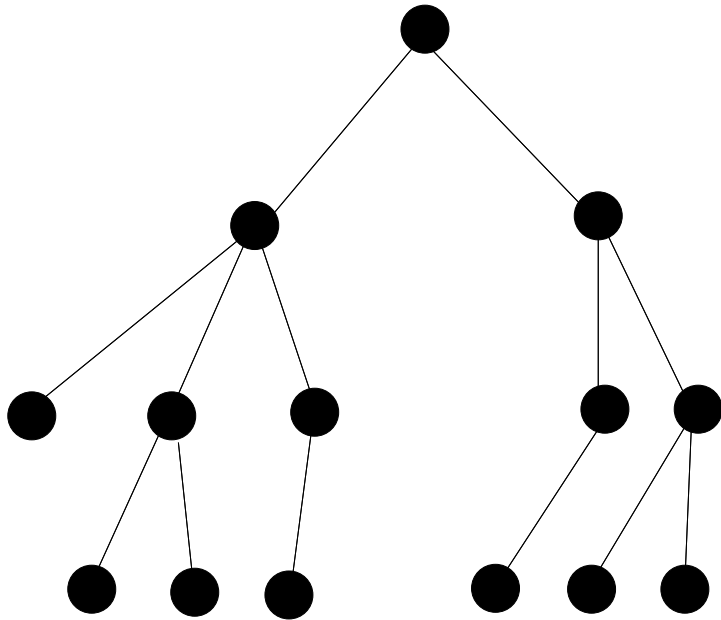
$$\begin{bmatrix} H & A \\ A^T & 0 \end{bmatrix}$$

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



Multifrontal method

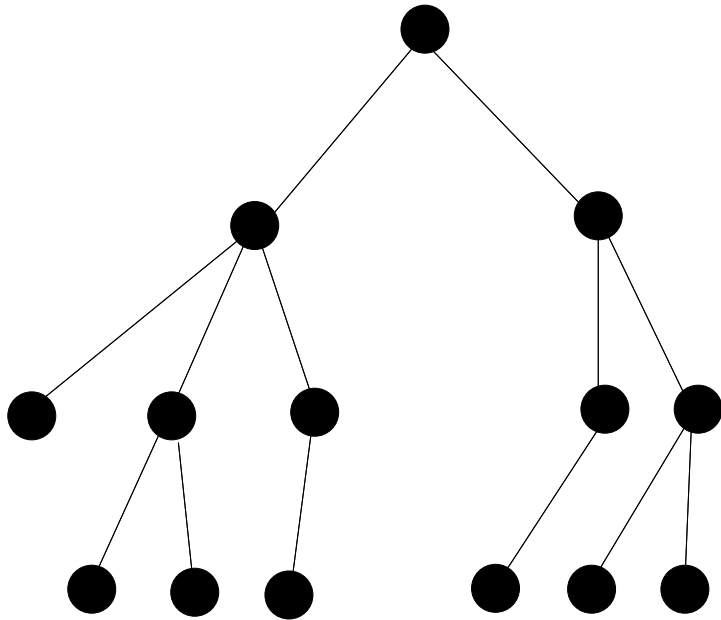
ASSEMBLY TREE



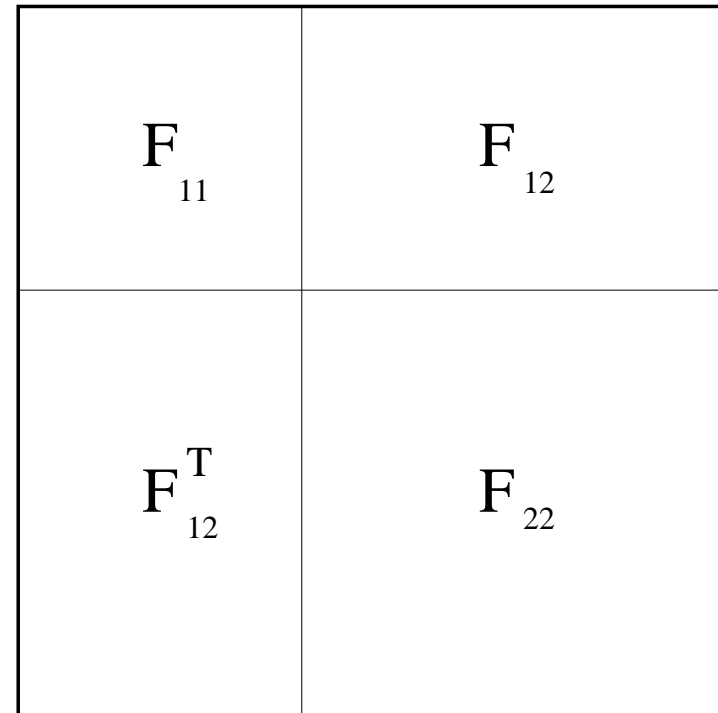


Multifrontal method

ASSEMBLY TREE



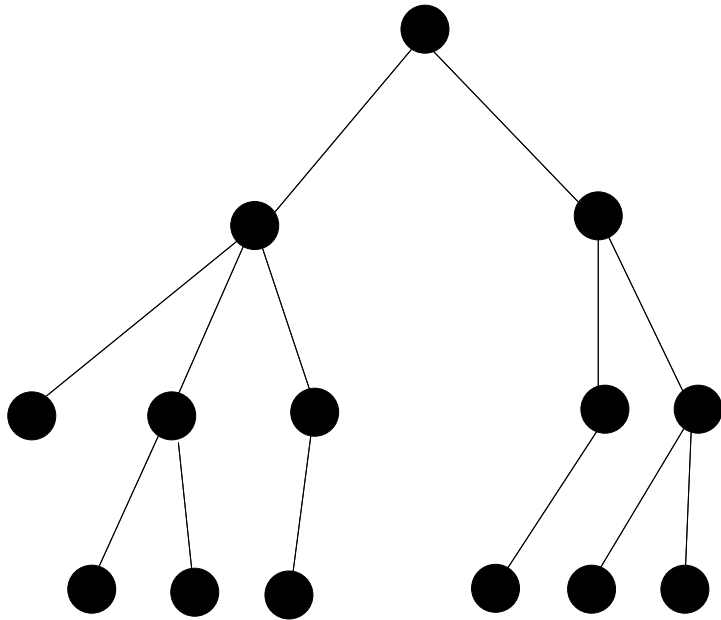
AT EACH NODE





Multifrontal method

ASSEMBLY TREE



AT EACH NODE

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

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



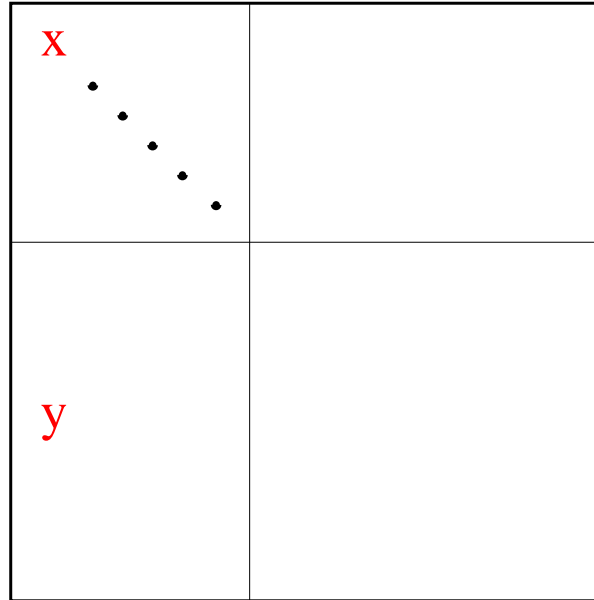
Multifrontal method

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

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



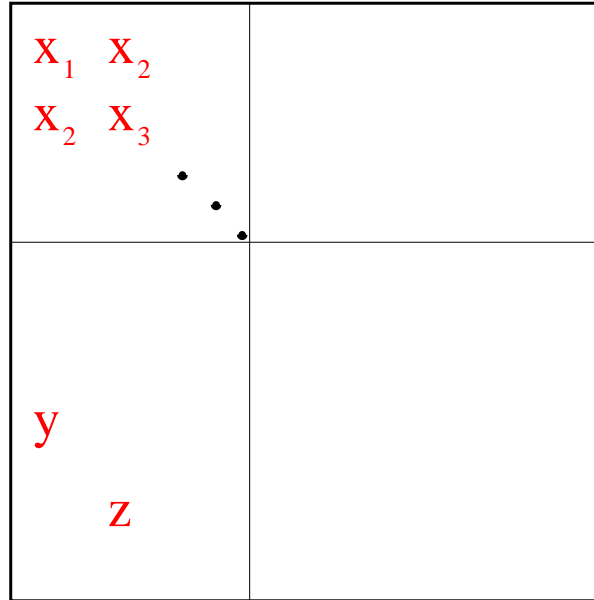
Pivoting (1×1)



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



Pivoting (2×2)



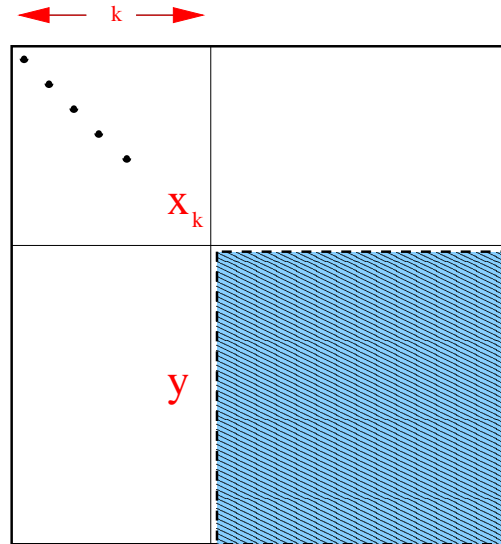
For the indefinite case, we can choose 2×2 **pivot** where we require

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

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



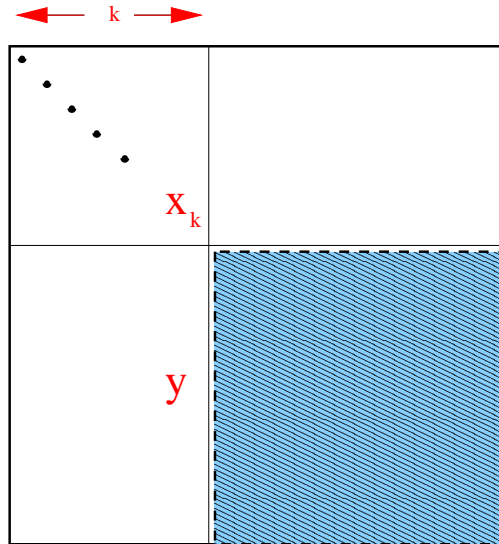
Pivoting



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



Pivoting

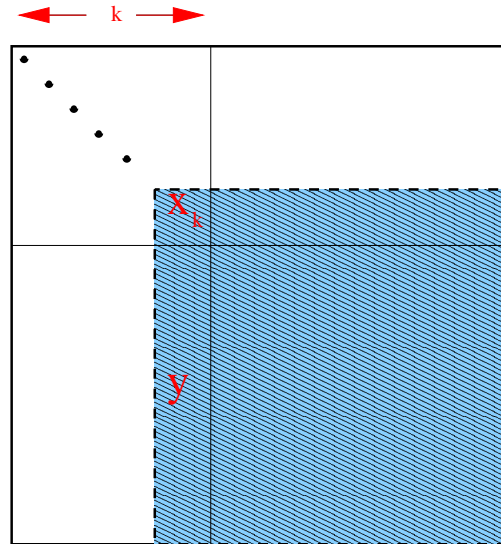


If we assume that $k - 1$ pivots are chosen but $|x_k| < u|y|$:

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



Pivoting

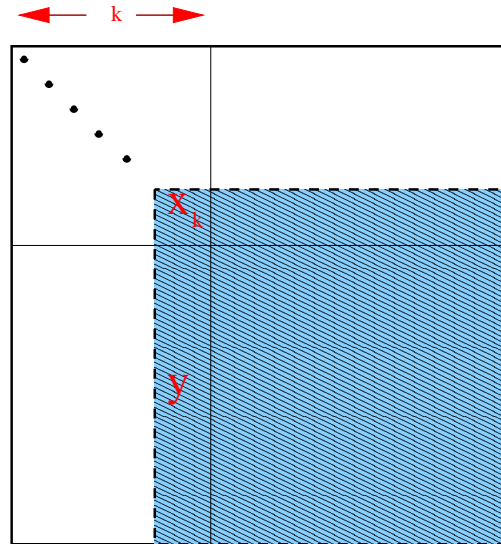


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- **DELAY** the pivot and then send to the parent a larger Schur complement.



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- we can either take the **RISK** and use it or
- **DELAY** the pivot and then send to the parent a larger Schur complement.

This can cause more work and storage



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Static Pivoting

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

$$x_k + \tau$$

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)



Static Pivoting

We thus have factorized

$$A + E = LDL^T = M$$

where $|E| \leq \tau I$



Static Pivoting

We thus have factorized

$$A + E = LDL^T = M$$

where $|E| \leq \tau I$

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



Static Pivoting

If $\rho(M^{-1}E) > 1$ then

PLAN A (Iterative Refinement Algorithm) fails!!!



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Flexible GMRES



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.

```

```

procedure [x] =FGMRES(A,Mi,b)
     $x_0 = M_0^{-1}b$ ,  $r_0 = b - Ax_0$  and  $\beta = ||r_0||$ 
     $v_1 = r_0 / \beta$ ;  $k=0$ ;
    while  $||r_k|| > \mu(||b|| + ||A|| ||x_k||)$ 
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end procedure.

```




Roundoff error 1

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

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

The perturbation δA must have a norm smaller than τ , in order to not dominate the global error.



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Roundoff error 1

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$$||\hat{L}||\hat{D}||\hat{L}^T|| \approx \frac{n}{\tau} \implies \varepsilon \leq \frac{\tau^2}{n^2}$$

Moreover, we assume that

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



Roundoff error FGMRES

Theorem 1.

$$\sigma_{\min}(\bar{H}_k) > c_7(k, 1)\varepsilon \|\bar{H}_k\| + \mathcal{O}(\varepsilon^2) \quad \forall k,$$

$$|\bar{s}_k| < 1 - \varepsilon, \quad \forall k,$$

(where \bar{s}_k are the sines computed during the Givens algorithm)
and

$$2.12(n+1)\varepsilon < 0.01 \text{ and } 18.53\varepsilon n^{\frac{3}{2}} \kappa(C^{(k)}) < 0.1 \quad \forall k$$

$$\exists \hat{k}, \quad \hat{k} \leq n$$

such that, $\forall k \geq \hat{k}$, we have

$$\|b - A\bar{x}_k\| \leq c_1(n, k)\varepsilon \left(\|b\| + \|A\| \|\bar{x}_0\| + \|A\| \|\bar{Z}_k\| \|\bar{y}_k\| \right) + \mathcal{O}(\varepsilon^2).$$



Roundoff error FGMRES

Moreover, if $M_i = M, \forall i$,

$$\rho = 1.3 \|\hat{W}_k\| + c_2(k, 1)\varepsilon \|M\| \|\bar{Z}_k\| < 1 \quad \forall k < \hat{k},$$

where

$$\hat{W}_k = [M\bar{z}_1 - \bar{v}_1, \dots, M\bar{z}_k - \bar{v}_k],$$

we have:

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

$$\gamma = \frac{1.3}{1 - \rho}.$$



Roundoff error FGMRES

Theorem 2

Under the Hypotheses of Theorem 1, and

$$\mathbf{c}(n)\varepsilon |||\hat{L}||\hat{D}||\hat{L}^T||| < \tau$$

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

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

we have

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

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



Roundoff error right preconditioned GMRES

Theorem 3

We assume of applying Iterative Refinement for solving $M(\bar{x}_k - \bar{x}_0) = \bar{V}_k \bar{y}_k$ at last step.

Under the Hypotheses of Theorem 1 and $c(n)\varepsilon \kappa(M) < 1$

$$\exists \hat{k}, \quad \hat{k} \leq n$$

such that, $\forall k \geq \hat{k}$, we have

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



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



MA57 tests

	n	nnz(L)+nnz(D)	Factorization time
CONT_201	80595	9106766	9.0 sec
CONT_300	180895	22535492	28.8 sec

MA57 without static pivot



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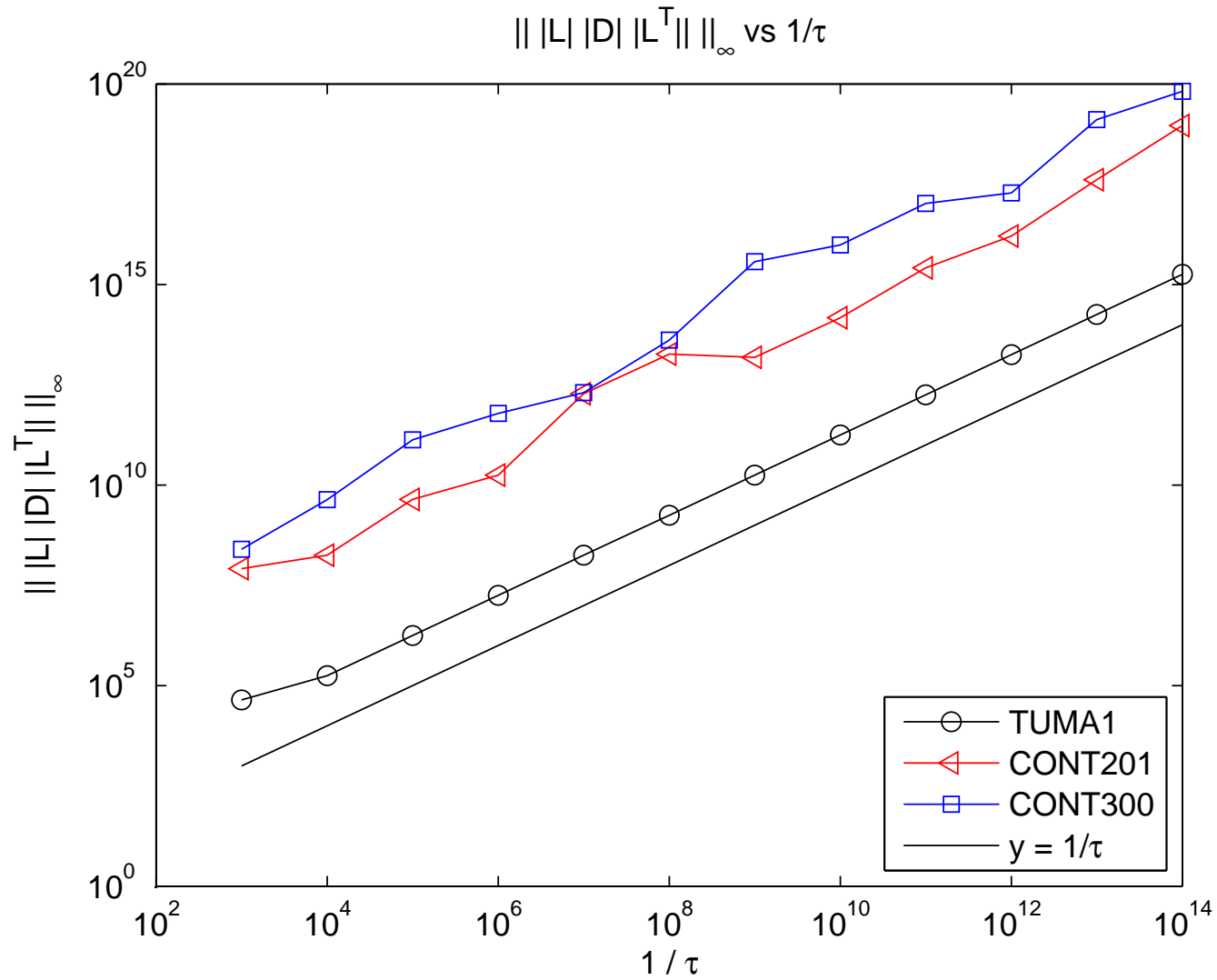
MA57 without static pivot

	nnz(L)+nnz(D)+ FGMRES (#it)	Factorization time	# static pivots
CONT_201	5563735 (6)	3.1 sec	27867
CONT_300	12752337 (8)	8.9 sec	60585

MA57 with static pivot $\tau = 10^{-8}$

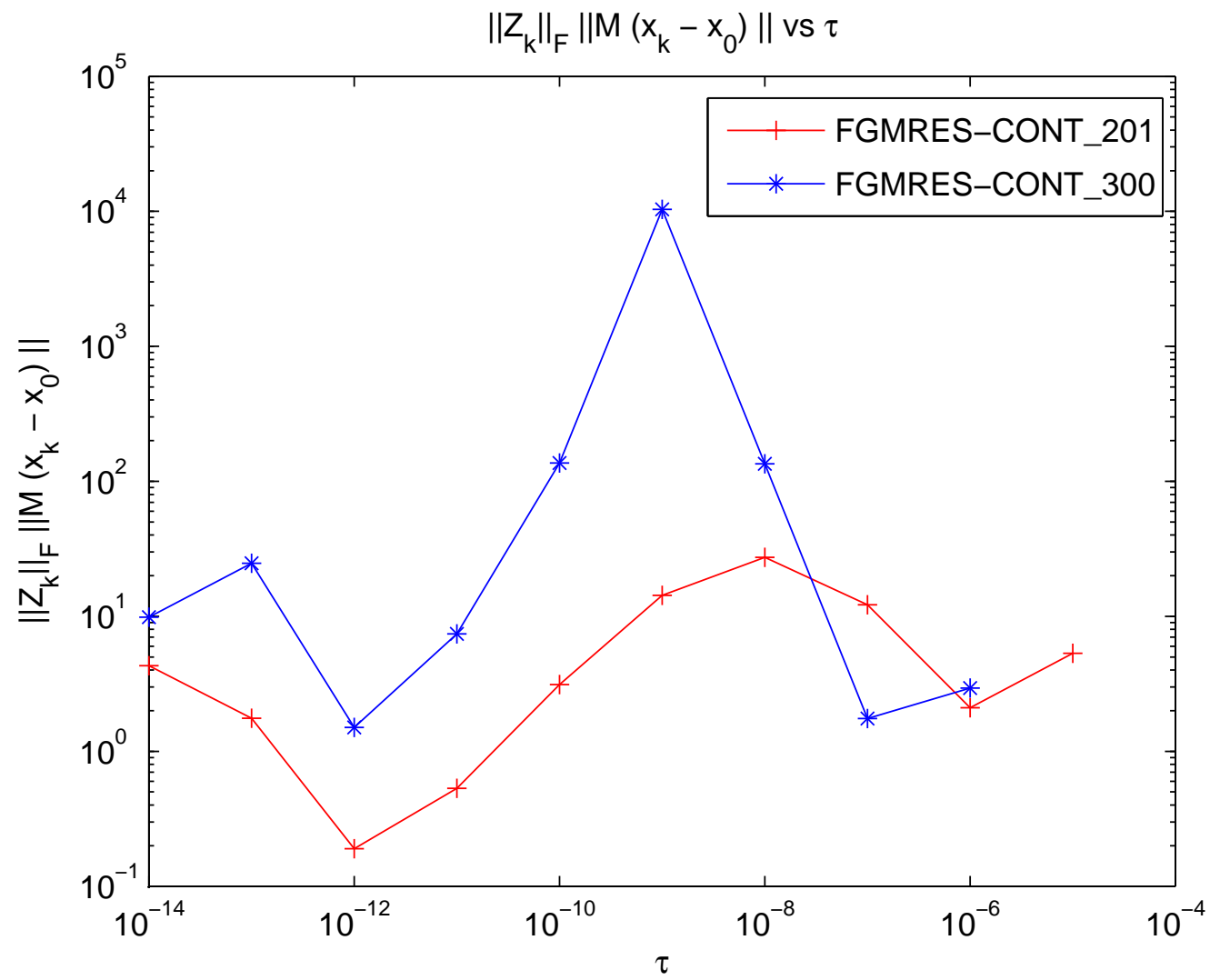


$|||\hat{L}|||\hat{D}|||\hat{L}^T|||$ vs $1/\tau$



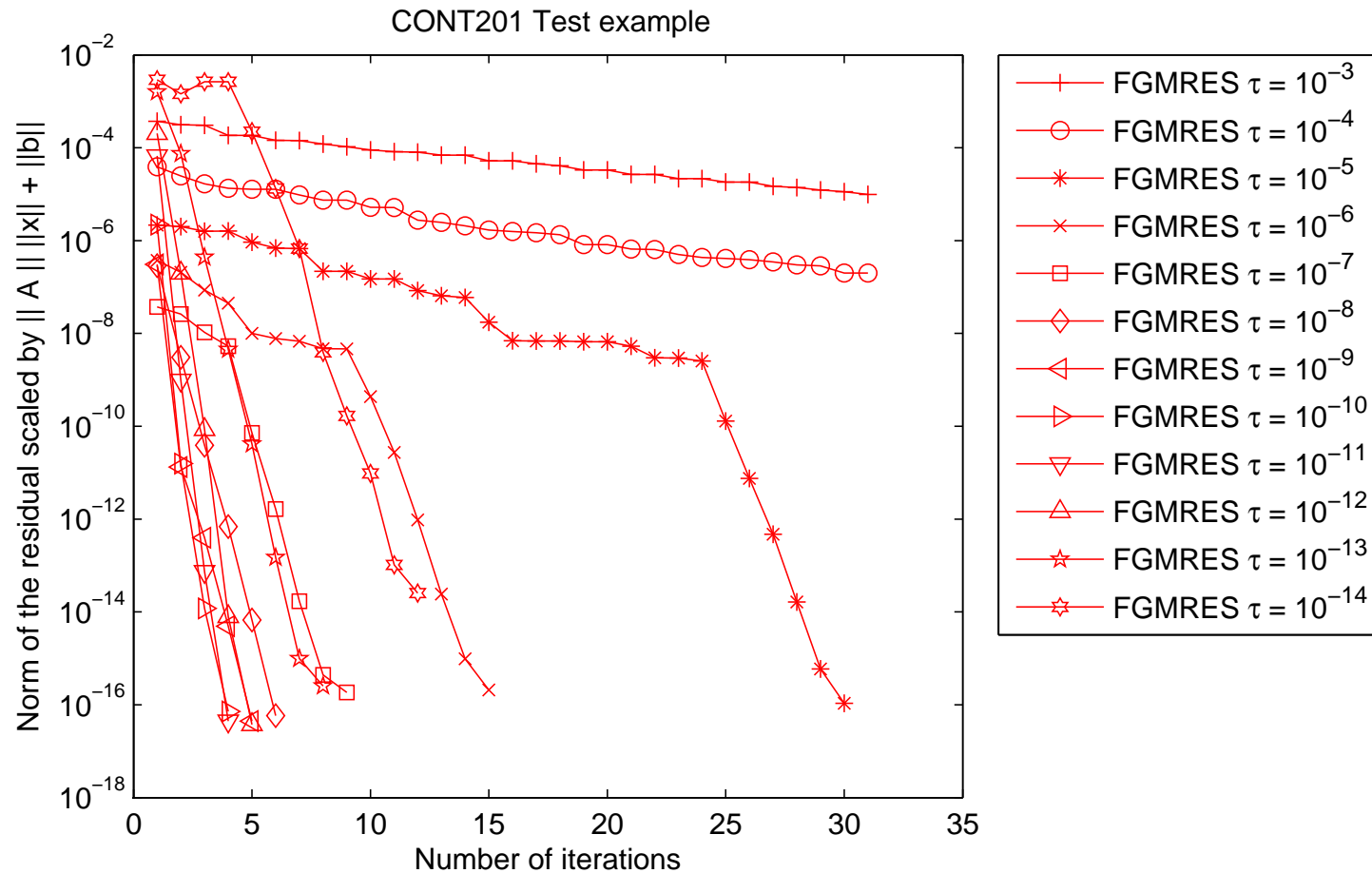


$$||\bar{Z}_k||_F ||M(x_k - x_0)|| \text{ vs } \tau$$





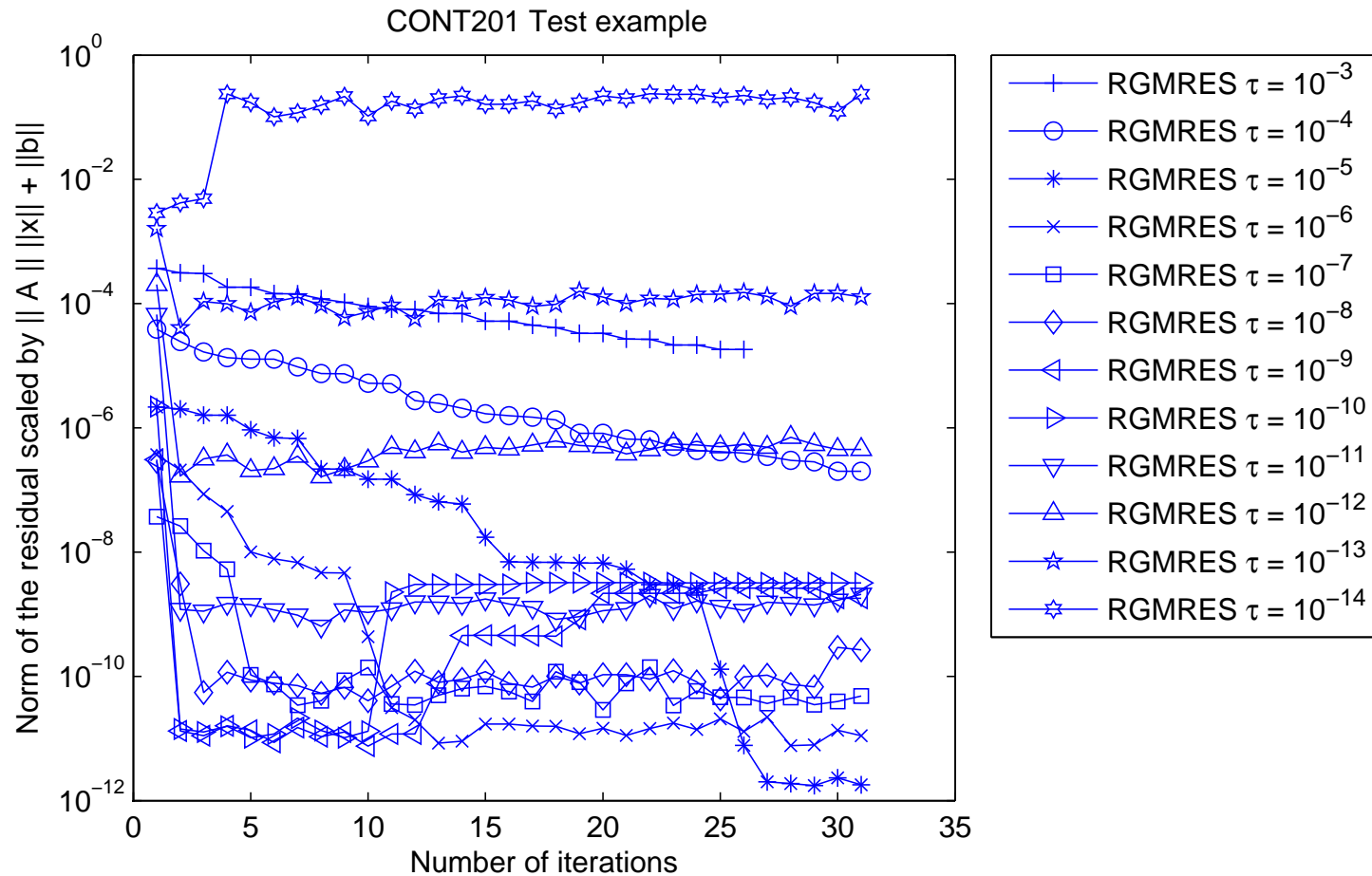
Numerical experiments



FGMRES on CONT-201 test example



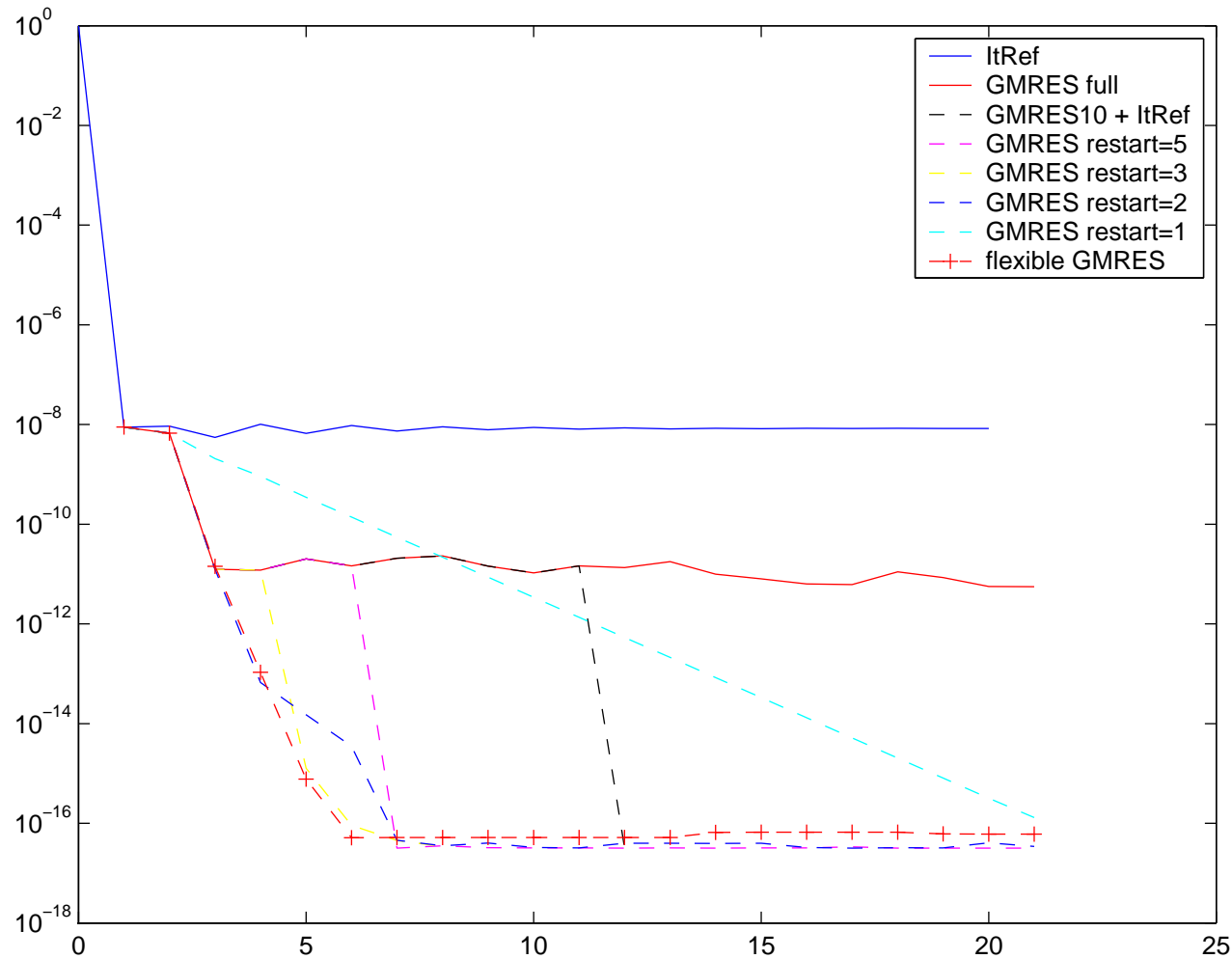
Numerical experiments



GMRES on CONT-201 test example



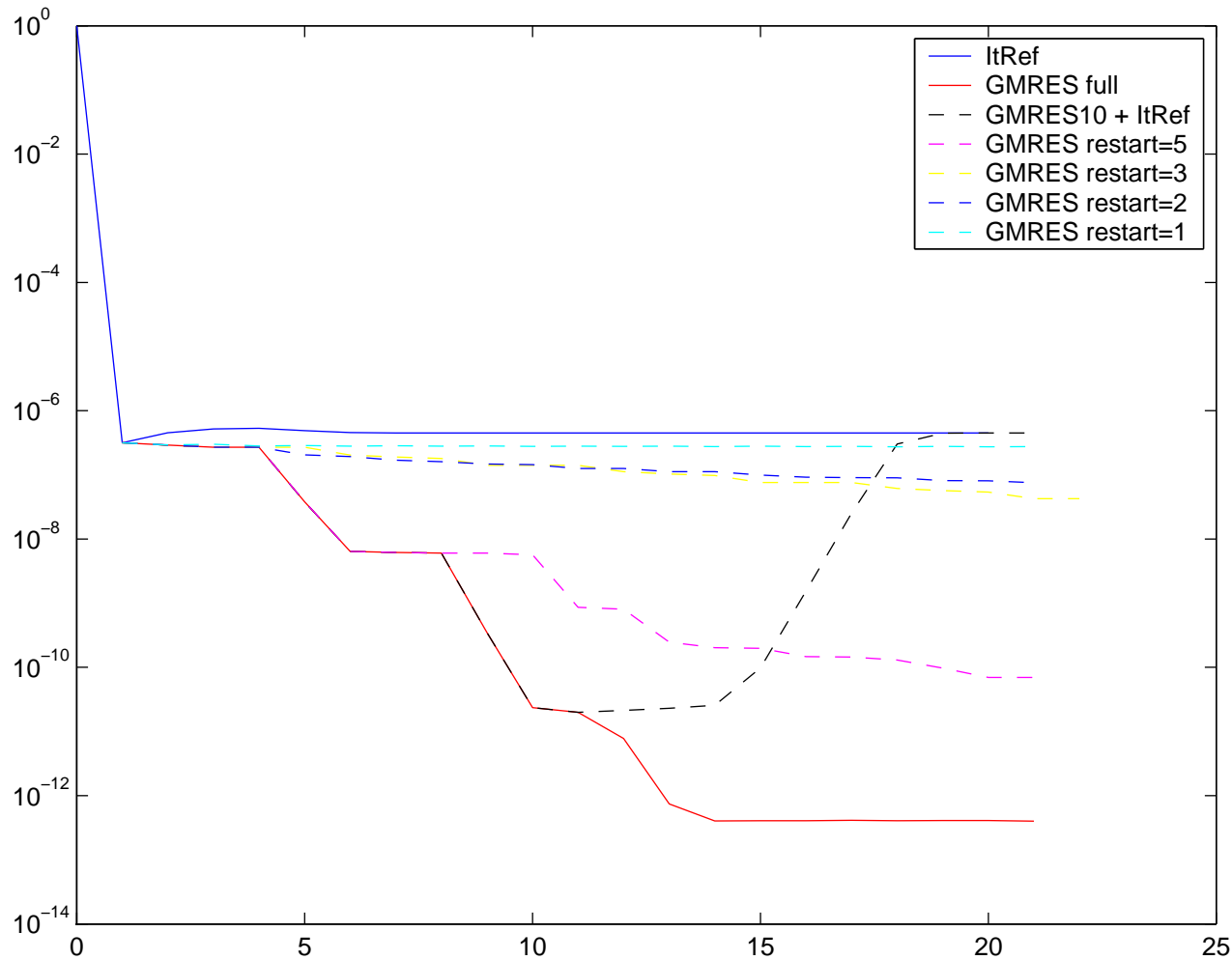
Numerical experiments



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



Numerical experiments



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



Summary

- IR with static pivoting is very sensitive to τ and not robust



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- Gains from restarting. Makes GMRES more robust, saves storage in FGMRES (but not really needed)
- Understanding of why $\tau \approx \sqrt{\varepsilon}$ is best.
- PLAN B is working