

# Numerical solution of systems of linear matrix equations and applications

# V. Simoncini

# Dipartimento di Matematica, Università di Bologna valeria.simoncini@unibo.it

#### The problem

Find  $\mathbf{X} \in \mathbb{R}^{n_1 \times n_2}$  and  $\mathbf{P} \in \mathbb{R}^{m \times n_2}$  such that

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1$$
$$B \mathbf{X} = F_2$$

with  $A_i \in \mathbb{R}^{n_i \times n_i}$ ,  $B \in \mathbb{R}^{m \times n_1}$ ,  $F_1 \in \mathbb{R}^{n_1 \times n_2}$ ,  $F_2 \in \mathbb{R}^{m \times n_2}$ ,  $m \le n_1$ 

#### The problem

Find  $\mathbf{X} \in \mathbb{R}^{n_1 \times n_2}$  and  $\mathbf{P} \in \mathbb{R}^{m \times n_2}$  such that

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1$$
$$B \mathbf{X} = F_2$$

with  $A_i \in \mathbb{R}^{n_i \times n_i}$ ,  $B \in \mathbb{R}^{m \times n_1}$ ,  $F_1 \in \mathbb{R}^{n_1 \times n_2}$ ,  $F_2 \in \mathbb{R}^{m \times n_2}$ ,  $m \le n_1$ 

Emerging matrix formulation of different application problems

- Constraint control
- Mixed formulations of stochastic diffusion problems
- Discretized deterministic/stochastic (Navier-)Stokes equations
- ...

#### A natural generalization

Find  $\mathbf{X} \in \mathbb{R}^{n_2 \times n_1}$ ,  $\mathbf{Y} \in \mathbb{R}^{n_1 \times n_2}$  and  $\mathbf{P} \in \mathbb{R}^{n_1 \times n_1}$  such that

$$A_{2}\mathbf{X} + \mathbf{X}A_{1} + B^{T}\mathbf{P} = F_{1}$$
$$A_{1}\mathbf{Y} + \mathbf{Y}A_{2} + \mathbf{P}B = F_{2}$$
$$B\mathbf{X} + \mathbf{Y}B^{T} = F_{3}$$

with corresponding dimensions for the coefficient matrices and rhs

e.g., MAC discretization of Navier-Stokes equation

#### An example. Regulator equations in contraint Control

Consider the time-invariant dynamical linear system

$$\dot{x} = Ax + Bu, \quad y = Cx \tag{*}$$

and the reference model  $(\dot{\widehat{x}})=\widehat{A}\widehat{x}+\widehat{B}\widehat{u}$  ,  $\widehat{y}=\widehat{C}\widehat{x}$ 

#### Theorem (Duan-Zhang, 2007)

Let K be a stabilizing gain for the dynamical system (\*) and assume  $\mathbf{X}, \mathbf{P}$  satisfy the equations

$$A\mathbf{X} - \mathbf{X}\widehat{A} + B\mathbf{P} = 0, \quad C\mathbf{X} = \widehat{C}.$$
 (1)

When the controller  $u = u_s + u_c$  with  $u_s = Kx$  and  $u_c = (\mathbf{P} - K\mathbf{X})\hat{x}$  is applied to (\*), it holds that  $\lim_{t\to\infty} (y(t) - \hat{y}(t)) = 0$ .

Also tracking (see, e.g., Wonham (1979), Duan (2004), Saberietal (1999))

An example. Mixed FE formulation of stochastic Galerkin diffusion pb

$$c^{-1}\vec{u} - \nabla p = 0,$$
  
$$-\nabla \cdot \vec{u} = f,$$

Assume that  $c^{-1} = c_0 + \sum_{r=1}^{\ell} \sqrt{\lambda_r} c_r(\vec{x}) \xi_r(\omega)$  and that an appropriate class of finite elements is used for the discretization of the problem (see, e.g., the derivation in Elman-Furnival-Powell, 2010) After discretization the problem reads:

After discretization the problem reads:

$$\begin{bmatrix} G_0 \otimes K_0 + \sum_{r=1}^{\ell} \sqrt{\lambda} G_r \otimes K_r & G_0^T \otimes B_0^T \\ G_0 \otimes B_0 \end{bmatrix} \begin{bmatrix} u \\ p \end{bmatrix} = \begin{bmatrix} 0 \\ f \end{bmatrix}$$

An example. Mixed FE formulation of stochastic Galerkin diffusion pb

$$c^{-1}\vec{u} - \nabla p = 0,$$
  
$$-\nabla \cdot \vec{u} = f,$$

Assume that  $c^{-1} = c_0 + \sum_{r=1}^{\ell} \sqrt{\lambda_r} c_r(\vec{x}) \xi_r(\omega)$  and that an appropriate class of finite elements is used for the discretization of the problem (see, e.g., the derivation in Elman-Furnival-Powell, 2010)

After discretization the problem reads:

$$\begin{bmatrix} G_0 \otimes K_0 + \sum_{r=1}^{\ell} \sqrt{\lambda} G_r \otimes K_r & G_0^T \otimes B_0^T \\ G_0 \otimes B_0 \end{bmatrix} \begin{bmatrix} u \\ p \end{bmatrix} = \begin{bmatrix} 0 \\ f \end{bmatrix}$$

For  $\ell = 1$  we obtain

$$K_0 \mathbf{X} G_0 + K_1 \mathbf{X} G_1 + B_0^T \mathbf{P} G_0 = 0, \qquad B_0 \mathbf{X} G_0 = F$$

The two matrix equation case. Computational strategies

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1$$
$$B \mathbf{X} = F_2$$

Kronecker formulation:

$$\begin{bmatrix} \mathcal{A} & \mathcal{B}^T \\ \mathcal{B} & \mathcal{O} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \end{bmatrix}, \quad \mathcal{A} = I \otimes A_1 + A_2^T \otimes I, \quad \mathcal{B} = B \otimes I$$

with  $\mathbf{x} = \operatorname{vec}(\mathbf{X})$ ,  $\mathbf{p} = \operatorname{vec}(\mathbf{P})$ ,  $f_1 = \operatorname{vec}(F_1)$  and  $f_2 = \operatorname{vec}(F_2)$ 

Extremely rich literature from saddle point algebraic linear systems

**Problem:** Coefficient matrix has size  $(n_1n_2 + mn_2) \times (n_1n_2 + mn_2)$ 

The two matrix equation case. Computational strategies. Cont'd

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1$$
$$B \mathbf{X} = F_2$$

\* Derive numerical strategies that directly work with the matrix equations:

- Small scale: Nullspace method
- Small and medium scale: Schur complement method (also directly applicable to three matrix equations)
- Large scale: Iterative method for low rank  $F_i$ , i = 1, 2

"Small and medium scale" actually means "Large scale" for the Kronecker form!

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1 \qquad (1)$$
$$B \mathbf{X} = F_2 \qquad (2)$$

$$U_0$$
 s.t.  $\mathsf{Range}(U_0) = \mathrm{Null}(B), \ U_0^T U_0 = I$   
 $U_1$  s.t.  $\mathsf{Range}(U_1) = \mathrm{Range}(B^T), \ U_1^T U_1 = I \implies \mathbf{X} = U_0 \hat{\mathbf{X}} + U_1 \mathbf{X}_\perp$ 

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1 \qquad (1)$$
$$B \mathbf{X} = F_2 \qquad (2)$$

$$U_0 \text{ s.t. } \operatorname{Range}(U_0) = \operatorname{Null}(B), \ U_0^T U_0 = I$$
  

$$U_1 \text{ s.t. } \operatorname{Range}(U_1) = \operatorname{Range}(B^T), \ U_1^T U_1 = I \quad \Rightarrow \quad \mathbf{X} = U_0 \hat{\mathbf{X}} + U_1 \mathbf{X}_{\perp}$$
  
\* From (2),  

$$\mathbf{X}_{\perp} = (BU_1)^{-1} F_2$$

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1 \qquad (1)$$
$$B \mathbf{X} = F_2 \qquad (2)$$

$$U_0 \text{ s.t. } \operatorname{Range}(U_0) = \operatorname{Null}(B), \ U_0^T U_0 = I$$
  

$$U_1 \text{ s.t. } \operatorname{Range}(U_1) = \operatorname{Range}(B^T), \ U_1^T U_1 = I \quad \Rightarrow \quad \mathbf{X} = U_0 \hat{\mathbf{X}} + U_1 \mathbf{X}_{\perp}$$
  
\* From (2),  

$$\mathbf{X}_{\perp} = (BU_1)^{-1} F_2$$

\* From (1), multiplying by  $U_0^T$ 

$$U_0^T A_1 U_0 \hat{\mathbf{X}} + \hat{\mathbf{X}} A_2 = -U_0^T A_1 U_1 \mathbf{X}_\perp + U_0^T F_1$$

A Sylvester equation, giving  $\hat{\boldsymbol{X}}$ 

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1 \qquad (1)$$
$$B \mathbf{X} = F_2 \qquad (2)$$

$$U_0 \text{ s.t. } \operatorname{Range}(U_0) = \operatorname{Null}(B), \ U_0^T U_0 = I$$
  

$$U_1 \text{ s.t. } \operatorname{Range}(U_1) = \operatorname{Range}(B^T), \ U_1^T U_1 = I \quad \Rightarrow \quad \mathbf{X} = U_0 \hat{\mathbf{X}} + U_1 \mathbf{X}_{\perp}$$
  
\* From (2),  

$$\mathbf{X}_{\perp} = (BU_1)^{-1} F_2$$

\* From (1), multiplying by  $U_0^T$ 

$$U_0^T A_1 U_0 \hat{\mathbf{X}} + \hat{\mathbf{X}} A_2 = -U_0^T A_1 U_1 \mathbf{X}_\perp + U_0^T F_1$$

- A Sylvester equation, giving  $\hat{\mathbf{X}}$
- \* From (1), multiplying by  $U_1^T$

$$U_{1}^{T}A_{1}U_{1}\mathbf{X}_{\perp} + U_{1}^{T}A_{1}U_{0}\hat{\mathbf{X}} + \mathbf{X}_{\perp}A_{2} + U_{1}^{T}B^{T}\mathbf{P} = U_{1}^{T}F_{1}$$

So that  $\mathbf{P} = (U_1^T B^T)^{-1} (U_1^T F_1 - U_1^T A_1 U_0 \hat{\mathbf{X}} - \mathbf{X}_{\perp} A_2 - U_1^T A_1 U_1 \mathbf{X}_{\perp})$ 

Large scale problem. Iterative method. 1/3

$$A_1 \mathbf{X} + \mathbf{X} A_2 + B^T \mathbf{P} = F_1$$
$$B \mathbf{X} = F_2$$

Rewrite as

$$\begin{bmatrix} A_1 & B^T \\ B & 0 \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{P} \end{bmatrix} + \begin{bmatrix} I_{n_1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{P} \end{bmatrix} A_2 = \begin{bmatrix} F_1 \\ F_2 \end{bmatrix} \quad \Leftrightarrow \quad \mathcal{M}\mathbf{Z} + \mathcal{D}_0\mathbf{Z}A_2 = F$$

with

$$\mathcal{M}, \mathcal{D}_0 \in \mathbb{R}^{(n_1+m) \times (n_1+m)}$$

 $A_2 \in \mathbb{R}^{n_2 \times n_2}$  nonsingular

 $\mathcal{D}_0$  highly singular

If  $F \approx$  low rank, exploit projection-type strategies for Sylvester equations

Large scale problem. Iterative method. 2/3

$$\begin{bmatrix} A_1 & B^T \\ B & 0 \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{P} \end{bmatrix} + \begin{bmatrix} I_{n_1} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{P} \end{bmatrix} A_2 = \begin{bmatrix} F_1 \\ F_2 \end{bmatrix}, \quad \Leftrightarrow \quad \mathcal{M}\mathbf{Z} + \mathcal{D}_0\mathbf{Z}A_2 = F$$

with F low rank. We rewrite the matrix equation as

$$\mathbf{Z}A_2^{-1} + \mathcal{M}^{-1}\mathcal{D}_0\mathbf{Z} = \widehat{F}, \qquad \widehat{F} = \mathcal{M}^{-1}FA_2^{-1}$$

which is a Sylvester equation with one singular coefficient matrix

$$\Rightarrow \qquad \mathbf{Z} \approx \widetilde{\mathbf{Z}}_k = V_k \mathcal{Z}_k W_k^T, \quad \text{for some } \mathcal{Z}_k$$

with  $\operatorname{Range}(V_k)$ ,  $\operatorname{Range}(W_k)$  appropriate approximation spaces of small dimensions

### Large scale problem. Iterative method. 3/3

$$\mathbf{Z}A_2^{-1} + \mathcal{M}^{-1}\mathcal{D}_0\mathbf{Z} = \widehat{F}_l\widehat{F}_r^T \quad \Rightarrow \quad \mathbf{Z}\approx \widetilde{\mathbf{Z}}_k = V_k\mathcal{Z}_kW_k^T$$

Choosing  $V_k, W_k$ . Let  $K_k(T, F) = \text{Range}([F, TF, T^2F, \dots, T^{k-1}F])$ .

Large scale problem. Iterative method. 3/3

$$\mathbf{Z}A_2^{-1} + \mathcal{M}^{-1}\mathcal{D}_0\mathbf{Z} = \widehat{F}_l\widehat{F}_r^T \quad \Rightarrow \quad \mathbf{Z}\approx\widetilde{\mathbf{Z}}_k = V_k\mathcal{Z}_kW_k^T$$

Choosing  $V_k, W_k$ . Let  $K_k(T, F) = \text{Range}([F, TF, T^2F, \dots, T^{k-1}F])$ . A possible strategy:

- $W_k = \mathbb{E}\mathbb{K}_k(A_2^{-T}, \widehat{F}_r) := K_k(A_2^{-T}, \widehat{F}_r) + K_k(A_2^{T}, A_2^{T}\widehat{F}_r)$ Extended Krylov subspace
- $V_k = K_k(\mathcal{M}^{-1}\mathcal{D}_0, \widehat{F}_l) + K_k((\mathcal{M}^{-1}\mathcal{D}_0 + \sigma I)^{-1}, \widehat{F}_l)$ Augmented Krylov subspace,  $\sigma \in \mathbb{R}$ (see, e.g., Shank-Simoncini (2013))

Note: 
$$\mathcal{M}$$
 has size  $(n_1 + m) \times (n_1 + m)$   
(Compare with  $(n_1n_2 + mn_2) \times (n_1n_2 + mn_2)$  of the Kronecker form)

#### Numerical experiments

 $\begin{array}{l} A_{1}\mathbf{X} - \mathbf{X}A_{2} + B^{T}\mathbf{P} = 0, \qquad B\mathbf{X} = F_{2} \quad \text{vs} \quad \mathcal{A}\mathbf{z} = f \\ A_{1} \rightarrow \mathcal{L}_{1} = -u_{xx} - u_{yy} \\ A_{2} \rightarrow \mathcal{L}_{2} = -(e^{-10xy}u_{x})_{x} - (e^{10xy}u_{y})_{y} + 10(x+y)u_{x} \\ [F_{1};F_{2}] \text{ rank-1 matrix} \\ B = \text{bidiag}(-1,\underline{1}), \ (n_{2} - n_{1}) \times n_{2}, \qquad \text{iterative: tol} = 10^{-6}, \ \sigma = 10^{-2} \end{array}$ 

#### Elapsed time

$n_1$	$n_2$	$size(\mathcal{A})$	Monolithic	Direct Nullspace	Matrix eqns
400	100	79,000	6.9769e-02	9.4012e-02	3.1523e-02 (4)
900	225	401,625	3.4808e-01	6.3597e-01	5.0447e-02 (4)
1600	400	1272,000	1.1319e+00	4.7888e+00	7.8018e-02 (4)
2500	625	3109,375	3.1212e+00	1.5063e+01	1.5282e-01 (5)
3600	900	6453,000	1.0210e+01	3.9419e+01	2.8053e-01 (5)
4900	1225	11,962,125	3.7699e+01	1.0721e+02	1.4754e+00 (5)

Numerical experiments. 1D stochastic Stokes problem. 1/3

$$\begin{bmatrix} \mathcal{H} & \mathcal{B}^T \\ \mathcal{B} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \end{bmatrix}, \qquad \mathcal{H} = (\nu_0 G_0 + \nu_1 G_1) \otimes A_x, \quad \mathcal{B} = G_0 \otimes B_x$$

where  $\nu=\nu_0+\nu_1\xi(\omega)$  uncertain viscosity,  $\xi$  random variable

Then

$$A_x \mathbf{X} G_0 \nu_0 + A_x \mathbf{X} G_1 \nu_1 + B_x^T \mathbf{P} G_0 = F_1, \quad B_x \mathbf{X} = F_2$$

with  $G_0 = I$ . This corresponds to

$$\begin{bmatrix} \nu_0 A_x & B_x^T \\ B_x & 0 \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{P} \end{bmatrix} + \begin{bmatrix} \nu_1 A_x \\ 0 \end{bmatrix} \begin{bmatrix} \mathbf{X} \\ \mathbf{P} \end{bmatrix} G_1 = \begin{bmatrix} F1 \\ F2 \end{bmatrix}$$

that is

$$\mathcal{M}\mathbf{Z} + \mathcal{D}_0\mathbf{Z}G_1 = F$$

Numerical experiments. 1D stochastic Stokes problem. 2/3

$$\mathcal{M}\mathbf{Z} + \mathcal{D}_0\mathbf{Z}G_1 = F$$
 vs  $\mathcal{A}\mathbf{z} = f$ 

$n_1$	$n_2$	$n_B$	$size(\mathcal{A})$	Monolithic	Monolithic	Iterative
				direct	MINRES	$\mathbb{EK}(\sigma)$
1256	4	389	6,580	0.1852	0.146 (11)	0.19 (2)
3526	4	990	18,064	0.9063	0.275 (11)	0.52 (2)
9812	4	2615	49,708	4.6418	0.981 (10)	2.09 (2)

 $\nu_0 = 1/10, \nu_1 = 3\nu_0/10$  Powell-Silvester (2012)

Numerical experiments. 1D stochastic Stokes problem. 3/3

$$\mathcal{M}\mathbf{Z} + \mathcal{D}_0\mathbf{Z}G_1 = F$$
 vs  $\mathcal{A}\mathbf{z} = f$ 

$n_1$	$n_2$	$n_B$	$size(\mathcal{A})$	Monolithic	Monolithic	Iterative
				direct	MINRES	$\mathbb{EK}(\sigma)$
1256	165	389	271,425	2.91	1.53 (11)	0.20 (2)
3526	165	990	745,140	12.16	7.43 (11)	0.45 (2)
9812	165	2615	2050,455	-	-	1.87 (2)

 $\nu_0 = 1/10, \nu_1 = 3\nu_0/10$  Powell-Silvester (2012)

- $n_2$  could be much larger,  $n_2 = O(10^3)$
- Memory requirements are very limited,  $\widetilde{\mathbf{Z}} = Z_1 Z_2^T$  of very low rank

#### Numerical experiments. 2D stochastic Stokes problem

 $\begin{bmatrix} \mathcal{H} & \mathcal{B}^T \\ \mathcal{B} & 0 \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{p} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \end{bmatrix}, \quad \begin{array}{l} \mathcal{H} = \text{blkdiag}((\nu_0 G_0 + \nu_1 G_1) \otimes A_x, (\nu_0 G_0 + \nu_1 G_1) \otimes A_y) \\ \mathcal{B} = [G_0 \otimes B_x, G_0 \otimes B_y] \end{bmatrix}$ 

$$\mathcal{M}\mathbf{Z} + \mathcal{D}_0\mathbf{Z}G_1 = F$$
 vs  $\mathcal{A}\mathbf{z} = f$ 

$n_1$	$n_2$	$size(\mathcal{A})$	Monolithic	Monolithic	Iterative
			direct	MINRES	$\mathbb{EK}(\sigma)$
2512	4	11,604	0.55	0.12 (12)	0.28 (2)
7052	4	32,168	3.73	0.36 (12)	1.22 (2)
19624	4	88,956	11.93	1.51 (12)	4.37 (2)
$n_1$	$n_2$	$size(\mathcal{A})$	Monolithic	Monolithic	Iterative
			direct	MINRES	$\mathbb{EK}(\sigma)$
2512	165	478 665	7.60	3.16 (17)	0.33 (2)
7052	165	1 326 930	34.08	15.52 (18)	1.32 (2)
19624	165	3 669 435	-	-	5.69 (3)

$$\nu_0 = 1/10, \nu_1 = 3\nu_0/10$$
 Powell-Silvester (2012)

# Conclusions and further comments

# ... A new matrix-oriented methodology

- Matrix formulation is computationally effective and memory saving
- Very preliminary numerical results are encouraging
- Three matrix equation solver effective via matrix-oriented Schur complement
- Operator  $\mathcal{L}: X \to A_1X + XA_2$  could be replaced with  $\mathcal{L}: X \to \sum_k A_k XG_k$

(work in progress with C. Powell)

For further information

http://www.dm.unibo.it/~simoncin