

# Solving Generalized Lyapunov Equations with guarantees: application to the Reduction of Linear Switched Systems.

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Abstract

We deal with the efficient and certified approximation of the *generalized Lyapunov equation* (GLEs)

$$\mathbf{A}\mathbf{X} + \mathbf{X}\mathbf{A}^\top + \sum_{j=1}^M \left( \mathbf{N}_j \mathbf{X} \mathbf{N}_j^\top \right) + \mathbf{B}\mathbf{B}^\top = \mathbf{0}, \quad (1)$$

where  $\mathbf{A}, \mathbf{N}_j \in \mathbb{R}^{n \times n}$ ,  $\mathbf{A}$  is Hurwitz, i.e., its spectrum is contained in the open left-half complex plane, and  $\mathbf{B} \in \mathbb{R}^{n \times m}$  with  $m$  typically much smaller than  $n$ . GLEs with these features naturally arise in the context of *model order reduction* (MOR) of bilinear control systems [2, 5] and linear parameter-varying systems as well as in the context of stochastic differential equations for stability analysis [4]. For switched linear systems of the form

$$\Sigma_q \quad \begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}_{q(t)} \mathbf{x}(t) + \mathbf{B}_{q(t)} \mathbf{u}(t), & \mathbf{x}(t_0) = \mathbf{0}, \\ \mathbf{y}(t) = \mathbf{C}_{q(t)} \mathbf{x}(t), \end{cases} \quad (2)$$

the authors of [6] introduced a balancing-based MOR method that requires the solution of certain GLEs. In (2),  $q: \mathbb{R} \rightarrow \mathcal{J} := \{1, \dots, M\}$  is the external switching signal, which we assume to be an element of the set of allowed switching signals

$$\mathcal{S} := \{q: \mathbb{R} \rightarrow \mathcal{J} \mid q \text{ is right continuous with locally finite number of jumps}\}. \quad (3)$$

The symbols  $\mathbf{x}(t) \in \mathbb{R}^n$ ,  $\mathbf{u}(t) \in \mathbb{R}^m$ , and  $\mathbf{y}(t) \in \mathbb{R}^p$  denote the *state*, the controlled *input*, and the measured *output*, respectively. The system matrices  $\mathbf{A}_j \in \mathbb{R}^{n \times n}$ ,  $\mathbf{B}_j \in \mathbb{R}^{n \times m}$ , and  $\mathbf{C}_j \in \mathbb{R}^{p \times n}$  correspond to the *ordinary differential equation* (ODE) active in mode  $j \in \mathcal{J}$ . Typically one refers to (2) as the *full-order model* (FOM). Sample applications of switched systems include robot manipulators, traffic management, automatic gear shifting, and power systems; see for instance [3] and the references therein.

If (2) has to be evaluated repeatedly, for instance, in a simulation context for different inputs or switching signals, or if matrix equalities or inequalities in the context of synthesis have to be solved, then a large dimension  $n$  of the state renders this a computationally expensive task. In such scenarios, one can rely on MOR and replace (2) by the *reduced-order model* (ROM)

$$\tilde{\Sigma}_q \quad \begin{cases} \dot{\tilde{\mathbf{x}}}(t) = \tilde{\mathbf{A}}_{q(t)} \tilde{\mathbf{x}}(t) + \tilde{\mathbf{B}}_{q(t)} \mathbf{u}(t), & \tilde{\mathbf{x}}(t_0) = \mathbf{0}, \\ \tilde{\mathbf{y}}(t) = \tilde{\mathbf{C}}_{q(t)} \tilde{\mathbf{x}}(t), \end{cases} \quad (4)$$

with  $\tilde{\mathbf{A}}_j \in \mathbb{R}^{r \times r}$ ,  $\tilde{\mathbf{B}}_j \in \mathbb{R}^{r \times m}$ , and  $\tilde{\mathbf{C}}_j \in \mathbb{R}^{p \times r}$ , and  $r \ll n$ . In many cases, see for instance [1], the reduced system matrices are obtained via Petrov–Galerkin projection, i.e., one constructs matrices  $\mathbf{V}, \mathbf{W} \in \mathbb{R}^{n \times r}$  and then defines

$$\tilde{\mathbf{A}}_j := \mathbf{W}^\top \mathbf{A}_j \mathbf{V}, \quad \tilde{\mathbf{B}}_j := \mathbf{W}^\top \mathbf{B}_j, \quad \tilde{\mathbf{C}}_j := \mathbf{C}_j \mathbf{V}. \quad (5)$$

The goal of MOR is thus to derive in a computationally efficient and robust way the matrices  $\mathbf{W}, \mathbf{V}$  such that the error  $\mathbf{y} - \tilde{\mathbf{y}}$  is small in some given norm. One way to do so, originally presented in [6],

is to solve opportune defined GLEs to obtain the projection matrices  $\mathbf{W}, \mathbf{V}$  and thus the reduced system (5). Therefore, solving efficiently large-scale generalized Lyapunov equation becomes crucial for MOR. More in detail the MOR algorithm from [6] proceeds in two steps. First, we have to define the matrices  $\mathbf{A} := \mathbf{A}_1$  and  $\mathbf{N}_j := \mathbf{A}_j - \mathbf{A}_1$  for  $j = 1, \dots, M$  and solve the GLEs

$$\mathbf{A}\mathcal{P} + \mathcal{P}\mathbf{A}^\top + \sum_{j=1}^M \left( \mathbf{N}_j \mathcal{P} \mathbf{N}_j^\top + \mathbf{B}_j \mathbf{B}_j^\top \right) = \mathbf{0}, \quad (6a)$$

$$\mathbf{A}^\top \mathcal{Q} + \mathcal{Q}\mathbf{A} + \sum_{j=1}^M \left( \mathbf{N}_j^\top \mathcal{Q} \mathbf{N}_j + \mathbf{C}_j^\top \mathbf{C}_j \right) = \mathbf{0}. \quad (6b)$$

Note that the matrix equations in (6) are of the form (1) by defining  $\mathbf{B} := [\mathbf{B}_1, \dots, \mathbf{B}_M]$  for (6a) and  $\mathbf{C} := [\mathbf{C}_1^\top, \dots, \mathbf{C}_M^\top]$ , taking the transport on the other matrices for (6b). The symmetric and positive semi-definite solutions  $\mathcal{P}, \mathcal{Q} \in \mathbb{R}^{n \times n}$  are referred to as the Gramians of (2). Second, let  $\mathcal{P} = \mathbf{S}\mathbf{S}^\top$  and  $\mathcal{Q} = \mathbf{R}\mathbf{R}^\top$  and compute the *singular value decomposition* (SVD) of the product of the Gramians factors

$$\mathbf{S}^\top \mathbf{R} = [\mathbf{U}_1, \mathbf{U}_2] \begin{bmatrix} \boldsymbol{\Sigma}_1 & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_2 \end{bmatrix} [\mathbf{V}_1, \mathbf{V}_2]^\top, \quad (7)$$

and the projection matrices  $\mathbf{V}$  and  $\mathbf{W}$  are obtained via

$$\mathbf{V} = \mathbf{S}\mathbf{U}_1\boldsymbol{\Sigma}_1^{-1/2} \quad \text{and} \quad \mathbf{W} = \mathbf{R}\mathbf{V}_1\boldsymbol{\Sigma}_1^{-1/2}. \quad (8)$$

This procedure is denoted as square-root balanced truncation (see [1, Sec. 7.3]). The use of the solutions of (6) as system Gramians is justified by [6, Thm. 3], where the authors show that the image of  $\mathcal{P}$  and  $\mathcal{Q}$  encode the reachability set and observability set of the switched system (2).

**Main contributions:** To deal with the large-scale setting, we apply the stationary algorithm from [7] in combination with a subspace projection framework [8] to solve GLEs. We emphasize that this is a common strategy in the literature when dealing with GLEs. Our first contribution is the derivation of efficiently computable error estimates such that for any prescribed user tolerance  $\text{tol}$  an approximation  $\tilde{\mathbf{X}}$  of (1) with guaranteed bound  $\|\mathbf{X} - \tilde{\mathbf{X}}\|_2 \leq \text{tol}$  can be computed. Second, we show how the numerical error introduced in approximating (1) may deteriorate the quality and the stability of the ROM (4). This motivates us to propose a novel strategy that, by relying on the error certification provided by our algorithm, ensures stability and error certification of the MOR system. Finally, the results are validated through a synthetic example and a switched system arising from a parametric *partial differential equation* (PDE).

## References

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