

DEFLATED AND AUGMENTED KRYLOV SUBSPACE METHODS: A FRAMEWORK FOR DEFLATED BICG AND RELATED SOLVERS*

MARTIN H. GUTKNECHT†

Abstract. We present an extension of the framework of Gaul et al. (*SIAM J. Matrix Anal. Appl.* **34**, 495–518 (2013)) for deflated and augmented Krylov subspace methods satisfying a Galerkin condition to more general Petrov–Galerkin conditions. The main goal is to apply the framework to the biconjugate gradient method (BiCG) and some of its generalizations, including BiCGSTAB and IDR(s). For such applications the assumptions of Gaul et al. were too restrictive. Our abstract approach does not depend on particular recurrences and thus simplifies the derivation of theoretical results. It easily leads to a variety of realizations by specific algorithms. We do not go into algorithmic details, but we show that for every method there are two different approaches for extending it by augmentation and deflation: one that explicitly takes care of the augmentation space in every step, and one that applies the unchanged basic algorithm to a projected problem but requires a correction step at the end. The latter approach typically generates nested sequences of Krylov subspaces for a singular operator that is associated with the projected problem. The deflated BiCG method requires two such sequences, but it also allows us to solve two dual linear systems at the price of one, a property that does no longer hold for the closely related deflated biconjugate residual method (BiCR). Deflated Lanczos-type product methods fit in our new framework too. The question of how to extract the augmentation and deflation subspaces is not addressed here.

Key words. Krylov subspace methods, augmentation, deflation, Krylov subspace recycling, BiCG, biconjugate gradient method, BiCR, biconjugate residual method, BiCGStab, block BiCG, ML(s)BiCG, ML(s)BiCGStab, IDR(s).

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1. Introduction. We consider the solution of a given linear algebraic system $\mathbf{Ax} = \mathbf{b}$, with $\mathbf{A} \in \mathbb{C}^{N \times N}$ nonsingular and $\mathbf{b} \in \mathbb{C}^N$, with a Krylov subspace method that is based on a Petrov–Galerkin condition. Such a method produces a sequence of approximate solutions \mathbf{x}_n chosen from an affine **solution search space**¹ $\mathbf{x}_0 + \mathcal{S}_n$, such that their residuals $\mathbf{r}_n := \mathbf{b} - \mathbf{Ax}_n$, which lie in the corresponding affine **residual search space** $\mathbf{r}_0 + \mathbf{AS}_n$, satisfy a **Petrov–Galerkin condition**:

$$\mathbf{x}_n \in \mathbf{x}_0 + \mathcal{S}_n, \quad \mathbf{r}_n \in \mathbf{r}_0 + \mathbf{AS}_n, \quad \mathbf{r}_n \perp \mathbf{B}^H \tilde{\mathcal{S}}_n. \quad (1.1)$$

Here $\tilde{\mathcal{S}}_n$ is a linear test space that is assumed to have the same dimension as \mathcal{S}_n , while $\mathbf{B} \in \mathbb{C}^{N \times N}$ is a nonsingular matrix, which we may think of as a possibly indefinite inner product matrix. The inclusion of such an optional \mathbf{B} has been promoted by Young and Jea [56], Ashby, Manteuffel, and Saylor [7], and by many others. In Gaul et al. [25] this was in particular used to cover deflated CG and deflated MINRES in the same framework. For the biconjugate gradient method (BiCG) [18, 32] based on the non-Hermitian Lanczos process this generalization was introduced in [26, 27], but seen to be more restrictive: \mathbf{A} and \mathbf{B} must commute. Here, for deflated BiCG, we will encounter an additional restriction.

In many applications, deflation and augmentation techniques have been successfully applied to speed up the convergence of Krylov subspace methods. This is typically achieved by removing from the problem eigenvalues of \mathbf{A} that are close to 0, a

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†Seminar for Applied Mathematics, ETH Zurich, CH-8092 Zurich, Switzerland (mhg@math.ethz.ch). The work was started while the author visited the TU Berlin, supported by the DFG Forschungszentrum MATHEON and the Mercator Visiting Professorship Program of the DFG.

¹For simplicity we will sometimes refer to the subspace \mathcal{S}_n as the (solution) search space.

process called **deflation**. In the non-Hermitian case addressed here additional spectral properties may be important for the effectiveness of deflation. In any case, recall that we want to find $\mathbf{A}^{-1}\mathbf{b} = \mathbf{x}_0 + \mathbf{A}^{-1}\mathbf{r}_0$; so we need $\mathbf{A}^{-1}\mathbf{r}_0$. Assume the known columns of $\mathbf{U} \in \mathbb{C}^{N \times k}$ span an approximately invariant subspace \mathcal{U} of \mathbf{A} , and let $\mathbf{Z} := \mathbf{A}\mathbf{U}$, $\mathcal{Z} := \mathbf{A}\mathcal{U}$. Note that the images of the restriction $\mathbf{A}^{-1}|_{\mathcal{Z}}$ are trivial to compute: if $\mathbf{z} = \mathbf{Z}\mathbf{c} \in \mathcal{Z}$, then $\mathbf{A}^{-1}\mathbf{z} = \mathbf{U}\mathbf{c}$. This still holds if \mathcal{U} is not an invariant subspace. Assume further that we know another k -dimensional subspace $\tilde{\mathcal{U}}$ such that \mathbb{C}^N splits up according to $\mathcal{Z} \oplus (\mathbf{B}^H\tilde{\mathcal{U}})^\perp = \mathbb{C}^N$, where this direct sum need not be an orthogonal decomposition. (Of course, it is if we choose $\tilde{\mathcal{U}} := \mathbf{B}^{-H}\mathcal{Z}$.) We can split up \mathbf{r}_0 accordingly: by applying the projection \mathbf{P} with null space $\mathcal{N}(\mathbf{P}) = \mathcal{Z}$ and range $\mathcal{R}(\mathbf{P}) = (\mathbf{B}^H\tilde{\mathcal{U}})^\perp$ we can construct $\hat{\mathbf{r}}_0 := \mathbf{P}\mathbf{r}_0 \in (\mathbf{B}^H\tilde{\mathcal{U}})^\perp$ such that

$$\mathbf{r}_0 = \underbrace{\mathbf{r}_0 - \hat{\mathbf{r}}_0}_{\in \mathcal{N}(\mathbf{P}) = \mathcal{Z}} + \underbrace{\hat{\mathbf{r}}_0}_{\in \mathcal{R}(\mathbf{P}) = (\mathbf{B}^H\tilde{\mathcal{U}})^\perp}. \quad (1.2)$$

Here, $\mathbf{A}^{-1}(\mathbf{r}_0 - \hat{\mathbf{r}}_0)$ is trivial to compute. So, it remains to compute $\mathbf{A}^{-1}\hat{\mathbf{r}}_0$. This problem can be addressed with a Krylov solver. In the ideal situation where \mathcal{U} and, hence, \mathcal{Z} are exactly invariant and represent all the eigenvalues close to 0, $\hat{\mathbf{r}}_0$ will not have an eigenvector component associated with a small eigenvalue if $\tilde{\mathcal{U}}$ has been chosen the right way, namely such that $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$ is also \mathbf{A} -invariant and represents the other eigenvalues of \mathbf{A} ; see [29]. Then, in theory, we could just replace \mathbf{A} by a singular, ‘deflated’ matrix $\hat{\mathbf{A}}$ (defined later) and apply the solver with the initial approximation $\hat{\mathbf{x}}_0 := \mathbf{0}$ to $\hat{\mathbf{A}}\hat{\mathbf{x}} = \hat{\mathbf{r}}_0$ (instead of $\mathbf{A}\hat{\mathbf{x}} = \hat{\mathbf{r}}_0$) with the solution restricted to $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$. In this situation, for both $\hat{\mathbf{A}}\hat{\mathbf{x}} = \hat{\mathbf{r}}_0$ and $\mathbf{A}\hat{\mathbf{x}} = \hat{\mathbf{r}}_0$, the solver will just act on $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$. In a more realistic situation, neither \mathcal{Z} nor $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$ will be exactly \mathbf{A} -invariant. *A fortiori* it is important to solve the so restricted system $\hat{\mathbf{A}}\hat{\mathbf{x}} = \hat{\mathbf{r}}_0$, which is typically much better conditioned than $\mathbf{A}\hat{\mathbf{x}} = \hat{\mathbf{r}}_0$. In the non-restricted latter system any components of $\hat{\mathbf{r}}_0$ that belong to small eigenvalues of \mathbf{A} might get dramatically amplified. Using $\hat{\mathbf{A}}$ restricted to $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$ instead of \mathbf{A} will make the Krylov solver behave more stably with respect to such bad components of $\hat{\mathbf{r}}_0$ and also with respect to roundoff.

The Krylov subspaces $\hat{\mathcal{K}}_n$ generated by $\hat{\mathbf{A}}$ from the initial projected residual $\hat{\mathbf{r}}_0$ will be contained in $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$. As suggested by (1.2), to represent (or at least approximate) $\mathbf{A}^{-1}\mathbf{r}_0$ we could use approximations $\hat{\mathbf{x}}_n$ of $\mathbf{A}^{-1}\hat{\mathbf{r}}_0$ shifted by $\mathbf{A}^{-1}(\mathbf{r}_0 - \hat{\mathbf{r}}_0) \in \mathcal{U}$. Hence, we ‘augment’ $\hat{\mathcal{K}}_n$ by \mathcal{U} . So, this approach involves both ‘deflation’ of approximate eigenvalues and ‘augmentation’ of the Krylov subspaces $\hat{\mathcal{K}}_n$. However, for simplicity we will often just refer to ‘deflated’ methods (as most other authors do) when we actually mean ‘deflated and augmented’ methods. In fact, deflation makes no sense without augmentation here, while methods exist that apply augmentation of the search space but no deflation of the matrix. We also need to mention that some authors use the seemingly more general terminology ‘Krylov subspace recycling methods’ for deflated and augmented Krylov subspace methods [4, 5, 31, 41].

There are various options for choosing $\tilde{\mathcal{U}}$ and $\hat{\mathbf{A}}$. For example, in the conjugate gradient (CG) method for Hermitian positive definite (Hpd) systems the goal will be to maintain the property that the error vectors have minimum energy norm (or, equivalently, that \mathbf{r}_n is orthogonal to the solution search space). This has been achieved by the algorithms of Nicolaides [39] and Dostál [12], and more than ten years later, by those of Erhel and Guyomarc’h [14] and Saad, Yeung, Erhel, and Guyomarc’h [43]. Likewise, for the biconjugate gradient (BiCG) method the goal will be to maintain the property that the residuals are orthogonal to the search space for the solution of a dual problem. This will be achieved here.

Similarly, one can aim for a method where the 2-norm of the residuals is minimal, as in the recycling MINRES (RMINRES) method of Wang, de Sturler, and Paulino [52] or in a corresponding deflated GMRES method, of which several versions have been proposed [10, 11, 25, 29, 34, 35]. Even if we assume that the procedure for choosing the approximately invariant subspace is fixed, there are various options for defining the restricted matrix $\widehat{\mathbf{A}}$, and we will concentrate here on a particular way to do that.

The deflated versions of CG and MINRES mentioned above, as well as a deflated GMRES method have been characterized in the framework of [25]. In the present paper we extend the framework of [25], which assumed a Galerkin condition to hold for the residuals, to the more general Petrov–Galerkin condition (1.1), which allows for two different spaces \mathcal{S}_n and $\widetilde{\mathcal{S}}_n$. This generalization is significant, since it allows to study and characterize methods based on the non-Hermitian Lanczos process such as the biconjugate gradient method (BiCG) and some of its generalizations, including BiCGSTAB [50] and IDR(s) [48]. For an introduction to BiCG and related algorithms published up to 1996 see [27]; for an introduction to IDR(s), see [48] or [28].

We need to admit that the above described recipe for a deflation and augmentation method based on the splitting (1.2) and the iterative solution of $\widehat{\mathbf{A}}\widehat{\mathbf{x}} = \widehat{\mathbf{r}}_0$ does not exactly reflect the methods cited above and those proposed here later. In fact, it would yield residuals $\mathbf{r}_n := \mathbf{r}_0 - (\mathbf{r}_0 - \widehat{\mathbf{r}}_0) - \widehat{\mathbf{A}}\widehat{\mathbf{x}}_n = \widehat{\mathbf{r}}_0 - \widehat{\mathbf{A}}\widehat{\mathbf{x}}_n =: \widehat{\mathbf{r}}_n$ whose component in \mathcal{Z} does not depend on n . In contrast, the component in \mathcal{Z} of our residuals \mathbf{r}_n will depend on n since they are forced to fulfill a Petrov–Galerkin condition that depends on n ; see (2.3) below.

We also need to mention that there are other ways to recycle Krylov subspace information that do not fit into our new framework. For example, it has been suggested to augment the Krylov subspace basis, but to project the residuals not in every step but only occasionally [34, 35], or even just for modifying the initial approximation \mathbf{x}_0 as in INITCG by Erhel and Guyomarc’h [14]. Another approach is to apply a nonsingular preconditioner based on spectral information instead of the singular preconditioners used for deflation. For partial overviews of augmentation and deflation methods see, e.g., [10, 13, 25, 29, 35, 41, 44].

The framework of [29] differs from the one here in that it promotes Krylov subspace methods with ‘true’ deflation in the sense that $\mathbf{A}|_{\mathcal{Z}} = \mathbf{O}|_{\mathcal{Z}}$ and $\mathbf{A}|_{\widetilde{\mathcal{Z}}^\perp} = \widehat{\mathbf{A}}|_{\widetilde{\mathcal{Z}}^\perp}$ if \mathcal{Z} is exactly \mathbf{A} -invariant and $\widetilde{\mathcal{Z}}$ is the corresponding \mathbf{A}^H -invariant subspace. Sometimes this property will also be achieved here. Another difference is that [29] concentrates on coordinate space based methods, that is, methods like GMRES where bases of the Krylov subspaces are constructed first and the linear system is expressed in terms of the coordinates with respect to these bases. The solution of the so transplanted deflated and augmented problem is then described for a number of such methods.

Outline. In Section 2 we define and characterize a family of augmented and deflated Krylov subspace methods for non-Hermitian problems. The characteristic properties of particular methods are treated in Sections 3–6. As mentioned above, we notably cover a number of (non-Hermitian) Lanczos-type methods including BiCG, the biconjugate residual method (BiCR), and some related methods such as BiCG-STAB, ML(s)BiCG, ML(s)BiCGSTAB, and IDR(s). Finally, Section 7 is devoted to spectral result for the deflated operator $\widehat{\mathbf{A}}$.

2. A generalized framework for deflated and augmented Krylov subspace methods. In this section we extend the general framework for deflation and augmentation described in [25] in order to include Krylov subspace methods for non-

Hermitian matrices that are based on a Petrov–Galerkin condition. We start from the basic setting of (1.1), where we now assume that both the search space \mathcal{S}_n and the test space $\tilde{\mathcal{S}}_n$ are augmented:

$$\mathcal{S}_n = \hat{\mathcal{K}}_n + \mathcal{U}, \quad \tilde{\mathcal{S}}_n = \hat{\mathcal{L}}_n + \tilde{\mathcal{U}}. \quad (2.1)$$

Here, \mathcal{U} and $\tilde{\mathcal{U}}$ are called the augmentation spaces. Their suitable choice has been quickly addressed in the introduction; many suggestions for selected types of problems can be found in the literature; see, e.g., [1, 4, 5, 11, 31, 34, 35, 41, 52]. Theoretical results on invariant subspaces will be given in Section 7.

For the moment we leave it open how the subspaces $\hat{\mathcal{K}}_n$ and $\hat{\mathcal{L}}_n$ are defined. In the most typical situation they are Krylov subspaces or block Krylov subspaces, but we will also encounter situations where their structure is more complicated. We assume that both have the same dimension n , and that the columns of \mathbf{V}_n and $\tilde{\mathbf{V}}_n \in \mathbb{C}^{N \times n}$ form bases of $\hat{\mathcal{K}}_n$ and $\hat{\mathcal{L}}_n$, respectively. Similarly, the columns of \mathbf{U} and $\tilde{\mathbf{U}}$ form bases of the augmentation spaces \mathcal{U} and $\tilde{\mathcal{U}}$. Of course, \mathcal{U} and $\tilde{\mathcal{U}}$ may be redefined when an algorithm is restarted, but we will not account for that in our notation. Let us further define

$$\mathbf{Z} := \mathbf{A}\mathbf{U}, \quad \tilde{\mathbf{Z}} := \mathbf{A}\tilde{\mathbf{U}}$$

and, for later use,

$$\tilde{\mathbf{Z}} := \mathbf{A}^H \tilde{\mathbf{U}}, \quad \tilde{\tilde{\mathbf{Z}}} := \mathbf{A}^H \tilde{\tilde{\mathbf{U}}}.$$

Then \mathbf{x}_n and \mathbf{r}_n can be represented as²

$$\mathbf{x}_n = \mathbf{x}_0 + \mathbf{V}_n \mathbf{c}_n + \mathbf{U} \mathbf{u}_n, \quad (2.2)$$

$$\mathbf{r}_n = \mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n - \mathbf{Z} \mathbf{u}_n, \quad (2.3)$$

with some **coordinate vectors** $\mathbf{c}_n \in \mathbb{C}^n$ and $\mathbf{u}_n \in \mathbb{C}^k$.

With the choice (2.1) the Petrov–Galerkin condition in (1.1) implies that

$$\mathbf{r}_n \perp \mathbf{B}^H \hat{\mathcal{L}}_n \quad \text{and} \quad \mathbf{r}_n \perp \mathbf{B}^H \tilde{\mathcal{U}}. \quad (2.4)$$

At left, we have a condition involving a growing test space as it is typical for Krylov subspace solvers based on a Galerkin or Petrov–Galerkin condition, while at right, we have an orthogonality condition that compensates for the deflation and will allow us to reduce the search and test spaces. Let us first concentrate on the second condition, which turns into the equality

$$\mathbf{0} = \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{r}_n = \tilde{\mathbf{U}}^H \mathbf{B} (\mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n - \mathbf{A}\mathbf{U} \mathbf{u}_n) = \tilde{\mathbf{U}}^H \mathbf{B} (\mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n) - \mathbf{E} \mathbf{u}_n,$$

where $\mathbf{E} := \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{A} \mathbf{U}$. In the following, we will assume that \mathbf{E} is nonsingular, so that we obtain for \mathbf{u}_n in terms of \mathbf{c}_n the explicit formula

$$\mathbf{u}_n = \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} (\mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n). \quad (2.5)$$

Using this and $\mathbf{r}_0 := \mathbf{b} - \mathbf{A}\mathbf{x}_0$ in (2.2) and (2.3) gives

$$\begin{aligned} \mathbf{x}_n &= \mathbf{x}_0 + \mathbf{V}_n \mathbf{c}_n + \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} (\mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n) \\ &= \left(\mathbf{I} - \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{A} \right) (\mathbf{x}_0 + \mathbf{V}_n \mathbf{c}_n) + \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{b}, \end{aligned} \quad (2.6)$$

$$\begin{aligned} \mathbf{r}_n &= \mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n - \mathbf{A} \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} (\mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n) \\ &= \left(\mathbf{I} - \mathbf{A} \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \right) (\mathbf{r}_0 - \mathbf{A}\mathbf{V}_n \mathbf{c}_n). \end{aligned} \quad (2.7)$$

	definition	null space	range	further properties
\mathbf{E}	$\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{A} \mathbf{U}$	$\{\mathbf{0}\}$	\mathbb{C}^k	assumed to be nonsingular
\mathbf{M}	$\mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H$	$\tilde{\mathcal{U}}^\perp$	\mathcal{U}	$\text{rank } \mathbf{M} = k$
\mathbf{P}	$\mathbf{I} - \mathbf{A} \mathbf{M} \mathbf{B}$	\mathcal{Z}	$(\mathbf{B}^H \tilde{\mathcal{U}})^\perp$	$\mathbf{P}^2 = \mathbf{P}$
\mathbf{Q}	$\mathbf{I} - \mathbf{M} \mathbf{B} \mathbf{A}$	\mathcal{U}	$(\mathbf{A}^H \mathbf{B}^H \tilde{\mathcal{U}})^\perp$	$\mathbf{Q}^2 = \mathbf{Q}$
$\hat{\mathbf{A}}$	$\mathbf{P} \mathbf{A}$	\mathcal{U}	$(\mathbf{B}^H \tilde{\mathcal{U}})^\perp$	$\hat{\mathbf{A}} = \mathbf{P} \mathbf{A} = \mathbf{A} \mathbf{Q} = \mathbf{P} \mathbf{A} \mathbf{Q}$
$\hat{\mathbf{A}}^H$	$\mathbf{Q}^H \mathbf{A}^H$	$\mathbf{B}^H \tilde{\mathcal{U}}$	\mathcal{U}^\perp	$\hat{\mathbf{A}}^H = \mathbf{Q}^H \mathbf{A}^H = \mathbf{A}^H \mathbf{P}^H = \mathbf{Q}^H \mathbf{A}^H \mathbf{P}^H$
$\tilde{\mathbf{E}}$	$\mathbf{U}^H \mathbf{B}^H \mathbf{A}^H \tilde{\mathbf{U}}$	$\{\mathbf{0}\}$	\mathbb{C}^k	assumed to be nonsingular
$\tilde{\mathbf{M}}$	$\tilde{\mathbf{U}} \tilde{\mathbf{E}}^{-1} \mathbf{U}^H$	\mathcal{U}^\perp	$\tilde{\mathcal{U}}$	$\text{rank } \tilde{\mathbf{M}} = k$
$\tilde{\mathbf{P}}$	$\mathbf{I} - \mathbf{A}^H \tilde{\mathbf{M}} \mathbf{B}^H$	$\tilde{\mathcal{Z}}$	$(\mathbf{B} \mathcal{U})^\perp$	$\tilde{\mathbf{P}}^2 = \tilde{\mathbf{P}}$
$\tilde{\mathbf{Q}}$	$\mathbf{I} - \tilde{\mathbf{M}} \mathbf{B}^H \mathbf{A}^H$	$\tilde{\mathcal{U}}$	$(\mathbf{A} \mathbf{B} \mathcal{U})^\perp$	$\tilde{\mathbf{Q}}^2 = \tilde{\mathbf{Q}}$
$\tilde{\hat{\mathbf{A}}}$	$\tilde{\mathbf{P}} \mathbf{A}^H$	$\tilde{\mathcal{U}}$	$(\mathbf{B} \mathcal{U})^\perp$	$\tilde{\hat{\mathbf{A}}} = \tilde{\mathbf{P}} \mathbf{A}^H = \mathbf{A}^H \tilde{\mathbf{Q}} = \tilde{\mathbf{P}} \mathbf{A}^H \tilde{\mathbf{Q}}$
$\tilde{\hat{\mathbf{A}}}^H$	$\tilde{\mathbf{Q}}^H \mathbf{A}$	$\mathbf{B} \mathcal{U}$	$\tilde{\mathcal{U}}^\perp$	$\tilde{\hat{\mathbf{A}}}^H = \tilde{\mathbf{Q}}^H \mathbf{A} = \mathbf{A} \tilde{\mathbf{P}}^H = \tilde{\mathbf{Q}}^H \mathbf{A} \tilde{\mathbf{P}}^H$

TABLE 2.1

Basic properties of the projections and other operators used in this paper. All these properties are easy to verify, and thus formal proofs are skipped for brevity. Note that \mathbf{E} and $\tilde{\mathbf{E}}$ are $k \times k$ matrices, while all the other matrices have size $N \times N$.

After introducing

$$\mathbf{M} := \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H, \quad \mathbf{P} := \mathbf{I} - \mathbf{A} \mathbf{M} \mathbf{B}, \quad \mathbf{Q} := \mathbf{I} - \mathbf{M} \mathbf{B} \mathbf{A} \quad (2.8)$$

(2.6) and (2.7) take the form

$$\mathbf{x}_n = \mathbf{Q} (\mathbf{x}_0 + \mathbf{V}_n \mathbf{c}_n) + \mathbf{M} \mathbf{B} \mathbf{b}, \quad (2.9)$$

$$\mathbf{r}_n = \mathbf{P} (\mathbf{r}_0 - \mathbf{A} \mathbf{V}_n \mathbf{c}_n), \quad (2.10)$$

exactly as in [25].³ Note that \mathbf{u}_n has been eliminated and does no longer appear here. See Table 2.1 for some properties of the matrices \mathbf{M} , \mathbf{P} , and \mathbf{Q} . In particular, \mathbf{P} and \mathbf{Q} are projections, which, in general, are oblique.

Imposing the first orthogonality condition of (2.4) will yield \mathbf{c}_n . To this end, let⁴

$$\hat{\mathbf{x}}_n := \mathbf{x}_0 + \mathbf{V}_n \mathbf{c}_n \in \mathbf{x}_0 + \hat{\mathcal{K}}_n, \quad \hat{\mathbf{r}}_n := \mathbf{P} (\mathbf{b} - \mathbf{A} \hat{\mathbf{x}}_n); \quad (2.11)$$

in particular, $\hat{\mathbf{x}}_0 := \mathbf{x}_0$ and $\hat{\mathbf{r}}_0 := \mathbf{P} \mathbf{r}_0 \perp \mathbf{B}^H \tilde{\mathcal{U}}$. Then $\mathbf{x}_n = \mathbf{Q} \hat{\mathbf{x}}_n + \mathbf{M} \mathbf{B} \mathbf{b}$, and by inserting (2.10) the first orthogonality condition becomes

$$\mathbf{r}_n = \mathbf{P} (\mathbf{b} - \mathbf{A} \hat{\mathbf{x}}_n) = \hat{\mathbf{r}}_n \perp \mathbf{B}^H \hat{\mathcal{L}}_n.$$

Thus we have shown the following theorem, which generalizes Theorem 3.2 in [25].

THEOREM 2.1. *Let $\mathbf{A}, \mathbf{B} \in \mathbb{C}^{N \times N}$ and $\mathbf{U}, \tilde{\mathbf{U}} \in \mathbb{C}^{N \times k}$ be such that $\mathbf{E} := \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{A} \mathbf{U}$ is nonsingular, so that the matrices $\mathbf{M}, \mathbf{P}, \mathbf{Q}$ of (2.8) are well defined. Let $\mathcal{U} := \mathcal{R}(\mathbf{U})$, $\tilde{\mathcal{U}} := \mathcal{R}(\tilde{\mathbf{U}})$, and, for some $n \geq 1$, let $\hat{\mathcal{K}}_n$ and $\hat{\mathcal{L}}_n$ be two subspaces of dimension n . Then the two pairs of conditions*

$$\mathbf{x}_n \in \mathbf{x}_0 + \hat{\mathcal{K}}_n + \mathcal{U}, \quad \mathbf{r}_n \perp \mathbf{B}^H (\hat{\mathcal{L}}_n + \tilde{\mathcal{U}}) \quad (2.12)$$

²Of course, if we do not have direct sums in (2.1), the representation may be non-unique, which might cause a problem.

³Take into account that our \mathbf{B} corresponds to \mathbf{B}^H in [25]. Also note that $\mathbf{E}, \mathbf{M}, \mathbf{P}$, and \mathbf{Q} depend on \mathbf{B} , a dependence that was made explicit in the notation of [25].

⁴What was $\hat{\mathbf{x}}_n$ in Section 1 is now called $\hat{\mathbf{x}}_n - \mathbf{x}_0$.

and

$$\widehat{\mathbf{x}}_n \in \mathbf{x}_0 + \widehat{\mathcal{K}}_n, \quad \widehat{\mathbf{r}}_n \perp \mathbf{B}^H \widehat{\mathcal{L}}_n, \quad (2.13)$$

if determining \mathbf{x}_n and $\widehat{\mathbf{x}}_n$ uniquely, are equivalent in the sense that

$$\mathbf{x}_n = \mathbf{Q}\widehat{\mathbf{x}}_n + \mathbf{M}\mathbf{B}\mathbf{b} \quad \text{and} \quad \mathbf{r}_n = \widehat{\mathbf{r}}_n. \quad (2.14)$$

The rationale behind considering both (2.12) and (2.13) is that in an algorithm based on (2.12) we choose \mathbf{x}_n from an augmented search space and enforce $\mathbf{r}_n \perp \mathbf{B}^H(\widehat{\mathcal{L}}_n + \widetilde{\mathcal{U}})$; in contrast, an algorithm based on (2.13) chooses $\widehat{\mathbf{x}}_n$ from a smaller space and fulfills $\widehat{\mathbf{r}}_n \perp \mathbf{B}^H \widetilde{\mathcal{U}}$ by construction — because $\widehat{\mathbf{r}}_n \in \mathcal{R}(\mathbf{P}) = (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$ —, and then requires just to enforce $\widehat{\mathbf{r}}_n \perp \mathbf{B}^H \widehat{\mathcal{L}}_n$.

We can conclude that for each augmented and deflated iterative method characterized by the choices for \mathbf{B} , \mathcal{U} , $\widetilde{\mathcal{U}}$, $\widehat{\mathcal{K}}_n$, and $\widehat{\mathcal{L}}_n$ there are two equivalent approaches to realize the method — even before we come to the additional freedom of choosing the recurrences that yield the iterates and residuals fulfilling the given conditions (1.1) with the additive structure (2.1). The conditions (2.12) represent the ‘*explicit deflation and augmentation approach*’, where the augmentation space \mathcal{U} is explicitly included in the search space. In the equivalent conditions (2.13) the explicit inclusion of \mathcal{U} is replaced by a suitable projection of a restricted problem: we first construct iterates $\widehat{\mathbf{x}}_n \in \mathbf{x}_0 + \widehat{\mathcal{K}}_n$ without component in \mathcal{U} such that the ‘*projected residuals*’ $\widehat{\mathbf{r}}_n = \mathbf{P}(\mathbf{b} - \mathbf{A}\widehat{\mathbf{x}}_n)$ satisfy the simplified Petrov–Galerkin condition of (2.13); then we apply the affine correction (2.14). Interestingly, the projected residuals are equal to the original ones. We call this the ‘*implicit deflation and augmentation approach*’. Of course, in both approaches the restriction $\mathbf{r}_n \perp \mathbf{B}^H \widetilde{\mathcal{U}}$ is taken care of — either explicitly or by using the projection \mathbf{P} — but there is a fundamental difference in the two approaches that is apparent from the existence of the nontrivial relationship (2.14).

While the choice of \mathbf{U} and $\widetilde{\mathbf{U}}$ is problem dependent and will not be addressed here, the most important options for \mathbf{B} , $\widehat{\mathcal{K}}_n$, and $\widehat{\mathcal{L}}_n$ will be discussed now and in the following sections. So far we have left it open how $\widehat{\mathcal{K}}_n$ and $\widehat{\mathcal{L}}_n$ are defined. Not every pair of subspaces will make sense. In the theorem we limit the choice by requesting that both \mathbf{x}_n and $\widehat{\mathbf{x}}_n$ are uniquely determined by (2.12) and (2.13), respectively. By our derivation, every solution \mathbf{x}_n of (2.12) yields a solution of (2.13), and due to the uniqueness assumption, the reverse holds too.

We are not really interested in utmost generality. The methods we aim at are all Krylov subspace methods or block Krylov subspace methods satisfying suitable Petrov–Galerkin conditions.

According to its definition, $\widehat{\mathbf{r}}_n$ is the residual of the approximate solution $\widehat{\mathbf{x}}_n$ of the projected or deflated linear system

$$\mathbf{P}\mathbf{A}\widehat{\mathbf{x}} = \mathbf{P}\mathbf{b}. \quad (2.15)$$

Since $\widehat{\mathbf{x}}_n - \mathbf{x}_0 \in \widehat{\mathcal{K}}_n$, and since both sides of the system lie in $\mathcal{R}(\mathbf{P}) = (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$, we want to solve it by a Krylov subspace method that is fully restricted to $(\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$. Defining

$$\widehat{\mathbf{A}} := \mathbf{P}\mathbf{A} = \mathbf{A}\mathbf{Q} = \mathbf{P}\mathbf{A}\mathbf{Q} \quad (2.16)$$

we can write

$$\widehat{\mathbf{r}}_n = \mathbf{P}(\mathbf{b} - \mathbf{A}\mathbf{x}_0) - \mathbf{P}\mathbf{A}(\widehat{\mathbf{x}}_n - \mathbf{x}_0) = \widehat{\mathbf{r}}_0 - \widehat{\mathbf{A}}(\widehat{\mathbf{x}}_n - \mathbf{x}_0) \in \widehat{\mathbf{r}}_0 + \widehat{\mathbf{A}}\widehat{\mathcal{K}}_n.$$

Thus, instead of (2.15) we can solve the equivalent singular system

$$\widehat{\mathbf{A}}(\widehat{\mathbf{x}} - \mathbf{x}_0) = \widehat{\mathbf{r}}_0 \quad (2.17)$$

subject to $\widehat{\mathbf{x}} - \mathbf{x}_0 \in (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$. Obviously, the most straightforward approach is to start the iteration with $\widehat{\mathbf{x}}_0 = \mathbf{x}_0$ and to build up the nested sequence of Krylov subspaces

$$\widehat{\mathcal{K}}_n := \mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0) := \text{span} \{\widehat{\mathbf{r}}_0, \widehat{\mathbf{A}}\widehat{\mathbf{r}}_0, \dots, \widehat{\mathbf{A}}^{n-1}\widehat{\mathbf{r}}_0\} \subseteq (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp. \quad (2.18)$$

Moreover, since we are heading for BiCG, the first choice for $\widehat{\mathcal{L}}_n$ will be the dual space of $\widehat{\mathcal{K}}_n$, namely

$$\widehat{\mathcal{L}}_n := \mathcal{K}_n(\widehat{\mathbf{A}}^H, \widehat{\mathbf{y}}_0) := \text{span} \{\widehat{\mathbf{r}}_0, \widehat{\mathbf{A}}^H \widehat{\mathbf{r}}_0, \dots, (\widehat{\mathbf{A}}^H)^{n-1} \widehat{\mathbf{y}}_0\} \subseteq \mathcal{U}^\perp \quad (2.19)$$

with a suitable $\widehat{\mathbf{y}}_0 \perp \mathcal{U}$. Later we will come across other suitable choices satisfying

$$\widehat{\mathcal{K}}_n \subseteq \mathcal{R}(\widehat{\mathbf{A}}) = (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp \quad \text{and} \quad \widehat{\mathcal{L}}_n \subseteq \mathcal{R}(\widehat{\mathbf{A}}^H) = \mathcal{U}^\perp. \quad (2.20)$$

So, the choice (2.18), (2.19) should just be considered as the basic example that fits into our framework.

REMARK 2.2. *Although $\widehat{\mathbf{r}}_0 \in (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$ and $\mathcal{R}(\widehat{\mathbf{A}}) = \mathcal{R}(\mathbf{P}) = (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$, and thus $\widehat{\mathcal{K}}_n \subseteq (\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$, we cannot be sure that $\widehat{\mathbf{A}}|_{(\mathbf{B}^H \widetilde{\mathcal{U}})^\perp}$ is nonsingular. In fact, $\mathcal{N}(\widehat{\mathbf{A}}) = \mathcal{U}$ and $\mathcal{R}(\widehat{\mathbf{A}})$ may have a nontrivial intersection. In other words, when solving the singular system (2.17) by a Krylov subspace method fully restricted to $(\mathbf{B}^H \widetilde{\mathcal{U}})^\perp$ we may still apply it to a singular system, whence even GMRES may break down; see e.g., [9, 23] and, regarding breakdowns in deflation methods, [10, 25, 29]. However, if \mathcal{U} and $\mathbf{B}^H \widetilde{\mathcal{U}}$ indeed approximate the right invariant subspace of \mathbf{A} and the left invariant subspace of $\overline{\mathbf{A}}$ (the complex conjugate of \mathbf{A}), respectively, which belong to the small eigenvalues of \mathbf{A} , it is most likely that $\widehat{\mathbf{A}}|_{(\mathbf{B}^H \widetilde{\mathcal{U}})^\perp}$ is nonsingular. For the case of exactly invariant subspaces, see Section 7, in particular Corollary 7.2.*

REMARK 2.3. *In contrast to the possibly nontrivial intersection of $\mathcal{R}(\widehat{\mathbf{A}})$ and \mathcal{U} we have $\mathcal{R}(\widehat{\mathbf{A}}) \cap \mathcal{Z} = \{\mathbf{0}\}$. In fact, $\mathcal{R}(\widehat{\mathbf{A}}) \cap \mathcal{Z} = \mathcal{R}(\mathbf{P}) \cap \mathcal{N}(\mathbf{P}) = \{\mathbf{0}\}$ because \mathbf{P} is a projector.*

REMARK 2.4. *Note that even when $\widetilde{\mathcal{U}} = \mathcal{U}$ and $\widehat{\mathcal{K}}_n = \widehat{\mathcal{L}}_n$ the assumptions of Theorem 2.1 are more general than those in the corresponding Theorem 3.2 of [25] since $\widehat{\mathcal{K}}_n$ and $\widehat{\mathcal{L}}_n$ need not be Krylov subspaces here.*

3. Deflated BiCG. The iterates \mathbf{x}_n and their residuals \mathbf{r}_n of BiCG are mathematically characterized by relations of the form (1.1) with $\mathbf{B} = \mathbf{I}$ and

$$\mathcal{S}_n = \mathcal{K}_n(\mathbf{A}, \mathbf{r}_0), \quad \widetilde{\mathcal{S}}_n = \mathcal{K}_n(\mathbf{A}^H, \widetilde{\mathbf{y}}_0), \quad (3.1)$$

where $\widetilde{\mathbf{y}}_0$ has to satisfy $\langle \widetilde{\mathbf{y}}_0, \mathbf{B}\mathbf{r}_0 \rangle \neq 0$. This choice allows for the existence of three-term recurrences (or pairs of coupled two-term recurrences) for these iterates and residuals.

As has been pointed out in [26] and [27], the BiCG method can be generalized to include a formal inner product matrix \mathbf{B} , but for the short recursions to persist we need that \mathbf{B} commutes with \mathbf{A} , that is, $\mathbf{B}\mathbf{A} = \mathbf{A}\mathbf{B}$. An implementation of this **Generalized BiCG (GENBiCG) method** can be obtained from any BiCG algorithm by replacing the Euclidean inner product $\langle \widetilde{\mathbf{y}}, \mathbf{y} \rangle = \widetilde{\mathbf{y}}^H \mathbf{y}$ by a formal \mathbf{B} -inner product $\langle \widetilde{\mathbf{y}}, \mathbf{y} \rangle_{\mathbf{B}} := \langle \widetilde{\mathbf{y}}, \mathbf{B}\mathbf{y} \rangle = \widetilde{\mathbf{y}}^H \mathbf{B}\mathbf{y}$. The special case $\mathbf{B} := \mathbf{A}$ of the method has recently been introduced as the **Biconjugate Residual (BiCR) method** by Sogabe, Sugihara,

and Zhang [46]. They optimized the recurrences for this case and showed by numerical experiments that this method converges typically smoother than BiCG. In the sequel, BiCR and related methods such as BiCRSTAB have become popular in China and Japan; see, e.g., [3, 30].

In n steps a BiCG or GENBiCG algorithm generates a basis $\{\mathbf{r}_0, \dots, \mathbf{r}_n\}$ of $\mathcal{K}_{n+1}(\mathbf{A}, \mathbf{r}_0)$ consisting of residual vectors and a basis $\{\tilde{\mathbf{y}}_0, \dots, \tilde{\mathbf{y}}_n\}$ of $\mathcal{K}_{n+1}(\mathbf{A}^H, \tilde{\mathbf{y}}_0)$ in such a way that $\langle \tilde{\mathbf{y}}_k, \mathbf{B}\mathbf{r}_\ell \rangle = 0$ if $k \neq \ell$ and $\langle \tilde{\mathbf{y}}_k, \mathbf{B}\mathbf{r}_k \rangle \neq 0$. Such bases are called ‘biorthogonal’ or, if $\langle \tilde{\mathbf{y}}_k, \mathbf{B}\mathbf{r}_\ell \rangle = \delta_{k,\ell}$ (with the Kronecker δ), ‘biorthonormal’ or ‘dual’. (In our terminology we drop the dependence on \mathbf{B} .) The vectors $\tilde{\mathbf{y}}_0, \dots, \tilde{\mathbf{y}}_n$ are often referred to as ‘shadow residuals’. They may be chosen as unit vectors unless we want to solve at once a pair of dual linear systems $\mathbf{A}\mathbf{x} = \mathbf{b}$ and $\mathbf{A}^H\tilde{\mathbf{x}} = \tilde{\mathbf{b}}$; see Section 4. For GENBiCG not to break down we need $\langle \tilde{\mathbf{y}}_n, \mathbf{B}\mathbf{r}_n \rangle \neq 0$ and $\langle \tilde{\mathbf{y}}_n, \mathbf{A}\mathbf{B}\mathbf{r}_n \rangle \neq 0$ for all n till convergence. Otherwise, there will be a **Lanczos breakdown** or a **pivot breakdown**, respectively. These are rare, however, and, except for the extremely rare occasion of an incurable breakdown, they can be avoided with look-ahead techniques; see, e.g., [22, 27].

To find augmented and deflated BiCG and GENBiCG methods we still start from (1.1) but now choose \mathcal{S} and $\tilde{\mathcal{S}}$ of the structure (2.1) with $\tilde{\mathcal{K}}_n$ and $\tilde{\mathcal{L}}_n$ as in (2.18) and (2.19). For generating these subspaces with the non-Hermitian Lanczos process we will need that $\hat{\mathbf{A}}\mathbf{B} = \mathbf{B}\hat{\mathbf{A}}$ on $\mathcal{R}(\hat{\mathbf{A}}) = \mathcal{R}(\mathbf{P})$, that is, $\hat{\mathbf{A}}\mathbf{B}\mathbf{P} = \mathbf{B}\hat{\mathbf{A}}\mathbf{P}$. Therefore, we will assume that \mathbf{B} commutes with \mathbf{A} and \mathbf{P} . In particular, $\mathcal{R}(\mathbf{P}) = (\mathbf{B}^H\tilde{\mathcal{U}})^\perp$ must then be an invariant subspace of \mathbf{B} , which is a severe restriction unless $\mathbf{B} = \mathbf{I}$.

As before, we could represent \mathbf{x}_n and \mathbf{r}_n as in (2.2) and (2.3), and $\tilde{\mathbf{y}}_n$ by, say,

$$\tilde{\mathbf{y}}_n = \left(\tilde{\mathbf{r}}_0 - \mathbf{A}^H\tilde{\mathbf{V}}_n\tilde{\mathbf{c}}_n - \tilde{\mathbf{Z}}\tilde{\mathbf{u}}_n \right) / \tilde{\eta}_n, \quad (3.2)$$

where the scalar $\tilde{\eta}_n$ can be chosen to scale $\tilde{\mathbf{y}}_n$. These representations could be used to derive recursions for \mathbf{x}_n , \mathbf{r}_n , and $\tilde{\mathbf{y}}_n$; however, they are not needed since Theorem 2.1 holds: we can apply BiCG or GENBiCG to the singular system $\hat{\mathbf{A}}\tilde{\mathbf{x}} = \tilde{\mathbf{b}}$ and, after convergence, use the correction formula (2.14) to obtain \mathbf{x}_n . Using this implicit approach these methods can be implemented in the very simple way that is outlined in Algorithm 1 for deflated GENBiCG. For deflated BiCG choose $\mathbf{B} = \mathbf{I}$. By construction, the initial projected residual $\hat{\mathbf{r}}_0$ lies in the range of $\hat{\mathbf{A}}$. The initial shadow residual $\tilde{\mathbf{y}}_0$ gets projected into the range of $\hat{\mathbf{A}}^H$ by setting $\hat{\tilde{\mathbf{y}}}_0 := \mathbf{Q}^H\tilde{\mathbf{y}}_0$.

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1 function [ $n, \mathbf{x}_n, \mathbf{r}_n$ ] = DeflGenBiCG( $\mathbf{A}, \mathbf{B}, \mathbf{b}, \mathbf{x}_0, \tilde{\mathbf{y}}_0, \mathbf{U}, \tilde{\mathbf{U}}$ )
   input :  $\mathbf{b}, \mathbf{x}_0, \tilde{\mathbf{y}}_0, \mathbf{U}, \tilde{\mathbf{U}}$ ;
           code for  $\mathbf{A}, \mathbf{B}, \mathbf{E}, \mathbf{M}, \mathbf{P}, \mathbf{Q}, \hat{\mathbf{A}}$  [see Table (2.1)]
   output: approximate solution  $\mathbf{x}_n$  of  $\mathbf{A}\mathbf{x} = \mathbf{b}$ ; corresponding  $n, \mathbf{r}_n$ 
2  $\mathbf{r}_0 := \mathbf{b} - \mathbf{A}\mathbf{x}_0$ ;  $\hat{\mathbf{r}}_0 := \mathbf{P}\mathbf{r}_0$ ;  $\hat{\tilde{\mathbf{y}}}_0 := \mathbf{Q}^H\tilde{\mathbf{y}}_0$ ;  $\mathbf{h}_0 := \mathbf{0}$ ;
3 [ $n, \mathbf{h}_n, \hat{\mathbf{r}}_n$ ] = GenBiCG( $\hat{\mathbf{A}}, \mathbf{B}, \hat{\mathbf{r}}_0, \mathbf{h}_0, \hat{\tilde{\mathbf{y}}}_0$ ); [apply GENBiCG to  $\hat{\mathbf{A}}\mathbf{h} = \hat{\mathbf{r}}_0$ ]
4  $\hat{\mathbf{x}}_n := \mathbf{h}_n + \mathbf{x}_0$ ;  $\mathbf{x}_n := \mathbf{Q}\hat{\mathbf{x}}_n + \mathbf{M}\mathbf{B}\mathbf{b}$ ;  $\mathbf{r}_n := \hat{\mathbf{r}}_n$ ; [see Eqn. (2.14)]

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Algorithm 1: DEFLGENBiCG. This outline of our augmented and deflated GENBiCG algorithm for solving $\mathbf{A}\mathbf{x} = \mathbf{b}$ illustrates the application of Theorem 2.1 when the basic method is GENBiCG, which is assumed to be implemented in function $[n, \mathbf{x}_n, \mathbf{r}_n] = \text{GenBiCG}(\mathbf{A}, \mathbf{B}, \mathbf{b}, \mathbf{x}_0, \tilde{\mathbf{y}}_0)$ for a system of the form $\mathbf{A}\mathbf{x} = \mathbf{b}$, using the initial approximation \mathbf{x}_0 and the initial shadow residual $\tilde{\mathbf{y}}_0$.

Note that in the Hermitian case of deflated BiCG, where $\mathbf{A} = \mathbf{A}^H$, $\mathbf{B} = \mathbf{I}$, $\tilde{\mathcal{U}} = \mathcal{U}$,

and $\widehat{\mathcal{L}}_n = \widehat{\mathcal{K}}_n$, the conditions (2.12) turn into those of deflated CG. This is not true for the Recycling BiCG (RBiCG) method proposed by Ahuja [4]. In our notation, that method defines $\widehat{\mathbf{A}} := \mathbf{P}\mathbf{A}\mathbf{P}$ with $\mathbf{P} := \mathbf{P}_\mathbf{A} := \mathbf{I} - \mathbf{A}\mathbf{M}\mathbf{A}$ based on the choice $\mathbf{B} = \mathbf{A}$, and it uses then the Petrov–Galerkin conditions

$$\mathbf{r}_n \perp \widehat{\mathcal{L}}_n + \widetilde{\mathcal{Z}}, \quad \widetilde{\mathbf{r}}_n \perp \widehat{\mathcal{K}}_n + \mathcal{Z}. \quad (3.3)$$

In particular, \mathbf{r}_n is not orthogonal to the shadow search space for the approximate solutions: the Petrov–Galerkin conditions (3.3) are not incidences of our conditions $\mathbf{r}_n \perp \mathbf{B}^H \widetilde{\mathcal{S}}_n$ and $\widetilde{\mathbf{r}}_n \perp \mathbf{B}\mathcal{S}_n$ in (1.1) and (4.2) below. Instead, Ahuja [4] makes use of two different formal inner products when setting up the Petrov–Galerkin conditions for the two parts of the test spaces.

If $\widetilde{\mathcal{U}} = \mathcal{U}$ and $\widehat{\mathcal{L}}_n = \widehat{\mathcal{K}}_n (\forall n)$ our framework reduces to the one of [25]. Some basic facts about the methods covered in this section and there are compiled in Table 3.1.

Method	\mathbf{B}	$\widetilde{\mathcal{U}}$	$\widehat{\mathcal{K}}_n$	$\widehat{\mathcal{L}}_n$	Requirements
Deflated BiCG	\mathbf{I}	$\widetilde{\mathcal{U}}$	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	$\mathcal{K}_n(\widehat{\mathbf{A}}^H, \widehat{\mathbf{y}}_0)$	–
Defl. GENBiCG	\mathbf{B}	$\widetilde{\mathcal{U}}$	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	$\mathcal{K}_n(\widehat{\mathbf{A}}^H, \widehat{\mathbf{y}}_0)$	$\widehat{\mathbf{A}}\mathbf{B}\mathbf{P} = \mathbf{B}\widehat{\mathbf{A}}\mathbf{P}$
Deflated CG	\mathbf{I}	\mathcal{U}	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	\mathbf{A} HpD
Deflated CR	\mathbf{A}	\mathcal{U}	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	\mathbf{A} HpD
Deflated MINRES	\mathbf{A}	\mathcal{U}	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	$\mathbf{A} = \mathbf{A}^H$
Deflated GMRES, GCR	\mathbf{A}^H	\mathcal{U}	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widehat{\mathbf{r}}_0)$	–

TABLE 3.1

The formal inner product matrix \mathbf{B} and the subspaces $\widehat{\mathcal{K}}_n$ and $\widehat{\mathcal{L}}_n$ for the methods of Section 3 and for some of the methods of [25]. Note that \mathbf{B} in [25] corresponds to our \mathbf{B}^H . On the first two lines, $\widehat{\mathbf{y}}_0 := \mathbf{Q}^H \widetilde{\mathbf{y}}_0$, where $\widetilde{\mathbf{y}}_0$ is any suitably chosen initial shadow residual. In the case where we also solve a dual problem $\mathbf{A}^H \widetilde{\mathbf{x}} = \widetilde{\mathbf{b}}$ (see Section 4), $\widetilde{\mathbf{y}}_0 := \widetilde{\mathbf{r}}_0 := \widetilde{\mathbf{b}} - \mathbf{A}^H \widetilde{\mathbf{x}}_0$ is the initial residual of the dual problem. In this latter case, deflated GENBiCG with $\mathbf{B} \neq \mathbf{I}$ will require to generate additionally yet another pair of sequences of Krylov subspaces. Except for deflated GMRES and GCR all the methods listed in the table can be implemented with three-term or coupled two-term recurrences.

4. Solving pairs of dual linear systems. The non-Hermitian (or two-sided) Lanczos process and BiCG make use of duality. For $n = 1, 2, \dots$ until it terminates or brakes down, the (generalized) Lanczos process generates dual (or at least biorthogonal) bases $\{\mathbf{y}_0, \dots, \mathbf{y}_{n-1}\}$ and $\{\widetilde{\mathbf{y}}_0, \dots, \widetilde{\mathbf{y}}_{n-1}\}$ for the Krylov subspaces $\mathcal{K}_n(\mathbf{A}, \mathbf{y}_0)$ and $\mathcal{K}_n(\mathbf{A}^H, \widetilde{\mathbf{y}}_0)$, respectively. The replacement of \mathbf{y}_k by the residual \mathbf{r}_k is just a question of rescaling. To fully profit from duality we may assume that we have to solve both $\mathbf{A}\mathbf{x} = \mathbf{b}$ and its dual system

$$\mathbf{A}^H \widetilde{\mathbf{x}} = \widetilde{\mathbf{b}}. \quad (4.1)$$

We denote by $\widetilde{\mathbf{x}}_n$ its approximate solutions and by $\widetilde{\mathbf{r}}_n := \widetilde{\mathbf{b}} - \mathbf{A}^H \widetilde{\mathbf{x}}_n$ the corresponding residuals. An example for the occurrence of pairs of dual systems in practice is interpolatory model reduction; see, e.g., [5, 8]. A simple extension of BiCG, which is based on coupled two-term recursions for the non-Hermitian Lanczos process, allows us to solve both systems at once at the cost of two matrix-vector products (MVs) per iteration, one with \mathbf{A} and one with \mathbf{A}^H . So, essentially the cost is the same as solving just one system with BiCG. The iterates $\widetilde{\mathbf{x}}_n$ of the dual system are mathematically characterized by

$$\widetilde{\mathbf{x}}_n \in \widetilde{\mathbf{x}}_0 + \widetilde{\mathcal{S}}_n, \quad \widetilde{\mathbf{r}}_n \in \widetilde{\mathbf{r}}_0 + \mathbf{A}^H \widetilde{\mathcal{S}}_n, \quad \widetilde{\mathbf{r}}_n \perp \mathbf{B}\mathcal{S}_n \quad (4.2)$$

with \mathcal{S}_n and $\tilde{\mathcal{S}}_n$ as in (3.1), except that we have to choose $\tilde{\mathbf{y}}_0 := \tilde{\mathbf{r}}_0$. That is, the residuals $\tilde{\mathbf{r}}_n$ of the dual system replace the shadow residuals $\tilde{\mathbf{y}}_n$ of BiCG.

In this section we aim at solving a pair of dual systems efficiently with a suitable deflation and augmentation method, as Ahuja [4] did, and our natural targets are deflated BiCG and GENBiCG. To this end we first address the question of how to solve the dual problem by deflated BiCG or GENBiCG, and then we hope to solve both the basic and the dual systems at essentially the price of solving one.

To solve the dual system, we start from (4.2) (instead of (1.1)) choosing \mathcal{S} and $\tilde{\mathcal{S}}$ of the structure

$$\mathcal{S}_n = \tilde{\mathcal{K}}_n + \mathcal{U}, \quad \tilde{\mathcal{S}}_n = \tilde{\mathcal{L}}_n + \tilde{\mathcal{U}}. \quad (4.3)$$

with Krylov subspaces $\tilde{\mathcal{K}}_n$ and $\tilde{\mathcal{L}}_n$ that still need to be specified. Analogously to (2.2) and (2.3) we represent the iterates and residuals of the dual linear system as

$$\tilde{\mathbf{x}}_n = \tilde{\mathbf{x}}_0 + \tilde{\mathbf{V}}_n \tilde{\mathbf{c}}_n + \tilde{\mathbf{U}} \tilde{\mathbf{u}}_n, \quad (4.4)$$

$$\tilde{\mathbf{r}}_n = \tilde{\mathbf{r}}_0 - \mathbf{A}^H \tilde{\mathbf{V}}_n \tilde{\mathbf{c}}_n - \tilde{\mathbf{Z}} \tilde{\mathbf{u}}_n \quad (4.5)$$

with coordinate vectors $\tilde{\mathbf{c}}_n \in \mathbb{C}^n$ and $\tilde{\mathbf{u}}_n \in \mathbb{C}^k$, where now the columns of $\tilde{\mathbf{V}}_n$ form a basis of $\tilde{\mathcal{L}}_n$. To define a projected problem that yields the appropriate splitting of the search spaces for any \mathbf{B} that commutes with \mathbf{A} and \mathbf{P} , we let

$$\tilde{\mathbf{E}} := \mathbf{U}^H \mathbf{B}^H \mathbf{A}^H \tilde{\mathbf{U}}, \quad \tilde{\mathbf{M}} := \tilde{\mathbf{U}} \tilde{\mathbf{E}}^{-1} \mathbf{U}^H \quad (4.6)$$

assuming that $\tilde{\mathbf{E}}$ is nonsingular, and then define

$$\tilde{\mathbf{P}} := \mathbf{I} - \mathbf{A}^H \tilde{\mathbf{M}} \mathbf{B}^H, \quad \tilde{\mathbf{Q}} := \mathbf{I} - \tilde{\mathbf{M}} \mathbf{B}^H \mathbf{A}^H; \quad (4.7)$$

see Table 2.1. $\tilde{\mathbf{P}}$ is the oblique projection on $(\mathbf{B}\mathcal{U})^\perp$ along $\tilde{\mathcal{Z}}$, and $\tilde{\mathbf{Q}}$ is the oblique projection on $(\mathbf{A}\mathbf{B}\mathcal{U})^\perp$ along $\tilde{\mathcal{U}}$. Note that due to the commutativity assumption $\tilde{\mathbf{E}} = \mathbf{E}^H$, $\tilde{\mathbf{M}} = \mathbf{M}^H$ and $\mathcal{R}(\tilde{\mathbf{Q}}) = (\mathbf{B}^H \tilde{\mathcal{Z}})^\perp$, $\mathcal{R}(\tilde{\mathbf{P}}) = (\mathbf{B}\mathcal{Z})^\perp$ now. Finally, we need to introduce iterates and residuals for the corresponding projected dual linear system:

$$\hat{\tilde{\mathbf{x}}}_n := \tilde{\mathbf{x}}_0 + \tilde{\mathbf{V}}_n \tilde{\mathbf{c}}_n \in \tilde{\mathbf{x}}_0 + \tilde{\mathcal{L}}_n, \quad \hat{\tilde{\mathbf{r}}}_n := \tilde{\mathbf{P}}(\tilde{\mathbf{b}} - \mathbf{A}^H \hat{\tilde{\mathbf{x}}}_n); \quad (4.8)$$

in particular, $\hat{\tilde{\mathbf{x}}}_0 := \tilde{\mathbf{x}}_0$ and $\hat{\tilde{\mathbf{r}}}_0 := \tilde{\mathbf{P}}\tilde{\mathbf{r}}_0 \perp \mathbf{B}\mathcal{U}$. Then the following analog of Theorem 2.1 can be quickly established.

THEOREM 4.1. *Modify the assumptions of Theorem 2.1 by letting now $\tilde{\mathbf{E}} := \mathbf{U}^H \mathbf{B}^H \mathbf{A}^H \tilde{\mathbf{U}}$ (instead of \mathbf{E}) be nonsingular, so that the matrices $\tilde{\mathbf{M}}, \tilde{\mathbf{P}}, \tilde{\mathbf{Q}}$ of (4.6) and (4.7) are well defined. Then the two pairs of conditions*

$$\tilde{\mathbf{x}}_n \in \tilde{\mathbf{x}}_0 + \tilde{\mathcal{L}}_n + \tilde{\mathcal{U}}, \quad \tilde{\mathbf{r}}_n \perp \mathbf{B}(\tilde{\mathcal{K}}_n + \mathcal{U}) \quad (4.9)$$

and

$$\hat{\tilde{\mathbf{x}}}_n \in \tilde{\mathbf{x}}_0 + \tilde{\mathcal{L}}_n, \quad \hat{\tilde{\mathbf{r}}}_n \perp \mathbf{B}\tilde{\mathcal{K}}_n, \quad (4.10)$$

if determining $\tilde{\mathbf{x}}_n$ and $\hat{\tilde{\mathbf{x}}}_n$ uniquely, are equivalent in the sense that

$$\tilde{\mathbf{x}}_n = \tilde{\mathbf{Q}} \hat{\tilde{\mathbf{x}}}_n + \tilde{\mathbf{M}} \mathbf{B}^H \tilde{\mathbf{b}} \quad \text{and} \quad \tilde{\mathbf{r}}_n = \hat{\tilde{\mathbf{r}}}_n. \quad (4.11)$$

Hence, again we can either directly aim at $\tilde{\mathbf{x}}_n$ and $\tilde{\mathbf{r}}_n$ satisfying (4.9), or first compute $\hat{\tilde{\mathbf{x}}}_n, \hat{\tilde{\mathbf{r}}}_n$ satisfying (4.10) and then apply (4.11). The proof of Theorem 4.1 is fully analogous to the one of Theorem 2.1.

Now, recall that $\hat{\tilde{\mathbf{r}}}_n$ is the residual of the approximate solution $\hat{\tilde{\mathbf{x}}}_n$ of the system

$$\tilde{\mathbf{P}}\mathbf{A}^H\hat{\tilde{\mathbf{x}}} = \tilde{\mathbf{P}}\tilde{\mathbf{b}}, \quad (4.12)$$

which is equivalent to

$$\tilde{\mathbf{A}}(\hat{\tilde{\mathbf{x}}} - \tilde{\mathbf{x}}_0) = \hat{\tilde{\mathbf{r}}}_0, \quad \text{where } \tilde{\mathbf{A}} := \tilde{\mathbf{P}}\mathbf{A}^H = \mathbf{A}^H\tilde{\mathbf{Q}} = \tilde{\mathbf{P}}\mathbf{A}^H\tilde{\mathbf{Q}} \quad (4.13)$$

(cf. Table 2.1). Here both sides of the system lie in $\mathcal{R}(\tilde{\mathbf{P}}) = (\mathbf{B}\mathbf{U})^\perp$, and, by assumption, $\hat{\tilde{\mathbf{x}}}_n - \tilde{\mathbf{x}}_0 \in \tilde{\mathcal{L}}_n$. We want to solve (4.12) by a Krylov subspace method restricted to $(\mathbf{B}\mathbf{U})^\perp$ and, hence, we aim for $\tilde{\mathcal{L}}_n \subseteq (\mathbf{B}\mathbf{U})^\perp$. Obviously, for solving the projected dual system the natural choice for the Krylov search subspaces is

$$\tilde{\mathcal{L}}_n := \mathcal{K}_n(\tilde{\mathbf{A}}, \hat{\tilde{\mathbf{r}}}_0) = \mathcal{K}_n(\tilde{\mathbf{P}}\mathbf{A}^H, \hat{\tilde{\mathbf{r}}}_0) \subseteq (\mathbf{B}\mathbf{U})^\perp. \quad (4.14)$$

We conclude that for solving $\mathbf{A}^H\tilde{\mathbf{x}} = \tilde{\mathbf{b}}$ by an augmented and deflated GENBICG method there are, for given \mathbf{A} , \mathbf{B} , \mathbf{U} , and $\tilde{\mathbf{U}}$, well-defined projections $\tilde{\mathbf{P}}$, $\tilde{\mathbf{Q}}$, and a corresponding projected singular operator $\tilde{\mathbf{A}}$ that allow us to solve instead of $\mathbf{A}^H\tilde{\mathbf{x}} = \tilde{\mathbf{b}}$ the deflated system $\tilde{\mathbf{A}}(\hat{\tilde{\mathbf{x}}} - \tilde{\mathbf{x}}_0) = \hat{\tilde{\mathbf{r}}}_0$. Constructing $\hat{\tilde{\mathbf{x}}}_n$ and $\hat{\tilde{\mathbf{r}}}_n := \tilde{\mathbf{P}}(\tilde{\mathbf{b}} - \mathbf{A}^H\hat{\tilde{\mathbf{x}}}_n)$ with GENBICG using only short recurrences requires in particular to compute in addition to the basis vectors $\hat{\tilde{\mathbf{r}}}_\ell$ of $\tilde{\mathcal{L}}_n$ a set of dual basis vectors $\hat{\tilde{\mathbf{y}}}_k$ of the dual Krylov subspace

$$\tilde{\mathcal{K}}_n := \mathcal{K}_n(\tilde{\mathbf{A}}^H, \hat{\tilde{\mathbf{y}}}_0) = \mathcal{K}_n(\mathbf{A}, \tilde{\mathbf{P}}^H\hat{\tilde{\mathbf{y}}}_0) \subseteq \tilde{\mathbf{U}}^\perp \quad (4.15)$$

satisfying $\langle \hat{\tilde{\mathbf{r}}}_i, \mathbf{B}\hat{\tilde{\mathbf{y}}}_k \rangle = \delta_{i,k}$. Here, \mathbf{B}^H must commute with $\tilde{\mathbf{A}}$. This means that \mathbf{B} must commute with \mathbf{A} and $\tilde{\mathbf{P}}^H$.

So, in general, for solving both the basic and the dual problem by an augmented and deflated GENBICG method we need to build up four Krylov subspaces:

$$\hat{\mathcal{K}}_n := \mathcal{K}_n(\hat{\mathbf{A}}, \hat{\mathbf{r}}_0), \quad \hat{\mathcal{L}}_n := \mathcal{K}_n(\hat{\mathbf{A}}^H, \hat{\mathbf{y}}_0), \quad \tilde{\mathcal{L}}_n := \mathcal{K}_n(\tilde{\mathbf{A}}, \hat{\tilde{\mathbf{r}}}_0), \quad \tilde{\mathcal{K}}_n := \mathcal{K}_n(\tilde{\mathbf{A}}^H, \hat{\tilde{\mathbf{y}}}_0). \quad (4.16)$$

This means that, in general, the computational cost of building up these Krylov subspaces, that is, for generating the iterates and residuals, is twice as much as we would have hoped for since only $\mathcal{K}_n(\mathbf{A}, \mathbf{r}_0)$ and $\mathcal{K}_n(\mathbf{A}^H, \tilde{\mathbf{r}}_0)$ are needed for non-deflated BICG and GENBICG. Fortunately, in the case $\mathbf{B} = \mathbf{I}$ of BiCG this cost reduces again to half, as the following simple result shows.

THEOREM 4.2. *If $\mathbf{B} = \mathbf{I}$, the following equalities hold:*

$$\mathbf{P}^H = \tilde{\mathbf{Q}}, \quad \mathbf{Q}^H = \tilde{\mathbf{P}},$$

and, hence,

$$\hat{\mathbf{A}}^H = \tilde{\mathbf{A}}.$$

Therefore, if we choose $\hat{\tilde{\mathbf{y}}}_0 := \hat{\tilde{\mathbf{r}}}_0$ and $\hat{\tilde{\mathbf{y}}}_0 := \hat{\tilde{\mathbf{r}}}_0$, the four Krylov subspaces in (4.16) reduce to two, $\hat{\mathcal{K}}_n = \tilde{\mathcal{K}}_n$ and $\hat{\mathcal{L}}_n = \tilde{\mathcal{L}}_n$.

Proof. $\mathbf{P}^H = \mathbf{I} - \mathbf{M}^H\mathbf{A}^H = \tilde{\mathbf{Q}}$ and $\mathbf{Q}^H = \mathbf{I} - \mathbf{A}^H\mathbf{M}^H = \tilde{\mathbf{P}}$ yield $\hat{\mathbf{A}}^H = \mathbf{Q}^H\mathbf{A}^H = \tilde{\mathbf{P}}\mathbf{A}^H = \tilde{\mathbf{A}}$ \square

So, only in the case $\mathbf{B} = \mathbf{I}$ the residuals of the dual problem can serve as the shadow residuals of the basic problem, and *vice versa*. In other words, only in this case the deflated dual problem is equal to the dual of the deflated problem! Hence, it is not worthwhile to choose $\mathbf{B} \neq \mathbf{I}$ (e.g., deflated BiCR) for solving pairs of dual problems.

5. Block Krylov spaces, deflated block BiCG, and deflated ML(s)BiCG.

Our theorems on the equivalence of the explicit and implicit approaches to augmentation and deflation carry over to block Krylov subspace methods based on Galerkin or Petrov–Galerkin conditions. We illustrate this claim here by discussing a fairly general version of **block BiCG**.

Given an $N \times r$ matrix \mathbf{R}_0 whose columns $\mathbf{r}_0^{(i)}$ may come from the initial residuals of r given linear systems $\mathbf{A}\mathbf{x}^{(i)} = \mathbf{b}^{(i)}$ ($i = 1, \dots, r$) we consider block Krylov subspaces of the form

$$\mathcal{K}_{j;\ell}(\mathbf{A}, \mathbf{R}_0) := \sum_{i=1}^{\ell} \mathcal{K}_{j+1}(\mathbf{A}, \mathbf{r}_0^{(i)}) + \sum_{i=\ell+1}^r \mathcal{K}_j(\mathbf{A}, \mathbf{r}_0^{(i)}) \quad (5.1)$$

with $0 \leq \ell \leq r - 1$. Likewise we consider an $N \times s$ matrix $\tilde{\mathbf{R}}_0$ with columns $\tilde{\mathbf{r}}_0^{(i)}$ and the corresponding shadow block Krylov subspaces

$$\mathcal{K}_{\tilde{j};\tilde{\ell}}(\mathbf{A}^H, \tilde{\mathbf{R}}_0) := \sum_{i=1}^{\tilde{\ell}} \mathcal{K}_{\tilde{j}+1}(\mathbf{A}^H, \tilde{\mathbf{r}}_0^{(i)}) + \sum_{i=\tilde{\ell}+1}^s \mathcal{K}_{\tilde{j}}(\mathbf{A}^H, \tilde{\mathbf{r}}_0^{(i)}) \quad (5.2)$$

with $0 \leq \tilde{\ell} \leq s - 1$. (From now on we denote the initial shadow residuals by $\tilde{\mathbf{r}}_0^{(i)}$, even if they are not initial residuals of a dual linear system.) These two definitions allow for incomplete blocks. Blocks are complete when $\ell = 0$ or $\tilde{\ell} = 0$, respectively, and, hence, the first sums in (5.1) and (5.2) are empty. Some algorithms work with complete blocks only, others create successively bases for all Krylov subspaces $\mathcal{K}_{j;\ell}(\mathbf{A}, \mathbf{R}_0)$ and $\mathcal{K}_{\tilde{j};\tilde{\ell}}(\mathbf{A}^H, \tilde{\mathbf{R}}_0)$. The latter applies in particular to the so-called ‘band’ Lanczos algorithms, both in the symmetric [42, 20] and the non-symmetric case [6, 21].

5.1. Deflated block BiCG and block GENBiCG. Standard treatments of block BiCG [40] assume that $r = s$, but this restriction can (and must) be avoided, because at some point residuals or shadow residuals may turn out to be linearly dependent. A suitable remedy to this deficiency consists in reducing r or s from then on, a process that is also called deflation, see [6, 33]. For simplicity we assume here that such a deflation of the spanning set is not needed before we are satisfied with the reduction of the residual norm and stop the computation anyway. In other words, we assume that for the iteration numbers n of interest, say, for $1 \leq n \leq M$ there are well defined values of j, ℓ and $\tilde{j}, \tilde{\ell}$ such that $n = jr + \ell = \tilde{j}s + \tilde{\ell}$ and

$$\dim \mathcal{K}_{j;\ell}(\mathbf{A}, \mathbf{R}_0) = jr + \ell, \quad \dim \mathcal{K}_{\tilde{j};\tilde{\ell}}(\mathbf{A}^H, \tilde{\mathbf{R}}_0) = \tilde{j}s + \tilde{\ell}.$$

Here our notation assumes that in (5.1) and (5.2) $\mathcal{K}_0(\cdot, \cdot) := \{\mathbf{0}\}$. Of course, in practice the possible need to deal with nearly linearly dependent residuals or shadow residuals requires extra care, but this topic is not within the scope of this paper.

We also assume that there are Arnoldi-like or Lanczos-like recursions for creating bases of the corresponding block Krylov subspaces. Let \mathbf{Y}_n and $\tilde{\mathbf{Y}}_n$ be matrices with the first n vectors of these bases. For block BiCG we might aim at making $\mathbf{D}_M := \tilde{\mathbf{Y}}_M^H \mathbf{B} \mathbf{Y}_M$ diagonal, so that the bases are biorthogonal, as in the band Lanczos process without look-ahead [6, 21]. But there are good reasons to relax the biorthogonality condition (which is, in fact, the Petrov–Galerkin condition) and aim at a matrix \mathbf{D} that is block diagonal only, but well conditioned; this can be enhanced by allowing local pivoting of the basis vectors or even more general linear transformations; see [33]. In either case we may apply our framework by replacing in such a block BiCG

the operator \mathbf{A} by $\widehat{\mathbf{A}}$ and by accordingly renaming the nested matrices of the bases as $\widehat{\mathbf{Y}}_n$ and $\widetilde{\mathbf{Y}}_n$, respectively, and renaming the generating block Krylov subspaces as

$$\widehat{\mathcal{K}}_n := \mathcal{R}(\widehat{\mathbf{Y}}_n), \quad \widehat{\mathcal{L}}_n := \mathcal{R}(\widetilde{\mathbf{Y}}_n). \quad (5.3)$$

Again, for block GENBICG applied to a pair of dual linear systems we would need to construct two additional sequences of block Krylov subspaces generated by $\widehat{\mathbf{A}}$ and by $\widetilde{\mathbf{A}}^H$, respectively. Therefore, choosing $\mathbf{B} \neq \mathbf{I}$ for pairs of dual problems will be hardly worth this trouble.

Recall that in Section 2 we did not assume that $\widehat{\mathcal{K}}_n$ and $\widehat{\mathcal{L}}_n$ are standard Krylov subspaces, but just that they are subspaces of the same dimension. So now, if we consider any particular system, say, $\mathbf{A}\mathbf{x}^{(io)} = \mathbf{b}^{(io)}$ and substitute $\mathbf{x} := \mathbf{x}^{(io)}$, $\mathbf{b} := \mathbf{b}^{(io)}$, we can apply the results of Sections 2 and 3, in particular Theorem 2.1. This means that we can implement augmentation and deflation by applying block BiCG to a projected system and afterwards apply the usual correction step (2.14). Of course, this applies to each of the r basic systems. Note that, in theory, it makes no difference whether we solve just one or all r basic systems, and that there is no need to assume that initially $r = s$.

5.2. Deflated ML(s)BiCG. In principle, even if just one system has to be solved, we could attempt this by choosing for the search space a block Krylov subspace $\mathcal{K}_{j;\ell}(\mathbf{A}, \mathbf{R}_0)$ with $r > 1$ and a matrix \mathbf{R}_0 whose first column is the initial residual, while the others are chosen mutually orthogonal. However, we believe that the gain in convergence speed compared to the corresponding ordinary Krylov solver will usually not justify the additional cost and complications of applying a block solver with $r > 1$.

A more promising approach to solving a single system consists in applying a block BiCG algorithm with $r = 1$ and $s > 1$. Such a variation of BiCG called **ML(s)BiCG** was introduced by Yeung and Chan [54]. The basic idea was to replace the left shadow Krylov subspaces $\mathcal{K}_n(\mathbf{A}^H, \widetilde{\mathbf{r}}_0)$ of BiCG by block Krylov subspaces that are generated from s linearly independent initial shadow residuals. Assuming $n = \widetilde{j}s + \widetilde{\ell}$ we can characterize the iterates \mathbf{x}_n of ML(s)BiCG by

$$\mathbf{x}_n \in \mathbf{x}_0 + \mathcal{K}_n(\mathbf{A}, \mathbf{r}_0), \quad \mathbf{r}_n \in \mathbf{r}_0 + \mathbf{A}\mathcal{K}_n(\mathbf{A}, \mathbf{r}_0), \quad \mathbf{r}_n \perp \mathbf{B}^H \mathcal{K}_{\widetilde{j};\widetilde{\ell}}(\mathbf{A}^H, \widetilde{\mathbf{R}}_0) \quad (5.4)$$

with $\mathbf{B} = \mathbf{I}$ unless we want to generalize the method. But, unfortunately, a straightforward implementation of ML(s)BiCG is not (yet) competitive due to the high cost of generating s shadow Krylov subspaces.

For deflated ML(s)BiCG we use for $\widehat{\mathcal{K}}_n$ the standard choice (2.18) and for $\widehat{\mathcal{L}}_n$, when $n = \widetilde{j}s + \widetilde{\ell}$, the block Krylov subspaces

$$\widehat{\mathcal{L}}_n := \widehat{\mathcal{L}}_{\widetilde{j}s+\widetilde{\ell}} := \mathcal{K}_{\widetilde{j};\widetilde{\ell}}(\widehat{\mathbf{A}}^H, \widetilde{\mathbf{R}}_0) \subseteq \mathcal{U}^\perp,$$

where $\widetilde{\mathbf{R}}_0$ must have s linearly independent columns $\widetilde{\mathbf{r}}_0^{(i)} \perp \mathcal{U}$ ($i = 1, \dots, s$). (We avoid the notation $\widehat{\widetilde{\mathbf{r}}}_0^{(i)}$ and $\widehat{\widetilde{\mathbf{R}}}_0$ from now on.)

6. Lanczos-type product methods, deflated BICGSTAB, and deflated IDR(s). The BiCG and block BiCG methods require the application of \mathbf{A}^H , which may make their usage costly or even impossible. It was Sonneveld who introduced with IDR [53] and CGS [47] two methods based on the same glorious idea that allowed him to avoid multiplication by \mathbf{A}^H and, at the same time, to double the degree of the BiCG residual polynomials nearly for free. Van der Vorst's ubiquitous BiCG-STAB [50], which can be seen to be mathematically equivalent to a version of IDR,

makes use of the same idea. Often such methods are called Lanczos-type product methods (LTPMs) now, see, e.g., [27]. Yeung and Chan [54] applied the same idea to their $\text{ML}(s)\text{BiCG}$ method, which they only introduced as a tool for deriving the more effective and less costly $\text{ML}(s)\text{BiCGSTAB}$ method. Sonneveld and van Gijzen's recently generalized the IDR approach to the $\text{IDR}(s)$ method [48], which in exact arithmetic can be seen to produce every $s+1$ steps the same approximants as $\text{ML}(s)\text{BiCGSTAB}$, but is known to be more stable under roundoff. Both $\text{ML}(s)\text{BiCGSTAB}$ and $\text{IDR}(s)$ reduce mathematically to BiCGSTAB if $s=1$. In this section we are going to show how all these methods fit into our framework for deflation and augmentation.

6.1. Deflated BiCGSTAB and $\text{ML}(s)\text{BiCGSTAB}$. After j full steps of **BiCG-STAB** the residual lies in $\mathbf{r}_0 + \mathcal{K}_{2j}(\mathbf{A}, \mathbf{r}_0)$ and will therefore be denoted by \mathbf{r}_{2j} here⁵. This residual is of the product form

$$\mathbf{r}_{2j} = \Omega_j(\mathbf{A}) \mathbf{r}_j^{\text{BiCG}},$$

where $\mathbf{r}_j^{\text{BiCG}}$ denotes the j th BiCG residual and $\Omega_j(\mathbf{A}) := (\mathbf{I} - \omega_1 \mathbf{A}) \cdots (\mathbf{I} - \omega_j \mathbf{A})$ is a polynomial in \mathbf{A} whose parameters ω_k are determined during the iteration by a local residual norm minimization. If we allow for a formal inner product matrix \mathbf{B} that commutes with \mathbf{A} , $\mathbf{r}_j^{\text{BiCG}}$ must satisfy

$$\mathbf{r}_j^{\text{BiCG}} \perp \mathbf{B}^H \mathcal{K}_j(\mathbf{A}^H, \tilde{\mathbf{r}}_0).$$

Consequently, we can say that for BiCGSTAB the residual \mathbf{r}_{2j} is characterized by

$$\mathbf{r}_{2j} \in \Omega_j(\mathbf{A}) (\mathbf{r}_0 + \mathbf{A} \mathcal{K}_j(\mathbf{A}, \mathbf{r}_0)), \quad (6.1a)$$

$$[\Omega_j(\mathbf{A})]^{-1} \mathbf{r}_{2j} \perp \mathbf{B}^H \mathcal{K}_j(\mathbf{A}^H, \tilde{\mathbf{R}}_0). \quad (6.1b)$$

This is the case $s=1$, $n=2j$ of the more general formulas we give next.

For **$\text{ML}(s)\text{BiCGSTAB}$** , if we let $n = j(s+1) + \ell$, where $0 \leq \ell \leq s$ and $j = 0, 1, 2, \dots$, the residuals \mathbf{r}_n are characterized by

$$\mathbf{r}_n \in \Omega_j(\mathbf{A}) (\mathbf{r}_0 + \mathbf{A} \mathcal{K}_{js+\ell}(\mathbf{A}, \mathbf{r}_0)), \quad (6.2a)$$

$$[\Omega_j(\mathbf{A})]^{-1} \mathbf{r}_n \perp \mathbf{B}^H \mathcal{K}_{j;\ell}(\mathbf{A}^H, \tilde{\mathbf{R}}_0). \quad (6.2b)$$

Both $\mathcal{K}_{js+\ell}(\mathbf{A}, \mathbf{r}_0)$ and $\mathcal{K}_{j;\ell}(\mathbf{A}^H, \tilde{\mathbf{R}}_0)$ have, for sufficiently small j , dimension $js + \ell = n - j$. Now, note that (6.2b) is equal to

$$\mathbf{r}_n^H [\Omega_j(\mathbf{A})]^{-H} \mathbf{B}^H \mathcal{K}_{j;\ell}(\mathbf{A}^H, \tilde{\mathbf{R}}_0) = \mathbf{0}^T,$$

which in turn, again due to the commutativity, can be written as

$$\mathbf{r}_n \perp \mathbf{B}^H \mathcal{L}_n \quad (6.3)$$

with

$$\mathcal{L}_n := \mathcal{L}_{j;\ell} := [\Omega_j(\mathbf{A})]^{-H} \mathcal{K}_{j;\ell}(\mathbf{A}^H, \tilde{\mathbf{R}}_0) = \mathcal{K}_{j;\ell}(\mathbf{A}^H, [\Omega_j(\mathbf{A})]^{-H} \tilde{\mathbf{R}}_0). \quad (6.4)$$

⁵In the attempt to fit the methods in our framework we are using here a numbering of the iterates and residuals that differs from the usual one for BiCGSTAB and $\text{ML}(s)\text{BiCGSTAB}$. On the other hand, fortunately, it agrees with the standard numbering for $\text{IDR}(s)$. But, for example, our odd numbered BiCGSTAB residuals \mathbf{r}_{2j+1} correspond to intermediate quantities in the original BiCGSTAB algorithm.

The simple, but crucial step from (6.2b) to (6.3)–(6.4) has been pointed out by Simoncini and Szyld [45] in connection with the IDR(s) method (see below). It means that BiCGSTAB and ML(s)BiCGSTAB can be viewed as Petrov–Galerkin methods with residual test spaces \mathcal{L}_n that are rational Krylov subspaces, which have dimension $n - j$ (as long as $\mathcal{K}_{j;\ell}(\mathbf{A}^H, \tilde{\mathbf{R}}_0)$ is not affected by dimension loss). Alternatively, for each n , they can be viewed as polynomial Krylov subspaces with an initial vector that depends on j . Since we can keep j or even n fixed when applying Theorem 2.1, BiCGSTAB and ML(s)BiCGSTAB fit into our general framework of Section 2. Deflated versions of these methods are now obtained quickly by replacing \mathbf{A} by $\hat{\mathbf{A}}$, \mathbf{r}_0 by $\hat{\mathbf{r}}_0$, and by choosing $\tilde{\mathbf{R}}_0$ such that $\mathcal{R}(\tilde{\mathbf{R}}_0) \subseteq \mathcal{U}^\perp$ in order to define projected search and test spaces $\hat{\mathcal{K}}_n$ and $\hat{\mathcal{L}}_n$ for the singular projected linear system (2.17) with the deflated matrix $\hat{\mathbf{A}}$.

An expression for the solution search space of ML(s)BiCGSTAB can be found as follows. We define polynomials Ψ_j of degree $j - 1$ such that

$$\Omega_j(\mathbf{A}) = \mathbf{I} - \mathbf{A}\Psi_j(\mathbf{A}).$$

Then we can rewrite (6.2a) as

$$\mathbf{b} - \mathbf{A}\mathbf{x}_n \in (\mathbf{I} - \mathbf{A}\Psi_j(\mathbf{A}))\mathbf{b} - \mathbf{A}\Omega_j(\mathbf{A})\mathbf{x}_0 + \mathbf{A}\Omega_j(\mathbf{A})\mathcal{K}_{j;s+\ell}(\mathbf{A}, \mathbf{r}_0),$$

which leads to

$$\mathbf{x}_n \in \mathbf{x}_{j;0} + \Omega_j(\mathbf{A})\mathcal{K}_{j;s+\ell}(\mathbf{A}, \mathbf{r}_0) \quad \text{where} \quad \mathbf{x}_{j;0} := \Psi_j(\mathbf{A})\mathbf{b} + \Omega_j(\mathbf{A})\mathbf{x}_0. \quad (6.5)$$

So, unlike in most other Krylov subspace solvers, the shift vector of the affine solution search space is not constant, but depends on the index j . The same is true for other LTPMs. In particular, BiCGSTAB is here included as case $s = 1$. This feature reveals a major difference between these methods and classical Galerkin or Petrov–Galerkin based Krylov subspace solvers like CG, BICG, MINRES, GMRES, etc.

6.2. Deflated IDR(s). For $n = j(s + 1)$, the IDR(s) residuals do not differ in their mathematical characterization from those of ML(s)BiCGSTAB. We cover here again a generalization, where \mathbf{B} can be any matrix commuting with \mathbf{A} (while $\mathbf{B} = \mathbf{I}$ in standard IDR(s)). The Petrov–Galerkin condition (6.2b) is relaxed by replacing the test space $\mathcal{K}_{j;\ell}(\mathbf{A}^H, \tilde{\mathbf{R}}_0)$ by the smaller space $\mathcal{K}_{j;0}(\mathbf{A}^H, \tilde{\mathbf{R}}_0)$:

$$\mathbf{r}_n \in \Omega_j(\mathbf{A})(\mathbf{r}_0 + \mathbf{A}\mathcal{K}_{j;s+\ell}(\mathbf{A}, \mathbf{r}_0)), \quad (6.6a)$$

$$[\Omega_j(\mathbf{A})]^{-1}\mathbf{r}_n \perp \mathbf{B}^H\mathcal{K}_{j;0}(\mathbf{A}^H, \tilde{\mathbf{R}}_0). \quad (6.6b)$$

Consequently, (6.3) persists if (6.4) is replaced by

$$\mathcal{L}_n := \mathcal{L}_{j;\ell} := [\Omega_j(\mathbf{A})]^{-H}\mathcal{K}_{j;0}(\mathbf{A}^H, \tilde{\mathbf{R}}_0) = \mathcal{K}_{j;0}(\mathbf{A}^H, [\Omega_j(\mathbf{A})]^{-H}\tilde{\mathbf{R}}_0), \quad (6.7)$$

but this characterization does not uniquely define iterates and residuals unless $\ell = 0$. Only in the latter case they are unique, and in fact the same as in ML(s)BiCGSTAB. Different IDR(s) algorithms [48, 51] may yield for $\ell \neq 0$ different iterates, even in exact arithmetic; the choice is made unique only by the particular form of the recurrences. If we included the corresponding restrictions here, the method would still fit into our framework. The recipe for a deflated IDR(s) is then the same as for ML(s)BiCGSTAB.

As a summary the spaces $\hat{\mathcal{K}}_n$ and $\hat{\mathcal{L}}_n$ that are used to embed the featured methods of Sections 5 and 6 into our framework are compiled in Table 6.1. More could be added. For block BICG we restrict ourselves here to the classical version [40], where $r = s$.

Method	$\widehat{\mathcal{K}}_n$	$\widehat{\mathcal{L}}_n$	Requirements
Deflated block BiCG	$\mathcal{K}_{j;\ell}(\widehat{\mathbf{A}}, \mathbf{R}_0)$	$\mathcal{K}_{j;\ell}(\widehat{\mathbf{A}}^H, \widetilde{\mathbf{R}}_0)$	$n = js + \ell$
Deflated ML(s)BiCG	$\mathcal{K}_n(\widehat{\mathbf{A}}, \widetilde{\mathbf{r}}_0)$	$\mathcal{K}_{j;\ell}(\widehat{\mathbf{A}}^H, \widetilde{\mathbf{R}}_0)$	$n = js + \ell$
Deflated ML(s)BiCGSTAB	$\mathcal{K}_{js+\ell}(\widehat{\mathbf{A}}, \Omega_j(\widehat{\mathbf{A}})\mathbf{r}_0)$	$\mathcal{K}_{j;\ell}(\widehat{\mathbf{A}}^H, [\Omega_j(\widehat{\mathbf{A}})]^{-H}\widetilde{\mathbf{R}}_0)$	$n = j(s+1) + \ell$
Deflated BiCGSTAB	$\mathcal{K}_{js+\ell}(\widehat{\mathbf{A}}, \Omega_j(\widehat{\mathbf{A}})\mathbf{r}_0)$	$\mathcal{K}_{j;\ell}(\widehat{\mathbf{A}}^H, [\Omega_j(\widehat{\mathbf{A}})]^{-H}\widetilde{\mathbf{r}}_0)$	$n = 2j + \ell$
Deflated IDR(s)	$\mathcal{K}_{js+\ell}(\widehat{\mathbf{A}}, \Omega_j(\widehat{\mathbf{A}})\mathbf{r}_0)$	$\mathcal{K}_{j;0}(\widehat{\mathbf{A}}^H, [\Omega_j(\widehat{\mathbf{A}})]^{-H}\widetilde{\mathbf{R}}_0)$	$n = j(s+1) + \ell$

TABLE 6.1

Featured methods of Sections 5 and 6 with corresponding subspaces $\widehat{\mathcal{K}}_n$ and $\widehat{\mathcal{L}}_n$ in the case $\mathbf{B} = \mathbf{I}$.

7. Invariant deflation spaces. In this section we discuss the spectral properties of the deflated operator $\widehat{\mathbf{A}} := \mathbf{PA}$ assuming invariant deflation spaces. We extend results of the framework for Galerkin based methods from [25] to our new framework on Petrov–Galerkin methods.

While our basic equivalence theorem, Thm. 2.1, made no assumption on a relation between \mathbf{A} and $\widehat{\mathbf{A}}$, we have seen that a natural choice for $\widehat{\mathbf{A}}$ is given by (2.16), $\widehat{\mathbf{A}} := \mathbf{PA} = \mathbf{AQ} = \mathbf{PAQ}$. What can we then say about the spectrum of $\widehat{\mathbf{A}}$? Since the projection \mathbf{P} has the null space $\mathcal{Z} = \mathbf{AU}$, $\widehat{\mathbf{A}} = \mathbf{PA}$ has the null space \mathcal{U} for any choice of this k -dimensional deflation space. So, the spectrum of $\widehat{\mathbf{A}}$ always contains the eigenvalue zero with algebraic and geometric multiplicity k .

If \mathcal{U} is an invariant subspace of \mathbf{A} , then, clearly, the corresponding eigenvalues are moved to zero in the transition to $\widehat{\mathbf{A}}$. But in this case, and in a somewhat dual situation, we can say even more. Let \mathbf{A} have the partitioned Jordan decomposition

$$\mathbf{A} = \mathbf{SJS}^{-1} = \begin{bmatrix} \mathbf{S}_1 & \mathbf{S}_2 \end{bmatrix} \begin{bmatrix} \mathbf{J}_1 & \mathbf{O} \\ \mathbf{O} & \mathbf{J}_2 \end{bmatrix} \begin{bmatrix} \widetilde{\mathbf{S}}_1^H \\ \widetilde{\mathbf{S}}_2^H \end{bmatrix}, \quad (7.1)$$

where $\mathbf{S}_1, \widetilde{\mathbf{S}}_1 \in \mathbb{C}^{N \times k}$, $\mathbf{S}_2, \widetilde{\mathbf{S}}_2 \in \mathbb{C}^{N \times (N-k)}$, $\mathbf{J}_1 \in \mathbb{C}^{k \times k}$, and $\mathbf{J}_2 \in \mathbb{C}^{(N-k) \times (N-k)}$. The spectra of \mathbf{J}_1 and \mathbf{J}_2 need not be disjoint, but in applications of deflation and augmentation methods they most likely are.

Starting from this Jordan form of \mathbf{A} in the following theorem we derive the Jordan form of $\widehat{\mathbf{A}} = \mathbf{PA}$ under the assumption that (1) \mathcal{U} is a right invariant subspace of \mathbf{A} spanned by the columns of \mathbf{S}_1 , or (2) $\mathbf{B}^H \widetilde{\mathcal{U}}$ is a left invariant subspace of $\overline{\mathbf{A}}$ (the complex conjugate of \mathbf{A}) spanned by the columns of $\widetilde{\mathbf{S}}_1$, or (3) both holds.

THEOREM 7.1. *Suppose that the matrix $\mathbf{A} \in \mathbb{C}^{N \times N}$ has a partitioned Jordan decomposition of the form (7.1). Then the following three assertions hold:*

- (1) *Assume $\mathcal{U} = \mathcal{R}(\mathbf{S}_1)$, $\mathbf{U} \in \mathbb{C}^{N \times k}$ is any matrix satisfying $\mathcal{R}(\mathbf{U}) = \mathcal{U}$, and $\widetilde{\mathbf{U}} \in \mathbb{C}^{N \times k}$ is such that $\mathbf{E} := \widetilde{\mathbf{U}}^H \mathbf{BAU}$ is nonsingular. Then*

$$\widehat{\mathbf{A}} := \mathbf{PA} = \begin{bmatrix} \mathbf{U} & \mathbf{PS}_2 \end{bmatrix} \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{J}_2 \end{bmatrix} \begin{bmatrix} \mathbf{U} & \mathbf{PS}_2 \end{bmatrix}^{-1} \quad (7.2)$$

$$\text{with } \begin{bmatrix} \mathbf{U} & \mathbf{PS}_2 \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{B}^H \widetilde{\mathbf{U}} (\mathbf{U}^H \mathbf{B}^H \widetilde{\mathbf{U}})^{-1} & \widetilde{\mathbf{S}}_2 \end{bmatrix}^H. \quad (7.3)$$

This holds, in particular, for $\mathbf{U} = \mathbf{S}_1$.

- (2) *Assume $\mathbf{B}^H \widetilde{\mathcal{U}} = \mathcal{R}(\widetilde{\mathbf{S}}_1)$, $\widetilde{\mathbf{U}} \in \mathbb{C}^{N \times k}$ is any matrix satisfying $\mathcal{R}(\widetilde{\mathbf{U}}) = \widetilde{\mathcal{U}}$, and*

$\mathbf{U} \in \mathbb{C}^{N \times k}$ is such that $\mathbf{E} := \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{A} \mathbf{U}$ is nonsingular. Then

$$\hat{\mathbf{A}} := \mathbf{P} \mathbf{A} = \begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix} \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{J}_2 \end{bmatrix} \begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix}^{-1} \quad (7.4)$$

$$\text{with } \begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{B}^H \tilde{\mathbf{U}} (\mathbf{U}^H \mathbf{B}^H \tilde{\mathbf{U}})^{-1} & \mathbf{Q}^H \tilde{\mathbf{S}}_2 \end{bmatrix}^H. \quad (7.5)$$

This holds, in particular, for $\tilde{\mathbf{U}} = \mathbf{B}^{-H} \tilde{\mathbf{S}}_1$.

(3) Assume $\mathbf{U} = \mathcal{R}(\mathbf{S}_1)$ and $\mathbf{B}^H \tilde{\mathbf{U}} = \mathcal{R}(\tilde{\mathbf{S}}_1)$. Moreover, let $\mathbf{U} \in \mathbb{C}^{N \times k}$ satisfy $\mathcal{R}(\mathbf{U}) = \mathbf{U}$, and let $\tilde{\mathbf{U}} \in \mathbb{C}^{N \times k}$ satisfy $\mathcal{R}(\tilde{\mathbf{U}}) = \tilde{\mathbf{U}}$. Then $\mathbf{E} := \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{A} \mathbf{U}$ is nonsingular and

$$\hat{\mathbf{A}} := \mathbf{P} \mathbf{A} = \begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix} \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{J}_2 \end{bmatrix} \begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix}^{-1} \quad (7.6)$$

$$\text{with } \begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{B}^H \tilde{\mathbf{U}} (\mathbf{U}^H \mathbf{B}^H \tilde{\mathbf{U}})^{-1} & \tilde{\mathbf{S}}_2 \end{bmatrix}^H. \quad (7.7)$$

This holds, e.g., for $\mathbf{U} = \mathbf{S}_1$ and $\tilde{\mathbf{U}} = \mathbf{B}^{-H} \tilde{\mathbf{S}}_1$, in which case $\mathbf{U}^H \mathbf{B}^H \tilde{\mathbf{U}} = \mathbf{I}$.

In all three cases the spectrum $\Lambda(\hat{\mathbf{A}})$ of $\hat{\mathbf{A}}$ is given by $\Lambda(\hat{\mathbf{A}}) = \{0\} \cup \Lambda(\mathbf{J}_2)$.

Proof. (1) By assumption, there exists a nonsingular matrix $\mathbf{R} \in \mathbb{C}^{k \times k}$ with $\mathbf{A} \mathbf{U} = \mathbf{U} \mathbf{R}$. Hence, since $\mathbf{E} := \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{A} \mathbf{U}$ is nonsingular, so is $\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{U}$, and $\mathbf{E}^{-1} = \mathbf{R}^{-1} (\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{U})^{-1}$. Therefore,

$$\mathbf{P} := \mathbf{I} - \mathbf{A} \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} = \mathbf{I} - \mathbf{U} (\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{U})^{-1} \tilde{\mathbf{U}}^H \mathbf{B}. \quad (7.8)$$

Now, recall that $\mathcal{N}(\mathbf{P}) = \mathcal{Z}$ and $\mathcal{R}(\mathbf{P}) = (\mathbf{B}^H \tilde{\mathbf{U}})^\perp$, which translate into

$$\mathbf{P} \mathbf{A} \mathbf{U} = \mathbf{0} \quad \text{and} \quad \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{P} = \mathbf{0},$$

respectively. From (7.8) and the first equation we get

$$\mathbf{P} \mathbf{A} (\mathbf{P} \mathbf{S}_2) = \mathbf{P} \mathbf{A} \left(\mathbf{I} - \mathbf{U} (\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{U})^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \right) \mathbf{S}_2 = \mathbf{P} \mathbf{A} \mathbf{S}_2 = (\mathbf{P} \mathbf{S}_2) \mathbf{J}_2,$$

which along with $\mathbf{P} \mathbf{A} \mathbf{U} = \mathbf{0}$ will yield (7.2) once we will have proven that $\begin{bmatrix} \mathbf{U} & \mathbf{P} \mathbf{S}_2 \end{bmatrix}$ is nonsingular.

Next, from $\tilde{\mathbf{S}}_2^H \mathbf{S}_1 = \mathbf{0}$ we see that $\tilde{\mathbf{S}}_2^H \mathbf{U} = \mathbf{0}$ and thus, by (7.8), $\tilde{\mathbf{S}}_2^H \mathbf{P} = \tilde{\mathbf{S}}_2^H$. Collecting $\tilde{\mathbf{S}}_2^H \mathbf{U} = \mathbf{0}$, $\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{P} = \mathbf{0}$, and $\tilde{\mathbf{S}}_2^H \mathbf{P} \mathbf{S}_2 = \tilde{\mathbf{S}}_2^H \mathbf{S}_2 = \mathbf{I}$, we obtain altogether

$$\begin{bmatrix} (\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{U})^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \\ \tilde{\mathbf{S}}_2^H \end{bmatrix} \begin{bmatrix} \mathbf{U} & \mathbf{P} \mathbf{S}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix},$$

which proves the nonsingularity and (7.3).

(2) From $\tilde{\mathbf{S}}_1^H \mathbf{S}_2 = \mathbf{0}$ and $\mathbf{B}^H \tilde{\mathbf{U}} = \mathcal{R}(\tilde{\mathbf{S}}_1)$ it follows that $\tilde{\mathbf{U}}^H \mathbf{B} \mathbf{S}_2 = \mathbf{0}$. Using the definition of \mathbf{P} and the invariance of \mathbf{S}_2 we see that

$$\mathbf{P} \mathbf{A} \mathbf{S}_2 = \left(\mathbf{I} - \mathbf{A} \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \right) \mathbf{A} \mathbf{S}_2 = \mathbf{S}_2 \mathbf{J}_2 - \mathbf{A} \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \mathbf{S}_2 \mathbf{J}_2 = \mathbf{S}_2 \mathbf{J}_2,$$

$$\mathbf{P} \mathbf{A} \mathbf{U} = \left(\mathbf{I} - \mathbf{A} \mathbf{U} \mathbf{E}^{-1} \tilde{\mathbf{U}}^H \mathbf{B} \right) \mathbf{A} \mathbf{U} = \mathbf{A} \mathbf{U} - \mathbf{A} \mathbf{U} \mathbf{E}^{-1} \mathbf{E} = \mathbf{0},$$

which yields (7.4) if $\begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix}$ is indeed nonsingular.

Indeed, since $\mathbf{B}^H\tilde{\mathcal{U}} = \mathcal{R}(\tilde{\mathbf{S}}_1)$, there exists a nonsingular $\tilde{\mathbf{R}} \in \mathbb{C}^{k \times k}$ such that $\tilde{\mathbf{U}}^H\mathbf{B}\mathbf{A} = \tilde{\mathbf{R}}\tilde{\mathbf{U}}^H\mathbf{B}$. And since $\mathbf{E} = \tilde{\mathbf{U}}^H\mathbf{B}\mathbf{A}\mathbf{U} = \tilde{\mathbf{R}}\tilde{\mathbf{U}}^H\mathbf{B}\mathbf{U}$ is nonsingular, so is $\tilde{\mathbf{U}}^H\mathbf{B}\mathbf{U}$. Moreover, from $\mathcal{N}(\mathbf{Q}) = \mathcal{U}$ we have $\mathbf{Q}\mathbf{U} = \mathbf{0}$, so that

$$\begin{bmatrix} (\tilde{\mathbf{U}}^H\mathbf{B}\mathbf{U})^{-1}\tilde{\mathbf{U}}^H\mathbf{B} \\ \tilde{\mathbf{S}}_2^H\mathbf{Q} \end{bmatrix} \begin{bmatrix} \mathbf{U} & \mathbf{S}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{S}}_2^H\mathbf{Q}\mathbf{S}_2 \end{bmatrix}.$$

Here, inserting \mathbf{Q} and noting again that $\mathbf{A}\mathbf{S}_2 = \mathbf{S}_2\mathbf{J}_2$ and $\tilde{\mathbf{U}}^H\mathbf{B}\mathbf{S}_2 = \mathbf{0}$, we get

$$\tilde{\mathbf{S}}_2^H\mathbf{Q}\mathbf{S}_2 = \tilde{\mathbf{S}}_2^H \left(\mathbf{I} - \mathbf{U}\mathbf{E}^{-1}\tilde{\mathbf{U}}^H\mathbf{B}\mathbf{A} \right) \mathbf{S}_2 = \tilde{\mathbf{S}}_2^H\mathbf{S}_2 - \tilde{\mathbf{S}}_2^H\mathbf{U}\mathbf{E}^{-1}\tilde{\mathbf{U}}^H\mathbf{B}\mathbf{S}_2\mathbf{J}_2 = \tilde{\mathbf{S}}_2^H\mathbf{S}_2 = \mathbf{I},$$

which establishes (7.5).

(3) From $\mathcal{U} = \mathcal{R}(\mathbf{S}_1)$ and $\mathbf{B}^H\tilde{\mathcal{U}} = \mathcal{R}(\tilde{\mathbf{S}}_1)$ we can conclude that for some nonsingular $k \times k$ matrices \mathbf{R} , \mathbf{N} , and $\tilde{\mathbf{N}}$ we have

$$\mathbf{E} := \tilde{\mathbf{U}}^H\mathbf{B}\mathbf{A}\mathbf{U} = \tilde{\mathbf{U}}^H\mathbf{B}\mathbf{U}\mathbf{R} = \tilde{\mathbf{N}}^H\tilde{\mathbf{S}}_1^H\mathbf{S}_1\mathbf{N}\mathbf{R} = \tilde{\mathbf{N}}^H\mathbf{N}\mathbf{R}.$$

Therefore, \mathbf{E} is nonsingular as needed. The seeming discrepancy between the formulas (7.2)–(7.7) is resolved by noting that now $\mathbf{P}\mathbf{S}_2 = \mathbf{S}_2$ and $\mathbf{Q}^H\mathbf{S}_2 = \tilde{\mathbf{S}}_2$. \square

There are ways to reformulate the assumptions and conclusions of Theorem 7.1. For example, the assumption $\mathcal{U} = \mathcal{R}(\mathbf{S}_1)$ is equivalent to $\mathcal{U}^\perp = \mathcal{R}(\tilde{\mathbf{S}}_2)$, and the assumption $\mathbf{B}^H\tilde{\mathcal{U}} = \mathcal{R}(\tilde{\mathbf{S}}_1)$ is equivalent to $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp = \mathcal{R}(\mathbf{S}_2)$.

In particular, assertions (2) and (3) of Theorem 7.1 imply the following.

COROLLARY 7.2. *Let $\hat{\mathbf{A}} := \mathbf{P}\mathbf{A}$ and assume that $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$ is \mathbf{A} -invariant. Then \mathbf{A} and $\hat{\mathbf{A}}$ are identical when restricted to $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$:*

$$\hat{\mathbf{A}}|_{(\mathbf{B}^H\tilde{\mathcal{U}})^\perp} = \mathbf{A}|_{(\mathbf{B}^H\tilde{\mathcal{U}})^\perp}. \quad (7.9)$$

Moreover, if also \mathcal{U} is \mathbf{A} -invariant, then

$$\mathcal{U} \oplus (\mathbf{B}^H\tilde{\mathcal{U}})^\perp = \mathbb{C}^N \quad (7.10)$$

is the direct decomposition of \mathbb{C}^N in the nullspace and range of \mathbf{P} .

Proof. The result is a consequence of Theorem 7.1. But it is easy to prove it directly. Assume the $N - k$ columns of \mathbf{W} form a basis of $(\mathbf{B}^H\tilde{\mathcal{U}})^\perp$. Due to the \mathbf{A} -invariance there is a square matrix $\hat{\mathbf{R}}$ of order $N - k$ such that $\mathbf{A}\mathbf{W} = \mathbf{W}\hat{\mathbf{R}}$. Note that $\mathbf{P}\mathbf{W} = \mathbf{W}$ since \mathbf{P} projects on the range of \mathbf{W} . Consequently,

$$\hat{\mathbf{A}}\mathbf{W} = \mathbf{P}\mathbf{A}\mathbf{W} = \mathbf{P}\mathbf{W}\hat{\mathbf{R}} = \mathbf{W}\hat{\mathbf{R}} = \mathbf{A}\mathbf{W},$$

which proves (7.9).

If also \mathcal{U} is \mathbf{A} -invariant, then $\mathcal{U} = \mathcal{Z} = \mathcal{N}(\mathbf{P})$. \square

Assertions (1) and (2) of Theorem 7.1 generalize Theorem 3.3 of Gaul et al. [25]. As has been noted there, special cases of those results have appeared in the literature before: for symmetric and positive definite matrices \mathbf{A} and $\mathbf{B} = \mathbf{I}$ in Frank and Vuik [19] and in Nabben and Vuik [36, 37], and for nonsymmetric \mathbf{A} and $\mathbf{B} = \mathbf{I}$ in Erlangga and Nabben [15, 16] and Yeung, Tang and Vuik [55].

The situation of Corollary 7.2 has been aimed at, at least approximately, with the oblique projections \mathbf{P} and the corresponding deflated operator $\hat{\mathbf{A}} := \mathbf{P}\mathbf{A}\mathbf{P}$ used in [29].

8. Conclusions. In this paper we introduced a framework for augmented and deflated Krylov subspace methods based on a Petrov–Galerkin condition. This class of methods includes first of all the biconjugate gradient (BiCG) method, but also corresponding block methods and Lanczos-type product methods (LPTMs), including some of today’s most competitive methods, such as BiCGSTAB and IDR(s). We also cover the biconjugate residual (BiCR) method, which is the standard example of a generalized BiCG (GENBiCG) method.

Our basic result is that augmented and deflated variants of all these methods can be realized by just applying the basic, non-deflated method first to a deflated (or, projected) linear system, whose matrix is singular, followed by a correction step that must be applied to the resulting approximate solution. This is an implicit way to realize augmentation and deflation; it can be mathematically characterized by the conditions (2.13) and the affine transformation (2.14). For GENBiCG this implicit approach leads immediately to what we list as Algorithm 1 (DEFLGENBiCG). Deflated standard BiCG is covered as the special case $\mathbf{B} = \mathbf{I}$. Amazingly, any deflated and augmented LTPM can be implemented in the same way as deflated BiCG: all we need is to replace `GenBiCG` on line 3 of Algorithm 1 by the name of the chosen LTPM code. We also discuss the case where the BiCG or the GENBiCG method is applied to a pair of dual linear systems, where the first has as matrix \mathbf{A} and the other \mathbf{A}^H .

Further results concern the spectrum of the deflated matrix under the assumption of invariant deflation subspaces. The efficiency of deflation and augmentation methods in practice has been documented widely in the literature. Many of the references we give contain numerical examples of real-world problems.

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