# AN ALGORITHM FOR THE SOLUTION OF BORDERED ABD LINEAR SYSTEMS ARISING FROM BOUNDARY VALUE PROBLEMS 

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#### Abstract

We consider linear systems with coefficient matrices of Bordered ABD structure. They arise in the discretization of BVPs for ordinary and partial differential equations with non-separated boundary conditions. We report on tests (and comparisons with the well-known code COLROW) of the Fortran 90 cyclic reduction algorithm BABDCR, inserted in a modified version of the BVP code MIRKDC. Also, a distributed parallel version of BABDCR is implemented and tested for possible use replacing the BABD code RSCALE in the parallel version of MIRKDC.


## 1 INTRODUCTION

Almost Block Diagonal (ABD) and Bordered ABD (BABD) [1] linear systems arise in discretizing Boundary Value Problems (BVPs) with, respectively, separated and non-separated boundary conditions, for both ordinary and partial differential equations. The coefficient matrices associated with ABD linear systems are characterized as follows: the nonzero elements are grouped in block rows, there is no intersection between the nonzero columns of two nonconsecutive block rows; and, the main diagonal entries always lie inside the nonzero blocks. BABD matrices must also satisfy: the first (or the last) block row has an additional block in the right-upper (left-lower) corner whose columns only intersect the nonzero columns of the last (first) block row. In Figs. 1 and 2, we show the ABD and BABD structures arising most frequently in BVP solvers. All the nonzero blocks in the ABD and BABD structures respectively are considered dense.

$$
\left(\begin{array}{ccccc}
B_{\text {top }} & & & & \\
S_{0} & R_{1} & & & \\
& S_{1} & R_{2} & & \\
& & \ddots & \ddots & \\
& & & S_{N-1} & R_{N} \\
& & & & B_{b o t}
\end{array}\right)\left(\begin{array}{c}
x_{0} \\
x_{1} \\
\vdots \\
x_{N-1} \\
x_{N}
\end{array}\right)=\left(\begin{array}{c}
d_{a} \\
f_{1} \\
f_{2} \\
\vdots \\
f_{N} \\
d_{b}
\end{array}\right)
$$

Figure 1: ABD linear system: $S_{i}, R_{i} \in \mathbb{R}^{m \times m}, B_{t o p} \in \mathbb{R}^{m_{0} \times m}, B_{b o t} \in \mathbb{R}^{\left(m-m_{0}\right) \times m}, f_{i}, x_{i} \in \mathbb{R}^{m}, d_{a} \in \mathbb{R}^{m_{0}}$, $d_{b} \in \mathbb{R}^{m-m_{0}}$.

$$
\left(\begin{array}{ccccc}
B_{a} & & & & B_{b} \\
S_{0} & R_{1} & & & \\
& S_{1} & R_{2} & & \\
& & \ddots & \ddots & \\
& & & S_{N-1} & R_{N}
\end{array}\right)\left(\begin{array}{c}
x_{0} \\
x_{1} \\
\vdots \\
x_{N-1} \\
x_{N}
\end{array}\right)=\left(\begin{array}{c}
d \\
f_{1} \\
f_{2} \\
\vdots \\
f_{N}
\end{array}\right)
$$

Figure 2: BABD linear system: $S_{i}, R_{i}, B_{a}, B_{b} \in \mathbb{R}^{m \times m}, x_{i}, f_{i}, d \in \mathbb{R}^{m}$.

### 1.1 Solvers for ABD systems

For a historical view of solving ABD systems see [1, 11]. The first ABD code was SOLVEBLOK [8]; as for standard LU factorization applied to banded systems, it uses Gaussian elimination with partial pivoting to ensure stability and so requires fill-in. Varah's alternate row and column stable elimination [18] exploits the structure of the ABD matrices to avoid this fillin. The packages COLROW and ARCECO in [9] are based on a modified version of Varah's procedure. Numerical experiments reported in [9] demonstrate the effectiveness of COLROW and ARCECO, and their superiority over SOLVEBLOK on systems arising from BVPs. Modifications have been proposed to these packages to deal with more specific structures of the coefficient matrix (see [1] and the references therein).

### 1.2 ABD and BABD solvers in BVODE packages

Most modern nonlinear BVP packages employ ABD packages. The BVP code COLSYS [4] uses SOLVEBLOK to solve ABD linear systems arising from using orthogonal spline collocation (OSC) at Gauss points with B-spline bases. COLNEW [5] uses a modified version of SOLVEBLOK to solve ABD linear systems arising from using OSC at Gauss points with monomial spline bases. The Mono Implicit Runge Kutta (MIRK) code with defect control MIRKDC [10] uses COLROW as a solver for ABD systems. Modified versions of COLROW are used in TWPBVP [7], a deferred correction code, in COLMOD [17], a modified version of COLNEW, and in $A C D C$ [6], which uses automatic continuation and OSC at Lobatto points to solve singularly perturbed BVODEs. The code PMIRKDC, a parallel version of MIRKDC, uses the BABD package RSCALE which has a shared memory parallel implementation.

We propose $B A B D C R$ as an alternative to COLROW for the solution of BABD systems, and to RSCALE in a parallel environment. In Section 3, we discuss a modified version of MIRKDC which is effective for solving BVPs with non-separated boundary conditions. Numerical tests comparing BABDCR with COLROW and RSCALE are presented in Section 4, In Section 5, we present numerical results from a distributed memory implementation of $B A B D C R$.

## 2 THE BABDCR PACKAGE

$B A B D C R$ [3, 2] solves BABD systems as in Fig. 2, The algorithm cyclically reduces the BABD matrix to derive systems of lower dimension with the same BABD structure. Suppose that the matrix in Fig. 2 is nonsingular; we reduce each pair of block row equations, for $i=$ $2 j-1, j=1,2, \ldots,\lfloor N / 2\rfloor$,

$$
\left(\begin{array}{ccc}
S_{i-1} & R_{i} &  \tag{1}\\
& S_{i} & R_{i+1}
\end{array}\right)\left(\begin{array}{c}
x_{i-1} \\
x_{i} \\
x_{i+1}
\end{array}\right)=\binom{f_{i}}{f_{i+1}}
$$

into one block row equation

$$
\begin{equation*}
S_{i-1}^{\prime} x_{i-1}+R_{i+1}^{\prime} x_{i+1}=f_{i+1}^{\prime} \tag{2}
\end{equation*}
$$

involving only the unknowns $x_{i-1}$ and $x_{i+1}$. Since the columns overlapped by the $2 m \times m$ matrix $\binom{R_{i}}{S_{i}}$ are linearly independent, we use a LU factorization with partial pivoting

$$
P_{i}\binom{R_{i}}{S_{i}}=\binom{L_{i}}{T_{i}} U_{i}=\left(\begin{array}{cc}
L_{i} &  \tag{3}\\
T_{i} & I
\end{array}\right)\binom{U_{i}}{0}
$$

where we premultiply (1) by the permutation matrix $P_{i}$ and the inverse of the lower triangular matrix in (3) to obtain

$$
\begin{align*}
\left(\begin{array}{cc}
L_{i} & \\
T_{i} & I
\end{array}\right)^{-1} P_{i}\left(\begin{array}{ccc}
S_{i-1} & R_{i} & \\
& S_{i} & R_{i+1}
\end{array}\right) & \equiv\left(\begin{array}{ccc}
\tilde{S}_{i-1} & U_{i} & \tilde{R}_{i+1} \\
S_{i-1}^{\prime} & R_{i+1}^{\prime}
\end{array}\right), \\
\left(\begin{array}{cc}
L_{i} & \\
T_{i} & I
\end{array}\right)^{-1} P_{i}\binom{f_{i}}{f_{i+1}} & \equiv\binom{\tilde{f}_{i}}{f_{i+1}^{\prime}}, \tag{4}
\end{align*}
$$

where $S_{i-1}^{\prime}, R_{i+1}^{\prime}$ and $f_{i+1}^{\prime}$ are the blocks of the reduced equation (2). After $k$ steps of reduction, the coefficient matrix obtained is of size $\lceil N / s\rceil+1$ where $s=2^{k}$, and can be further reduced
by combining two successive block row equations (for each $i=(2 j-1) s+1$, with $j=$ $1,2, \ldots,\lfloor\lceil N / s\rceil / 2\rfloor)$

$$
\left(\begin{array}{ccc}
S_{i-s}^{(k)} & R_{i}^{(k)} & \\
& S_{i}^{(k)} & R_{i+s}^{(k)}
\end{array}\right)\left(\begin{array}{c}
x_{i-s} \\
x_{i} \\
x_{i+s}
\end{array}\right)=\binom{f_{i}^{(k)}}{f_{i+s}^{(k)}}
$$

to give the block row equation $S_{i-s}^{(k+1)} x_{i-s}+R_{i+s}^{(k+1)} x_{i+s}=f_{i+s}^{(k+1)}$. The reduction ends after $p=\left\lceil\log _{2} N\right\rceil$ steps with the $2 \times 2$ block linear system

$$
\left(\begin{array}{cc}
B_{a} & B_{b}  \tag{5}\\
S_{0}^{(p)} & R_{N}^{(p)}
\end{array}\right)\binom{x_{0}}{x_{N}}=\binom{d}{f_{N}^{(p)}} .
$$

The algorithm then proceeds by solving (5) and using a back-substitution phase to compute the unknowns $x_{1}, \ldots, x_{N-1}$.

The null blocks in equation (4) permit us to reduce the memory requirement and the computational cost. In the reduction, after $k+1$ steps, we save the matrices $S_{i-s}^{(k+1)}$ and $R_{i+s}^{(k+1)}$ in place of $S_{i-s}^{(k)}$ and $R_{i+s}^{(k)}$, the product $T_{i} L_{i}^{-1}$ in place of $S_{i}^{(k)}$ and the vector $f_{i+s}^{(k+1)}$ in place of $f_{i+s}^{(k)}$, respectively. In the back-substitution phase, we save the first $m$ elements of $P_{i}^{(k)}\binom{f_{i}^{(k)}}{f_{i+s}^{(k)}}$ in place of $f_{i}^{(k)}$. The additional memory required has size $m \times m$ for each of the $N-1$ reductions corresponding to the first $m$ rows of $P_{i}^{(k)}\binom{S_{i-s}^{(k)}}{R_{i+s}^{(k)}}$. To leading order in powers of $m$ and $N$ the computational cost of the factorization is $\frac{14}{3} m^{3} N$ flops and of the back-substitution is $6 m^{2} N$.

## 3 BVPS AND THE MIRKDC/PMIRKDC CODES

MIRKDC [10] solves BVPs

$$
\begin{equation*}
\mathbf{y}^{\prime}=\mathbf{f}(t, \mathbf{y}(t)), \quad t \in[a, b] \tag{6}
\end{equation*}
$$

where $\mathbf{y} \in \mathbb{R}^{m}$ and $\mathrm{f}: \mathbb{R} \times \mathbb{R}^{m} \rightarrow \mathbb{R}^{m}$, with separated BCs

$$
\begin{equation*}
\mathbf{g}(\mathbf{y}(a), \mathbf{y}(b))=\binom{\mathbf{g}_{0}(\mathbf{y}(a))}{\mathbf{g}_{1}(\mathbf{y}(b))}=0 . \tag{7}
\end{equation*}
$$

It uses Mono-Implicit Runge Kutta (MIRK) formulas to discretize (6) on a subdivision $\left\{t_{i}\right\}_{i=0}^{N}$ of $[a, b]$. A continuous solution approximation is obtained by means of a Continuous MIRK (CMIRK) scheme, and is used to provide defect control and mesh selection capabilities. The MIRK scheme applied to the BVP system (6)-(7) on $N$ subintervals, yields the nonlinear system

$$
\boldsymbol{\Phi}(\mathbf{Y})=\left(\boldsymbol{\Phi}_{0}(\mathbf{Y})^{T}, \ldots, \boldsymbol{\Phi}_{N}(\mathbf{Y})^{T}\right)^{T}=0, \quad \text { where } \boldsymbol{\Phi}_{i}: \mathbb{R}^{m(N+1)} \longrightarrow \mathbb{R}^{m}
$$

and $\mathbf{Y}=\left(\mathbf{y}_{0}^{T}, \ldots, \mathbf{y}_{N}^{T}\right)^{T}, \mathbf{y}_{j} \in \mathbb{R}^{m}$. This is solved using a modified version of the Newton iteration described by $\mathbf{Y}^{(q+1)}=\mathbf{Y}^{(q)}+\Delta \mathbf{Y}^{(q)}$, for $q=0,1, \ldots$, where

$$
\begin{equation*}
\left[\frac{\partial \boldsymbol{\Phi}\left(\mathbf{Y}^{(q)}\right)}{\partial \mathbf{Y}}\right] \Delta \mathbf{Y}^{(q)}=-\boldsymbol{\Phi}\left(\mathbf{Y}^{(q)}\right) \tag{8}
\end{equation*}
$$

given $Y^{(0)}$. For separated boundary conditions (7), the ABD linear system arising in (8) is as shown in Fig. 1] with

$$
S_{i}=-I-h_{i} K_{i, i}, \quad R_{i}=I-h_{i} K_{i+1, i},
$$

where the dense block $K_{i, j}$ depends on $\mathbf{f}$ and on the Runge-Kutta formulas chosen.
MIRKDC uses COLROW to solve systems of the form (8). The computational cost of this ABD solver, to leading order in $m$ and $m_{0}$ (the number of boundary conditions at $x=a$ ), is $\left(\frac{5}{3} m^{3}+m m_{0}^{2}\right) N$ flops for the factorization and $4 m^{2} N$ for the solution. This means that its computational cost varies from approximately $\frac{5}{3} m^{3} N$ and $\frac{8}{3} m^{3} N$ (when $m_{0} \approx 0$ and $m_{0} \approx m$, respectively), and is $\frac{23}{12} m^{3} N$ in the most commonly occurring case where $m_{0} \approx \frac{m}{2}$. COLROW does not require fill-in vectors.

Since linear algebra is the most expensive (in term of execution times) part of MIRKDC and since COLROW is a sequential algorithm, the parallel version (written for a shared memory computer) PMIRKDC [14] uses the parallel linear system solver RSCALE. This package solves BABD systems and has a computational cost of approximately $\frac{20}{3} m^{3} N$ and $6 m^{2} N$ for the factorization and the solution, respectively. Moreover, it requires fill-in vectors of length $m^{2}(N+1)$.

Our sequential variant, MIRKDC_NS, solves BVPs (6) with non-separated boundary conditions

$$
\begin{equation*}
\mathbf{g}(\mathbf{y}(a), \mathbf{y}(b))=0 \tag{9}
\end{equation*}
$$

We stress that (6), (9) may also be solved directly by MIRKDC by recasting the problem in the form

$$
\begin{equation*}
\mathbf{y}^{\prime}=\mathbf{f}(t, \mathbf{y}(t)), \quad \mathbf{z}^{\prime}=0, \quad t \in[a, b], \tag{10}
\end{equation*}
$$

with separated boundary conditions

$$
\begin{equation*}
\mathbf{y}(a)-\mathbf{z}(a)=0, \quad \mathbf{g}(\mathbf{z}(b), \mathbf{y}(b))=0 . \tag{11}
\end{equation*}
$$

If the function $\mathbf{g}$ in (9) comprises $k$ nonseparated and $m-k$ separated boundary conditions with $m_{0}$ boundary conditions at $x=a$, then the size of the equivalent BVP is $(m+k)$ with $\left(m_{0}+k\right)$ boundary conditions at $x=a$.

MIRKDC_NS is equivalent to MIRKDC. The only essential difference is that the linear systems (8) have a BABD structure as in Fig. 22 and are solved using BABDCR. We made the following further modifications in MIRKDC:

- The permutation array of length $m(N+1)$ becomes one of length $2 m N$;
- The fill-in described in Section 2, adds $m^{2}(N-1)$ locations in the array containing blocks $S_{i}, R_{i}$ of the current BABD Jacobian in (8);
- The arrays containing blocks $B_{a}, B_{b}$ of the Jacobian in (8), in Fig. 2, are of dimension $m \times m$ instead of $m_{0} \times m,\left(m-m_{0}\right) \times m$, respectively;
- In $B A B D C R$ the right hand side is overwritten by the solution (COLROW does not overwrite the solution). Therefore, before calling $B A B D C R$, the right hand side must already occupy the locations where the solution will be placed.


## 4 COMPARING THE LINEAR SYSTEM SOLVERS

We compare BABDCR with COLROW and RSCALE on the ABD and BABD linear systems generated by the codes MIRKDC and MIRKDC_NS respectively. In our experiments, we use a fourth order method, based on the optimal 4-th order, 3-stage MIRK scheme, see [10].

Consider the ABD linear systems generated by MIRKDC applied to a linear BVP

$$
\begin{equation*}
\mathbf{y}^{\prime}=M \mathbf{y}(t), \quad M \in \mathbb{R}^{m \times m} \tag{12}
\end{equation*}
$$

with linear boundary conditions

$$
B_{t o p} \mathbf{y}(a)=\mathbf{d}_{a} \in \mathbb{R}^{m_{0}}, \quad B_{b o t} \mathbf{y}(b)=\mathbf{d}_{b} \in \mathbb{R}^{m-m_{0}}
$$

First, we fix $m=20$ and $m_{0}=10$ then $m=40$ and $m_{0}=20 . B_{\text {top }}, B_{\text {bot }}$, both of full rank $m_{0}=m-m_{0}$, and $M$ are randomly generated full matrices. The matrix $M$ is obtained by computing $M=Q \Lambda Q^{T}$ where $Q$ is an orthogonal matrix arising from the QR factorization of a random matrix and $\Lambda$ is a diagonal matrix with $m / 2$ positive and $m / 2$ negative values of moderate size such that the resulting BVP is well conditioned. BABDCR and RSCALE use

$$
B_{a}=\binom{B_{\text {top }}}{0}, B_{b}=\binom{0}{B_{b o t}} \in \mathbb{R}^{m \times m}, \quad \mathbf{d}=\binom{\mathbf{d}_{a}}{\mathbf{d}_{b}} \in \mathbb{R}^{m}
$$

to obtain a BABD system as in Fig. 2.
Overall timings and errors, given in Tables 1 and 2, show that COLROW is more than twice as fast as $B A B D C R$ and more than four times as fast as RSCALE. The errors for COLROW and $B A B D C R$ are similar, but $R S C A L E$ is less accurate. These computational costs are close to the predictions of theory. Since $m_{0}=m / 2$, COLROW should be approximately 2.4 and 3.5 times faster then $B A B D C R$ and $R S C A L E$, respectively.

|  | time |  |  | error |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ | $\mathrm{~N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ |
| BABDCR | $3.71 \mathrm{e}-02$ | $7.12 \mathrm{e}-02$ | 0.152 | $1.65 \mathrm{e}-13$ | $2.88 \mathrm{e}-13$ | $3.46 \mathrm{e}-13$ |
| COLROW | $1.46 \mathrm{e}-02$ | $2.83 \mathrm{e}-02$ | $6.34 \mathrm{e}-02$ | $1.55 \mathrm{e}-13$ | $2.05 \mathrm{e}-13$ | $7.08 \mathrm{e}-13$ |
| RSCALE | $6.83 \mathrm{e}-02$ | 0.136 | 0.274 | $2.54 \mathrm{e}-12$ | $6.02 \mathrm{e}-12$ | $3.01 \mathrm{e}-11$ |

Table 1: ABD systems generated by MIRKDC applied to a linear BVP of size $m=20$.

|  | time |  |  | error |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ | $\mathrm{~N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ |
| BABDCR | 0.213 | 0.461 | 0.924 | $6.51 \mathrm{e}-13$ | $9.20 \mathrm{e}-13$ | $1.64 \mathrm{e}-12$ |
| COLROW | $8.69 \mathrm{e}-02$ | 0.201 | 0.402 | $7.02 \mathrm{e}-13$ | $5.36 \mathrm{e}-13$ | $8.07 \mathrm{e}-13$ |
| RSCALE | 0.481 | 0.972 | 1.950 | $1.66 \mathrm{e}-11$ | $3.20 \mathrm{e}-11$ | $2.74 \mathrm{e}-10$ |

Table 2: ABD systems generated by MIRKDC applied to a linear BVP of size $m=40$.

For BABD linear systems, we apply MIRKDC_NS to a linear BVP (12) with non-separated boundary conditions

$$
B_{a} \mathbf{y}(a)+B_{b} \mathbf{y}(b)=\mathbf{d} \in \mathbb{R}^{m} .
$$

For $m=20$ we investigate two cases:
(a) $M$ is a well-conditioned matrix with eigenvalues $-102,-10,-7,-4,-3,-2.5,-1.3,-1,-0.5$, $-0.4,0.2,0.3,1,1,2,2.5,3,4,11,25 ;$
(b) $M$ is an ill-conditioned matrix with eigenvalues $-9,-3.5,-3,-2,-2,-1.5,-1.5,-1.25,-0.5$, $-1 \mathrm{e}-08,0.25,0.5,0.5,1,3,4,5,7,8,1 \mathrm{e}+08$.

For $m=40$ we just consider a well-conditioned case with $M$ having eigenvalues -102, -90, $-75,-53,-51,-42.5,-38,-30,-27,-14,-13,-12.5,-9.3,-8,-5.5,-4,-2.5,-1.3,-1,-0.5,0.2,0.3$, $1,1,2,2.5,3,4,11,15,20.5,25,28,33,40,45,46,50.5,54,57$

To use COLROW, we convert the BABD system to an ABD linear system with blocks of double the size, see Fig. 3, In the case of $k$ nonseparated boundary conditions and $m_{0}=$ $\lfloor(m-k) / 2\rfloor$ separated boundary conditions at $x=a$, we observe that $B A B D C R$ is faster than COLROW when $k>\lceil m / 3\rceil$. Since, in our example, the number of nonseparated boundary conditions is $k=m$, the computational cost of COLROW is approximately $\frac{46}{3} m^{3} N$ for the factorization and $16 m^{2} N$ for the solution. So, theoretically $B A B D C R$ is more than three times as fast as COLROW.

Figure 3: ABD system of doubled size (corresponding to the BABD system in Fig. 2). $\mathbf{z}_{i}, i=0, \ldots, N$ are the new unknowns, $\mathbf{z}_{N}=\mathbf{z}_{N-1}=\ldots=\mathbf{z}_{0}=\mathbf{x}_{0}$.

In Tables 3.4 we compare the errors and timings of the three linear solvers. From the results in Table 3, for the cases (a) and (b) BABDCR is approximately 3 times as fast as COLROW and more than 1.5 times as fast as RSCALE. Timings associated with COLROW include converting the linear system from BABD to ABD structure in Fig. 3 (which is between $10 \%$ and $15 \%$ of the total time taken by COLROW ). The errors associated with BABDCR and COLROW are similar, and RSCALE is the least accurate algorithm. The errors of the three methods for case (b), are given in Table 4. These errors are large, because the BVP is ill-conditioned. Observe that BABDCR and COLROW are still significantly more accurate than RSCALE. Table 5 for $m=40$ in comparison with Table 3 for $m=20$ shows that the relative costs of the three algorithms increase consistently cubically with $m$.

|  | $\mathrm{N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ |
| :---: | :---: | :---: | :---: |
| BABDCR | $3.61 \mathrm{e}-02$ | $7.03 \mathrm{e}-02$ | 0.151 |
| COLROW | 0.102 | 0.224 | 0.464 |
| RSCALE | $6.83 \mathrm{e}-02$ | 0.136 | 0.287 |

Table 3: Timings for the solution of BABD systems generated by MIRKDC_NS applied to a linear BVP with $m=20$. (For COLROW the timings without the conversion phase are $0.0859,0.190,0.394$ for $\mathrm{N}=256,512,1024$ respectively.)

|  |  | case (a) |  |  | case (b) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ | $\mathrm{~N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ |
| BABDCR | $7.62 \mathrm{e}-13$ | $1.22 \mathrm{e}-12$ | $1.19 \mathrm{e}-12$ | $6.28 \mathrm{e}-04$ | $2.22 \mathrm{e}-04$ | $8.00 \mathrm{e}-05$ |
| COLROW | $7.53 \mathrm{e}-13$ | $4.10 \mathrm{e}-13$ | $1.25 \mathrm{e}-12$ | $2.80 \mathrm{e}-04$ | $2.16 \mathrm{e}-04$ | $9.25 \mathrm{e}-05$ |
| RSCALE | $5.17 \mathrm{e}-12$ | $2.90 \mathrm{e}-11$ | $6.02 \mathrm{e}-11$ | $1.90 \mathrm{e}-02$ | $8.55 \mathrm{e}-03$ | $1.08 \mathrm{e}-02$ |

Table 4: Errors for the solution of BABD systems generated by MIRKDC_NS with $m=20$.

|  | $\mathrm{N}=256$ | $\mathrm{~N}=512$ | $\mathrm{~N}=1024$ |
| :---: | :---: | :---: | :---: |
| BABDCR | 0.211 | 0.449 | 0.924 |
| COLROW | 0.740 | 1.481 | 2.971 |
| RSCALE | 0.481 | 0.967 | 1.949 |

Table 5: Timings for the solution of BABD systems generated by MIRKDC_NS applied to a linear BVP with $m=40$. (For COLROW the timings without the conversion phase are $0.684,1.370,2.746$ for $\mathrm{N}=256,512,1024$ respectively.)

To emphasize the advantages of $B A B D C R$, Tables 4-4 give statistics for one call to MIRKDC_NS applied to the BVP (6), (9) and to MIRKDC applied to the equivalent BVP of double the size (10) with separated boundary conditions (11). The columns represent the size, $N$, of the computed mesh (initially set equal to 256) and the number (with the timings) of the factorizations performed and linear system solutions on that mesh. Then, in the last two rows, we give the total time for the linear algebra calls and for the remaining operations.

Both codes were applied to the problem with $M$ having eigenvalues as in case (a) using the MIRK/CMIRK scheme of order 4 [10]. From Tables 4 and 4, starting from the same mesh, the same number of factorizations and linear system solutions are required. Observe that $B A B D C R$ in MIRKDC_NS saves more than one half of the linear algebra time in comparison with COL$R O W$. Since the error given by the two codes is similar and the time required outside the linear algebra calls remains constant, we expect that, in general, for a well-conditioned BVP with nonseparated boundary conditions, the two codes will perform the same number of factorizations and linear system solutions and that MIRKDC_NS will run faster than MIRKDC.

| MESH | $\sharp$ FACTs | time | $\sharp$ SOLVEs | time |
| :---: | :---: | :---: | :---: | :---: |
| 256 | 1 | $0.32 \mathrm{e}-01$ | 2 | $0.98 \mathrm{e}-02$ |
| 224 | 1 | $0.25 \mathrm{e}-01$ | 2 | $0.78 \mathrm{e}-02$ |
| 246 | 1 | $0.29 \mathrm{e}-01$ | 2 | $0.78 \mathrm{e}-02$ |
| Total: | 3 | $0.87 \mathrm{e}-01$ | 6 | $0.25 \mathrm{e}-01$ |
| Total monitored Linear Algebra time: |  |  |  | 0.11 secs. |
| Total monitored non Linear Algebra time: | 0.12 secs. |  |  |  |

Table 6: MIRKDC_NS (using $B A B D C R$ ) applied to the linear problem in case (a) with an initial mesh of 256 points and error tolerance 1e-07.

## 5 PARALLEL IMPLEMENTATION OF BABDCR

In the previous section we observed the superiority in timings of MIRKDC_NS (using BAB$D C R$ ) over MIRKDC (using COLROW) when BVPs with nonseparated boundary conditions are

| MESH | $\sharp$ FACTs | time | $\sharp$ SOLVEs | time |
| :---: | :---: | :---: | :---: | :---: |
| 256 | 1 | 0.11 | 2 | $0.16 \mathrm{e}-01$ |
| 224 | 1 | $0.75 \mathrm{e}-01$ | 2 | $0.12 \mathrm{e}-01$ |
| 246 | 1 | $0.82 \mathrm{e}-01$ | 2 | $0.14 \mathrm{e}-01$ |
| Total: | 3 | 0.27 | 6 | $0.41 \mathrm{e}-01$ |
| Total monitored Linear Algebra time: |  |  |  | 0.31 secs. |
| Total monitored non Linear Algebra time: | 0.12 secs. |  |  |  |

Table 7: MIRKDC (using COLROW) applied to the linear problem of doubled size in case (a) with an initial mesh of 256 points and error tolerance 1e-07.
solved. Here, we show that a parallel implementation of $B A B D C R$ also pays off in this context.
To this aim, we consider a straightforward distributed memory parallel implementation of $B A B D C R$ that uses MPI procedures [16] to implement the clearly defined parallel structures visible in the CR algorithm. We preliminarily observe that all the reductions from (1) to (2) may be performed in parallel if the two adjacent block rows are stored in the same processor. Therefore, following the idea in PMIRKDC [14], we suppose that the original BVP has been discretized in order so that each processor is only involved with a subinterval of $[a, b]$. This implies that, before calling the factorization procedure, each processor has been assigned some consecutive block rows of the original matrix and the boundary conditions. In the factorization step, the first reductions are computed in parallel on all the $p$ processors without any communication. When each processor has one block row of the reduced matrix, than it is necessary to perform a send/receive communication before each additional reduction step. This means that, if $N \gg p$, the computational cost of the factorization is reduced by a factor $p$ and requires $\left\lceil\log _{2} p\right\rceil$ communications of blocks of size $m \times 2 m$. We proceed analogously for the linear system solution, where each vector which is sent/received has length $m$. Finally, each processor only computes its own part of the solution. See [15] for more details and [2] for the original proposal.

We use a cluster of 32 processors ( 2.4 GHz Intel Xeon, 4 Mb L2 cache) with the Intel Fortran compiler 8.1 for Linux. In Table 8 we show the speedup of the algorithm. Here, the speedup is defined as the ratio between the execution time (time of factorization plus time of solution) of the serial version of the algorithm and the execution time of the parallel version run on the specified number of processors. (The time for the serial version on one processor and for the parallel version run on one processor are essentially the same.) Note that the cyclic reduction algorithm has improved speed-up as the dimension $m$ increases. Particularly, for 32 processors we need large values of $m$ to observe almost linear speedup. In fact, since the factorization of an $m \times m$ matrix is the principal cost in each reduction, as $m$ increases the arithmetic cost $O\left(m^{3}\right)$ prevails over the time spent in the communication $O\left(m^{2}\right)$.

The slightly better than linear speedup (observed in many cases for $m>4$ ) is at least in part due to a cache effect. In the serial version $(p=1)$ all the data is stored on a single processor, and the cache ( 4 Mbytes ) is always full hence requiring frequent data transfers from main memory. So, memory access takes longer than for the parallel runs with $p>1$ processors where the data is shared over the processors, each with its own 4Mbytes cache memory, resulting in needing fewer accesses to main memory.

Direct comparisons with PMIRKDC[14] using RSCALE are not possible since PMIRKDC is designed specifically for shared memory architectures and a distributed memory version would require redesign of parts of the algorithm, not simply a change of implementation language.

|  | $p=2$ | $p=4$ | $p=8$ | $p=16$ | $p=32$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $m=4$ | 1.983 | 3.398 | 5.474 | 6.426 | 6.978 |
| $m=16$ | 2.052 | 4.109 | 7.913 | 15.116 | 24.965 |
| $m=64$ | 2.069 | 4.141 | 7.940 | 15.263 | 25.458 |
| $m=256$ | 2.169 | 4.395 | 8.536 | 16.316 | 29.519 |

Table 8: Speedup for the parallel $B A B D C R$ algorithm with $N=1024$.

## 6 CONCLUSIONS

COLROW has long been considered a fast code for solving ABD linear systems and is widely used in packages for the solution of BVPs with separated boundary conditions. In these packages, the solution of problems with non-separated boundary conditions can only be achieved by modifying the original problem to give a new problem of double the size with separated boundary conditions. Starting from the BVP package MIRKDC, we have shown that $B A B D C R$ runs faster than COLROW and with approximately the same accuracy when the original problem has non-separated boundary conditions. In addition, when it is possible to use a distributed parallel computer (with a moderate number of processors) the implementation of $B A B D C R$ within a version of MIRKDC leads to close to linear speedup.

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