# An automatic multistep method for solving stiff initial value problems 

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#### Abstract

A multistep method with matricial coefficients is developed. It can be used to solve stiff initial value problems of the form $y^{\prime}=A y+g(x, y)$. This method bears the nature of the classical Adams-Bashforth-Moulton PC formula and can be shown to be consistent, convergent and $A$-stable. A careful reformulation of this method legitimatizes the implementation of this algorithm in a variable-step variable-order fashion. Numerical test results from a PECE mode of this method show its possible advantages.


Keywords: Stiff IVPs, Adams PC formula, variable-step variable-order multistep method.

## 1. Introduction

Since the codes DVDQ of Krogh [14] and DIFSUB of Gear [10,11] were developed, the effectiveness of a variable-step variable-order formulation of the classical Adams method has gained a great recognition in solving general initial value problems. This spirit was also carried on by Shampine and Gordon in their code STEP [26] which is known to be among the most effective and the most carefully decumented available at this time. Though the code STEP can diagnose the stiffness, still not is it adequate for handling stiff systems. The reason for this shortcoming is well understood from the Dahlquist stability theory [5]. It is also generally believed that most of the methods used for solving stiff systems are necessarily implicit [ $5,17,27]$ and hence demand the use of some expensive Newton-like iterations [12].

In this paper we consider a special class of stiff systems, i.e. a stiff initial value problem of the form

$$
\begin{equation*}
y^{\prime}=A y+g(x, y), \quad y(a)=y_{0}, \quad x \in[a, b] \tag{1.1}
\end{equation*}
$$

where $A$ is an $n \times n$ real constant matrix of which all eigenvalues have negative real parts and $\|\partial g / \partial y\|$ is small relative to $\|A\|$. It deserves to note that a much larger class of problems

$$
\begin{equation*}
y^{\prime}=A(x) y+g(x, y), \quad y(a)=y_{0} \tag{1.2}
\end{equation*}
$$

can also be considered by rewriting it in the form

$$
\begin{equation*}
y^{\prime}=A y+\{[A(x)-A] y+g(x, y)\}, \quad y(a)=y_{0} \tag{1.3}
\end{equation*}
$$

if $A$ can be chosen to satisfy conditions of (1.1) and to keep $\|A(x)-A\|$ uniformly small for at least a short period of $x$. A multistep method which does not suffer from the difficulties mentioned above is developed for solving (1.1). This method bears the merit of the classical predictor-corrector schemes and can be regarded as the nature extension of the code STEP to matricial coefficients. As a result, we may take a great advantage of the software designs of the code STEP.

The development of this method is also motivated by several other researchers. The formulations considered by Certaine [4], Lawson [19], Lee and Preiser [20] are special cases of our consideration. The methods suggested by Jain [13], Miranker [22,23], Murphy [24], Lambert and Sigurdsson [16] are different from our method only in the numerical representations of the integrals which will be introduced in the next section.

We begin at Section 2 with the basic fixed-step formulation of this multistep method. After defining a generalized Adams-Bashforth-Moulton PECE mode, we then state some theorems concerning the consistency, convergence and $A$-stability of this mode. These theorems can easily be generalized to the variable-step variable-order case [26]. In Section 3 a variable-step PECE mode is reformulated. This approach makes it possible to calculate the matricial coefficients to any desired order in a very efficient way. In the special case when $A=0$, this derivation coincides with that by Shampine and Gordon. Finally we present some test results in Section 4 to evidence the possible effectiveness of this method.

## 2. Basic formulation - fixed-step scheme

Let $x_{k}$ denote the $k$ th mesh point along the variable axis and $h_{k+1}=x_{k+1}-x_{k}$ the step size to be used at the next move. We shall use $y_{k}$ to represent a numerical approximation to the exact solution $y\left(x_{k}\right)$ at the mesh point $x_{k}$. Let $g_{k}=g\left(x_{k}, y_{k}\right)$. By considering the integral equation

$$
\begin{equation*}
y\left(x_{n+1}\right)=\mathrm{e}^{A h_{n+1}} y\left(x_{n}\right)+\mathrm{e}^{A x_{n+1}} \int_{x_{n}}^{x_{n+1}} \mathrm{e}^{-A \tau} g(\tau, y(\tau)) \mathrm{d} \tau \tag{2.1}
\end{equation*}
$$

which is equivalent to problem (1.1), we are motivated to form the following formula

$$
\begin{equation*}
y_{n+1}=\mathrm{e}^{A h_{n+1}} y_{n}+h_{n+1} \sum_{i=0}^{k} \Phi_{k i} g_{n-i+1} . \tag{2.2}
\end{equation*}
$$

The summation in (2.2) is an approximation to the integral

$$
\begin{equation*}
\int_{0}^{1} \mathrm{e}^{A(1-\alpha) h_{n+1}} g\left(x_{n}+\alpha h_{n+1}, y\left(x_{n}+\alpha h_{n+1}\right)\right) \mathrm{d} \alpha \tag{2.3}
\end{equation*}
$$

where $\alpha=\left(\tau-x_{n}\right) / h_{n+1}$, and $\Phi_{k i}$ 's are some matricial coefficients to be determined.
Let us consider the fixed-step explicit scheme first. Assuming $\Phi_{k 0}=0$ in (2.2) and regarding $g$ as a function of $\alpha$, we use a vector-valued polynomial $P(\alpha)$ of degree $<k$ to interpolate $g$ componentwise at points $x_{n-k+1}, \ldots, x_{n}$ so that $P(1-i)=g_{n-i+1}$ for $i=1, \ldots, k$. This polynomial is given by the Lagrangian formula

$$
\begin{equation*}
P(\alpha)=\sum_{i=1}^{k} g_{n-i+1} \prod_{\substack{j=1 \\ j \neq i}}^{k} \frac{\alpha+j-1}{j-i} . \tag{2.4}
\end{equation*}
$$

Now the integral (2.3) is approximated by

$$
\begin{equation*}
\int_{0}^{1} \mathrm{e}^{A(1-\alpha) h} P(\alpha) \mathrm{d} \alpha=\sum_{i=1}^{k}\left(\int_{0}^{1} \mathrm{e}^{A(1-\alpha) h} \prod_{\substack{j=1 \\ j=i}}^{k} \frac{\alpha+j-1}{j-1} \mathrm{~d} \alpha\right) g_{n-i+1} \tag{2.5}
\end{equation*}
$$

where $h_{n+1}$ is abbreviated as $h$. Comparing (2.2) and (2.5), we see it is reasonable to choose $\Phi_{k i}$ in (2.2) as

$$
\begin{equation*}
\Phi_{k i}=\int_{0}^{1} \mathrm{e}^{A(1-\alpha) h} \prod_{\substack{j=1 \\ j=1}}^{k} \frac{\alpha+j-1}{j-i} \mathrm{~d} \alpha . \tag{2.6}
\end{equation*}
$$

As an example, when $k=4$, (2.2) becomes

$$
\begin{align*}
p_{n+1}= & \mathrm{e}^{A h} y_{n}+h \int_{0}^{1} \mathrm{e}^{A(1-\alpha) h}\left[\frac{1}{6}(\alpha+1)(\alpha+2)(\alpha+3) g_{n}\right. \\
& \left.-\frac{1}{2} \alpha(\alpha+2)(\alpha+3) g_{n-1}+\frac{1}{2} \alpha(\alpha+1)(\alpha+3) g_{n-2}-\frac{1}{2} \alpha(\alpha+1)(\alpha+2) g_{n-3}\right] \mathrm{d} \alpha . \tag{2.7}
\end{align*}
$$

Here the notation $p_{n+1}$ is used to indicate that it is the 'predicted value' of $y\left(x_{n+1}\right)$. The scheme (2.2) along with (2.6) is called a generalized Adams-Bashforth formula of order $k$ because, if $A=0,(2.2)$ is reduced to
the classical linear multistep scheme. The word 'order' will be justified later. An implicit scheme of order $k+1$ can be formed in exactly the same way if the polynomial $P^{*}(\alpha)$ interpolating the prints $x_{n-k+1}, \ldots$, $x_{n+1}$ with values $P^{*}(1-\alpha)=g_{n-i+1}$ for $i=0, \ldots, k$ is used. The resulting matricial coefficients of this implicit scheme is denoted by $\Phi_{k i}^{*}$. It is worth noting that

$$
\sum_{i=0}^{k} \Phi_{k i}^{*}=\sum_{i=1}^{k} \Phi_{k i}=\int_{0}^{1} \mathrm{e}^{A(1-\alpha) h} \mathrm{~d} \alpha
$$

is always bounded. Now we make the following definition.
Definition 2.1. By a ( $k, k+1$ )-order PECE mode we mean the numerical scheme consisting of a predictor of order $k$ and a corrector of order $k+1$ in the form of (2.2), i.e.

$$
\begin{array}{ll}
\mathrm{P}: & p_{n+1}=\mathrm{e}^{A h} y_{n}+h \sum_{i=1}^{k} \Phi_{k i} g_{n-i+1}, \\
\mathrm{E}: & g_{n+1}^{p}=g\left(x_{n+1}, p_{n+1}\right) \\
\mathrm{C}: & y_{n+1}=\mathrm{e}^{A h} y_{n}+h \sum_{i=1}^{k} \Phi_{k i}^{*} g_{n-i+1}+h \Phi_{k 0}^{*} g_{n+1}^{p}, \\
\mathrm{E}: & g_{n+1}=g\left(x_{n+1}, y_{n+1}\right) . \tag{2.8}
\end{array}
$$

Apparently, to compute these matricial coefficients is not an easy and economical task. The situation is even worsened when the variable-step scheme is to be adopted. The algorithm we develop in the next section, however, helps to facilitate this difficulty. In fact, we shall see in that algorithm only matrix multiplications are involved. Let us conclude this section with three major theorems concerning the consistency, convergence and $A$-stability of the mode (2.8). They are obvious extensions of classical results [26].

Theorem 2.2. Assume $g \in C^{k+1}$, then the local truncation error $\mathcal{Q}^{p}\left(y\left(x_{n}\right), h\right)$, defined by

$$
\begin{equation*}
\mathcal{E}^{p}\left(y\left(x_{n}\right), h\right)=y\left(x_{n+1}\right)-\mathrm{e}^{A h} y\left(x_{n}\right)-h \sum_{i=1}^{k} \Phi_{k i} g\left(x_{n-i+1}, y\left(x_{n-i+1}\right)\right) \tag{2.9}
\end{equation*}
$$

of the explicit scheme (2.2) with step number $k$ is $\mathrm{O}\left(h^{k+1}\right)$. With a similar definition the local truncation error $\mathcal{E}\left(y\left(x_{n}\right), h\right)$ of the implicit scheme is $\mathrm{O}\left(h^{k+2}\right)$.

Theorem 2.3. Let the ( $k, k+1$ )-order PECE mode (2.8) be applied to solve problem (1.1) on $[a, b]$. Suppose $g \in C^{1}$ and $\|\partial g / \partial y\| \leqslant L_{g}$ for some constant $L_{g}>0$. If all starting values $y_{i}$ for $i=1, \ldots, k-1$ satisfy $\left\|y\left(x_{i}\right)-y_{i}\right\| \leqslant E_{0}$, then for $x_{n} \in[a, b]$ we have

$$
\begin{equation*}
\left\|y\left(x_{n}\right)-y_{n}\right\| \leqslant\left[E_{0}+\frac{\partial}{h \Lambda}\right] \mathrm{e}^{\left(x_{n}-a\right) \Lambda} \tag{2.10}
\end{equation*}
$$

where

$$
\begin{align*}
& \Lambda=L_{g}\left(\alpha^{*}+h L_{g}\left\|\Phi_{k 0}^{*}\right\| \alpha\right), \\
& \delta=\max _{n}\left\|h \Phi_{k 0}^{*} \frac{\partial g}{\partial y} \mathcal{L}^{p}\left(y\left(x_{n}\right), h\right)+\mathcal{E}\left(y\left(x_{n}\right), h\right)\right\|,  \tag{2.11}\\
& \alpha=\sum_{i=1}^{k}\left\|\Phi_{k i}\right\| \text { and } \alpha^{*}=\sum_{i=0}^{k}\left\|\Phi_{k i}^{*}\right\| .
\end{align*}
$$

In particular, if $g \in C^{k+1}$ and $E_{0}=\mathrm{O}\left(h^{k+1}\right)$, then $\left\|y\left(x_{n}\right)-y_{n}\right\|=\mathrm{O}\left(h^{k+1}\right)$.
Theorem 2.4. The multistep scheme (2.2) based on the Padé approximation to all its matrix exponentials is $A$-stable.

## 3. Efficient formulation - variable-step scheme

The subroutine STEP in [26] gives an efficient way of generating coefficients for the linear multistep method which results in substantial savings of the overhead and memory storages. We now reformulate their settings in the matrix form. It will be seen at the end of this section that all the advantages of STEP are preserved.

Let the following quantities be defined.

$$
\begin{align*}
& h_{i}=x_{i}-x_{i} \quad 1, \quad s=\frac{x-x_{n}}{h_{n+1}}, \\
& \psi_{i}(n+1)=h_{n+1}+\cdots+h_{n-i+2}, \quad i \geqslant 1 \\
& \alpha_{i}(n+1)=\frac{h_{n+1}}{\psi_{i}(n+1)}, \quad i \geqslant 1,  \tag{3.1}\\
& \beta_{1}(n+1)=1, \quad \beta_{i}(n+1)=\frac{\psi_{1}(n+1) \psi_{2}(n+1) \cdots \psi_{i-1}(n+1)}{\psi_{1}(n) \psi_{2}(n) \cdots \psi_{i-1}(n)}, \quad i>1, \\
& \phi_{1}(n)=g\left[x_{n}\right]=g_{n}, \quad \phi_{i}(n)=\psi_{1}(n) \cdots \psi_{i-1}(n) g\left[x_{n}, x_{n-1}, \ldots, x_{n-i+1}\right], \quad i>1 .
\end{align*}
$$

Recall that the predicted value of $y\left(x_{n+1}\right)$ is the vector

$$
\begin{equation*}
p_{n+1}=\mathrm{e}^{A h_{n+1}} y_{n}+\int_{x_{n}}^{x_{n+1}} \mathrm{e}^{A\left(x_{n+1}-\tau\right)} p_{k, n}(\tau) \mathrm{d} \tau \tag{3.2}
\end{equation*}
$$

where $p_{k, n}$ is the interpolating polynomial given by

$$
\begin{equation*}
p_{k, n}(x)=g\left[x_{n}\right]+\left(x-x_{n}\right) g\left[x_{n}, x_{n-1}\right]+\cdots+\left(x-x_{n}\right) \cdots\left(x-x_{n-k+2}\right) g\left[x_{n}, \ldots, x_{n-k+1}\right] . \tag{3.3}
\end{equation*}
$$

A typical term, for $i \geqslant 2$, of $p_{k . n}(x)$ can be written as

$$
\begin{align*}
(x & \left.-x_{n}\right) \cdots\left(x-x_{n-i+2}\right) g\left[x_{n}, \ldots, x_{n-i+1}\right]= \\
& =\left(s h_{n+1}\right)\left(s h_{n+1}+h_{n}\right) \cdots\left(s h_{n+1}+h_{n}+\cdots+h_{n-i+3}\right) \frac{\phi_{i}(n)}{\psi_{1}(n) \cdots \psi_{i-1}(n)} \\
& =\left(\frac{s h_{n+1}}{\psi_{1}(n+1)}\right)\left(\frac{s h_{n+1}+h_{n}}{\psi_{2}(n+1)}\right) \cdots\left(\frac{s h_{n+1}+\psi_{i-2}(n)}{\psi_{i-1}(n+1)}\right) \beta_{i}(n+1) \phi_{i}(n) . \tag{3.4}
\end{align*}
$$

If we introduce quantities $c_{i, n}(s)$ and $\phi_{i}^{*}(n)$ defined by

$$
c_{i, n}(s)= \begin{cases}1, & i=1,  \tag{3.5}\\ \frac{s h_{n+1}}{\psi_{1}(n+1)}, & i=2, \\ \left(\frac{s h_{n+1}}{\psi_{1}(n+1)}\right)\left(\frac{s h_{n+1}+h_{n}}{\psi_{2}(n+1)}\right) \ldots\left(\frac{s h_{n+1}+\psi_{i-2}(n)}{\psi_{i-1}(n+1)}\right), & i \geqslant 3,\end{cases}
$$

and

$$
\begin{equation*}
\phi_{i}^{*}(n)=\beta_{i}(n+1) \phi_{i}(n), \tag{3.6}
\end{equation*}
$$

then (3.3) can be written as

$$
\begin{equation*}
p_{k, n}(x)=\sum_{i=1}^{k} c_{i, n}(s) \phi_{i}^{*}(n) \tag{3.7}
\end{equation*}
$$

and (3.2) becomes

$$
\begin{equation*}
p_{n+1}=\mathrm{e}^{A h_{n+1}} y_{n}+h_{n+1} \sum_{i=1}^{k}\left(\int_{0}^{1} \mathrm{e}^{A(1-s) h_{n+1}} c_{i, n}(s) \mathrm{d} s\right) \phi_{i}^{*}(n) \tag{3.8}
\end{equation*}
$$

Let

$$
\begin{equation*}
d_{i, n}(s)=\mathrm{e}^{A(1-s) n_{n+1}} c_{i, n}(s) \tag{3.9}
\end{equation*}
$$

it follows that

$$
d_{i, n}(s)= \begin{cases}\mathrm{e}^{A(1-s) h_{n+1}}, & i=1  \tag{3.10}\\ \mathrm{e}^{\left(A(1-s) h_{n+1}\right.} s, & i=2 \\ {\left[\alpha_{i-1}(n+1) s+\frac{\psi_{i-2}(n)}{\psi_{i-1}(n)}\right] d_{i-1 . n}(s),} & i \geqslant 3\end{cases}
$$

and

$$
\begin{equation*}
p_{n+1}=\mathrm{e}^{A h_{n+1} y_{n}+h_{n+1}} \sum_{i=1}^{k}\left(\int_{0}^{1} d_{i, n}(s) \mathrm{d} s\right) \phi_{i}^{*}(n) . \tag{3.11}
\end{equation*}
$$

Observe, for a fixed $n$ and any $i \geqslant 3$,

$$
\begin{align*}
\left.\int_{0}^{s} d_{i, n}\left(s_{0}\right) \mathrm{d} s_{0}\right)= & \int_{0}^{s}\left[\alpha_{i-1}(n+1) s_{0}+\frac{\psi_{i-2}(n)}{\psi_{i-1}(n)}\right] \mathrm{d}\left(\int_{0}^{s_{0}} d_{i-1, n}\left(s_{1}\right) \mathrm{d} s_{1}\right) \\
= & {\left[\alpha_{i-1}(n+1) s+\frac{\psi_{i-2}(n)}{\psi_{i-1}(n)}\right] \int_{0}^{s} d_{i-1, n}\left(s_{0}\right) \mathrm{d} s_{0} } \\
& -\int_{0}^{s} \alpha_{i-1}(n+1) \int_{0}^{s_{1}} d_{i-1, n}\left(s_{0}\right) \mathrm{d} s_{0} \mathrm{~d} s_{1} \tag{3.12}
\end{align*}
$$

If we define

$$
\begin{equation*}
d_{i, n}^{(q)}(s)=\int_{0}^{s} \int_{0}^{s_{4-1}} \cdots, \int_{0}^{s_{1}} d_{i, n}\left(s_{0}\right) \mathrm{d} s_{0} \mathrm{~d} s_{1} \cdots \mathrm{~d} s_{q-1} \tag{3.13}
\end{equation*}
$$

then (3.12) is equivalent to

$$
\begin{equation*}
d_{i, n}^{(1)}(s)=\left[\alpha_{i-1}(n+1) s+\frac{\psi_{i-2}(n)}{\psi_{i-1}(n)}\right] d_{i-1, n}^{(1)}(s)-\alpha_{i-1}(n+1) d_{i-1 . n}^{(2)}(s) . \tag{3.14}
\end{equation*}
$$

It is not hard to show now, by induction and integration by parts, the following identity holds for any $i \geqslant 3$.

$$
\begin{equation*}
d_{i, n}^{(q)}(s)=\left[\alpha_{i-1}(n+1) s+\frac{\psi_{i-2}(n)}{\psi_{i-1}(n)}\right] d_{i-1, n}^{(q)}(s)-q \alpha_{i-1}(n+1) d_{i-1, n}^{(q 11)}(s) \tag{3.15}
\end{equation*}
$$

Scaling these quantities by

$$
\begin{equation*}
\omega_{i . q}=(q-1)!d_{i, n}^{(q)}(1) \tag{3.16}
\end{equation*}
$$

we then arrive at one of the important identifies

$$
\begin{equation*}
\omega_{i, q}=\omega_{i-1 . q}-\alpha_{i-1}(n+1) \omega_{i-1 . q+1} \quad \text { for } i \geqslant 3 . \tag{3.17}
\end{equation*}
$$

Up to this point, all these quantities we have derived are formally then same as those by Shampine and Gordon [26] except that these are in matrix form. When $A$ is identically zero, the quantities defined in (3.10), (3.12), (3.15) and (3.17) become diagonal matrices and, in fact, each diagonal matrix is of the form $c I$ where the scalar $c$ is the coefficient used by Shampine and Gordon. In this case, the quantites for $i=1$ and $i=2$ can be handled trivially. In the other case when $A$ is a matrix as stated in problem (1.1), it can be shown from (3.13) that $d_{1 . n}^{(1)}(s)$ satisfies the equation

$$
\begin{equation*}
\left(-A h_{n+1}\right) d_{1, n}^{(1)}(s)=\mathrm{e}^{A(1-s) h_{n+1}}-\mathrm{e}^{A h_{n+1}} \tag{3.18}
\end{equation*}
$$

and, by induction, $d_{1, n}^{(q)}(s)$ satisfies

$$
\begin{equation*}
\left(-A h_{n+1}\right) d_{1, n}^{(q)}(s)=d_{1, n}^{(q-1)}(s)-\frac{s^{q-1}}{(1-q)!} \mathrm{e}^{A h_{n+1}} \tag{3.19}
\end{equation*}
$$

for all $q \geqslant 2$. Similarly, we have

$$
\begin{align*}
& \left(-A h_{n+1}\right) d_{2, n}^{(1)}(s)=s \mathrm{e}^{A(1-s) h_{n+1}}-d_{1 . n}^{(1)}(s), \\
& \left(-A h_{n+1}\right) d_{2, n}^{(q)}(s)=d_{2, n}^{(q-1)}(s)-d_{1 . n}^{(q)}(s) \quad \text { for } q \geqslant 2 . \tag{3.20}
\end{align*}
$$

Resorting to the definition (3.16), we obtain

$$
\begin{align*}
& \left(-A h_{n+1}\right) \omega_{1,1}=I-\mathrm{e}^{A h_{n+1}}, \\
& \left(-A h_{n+1}\right) \omega_{1, q}=(q-1) \omega_{1 . q-1}-\mathrm{e}^{A h_{n+1}} \quad \text { for } q \geqslant 2,  \tag{3.21}\\
& \left(-A h_{n+1}\right) \omega_{2.1}=I-\omega_{1.1}, \quad\left(-A h_{n+1}\right) \omega_{2 . q}=(q-1) \omega_{2, q-1}-\omega_{1, q} \quad \text { for } q \geqslant 2
\end{align*}
$$

In general, $\omega_{1 . q}$ and $\omega_{2 . q}$ for every $q \geqslant 1$ can be solved directly from (3.21) once $A^{-1}$ is known. But for the case when $A$ is very ill-conditioned or even is singular, it would be wise to reformulate the problem in a way similar to (1.3) so that $A$ is better conditioned and nonsingular.

Since $d_{i, n}^{(1)}(1)=\omega_{i, 1}$, the scheme (3.11) becomes

$$
\begin{equation*}
p_{n+1}=\mathrm{e}^{A n_{n+1}} y_{n}+h_{n+1} \sum_{i=1}^{k} \omega_{i, 1} \phi_{i}^{*}(n) . \tag{3.22}
\end{equation*}
$$

We now make a correction on this predicted value. The corrected value of $y\left(x_{n+1}\right)$ is given by

$$
\begin{equation*}
y_{n+1}=\mathrm{e}^{A h_{n+1}} y_{n}+\int_{x_{n}}^{x_{n+1}} \mathrm{e}^{A\left(x_{n+1}-\tau\right)} p_{k+1 . n}^{*}(\tau) \mathrm{d} \tau \tag{3.23}
\end{equation*}
$$

where $p_{k+1, n}^{*}(\tau)$ is the interpolating polynomial of degree $<k+1$ such that $p_{k+1, n}^{*}\left(x_{n-i+1}\right)=g_{n-i+1}$ for $i=1, \ldots, k$ and $p_{k+1 . n}^{*}\left(x_{n+1}\right)=g\left(x_{n+1}, p_{n+1}\right)$. Since

$$
\begin{align*}
p_{k+1, n}^{*}(x) & =p_{k, n}(x)+\left(x-x_{n}\right) \cdots\left(x-x_{n-k+1}\right) g^{p}\left[x_{n+1}, \ldots, x_{n-k+1}\right] \\
& =p_{k, n}(x)+\left(s h_{n+1}\right) \cdots\left(s h_{n+1}+\cdots h_{n-k+2}\right) \frac{\phi_{k+1}^{p}(n+1)}{\psi_{1}(n+1) \cdots \psi_{k}(n+1)} \\
& =p_{k, n}(x)+c_{k+1 . n}(s) \phi_{k+1}^{p}(n+1) \tag{3.24}
\end{align*}
$$

where the superscript $p$ is used to indicate that the value $g_{n+1}$ is replaced by $g\left(x_{n+1}, p_{n+1}\right)$, we can substitute (3.24) into (3.23) to get

$$
\begin{equation*}
y_{n+1}=p_{n+1}+h_{n+1} \omega_{k+1,1} \phi_{k+1}^{p}(n+1) . \tag{3.25}
\end{equation*}
$$

To appreciate the above scheme we illustrate the inter-relation between the coefficients of (3.17)) and (3.21) in Table 1. The arrows emanate from the generators and point to the generated values.

Table 1


Several advantages are manifestly clear now:
(i) We only need to computer $A^{-1}$ once and for all throughout the calling of the whole algorithm because $\left(A h_{\text {new }}\right)^{-1}=\left(A h_{\text {old }}\right)^{-1} \cdot h_{\text {old }} / h_{\text {new }}$ can be updated by scalar multiplications.
(ii) If the st p succeeds and the step size is doubled, then $\mathrm{e}^{A h_{\mathrm{ncw}}}=\left(\mathrm{e}^{A h_{\text {old }}}\right)^{2}$ can be obtained by matrix multiplications. Furthermore, any reasonable step size selection mechanism should not cause frequent reductions of step size, so the overhead resulting from the computation of $\mathrm{e}^{A h}$ is expected to be small in the long run.
(iii) When the classical implicit linear multistep scheme with step size $h$

$$
\begin{equation*}
\sum_{i=0}^{k} \alpha_{i} y_{n-i+1}=h \sum_{i=0}^{k} \beta_{i} f_{n-i+1} \tag{3.26}
\end{equation*}
$$

is applied to solve problem (1.1), at each step one has to solve the nonlinear equation

$$
\begin{equation*}
y_{n+1}=h \beta_{0} f\left(x_{n+1}, y_{n+1}\right)+\omega \tag{3.27}
\end{equation*}
$$

where

$$
f(x, y)=A y+g(x, y) \quad \text { and } \quad \omega=h \sum_{i=1}^{k} \beta_{i} f_{n-i+1}-\sum_{i=1}^{k} \alpha_{i} y_{n-i+1}
$$

( $\omega$ is a known quantity at the current state). In order to apply the contraction mapping theorem, it is required to have

$$
\begin{equation*}
k=h\left|\beta_{0}\right| L_{f}<1 \tag{3.28}
\end{equation*}
$$

where $L_{f}$ is the Lipschitz constant for $f$. In constrast, when an implicit multistep scheme (2.2) with step size $\hat{h}$ is applied, the nonlinear equation to be solved becomes

$$
\begin{equation*}
y_{n+1}=\hat{h} \Phi_{k 0} g\left(x_{n+1}, y_{n+1}\right)+\hat{\omega} \tag{3.29}
\end{equation*}
$$

where $\hat{\omega}=\hat{h} \sum_{i=1}^{k} \Phi_{k i} g_{n-i+1}-\mathrm{e}^{A \hat{h}} y_{n}$. Again we require the condition

$$
\begin{equation*}
\hat{k}=\hat{h}\left\|\Phi_{k 0}\right\| L_{g}<1 \tag{3.30}
\end{equation*}
$$

Under the assumption that the iterative method used to solve (3.27) and (3.29) converges at the same rate, it is seen that

$$
\begin{equation*}
\frac{\hat{h}}{h}=\frac{\left|\beta_{0}\right|}{\left\|\Phi_{k 0}\right\|} \frac{L_{f}}{L_{g}} . \tag{3.31}
\end{equation*}
$$

Thus for the problem (1.1) where $L_{f}$ is much greater than $L_{g}$, the step size $\hat{h}$ of our scheme (2.2) can be chosen significantly larger than that of the linear scheme (3.26).
(iv) Apart from the facts that $\omega_{i q}$ 's are matrices, $\phi_{i}$ 's are defined over $g$, and $\omega_{i q}$ 's for $i=1$ or 2 are generated according to (3.21), symbolically (3.17) and (3.1) are exactly the same as those in [26]. Therefore, the efficient software designs of the code STEP can be perfectly transfered into our code. This advantage includes the substantial reduction of the overhead and the memory storages. In particular, the PECE mode (2.8) which advances from $x_{n}$ to $x_{n+1}$ is now given by

Computing $\omega_{i, 1}, i=1, \ldots, k+1$;

$$
\begin{array}{ll}
\mathrm{P}: & \phi_{i}^{*}(n)=\beta_{i}(n+1) \phi_{i}(n), \quad i=1, \ldots, k, \\
& p_{n+1}=\mathrm{e}^{A h_{n+1}} y_{n}+h_{n+1} \sum_{i=1}^{k} \omega_{i, 1} \phi_{i}^{*}(n), \\
& \phi_{k+1}^{\mathrm{e}}(n+1)=0, \\
& \phi_{i}^{\mathrm{e}}(n+1)=\phi_{i+1}^{\mathrm{e}}(n+1)+\phi_{i}^{*}(n), \quad i=k, \ldots, 1 ; \\
\mathrm{E}: & g_{n+1}^{p}=g\left(x_{n+1}, p_{n+1}\right) ;
\end{array}
$$

$$
\begin{array}{ll}
\mathrm{C}: & y_{n+1}=p_{n+1}+h_{n+1} \omega_{k+1.1}\left(g_{n+1}^{p}-\phi_{1}^{\mathrm{e}}(n+1)\right) \\
\mathrm{E}: & g_{n+1}=g\left(x_{n+1}, y_{n+1}\right) \\
& \phi_{k+1}(n+1)=g_{n+1}-\phi_{1}^{\mathrm{e}}(n+1), \\
& \phi_{i}(n+1)=\phi_{i}^{\mathrm{e}}(n+1)+\phi_{k+1}(n+1), \quad k=1 \ldots \ldots, 1 . \tag{3.32}
\end{array}
$$

## 4. Numerical examples

Test results of problems representing both linear and nonlinear stiff systems are presented in this section. We also give an 'informal' comparison of our algorithm NLMSUB with Gear's DIFSUB or Lawson's IRKSUB by listing their test data from the reference. It should he emphasized that the principal objective of these tests is to confirm the workability of this multistep method rather than to make the detailed comparison with available methods, although several results seem to reveal some significant advantages.

The subroutine NLMSUB is developed based on the prototype code STEP. We replace the scalar coefficients in STEP by matricial coefficients which are generated according to the scheme (3.17) and (3.21). The matrix exponential $\mathrm{e}^{A h}$ is calculated by Ward's method [25,33]. Finally and most importantly, the error control mechanism is modified so as to fit into our matrix formulation: The actual treatments would be too tedious to discuss here and we would rather avoid the details.

Problem 1 [18].

$$
\begin{aligned}
& y^{\prime}=U\left[\begin{array}{rrrr}
0, & 1, & 0, & 0 \\
-1, & 0, & 0, & 0 \\
0, & 0, & -100, & -900 \\
0, & 0, & 900, & -100
\end{array}\right] U^{\mathbf{T}} y+u\left[\begin{array}{l}
x^{2}+2 x \\
x^{2}-2 x \\
-800 x+1 \\
-1000 x-1
\end{array}\right] ; \quad y(0)=\left[\begin{array}{l}
1 \\
0 \\
0 \\
1
\end{array}\right], \\
& U=\frac{1}{2}\left[\begin{array}{rrrr}
-1, & 1, & 1, & 1 \\
1, & -1, & 1, & 1 \\
1, & 1, & -1, & 1 \\
1, & 1, & 1, & -1
\end{array}\right] \text { and } x \in[0,25] .
\end{aligned}
$$

Test results (with local error control $10^{-7}$ ) are given in Table 2.
Notation. The maximum error ERR is measured by $-\log \left(\sum\left[y_{i}(x)-y_{i}\right]^{2}\right)^{1 / 2}$ on the CYBER 750 system.
Remarks. This problem fits exactly into our model and hence we expect accurate numerical outputs. The large angles formed by its eigenvalues ( $-100 \pm 900 \mathrm{i}$ and $\pm \mathrm{i}$ ) with the negative real axis give Gear's method some hardtime as is expected. The matrix $U$ is used to couple all components and hence makes the problem more complicated. The computation in our algorithm actually terminated at $x=39.21$ instead of 25 whereas the next allowable step size was as large as 39 . So conceivably the above data is to be even more prominent if the integration range is $[0,80]$. Since the numerical difficulty for a stiff system usually appears in the steady-state part, our method seems to be more efficient for at least this class of problems.

Table 3
Table 2

|  | DIFSUB | IRKSUB | NLMSUB |
| :--- | :---: | :---: | :---: |
| ERR | 4.55 | 4.22 | 6.75 |
| STEP | 2982 | 532 | 25 |
| FNS | 8332 | 2986 | 51 |
| JACOB | 37 | 41 | 0 |
| PADE | 0 | 0 | 1 |
| TIME | 106.03 | 41.88 | 0.19 |


|  | DIFSUB | IRKSUB | NLMSUB |
| :--- | :---: | :---: | :---: |
| ERR | 5.31 | 5.40 | 5.23 |
| STEP | 650 | 1575 | 286 |
| FNS | 1839 | 18805 | 322 |
| JACOB | 66 | 319 | 0 |
| INV | 66 | 957 | 37 |
| PADE | 0 | 0 | 36 |
| TIME | 0.597 | 6.171 | 1.776 |

Problem 2 [7].

$$
y^{\prime}=\left[\begin{array}{rrrr}
-1, & 0, & 0, & 0 \\
0, & -10, & 0, & 0 \\
0, & 0, & -40, & 0 \\
0, & 0, & 0, & -100
\end{array}\right] y+\left[\begin{array}{l}
2 \\
20 y_{1}^{2} \\
80\left(y_{1}^{2}+y_{2}^{2}\right) \\
200\left(y_{1}^{2}+y_{2}^{2}+y_{3}^{2}\right.
\end{array}\right] ; \quad y(0)=\left[\begin{array}{l}
1 \\
1 \\
1 \\
1
\end{array}\right]
$$

where $x \in[0,20]$.
Test results (with local error control $10^{-6}$ ) are given in Table 3.
Remarks. This problem has a very strong nonlinear coupling from the smooth components to the transient components and hence causes great difficulty. In fact, this coupling causes the trasient components to have very large positive derivative at the initial phase. This tendency eventually is diminished and the order is lowered when the smooth components cannot match the rapid decay of the transient. It is probably due to this reason that the step size has to be changed frequently.

Problem 3 [15].

$$
y^{\prime}=U\left[\begin{array}{rrrr}
-\beta_{1}, & \beta_{2}, & 0, & 0 \\
-\beta_{2}, & -\beta_{1}, & 0, & 0 \\
0, & 0, & -100, & 0 \\
0, & 0, & 0, & -0.1
\end{array}\right] U^{\mathrm{T}} y+U\left[\begin{array}{l}
\frac{z_{1}^{2}-z_{2}^{2}}{2} \\
z_{1} z_{2} \\
z_{3} \\
z_{4}^{2}
\end{array}\right] ; \quad y(0)=U\left[\begin{array}{r}
-2 \\
0 \\
-1 \\
-1
\end{array}\right]
$$

where $z=U y$ and $x \in[0,50]$.
Test results (with local error control $10^{-4}$ ) are given in Table 4.

Remarks. It can be shown that eigenvalues of the Jacobian matrix of the above system are given by $z_{1}-\beta_{1} \pm\left|z_{2}-\beta_{2}\right| i, 2 z_{3}-100$ and $2 z_{4}-0.1$. By varying values of $\beta_{1}$ and $\beta_{2}$, this nonlinear system will present different characteristics. When $\beta_{1}=-10$ and $\beta_{2}=0$, all eigenvalues are real numbers because $z_{2}(x) \equiv 0$. One has to note, however, that this actually is a mixed-type problem because of the presence of positive eigenvalues in the transient region. If $\beta_{1}=1$ and $\beta_{2}=100$, then all eigenvalues have negative real parts and the first two form very large angles (nearly $88^{\circ}$ ) with the negative $x$-axis. The accuracy returned is satisfactory, but the step sizes used are relatively small (average $6.2 \times 10^{-2}$ ). When $\beta_{1}=10$ and $\beta_{2}=100$, we have similar distribution of eigenvalues (with angles nearly $84^{\circ}$ ), but the step sizes used are relatively large (average $5.2 \times 10^{-1}$ ). The reason for this contrast is not clear. If $\beta_{1}=-10$ and $\beta_{2}=10$, then again this is a mixed-type problem of which some eigenvalues are moving from the right half-plane to the left half-plane. The result shows a frequent reduction on the step size whereas the 'global error' implies a larger step size could have been used. Probably this is due to the deficiency of the error control mechanism that we used.

Table 4

|  | $\beta_{1}=-10$ | $\beta_{1}=1$ | $\beta_{1}=10$ | $\beta_{1}=-10$ |
| :--- | :---: | :---: | :---: | :---: |
|  | $\beta_{1}=0$ | $\beta_{2}=100$ | $\beta_{2}=100$ | $\beta_{2}=10$ |
| ERR | 2.84 | 3.45 | 3.70 | 5.35 |
| STEP | 63 | 809 | 96 | 1866 |
| FNS | 127 | 1619 | 195 | 3933 |
| INV | 4 | 3 | 6 | 200 |
| PADE | 3 | 2 | 5 | 199 |
| TIME | 0.440 | 2.711 | 0.667 | 17.942 |

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