## RESEARCH ARTICLE

# On the Review of Linear Multistep Methods as Fixed Point Iterative Methods in the Solution of a Coupled System of Initial Value Differential Problem 

Eziokwu C. Emmanuel<br>Departments of Mathematics, Micheal Okpara University of Agriculture, Umudike, Abia, Nigeria

Received: 27-02-2021; Revised: 20-03-2022; Accepted: 20-04-2022


#### Abstract

The linear multi-step method, $x_{n+k}=\sum_{j=0}^{k-1} \alpha_{j} x_{n+j}+h \sum_{j=0}^{k} \beta_{j} \beta_{j} f_{n+j} ; k \geq 1$, a numerical method for solving the initial value problem $x^{\prime}=f(t, x), x\left(t_{0}\right)=x_{0}$ is hereby analytically reviewed and observations show that the linear multistep method is a typical Picard's fixed point iterative formula with a differential operator endowed with some numerical reformulations instead of the usual integral operator as in the traditional Picard's method. The study also shows that any given linear multistep iterative method will be convergent to a fixed point if and only if it is consistent and stable. This was adequately illustrated with an example as is contained in section three of this work.


Key words: Linear multistep, Fixed point iterative method, Consistence, Stability convergence 2020 Mathematics Subject Classifications: 47J26 and 46N40

## INTRODUCTION

Consider the differential equation

$$
\begin{equation*}
\dot{\mathrm{x}}=\mathrm{f}(\mathrm{t}, \mathrm{x}) ; \mathrm{x}\left(\mathrm{t}_{0}\right)=\mathrm{x}_{0} \ldots \tag{1.1}
\end{equation*}
$$

A computational method for determining the sequence $\left\{x_{n}\right\}$ that takes the form of a linear relationship between $\mathrm{x}_{\mathrm{n}+\mathrm{j}}, \mathrm{f}_{\mathrm{n}+\mathrm{j}} ;=0,1, \ldots \mathrm{k}$ is called the linear multistep method of step number k or k - step method;

$$
f_{n+j}=f\left(t_{n+j}, x_{n+j}\right)=f\left(t_{n+j}, x\left(t_{n+j}\right)\right) .
$$

The general linear multistep method ${ }^{[1-4]}$ may be given thus -

$$
\begin{equation*}
\mathrm{x}_{\mathrm{n}+\mathrm{k}}=\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}}+\mathrm{h} \sum_{\mathrm{j}=0}^{\mathrm{k}} \beta_{\mathrm{j}} \beta_{\mathrm{j}} \mathrm{f}_{\mathrm{n}+\mathrm{j}} \ldots \tag{1.2}
\end{equation*}
$$

Where $\alpha_{\mathrm{j}}$ and $\beta_{\mathrm{j}}$ are constants, $\alpha_{\mathrm{k}} \neq 0$ and not both $\alpha_{0}$ and $\beta_{0}$ are zeros. We may without loss of

## Address for correspondence:

Eziokwu C. Emmanuel
E-mail: okereemm@yahoo.com
generality, and for the avoidance of arbitrariness set $\alpha_{k}=1$ throughout.
Suppose in (1.2), $\beta_{\mathrm{k}}=0$ then it is called an explicit method since it yields the current value $x_{n+k}$ directly in terms ofx $x_{n+j}, f_{n+j} ; j=0,1, \ldots, k-1$ which by the stage of computation have already been calculated. ${ }^{[5-8]}$ If, however, $\mathrm{B}_{\mathrm{k}} \neq 0$, then (1.2) is called an implicit method which requires the solution at each stage of the computation of the equation

$$
\begin{equation*}
x_{n+k}=h \beta_{k} f+\left(t_{n+k}, x_{n+k}+g \ldots\right. \tag{1.3}
\end{equation*}
$$

Were $g$ is a known function of the previously calculated values, $x_{n+j}, f_{n+j} ; j=0,1, \ldots, k-1$
If the lipschittz condition is applied onfand $m=l h\left|\mathrm{~B}_{\mathrm{k}}\right|$, we observe that the unique solution exists as seen in the theorem (3.1) and that the unique solution for $\mathrm{X}_{\mathrm{n}+\mathrm{k}}$ exists as well where the computational iteration converges to $\mathrm{x}_{\mathrm{n}+\mathrm{k}}$ if

$$
\ell \mathrm{h}\left|\mathrm{~B}_{\mathrm{k}}\right|<\mid \text { i.e. } \mathrm{h}<\frac{1}{\left.\ell \mathrm{~h}\right|^{2}{ }_{\mathrm{k}} \mid}
$$

We, therefore, see that; ${ }^{[9-12]}$ implicit methods call for a substantially greater deal of computational
efforts than the explicit method whereas, on the other hands, for a given step number, implicit methods can be made more accurate than the explicit ones. Moreover, they have favorable stability properties as will be seen in Section 3.

## MAIN RESULT ON LINEAR MULTISTEPITERATIVE METHODS:

Analytical study of the linear multistep methods has revealed the following facts:-
a. That the domain of existence of solution of the linear multistep methods is the complete metric space.
b. That the solution of the linear multistep method converges in the complete metric space.
c. That the initial value problem $\mathrm{x}^{\prime}=f(t, x) ; x\left(t_{0}\right)=x_{0}$ solvable by the linear multistep in the complete metric space is a continuous function.
d. That the linear multistep method satisfies the conditions of the Banach contraction mapping principle.
e. That the linear multistep method is exactly the Picard's iterative method with a differential operator instead of the usual integral operator. Theorem 2.1: Let $X$ be a complete metric space and let R be a region in $(t, x)$ plane containing $\left(t_{0}, x_{0}\right)$ for $X_{0}, x \in X$. Suppose, given

$$
\begin{equation*}
\dot{x}=f(t, x) ; x\left(t_{0}\right)=x_{0} \ldots \tag{2.0}
\end{equation*}
$$

A differential equation where $f(t, x)$ is continuous. If the map f in (2.1) is Lipschitzian and with constant $K<1$, then the initial value problem (2.1) by the linear multistep method has a unique fixed point.

$$
x^{*}=x_{n+k}=\sum_{j=0}^{k-1} \alpha_{j} x_{n+j}+h \sum_{j=0}^{k} \beta_{j} f_{n+j} \ldots
$$

With a two-step predictor-corrector method.
i.e.The predictor: $\mathrm{x}_{\mathrm{j}+1}^{(\mathrm{j})}=\sum_{\mathrm{j}=0}^{\mathrm{n}} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{j}}+\mathrm{h} \sum_{\mathrm{j}=0}^{\mathrm{n}} \beta_{\mathrm{j}} \mathrm{f}_{\mathrm{j}}$

The corrector: : ${ }_{j+1}^{(j)}=\sum_{j=0}^{n} \alpha_{j} x_{j+1}^{(j)}+h \sum_{j=0}^{n} \beta_{j+1} f_{j+1}$
For $\mathrm{x}_{\mathrm{n}+\mathrm{k}}$ satisfying. $\mathrm{h}<\frac{1}{\left.\ell \mathrm{~h}\right|^{2}{ }_{k} \mid}, \mathrm{m}=\left.\ell \mathrm{h}\right|^{2}{ }_{\mathrm{k}} \mid$

## Proof

Let $\mathrm{x}_{1}=\mathrm{f}\left(\mathrm{x}_{0}\right)$

$$
\begin{gather*}
x_{2}=f\left(x_{1}\right)=f\left(f\left(x_{0}\right)\right)=f^{2}\left(x_{0}\right) \\
x_{3}=f\left(x_{2}\right)=f\left(f^{2}\left(x_{0}\right)\right)=f^{3}\left(x_{0}\right) \\
x_{n}=f\left(x_{n-1}\right)=f\left(f^{n-1}\left(x_{0}\right)\right)=f^{n}\left(x_{0}\right) \\
x_{n+k}=f\left(x_{n+k-1}\right)=f\left(f^{n+k-1}\left(x_{0}\right)\right)=f^{n+k}\left(x_{0}\right) \ldots \tag{2.1}
\end{gather*}
$$

We have constructed a sequence $\left\{x_{n}\right\}_{\mathrm{n}=0}$ in $(X, \rho)$. We shall prove that this sequence is Cauchy.
First, we compute
$\rho\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}}, \mathrm{x}_{\mathrm{n}+\mathrm{k}+1}\right)=\rho\left(\mathrm{f}\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}}\right), \mathrm{f}\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}+1}\right)\right.$ Using
$\leq K \rho\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}-2} \mathrm{X}_{\mathrm{n}+\mathrm{k}-1}\right)$ Since is a contraction
$=K \rho\left(f_{n+k-2}, f_{n+k-1}\right)$ Using (2.1)
$\leq \mathrm{K}\left[\mathrm{K} \rho\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}-2}, \mathrm{X}_{\mathrm{n}+\mathrm{k}-1}\right)\right]$ Since is a contraction
$=K^{2 \rho}\left(\mathrm{X}_{\mathrm{n}+\mathrm{k}-2}, \mathrm{x}_{\mathrm{n}+\mathrm{k}-1}\right)$
$K^{n+k} \rho\left(\mathrm{x}_{0}, \mathrm{x}_{1}\right)$
i.e. $K \rho\left(x_{n+k}, x_{n+k+1}\right) \leq K^{n+k} \rho\left(x_{0}, x_{1}\right) \ldots$

We can now show that $\left\{\mathrm{X}_{\mathrm{n}+\mathrm{k}}\right\}_{\mathrm{n}=0}$ is Cauchy.
Let $\mathrm{m}+k>n+k$. Then
$\rho\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}}, \mathrm{x}_{\mathrm{m}+\mathrm{k}}\right) \leq \rho\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}}, \mathrm{x}_{\mathrm{m}+\mathrm{k}}\right)+\rho\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}-1}, \mathrm{x}_{\mathrm{m}+\mathrm{k}-2}\right)$
$+\ldots+\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}-1}, \mathrm{x}_{\mathrm{m}+\mathrm{k}}\right)$
$\leq \mathrm{K}^{\mathrm{n}+\mathrm{k}} \rho\left(\mathrm{x}_{0}, \mathrm{x}_{1}\right)+\mathrm{K}^{\mathrm{n}+\mathrm{k}-1} \rho\left(\mathrm{x}_{0}, \mathrm{x}_{1}\right)$
$+\ldots+K^{n+k-1} \rho\left(x_{0}, x_{1}\right) \quad U s i n g$ (2.2)
$=\mathrm{K}^{\mathrm{n}+\mathrm{k}} \rho\left(\mathrm{x}_{0}, \mathrm{x}_{1}\right)\left(1+\mathrm{k}+\mathrm{k}^{2}+\ldots+\mathrm{k}^{\mathrm{n}+\mathrm{m}-1}+\mathrm{k}^{\mathrm{n}+\mathrm{k}}+\ldots\right)$
Since the series on the right hand side is a geometric progression with common ratio $<1$, it sum to infinity is $\frac{1}{1-\mathrm{k}}$. Hene, we have from above that

$$
\begin{aligned}
& \rho\left(\mathrm{x}_{\mathrm{n}}, \mathrm{x}_{\mathrm{m}}\right) \leq \mathrm{k}^{\mathrm{n}-\mathrm{k}} \rho\left(\mathrm{x}_{0}, \mathrm{x}_{1}\right)\left(\frac{1}{1-\mathrm{k}}\right) \rightarrow 0 \\
& \text { as } \mathrm{n}-\mathrm{k} \rightarrow \infty \sin \text { ce } \mathrm{k}<1
\end{aligned}
$$

Hence, the sequence $\left\{\mathrm{x}_{\mathrm{n}+\mathrm{k}}\right\}_{\mathrm{n}=0}$ is a Cauchy sequence in $X$ and since $X$ is complete,
$\left\{\mathrm{x}_{\mathrm{n}+\mathrm{k}}\right\}_{\mathrm{n}=0}^{\infty}$ Converges to a point in $X$.]

$$
\begin{equation*}
\text { Let } x_{n+k} \rightarrow x^{*} \text { as } h \rightarrow \infty \ldots \tag{2.3}
\end{equation*}
$$

Since f is a contraction and hence is continuous it follows from (2.3) that
$\mathrm{f}\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}}\right) \rightarrow \mathrm{f}\left(\mathrm{x}^{*}\right)$ as $\mathrm{n} \rightarrow \infty$. But $\mathrm{f}\left(\mathrm{x}_{\mathrm{n}+\mathrm{k}}\right)=\mathrm{x}_{\mathrm{n}+\mathrm{k}+1}$ from (2.2). So

$$
\begin{equation*}
x_{n+k+1}=f\left(x_{n+k}\right)=f\left(x^{*}\right) \ldots \tag{2.4}
\end{equation*}
$$

However, limits are unique in a metric space, so from (2.3) and (2.4), we obtain that

$$
\begin{equation*}
f\left(x^{*}\right)=x^{*} \ldots \tag{2.5}
\end{equation*}
$$

Hence, f has a unique fixed point in $X$. We shall now prove that this fixed point is unique. Suppose for contradiction, there exists $y^{*} \in \mathrm{X}$ such that

$$
\begin{equation*}
y^{*}=x^{*} \text { and }\left(y^{*}\right)=y^{*} \ldots \tag{2.6}
\end{equation*}
$$

Then, from (2.5) and (2.6)

$$
\rho\left(x^{*}, y^{*}\right)=\rho\left(f\left(x^{*}\right), f\left(y^{*}\right)\right) \leq k \rho\left(x^{*}, y^{*}\right)
$$

So that
$(k-1) \rho\left(x^{*}, y^{*}\right) \geq 0$ and $\rho\left(x^{*}, y^{*}\right)=0$.
We can divide by it to get $\mathrm{k}-1 \geq 0$, that is, $\mathrm{k} \geq 1$ which is a contradiction.
Hence $x^{*}=y^{*}$ and the fixed point is unique.
Therefore,

$$
\mathrm{x}_{\mathrm{n}+\mathrm{k}}=\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}}+\mathrm{h} \sum_{\mathrm{j}=0}^{\mathrm{k}} \beta_{\mathrm{j}} \mathrm{f}_{\mathrm{n}+\mathrm{j}} ; \mathrm{a} \leq \mathrm{t}_{\mathrm{n}} \leq \mathrm{n}
$$

Is the linear multistep fixed point iterative formular for the initial value problem

$$
\dot{\mathrm{x}}=\mathrm{f}(\mathrm{t}, \mathrm{x}) ; \mathrm{x}\left(\mathrm{t}_{0}\right)=\mathrm{x}_{0}
$$

Of the ordinary differential type.
Finally, to be sufficiently sure, we also show that

$$
x^{*}=x_{n+k}=\sum_{j=0}^{k-1} \alpha_{j} x_{n+j}+h \sum_{j=0}^{k} \beta_{j} f_{n+j}
$$

Satisfies the lipschitz condition.

$$
\begin{gathered}
\left|x^{*}-y^{*}\right|=\left|x_{n+k}-y_{n+k}\right| \\
\left.=\mid \sum_{j=0}^{k-1} \alpha_{j} x_{n+j}+h \sum_{j=0}^{k} \beta_{j} f_{n+j}\right)-\left(\sum_{j=0}^{k-1} \alpha_{j} y_{n+j}+h \sum_{j=0}^{k} \beta_{j} f_{n+j}^{*}\right) \mid \\
\leq \sum_{j=0}^{k-1} \alpha_{j}\left|x_{n+j}-y_{n+j}\right|+h \sum_{j=0}^{k} \beta_{j}\left|f_{n+j}-f_{n+j}^{*}\right| \\
=k_{1} \sum_{j=0}^{k-1}\left|x_{n+j}-y_{n+j}\right|+k_{2} \sum_{j=0}^{k}\left|f_{n+j}-f_{n+j}^{*}\right| \\
=\left(k_{1}+k_{2}\right)\left|\sum_{j=0}^{k-1} z_{n+j}+\sum_{j=0}^{k} f_{m+k}\right| \\
=K \sum_{j=0}^{k}\left|z_{n+j}+f_{m+j}\right|
\end{gathered}
$$

Hence, $\mathrm{x}^{*}=\mathrm{x}_{\mathrm{n}+\mathrm{k}}$ is Lipschitizian and is a continuous map with the above fixed point.
Also in the same pattern, iterative methods for the respective linear multistep methods are as follows:
A. The Explicit Methods are:-
i. Euler:

$$
x_{n+1}=x_{n}+h f_{n}
$$

ii. The midpoints method:

$$
x_{n+2}=x_{n}+2 h f_{n+1}
$$

iii. Milne's method:

$$
x_{n+1}=x_{n-3}+\frac{4 h}{3}\left[2 f_{n-2}+f_{n-1}+2 f_{n}\right]
$$

iv. Adam's method:

$$
x_{n+1}=x_{n}+\frac{h}{24}\left[55 f_{n}-59 f_{n-1}+35 f_{n-2}-9 f_{n-3}\right]
$$

v. The Generalized predictor method:

$$
x_{j+1}^{(j)}=\sum_{j=0}^{n} \alpha_{j} x_{j}+h \sum_{j=1}^{n} \beta_{j} f_{j}
$$

## B. The Implicit Methods are:-

i. Trapezoidal method:

$$
x_{n+1}^{(j+1)}=x_{n}+\frac{h^{2}}{6}\left[f_{n}+f_{n+1}^{(j)}\right]
$$

ii. Simpson's method:

$$
x_{n+2}^{(j+1)}=x_{n}+\frac{h}{3}\left[f_{n+1}^{(j)}+4 f_{n+1}+f_{n}\right]
$$

iii. Simpson's method:

$$
x_{n+2}^{(j+1)}=x_{n-2}+\frac{h}{3}\left[f_{n-1}+4 f_{n}+f_{n+1}^{(j)}\right]
$$

iv. Adams Moulton's method

$$
x_{n+2}^{(j+1)}=x_{n}+\frac{h}{3}\left[9 f_{n+1}+19 f_{n}-5 f_{n-1}+f_{n-2}\right]
$$

v. Milne's corrector method:

$$
\mathrm{x}_{\mathrm{n}+1}^{(j+1)}=\mathrm{x}_{\mathrm{n}-2}+\frac{\mathrm{h}}{3}\left[\mathrm{f}_{\mathrm{n}-1}+4 \mathrm{f}_{\mathrm{n}}+\mathrm{f}_{\mathrm{n}+1}^{(\mathrm{j})}\right] ; \mathrm{n}=1
$$

vi. The Generalized corrector method

$$
x_{j+1}^{(j)}=\sum_{j=0}^{n} \alpha_{j} x_{j+1}^{(j)}+h \sum_{j=1}^{n} \beta_{j+1} f_{j+1}
$$

## C: The Generalized Iterative (Corrector Predictor) Methods are

$$
\begin{equation*}
x_{j+1}^{(j)}=\sum_{j=0}^{n} \alpha_{j} x_{j}+h \sum_{j=1}^{n} \beta_{j} \ldots \tag{C1}
\end{equation*}
$$

$$
\begin{equation*}
x_{j+1}^{(j)}=\sum_{j=0}^{n} \alpha_{j} x_{j+1}^{(j)}+h \sum_{j=1}^{n} \beta_{j+1} f_{j+1} \ldots \tag{C2}
\end{equation*}
$$

Here, $x_{j+1}^{(j+1)} \in X$ is the corrector points to be determined for all $\mathrm{j} \geq 0$ while $\mathrm{x}_{\mathrm{j}+1}^{(j+1)} \in \mathrm{X}$ is predetermined before $\mathrm{x}_{\mathrm{j}+1}^{(\mathrm{j}+1)} \in \mathrm{X}$. While the iterations are alternatively implement one after the other starting first with the predictor.
Note: The generalized compact form of C 1 and C 2 is as follows

$$
x_{n+k-1}=\sum_{j=0}^{k-1} \alpha_{j} x_{n+j}+h \sum_{j=0}^{k} \beta_{j} f_{n+j}
$$

## Convergence Analysis

Given the linear multistep method

$$
\begin{equation*}
\mathrm{x}_{\mathrm{n}+\mathrm{k}}=\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}}+\mathrm{h} \sum_{\mathrm{j}=0}^{\mathrm{k}} \beta_{\mathrm{j}} \mathrm{~F}_{\mathrm{n}+\mathrm{j}} ; \mathrm{a} \leq \mathrm{t}_{\mathrm{n}} \leq \mathrm{n} \ldots \tag{2.7}
\end{equation*}
$$

Theorem 2.2: ${ }^{[13-16]}$
Let $\mathrm{x}_{\mathrm{n}+\mathrm{j}}=\mathrm{x}\left(\mathrm{t}_{\mathrm{n}+\mathrm{j}}\right) ; \mathrm{j}=0,1,2, \ldots, \mathrm{k}-1$ denote its numerical solution

$$
T_{n+k}=\sum_{j=0}^{k-1} \alpha_{j} x\left(t_{n+j}\right)-h \sum_{j=0}^{k} \beta_{j} f\left(t_{n+j},\left(x_{n+j}\right)\right)
$$

The local truncation error and

$$
\tau_{\mathrm{n}+\mathrm{k}}=\frac{1}{\mathrm{~h}} \mathrm{~T}_{\mathrm{n}+\mathrm{k}}(\mathrm{x})
$$

Then, the linear multistep method (3.1) is said to be consistent if
$\tau(\mathrm{h})=\max \left|\mathrm{T}_{\mathrm{n}+\mathrm{k}}(\mathrm{x})\right| \rightarrow 0$ as $\mathrm{h} \rightarrow 0$ and $\sum(\mathrm{h})=0\left(\mathrm{~h}^{\mathrm{m}}\right)$
For some $\mathrm{m} \geq 1$ or equivalently (1.3.2) is said to be consistent if

$$
\begin{equation*}
\sum_{\mathrm{j}=0}^{\mathrm{k}} \alpha_{\mathrm{j}} ; \sum_{\mathrm{j}=0}^{\mathrm{k}} \mathrm{j} \alpha_{\mathrm{j}}+\sum_{\mathrm{j}=1} \beta_{\mathrm{j}}=1 \ldots \tag{2.8}
\end{equation*}
$$

## Proof:

If the numerical solution of a given linear multistep method is

$$
\begin{equation*}
x_{n+j}=x\left(t_{n+j}\right), j=0,1,2, \ldots, k-1 \ldots \tag{2.9}
\end{equation*}
$$

Moreover, the local truncation error is

$$
\begin{align*}
T_{n+k}= & \sum_{j=0}^{k-1} \alpha_{j} x\left(t_{n+j}\right)-h \sum_{j=0}^{k} \beta_{j} f\left(t_{n+j}, x_{n+j}\right) \ldots  \tag{2.10}\\
& \text { With } \tau_{n+k}(x)=\frac{1}{h} T_{n+k}(x), \ldots \tag{2.11}
\end{align*}
$$

We want to prove that the linear multistep method

$$
\begin{equation*}
x_{n+k}=\sum_{j=0}^{k-1} \alpha_{j} x_{n+j}+h \sum_{j=0}^{k} \beta_{j} f_{n+j}, a \leq t_{n+j} \leq n \tag{2.12}
\end{equation*}
$$

Is consistent if

$$
\begin{equation*}
\tau(\mathrm{h})=\max \left|\mathrm{T}_{\mathrm{n}+\mathrm{k}}(\mathrm{x})\right| \rightarrow 0 \text { as } \mathrm{h} \rightarrow 0 \ldots \tag{2.13}
\end{equation*}
$$

And
$\tau(\mathrm{h})=0\left(\mathrm{~h}^{\mathrm{m}}\right)$ For some $\mathrm{m} \geq 1 \ldots$
If $\mathrm{x}_{\mathrm{n}+\mathrm{j}}^{-}$denotes the numerical solution with the above exact values (1.2), then (2.14) yields
$\mathrm{x}_{\mathrm{n}+\mathrm{k}}+\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}}=\mathrm{h} \beta_{\mathrm{k}} \mathrm{f}\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}, \overline{\mathrm{x}}_{\mathrm{n}+\mathrm{k}}\right)+\mathrm{h} \sum_{\mathrm{k}=0}^{\mathrm{k}-1} \beta f\left(\mathrm{t}_{\mathrm{n}+\mathrm{j}}, \mathrm{x}_{\mathrm{n}+\mathrm{j}}\right) \ldots$

Applying localizing assumption on (2.15) means that no previous truncation error has been made and that

$$
x_{n+j}=x\left(t_{n+j}\right), j=0,1, \ldots, k-1
$$

So that we have

$$
\begin{align*}
& \overline{\mathrm{x}}_{\mathrm{n}+\mathrm{k}}+\sum_{\mathrm{j}=0}^{\mathrm{k}} \alpha_{\mathrm{j}} \overline{\mathrm{x}}\left(\mathrm{t}_{\mathrm{n}+\mathrm{j}}\right)=\mathrm{h} \beta_{\mathrm{k}} \mathrm{f}\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}, \overline{\mathrm{x}}_{\mathrm{n}+\mathrm{k}}\right) \\
& +\mathrm{h} \sum_{\mathrm{k}=0}^{\mathrm{k}-1} \beta_{\mathrm{j}} \mathrm{f}\left(\mathrm{t}_{\mathrm{n}+\mathrm{j}}, \overline{\mathrm{x}}_{\mathrm{n}+\mathrm{j}}\right) \ldots \tag{2.16}
\end{align*}
$$

Using the local truncation error earlier defined in (2.2), we now have

$$
\begin{align*}
& \left.\left.x\left(t_{n+k}\right)+\sum_{j=0}^{k-1} \alpha_{j} x\left(t_{n+j}\right)\right)=T_{n+k}+h \beta_{k} f\left(t_{n+k}\right)\right), x\left(t_{n+k}\right) \\
& +h \sum_{k=0}^{k-1} \beta_{j} f\left(t_{n+j}, x\left(t_{n+j}\right)\right) \ldots \tag{2.17}
\end{align*}
$$

Subtracting (2.16) from (2.17) we have
$x\left(t_{n+k}\right)-\bar{x}_{n+k}=T_{n+k}+h \beta_{k}\left[f\left(t_{n+k}, x\left(t_{n+k}\right)\right)\right.$
$-f\left(t_{n+k}, \bar{x}_{n+k}\right) \ldots$
If we apply mean value theorem on (3.1.10), We have

$$
\begin{aligned}
& \mathrm{f}\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}, \mathrm{x}\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}\right)\right)-\mathrm{f}\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}, \overline{\mathrm{x}}_{\mathrm{n}+\mathrm{k}}\right)= \\
& \left.\left(\mathrm{x}\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}\right)-\overline{\mathrm{x}}_{\mathrm{n}+\mathrm{k}}\right) \frac{\partial \mathrm{f}}{\partial \mathrm{x}} \right\rvert\,\left(\mathrm{t}_{\mathrm{n}+\mathrm{k},} \tau_{\mathrm{n}+\mathrm{k}}\right)
\end{aligned}
$$

Where $\eta_{n+k}$ lies between $\mathrm{x}_{\mathrm{n}+\mathrm{k}}^{-}$and $\mathrm{x}\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}\right)$ Therefore,
$\left[\left.1-h \beta_{k} \frac{\partial f}{\partial x} \right\rvert\,\left(t_{n+k}, \eta_{n+k}\right)\right]\left(x\left(t_{n+k}\right), \bar{x}_{n+k}\right)=T_{n+k} \cdots$

Let $e_{n+k}$ represent the error at $(\mathrm{n}+\mathrm{k})$ point, so that if the method is explicit $\beta_{\mathrm{k}}=0$ and then $\mathrm{T}_{\mathrm{n}+\mathrm{k}}=\mathrm{e}_{\mathrm{n}+\mathrm{k}}$ but if the method is implicit $\beta_{\mathrm{k}} \neq 0$ and
$\left.h \beta_{k}\left(\frac{\partial f}{\partial x}\right) \right\rvert\,\left(\mathrm{t}_{\mathrm{n}+\mathrm{k}}, \mathrm{n}_{\mathrm{n}+\mathrm{k}}\right)$ is small then $\mathrm{T}_{\mathrm{n}+\mathrm{k}} \approx \mathrm{e}_{\mathrm{n}+\mathrm{k}}$
Again let

$$
\begin{equation*}
\tau_{(n+k)}(x)=\frac{1}{h} T_{n+k}(x) \ldots \tag{2.20}
\end{equation*}
$$

For us to show that the approximate solution $\left\{\mathrm{x}_{\mathrm{n}} \mid \mathrm{t}_{0} \leq \mathrm{t}_{\mathrm{n}} \leq \mathrm{b}\right\}-1$ of (3.1.4) converges to the theoretical solution $\mathrm{x}(\mathrm{t})$ of the initial value problem

$$
\dot{\mathrm{x}}=\mathrm{f}(\mathrm{t}, \mathrm{x}) ; \mathrm{x}\left(\mathrm{t}_{0}\right)=\mathrm{x}_{0}
$$

We ${ }^{[13,14]}$ need to necessarily satisfy the consistency condition

$$
\begin{equation*}
\tau(\mathrm{h})=\max _{\mathrm{t}_{0} \leq \mathrm{t}_{\mathrm{n}} \leq b}\left|\mathrm{~T}_{\mathrm{n}+\mathrm{k}}(\mathrm{x})\right| \rightarrow 0 \text { ash } \rightarrow 0 \ldots \tag{2.21}
\end{equation*}
$$

Plus the condition that
$\tau(\mathrm{h})=0\left(\mathrm{~h}^{\mathrm{m}}\right)$, for some $\mathrm{m} \geq 1 \ldots$
By this, we ${ }^{[5]}$ show the only necessary and sufficient condition for the linear multistep (2.14) to be consistent is that

$$
\begin{equation*}
\sum_{j=0}^{k} \alpha_{j}=1 \text { and }-\sum_{j=0}^{k} j \alpha_{j}+\sum_{j=1}^{k} \beta_{j}=1 \ldots \tag{2.23}
\end{equation*}
$$

And for (2.23) above to be valid for all functions $\mathrm{x}(\mathrm{t})$ is for $\mathrm{x}(\mathrm{t})$ that are $\mathrm{m}+1$ times continuously differentiable to necessarily satisfy
$\sum_{\mathrm{j}=0}^{\mathrm{k}}(-\mathrm{j}) \alpha_{\mathrm{j}}+\sum_{\mathrm{j}=1}^{\mathrm{k}}(-\mathrm{j})^{\mathrm{i}-1} \beta_{\mathrm{j}}=1, \mathrm{i}=2, \ldots \mathrm{~m} \ldots$
Hence, we know that
$T_{n+k}(\alpha x+\beta w)=\alpha T_{n+k}(x)+\beta T_{n+k}(w) \ldots$

For all constants $\alpha, \beta$ and all differentiable functions $x, w$. we now examine the consequence of (2.19) and (2.20) by expanding $x(t)$ about $t_{n}$ using Taylor's theorem and we have
$x(t)=\sum_{j=0}^{k} \frac{1}{j}\left(t-t_{0}\right) x^{1}\left(t_{n}\right)+R_{m+1}(t)$

Assuming $\mathrm{x}(\mathrm{t})$ is $\mathrm{m}+1$ times continuously differentiable. Substituting into the truncation error
$T_{n+k}(x)=x\left(t_{n+k}\right)-\sum_{j=0}^{k} \alpha_{j} x\left(t_{n+j}\right)+h \sum_{j=1}^{k} \beta_{j} F\left(t_{n+j}\right) \ldots$

And also using (2.23)
$T_{n+k}(x)=\sum_{j=0}^{m-1} \frac{1}{j} x^{(j)}\left(t_{n}\right) T_{n+k}\left(\left(t-t_{n}\right)^{j}\right)+T_{n+k}\left(R_{m+1}\right) \ldots$

It becomes necessary ${ }^{[16,17]}$; Keller ${ }^{[18]}$ to calculate $T_{n+k}\left(t-t_{n}\right)^{j}$ For $j=0$

$$
\begin{equation*}
\mathrm{T}_{\mathrm{n}+\mathrm{k}}(1)=\mathrm{c}_{0} \equiv 1-\sum_{\mathrm{j}=0}^{\mathrm{k}} \alpha_{\mathrm{j}} \ldots \tag{2.29}
\end{equation*}
$$

For $\mathrm{j} \geq 1$ we have

$$
\begin{gather*}
T_{n+k}\left(t-t_{n}\right)^{j}=T_{n+k}\left(t-t_{n}\right)^{j} \\
=\left(\sum_{j=0}^{k} \alpha_{j}\left(t_{n+k}-t_{n}\right)^{j}+h \sum_{j=0}^{k} \beta_{j}^{i}\left(t_{n+j}-t_{n}\right)^{i=1}\right)=c_{1} h^{1} \ldots  \tag{2.30}\\
C_{j}=1-\left(\sum_{j=0}^{k}(-j)^{i} \alpha_{j}+i \sum_{j=1}^{k}(-j)^{i=1} \beta_{j}\right), i \geq 1
\end{gather*}
$$

This gives

$$
\begin{equation*}
\mathrm{T}_{\mathrm{n}+\mathrm{k}}(\mathrm{x})=\sum_{\mathrm{j}=1}^{\mathrm{m}} \frac{\mathrm{c}}{\mathrm{j}} \mathrm{~h}^{\mathrm{j}} \mathrm{x}^{(\mathrm{j})}\left(\mathrm{t}_{\mathrm{n}}\right)+\mathrm{T}_{\mathrm{n}+\mathrm{k}}\left(\mathrm{R}_{\mathrm{m}+1}\right) \ldots \tag{2.31}
\end{equation*}
$$

Moreover, if we write the remainder $\mathrm{R}_{\mathrm{m}+1}(\mathrm{t})$ as

$$
\mathrm{R}_{\mathrm{m}+1}(\mathrm{t})=\frac{1}{(\mathrm{~m}+1)!}\left(\mathrm{t}-\mathrm{t}_{\mathrm{n}}\right)^{\mathrm{m}+1} \mathrm{x}^{\mathrm{m}+1}\left(\mathrm{t}_{\mathrm{n}}\right)+\ldots
$$

Then,

$$
\begin{equation*}
T_{n+k} R_{m+1}(t)=\frac{C_{m+1}}{(m+1)!} h^{m+1} x^{m+1}\left(t_{n}\right)+0\left(h^{m+2}\right) \ldots \tag{2.32}
\end{equation*}
$$

To obtain the consistency condition (2.20), we need $\tau(h)-0(h)$ and this requires $T_{n+k}(x)=0\left(h^{2}\right)$. Using (2.19) with $\mathrm{m}=1$, we must have $\mathrm{C}_{0}, \mathrm{C}_{1}=0$ which gives the set of equations (2.22) which are referred to as consistency conditions in some texts. Finally, to obtain (3.1.14) for some $m \geq 1$, we must
have $T_{n+k}(x)=0\left(h^{m+1}\right)$. From (2.30) and (2.31), this will be true if and only if $\mathrm{C}_{\mathrm{i}}=0, \mathrm{i}=0,1,2 \ldots \mathrm{~m}$.
This proves the conditions (2.21) and completes the proof.
Theorem 2. ${ }^{[17-20]}$ Assume the consistency condition of (2.10), then the linear multistep method (1.2) is stable if and only if the following root conditions (2.11)-(2.12) are satisfied

$$
\begin{equation*}
\text { The root }\left|\mathrm{r}_{\mathrm{j}}\right|<1=j=0,1, \ldots, k \ldots \tag{2.33}
\end{equation*}
$$

$$
\begin{equation*}
\left|\mathrm{r}_{\mathrm{j}}\right|=1 \Longrightarrow \rho^{1}\left(\mathrm{r}_{\mathrm{j}}\right) \neq 0 \ldots \tag{2.34}
\end{equation*}
$$

Where

$$
\rho(r)=r^{k-1}-\sum_{j=0}^{k} \alpha_{j} r^{j}
$$

## Proof:

Given the linear multistep

$$
\begin{equation*}
\mathrm{x}_{\mathrm{n}+\mathrm{k}}+\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}}+\mathrm{h} \sum_{\mathrm{k}=0}^{\mathrm{k}-1} \beta_{\mathrm{j}} \mathrm{f}_{\mathrm{n}+\mathrm{j}} ; \mathrm{a} \leq \mathrm{t}_{\mathrm{n}+\mathrm{j}} \leq \mathrm{n} \ldots \tag{2.35}
\end{equation*}
$$

With the associated characteristic polynomial

$$
\begin{equation*}
P(r)=r^{k+1}-\sum_{j=0}^{k} \alpha_{j} r^{j} \ldots \tag{2.36}
\end{equation*}
$$

such that $P(1)=0$ by the consistency condition. Let $r_{0}, \ldots, r_{n}$ denote the respective roots of $P(r)$, repeated according to their multiplying and let $\mathrm{r}_{0}=1$.
The linear multistep method 2.8. Satisfies the root condition if

$$
\begin{align*}
& \left|\mathrm{r}_{\mathrm{j}}\right| \leq 1, \mathrm{j}=0,1, \ldots, \mathrm{k} \ldots  \tag{2.37}\\
& \left|\mathrm{r}_{\mathrm{j}}\right|=1 \Rightarrow \mathrm{P}^{1}\left(\mathrm{r}_{\mathrm{j}}\right) \neq 0 \ldots \tag{2.38}
\end{align*}
$$

Let (2.8) be stable we now prove that the root condition (2.37) and (2.38) are satisfied. By contradiction let
$\left|r_{j}(0)\right|>1$ for some j . This is to say we consider the initial value problem $x^{\wedge} 1 \equiv 0 ; x(0)=0$ with solution $x(t)=0$. So that (2.8) becomes

$$
\begin{equation*}
\mathrm{x}_{\mathrm{n}+\mathrm{k}}=\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}} ; \mathrm{n} \geq \mathrm{k} \ldots \tag{2.39}
\end{equation*}
$$

If we take $x_{0}=x_{1}=\ldots=x_{k}=0$, then the numerical solution clearly becomes $\mathrm{x}_{\mathrm{n}}=0$ for all $\mathrm{n} \geq 0$.
For perturbed initial values, let

$$
\begin{equation*}
z_{0}=\in, z_{1}=\in r_{1}(0), \ldots, z_{n}=\in r_{1}(0)^{p} \ldots \tag{2.40}
\end{equation*}
$$

And for these initial values

$$
\max _{0 \leq n-k}\left|\mathrm{x}_{\mathrm{n}}-\mathrm{z}_{\mathrm{n}}\right| \leq \in\left|\mathrm{r}_{1}(0)\right|^{\mathrm{p}}
$$

To bound the solution $\mathrm{e}_{\mathrm{n}}$ on $\left[\mathrm{x}_{0}, \mathrm{~b}\right]$, we must bound each term $\left[\mathrm{r}_{\mathrm{j}}(\mathrm{h} \lambda)\right]^{\mathrm{n}}$ to do so, consider the expansion

$$
\begin{equation*}
(\mathrm{U})=\mathrm{r}_{\mathrm{j}}(0)+\mathrm{Ur}_{\mathrm{j}}(\xi) \ldots \tag{2.46}
\end{equation*}
$$

For some $\xi$ between 0 and $U$. To compute $r_{j}{ }^{1}(u)$, differentiate the identity

$$
\begin{gather*}
p\left(r_{j}(u)\right)-u \sigma\left(r_{j}(u)\right)=0 \\
p^{1}\left(r_{j}(c u)\right)-r_{j}^{1}(u)-\left[\sigma_{j}(u)+u \sigma^{1}\left(r_{j}(u)\right)\left(r^{1}(u)\right)\right]=0 \\
r_{j}^{1}(u)\left[p^{1}\left(r_{j}(u)\right)-u \sigma^{1}\left(r_{j}(u)\right)=\sigma\left(r_{j}(u)\right)\right. \\
r_{j}^{1}(u)=\frac{\sigma(r(u))}{p\left(r_{j}(u)\right)-u r^{1}(r(u))} \cdots \tag{2.47}
\end{gather*}
$$

By assumption that $r_{j}(0)$ is a simple root of $\mathrm{p}(\mathrm{r})=0 ; 0 \leq \mathrm{j} \leq \mathrm{k}$, it follows that $\mathrm{p}^{1}\left(\mathrm{r}_{\mathrm{j}}(0)\right)=0$ and by continuity, $\mathrm{p}^{1}\left(\mathrm{r}_{\mathrm{j}}(\mathrm{u})\right) \neq 0$ for all sufficiently small values of $u$, the denominator in $(2.20)$ is non-zero and we can bound $\mathrm{r}_{\mathrm{j}}(\mathrm{u})\left|\mathrm{r}_{\mathrm{j}}(\mathrm{u})\right|=\mathrm{c}_{2}$ for all $|\mathrm{u}| \leq \mathrm{u}_{0}$ For some $\mathrm{U}_{0} \geq 0$.
Using this with (3.3.12) and the root condition (3.2.4), we [Stetter; ${ }^{[28]}$ Stetter ${ }^{[29]]}$ have

$$
\left|\left[\mathrm{r}_{\mathrm{j}}(\mathrm{~h} \lambda)\right]^{\mathrm{n}}\right| \leq\left|\mathrm{r}_{\mathrm{j}}(0)\right|+\mathrm{c}_{2}|(\mathrm{~h} \lambda)| \leq 1+\mathrm{c}_{2}|(\mathrm{~h} \lambda)|
$$

$\left|\left[r_{j}(h \lambda)\right]^{n}\right| \leq\left[1+c_{2}|(h \lambda)|\right]^{n} \leq e^{\mathrm{C}_{2 h|h|}} \leq \mathrm{e}^{\mathrm{c}_{2}}\left(\mathrm{bx}_{\mathrm{n}}\right)|\lambda|$
for all $0 \leq h \leq h_{0}$.
Combine this with (2.18) and (2.19) to get Max $\left|\mathrm{e}_{\mathrm{n}}\right|$ $\leq \mathrm{c}_{2} \leq|\varepsilon| \mathrm{e}^{\mathrm{c} 2}\left(\mathrm{bx}_{\mathrm{n}}\right)|\lambda|$ for an approximate constant $\mathrm{c}_{0}$. This concludes the proof.
Theorem2.3: ${ }^{[21-24]}$ The linear multistep method (1.2) is said to be convergent if and only if it is consistent and stable.

## Proof:

By this, we want proof that if the consistency condition is assumed, the linear multistep method
$\mathrm{x}_{\mathrm{n}+\mathrm{k}}=\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}}+\mathrm{h} \sum_{\mathrm{j}=0}^{\mathrm{k}} \beta_{\mathrm{j}} \mathrm{f}_{\mathrm{n}+\mathrm{j}} ; \mathrm{a} \leq \mathrm{t}_{\mathrm{n}+\mathrm{j}} \leq \mathrm{n}$
Is convergent if and only if the root conditions (2.10) and (2.11) are satisfied.

We assume first the root conditions are satisfied and then show the linear multi step (2.8)
Is convergent. To start, we use the problem $x=0$, $x(0)=0$ with the solution $x(t)=0$. Then, the multistep method (2.8) becomes

$$
\begin{equation*}
\mathrm{x}_{\mathrm{n}+\mathrm{k}}=\sum_{\mathrm{j}=0}^{\mathrm{k}-1} \alpha_{\mathrm{j}} \mathrm{x}_{\mathrm{n}+\mathrm{j}}, \mathrm{n} \geq \mathrm{k} \ldots \tag{2.49}
\end{equation*}
$$

With $\mathrm{x}_{0}, \ldots, \mathrm{x}_{\mathrm{k}}$

Satisfying $n(h)=\max \left|\mathrm{X}_{\mathrm{n}}\right| \rightarrow 0$ as $\mathrm{h} \rightarrow 0 \ldots$
Suppose ${ }^{[25-28]}$ that the not condition is violated, we will show that $(2.10)$ is not convergent to $x(t)=0$. Assume that some $\left|\mathrm{r}_{\mathrm{j}}(0)\right|>1$ then a satisfactory solution of (2.11) is

$$
\mathrm{x}_{\mathrm{n}}=\mathrm{h}\left[\mathrm{r}_{\mathrm{j}}(0)\right]^{\mathrm{n}} ; \mathrm{t}_{0} \leq \mathrm{t}_{\mathrm{n}} \leq \mathrm{b} \ldots
$$

Condition (2.10) is satisfied since $n(h)=\mid h\left(r_{j}\right.$ (0)) $\mid \rightarrow 0$ as $h \rightarrow 0$.

However, the solution (2.11) does not converge. First

$$
\operatorname{Max}\left|\mathrm{x}\left(\mathrm{t}_{\mathrm{n}}\right)-\mathrm{x}_{\mathrm{n}}\right|=\mathrm{h} \mid \mathrm{h}\left[\left.\mathrm{r}_{\mathrm{j}}(0)\right|^{\mathrm{N}(\mathrm{~h})} 0 \leq \mathrm{t}_{\mathrm{n}} \leq \mathrm{b}\right.
$$

Consider those values of $h=\frac{b}{\mathrm{~N}(\mathrm{~h})}$. Then, $L^{\prime}$
Hospital's rule can be used to show that

$$
\operatorname{Lim} \frac{\mathrm{b}}{\mathrm{~N}}|\mathrm{r}(0)|^{\mathrm{N}}=\infty
$$

Showing that (2.11) does not converge.
Conversely assume the root condition is satisfied as with theorem 2.2 ; it is rather difficult to give a general proof of converge for an arbitrary differential equation. The present proof is restricted to the exponential equation (2.14) and again we assume that the roots $r_{i}=0$ are distinct.
To simplify the proof, we will show that the term $\gamma_{0}\left[\mathrm{r}_{0}(\lambda \lambda)\right]^{\mathrm{n}}$ in the solution

$$
\mathrm{x}_{\mathrm{n}}=\sum_{\mathrm{j}=0}^{\mathrm{k}} \gamma_{\mathrm{j}}\left|\mathrm{r}_{\mathrm{j}}(\mathrm{~h} \lambda)\right|^{\mathrm{n}}
$$

Will converge to the solution $\mathrm{e}^{\lambda \mathrm{t}}$ on $[0, \mathrm{~b}]$. The remaining terms
$\gamma_{\mathrm{j}}\left|\mathrm{r}_{\mathrm{j}}(\mathrm{h} \lambda)\right|^{\mathrm{n}}, \mathrm{j}=1,2, \ldots, \mathrm{k}$ are parasitic solution to converge to zero as $h \rightarrow 0$. Expand $r_{-} 0(h \lambda)$ using Taylor's theorem,

$$
\mathrm{r}_{0}(\mathrm{~h} \lambda)=\mathrm{r}_{0}(0)+\mathrm{h} \lambda \mathrm{r}_{0}^{2}(0)+0\left(\mathrm{~h}^{2}\right)
$$

From (2.19) $r_{0}^{2}(0)=\frac{\sigma(1)}{\rho^{1}(1)}$ and using this consistency condition (2.11), this leads to $\mathrm{r}_{0}{ }^{2}(0)=1$. then

$$
\begin{gathered}
\mathrm{r}_{0}(\mathrm{~h} \lambda)=1+\mathrm{h} \lambda+0\left(\mathrm{~h}^{2}\right)=\mathrm{e}^{\mathrm{h} \lambda}+0\left(\mathrm{~h}^{2}\right) \\
{\left[\mathrm{r}_{0}(\mathrm{~h} \lambda)\right]^{\mathrm{n}}=\mathrm{e}^{\mathrm{hn} \lambda}\left[1+0\left(\mathrm{~h}^{2}\right)\right]^{\mathrm{n}}=\mathrm{e}^{\lambda \mathrm{t}}\left[1+0\left(\mathrm{~h}^{2}\right)\right]}
\end{gathered}
$$

Thus,

$$
\begin{equation*}
\max _{0 \leq t_{n} \leq b}\left[r_{0}(h \lambda)\right]=e^{\lambda t_{n}} \mid \rightarrow 0 \text { as } h \rightarrow 0 \ldots \tag{2.51}
\end{equation*}
$$

We ${ }^{[30,31]}$ must now show that the coefficient $\gamma_{0} \rightarrow 1$ as $h \rightarrow 1$. The coefficient $\gamma_{0}, \ldots, \gamma_{k}$ satisfy the linear system

$$
\begin{gather*}
\gamma_{0}+\gamma_{1}+\ldots+\gamma_{k}=\mathrm{x}_{0} \\
\gamma_{0}\left[\mathrm{r}_{0}(\mathrm{~h} \lambda)\right]+\ldots+\gamma_{\mathrm{k}}\left[\mathrm{r}_{\mathrm{k}}(\mathrm{~h} \lambda)\right]=\mathrm{x}_{1} \\
\gamma_{0}\left[\mathrm{r}_{0}(\mathrm{~h} \lambda)\right]^{\mathrm{k}}+\ldots+\gamma_{\mathrm{k}}\left[\mathrm{r}_{\mathrm{k}}(\mathrm{~h} \lambda)\right]^{\mathrm{k}}=\mathrm{x}_{2} \ldots \tag{2.52}
\end{gather*}
$$

The initial values $x_{0}, \ldots, x_{\mathrm{k}}$ are assumed to satisfy

$$
\mathrm{r}_{\mathrm{j}}(\mathrm{~h}) \max _{0 \leq \mathrm{n}-\mathrm{k}}\left|\mathrm{e}^{\Delta \mathrm{t}_{\mathrm{n}}}-\mathrm{x}_{\mathrm{n}}\right| \rightarrow 0 \text { ash } \rightarrow 0
$$

However, this implies

$$
\begin{equation*}
\operatorname{Lim} x_{\mathrm{n}}=1,0 \leq \mathrm{n} \leq p \ldots \tag{2.53}
\end{equation*}
$$

The coefficient $\gamma_{0}$ can be obtained using Cramer's rule to solve (3.3.5) then

$$
\gamma_{0}=\frac{\left|\begin{array}{cccc}
x_{0} & 1 & \cdots & 1 \\
x_{1} & r_{1} & & r_{k} \\
\vdots & & & \\
\mathrm{x}_{\mathrm{k}} & \mathrm{r}_{\mathrm{k}} & \cdots & \mathrm{r}_{\mathrm{k}}^{\mathrm{k}}
\end{array}\right|}{\left|\begin{array}{cccc}
1 & 1 & \cdots & 1 \\
\mathrm{r}_{0} & \mathrm{r}_{1} & \cdots & \mathrm{r}_{\mathrm{k}} \\
\vdots & & & \\
\mathrm{r}_{\mathrm{k}}^{\mathrm{k}} & \mathrm{r}_{1}^{\mathrm{k}} & \cdots & \mathrm{r}_{\mathrm{k}}^{\mathrm{k}}
\end{array}\right|}
$$

The denominator converges to the vandermonde determinant for $r_{0}(0)=1, r_{1}(0), \ldots, r_{k}(0)$; and this is non-zero since the roots are distinct. Using (2.13), the numerator converges to the same quantity as $h \rightarrow 0$. Therefore, $\gamma \rightarrow 1$ as $h \rightarrow 0$, using this, along with (2.10), the solution $\left\{x_{n}\right\}$ converges to $\mathrm{x}(\mathrm{t})=\mathrm{e}^{\lambda \mathrm{t}}$ on $[0, \mathrm{~b}]$. This completes the proof.

## ILLUSTRATIVE EXPERIMENT

Example 3.1 (problem statement)
Write a general-purpose function named HAMMING that solves a system offirst-order ordinary differential equations.

$$
\begin{gather*}
\frac{d y_{1}}{d x}=f_{1}\left(x, y_{1}, y_{2}, \ldots, y_{n}\right) \\
\frac{d y_{2}}{d x}=f_{2}\left(x, y_{1}, y_{2}, \ldots, y_{n}\right)  \tag{3.1}\\
\frac{d y_{n}}{d x}=f_{n}\left(x, y_{1}, y_{2}, \ldots, y_{n}\right),
\end{gather*}
$$

Using Hamming's predictor-corrector method embedded in $\mathrm{C}_{1}$ and $\mathrm{C}_{2}$ of page 6 , Section 2 and
also in, ${ }^{[3]}$ write a main program that solves the second-order ordinary differential equation.

$$
\begin{equation*}
\frac{\mathrm{d}^{2} \mathrm{y}}{\mathrm{dx}^{2}}=-\mathrm{y} \tag{3.2}
\end{equation*}
$$

Subject to the initial conditions

$$
\begin{equation*}
y(0)=0 \frac{d y}{d x}(0)=1 \tag{3.3}
\end{equation*}
$$

The program should call on the fourth-order Runge-kutta function RUNGE, see ${ }^{[3]}$ to find the essential starting values for Hamming's algorithm as

$$
\begin{align*}
& y_{1,0}=V_{o}  \tag{3.4}\\
& y_{2,0}=0
\end{align*}
$$

And thereafter, should call on HAMMING to calculate estimates of $y$ and $d y / d x$ on the interval [ $\left.0, \mathrm{x}_{\text {max }}\right]$. Evaluate the numerical solutions for several different step sizes, $h$, and compare the numerical results with the true solutions.

$$
\begin{align*}
& y(x)=\sin x  \tag{3.5}\\
& \frac{d y}{d x}=\cos x
\end{align*}
$$

## Method of Solution

Let $y_{j, i}$ be the final modification of the estimated solution for the $j$ th dependent variable, $y_{j}, x_{i}$, resulting from Hamming's method and left $f_{j, i}$ be the calculated estimate of $f_{j}$ at $\mathrm{x}_{i}$, that is,

$$
\begin{align*}
& \mathrm{y}_{\mathrm{j}, \mathrm{i}}=\mathrm{y}_{\mathrm{j}}\left(\mathrm{x}_{\mathrm{i}}\right) \\
& \mathrm{f}_{\mathrm{j}, \mathrm{i}}=\mathrm{f}_{\mathrm{j}}\left(\mathrm{x}_{\mathrm{i}}, \mathrm{y}_{1, \mathrm{i}}, \mathrm{y}_{2, \mathrm{i}}, \ldots, \mathrm{y}_{\mathrm{n}, \mathrm{i}}\right) . \tag{3.6}
\end{align*}
$$

Assume that $\mathrm{y}_{\mathrm{j}, \mathrm{i}} \mathrm{y}_{\mathrm{j}, \mathrm{i}-1}, \mathrm{y}_{\mathrm{j}, \mathrm{i}-2}, \mathrm{y}_{\mathrm{j}, \mathrm{i}-3}, \mathrm{f}_{\mathrm{j}, \mathrm{i},} \mathrm{f}_{\mathrm{j}, \mathrm{i}-1}, \mathrm{f}_{\mathrm{j}, 1-2,2}$ have already been found and are available for $j=1,2, \ldots$, $n$. Let an estimate of the local truncation error for the corrector equation (3.4) for the $j$ th dependent variable be denoted $e_{\mathrm{j}, \mathrm{i}}$. Then, assuming that the $\mathrm{e}_{\mathrm{j}, \mathrm{i}}, j=1,2, \ldots, \mathrm{n}$, are available, the procedure outlined for Hamming's method in the above may be modified to handle a system of $n$ simultaneous first-order ordinary differential equations by simply appending a leading subscript, $j$, to all if all $y$ and $f$ terms in (3.1) to (3.6). In terms of the new nomenclature, Steps 2 through 6 of the outline in the above are:
2. The predicted solutions are computed using the Milne predictor below;

$$
\begin{equation*}
y_{j, i+1,0}=y_{j, i-3}+\frac{4}{3} h f\left(2 f_{j, i}-f_{j, i-1}+2 f_{j, i,-}\right), j=1,2, \ldots, n \tag{3.7}
\end{equation*}
$$

3. The predicted solutions, $y_{j, i+1,0}$, are modified (assuming that the local truncation error estimates, $\mathrm{e}_{\mathrm{j}, \mathrm{i}+1}, j=1,2, \ldots, \mathrm{n}$, will not be significantly different from estimates $e_{j, i}$, $\mathrm{j}=1,2, \ldots, \mathrm{n}$ ) as in (3.5):

$$
\begin{equation*}
\mathrm{Y}_{\mathrm{j}, \mathrm{i}+1,0}=\mathrm{y}_{\mathrm{j}, \mathrm{i}+1,0}+\frac{112}{9} \mathrm{e}_{\mathrm{j}, \mathrm{i}}, \quad \mathrm{j}=1,2, \ldots, \mathrm{n} . \tag{3.8}
\end{equation*}
$$

4. The $j$ th corrector equation corresponding to (3.4) is applied for each dependent variable:
$y_{j, i+1,1}=+\frac{1}{8}\left[9 y_{j, i}-y_{j, i-2}+3 h\left(f_{j, i+1,0}+2 f_{j, i-1}\right)\right]$,
$j=1,2, \ldots, n$
Where

$$
\begin{equation*}
f_{j, i+1,0}=f\left(x_{i+1}, y_{1, i+1,0}, \ldots, y_{2, i+1,0}, y_{n, i+1,0}\right) \tag{3.10}
\end{equation*}
$$

The corrector in (3.5) is being applied just once for each variable, the customary practice. The corrector equations could, however, be applied more than once, as in (3.6). Note that the subscript $j$, in (3.6) is an iteration counter, and is not the index $j$, on the dependent variables used throughout this example.
5. Estimate the local truncation error for each of the corrector equations on the current interval as in (3.6)
$e_{j, i+1}=\frac{9}{121}\left(y_{j, i+1,1}-y_{j, i+1,0}\right), \quad j=1,2, \ldots, n$.
6. Make the final modifications of the solutions of the corrector equations as in (3.8)
$y_{j, i+1}=y_{j, i+1,1}-e_{j, i+1}, \quad j=1,2, \ldots, n$
After evaluation the $\mathrm{y}_{\mathrm{j}, i+1}$, the $n$ values $\mathrm{f}_{\mathrm{j}, \mathrm{i}+1}$ may be computed from (3.13) as
$f_{j, i+1}=f_{j}\left(x_{i+1} y_{1, i+1}, y_{2, i+1}, \ldots, y_{n, i+1}\right), \quad j=1,2, \ldots, n$.

If desired, the entire process may be repeated for the next interval by starting again at Step 2. Therefore, the function HAMING can be written to solving arbitrary system of first-order equations, provided that the $5 \mathrm{n}+2$ essential numbers, $\mathrm{xi}, \mathrm{h}$ and $y_{j, i-3}$,

$$
\left.\begin{array}{c}
\mathrm{f}_{\mathrm{j}, \mathrm{i}}, \mathrm{e}_{\mathrm{j}, \mathrm{i}}  \tag{3.14}\\
\mathrm{f}_{\mathrm{j}, \mathrm{i}-1}, \\
\mathrm{f}_{\mathrm{j}, \mathrm{i}-2},
\end{array}\right\} \mathrm{J}=1,2, \ldots, \mathrm{n},
$$

Are available for the function to use on entry to the predictor section, and the essential numbers and

$$
\left.\begin{array}{r}
y_{\mathrm{j}, \mathrm{i}},  \tag{3.15}\\
\mathrm{y}_{\mathrm{j}, \mathrm{i}-2}, \\
\mathrm{y}_{\mathrm{j}, \mathrm{i}+1,0,0}, \\
, f_{\mathrm{j}, \mathrm{i}, \mathrm{i}-2},
\end{array},\right\} \quad \mathrm{j}=1,2, \ldots, \mathrm{n},
$$

Then, write the calling program and function HAMMING, so that the matrices $Y$ and $F$, and the vector, e have the following contents at the indicated points in the algorithm.
Before entry into the corrector section of HAMMING:
$Y$ is unchanged from (3.16)

$$
\mathrm{F}=\left[\begin{array}{cccccc}
\mathrm{f}_{1, i+1} & \mathrm{f}_{2, i+1,0} & \cdots & f_{\mathrm{j}, \mathrm{i}+1,0} & \cdots & f_{\mathrm{n}, \mathrm{i}+1,0}  \tag{3.16}\\
\mathrm{f}_{1, \mathrm{i}} & \mathrm{f}_{2, \mathrm{i}} & \cdots & \mathrm{f}_{\mathrm{j}, \mathrm{i}} & \cdots & \mathrm{f}_{\mathrm{n}, \mathrm{i}} \\
\mathrm{f}_{1, \mathrm{i}-1} & \mathrm{f}_{2, \mathrm{i}-1} & \cdots & \mathrm{f}_{\mathrm{j}, \mathrm{i}-1} & \cdots & \mathrm{f}_{\mathrm{n}, \mathrm{i}-1}
\end{array}\right]
$$

$\mathrm{e}^{\prime}$ is unchanged from (3.16)
After return from the corrector section of HAMMING:

$$
\mathrm{Y}=\left[\begin{array}{ccccc} 
& & & &  \tag{3.17}\\
\mathrm{y}_{1, i+1} & \mathrm{y}_{2, \mathrm{i}+1} & \cdots & \mathrm{y}_{\mathrm{j}, \mathrm{i}+1} & \cdots \\
\mathrm{y}_{\mathrm{n}, \mathrm{i}, \mathrm{i}} & \mathrm{y}_{2, \mathrm{i}} & \cdots & \mathrm{y}_{\mathrm{j}, \mathrm{i}} & \cdots \\
\mathrm{y}_{\mathrm{n}, \mathrm{i}} \\
\mathrm{y}_{1, \mathrm{i}-1} & \mathrm{y}_{2,1-1} & \cdots & \mathrm{y}_{\mathrm{j}, \mathrm{i}-1} & \cdots \\
\mathrm{y}_{1, \mathrm{i}-2} & \mathrm{y}_{2, \mathrm{i},-1} & \cdots & \mathrm{y}_{\mathrm{j}, \mathrm{i}-2} & \cdots \\
\mathrm{y}_{\mathrm{n}, \mathrm{i}-2}
\end{array}\right]
$$

$F$ is unchanged from (3.20)

$$
\begin{equation*}
\mathrm{e}^{\prime}=\left[\mathrm{e}_{1, \mathrm{i}} \mathrm{e}_{2, \mathrm{i}} \cdots \mathrm{e}_{\mathrm{j}, \mathrm{i}} \cdots \mathrm{e}_{\mathrm{n}, \mathrm{i}}\right] \tag{3.18}
\end{equation*}
$$

If the calling program uses (3.14) to replace the elements in the first row of F after the return from the corrector section of HAMING, so that

$$
F=\left[\begin{array}{cccc}
f_{1, i+1} & f_{2, i+1} \cdots f_{j, i+1} \cdots & \cdots & f_{n, i+1}  \tag{3.19}\\
f_{1, i} & f_{2, i} \cdots & \cdots & f_{j, i} \cdots \\
f_{1, i, i-1} & f_{2, i-1} & \cdots f_{j, i, 1} \cdots & \cdots f_{n, i-1}
\end{array}\right]
$$

Then, the matrices Y and F and the vector $\mathrm{e}^{\prime}$ are ready for a call on the predictor section of HAMING for the next integration step. The independent variable is incremented in the predictor section, that is,

$$
\begin{equation*}
x_{\mathrm{i}+1}=x_{\mathrm{i}}+h \tag{3.20}
\end{equation*}
$$

So that the calling program will automatically have the proper value to calculate the $\mathrm{f}_{\mathrm{j}, 1+1,0}$ and $\mathrm{f}_{\mathrm{i}, i+1}$ from (3.10) and (3.14), respectively.
Assuming that the integration process begins at $\mathrm{x}=\mathrm{x}_{0}$ and that the only known conditions on (3.2) are

$$
\begin{align*}
& \mathrm{y}_{1,0}=\mathrm{c}_{1} \\
& \mathrm{y}_{2,0}=\mathrm{c}_{2}  \tag{3.21}\\
& \mathrm{y}_{\mathrm{n}, 0}=\mathrm{c}_{\mathrm{n}}
\end{align*}
$$

There is not enough information to calculate the elements of (3.17), (3.18), and (3.19). Therefore, HAMMING cannot be called directly when $x_{1}=x_{0}$. The usual procedure is to use a one-step method to integrate across the first steps to evaluate

$$
\left.\begin{array}{l}
\mathrm{y}_{\mathrm{j}, 1}  \tag{3.22}\\
\mathrm{y}_{\mathrm{j}, 2} \\
\mathrm{y}_{\mathrm{j}, 3}
\end{array}\right\} \quad \mathrm{j}=1,2, \ldots, \mathrm{n}
$$

With (3.15) and (3.16), the matrix Y of (3.17) is known for $\mathrm{i}=3$. The matrix F of (3.19) may be evaluated from (3.15) and (3.16) for $\mathrm{i}=3$. The vector of local truncation error estimates (3.14) for $\mathrm{i}=3$ is normally unknown, and should be set to zero unless better values are available from other sources. Hamming may then be called for the first time.
In the calling program that follows, the function RUNGE, already developed in, ${ }^{[3]}$ is used to generate the solutions of (3.22). Since RUNGE implements the fourth-order Runge-kutta method, the solutions of (3.27) should be comparable in accuracy with the solutions generated by the Hamming's predictor-corrector algorithm, also a fourth-order method.
The main program reads data values for $\mathrm{n}, \mathrm{x}_{0}, \mathrm{~h}, \mathrm{x}_{\text {max }}$, int, $\mathrm{y}_{1,0}, \mathrm{y}_{2,0}, \ldots, \mathrm{y}_{\mathrm{n}, 0}$. Here, int is the number of intergration steps between the printings of solution values. This program is a reasonably general one. However, the defining statements for computation of the derivative estimates (3.11) and (3.14) would be different for each system of differential equations.
For test purposes, the differential equation solved is (3.2), subject to the initial conditions of (3.3). First, the second-order equation must be written as a system or two first-order equations. Let $y_{1}=y$

$$
\begin{equation*}
y_{2}=\frac{d y}{d x} \tag{3.23}
\end{equation*}
$$

Then,

$$
\begin{align*}
& \frac{d y_{1}}{d x}=f_{1}\left(x, y_{1}, y_{2}\right)=\frac{d y}{d x}=y_{2}  \tag{3.24}\\
& \frac{d y_{2}}{d x}=f_{2}\left(x, y_{1}, y_{2}\right)=\frac{d^{2} y}{d x^{2}}=-y=-y_{1}
\end{align*}
$$

So that

$$
\begin{align*}
& \mathrm{f}_{1, \mathrm{i}}=\mathrm{y}_{2, \mathrm{i}} \\
& \mathrm{f}_{2}=-\mathrm{y}_{2, \mathrm{l}} \tag{3.25}
\end{align*}
$$

The initial conditions of (3.3)

$$
\begin{align*}
& y_{1,0}=0 \\
& y_{2,0}=1 \tag{3.26}
\end{align*}
$$

With a known program listing, given, we use the listed data below
Data

| $\mathrm{X}=$ | 0.0000 | $\mathrm{H}=$ | 1.000000 | $\mathrm{XMAX}=$ | 5.0000 |
| :--- | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{INT}=$ | 1 | $\mathrm{~N}=$ | 2 |  |  |
| $\mathrm{YR}(1)$ | $\mathrm{YR}(2)=$ |  | 0.00000 | 1.00000 |  |
| $\mathrm{X}=$ | 0.0000 | $\mathrm{H}=$ | 0.500000 | $\mathrm{XMAX}=$ | 5.0000 |
| $\mathrm{INT}=1$ | $\mathrm{~N}=$ | 2 |  |  |  |
| $\mathrm{YR}(1)$ | $\mathrm{YR}(2)$ |  | 0.00000 | 1.00000 |  |
| $\mathrm{X}=$ | 0.00000 | $\mathrm{H}=$ | 0.250000 | $\mathrm{XMAX}=$ | 5.00000 |
| $\mathrm{INT}=$ | 2 | $\mathrm{~N}=$ | 2 |  |  |
| $\mathrm{YR}(1)$ | $\mathrm{YR}(2)=$ | 0.00000 | 1.00000 |  |  |
| $\mathrm{X}=$ | 0.0000 | $\mathrm{H}=$ | 0.125000 | $\mathrm{XMAX}=$ | 5.0000 |
| $\mathrm{INT}=$ | 4 | $\mathrm{~N}=$ | 2 |  |  |
| $\mathrm{YR}(1)$ | $\mathrm{YR}(2)$ |  | 0.00000 | 1.00000 |  |
| $\mathrm{X}=$ | 0.0000 | $\mathrm{H}=$ | 0.062500 | $\mathrm{XMAX}=$ | 5.0000 |
| $\mathrm{INT}=$ | 8 | $\mathrm{~N}=$ | 2 |  |  |
| $\mathrm{YR}(1)$ | $\mathrm{YR}(2)=$ |  | 0.00000 | 1.00000 |  |
| $\mathrm{X}=$ | 0.0000 | $\mathrm{H}=$ | 0.031250 | $\mathrm{XMAX}=$ | 5.0000 |
| $\mathrm{INT}=$ | 16 | $\mathrm{~N}=$ | 2 |  |  |
| $\mathrm{YR}(1)$ | $\mathrm{YR}(2)$ |  | 0.00000 | 1.00000 |  |
| $\mathrm{X}=$ | 0.00000 | $\mathrm{H}=$ | 0.015625 | $\mathrm{XMAX}=$ | 5.00000 |
| $\mathrm{INT}=$ | 32 | $\mathrm{~N}=$ | 2 |  |  |
| $\mathrm{YR}(1)$ | $\mathrm{YR}(2)=$ |  | 0.00000 | 1.00000 |  |
|  |  |  |  |  |  |

Moreover, we have the following results

## Computer Output

Results for the first data set
$\mathrm{H}=0.100 \mathrm{D} 01$
$\mathrm{XMAX}=5.0000$
INT $=1$
$\mathrm{N}=2$
X Y (1) Y (2)

Emmanuel: Linear multistep methods as fixed point iterative methods

| $\mathbf{X}$ | $\mathbf{Y}(\mathbf{1})$ |  | $\mathbf{Y}(\mathbf{2})$ |  |
| :--- | :---: | :---: | :---: | :---: |
| 0.0 | 0.0 |  | 0.1000000 | 01 |
| 1.0000 | 0.8333333 D | 00 | 0.5416667 D | 00 |
| 2.0000 | 0.9027778 D | 00 | -0.4010417 D | 00 |
| 3.0000 | 0.1548032 D | 00 | -0.9695457 D | 00 |
| 4.0000 | -0.6638999 D | 00 | -0.6880225 D | 00 |
| 5.0000 | -0.1045312 D | 00 | 0.1429169 D | 00 |

Results for the second data set
$\mathrm{H}=0.500 \mathrm{D} 00$
$\mathrm{XMAX}=5.0000$
INT $=1$
$\mathrm{N}=2$

| $\mathbf{X}$ | $\mathbf{Y}(\mathbf{1})$ | $\mathbf{Y ( 2 )}$ |  |  |
| :--- | :---: | :---: | :---: | :---: |
| 0.0 | 0.0 |  | 0.1000000 D | 01 |
| 0.5000 | 0.4791667 D | 00 | 0.8776042 D | 00 |
| 1.0000 | 0.8410373 D | 00 | 0.5405884 D | 00 |
| 1.5000 | 0.9971298 D | 00 | 0.7142556 D | -01 |
| 2.0000 | 0.9104181 D | 00 | -0.4146978 D | 00 |
| 2.5000 | 0.6001440 D | 00 | -0.8012885 D | 00 |
| 3.0000 | 0.1422377 D | 00 | -0.9912065 D | 00 |
| 3.5000 | -0.3510641 D | 00 | -0.9387887 D | 00 |
| 4.0000 | -0.7588721 D | 00 | -0.6554891 D | 00 |
| 4.5000 | -0.9810034 D | 00 | -0.2112528 D | 00 |
| 5.0000 | -0.9627114 D | 00 | 0.2857746 D | 00 |

Results for the third data set
$\mathrm{H}=0.250 \mathrm{D} 00$
$\mathrm{XMAX}=5.0000$
INT $=2$
$\mathrm{N}=2$

| $\mathbf{X}$ | $\mathbf{Y}(\mathbf{1})$ | $\mathbf{Y ( 2 )}$ |  |  |
| :--- | :---: | :---: | :---: | :---: |
| 0.0 | 0.0 |  | 0.1000000 D | 01 |
| 0.5000 | 0.4791667 D | 00 | 0.8776042 D | 00 |
| 1.0000 | 0.8410373 D | 00 | 0.5405884 D | 00 |
| 1.5000 | 0.9971298 D | 00 | 0.7142556 D | -01 |
| 2.0000 | 0.9104181 D | 00 | -0.4146978 D | 00 |
| 2.5000 | 0.6001440 D | 00 | -0.8012885 D | 00 |
| 3.0000 | 0.1422377 D | 00 | -0.9912065 D | 00 |
| 3.5000 | -0.3510641 D | 00 | -0.9387887 D | 00 |
| 4.0000 | -0.7588721 D | 00 | -0.6554891 D | 00 |
| 4.5000 | -0.9810034 D | 00 | -0.2112528 D | 00 |
| 5.0000 | -0.9627114 D | 00 | 0.2857746 D | 00 |

Results for the fourth data set
$\mathrm{H}=0.125 \mathrm{D} 00$
XMAX $=5.0000$
$\mathrm{INT}=4$
$\mathrm{N}=2$

| $\mathbf{X}$ | $\mathbf{Y ( 1 )}$ | $\mathbf{Y ( 2 )}$ |  |  |
| :--- | :---: | :---: | :---: | :---: |
| 0.0 | 0.0 | 00 | 0.1000000 D | -01 |
| 0.5000 | 0.4794249 D | 00 | 0.8775832 D | 00 |
| 1.0000 | 0.8414708 D | 00 | 0.5403028 D | 00 |


| 1.5000 | 0.9974948 D | 00 | 0.5403028 D | -01 |
| :--- | :---: | :---: | :---: | :---: |
| 2.0000 | 0.9092971 D | 00 | -0.4161466 D | 00 |
| 2.5000 | 0.5984717 D | 00 | -0.8011433 D | 00 |
| 3.0000 | 0.1411195 D | 00 | -0.9899918 D | 00 |
| 3.5000 | -0.3507835 D | 00 | -0.9364555 D | 00 |
| 4.0000 | -0.7568022 D | 00 | -0.6536421 D | 00 |
| 4.5000 | -0.9775289 D | 00 | -0.2107944 D | 00 |
| 5.0000 | -0.9589223 D | 00 | 0.2836631 D | 00 |

Results for the fifth data set
$\mathrm{H}=0.625 \mathrm{D}-01$
XMAX $=5.0000$
$\mathrm{INT}=8$
$\mathrm{N}=2$

| $\mathbf{X}$ | $\mathbf{Y}(\mathbf{1})$ | $\mathbf{Y}(\mathbf{2})$ |  |  |
| :--- | :---: | :---: | :---: | :---: |
| 0.0 | 0.0 | 00 | 0.1000000 D | -01 |
| 0.5000 | 0.4794255 D | 00 | 0.8775826 D | 00 |
| 1.0000 | 0.8414710 D | 00 | 0.5403023 D | 00 |
| 1.5000 | 0.9974950 D | 00 | 0.7073721 D | -01 |
| 2.0000 | 0.9092974 D | 00 | -0.4161468 D | 00 |
| 2.5000 | 0.5984721 D | 00 | -0.8011436 D | 00 |
| 3.0000 | 0.1411200 D | 00 | -0.9899925 D | 00 |
| 3.5000 | -0.3507832 D | 00 | -0.9364566 D | 00 |
| 4.0000 | -0.7568025 D | 00 | -0.6536436 D | 00 |
| 4.5000 | -0.9775301 D | 00 | -0.2107958 D | 00 |
| 5.0000 | -0.9589242 D | 00 | 0.2836622 D | 00 |

Results for the sixth data set
$\mathrm{H}=0.312 \mathrm{D}-01$
XMAX $=5.0000$
$\mathrm{INT}=16$
$\mathrm{N}=2$

| $\mathbf{X}$ | $\mathbf{Y}(\mathbf{1})$ | $\mathbf{Y ( 2 )}$ |  |  |
| :--- | :---: | :---: | :---: | :---: |
| 0.0 | 0.0 | 00 | 0.1000000 D | -01 |
| 0.5000 | 0.4794255 D | 00 | 0.8775826 D | 00 |
| 1.0000 | 0.8414710 D | 00 | 0.5403023 D | 00 |
| 1.5000 | 0.9974950 D | 00 | 0.7073720 D | -01 |
| 2.0000 | 0.9092974 D | 00 | -0.4161468 D | 00 |
| 2.5000 | 0.5984721 D | 00 | -0.8011436 D | 00 |
| 3.0000 | 0.1411200 D | 00 | -0.9899925 D | 00 |
| 3.5000 | -0.3507832 D | 00 | -0.9364567 D | 00 |
| 4.0000 | -0.7568025 D | 00 | -0.6536436 D | 00 |
| 4.5000 | -0.9775301 D | 00 | -0.2107958 D | 00 |
| 5.0000 | -0.9589243 D | 00 | 0.2836622 D | 00 |

Results for the seventh data set
$\mathrm{H}=0.156 \mathrm{D}-01$
XMAX $=5.0000$
INT= 32
$\mathrm{N}=2$

| $\mathbf{X}$ | $\mathbf{Y}(\mathbf{1})$ | $\mathbf{Y}(\mathbf{2})$ |  |  |
| :--- | :---: | :---: | :---: | :---: |
| 0.0 | 0.0 | 00 | 0.1000000 D | -01 |
| 0.5000 | 0.4794255 D | 00 | 0.8775826 D | 00 |


| 1.0000 | 0.8414710 D | 00 | 0.5403023 D | 00 |
| :--- | :---: | :---: | :---: | :---: |
| 1.5000 | 0.9974950 D | 00 | 0.7073720 D | -01 |
| 2.0000 | 0.9092974 D | 00 | -0.4161468 D | 00 |
| 2.5000 | 0.5984721 D | 00 | -0.8011436 D | 00 |
| 3.0000 | 0.1411200 D | 00 | -0.9899925 D | 00 |
| 3.5000 | -0.3507832 D | 00 | -0.9364567 D | 00 |
| 4.0000 | -0.7568025 D | 00 | -0.6536436 D | 00 |
| 4.5000 | -0.9775301 D | 00 | -0.2107958 D | 00 |
| 5.0000 | -0.9589243 D | 00 | 0.2836622 D | 00 |

## DISCUSSION OF RESULTS

Double-precision arithmetic has been used for all calculations.
Differential equation (3.2) with initial conditions given by (3.2) has been solved on the interval $[0,5]$ with step-size $\mathrm{h}=1.0,0,0.25,0.125,0.0625$, 0.03125 , and 0.015625 to seven-place accuracy, the true solutions.
$y_{1}=y=\sin \square x$

$$
\begin{equation*}
y_{2}=\frac{d y}{d x}=\cos x, \tag{3.27}
\end{equation*}
$$

Are listed in Tables 1 and 2.
Results for step-sizes 0.03125 and 0.015625 (data sets 6 and 7) agree with the true values to seven figures. Results for larger step sizes are not of acceptable accuracy. The program has been run with even larger values of $h$ (results not shown) as well. For $h$ large enough, the solutions "blow up" in a fashion similar to that already observed for the Runge-kutta's method in Example 6.3 ${ }^{[29-32]}$

Table 1: True solutions,

|  | $\mathbf{X Y}=\boldsymbol{\operatorname { s i n } x d y} / \mathbf{d x}=\boldsymbol{\operatorname { c o s }} \mathbf{x}$ |  |
| :--- | :---: | :---: |
| 0.0 | 0.0000000 | 1.0000000 |
| 1.0 | 0.8414710 | 0.5403023 |
| 2.0 | 0.9092974 | -0.4161468 |
| 3.0 | 0.1411200 | -0.9899925 |
| 4.0 | -0.7568025 | -0.6536436 |
| 5.0 | -0.9589243 | 0.2836622 |

Table 2: Calculated solutions at $\mathrm{x}=5$

|  | Step size, $\mathbf{h} \mathbf{Y}_{\mathbf{1}} \mathbf{Y}_{\mathbf{2}}$ |  |
| :--- | :---: | :--- |
| 1.0 | -1.045312 | 0.1429169 |
| 0.5 | -0.9627114 | 0.2857746 |
| 0.25 | -0.9589062 | 0.2837483 |
| 0.125 | -0.9589223 | 0.2836631 |
| 0.0625 | -0.9589242 | 0.2836622 |
| 0.03125 | -0.9589243 | 0.2836622 |
| 0.015625 | -0.9589243 | 0.2836622 |
| True values | -0.9589243 | 0.2836622 |

In view of the periodic nature of the solution functions, it is not surprising that as the step size approaches the length of the functional period, the solutions become meaningless. Clearly, for step sizes larger than the period, virtually all local information about the curvature of the function is lost; it would be unreasonable to expect accurate solutions in such cases.

## CONCLUSION

The findings of the above experiment confirms that the linear multistep methods are indeed fixed point iteration methods as stated in the main result.

## REFERENCES

1. Boyce W, Dripeima R. Elementary Differential Equation. $3^{\text {rd }}$ ed. New York: John Wiley; 1977.
2. Brice C, Luther HA, James O. Wilkes-Applied Numerical Methods. New York: John Wiley and Sons Inc.; 1969. p. 390-404.
3. Bulirsch R, Stoer J. Numerical treatment of ordinary differential equations by extrapolation, methods. Num Math 1966;8:1-13.
4. Ceschino F, Kuntzman J. Numerical Solution of Initial Value Problems. Englewood Cliffs, N.J: Prentice-Hall; 1966.
5. Chidume C. Geometric Properties of Banach Spaces and Nonlinear Iterations. Italy: Abdus Salam International Centre for Theoretical Physics, Springer; 2009.
6. Coddington E, Levingson N. Theory of Ordinary Differential Equations. New York: McGraw-Hill; 1955.
7. Collatz, L. The Numerical Treatment of Differential Equations. $3^{\text {rd }}$ ed. New York: Springer-Verlag; 1966.
8. Dahlquist G. Numerical ordinary integration of differential equations. Math Scand 1956;4:33-50.
9. Enright W, Hull T, Lindberg B. Comparing numerical methods for stiff systems of O. D.E.S. BIT Num Math 1975;15:10-48.
10. Enright WH, Hull TE. Test results on initial value methods for non stiff O.D.E's. Num Anal 1976;13:944-61.
11. Fox P. In: Rice J, editor. DESUB: Integration of First Order System of Ordinary Differential Equations, in Mathematical Software. Vol. 477. New York: Academic Press; 1961. p. 507.
12. Gear CW. Numerical Initial Value Problem in Ordinary Differentia; Equations. Englewood Cliffs, N.J: Prentice Hall; 1971.
13. Gragg W. Extrapolation algorithms of ordinary initial value problems. SIAM J Numer Anal 1965;2:384-403.
14. Henrici P. Discrete Variable Methods in Ordinary Differential Equations. New York: John Wiley; 1962.
15. Hull TE, Enright WH, Fellen BM, Sedegewick AE. Comparing numerical methods for ordinary differential equations. SIAM J Num Anal 1972;9:603-37.
16. Argyros IK. Approximation Solution of Operator Equations with Applications. New Jersey, U.S.A:

Cameron University; 2006.
17. Issacson E, Keller H. Analysis of Numerical Methods. New York: John Wiley; 1966.
18. Keller H. Numerical Methods for Two Points Boundary Value Problems. Waltham: Ginn-Blaisdell, Waltham, Mass; 1968.
19. Keller H. Numerical solution of boundary value problems for ordinary differential equations: Survey and some recent results on difference methods. In: Azia A. editor. Numerical Solutions of Oundary Value Problems for Ordinary Differential Equations. New York: Academic Press; 1975. p. 27-88.
20. Atkinson KE. An introduction to Numerical Analysis. New York: John Wiley and Sons; 1981. p. 289-381.
21. Kreiss H. Difference Methods for Stiff Differentia; Equations Math. Research Centre Tech. Rep. 1699, Wisconsin: University of Wisconsin, Madison, Wis; 1976.
22. Lambert J. Computational Methods in Ordinary Differential Equations. New York: John Wiley; 1973.
23. Lapidus L, Scheisser W, editors. Numerical Methods for Differential Equations: Recent Developments in Algorithm Software. New York: New Applications,

Academic Press; 1976.
24. Lapidus, L, Seinfield J. Numerical Solution of Ordinary Differential Equations. New York: John Wiley; 1953.
25. Altman M. Contractors and Contractor Directors Theory and Applications. A new Approach to solving Equations. New York: Mercel Dekker, Inc.; 2005.
26. Raiston A. A First Course in Numerical Analysis. New York: McGraw-Hill; 1965.
27. Shampine L, Watts H. Global error estimation for ordinary differential equations. ACM Trans Math Soft 1976;2:172-86.
28. Stetter H. Analysis of Discretization Methods for Ordinary Differential Equations. New York: SpringerVerlag; 1973.
29. Stetter H. Local estimation of the global discretization error. Siam J Numer Anal 1971;8:512-23.
30. Van der Houwen PJ. Construction of Integration Formulas for Initial Values Problems. New York: North Holland Pub, Amsterdam; 1977.
31. Willoughby R, editor. Stiff Differential Systems. New York: Plenum Press; 1974.

