

## IMPROVING THE ORDER OF A FIFTH-ORDER FAMILY OF VECTORIAL FIXED POINT SCHEMES BY INTRODUCING MEMORY

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**Abstract.** In this paper, we present a family of iterative schemes for solving nonlinear systems with 3 real parameters. If we do not fix values for the parameters this family has order 2, but if we fix two of them we obtain order 5. Starting from the fifth-order family, we study different ways of introducing memory, thus obtaining 6 order methods. We also analyze the efficiency indices of the family and of the methods with memory obtained from it, and we compare them with each other, as well as compare them with other known classes of iterative methods with order 5 and 6. Several numerical experiments are carried out to see the behaviour of the discussed methods, including dynamical planes to compare the stability of the different iterative schemes.

**Key words:** Nonlinear system, fixed point methods, iterative scheme, methods with memory, dynamical planes.

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### 1. INTRODUCTION

Over time, iterative methods have become more important as they are useful tools for obtaining approximations to solutions  $\alpha$  of nonlinear systems  $F(x) = 0$ , where  $F : \mathbb{D} \subset \mathbb{R}^n \rightarrow \mathbb{R}^n$ , which partake of scientific, engineering and various other models (details can be found in [10, 11, 16, 21]).

What these iterative methods do is to obtain a sequence of approximations,  $\{x^{(k)}\}_{k \geq 0}$ , from an initial approximation  $x^{(0)}$ , which, under certain conditions, converge to the solution of  $F(x) = 0$ , see for example [6, 8]. One of the best known methods is Newton's method, whose expression is:

$$y^{(k)} = x^{(k)} - F'(x^{(k)})^{-1} F(x^{(k)}), \quad k = 1, 2, \dots \quad (1.1)$$

being  $F'(x^{(k)})$  the Jacobian matrix of  $F$  evaluated at  $x^{(k)}$ .

There are many practical situations where the calculations of Jacobian Matrix are expensive and/or it requires a great deal of time for them to be given or calculated. Therefore, derivative free methods are quite popular for finding the roots of nonlinear

equations as well as system of nonlinear equations. One of them is Traub-Steffensen’s family [20], which is given by

$$\begin{cases} w^{(k)} = x^{(k)} + \gamma F(x^{(k)}), \\ y^{(k)} = x^{(k)} - [w^{(k)}, x^{(k)}; F]^{-1} F(x^{(k)}), \end{cases} \quad k = 1, 2, \dots \tag{1.2}$$

where  $\gamma$  is a non-zero real parameter.

Expression (1.2) can be easily recovered from the well-known Newton’s method [20], by replacing the Jacobian matrix to the operator  $[w^{(k)}, x^{(k)}; F] \approx F'(x^{(k)})$ . For the particular value of  $\gamma = 1$  in expression (1.2), then scheme deduce to the well known Steffensen’s method [19] for systems of nonlinear equations that was introduced by Samanski in [17], with quadratic order of convergence, for every value of parameter  $\gamma$ .

Many methods have been developed which improve the convergence rate of the Steffensen’s method or Steffensen-type methods at the expense of additional evaluations of vector functions, divided difference and changes in the points of iterations. In past and recent years, several higher-order multi-point extension of Steffensen’s method or Steffensen-type have been proposed and analyzed in the available literature [1, 12, 15, 18]. All these modifications are in the direction of increasing the local order of convergence with the view of increasing their efficiency indices. Such constructions occasionally possess a better order of convergence and efficiency index.

In this paper, we propose a three-step family that has been obtained using Steffensen’s method as starting point. The iterative expression of the parametric family is as follows:

$$\begin{cases} y^{(k)} = x^{(k)} - [w^{(k)}, x^{(k)}; F]^{-1} F(x^{(k)}), \\ z^{(k)} = y^{(k)} - \delta [w^{(k)}, x^{(k)}; F]^{-1} F(y^{(k)}) \\ x^{(k+1)} = z^{(k)} - \beta \left( 2I - [w^{(k)}, x^{(k)}; F]^{-1} [z^{(k)}, y^{(k)}; F] \right) [w^{(k)}, x^{(k)}; F]^{-1} F(z^{(k)}), \end{cases} \tag{1.3}$$

where  $w^{(k)} = x^{(k)} + \gamma F(x^{(k)})$  and  $\gamma$  is a non-zero real parameter.

The rest of the manuscript is organized as follows. In Section 2, we study the order of convergence of the class of iterative methods without memory (1.3) and we introduce memory to this parametric family when  $\beta = 1$  and  $\delta = 1$ . In Section 3, we analyze the efficiency index and the computational efficiency index of the discussed methods, and we draw some figures to see the behaviour of them. We also compare these indexes with those of other family of order of convergence 5 and 6. In Section 4, we show some numerical experiments to see the performances of the discussed methods and confirm the theoretical results. Some conclusions conclude this paper.

## 2. CONVERGENCE ANALYSIS

Let  $F : D \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^n$  be a sufficiently differentiable function in a neighbourhood  $D$  that contains a solution  $\alpha$  of  $F(x) = 0$ , we consider the divided difference operator

$$[x + h, x; F] = \int_0^1 F'(x + th) dt, \tag{2.1}$$

defined by Genochi-Hermite in [13]. Using the Taylor expansion of  $F'(x+th)$  at point  $x$  and integrating, we obtain the following development

$$[x+h, x; F] = F'(x) + \frac{1}{2}F''(x)h + \frac{1}{6}F'''(x)h^2 + O(h^3). \quad (2.2)$$

We are going to use this expression in the proof of the following result.

**Theorem 2.1.** *Let  $F : D \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^n$  be a sufficiently differentiable function in a neighbourhood  $D$  of  $\alpha$  such that  $F(\alpha) = 0$ . We assume that the Jacobian matrix of  $F$  evaluated at  $\alpha$  is nonsingular. Let  $\gamma$ ,  $\beta$  and  $\delta$  real values. Then, taking an initial estimation  $x^{(0)}$  close enough to  $\alpha$ , the sequence of iterates  $\{x^{(k)}\}$  generated by the proposed family (1.3) converges to  $\alpha$  with order 2, and its error equation is:*

$$e_{k+1} = (-1 + \beta)(-1 + \delta)C_2(I + \gamma F'(\alpha))e_k^2 + O(e_k^3), \quad (2.3)$$

where  $C_j = \frac{1}{j}F'(\alpha)^{-1}F^{(j)}(\alpha)$  for  $j = 2, 3, \dots$ ,  $e_k = x^{(k)} - \alpha$  and  $F'(\alpha)$  is the Jacobian matrix of  $F$  evaluated at  $\alpha$ .

Moreover, if  $\delta = 1$  and  $\beta = 1$ , then the order of convergence is 5, and its error equation is

$$e_{k+1} = E(I + \gamma F'(\alpha))e_k^5 + O(e_k^6),$$

where

$$E = (C_2^2(5I + 3\gamma F'(\alpha)) + \gamma C_2 F'(\alpha) C_2(2 + \gamma F'(\alpha)))(2C_2^2 + \gamma C_2 F'(\alpha) C_2).$$

*Proof.* First, we consider the Taylor expansion of  $F(x^{(k)})$ ,  $F'(x^{(k)})$ ,  $F''(x^{(k)})$  and  $F'''(x^{(k)})$  around  $\alpha$ :

$$F(x^{(k)}) = F'(\alpha)(e_k + C_2 e_k^2 + C_3 e_k^3 + C_4 e_k^4 + C_5 e_k^5 + O(e_k^6)), \quad (2.4)$$

$$F'(x^{(k)}) = F'(\alpha)(I + 2C_2 e_k + 3C_3 e_k^2 + 4C_4 e_k^3 + 5C_5 e_k^4 + O(e_k^5)), \quad (2.5)$$

$$F''(x^{(k)}) = F'(\alpha)(2C_2 I + 6C_3 e_k + 12C_4 e_k^2 + 20C_5 e_k^3 + O(e_k^4)), \quad (2.6)$$

$$F'''(x^{(k)}) = F'(\alpha)(6C_3 I + 24C_4 e_k + 60C_5 e_k^2 + O(e_k^3)). \quad (2.7)$$

Applying the Genochi-Hermite formula, we obtain that

$$[w^{(k)}, x^{(k)}; F] = F'(\alpha)(I + Y_2 e_k + Y_3 e_k^2 + Y_4 e_k^3) + O(e_k^4),$$

being

$$Y_2 = C_2(2I + \gamma F'(\alpha)),$$

$$Y_3 = C_3(3I + 3\gamma F'(\alpha)\gamma^2 F'(\alpha)^2) + \gamma C_2 F'(\alpha) C_2,$$

$$Y_4 = C_4(4I + 6\gamma F'(\alpha) + 4\gamma^2 F'(\alpha)^2 + \gamma^2 F'(\alpha) C_2 F'(\alpha) + \gamma^2 F'(\alpha)^2 C_2) + \gamma C_2 F'(\alpha) C_3 + 3\gamma C_3 F'(\alpha) C_2.$$

The inverse of the divided difference operator can be expressed as

$$[w^{(k)}, x^{(k)}; F]^{-1} = (I + X_2 e_k + X_3 e_k^2 + X_4 e_k^3)F'(\alpha)^{-1} + O(e_k^4),$$

where

$$\begin{aligned} X_2 &= -Y_2, \\ X_3 &= -X_2Y_2 - Y_3, \\ X_4 &= -Y_4 - X_2Y_3 - X_3Y_2. \end{aligned}$$

Then, if we denote  $e_{y,k} = y^{(k)} - \alpha$ ,

$$\begin{aligned} e_{y,k} &= e_k - [w^{(k)}, x^{(k)}; F]^{-1}F(x^{(k)}) \\ &= -(X_2 + C_2)e_k^2 - (X_3 + C_3 + X_2C_2)e_k^3 - (X_4 + C_4 + X_3C_2 + X_2C_3)e_k^4 + O(e_k^5). \end{aligned}$$

Thus, we denote by  $S_i$ ,  $i = 2, 3, 4$ ,

$$\begin{aligned} S_2 &= -(X_2 + C_2), \\ S_3 &= -(X_3 + C_3 + X_2C_2), \\ S_4 &= -(X_4 + C_4 + X_3C_2 + X_2C_3). \end{aligned}$$

So,  $y^{(k)} - \alpha = S_2e_k^2 + S_3e_k^3 + S_4e_k^4 + O(e_k^5)$ .

Now, we consider the Taylor expansion of  $F(y^{(k)})$  around  $\alpha$ :

$$F(y^{(k)}) = F'(\alpha) (e_{y,k} + C_2e_{y,k}^2 + O(e_{y,k}^3)). \quad (2.8)$$

Thus we denote by  $Z_i$  the following expressions,

$$\begin{aligned} Z_3 &= -X_2S_2, \\ Z_4 &= -(X_2S_3 + X_3S_2 + C_2S_2^2). \end{aligned}$$

Then, one has that

$$\begin{aligned} z^{(k)} - \alpha &= e_{y,k} - \delta[w^{(k)}, x^{(k)}; F]^{-1}F(y^{(k)}) \\ &= (1 - \delta)S_2e_k^2 + ((1 - \delta)S_3 + \delta Z_3)e_k^3 + ((1 - \delta)S_4 + \delta Z_4)e_k^4 + O(e_k^5). \end{aligned}$$

We now consider the Taylor expansion of  $F'(y^{(k)})$ ,  $F''(y^{(k)})$  and  $F'''(y^{(k)})$  around  $\alpha$  being  $e_{y,k} = y^{(k)} - \alpha$  in the same way as was done for  $x^{(k)}$ .

Applying the Genochi-Hermite formula we obtain

$$[z^{(k)}, y^{(k)}; F] = F'(\alpha)(I + C_2(2 - \delta)S_2e_k^2 + C_2((2 - \delta)S_3 + \delta Z_3)e_k^3) + O(e_k^4).$$

Thus we denote by  $D_i$  the components of  $[z^{(k)}, y^{(k)}; F]$ , that is,

$$[z^{(k)}, y^{(k)}; F] = F'(\alpha)(I + D_2e_k^2 + D_3e_k^3) + O(e_k^4),$$

where

$$\begin{aligned} D_2 &= C_2(2 - \delta)S_2, \\ D_3 &= C_2((2 - \delta)S_3 + \delta Z_3). \end{aligned}$$

Thus,

$$2I - [w^{(k)}, x^{(k)}; F]^{-1}[z^{(k)}, y^{(k)}; F] = I - X_2e_k - (X_3 + D_2)e_k^2 + O(e_k^3).$$

If we denoted by  $A = 2I - [w^{(k)}, x^{(k)}; F]^{-1}[z^{(k)}, y^{(k)}; F]$ , then it follows that

$$A[w^{(k)}, x^{(k)}; F]^{-1} = (I - (D_2 + X_2^2)e_k^2)F'(\alpha)^{-1} + O(e_k^3).$$

Let us now consider the Taylor expansion of  $F(z^{(k)})$  around  $\alpha$

$$F(z^{(k)}) = F'(\alpha) (e_{z,k} + C_2 e_{z,k}^2 + O(e_{z,k}^3)), \tag{2.9}$$

being  $e_{z,k} = z^{(k)} - \alpha$ . Then,

$$\begin{aligned} x^{(k+1)} - \alpha &= (1 - \beta)e_{z,k} + \beta(D_2 + X_2^2)((1 - \delta)S_2 e_k^4 + ((1 - \delta)S_3 + \delta Z_3)e_k^5) \\ &\quad - \beta C_2(1 - \delta)^2 S_2 S_2 e_k^4 + ((1 - \delta)S_2((1 - \delta)S_3 + \delta Z_3) \\ &\quad + ((1 - \delta)S_3 + \delta Z_3)(1 - \delta)S_2)e_k^5 + O(e_k^6). \end{aligned}$$

We distinguish the following different cases for the parameters  $\beta$  and  $\delta$ :

- If  $\delta \neq 1$  and  $\beta \neq 1$ , then  $e_{k+1}$  has order of convergence 2 because  $e_{z,k}$  does to.
- If  $\delta = 1$  and  $\beta \neq 1$ , then  $e_{z,k}$  has order 3, so  $e_{k+1}$  also has order 3.
- If  $\delta \neq 1$  and  $\beta = 1$ , then we get order 4 since the term  $e_{z,k}$  cancels out but the terms having  $e_k^4$  do not.
- If  $\delta = 1$  and  $\beta = 1$ , then we are going to obtain the error expression. If we replace these values in the error expression what we get is

$$\begin{aligned} e_{k+1} &= (D_2 + X_2^2)Z_3 e_k^5 + Z_3 e_k^5 + O(e_k^6) \\ &= E(I + \gamma F'(\alpha)) e_k^5 + O(e_k^6), \end{aligned}$$

where

$$E = (C_2^2(5I + 3\gamma F'(\alpha)) + \gamma C_2 F'(\alpha) C_2(2I + \gamma F'(\alpha)))(2C_2^2 + \gamma C_2 F'(\alpha) C_2).$$

Therefore, it is proved that if  $\beta = 1$  and  $\delta = 1$  the resulting parametric family has order of convergence 5.  $\square$

We denoted by  $S_\gamma$  the parametric family (1.3) when  $\beta = 1$  and  $\delta = 1$ .

Now, we want to introduce memory to the family  $S_\gamma$ , in order to increase the order of convergence without adding new functional evaluations. To prove the order of convergence of the methods with memory we use the following Ortega-Rheinboldt's Theorem, which can be found in [13].

**Theorem 2.2.** *Let  $\phi$  be an iterative method with memory that generates a sequence  $\{x^{(k)}\}$  of approximations to the root  $\alpha$ , and let this sequence converges to  $\alpha$ . If there exist a nonzero constant  $\eta$  and positive numbers  $t_i, i = 0, \dots, m$  such that the inequality*

$$|e_{k+1}| \leq \eta \prod_{i=0}^m |e_{k-i}|^{t_i},$$

*holds, then the R-order of convergence of the iterative method  $\phi$  is at least  $p$ , where  $p$  is the unique positive root of the equation*

$$p^{m+1} - \sum_{i=0}^m t_i p^{m-i} = 0.$$

As we can see on the error equation, if  $I + \gamma F'(\alpha) = 0$ , then the order of convergence will be at least 6. But we don't know  $\alpha$ . For this reason we are going to approach  $F'(\alpha)$  by an expression that only depends on the previous iterations and their functional

evaluations, because we want to increase the order of convergence without increase the number of functional evaluations.

One way to approach  $F'(\alpha)$  is by the Kurchatov's operator of divided difference. In this case we are going to choose  $\gamma_k = -[2x^{(k)} - y^{(k-1)}, y^{(k-1)}; F]^{-1}$ , and by replacing  $\gamma$  in the iterative expression of the family  $S_\gamma$  we get a method with memory denoted by  $SK_y$ .

**Theorem 2.3.** *Let  $F : D \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^n$  be a sufficiently differentiable function in a neighbourhood  $D$  of  $\alpha$  such that  $F(\alpha) = 0$ . We assume that  $F'(\alpha)$  is nonsingular. Then, taking an initial estimation  $x^{(0)}$  close enough to  $\alpha$ , the sequence of approximations  $\{x^{(k)}\}$  generated by  $SK_y$  converges to  $\alpha$  with order of convergence 6.*

*Proof.* From the error equation when  $\beta = 1$  and  $\delta = 1$  we obtain that

$$e_{k+1} \sim (I + \gamma_k F'(\alpha))e_k^5 + O(e_k^6).$$

Let us consider the Taylor's expansion of  $F(y^{(k-1)})$ ,  $F'(y^{(k-1)})$ ,  $F''(y^{(k-1)})$  and  $F'''(y^{(k-1)})$  around  $\alpha$  in the same way as we do in the previous theorem.

Applying the Genochi-Hermite formula to  $A_k = [2x^{(k)} - y^{(k-1)}, y^{(k-1)}; F]$ , we obtain

$$A_k = F'(\alpha) (I + 2C_2 e_k - 2C_3 e_{y,k-1} e_k + C_3 e_{y,k-1}^2 + 4C_3 e_k^2) + O_3(e_k, e_{y,k-1}),$$

where  $O_3(e_k, e_{y,k-1})$  denoted all the terms  $e_k$  and  $e_{y,k-1}$  such that the sum of their exponents is at least 3.

Then, the inverse of the divided difference operator is

$$A_k^{-1} = (I - 2C_2 e_k - C_3 e_{y,k-1}^2 + 2C_3 e_{y,k-1} e_k + 4(C_2^2 - C_3) e_k^2) F'(\alpha)^{-1} + O_3(e_k, e_{y,k-1}).$$

Thus,

$$I + \gamma_k F'(\alpha) = 2C_2 e_k + C_3 e_{y,k-1}^2 - 2C_3 e_{y,k-1} e_k - 4(C_2^2 - C_3) e_k^2 + O_3(e_k, e_{y,k-1}).$$

Thus  $I + \gamma_k F'(\alpha)$  can have the behaviour of  $e_k$ ,  $e_k e_{y,k-1}$ ,  $e_k^2$  or  $e_{y,k-1}^2$ . Obviously, factors  $e_k e_{y,k-1}$  and  $e_k^2$  tend to be faster at 0 than  $e_k$ , so we have to see whether  $e_k$  or  $e_{y,k-1}^2$  converges faster.

Let us suppose that the R-order of the method is at least  $p$ . Therefore, it is satisfied

$$e_{k+1} \sim D_{k,p} e_k^p,$$

where  $D_{k,p}$  tends to the asymptotic error constant,  $D_p$ , when  $k \rightarrow \infty$ .

On the other hand, let us suppose that the sequence  $\{y^{(k)}\}$  has R-order  $p_1$ . Therefore, it is satisfied that

$$e_{y,k} \sim D_{k,p_1} e_k^{p_1},$$

where  $D_{k,p_1}$  tends to the asymptotic error constant,  $D_{p_1}$ , when  $k \rightarrow \infty$ .

It then follows that

$$\frac{e_k}{e_{y,k-1}^2} \sim \frac{e_{k-1}^p}{e_{k-1}^{2p_1}} \sim e_{k-1}^{p-2p_1}.$$

Thus, if  $p > 2p_1$  we have that  $\frac{e_k}{e_{y,k-1}^2}$  converges to 0, we have that the behaviour will be that of  $e_{y,k-1}^2$ , otherwise the behaviour will be as of  $e_k$ .

So, if we assume  $p > 2p_1$  we have  $I + \gamma_k F'(\alpha) \sim e_{y,k-1}^2$ . From the error equation and the above relationship it is obtained:

$$e_{k+1} \sim e_{y,k-1}^2 e_k^5 \sim e_{k-1}^{2p_1} e_k^5. \quad (2.10)$$

On the other hand, assuming that the  $R$ -order of the method is at least  $p$ , one has that

$$e_{k+1} \sim D_{k,p}(D_{k-1,p} e_{k-1}^p)^p = D_{k,p} D_{k-1,p}^p e_{k-1}^{p^2}. \quad (2.11)$$

In the same way that the relation (2.10) is obtained, and supposing that the sequence  $y^{(k)}$  has  $R$ -order  $p_1$ , we obtain that

$$e_{k+1} \sim e_{y,k-1}^2 (e_{k-1}^p)^5 \sim e_{k-1}^{2p_1} + e_{k-1}^{5p} \sim e_{k-1}^{5p+2p_1}. \quad (2.12)$$

On the other hand, by the error equation of  $e_{y,k}$ , we have

$$e_{y,k} \sim (I + \gamma_k F'(\alpha)) e_k^2 \sim e_{k-1}^{2p_1} (e_{k-1}^p)^2 \sim e_{k-1}^{2p+2p_1}. \quad (2.13)$$

Assuming that sequence  $\{y^{(k)}\}$  has  $R$ -order at least  $p_1$ , we have

$$e_{y,k} \sim e_k^{p_1} \sim e_{k-1}^{pp_1}. \quad (2.14)$$

Then, equating the exponents of  $e_{k-1}$  on (2.11) and on (2.12), and equating on the other hand the exponents of  $e_{k-1}$  on (2.13) and on (2.14) it follows that:

$$\begin{aligned} p^2 &= 5p + 2p_1, \\ pp_1 &= 2p + 2p_1 \end{aligned}$$

whose only positive solution is  $p = 6$  and  $p_1 = 3$ , so it is proved that the order of method  $SK_y$  is 6.  $\square$

Other ways to introduce memory to the class of iterative schemes when  $\beta = 1$  and  $\delta = 1$  are:

- If we choose  $\gamma_k = -[x^{(k)}, x^{(k-1)}, F]^{-1}$ , then substituting the  $S_\gamma$  family parameter for this approximation, yields a method with memory which we denote by  $SD_x$ .
- If we choose  $\gamma_k = -[2x^{(k)} - x^{(k-1)}, x^{(k-1)}, F]^{-1}$ , then substituting the  $S_\gamma$  family parameter for this approximation, yields a method with memory which we denote by  $SK_x$ .
- If we choose  $\gamma_k = -[x^{(k)}, y^{(k-1)}, F]^{-1}$ , then substituting the  $S_\gamma$  family parameter for this approximation, yields a method with memory which we denote by  $SD_y$ .
- If we choose  $\gamma_k = -[x^{(k)}, z^{(k-1)}, F]^{-1}$ , then substituting the  $S_\gamma$  family parameter for this approximation, yields a method with memory which we denote by  $SD_z$ .
- If we choose  $\gamma_k = -[2x^{(k)} - z^{(k-1)}, z^{(k-1)}, F]^{-1}$ , then substituting the  $S_\gamma$  family parameter for this approximation, yields a method with memory which we denote by  $SK_z$ .

In the following result, we establish the order of convergence that the previous methods with memory reach.

**Theorem 2.4.** *Let  $F : D \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^n$  be a sufficiently differentiable function in a neighbourhood  $D$  of  $\alpha$  such that  $F(\alpha) = 0$ . We assume that  $F'(\alpha)$  is nonsingular. Then, taking an initial estimation  $x^{(0)}$  close enough to  $\alpha$ , we have*

- *the sequence of iterates  $\{x^{(k)}\}$ , generated by method  $SD_x$ , converges to  $\alpha$  with order  $p = \frac{5+\sqrt{29}}{2} \approx 5.19$ .*
- *the sequence of iterates  $\{x^{(k)}\}$ , generated by method  $SK_x$ , converges to  $\alpha$  with order  $p = \frac{5+\sqrt{33}}{2} \approx 5.37$ .*
- *the sequence of iterates  $\{x^{(k)}\}$ , generated by method  $SD_y$ , converges to  $\alpha$  with order  $p = 3 + \sqrt{6} \approx 5.449$ .*
- *the sequence of iterates  $\{x^{(k)}\}$ , generated by method  $SD_z$ , converges to  $\alpha$  with order  $p = 3 + \sqrt{7} \approx 5.64$ .*
- *the sequence of iterates  $\{x^{(k)}\}$ , generated by method  $SK_z$ , converges to  $\alpha$  with order 6.*

### 3. EFFICIENCY INDEXES

Next, we study the efficiency index of our parametric family and the memory methods obtained from it. We compare this index with that of the family presented in [2, 3], which we denote by  $BM$ .

If  $d$  is the number of functional evaluations per iteration and  $p$  is the order of convergence of the method, then the efficiency index defined by Ostrowski in [14] is

$$I = p^{1/d}.$$

When we deal with a system  $F(x) = 0$  of size  $n$  times  $n$ ,  $n$  and  $n^2$  functional evaluations per iteration are required to compute  $F$  and  $F'$ , respectively. In addition,  $\frac{n^2-n}{2}$  evaluations are required for each divided difference operator. The sum of all functional evaluations is denoted by  $d$ .

Our parametric family  $S_\gamma$  performs 3 evaluations of  $F$  and calculates 2 divided difference operators, so the number of evaluations is

$$d = n^2 + 2n.$$

We have that in the case of methods with memory obtained from  $S_\gamma$ , we calculate a further divided difference so the number of evaluations would be equal to the above plus  $\frac{n^2-n}{2}$ , that is,  $d = \frac{3}{2}(n^2 + n)$ .

The efficiency index only takes into account the number of functional evaluations and the order of the method, but it does not consider the operations (products and quotients) performed to obtain the approximations, for this reason we are also going to study the computational cost of our methods and their computational efficiency index.

The  $IC$  or computational efficiency index is calculated in the following way

$$IC = p^{1/(d+op)},$$



being  $p$  the order of convergence,  $d$  the number of functional evaluations and  $op$  the number of computational operations performed. Operations such as product by a scalar or sum of vectors are not taken into account when calculating the operations performed. Multiplying a matrix by a vector requires  $n^2$  operations, which is the same number of operations needed to perform a divided difference operator.

On the other hand, to calculate a linear inverse operator, a system of linear equations of dimension  $n \times n$  must be solved, in which an LU decomposition of matrices is calculated and two triangular systems are solved, with a total cost of  $\frac{1}{3}n^3 + n^2 - \frac{1}{3}n$  operations.

However, in order to solve  $r$  linear systems with the same matrix of coefficients, the LU decomposition is performed only once, so that the total computational cost is only  $\frac{1}{3}n^3 + rn^2 - \frac{1}{3}n$ .

Our  $S_\gamma$  family computes 1 matrix-vector product, solves 4 linear systems with the same matrix and computes 2 different divided difference operators, so the number of operations is

$$op = \frac{1}{3}n^3 + 7n^2 - \frac{1}{3}n. \tag{3.1}$$

On the other hand, we have that in the case of the memory methods we calculate one more divided difference and solve a linear system with a different matrix, so the number of operations would be equal to the previous one plus  $n^2 + \frac{1}{3}n^3 + n^2 - \frac{1}{3}n$ , that is, the number of operations we perform is  $op = \frac{2}{3}n^3 + 9n^2 - \frac{2}{3}n$ .

Table ?? shows the number of functional evaluations and the number of operations of the proposed methods and the family  $BM$ .

TABLE 1. Number of functional evaluations and operations, per iteration, of  $S_\gamma$ ,  $SD_*$ ,  $SK_*$  and  $BM$

	$S_\gamma$	Memory methods	$BM$
$d$	$n^2 + 2n$	$\frac{3}{2}(n^2 + n)$	$2(n^2 + n)$
$op$	$\frac{1}{3}n^3 + 7n^2 - \frac{1}{3}n$	$\frac{2}{3}n^3 + 9n^2 - \frac{2}{3}n$	$n^3 + 6n^2 - n$

In the following figures, we have plotted the efficiency index and the computational efficiency index for different values of  $n$ , where  $n \times n$  is the size of the system to be solved. Of the methods with memory we have plotted those that obtain the lowest and the highest index, that is,  $SD_x$  is the method that will obtain the lowest index of all those with memory, and the  $SK_y$  method, the one with the highest index, although the latter has the same index as  $SK_z$ , so we choose only one as a representative.

FIGURE 1. Efficiency index

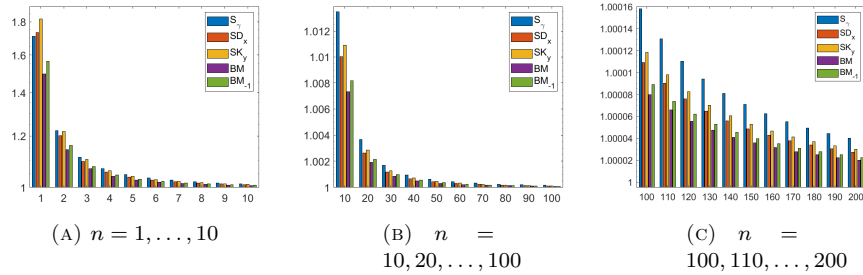
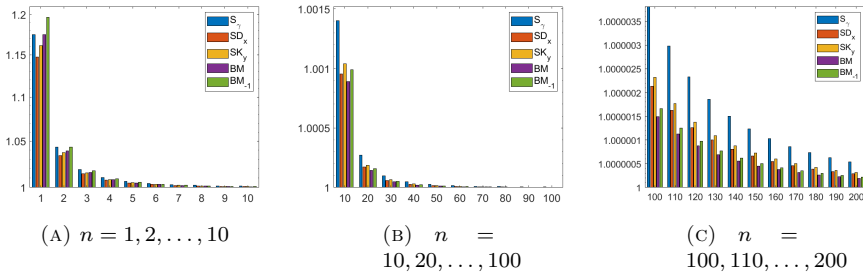


FIGURE 2. Computational efficiency index



As can be seen in the figures, the methods with the highest efficiency indexes are the methods of family  $S_\gamma$  and method  $SK_y$ , which has the same indexes as method  $SK_z$ .

#### 4. NUMERICAL EXPERIMENTS

In this section, we compare our class of iterative schemes  $S_\gamma$  and our methods with memory, by solving two classic problems of applied mathematics: the integral equation of Hammerstein and the partial derivative equation of Fisher. We also analyze an academic problem of size  $2 \times 2$  to represent the dynamical planes of the proposed schemes and we compare them under other point of view. We compare the our schemes with methods belonging to the parametric family introduced in [2] and [3].

For computational calculations, we have use Matlab 2020b with an arithmetic precision of a 200 digits. As stopping criterion we use

$$\|x^{(k+1)} - x^{(k)}\| + \|F(x^{(k+1)})\| < T,$$

where  $T$  is the tolerance, which will be different for each method. We also use a maximum of 50 iterations as stopping criterion.

The numerical results we are going to compare the methods in the different examples are

- the approximation obtained  $x^{(k+1)}$ ,
- the value  $\|F(x^{(k+1)})\|$ ,
- the distance between the lasts two iterations  $\|x^{(k+1)} - x^{(k)}\|$ ,
- the number of iterations that have been needed to verify the stopping criterion,
- the computational time,
- and the approximated computational order of convergence (ACOC), defined by Cordero and Torregrosa in [7], which has the following expression

$$p \approx ACOC = \frac{\ln(\|x^{(k+1)} - x^{(k)}\|_2 / \|x^{(k)} - x^{(k-1)}\|_2)}{\ln(\|x^{(k)} - x^{(k-1)}\|_2 / \|x^{(k-1)} - x^{(k-2)}\|_2)}.$$

**4.1. Hammerstein’s equation.** In this example, we consider the well-known Hammerstein integral equation (see [13]), which is given as follows:

$$x(s) = 1 + \frac{1}{5} \int_0^1 F(s, t)x(t)^3 dt, \tag{4.1}$$

being  $x \in \mathbb{C}[0, 1]$ ,  $s, t \in [0, 1]$  and the kernel  $F$  is

$$F(s, t) = \begin{cases} (1 - s)t & t \leq s, \\ s(1 - t) & s \leq t. \end{cases}$$

We transform the above equation into a finite-dimensional problem using the Gauss-Legendre quadrature formula given as  $\int_0^1 f(t)dt \approx \sum_{j=1}^7 \omega_j f(t_j)$ , where the nodes  $t_j$  and the weights  $t_j$  are determined for  $n = 7$  by the Gauss-Legendre quadrature formula. In this case, the abscissas and weights are in the following table.

$i$	Weights $\omega_i$	Nodes $t_i$
1	0.0647424831	0.0254460438
2	0.1398526957	0.1292344072
3	0.1909150252	0.2970774243
4	0.2089799185	0.5
5	0.1909150252	0.7029225757
6	0.1398526955	0.8707655928
7	0.0647424831	0.9745539561

Denoting the approaches of  $x(t_i)$  by  $x_i$  ( $i = 1, \dots, 7$ ), the following nonlinear system is obtained

$$5x_i - 5 - \sum_{j=1}^7 a_{ij}x_j^3 = 0,$$

where  $i = 1, \dots, 7$  and

$$a_{ij} = \begin{cases} w_j t_j (1 - t_i) & j \leq i, \\ w_j t_i (1 - t_j) & i < j. \end{cases}$$

Starting from an initial approximation

$$x^{(0)} = 0.5(1, \dots, 1)^T, \quad x^{(-1)} = y^{(-1)} = z^{(-1)} = 0.4(1, \dots, 1)^T$$

and with a tolerance  $10^{-50}$ , we obtain the approximations for different members of the parametric family, the results of which are contained in Table 2.

TABLE 2. Hammerstein’s equation results

Method	$\ x^{(k+1)} - x^{(k)}\ _2$	$\ F(x^{(k+1)})\ _2$	Iteration	ACOC	Time
$S_1$	$1.70931 \times 10^{-190}$	$2.41129 \times 10^{-951}$	4	4.9997	12.9578
$S_{-1}$	$2.1817 \times 10^{-96}$	$1.46237 \times 10^{-482}$	4	4.99841	12.3453
$SD_x$	$1.39146 \times 10^{-243}$	$3.58645 \times 10^{-1007}$	4	5.20041	18.1750
$SK_x$	$2.50789 \times 10^{-257}$	$2.536 \times 10^{-1007}$	4	5.39606	18.3734
$SD_y$	$1.62644 \times 10^{-272}$	$3.92876 \times 10^{-1007}$	4	5.44404	19.5078
$SK_y$	$9.09617 \times 10^{-54}$	$3.40949 \times 10^{-324}$	3	5.75784	14.8047
$SD_z$	$6.53589 \times 10^{-51}$	$4.11969 \times 10^{-290}$	3	5.44555	14.4000
$SK_z$	$2.52685 \times 10^{-54}$	$8.30666 \times 10^{-329}$	3	5.82853	14.8203
$BM_{-1}$	$1.00801 \times 10^{-56}$	$2.72453 \times 10^{-169}$	5	2.99948	15.4484
$BM_1$	$5.63171 \times 10^{-183}$	$9.85111 \times 10^{-917}$	4	4.99976	13.1969

**4.2. Fisher’s equation.** In this second example we are going to study the Fisher equation proposed in [9] by Fisher to model the diffusion process in population dynamics. The analytical expression of this equation in partial derivatives is as follows

$$u_t(x, t) = Du_{xx}(x, t) + ru(x, t) \left( 1 - \frac{u(x, t)}{p} \right), \quad x \in [a, b], \quad t \geq 0, \quad (4.2)$$

where  $D \leq 0$  is the diffusion constant,  $r$  is the growth level of the species and  $p$  is the carrying capacity.

In this case, we will study the Fisher equation for the values  $p = 1$ ,  $r = 1$  and  $D = 1$  in the interval  $[0, 1]$  and with the initial condition  $u(x, 0) = \text{sech}^2(\pi x)$  and zero boundary conditions.

We transform the Cauchy problem just described into a set of nonlinear systems by applying an implicit finite difference method, providing the estimated solution at time  $t_k$  from the one estimated at  $t_{k-1}$ . We denote the spatial step by  $h = \frac{1}{n_x}$  and the time step by  $k = \frac{T_{max}}{n_t}$ , where  $T_{max}$  is the final instant and  $n_x$  and  $n_t$  are the number of subintervals in  $x$  and  $t$ , respectively. Therefore, we define a mesh of the domain  $[0, 1] \times [0, T_{max}]$ , composed of points  $(x_i, t_j)$ , as follows

$$x_i = 0 + ih, \quad i = 0, \dots, n_x, \quad t_j = 0 + jk, \quad j = 0, \dots, n_t.$$

Our aim is to approximate the solution of the problem (4.2) at these points of the grid, solving as many nonlinear systems as  $t_j$  time nodes in the grid. To do so, we

use the following finite differences:

$$u_t(x, t) \approx \frac{u(x, t) - u(x, t - k)}{k}$$

$$u_{xx}(x, t) \approx \frac{u(x + h, t) - 2u(x, t) + u(x - h, t)}{h^2}.$$

We note that for the time step we use first-order backward divided differences and for the spatial step we use second-order centred divided differences. We denote  $u_{i,j}$  as the approximation of the solution in  $(x_i, t_j)$ , and, substituting it into the Cauchy problem, we obtain the system

$$ku_{i+1,j} + (kh^2 - 2k - h^2)u_{i,j} - kh^2u_{i,j}^2 + ku_{i-1,j} = -h^2u_{i,j-1},$$

for  $i = 1, 2, \dots, n_x - 1$  and  $j = 1, 2, \dots, n_t$ . The unknowns of this system are  $u_{1,j}, u_{2,j}, \dots, u_{n_x-1,j}$ , that is, the approximations of the solution at each spatial node for the fixed time  $t_j$ .

In this example, we will work with the parameters  $T_{max} = 10$ ,  $n_x = 10$  and  $n_t = 50$ . As we have said, it is necessary to solve as many systems as  $t_j$  time nodes, for each of these systems we use the parametric family to approximate its solution. Thus, starting from an initial approximation  $u_{i,0} = \text{sech}^2(\pi x_i)$ ,  $i = 0, \dots, n_x$ , with a tolerance of  $10^{-6}$ , and  $u_{i,-1} = u_{i,0} + 0.5 * \text{ones}(1, n_x)$ , we obtain the results shows in Table 3.

TABLE 3. Fisher’s equation results

Method	$\ x^{(k+1)} - x^{(k)}\ _2$	$\ F(x^{(k+1)})\ _2$	Iteration	ACOC	Time
$S_1$	$7.39203 \times 10^{-21}$	$1.2229 \times 10^{-106}$	3	5.1619	537.7188
$S_{-1}$	$2.17658 \times 10^{-7}$	$5.75334 \times 10^{-37}$	3	5.6847	359.7344
$S_{-0.1}$	$5.8197 \times 10^{-12}$	$1.63062 \times 10^{-60}$	3	5.2641	423.4063
$SD_x$	$4.4694 \times 10^{-28}$	$1.17155 \times 10^{-147}$	3	4.98119	599.0469
$SK_x$	$9.81953 \times 10^{-32}$	$1.19756 \times 10^{-192}$	3	5.95075	545.8906
$SD_y$	$8.19402 \times 10^{-30}$	$1.11985 \times 10^{-164}$	3	5.35656	540.1094
$SK_y$	$9.81953 \times 10^{-32}$	$1.19756 \times 10^{-192}$	3	5.95075	554.4531
$SD_z$	$1.13998 \times 10^{-30}$	$2.70935 \times 10^{-175}$	3	5.54171	558.5781
$SK_z$	$2.4707 \times 10^{-28}$	$2.19756 \times 10^{-145}$	3	5.95075	442.2344
$BM_1$	$1.98612 \times 10^{-17}$	$1.27687 \times 10^{-88}$	3	5.1119	426.4688
$BM_{-1}$	$3.28786 \times 10^{-7}$	$7.95903 \times 10^{-23}$	3	3.1967	345.5469
$BM_{-0.1}$	$2.97139 \times 10^{-8}$	$3.26295 \times 10^{-26}$	3	3.1592	406.0781

**4.3. An academic problem.** Next, we carry out the dynamical planes of the iterative methods that we have seen throughout the work and of the  $BM$  family with which we compare them. To do so, we start with some preliminary concepts about real dynamics.

The standard form of an iterative method with memory that uses only two previous iterations to calculate the next is:

$$x^{(k+1)} = \phi(x^{(k-1)}, x^{(k)}), \quad k \geq 1,$$

being  $x^{(0)}$  and  $x^{(1)}$  initial estimations. A function defined from  $\mathbb{R}^n \times \mathbb{R}^n$  to  $\mathbb{R}^n$  cannot have fixed points. Therefore, an auxiliary vectorial function  $O$  is defined by means of

$$O(x^{(k-1)}, x^{(k)}) = (x^{(k)}, x^{(k+1)}) = (x^{(k)}, \phi(x^{(k-1)}, x^{(k)})), \quad k = 1, 2, \dots$$

If  $(x^{(k-1)}, x^{(k)})$  is a fixed point of  $O$ , then

$$O(x^{(k-1)}, x^{(k)}) = (x^{(k-1)}, x^{(k)}),$$

and from the definition of  $O$ , we have that

$$(x^{(k-1)}, x^{(k)}) = (x^{(k)}, x^{(k+1)}).$$

The basin of attraction of a fixed point  $x^*$ , is defined as the set of pre-images of any order such that

$$\mathcal{A}(x^*) = \{y \in \mathbb{R}^n : O^m(y) \rightarrow x^*, \quad m \rightarrow \infty\}.$$

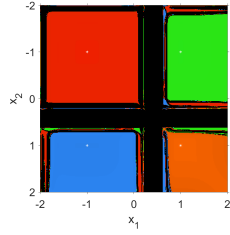
In this case we are going to see the dynamical planes of our methods associated to the following system:

$$\begin{cases} x_1^2 - 1 = 0, \\ x_2^2 - 1 = 0. \end{cases}$$

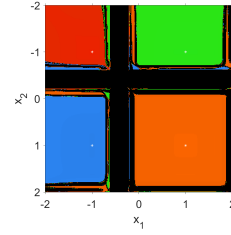
We know that the roots of the polynomial system are  $(-1, -1)^T$ ,  $(-1, 1)^T$ ,  $(1, -1)^T$  and  $(1, 1)^T$ .

To generate the dynamical planes, we choose a initial point and what we will do is apply our methods taking these point as the initial estimation, see [4, 5]. To choose the point we have generate a mesh of  $400 \times 400$  points. We have also defined that the maximum number of iterations that each initial estimate must do is 80, and that we will determine that the initial point converges to one of the solutions if the distance to that solution is less than  $10^{-3}$ . We paint in green the initial points that converge to the root  $(1, 1)^T$ , in orange the initial points that converge to the root  $(1, -1)^T$ , in red the initial points that converge to the root  $(-1, 1)^T$ , in blue the initial points that converge to the root  $(-1, -1)^T$  and in black the initial points that do not converge to any root.

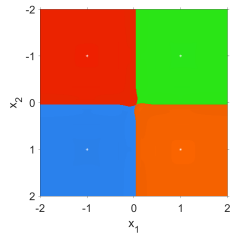
FIGURE 3. Dynamical planes of  $S_\gamma$  and their methods with memory and  $BM_\gamma$



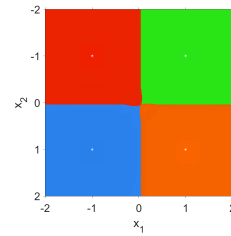
(A) Dynamical plane of  $S_{\gamma=1}$



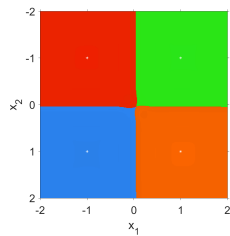
(B) Dynamical plane of  $S_{\gamma=-1}$



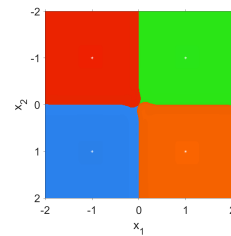
(C) Dynamical plane of  $SD_x$



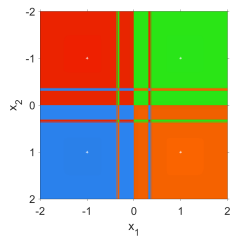
(D) Dynamical plane of  $SD_y$



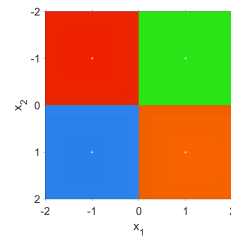
(E) Dynamical plane of  $SD_z$



(F) Dynamical plane of  $SK_x$ ,  $SK_y$  and  $SK_z$



(G) Dynamical plane of  $BM_{\gamma=1}$



(H) Dynamical plane of  $BM_{\gamma=-1}$

In Table 4, we show the results obtained for this system of equations with initial estimates  $x^{(0)} = (1.5, 1.5)^T$  and  $x^{(-1)} = y^{(-1)} = z^{(-1)} = (2, 2)^T$  and a tolerance  $10^{-100}$ .

TABLE 4

Method	$\ x^{(k+1)} - x^{(k)}\ _2$	$\ F(x^{(k)})\ $	Iteration	ACOC	Time
$S_1$	$1.1063 \times 10^{-161}$	$1.181 \times 10^{-804}$	5	4.9999	5.7469
$S_{-1}$	$2.6131 \times 10^{-129}$	$3.5177 \times 10^{-774}$	4	6	2.7297
$SD_x$	$3.98468 \times 10^{-508}$	$4.91427 \times 10^{-2637}$	5	5.1917	3.3453
$SK_x$	$1.25208 \times 10^{-144}$	$4.25698 \times 10^{-866}$	4	6.0	2.7297
$SD_y$	$7.09892 \times 10^{-111}$	$9.22571 \times 10^{-603}$	4	5.44552	6.1703
$SK_y$	$1.25208 \times 10^{-144}$	$4.25698 \times 10^{-866}$	4	6.0	2.5281
$SD_z$	$2.05457 \times 10^{-118}$	$5.67265 \times 10^{-667}$	4	5.6415	4.9922
$SK_z$	$1.25208 \times 10^{-144}$	$4.25698 \times 10^{-866}$	4	6.0	2.5016
$BM_1$	$2.85672 \times 10^{-403}$	$1.18911 \times 10^{-2014}$	5	5.0	6.0812
$BM_{-1}$	$7.69125 \times 10^{-167}$	$6.82466 \times 10^{-499}$	7	3.0	8.4000

## 5. CONCLUSIONS

As we have seen in the work, the parametric family (1.3) has order 2 for any value of  $\beta$ ,  $\delta$  and  $\gamma$ , but if we fix  $\beta = 1$  and  $\delta = 1$  we get that this resulting parametric family, which we denote by  $S_\gamma$ , has order 5. Using divided difference operators we introduce memory to this parametric family  $S_\gamma$  in different ways. By introducing the memory we have managed to increase the order to 6. We study the efficiency index and the computational efficiency index of our family and our memory methods and compare with other family of order 5 and 6, and we just saw that our family  $S_\gamma$  is better for every size of the system in both indexes. The numerical experiments have confirm the theoretical results and we can observe that our  $S_\gamma$  parametric family takes the fewer computational time in general, but that our methods with memory, especially the  $SK_y$  and  $SK_z$  methods, obtain better results. Not forgetting that in the academic example, the dynamic planes obtained for the methods with memory present larger basin of convergent initial approximations than those of the  $S_{gamma}$  and  $BM$  classes.

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## REFERENCES

- [1] I. Argyros, S. Regmi, *Undergraduate Research at Cameron University on Iterative Procedures in Banach and Other Spaces*, Nova Science Publisher, 2019.
- [2] I. Argyros, D. Sharma, C. Argyros, S. Parhi, S. Sunanda, *A family of fifth and sixth convergence order methods for nonlinear models*, *Symmetry*, **13**(2021).
- [3] R. Behl, E. Martinez, *A new high-order and efficient family of iterative techniques for nonlinear models*, *Complexity*, (2020).
- [4] F. Chicharro, A. Cordero, N. Garrido, N., J.R. Torregrosa, *Stability and applicability of iterative methods with memory*, *Journal of Mathematical Chemistry*, **57**(2019), 1282-1300.
- [5] F. Chicharro, A. Cordero, J.R. Torregrosa, *Drawing dynamical and parameters planes of iterative families and methods*, *The Scientific World Journal*, **2013**(2013).
- [6] A. Cordero, C. Jordan, E. Sanabria, J.R. Torregrosa, *Design, convergence and stability of a fourth-order class of iterative methods for solving nonlinear vectorial problems*, *Fractal and Fractional*, **5**(2021).
- [7] A. Cordero, J.R. Torregrosa, *Variants of Newton's method using fifth-order quadrature formulas*, *Appl. Math. Comput.*, **190**(2007), 686-698.
- [8] A. Cordero, E. Villalba, J.R. Torregrosa, P. Triguero-Navarro, *Convergence and stability of a parametric class of iterative schemes for solving nonlinear systems*, *Mathematics*, **9**(2021).
- [9] R. Fisher, *The wave of advance of advantageous genes*, *Annals of Eugenics*, **7**(1937), 355-369.
- [10] C. Grosan, A. Abraham, *A new approach for solving nonlinear equations systems*, *IEEE Trans. Syst. Man Cybernet Part A: Syst. Humans*, **38**(2008), 698-714.
- [11] J.J. Moré, *A collection of nonlinear model problems*, in: E.L. Allgower, K. Georg (Eds.), *Computational Solution of Nonlinear Systems of Equations*, *Lectures in Applied Mathematics*, vol. **26**, Amer. Math. Soc. Providence, RI, 1990, 723-762.
- [12] M. Narang, S. Bathia, A.S. Alshomrani, V. Kanwar, *General efficient class of Steffensen type methods with memory for solving systems on nonlinear equations*, *J. Comput. Appl. Math.*, **352**(2019), 23-39.
- [13] J. Ortega, W. Rheinboldt, *Iterative Solution of Nonlinear Equations in Several Variables*, Academic Press, New-York, 1970.
- [14] A.M. Ostrowski, *Solutions of Equations and System of Equations*, Academic Press, New York, 1960.
- [15] M.S. Petković, J.R. Sharma, *On some efficient derivative-free iterative methods with memory for solving systems of nonlinear equations*, *Numer. Algor.*, **71**(2016), 457-474.
- [16] S. Regmi, *Optimized Iterative Methods with Applications in Diverse Disciplines*, Nova Science Publisher, 2021.
- [17] V. Samanskii, *On a modification of the Newton method*, *Ukrain. Math.*, **19**(1967), 133-138.
- [18] J.R. Sharma, H. Arora, *Efficient higher order derivative-free multipoint methods with and without memory for systems of nonlinear equations*, *Int. J. Comput. Math.*, **95**(2018), 920-938.
- [19] J. Steffensen, *Remarks on iteration*, *Skand. Aktuarietidskr*, **16**(1933), 64-72.
- [20] J. Traub, *Iterative Methods for the Solution of Equations*, Prentice-Hall, 1964.
- [21] I.G. Tsoulos, A. Stavrakoudis, *On locating all roots of systems of nonlinear equations inside bounded domain using global optimization methods*, *Nonlinear Anal. Real World Appl.*, **11**(2010), 2465-2471.

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