

Received June 3, 2021, accepted June 18, 2021, date of publication June 23, 2021, date of current version July 5, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3091906

# Inertial Derivative-Free Projection Method for Nonlinear Monotone Operator Equations With Convex Constraints

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This work was supported in part by the Center of Excellence in Theoretical and Computational Science (TaCS-CoE), King Mongkut's University of Technology Thonburi, and in part by Thailand Science Research and Innovation (TSRI) Basic Research Fund: Fiscal year 2021 under Project 64A306000005.

This work did not involve human subjects or animals in its research.

**ABSTRACT** In this paper, we propose an inertial derivative-free projection method for solving convex constrained nonlinear monotone operator equations (CNME). The method incorporates the inertial step with an existing method called derivative-free projection (DFPI) method for solving CNME. The reason is to improve the convergence speed of DFPI as it has been shown and reported in several works that indeed the inertial step can speed up convergence. The global convergence of the proposed method is proved under some mild assumptions. Finally, numerical results reported clearly show that the proposed method is more efficient than the DFPI.

**INDEX TERMS** Monotone nonlinear operator, inertial algorithm, conjugate gradient, projection method.

## I. INTRODUCTION

Consider the problem of finding  $y \in \mathbf{E}$  such that

$$T(y) = 0, \quad (1)$$

where  $T : \mathbf{R}^n \rightarrow \mathbf{R}^n$  is a monotone and Lipschitz continuous operator and  $\mathbf{E}$  is a nonempty, closed and convex subset of  $\mathbf{R}^n$ . This problem has recently received remarkable attention as it arises in a number of applicable problems. For example, in constrained neural networks [1], nonlinear compressed sensing [2], [3], phase retrieval [4], [5], power flow equations [6], economic and chemical equilibrium problems [7], [8], non-negative matrix factorisation [9], [10], forecasting of financial market, portfolio selection models, price returns [11]–[13] and many more. As such, recently several derivative-free methods such as the conjugate gradient (CG) method have been proposed for solving problem (1). Given

The associate editor coordinating the review of this manuscript and approving it for publication was Gokhan Apaydin<sup>1</sup>.

an initial point  $y_0$ , the conjugate gradient method computes the next iterate as:

$$y_{k+1} = y_k + \alpha_k d_k, \quad k = 0, 1, 2, \dots,$$

where  $\alpha_k > 0$  is a step size and  $d_k$  is called the CG direction of search defined as

$$d_k := \begin{cases} -T(y_k) & \text{if } k = 0, \\ -T(y_k) + \beta_k d_{k-1} & \text{if } k > 0. \end{cases}$$

The parameter  $\beta_k$  is called the CG parameter. For more on derivative-free methods for solving (1), interested readers can refer to [14]–[35] and references therein.

Recently, several researchers are interested in how to improve the speed of convergence of existing iterative algorithms. One of the approach in this regard is the inertial extrapolation method where a new step called the inertial step is added to the existing step(s) of an iterative method. It has been shown that the inertial step enhance the speed of the existing methods such as methods for solving fixed

point problems, variational inequality problems, equilibrium problems, split feasibility problems, and so on. By choosing two starting points  $y_{-1}$  and  $y_0$ , the inertial term is defined as

$$v_k = y_k + \theta_k(y_k - y_{k-1}),$$

where  $\{\theta_k\}_{k=1}^\infty$  is a sequence satisfying certain condition. Inertial extrapolation method has been employed successfully in improving the convergence of the sequence generated by various algorithms. However, to the best of our knowledge, there is no theoretical proof to justify that, indeed, all one can find is numerical justification using some examples. However, the choice of the parameter  $\theta_k$  has an effect on the speed of convergence. For more on iterative methods with inertial extrapolation, the reader is referred to [36]–[41] and references therein.

Inspired by the inertial methods [36]–[41] and the derivative-free projection method proposed by Sun and Liu [17] which is an extension of the work of Cheng [42], we propose an inertial derivative-free projection method for finding solutions to problem (1). The method is based on the work of Sun and Liu [17], where the inertial term is incorporated in order speed up its convergence. The remaining part of this paper is organized as follows: the next section gives some preliminaries and the proposed algorithm, convergence results is provided in the third section, Numerical results in the fourth section and lastly the conclusion.

**Notation.** Unless otherwise stated, the symbol  $\|\cdot\|$  stands for Euclidean norm on  $\mathbf{R}^n$ .

## II. PROPOSED ALGORITHM

*Definition 2.1:* Let  $\mathbf{R}^n$  be an Euclidean space and  $T : \mathbf{R}^n \rightarrow \mathbf{R}^n$  be a mapping. Then  $T$  is

(i) Monotone, if

$$(T(y) - T(x))^T(y - x) \geq 0, \quad \forall y, x \in \mathbf{R}^n.$$

(ii)  $L$ -Lipschitz continuous, if there exists  $L > 0$  such that

$$\|T(y) - T(x)\| \leq L\|y - x\|, \quad \forall y, x \in \mathbf{R}^n.$$

*Definition 2.2:* Let  $\mathbf{E} \subset \mathbf{R}^n$  be closed and convex, the projection of  $y \in \mathbf{R}^n$  onto  $\mathbf{E}$  denoted by  $P_{\mathbf{E}}(y)$ , is defined as

$$P_{\mathbf{E}}(y) = \arg \min\{\|x - y\| \mid x \in \mathbf{E}\}.$$

*Lemma 2.3 ([43]):* Let  $\mathbf{E} \subset \mathbf{R}^n$  be nonempty closed and convex. Then the following inequality hold:

$$\|P_{\mathbf{E}}(y) - P_{\mathbf{E}}(x)\| \leq \|y - x\|, \quad \forall y, x \in \mathbf{R}^n$$

*Lemma 2.4 ([44]):* Let  $y, x \in \mathbf{R}^n$ . Then the following equality hold:

$$\|y + x\|^2 = \|y\|^2 + 2x^T(y + x).$$

*Lemma 2.5 ([45]):* Let  $\{y_k\}$  and  $\{x_k\}$  be sequences of non-negative real number satisfying the following relation

$$y_{k+1} \leq y_k + x_k,$$

where  $\sum_{k=1}^\infty x_k < \infty$ , then  $\lim_{k \rightarrow \infty} y_k$  exists.

*Lemma 2.6 ([46]):* A point  $y^* \in \mathbf{SOL}(\mathbf{T}, \mathbf{E})$  if and only if  $y^* = P_{\mathbf{E}}(y^* - \mu u)$  for some  $u = T(y^*)$  and  $\mu > 0$ .

We make use of the following assumptions.

*Assumption 1:*

- (a) The feasible set  $\mathbf{E}$  is a nonempty closed and convex subset of the Euclidean space  $\mathbf{R}^n$ .
- (b)  $T : \mathbf{R}^n \rightarrow \mathbf{R}^n$  is monotone and  $L$ -Lipschitz continuous.
- (c) The solution set  $\mathbf{SOL}(\mathbf{T}, \mathbf{E})$  of (1) is nonempty.

*Assumption 2:* Let  $\{\theta_k\}$  be a sequence of nonnegative real numbers satisfying the conditions:

$$\theta_k \in (0, 1), \quad \sum_{k=1}^\infty \theta_k \|y_k - y_{k-1}\| < \infty.$$

Based on the Sun and Liu [17] derivative-free projection method for monotone nonlinear equation with convex constraints called DFPI, we present an inertial derivative-free projection method for finding solutions to problem (1).

*Algorithm 2.7 (Inertial Derivative-Free Method (IDFPI):)*

**(S.0)** Choose a sequence  $\{\theta_k\}_{k=1}^\infty$  satisfying Assumption 2 and select the parameters:  $Tol > 0$ ,  $\rho \in (0, 1)$ ,  $\zeta > 0$ ,  $\sigma > 0$ . Select arbitrary points  $y_{-1}, y_0 \in \mathbf{E}$ . Set  $k := 0$ .

**(S.1)** Set

$$v_k = y_k + \theta_k(y_k - y_{k-1})$$

**(S.2)** Compute  $T(v_k)$ . If  $\|T(v_k)\| \leq Tol$ , stop. Otherwise, generate the search direction  $d_k$  by

$$d_k := \begin{cases} -T(v_k) & \text{if } k = 0, \\ -\left(1 + \beta_k \frac{T(v_k)^T d_{k-1}}{\|T(v_k)\|^2}\right) & \\ T(v_k) + \beta_k d_{k-1} & \text{if } k > 0, \end{cases} \quad (2)$$

where,

$$\beta_k := 0.01 \frac{\|T(v_k)\|}{\|d_{k-1}\|}. \quad (3)$$

**(S.3)** Compute a trial point  $x_k = v_k + \alpha_k d_k$ .

**(S.4)** Determine the step-size  $\alpha_k = \zeta \rho^i$  where  $i$  is the least nonnegative integer satisfying

$$-T(v_k + \alpha_k d_k)^T d_k \geq \sigma \alpha_k \|d_k\|^2. \quad (4)$$

**(S.5)** If  $x_k \in \mathbf{E}$  and  $\|T(x_k)\| \leq Tol$ , stop. Otherwise,

$$y_{k+1} = P_{\mathbf{E}}[v_k - \gamma_k T(x_k)], \quad (5)$$

where

$$\gamma_k := \frac{T(x_k)^T(v_k - x_k)}{\|T(x_k)\|^2}.$$

**(S.6)** Set  $k = k + 1$ , and go back to (S.1).

*Remark 2.8:* Let  $d_k$  be generated by (2)-(3) in Algorithm 2.7. Then

$$T(v_k)^T d_k = -\|T(v_k)\|^2. \quad (6)$$

### III. CONVERGENCE RESULT

*Lemma 3.1:* The line search condition (4) is well-defined. That is, for all  $k \geq 0$ , there exists a non negative integer  $i$  satisfying (4).

*Proof:* Suppose there is  $k_0 \geq 0$  for which (4) is not true for any non-negative integer  $i$ , i.e.,

$$-T(v_{k_0} + \zeta \rho^i d_{k_0})^T d_{k_0} < \sigma \zeta \rho^i \|d_{k_0}\|^2.$$

Using Assumption 1 (b) and allowing  $i \rightarrow \infty$ , we have that

$$-T(v_{k_0})^T d_{k_0} \leq 0. \tag{7}$$

On the other hand, from (6),

$$-T(v_{k_0})^T d_{k_0} = \|T(v_{k_0})\|^2 > 0,$$

which contradicts (7). Hence, (4) is well defined. ■

*Lemma 3.2:* Let  $\{y_k\}$  and  $\{x_k\}$  be generated via Algorithm 2.7. If  $y^* \in \text{SOL}(\mathbf{T}, \mathbf{E})$ , then under Assumption 1 and 2, it holds that

$$\|y_{k+1} - y^*\|^2 \leq \|v_k - y^*\| - \sigma^2 \|v_k - x_k\|^4.$$

Moreover, the sequence  $\{y_k\}$  and  $\{x_k\}$  are bounded and

$$\lim_{k \rightarrow \infty} \|v_k - x_k\| = 0. \tag{8}$$

*Proof:* By the monotonicity of the mapping  $T$ , we have

$$\begin{aligned} T(x_k)^T(v_k - y^*) &= T(x_k)^T(v_k - x_k) + T(x_k)^T(x_k - y^*) \\ &\geq T(x_k)^T(v_k - x_k) + T(y^*)^T(x_k - y^*) \\ &= T(x_k)^T(v_k - x_k) \end{aligned} \tag{9}$$

$$\begin{aligned} &= T(x_k)^T(-\alpha_k d_k) \\ &= \sigma \alpha_k^2 \|d_k\|^2 \\ &\geq \sigma \|v_k - x_k\|^2. \end{aligned} \tag{10}$$

By Lemma 2.3 (iii), (5), (9) and (10), it holds that for any  $y^* \in \text{SOL}(\mathbf{T}, \mathbf{E})$ ,

$$\begin{aligned} \|y_{k+1} - y^*\|^2 &= \|P_{\mathbf{E}}(v_k - \gamma_k T(x_k)) - y^*\|^2 \\ &\leq \|v_k - \gamma_k T(x_k) - y^*\|^2 \\ &= \|v_k - y^*\|^2 - 2\gamma_k T(x_k)^T(v_k - y^*) \\ &\quad + \gamma_k^2 \|T(x_k)\|^2 \\ &\leq \|v_k - y^*\|^2 - 2\gamma_k T(x_k)^T(v_k - x_k) \\ &\quad + \gamma_k^2 \|T(x_k)\|^2 \\ &\leq \|v_k - y^*\|^2 - \frac{T(x_k)^T(v_k - x_k)^2}{\|T(x_k)\|^2} \\ &\leq \|v_k - y^*\|^2 - \frac{\sigma^2 \|v_k - x_k\|^4}{\|T(x_k)\|^2}. \end{aligned} \tag{11}$$

From equation (11), we can deduce that

$$\begin{aligned} \|y_{k+1} - y^*\| &\leq \|v_k - y^*\| \\ &= \|y_k + \theta_k(y_k - y_{k-1}) - y^*\| \\ &\leq \|y_k - y^*\| + \theta_k \|y_k - y_{k-1}\|. \end{aligned} \tag{12}$$

Because  $\sum_{k=1}^{\infty} \theta_k \|y_k - y_{k-1}\| < \infty$ , then by Lemma 2.5, the limit of  $\{y_k - y^*\}$  exists and hence it is bounded. This implies that for all  $k$ , there exist  $M_0 > 0$  such that  $\|y_k - y^*\| \leq M_0$ . Therefore, for all  $k$  we can deduce that

$$\|y_k\| \leq M_1, \tag{13}$$

and

$$\|y_k - y_{k-1}\| \leq M,$$

where  $M_1 = M_0 + \|y^*\|$  and  $M = 2M_1$ .

Using the above relations, we can have

$$\|v_k\| \leq M_2, \quad \|v_k - y^*\| \leq M_2, \quad \text{where } M_2 = 2M.$$

Since  $H$  is Lipschitz continuous, we have

$$\|T(v_k)\| = \|T(v_k) - T(y^*)\| \leq L \|v_k - y^*\| \leq LM_2. \tag{14}$$

Also, using (14) and the monotonicity of  $T$ ,

$$\begin{aligned} T(x_k)^T(v_k - x_k) &= (T(x_k) - T(v_k))^T(v_k - x_k) \\ &\quad + T(v_k)^T(v_k - x_k) \\ &\leq T(v_k)^T(v_k - x_k) \\ &\leq \|T(v_k)\| \|v_k - x_k\| \\ &\leq LM_2 \|v_k - x_k\|. \end{aligned}$$

This together with (9) and (10) implies that

$$\|v_k - x_k\| \leq \frac{LM_2}{\sigma}.$$

Then, we have

$$\|x_k\| \leq \frac{LM_2}{\sigma} + \|v_k\|.$$

Hence the sequence  $\{x_k\}$  is bounded since  $\{v_k\}$  is bounded. Moreover as  $T$  is continuous and  $\{x_k\}$  is bounded, then  $\{T(x_k)\}$  is bounded. That is, there exists  $N > 0$  such that  $\|T(x_k)\| \leq N$ .

By the definition of  $v_k$  and (13) we have

$$\begin{aligned} \|v_k - y^*\|^2 &= \|y_k + \theta_k(y_k - y_{k-1}) - y^*\|^2 \\ &= \|y_k - y^*\|^2 \\ &\quad + 2\theta_k(y_k - y_{k-1})^T(y_k + \theta_k(y_k - y_{k-1}) - y^*) \\ &\leq \|y_k - y^*\|^2 + 2\theta_k \|y_k - y_{k-1}\| (\|y_k - y^*\| \\ &\quad + \theta_k \|y_k - y_{k-1}\|) \\ &\leq \|y_k - y^*\|^2 + 2M\theta_k \|y_k - y_{k-1}\| \\ &\quad + 2M\theta_k \|y_k - y_{k-1}\| \\ &= \|y_k - y^*\|^2 + 4M\theta_k \|y_k - y_{k-1}\|. \end{aligned} \tag{15}$$

Combining (15) with (11), we have

$$\begin{aligned} \|y_{k+1} - y^*\|^2 &\leq \|y_k - y^*\|^2 + 4M\theta_k \|y_k - y_{k-1}\| \\ &\quad - \frac{\sigma^2 \|v_k - x_k\|^4}{\|T(x_k)\|^2}. \end{aligned} \tag{16}$$

Thus, we have

$$\frac{\sigma^2 \|v_k - x_k\|^4}{\|T(x_k)\|^2} \leq \|y_k - y^*\|^2 + 4M\theta_k \|y_k - y_{k-1}\| - \|y_{k+1} - y^*\|^2. \quad (17)$$

Adding (17) for  $k = 0, 1, 2, \dots$  and the fact that  $\{T(x_k)\}$  is bounded, we have

$$\frac{\sigma^2}{N^2} \sum_{k=0}^{\infty} \|v_k - x_k\|^4 \leq \sum_{k=0}^{\infty} (\|y_k - y^*\|^2 + 4M\theta_k \|y_k - y_{k-1}\| - \|y_{k+1} - y^*\|^2). \quad (18)$$

Now, let  $S_k = \sum_{n=0}^k (\|y_n - y^*\|^2 - \|y_{n+1} - y^*\|^2)$ , then  $S_k = \sum_{n=0}^k (\|y_0 - y^*\|^2 - \|y_{k+1} - y^*\|^2)$ . As limit of  $\{\|y_k - y^*\|\}$  exists from (12) with limit say  $L_1$ , then

$$\left( \lim_{k \rightarrow \infty} S_k = \|y_0 - y^*\|^2 - L_1 \right) \in \mathbf{R}.$$

So,

$$\sum_{k=0}^{\infty} (\|y_k - y^*\|^2 - \|y_{k+1} - y^*\|^2) < \infty$$

$$\text{and } \sum_{k=0}^{\infty} \theta_k \|y_k - y_{k-1}\| < \infty.$$

Using (18) together with the above inequalities, we conclude that

$$\lim_{k \rightarrow \infty} \|v_k - x_k\| = 0.$$

*Remark 3.3:* By the definition of  $\{x_k\}$  and (8), we have

$$\lim_{k \rightarrow \infty} \alpha_k \|d_k\| = 0.$$

*Lemma 3.4:* Suppose Assumptions 1-2 hold and the sequence  $\{y_k\}$  and  $\{v_k\}$  are generated by Algorithm 2.7. Then

$$\lim_{k \rightarrow \infty} \|v_k - y_{k+1}\| = 0. \quad (19)$$

*Proof:*

Using definition of  $v_k$ ,

$$\begin{aligned} \|y_k - v_k\| &= \|y_k - (y_k + \theta_k(y_k - y_{k-1}))\| \\ &= \theta_k \|y_k - y_{k-1}\|. \end{aligned}$$

This implies that

$$\lim_{k \rightarrow \infty} \|y_k - v_k\| = 0. \quad (20)$$

Also,

$$\begin{aligned} \|y_k - x_k\| &= \|y_k - v_k + v_k - x_k\| \\ &\leq \|y_k - v_k\| + \|v_k - x_k\|. \end{aligned}$$

Using (8) and (20), we have

$$\lim_{k \rightarrow \infty} \|y_k - x_k\| = 0. \quad (21)$$

TABLE 1. Starting points.

SP	$y_{-1}$	$y_0$
$y_1$	$(0.2, \dots, 0.2)^T$	$(0.1, \dots, 0.1)^T$
$y_2$	$(0.2, \dots, 0.2)^T$	$(0.2, \dots, 0.2)^T$
$y_3$	$(0.5, \dots, 0.5)^T$	$(0.5, \dots, 0.5)^T$
$y_4$	$(1.2, \dots, 1.2)^T$	$(1.2, \dots, 1.2)^T$
$y_5$	$(1.5, \dots, 1.5)^T$	$(1.5, \dots, 1.5)^T$
$y_6$	$(2, \dots, 2)^T$	$(2, \dots, 2)^T$
$y_7$	$\text{rand}(n, 1)$	$\text{rand}(n, 1)$

**Note.** For DFPI algorithm [17], the starting point is  $y_0$ .

By Lemma 2.3, we have

$$\begin{aligned} \|y_{k+1} - y_k\| &= \|P_{\mathbf{E}}[v_k - \gamma_k T(x_k)] - y_k\| \\ &\leq \|v_k - \gamma_k T(x_k) - y_k\| \\ &\leq \|v_k - y_k\| + \|\gamma_k E(z_k)\| \\ &= \|v_k - y_k\| + \left\| \frac{T(x_k)^T (v_k - x_k)}{\|T(x_k)\|^2} T(x_k) \right\| \\ &\leq \|v_k - y_k\| + \|v_k - x_k\|. \end{aligned} \quad (22)$$

Thus, from (8) and (20), we have

$$\lim_{k \rightarrow \infty} \|y_{k+1} - y_k\| = 0. \quad (23)$$

Therefore,

$$\begin{aligned} \|y_{k+1} - v_k\| &= \|y_{k+1} - (y_k + \theta_k(y_k - y_{k-1}))\| \\ &\leq \|y_{k+1} - y_k\| + \theta_k \|y_k - y_{k-1}\|. \end{aligned}$$

Using (23) and Assumption 2, the desired equation is obtained.

*Theorem 3.5:* Let  $\{y_k\}$  be a sequence generated via Algorithm 2.7. Using Assumption 1 and 2, then  $\{y_k\}$  converge to an element of  $\mathbf{SOL}(\mathbf{T}, \mathbf{E})$ .

*Proof:* We know that the sequence  $\{y_k\}$  is bounded from (13). This implies that there exists a subsequence  $\{y_{k_j}\}$  of  $\{y_k\}$  such that  $\{y_{k_j}\}$  converge to some point  $\bar{y}$ . Also, we have that

$$\|v_{k_j} - y_{k_j}\| = \theta_{k_j} \|y_{k_j} - y_{k_j-1}\| \rightarrow 0, \text{ as } j \rightarrow \infty. \quad (24)$$

*Claim:*  $\bar{y} \in \mathbf{SOL}(\mathbf{T}, \mathbf{E})$ . Suppose on the contrary that  $\bar{y} \notin \mathbf{SOL}(\mathbf{T}, \mathbf{E})$ . Then from (19) and (24), we have that

$$\lim_{j \rightarrow \infty} y_{k_j+1} = \lim_{j \rightarrow \infty} P_{\mathbf{E}}(v_{k_j} - \gamma_{k_j} T(x_{k_j})) = \lim_{j \rightarrow \infty} y_{k_j} = \bar{y}. \quad (25)$$

Without loss of generality, if  $\gamma_{k_j} \rightarrow \gamma^*$  and  $T(x_{k_j}) \rightarrow T(x^*)$ . Then since  $T$  is continuous, we have  $T(x^*) = T(\bar{y})$ . Therefore, from (25)

$$P_{\mathbf{E}}(\bar{y} - \gamma^* T(x^*)) = \bar{y}.$$

It then follows from Lemma 2.6 that  $y^* \in \mathbf{SOL}(\mathbf{T}, \mathbf{E})$ , which is a contradiction. Hence, our claim holds. Substituting  $y^*$  with  $\bar{y}$  in (12), it is easy to see that  $\lim_{k \rightarrow \infty} \|y_k - \bar{y}\|$  exists

**TABLE 2.** Numerical experiments with different coefficients of  $\beta_k$  for problem 1-5 with  $n = 1000$ .

n=1000	SP	0.01			0.5			1.5			2		
		NOI	NFE	CPUT	NOI	NFE	CPUT	NOI	NFE	CPUT	NOI	NFE	CPUT
Problem 1	$y_1$	9	36	0.00568	36	144	0.021784	96	384	0.044784	188	752	0.10513
	$y_2$	10	40	0.003477	25	100	0.011812	126	504	0.059805	282	1128	0.11457
	$y_3$	6	24	0.003472	28	112	0.010859	84	336	0.033187	222	888	0.081797
	$y_4$	7	28	0.003033	26	104	0.008285	87	348	0.033013	319	1276	0.1232
	$y_5$	7	28	0.00311	18	72	0.008741	102	408	0.049486	91	364	0.043828
	$y_6$	7	28	0.002948	28	112	0.010702	114	456	0.045376	175	700	0.094839
	$y_7$	19	76	0.006554	26	104	0.010181	191	764	0.077315	-	-	-
Problem 2	$y_1$	11	43	0.069731	11	43	0.004505	11	43	0.004516	11	43	0.005377
	$y_2$	13	51	0.004297	13	51	0.004481	13	51	0.00571	13	51	0.004752
	$y_3$	12	46	0.005032	12	46	0.004509	12	46	0.004683	12	46	0.00444
	$y_4$	13	49	0.005324	13	49	0.006814	13	49	0.004967	13	49	0.005646
	$y_5$	14	53	0.005046	14	53	0.005374	14	53	0.005185	14	53	0.00466
	$y_6$	12	44	0.004429	12	44	0.006134	12	44	0.004458	12	44	0.004317
	$y_7$	14	53	0.00526	25	95	0.008445	179	713	0.090395	-	-	-
Problem 3	$y_1$	13	52	0.063903	13	52	0.004482	13	52	0.00409	13	52	0.004058
	$y_2$	13	52	0.004457	13	52	0.004565	13	52	0.004368	13	52	0.003968
	$y_3$	14	56	0.004882	14	56	0.004492	14	56	0.003748	14	56	0.004461
	$y_4$	14	56	0.005488	14	56	0.004633	14	56	0.004022	14	56	0.005487
	$y_5$	14	56	0.004491	14	56	0.005229	14	56	0.004916	14	56	0.004376
	$y_6$	15	60	0.005917	15	60	0.005052	15	60	0.003972	15	60	0.004675
	$y_7$	14	56	0.004507	114	456	0.039936	-	-	-	-	-	-
Problem 4	$y_1$	13	52	0.016113	13	52	0.004009	13	52	0.005635	13	52	0.004117
	$y_2$	13	52	0.00361	13	52	0.003692	13	52	0.003629	13	52	0.003991
	$y_3$	13	52	0.004013	13	52	0.004321	13	52	0.004246	13	52	0.003573
	$y_4$	13	52	0.003393	13	52	0.003838	13	52	0.004084	13	52	0.003938
	$y_5$	14	56	0.005	14	56	0.006158	14	56	0.004706	14	56	0.00564
	$y_6$	14	56	0.00404	14	56	0.005038	14	56	0.003816	14	56	0.003763
	$y_7$	15	60	0.004885	23	92	0.006901	153	612	0.040723	-	-	-
Problem 5	$y_1$	22	83	0.02265	25	93	0.006098	185	734	0.053499	-	-	-
	$y_2$	18	68	0.005	26	98	0.006317	144	567	0.039396	-	-	-
	$y_3$	22	86	0.006487	25	98	0.007825	176	696	0.05854	-	-	-
	$y_4$	20	80	0.006677	27	108	0.007371	142	568	0.036509	-	-	-
	$y_5$	23	92	0.00758	28	112	0.007031	159	636	0.042945	-	-	-
	$y_6$	33	132	0.015034	26	104	0.007602	142	568	0.038659	-	-	-
	$y_7$	39	155	0.014079	34	134	0.011338	161	639	0.045031	-	-	-

by Lemma 2.5. Since  $\bar{y}$  is an accumulation point of  $\{y_k\}$ , we obtain that  $\{y_k\}$  converges to  $\bar{y}$ .

**IV. NUMERICAL EXAMPLES**

By comparing the proposed inertial algorithm (Iner. DFPI) to the DFPI algorithm in [17], we show the numerical efficiency and computational advantage of the proposed inertial algorithm (Iner. DFPI) in this section. The MATLAB implementation of the algorithms was executed on a Windows 10 computer with Intel(R) Core(TM) i7 processor with 8.0GB of RAM and CPU of 2.30GHz using MATLAB R2019b software. The numerical experiment made use of the following test problems to measure the efficiency and robustness of the proposed inertial algorithm (Iner. DFPI).

*Problem 1:* Modified exponential function [47]

$$t_1(y) = e^{y^1} - 1$$

$$t_i(y) = e^{y^i} + y_i - 1, \quad i = 2, \dots, n,$$

$$\mathbf{E} = \mathbf{R}_+^n.$$

*Problem 2:* Logarithmic function [47]

$$t_i(y_i) = \log(y_i + 1) - \frac{y_i}{n}, \quad i = 1, 2, \dots, n,$$

$$\mathbf{E} = \mathbf{R}_+^n.$$

*Problem 3:* Nonsmooth function [48]

$$t_i(y) = 2y_i - \sin(|y_i|), \quad \text{for } i = 1, 2, \dots, n,$$

$$\mathbf{E} = \{y \in \mathbf{R}_+^n : y \geq 0, \sum_{i=1}^n y_i \leq n\}.$$

*Problem 4:* Strictly convex function I [47]

$$t_i(y) = e^{y^i} - 1, \quad i = 1, 2, \dots, n,$$

$$\mathbf{E} = \mathcal{R}_+^n.$$

*Problem 5:* Strictly convex function II [47]

$$t_i(y) = \left(\frac{i}{n}\right) e^{y^i} - 1, \quad i = 1, 2, \dots, n,$$

$$\mathbf{E} = \mathbf{R}_+^n.$$

TABLE 3. Numerical experiments with different coefficients of  $\beta_k$  for problem 6-10 with  $n = 1000$ .

n=1000	0.01			0.5			1.5			2			
	SP	NOI	NFE	CPUT	NOI	NFE	CPUT	NOI	NFE	CPUT	NOI	NFE	CPUT
Problem 6	$y_1$	16	64	0.028171	16	64	0.008079	74	296	0.039752	530	2120	0.27322
	$y_2$	16	64	0.006196	16	64	0.007641	73	292	0.038947	529	2116	0.26621
	$y_3$	16	64	0.007024	16	64	0.007142	74	296	0.03997	524	2096	0.24974
	$y_4$	15	60	0.007648	15	60	0.007185	72	288	0.031371	510	2040	0.2355
	$y_5$	15	60	0.007387	15	60	0.007385	70	280	0.03291	496	1984	0.24424
	$y_6$	15	60	0.0087	15	60	0.007901	65	260	0.031665	467	1868	0.2211
	$y_7$	16	64	0.007314	16	64	0.007423	43	172	0.020312	489	1956	0.22663
Problem 7	$y_1$	8	32	0.024297	8	32	0.00364	8	32	0.004126	8	32	0.00538
	$y_2$	7	28	0.00333	7	28	0.002719	7	28	0.002391	7	28	0.003311
	$y_3$	6	24	0.01827	6	24	0.002887	6	24	0.0024	6	24	0.003263
	$y_4$	7	28	0.004197	7	28	0.002811	7	28	0.003058	7	28	0.003245
	$y_5$	8	32	0.004041	8	32	0.004093	8	32	0.00396	8	32	0.003798
	$y_6$	8	31	0.003253	8	31	0.003851	8	31	0.003888	8	31	0.003131
	$y_7$	9	36	0.004528	21	84	0.007788	456	1824	0.16334	410	1640	0.3094
Problem 8	$y_1$	9	32	0.018072	9	32	0.004243	9	32	0.004036	9	32	0.004227
	$y_2$	9	32	0.003068	9	32	0.003102	9	32	0.003234	9	32	0.003993
	$y_3$	9	32	0.003516	9	32	0.0029	9	32	0.00361	9	32	0.003437
	$y_4$	9	32	0.00303	9	32	0.003161	9	32	0.00347	9	32	0.003267
	$y_5$	9	32	0.003866	9	32	0.003489	9	32	0.003431	9	32	0.005727
	$y_6$	9	32	0.003614	9	32	0.002902	9	32	0.00275	9	32	0.004086
	$y_7$	87	317	0.020828	-	-	-	-	-	-	-	-	-
Problem 9	$y_1$	5	20	0.016153	5	20	0.001863	5	20	0.001487	5	20	0.002629
	$y_2$	5	20	0.001592	5	20	0.00164	5	20	0.001465	5	20	0.001785
	$y_3$	5	20	0.002472	5	20	0.001823	5	20	0.001626	5	20	0.002922
	$y_4$	6	24	0.001959	6	24	0.001971	6	24	0.002312	6	24	0.002833
	$y_5$	6	24	0.002435	6	24	0.002336	6	24	0.002423	6	24	0.003877
	$y_6$	6	24	0.001855	6	24	0.001686	6	24	0.00168	6	24	0.00189
	$y_7$	5	20	0.001481	5	20	0.002654	5	20	0.001523	5	20	0.001975
Problem 10	$y_1$	9	36	0.021723	9	36	0.006713	9	36	0.006291	9	36	0.010543
	$y_2$	10	40	0.00665	10	40	0.006561	10	40	0.007961	10	40	0.009544
	$y_3$	1	3	0.000977	1	3	0.001388	1	3	0.00115	1	3	0.002128
	$y_4$	1	4	0.001237	1	4	0.001396	1	4	0.00149	1	4	0.001539
	$y_5$	1	3	0.001488	1	3	0.001946	1	3	0.001396	1	3	0.002452
	$y_6$	1	4	0.001899	1	4	0.002218	1	4	0.001877	1	4	0.002951
	$y_7$	11	44	0.007231	45	180	0.028201	447	1788	0.24792	405	1620	0.67977

Problem 6: Tridiagonal exponential function [47]

$$\begin{aligned}
 t_1(y) &= y_1 - e^{\cos(l(y_1+y_2))} \\
 t_i(y) &= y_i - e^{\cos(l(y_{i-1}+y_i+y_{i+1}))}, \quad i = 2, \dots, n-1, \\
 t_n(y) &= y_n - e^{\cos(l(y_{n-1}+y_n))}, \\
 l &= \frac{1}{n+1} \text{ and } \mathbf{E} = \mathbf{R}_+^n.
 \end{aligned}$$

Problem 7: Nonsmooth function II [49]

$$\begin{aligned}
 t_i(y) &= y_i - \sin(|y_i - 1|), \text{ for } i = 1, 2, \dots, n, \\
 \mathbf{E} &= \left\{ y \in \mathbf{R}_+^n : y \geq -1, \sum_{i=1}^n y_i \leq n \right\}.
 \end{aligned}$$

Problem 8: Penalty function I [16]

$$\begin{aligned}
 \xi_i &= \sum_{i=1}^n y_i^2, \quad c = 10^{-5}, \\
 t_i(y) &= 2c(y_i - 1) + 4(\xi_i - 0.25)y_i, \quad i = 1, 2, \dots, n, \\
 \mathbf{E} &= \mathbf{R}_+^n.
 \end{aligned}$$

Problem 9: Pursuit-Evasion problem [16]

$$\begin{aligned}
 t_i(y) &= 8^{0.5}y_i - 1, \quad i = 1, 2, \dots, n, \\
 \mathbf{E} &= \mathbf{R}_+^n.
 \end{aligned}$$

Problem 10: Pursuit-Evasion problem [16]

$$\begin{aligned}
 t_i(y) &= e^{y_i^2} + 3 \sin y_i \cos y_i - 1, \quad i = 1, 2, \dots, n, \\
 \mathbf{E} &= \mathbf{R}_+^n.
 \end{aligned}$$

Note that, the mapping  $T$  is taken as

$$T(y) = (t_1(y), t_2(y), \dots, t_n(y))^T,$$

and recall that, the inertial-type algorithm is an iterative procedure in which subsequent iterates are obtained using the preceding two iterates. As such, for the proposed inertial algorithm (Iner. DFPI), the two preceding iterates used in obtaining the initial iterates are as follows:

**Note.** For DFPI algorithm [17], the starting point is  $y_0$ .

The above listed problems are solved with dimensions  $n = 1000, 5000, 10,000, 50,000$  and  $100,000$ . The parameters

**TABLE 4.** Numerical experiments with different sequences  $\{\theta_k\}$  for problem 1-5 with  $n = 1000$ .

n = 1000	SP	$\theta_k = \frac{1}{(2k+5)^2}$			$\theta_k = \frac{1}{\exp(k+1)^{k+1}}$			$\theta_k = \frac{1}{(k+1)^2}$		
		NOI	NFE	CPUT	NOI	NFE	CPUT	NOI	NFE	CPUT
Problem 1	y1	9	36	0.009119	9	36	0.019343	0	0	0.003002
	y2	10	40	0.009186	10	40	0.013494	10	40	0.024327
	y3	6	24	0.007353	6	24	0.006644	6	24	0.016818
	y4	7	28	0.008871	7	28	0.009398	7	28	0.017854
	y5	7	28	0.003838	7	28	0.011266	7	28	0.011046
	y6	7	28	0.008816	7	28	0.008429	7	28	0.009511
	y7	19	76	0.020365	19	76	0.012149	20	80	0.01573
Problem 2	y1	11	43	0.062537	11	43	0.011218	0	0	0.002089
	y2	13	51	0.009315	13	51	0.00942	13	51	0.013417
	y3	12	46	0.011573	12	46	0.008909	12	46	0.012356
	y4	13	49	0.011216	13	49	0.009268	13	49	0.016215
	y5	14	53	0.010668	14	53	0.029236	14	53	0.016043
	y6	12	44	0.008497	12	44	0.00864	12	44	0.013048
	y7	14	53	0.010962	14	53	0.01112	14	53	0.01145
Problem 3	y1	13	52	0.081519	13	52	0.009919	0	0	0.001735
	y2	13	52	0.010098	13	52	0.009571	13	52	0.008503
	y3	14	56	0.009522	14	56	0.010984	14	56	0.011609
	y4	14	56	0.012593	14	56	0.013154	14	56	0.013062
	y5	14	56	0.010016	14	56	0.011638	14	56	0.010194
	y6	15	60	0.0169	15	60	0.011157	15	60	0.018817
	y7	14	56	0.015987	14	56	0.006418	14	56	0.013272
Problem 4	y1	13	52	0.027212	12	48	0.007644	0	0	0.002682
	y2	13	52	0.008549	13	52	0.006964	13	52	0.00497
	y3	13	52	0.011045	13	52	0.006538	13	52	0.011129
	y4	13	52	0.008611	13	52	0.010887	13	52	0.008666
	y5	14	56	0.00786	14	56	0.009174	14	56	0.015178
	y6	14	56	0.008609	14	56	0.006611	14	56	0.00971
	y7	15	60	0.009977	15	60	0.009921	15	60	0.007715
Problem 5	y1	22	83	0.014915	22	83	0.012003	23	87	0.008566
	y2	18	68	0.010097	18	68	0.011021	18	68	0.011365
	y3	22	86	0.009015	22	86	0.012862	22	86	0.009067
	y4	20	80	0.015665	20	80	0.017248	20	80	0.00942
	y5	23	92	0.01444	23	92	0.022297	23	92	0.012842
	y6	33	132	0.032199	33	132	0.038352	33	132	0.025196
	y7	32	127	0.020831	38	150	0.038326	36	143	0.026164

**TABLE 5.** Numerical experiments with different sequences  $\{\theta_k\}$  for problem 6-10 with  $n = 1000$ .

n = 1000	SP	$\theta_k = \frac{1}{(2k+5)^2}$			$\theta_k = \frac{1}{\exp(k+1)^{k+1}}$			$\theta_k = \frac{1}{(k+1)^2}$		
		NOI	NFE	CPUT	NOI	NFE	CPUT	NOI	NFE	CPUT
Problem 6	y1	16	64	0.080299	16	64	0.017491	16	64	0.016929
	y2	16	64	0.013439	16	64	0.011797	16	64	0.011792
	y3	16	64	0.018681	16	64	0.012646	16	64	0.017659
	y4	15	60	0.014368	15	60	0.013669	15	60	0.016687
	y5	15	60	0.013089	15	60	0.017483	15	60	0.014834
	y6	15	60	0.014044	15	60	0.016498	15	60	0.024312
	y7	16	64	0.012709	16	64	0.021474	16	64	0.013924
Problem 7	y1	8	32	0.032771	8	32	0.006973	8	32	0.013911
	y2	7	28	0.005828	7	28	0.008311	7	28	0.008
	y3	6	24	0.037642	6	24	0.005015	6	24	0.00695
	y4	7	28	0.006844	7	28	0.008496	7	28	0.011212
	y5	8	32	0.009869	8	32	0.006206	8	32	0.008115
	y6	8	31	0.014343	8	31	0.011633	8	31	0.014518
	y7	9	36	0.007226	9	36	0.006186	9	36	0.006638
Problem 8	y1	10	34	0.03011	10	34	0.004109	9	31	0.010335
	y2	10	34	0.00805	10	34	0.004493	10	34	0.005206
	y3	10	34	0.00437	10	34	0.005042	10	34	0.00788
	y4	10	34	0.009151	10	34	0.007257	10	34	0.003722
	y5	10	34	0.008475	10	34	0.006482	10	34	0.00584
	y6	10	34	0.006564	10	34	0.005847	10	34	0.005513
	y7	12	39	0.010024	12	39	0.006773	13	42	0.008748
Problem 9	y1	5	20	0.039191	5	20	0.007925	5	20	0.009406
	y2	5	20	0.004174	5	20	0.005295	5	20	0.005742
	y3	5	20	0.002224	5	20	0.003368	5	20	0.007404
	y4	6	24	0.007065	6	24	0.014478	6	24	0.007671
	y5	6	24	0.003812	6	24	0.004744	6	24	0.007709
	y6	6	24	0.002333	6	24	0.002989	6	24	0.004279
	y7	5	20	0.008178	5	20	0.006976	5	20	0.006137
Problem 10	y1	9	36	0.089549	9	36	0.016183	0	0	0.00387
	y2	10	40	0.019257	10	40	0.018461	10	40	0.0118
	y3	1	3	0.002148	1	3	0.003585	1	3	0.004648
	y4	1	4	0.005166	1	4	0.00363	1	4	0.002651
	y5	1	3	0.004204	1	3	0.003815	1	3	0.004593
	y6	1	4	0.009407	1	4	0.0036	1	4	0.00679
	y7	11	44	0.024152	11	44	0.019788	11	44	0.021147

$\theta_k = \frac{1}{(2k+5)^2}$ ,  $\zeta = 1$ ,  $\rho = 0.7$ ,  $\sigma = 0.01$  were chosen for the Iner. DFPI algorithm to obtain the best possible results.

**TABLE 6.** Numerical results for IDFPI and DFPI algorithms on problem 1.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	9	36	0.017162	6.68E-07	76	403	0.024481	7.21E-07
	y2	10	40	0.012476	5.19E-07	74	394	0.024509	6.86E-07
	y3	6	24	0.004145	2.76E-07	76	405	0.024232	7.26E-07
	y4	7	28	0.007213	4.53E-07	76	406	0.026091	5.12E-07
	y5	7	28	0.009987	2.98E-07	49	270	0.019812	8.46E-07
	y6	7	28	0.005634	2.47E-07	90	478	0.036841	5.10E-07
	y7	19	76	0.009093	8.82E-07	75	400	0.024059	7.17E-07
5000	y1	7	28	0.010122	7.08E-07	82	434	0.10282	8.03E-07
	y2	8	32	0.01214	7.91E-07	72	384	0.079772	1.37E-10
	y3	6	24	0.010519	4.74E-07	87	461	0.09622	8.07E-07
	y4	7	28	0.011582	5.70E-07	73	392	0.082718	5.71E-07
	y5	7	28	0.010631	4.47E-07	58	316	0.069378	9.41E-07
	y6	7	28	0.012023	4.64E-07	88	469	0.1209	5.67E-07
	y7	21	84	0.028841	4.15E-07	78	416	0.098002	7.90E-07
10000	y1	7	28	0.019183	4.89E-07	81	429	0.17261	1.93E-14
	y2	7	28	0.016653	8.52E-07	83	441	0.18057	5.39E-07
	y3	6	24	0.014861	6.41E-07	89	472	0.21044	5.70E-07
	y4	7	28	0.017194	6.94E-07	70	377	0.17188	8.07E-07
	y5	7	28	0.023033	5.83E-07	90	479	0.19026	7.81E-07
	y6	7	28	0.021992	6.39E-07	89	476	0.22891	7.77E-15
	y7	21	84	0.054409	5.30E-07	93	492	0.19355	5.62E-07
50000	y1	6	24	0.067682	2.67E-07	75	399	0.68515	2.15E-14
	y2	6	24	0.054711	2.58E-07	75	399	0.69894	1.18E-13
	y3	7	28	0.12306	1.03E-07	75	400	0.67299	1.25E-13
	y4	8	32	0.094062	2.09E-07	72	389	0.96128	3.20E-10
	y5	8	32	0.074329	1.26E-07	82	445	0.80865	6.53E-07
	y6	8	32	0.10103	8.10E-08	84	459	0.86014	8.22E-15
	y7	22	88	0.25757	5.05E-07	90	478	1.0839	6.27E-07
100000	y1	6	24	0.12284	1.69E-07	73	389	1.6516	6.06E-14
	y2	6	24	0.10121	1.47E-07	81	431	1.4517	9.10E-15
	y3	7	28	0.11899	1.07E-07	82	438	1.3592	8.99E-07
	y4	8	32	0.31637	2.11E-07	79	430	1.2955	1.80E-13
	y5	8	32	0.17021	1.29E-07	87	475	3.2752	8.66E-15
	y6	8	32	0.17119	8.56E-08	86	480	1.5122	8.04E-07
	y7	22	88	0.60812	7.15E-07	91	485	1.4229	7.04E-07

**TABLE 7.** Numerical results for IDFPI and DFPI algorithms on problem 2.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	11	43	0.005001	8.52E-07	3	9	0.058465	5.17E-07
	y2	13	51	0.004356	3.18E-07	4	12		

TABLE 8. Numerical results for IDFPI and DFPI algorithms on problem 3.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	13	52	0.006685	4.82E-07	22	110	0.071091	7.52E-07
	y2	13	52	0.005691	9.91E-07	23	115	0.007863	7.47E-07
	y3	14	56	0.003863	6.78E-07	24	120	0.008379	8.92E-07
	y4	14	56	0.005027	8.58E-07	25	125	0.009312	8.38E-07
	y5	14	56	0.006172	4.93E-07	25	125	0.012101	8.90E-07
	y6	15	60	0.00505	6.63E-07	25	125	0.009162	8.19E-07
	y7	14	56	0.007421	7.33E-07	24	120	0.014291	9.51E-07
5000	y1	14	56	0.017961	3.23E-07	23	115	0.039916	8.41E-07
	y2	14	56	0.013373	6.65E-07	24	120	0.042328	8.36E-07
	y3	15	60	0.017098	4.55E-07	25	125	0.042063	9.98E-07
	y4	15	60	0.018924	5.76E-07	26	130	0.040312	9.36E-07
	y5	15	60	0.015824	3.31E-07	26	130	0.040585	9.95E-07
	y6	16	64	0.016746	4.45E-07	27	134	0.042017	0
	y7	15	60	0.018791	4.99E-07	26	130	0.045348	5.35E-07
10000	y1	14	56	0.026742	4.57E-07	24	118	0.082392	0
	y2	14	56	0.030263	9.40E-07	24	118	0.066964	0
	y3	15	60	0.033116	6.43E-07	26	128	0.068461	0
	y4	15	60	0.029508	8.14E-07	27	133	0.065645	0
	y5	15	60	0.030222	4.68E-07	28	139	0.065254	0
	y6	16	64	0.033895	6.29E-07	28	139	0.062041	0
	y7	15	60	0.035151	7.06E-07	26	130	0.073951	7.60E-07
50000	y1	15	60	0.10247	3.07E-07	25	123	0.20488	0
	y2	15	60	0.1067	6.31E-07	25	123	0.20469	3.70E-22
	y3	16	64	0.20393	4.32E-07	25	123	0.20252	0
	y4	16	64	0.10433	5.46E-07	29	147	0.24523	9.26E-07
	y5	16	64	0.1076	3.14E-07	28	141	0.27392	0
	y6	17	68	0.27182	4.22E-07	28	141	0.23675	0
	y7	16	64	0.14651	4.73E-07	27	133	0.28916	4.88E-23
100000	y1	15	60	0.21037	4.34E-07	25	125	0.61769	9.40E-07
	y2	15	60	0.31285	8.92E-07	25	123	0.40009	0
	y3	16	64	0.23906	6.10E-07	26	128	0.40665	0
	y4	16	64	0.26002	7.73E-07	28	142	0.81468	0
	y5	16	64	0.25336	4.44E-07	28	142	0.52701	0
	y6	17	68	0.22276	5.97E-07	28	143	0.45238	0
	y7	16	64	0.4129	6.68E-07	27	134	0.56451	1.32E-22

TABLE 9. Numerical results for IDFPI and DFPI algorithms on problem 4.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	13	52	0.004035	4.10E-07	22	110	0.022312	6.82E-07
	y2	13	52	0.00492	7.01E-07	23	115	0.006507	6.15E-07
	y3	13	52	0.004044	7.14E-07	24	120	0.006548	5.54E-07
	y4	13	52	0.004554	9.53E-07	22	110	0.010051	5.79E-07
	y5	14	56	0.005693	8.47E-07	25	126	0.008113	5.94E-07
	y6	14	56	0.003309	7.79E-07	24	121	0.007482	9.98E-07
	y7	15	60	0.005889	3.52E-07	24	120	0.012266	5.25E-07
5000	y1	13	52	0.012538	9.17E-07	23	115	0.022903	7.62E-07
	y2	14	56	0.012422	4.70E-07	24	120	0.024653	6.88E-07
	y3	14	56	0.010397	4.79E-07	25	125	0.023646	6.20E-07
	y4	14	56	0.011449	6.39E-07	23	115	0.02075	6.47E-07
	y5	15	60	0.015644	5.68E-07	26	131	0.024758	6.64E-07
	y6	15	60	0.015205	5.22E-07	24	122	0.024551	6.33E-07
	y7	15	60	0.013931	8.16E-07	25	125	0.022842	5.91E-07
10000	y1	14	56	0.018642	3.89E-07	24	120	0.041772	5.39E-07
	y2	14	56	0.020051	6.65E-07	24	120	0.039254	9.73E-07
	y3	14	56	0.022804	6.77E-07	25	125	0.043002	8.76E-07
	y4	14	56	0.020417	9.04E-07	26	131	0.051036	9.36E-07
	y5	15	60	0.023572	8.04E-07	26	131	0.043001	9.39E-07
	y6	15	60	0.022412	7.39E-07	27	138	0.044418	9.36E-07
	y7	16	64	0.023027	3.49E-07	25	125	0.051145	8.37E-07
50000	y1	14	56	0.13458	8.70E-07	25	125	0.1406	6.03E-07
	y2	15	60	0.076105	4.46E-07	26	128	0.14453	0
	y3	15	60	0.074626	4.54E-07	26	130	0.3076	9.80E-07
	y4	15	60	0.078944	6.06E-07	-	-	-	-
	y5	16	64	0.087076	5.39E-07	-	-	-	-
	y6	16	64	0.090052	4.96E-07	30	157	0.18098	0
	y7	16	64	0.092506	7.71E-07	27	136	0.14182	7.33E-07
100000	y1	15	60	0.22368	3.69E-07	25	125	0.25496	8.52E-07
	y2	15	60	0.14734	6.31E-07	-	-	-	-
	y3	15	60	0.14545	6.42E-07	26	129	0.66636	0
	y4	15	60	0.21704	8.58E-07	-	-	-	-
	y5	16	64	0.16062	7.63E-07	32	169	0.91603	0
	y6	16	64	0.16709	7.01E-07	34	186	0.41102	0
	y7	17	68	0.26252	3.25E-07	28	141	0.29815	5.18E-07

To illustrate in detail the efficiency and robustness of Iner. DFPI, we start by performing some numerical experiments with different coefficients of the parameter  $\beta_k$  and the results are reported in Table 2 and 3. It can be observed from the

TABLE 10. Numerical results for IDFPI and DFPI algorithms on problem 5.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	22	83	0.006723	3.36E-07	27	125	0.025308	7.64E-07
	y2	18	68	0.004817	3.58E-07	27	127	0.013897	5.68E-07
	y3	22	86	0.007747	3.16E-07	30	142	0.009465	5.36E-07
	y4	20	80	0.007736	9.38E-07	26	130	0.00958	5.96E-07
	y5	23	92	0.007882	5.80E-07	27	134	0.010308	9.66E-07
	y6	33	132	0.013091	3.68E-07	26	132	0.011363	7.39E-07
	y7	36	143	0.015021	9.85E-07	33	173	0.012412	7.77E-07
5000	y1	22	83	0.023041	3.36E-07	27	125	0.028866	9.11E-07
	y2	18	68	0.017824	7.77E-07	28	132	0.031948	6.88E-07
	y3	23	90	0.019053	6.89E-07	32	150	0.033963	6.55E-07
	y4	21	84	0.018336	6.11E-07	27	135	0.040092	8.11E-07
	y5	27	108	0.033345	3.04E-07	30	147	0.03638	6.11E-07
	y6	46	184	0.077517	3.86E-07	27	137	0.032325	9.59E-07
	y7	51	203	0.074716	5.05E-07	43	243	0.052204	7.93E-07
10000	y1	25	95	0.042456	8.93E-07	29	138	0.050406	9.96E-07
	y2	19	72	0.033543	3.32E-07	28	132	0.047778	9.91E-07
	y3	23	90	0.040511	8.91E-07	32	150	0.053794	9.38E-07
	y4	21	84	0.031568	9.96E-07	32	155	0.0541	5.90E-07
	y5	28	112	0.05547	9.14E-07	30	147	0.062782	8.87E-07
	y6	50	200	0.18221	3.37E-07	31	154	0.055032	5.36E-07
	y7	60	239	0.18747	5.93E-07	38	205	0.074963	9.59E-07
50000	y1	48	187	0.60608	3.42E-07	39	219	0.33566	7.35E-07
	y2	19	72	0.12914	7.62E-07	37	194	0.26823	5.90E-07
	y3	26	102	0.1525	3.17E-07	33	157	0.20113	5.81E-07
	y4	34	136	0.3022	8.46E-07	34	163	0.22611	6.85E-07
	y5	35	140	0.37456	8.13E-07	33	162	0.22718	9.63E-07
	y6	75	300	1.3335	6.68E-07	33	162	0.21739	6.33E-07
	y7	88	351	1.4975	5.17E-07	35	167	0.2218	5.56E-07
100000	y1	64	251	1.7805	8.73E-07	37	181	0.4819	8.65E-07
	y2	20	76	0.2093	3.27E-07	37	183	0.44101	5.07E-07
	y3	26	102	0.37068	5.05E-07	33	159	0.40582	5.19E-07
	y4	35	140	0.72236	5.66E-07	34	166	0.42738	7.31E-07
	y5	40	160	0.77446	6.02E-07	35	173	0.47046	5.55E-07
	y6	75	300	2.5582	4.79E-07	35	177	0.56666	8.85E-07
	y7	98	391	3.6313	3.21E-07	35	168	0.43766	7.18E-07

TABLE 11. Numerical results for IDFPI and DFPI algorithms on problem 6.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	16	64	0.010483	3.56E-07	27	135	0.033919	6.16E-07
	y2	16	64	0.009273	3.42E-07	27	135	0.014032	5.92E-07
	y3	16	64	0.008048	3.01E-07	27	135	0.013855	5.22E-07
	y4	15	60	0.007367	6.87E-07	26	130	0.01828	7.14E-07
	y5	15	60	0.005634	5.52E-07	26	130	0.014308	5.73E-07
	y6	15	60	0.006965	3.25E-07	25	125	0.019782	6.76E-07
	y7	16	64	0.010309	3.05E-07	27	135	0.016674	5.22E-07
5000	y1	16	64	0.029797	7.98E-07	28	140	0.062147	6.90E-07
	y2	16	64	0.027649	7.66E-07	28	140	0.053856	6.63E-07
	y3	16	64	0.025924	6.75E-07	28	140	0.053509	5.84E-07
	y4	16	64	0.02971	4.62E-07	27	135	0.051204	8.00E-07
	y5	16	64	0.025478	3.71E-07	27	135	0.056674	6.42E-07
	y6	15	60	0.023231	7.29E-07	26	130	0.050872	7.57E-07
	y7	16	64	0.026982	6.80E-07	28	140	0.071807	5.90E-07
10000	y1	17	68	0.060317	3.39E-07	29	146	0.11459	7.32E-07
	y2	17	68	0.049807	3.25E-07	29	146	0.11246	7.04E-07
	y3	16	64	0.047161	9.55E-07	29	146	0.11393	6.20E-07
	y4	16	64	0.045383	6.54E-07	28	140	0.11162	5.66E-07
	y5	16	64	0.055288	5.24E-07	27	135		

**TABLE 12.** Numerical results for IDFPI and DFPI algorithms on problem 7.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	8	32	0.003653	9.31E-08	7	35	0.088016	2.09E-07
	y2	7	28	0.002498	7.06E-07	7	35	0.002876	1.30E-07
	y3	6	24	0.002711	2.03E-07	5	25	0.002588	6.75E-07
	y4	7	28	0.004252	1.86E-07	7	35	0.003619	5.39E-07
	y5	8	32	0.004847	2.91E-07	7	35	0.005417	6.75E-07
	y6	8	31	0.002989	3.19E-07	7	33	0.003767	6.55E-07
	y7	9	36	0.003879	2.83E-07	10	50	0.005564	4.13E-07
5000	y1	8	32	0.011319	2.08E-07	7	35	0.012628	4.68E-07
	y2	8	32	0.010446	1.30E-07	7	35	0.010796	2.90E-07
	y3	6	24	0.007387	4.53E-07	6	30	0.009275	9.64E-08
	y4	7	28	0.008646	4.15E-07	8	40	0.011531	7.69E-08
	y5	8	32	0.011077	6.51E-07	8	40	0.012222	9.64E-08
	y6	8	31	0.011479	7.14E-07	8	38	0.012377	9.35E-08
	y7	9	36	0.012983	6.29E-07	10	50	0.016196	9.76E-07
10000	y1	8	32	0.016198	2.95E-07	7	35	0.019634	6.62E-07
	y2	8	32	0.017598	1.84E-07	7	35	0.018425	4.10E-07
	y3	6	24	0.015246	6.41E-07	6	30	0.017956	1.36E-07
	y4	7	28	0.014948	5.87E-07	8	40	0.021969	1.09E-07
	y5	8	32	0.018776	9.20E-07	8	40	0.020505	1.36E-07
	y6	9	35	0.019481	8.34E-08	8	40	0.024966	1.36E-07
	y7	9	36	0.025324	9.03E-07	11	55	0.033891	1.81E-07
50000	y1	8	32	0.074381	6.59E-07	8	40	0.078752	9.46E-08
	y2	8	32	0.057285	4.12E-07	7	35	0.06381	9.17E-07
	y3	7	28	0.05958	1.18E-07	6	30	0.071067	3.05E-07
	y4	8	32	0.11846	1.08E-07	9	47	0.08954	2.58E-07
	y5	9	36	0.076652	1.70E-07	9	47	0.087936	2.69E-07
	y6	9	35	0.0716	1.87E-07	9	47	0.091278	2.69E-07
	y7	10	40	0.20552	1.66E-07	11	55	0.12051	4.06E-07
100000	y1	8	32	0.11275	9.31E-07	8	41	0.14657	8.58E-07
	y2	8	32	0.11906	5.83E-07	8	40	0.1458	8.28E-08
	y3	7	28	0.22704	1.67E-07	6	30	0.10972	4.31E-07
	y4	8	32	0.12258	1.53E-07	9	47	0.17732	3.64E-07
	y5	9	36	0.13371	2.40E-07	9	47	0.2031	3.81E-07
	y6	9	35	0.24326	2.64E-07	9	47	0.16742	3.81E-07
	y7	10	40	0.16384	2.36E-07	11	56	0.24561	4.69E-07

**TABLE 13.** Numerical results for IDFPI and DFPI algorithms on problem 8.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	9	32	0.004774	6.76E-08	14	84	0.047306	9.29E-07
	y2	9	32	0.002911	6.76E-08	14	86	0.007059	9.29E-07
	y3	9	32	0.004649	6.76E-08	14	89	0.006651	9.29E-07
	y4	9	32	0.005168	6.76E-08	14	91	0.007693	9.29E-07
	y5	9	32	0.003576	6.76E-08	14	92	0.012985	9.29E-07
	y6	9	32	0.002819	6.76E-08	15	99	0.012506	9.29E-07
	y7	93	340	0.033585	9.32E-07	-	-	-	-
5000	y1	11	41	0.017931	2.99E-07	16	107	0.04506	4.92E-07
	y2	11	41	0.014838	2.99E-07	16	109	0.032913	4.92E-07
	y3	11	41	0.015599	2.99E-07	16	111	0.10903	4.92E-07
	y4	11	41	0.072565	2.99E-07	17	129	0.038967	4.92E-07
	y5	11	41	0.026755	2.99E-07	17	126	0.051708	4.92E-07
	y6	11	41	0.020458	2.99E-07	18	142	0.04588	4.92E-07
	y7	32	112	0.033263	8.56E-07	-	-	-	-
10000	y1	8	29	0.051059	4.42E-07	11	75	0.052377	6.02E-07
	y2	8	29	0.027061	4.42E-07	11	77	0.049877	6.02E-07
	y3	8	29	0.023059	4.42E-07	11	80	0.10928	6.02E-07
	y4	8	29	0.026803	4.42E-07	12	99	0.080173	6.02E-07
	y5	8	29	0.028654	4.42E-07	13	107	0.079948	6.02E-07
	y6	8	29	0.026353	4.42E-07	14	132	0.093111	6.02E-07
	y7	27	102	0.065685	7.89E-07	-	-	-	-
50000	y1	6	22	0.075446	1.89E-07	10	76	0.34388	4.68E-07
	y2	6	22	0.15044	1.89E-07	10	78	0.2456	4.68E-07
	y3	6	22	0.070266	1.89E-07	11	97	0.31595	4.68E-07
	y4	6	22	0.069065	1.89E-07	14	154	0.54484	4.68E-07
	y5	6	22	0.10305	1.89E-07	14	151	0.4634	4.68E-07
	y6	6	22	0.11076	1.89E-07	16	201	0.75152	4.68E-07
	y7	9	33	0.1275	7.76E-07	11	97	0.28241	4.68E-07
100000	y1	8	31	0.22729	1.95E-07	8	65	0.40538	1.73E-07
	y2	8	31	0.24876	1.95E-07	8	67	0.41492	1.73E-07
	y3	8	31	0.21451	1.95E-07	10	104	0.72037	1.73E-07
	y4	8	31	0.35928	1.95E-07	13	176	1.3032	1.73E-07
	y5	8	31	0.21663	1.95E-07	14	202	1.4652	1.73E-07
	y6	8	31	0.22028	1.95E-07	16	255	1.7952	1.73E-07
	y7	11	43	0.36981	6.82E-07	11	115	0.85792	1.73E-07

profile proposed by Dolan and Morè in [50] in order to summarize Table 6-15. The profile is defined as follows:

$$\rho(\tau) := \frac{1}{|T_P|} \left| \left\{ t_p \in T_P : \log_2 \left( \frac{t_{p,q}}{\min\{t_{p,q} : q \in Q\}} \right) \leq \tau \right\} \right|,$$

**TABLE 14.** Numerical results for IDFPI and DFPI algorithms on problem 9.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	5	20	0.002775	5.46E-07	14	84	0.025842	7.75E-07
	y2	5	20	0.001703	3.25E-07	14	84	0.00484	4.70E-07
	y3	5	20	0.00257	3.10E-07	14	84	0.006867	4.48E-07
	y4	6	24	0.003117	5.36E-08	15	90	0.004959	7.58E-07
	y5	6	24	0.002628	7.25E-08	16	96	0.006006	3.01E-07
	y6	6	24	0.001932	1.04E-07	16	96	0.005295	4.32E-07
	y7	5	20	0.001605	6.86E-07	15	90	0.007065	2.93E-07
5000	y1	6	24	0.032784	3.64E-08	15	90	0.023128	5.08E-07
	y2	5	20	0.004843	7.28E-07	15	90	0.013479	3.08E-07
	y3	5	20	0.00474	6.94E-07	15	90	0.019939	2.93E-07
	y4	6	24	0.005001	1.20E-07	16	96	0.018103	4.97E-07
	y5	6	24	0.028177	1.62E-07	16	96	0.059113	6.73E-07
	y6	6	24	0.005417	2.33E-07	16	96	0.02335	9.66E-07
	y7	6	24	0.004567	4.61E-08	15	90	0.018177	6.49E-07
10000	y1	6	24	0.009786	5.15E-08	15	90	0.035418	7.18E-07
	y2	6	24	0.013561	3.07E-08	15	90	0.033533	4.35E-07
	y3	5	20	0.009086	9.82E-07	15	90	0.036702	4.15E-07
	y4	6	24	0.009481	1.69E-07	16	96	0.039716	7.02E-07
	y5	6	24	0.02489	2.29E-07	16	96	0.033306	9.51E-07
	y6	6	24	0.012618	3.29E-07	17	103	0.034423	8.83E-07
	y7	6	24	0.009643	6.49E-08	15	90	0.03156	9.16E-07
50000	y1	6	24	0.040512	1.15E-07	16	96	0.22563	4.70E-07
	y2	6	24	0.038022	6.87E-08	15	90	0.1461	9.73E-07
	y3	6	24	0.04902	6.55E-08	15	90	0.11495	9.28E-07
	y4	6	24	0.039638	3.79E-07	18	109	0.22775	2.97E-07
	y5	6	24	0.034356	5.13E-07	18	110	0.18641	8.89E-07
	y6	6	24	0.039451	7.37E-07	20	126	0.17079	8.65E-07
	y7	6	24	0.047944	1.44E-07	16	96	0.21042	5.99E-07
100000	y1	6	24	0.070738	1.63E-07	16	96	0.30649	6.65E-07
	y2	6	24	0.096217	9.71E-08	16	96	0.26029	4.03E-07
	y3	6	24	0.1065	9.27E-08	16	96	0.41442	3.84E-07
	y4	6	24	0.084986	5.36E-07	18	110	0.33314	9.28E-07
	y5	6	24	0.071928	7.25E-07	20	126	0.32012	8.52E-07
	y6	7	28	0.089085	3.11E-08	22	142	0.53318	8.29E-07
	y7	6	24	0.096997	2.05E-07	16	96	0.2514	8.50E-07

**TABLE 15.** Numerical results for IDFPI and DFPI algorithms on problem 10.

n	SP	IDFPI				DFPI			
		NOI	NFE	CPUT	LNORM	NOI	NFE	CPUT	LNORM
1000	y1	9	36	0.007359	7.97E-07	17	119	0.050153	8.17E-07
	y2	10	40	0.006139	1.95E-07	18	126	0.017728	5.55E-07
	y3	1	3	0.001581	0	1	3	0.00131	0
	y4	1	4	0.001474	0	2	11	0.003299	0
	y5	1	3	0.001559	0	19	134	0.018093	7.43E-07
	y6	1	4	0.001463	0	19	135	0.026692	8.51E-07
	y7	11	44	0.011139	9.03E-07	19	133	0.019643	6.11E-07
5000	y1	10	40	0.026382	2.84E-07	18	126	0.056932	6.85E-07
	y2	10	40	0.025512	4.35E-07	19	133	0.060359	4.65E-07
	y3	1	3	0.002706	0	19	133	0.077922	8.49E-07
	y4	1	4	0.00444	0	20	141	0.085714	8.56E-07
	y5	1	3	0.002336	0	20	141	0.065807	6.23E-07
	y6	1	4	0.004291	0	21	151	0.06585	8.59E-07
	y7	12	48	0.03001	3.47E-07	20	140	0.072448	4.97E-07
10000	y1	10	40	0.047915	4.02E-07	18	126	0.12476	9.69E-07
	y2	10	40	0.053406	6.15E-07	19	133	0.12265	6.58E-07
	y3	1	3	0.004908	0	20	140	0.12326	4.51E-07
	y4	1	4	0.005123	0	21	148	0.15724	4.54E-07
	y5	1	3	0.003785	0	20	142	0.	

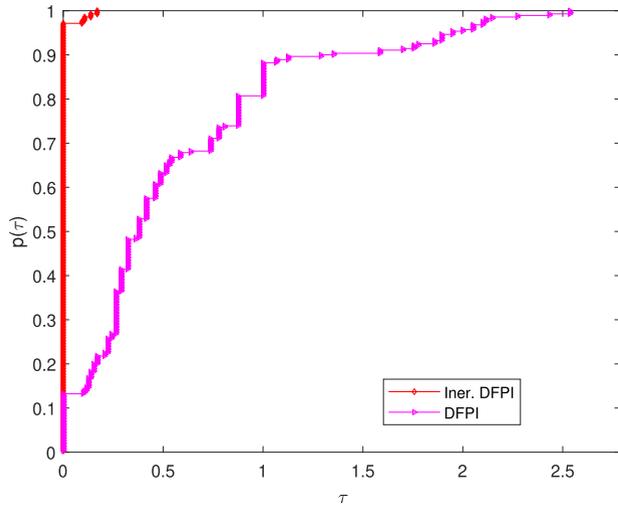


FIGURE 1. Performance profiles for the number of iterations.

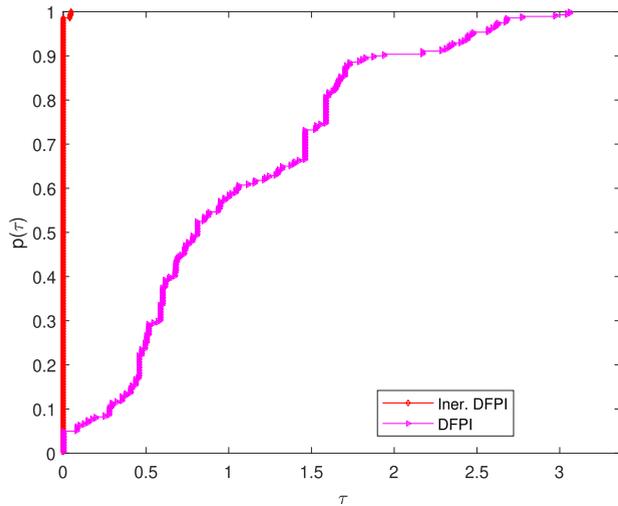


FIGURE 2. Performance profiles for the number of function evaluations.

$q \in Q$ . The performance profile tells the percentage of win by each solver. Figures 1, 2 and 3 illustrate the performance of the two solvers (Iner. DFPI and DFPI) where the performance indices are the number of iterations, the number of function evaluations and the CPU time in seconds as reported in Tables 2-11. It can be observed from the figures that Iner. DFPI algorithm performs better with a higher percentage win of at least 90% in all the three metrics, i.e., number of iterations, the number of function evaluations and the CPU time. As a consequence, we can conclude that Iner. DFPI algorithm is an efficient solver. It is worth mentioning that the good numerical performance of the Iner. DFPI algorithm is as a result of the inertial term  $v_k$ , suitable control parameters such as  $\rho$ ,  $\sigma$  and the sequence  $\{\theta_k\}$ .

A detailed report of our numerical experiments is reported in Table 6-15 in the appendix section. The abbreviations on the tables can be read as follows:

- n: denotes the dimension of the problem
- SP: denotes the starting points
- NOI: denotes the number of iterations

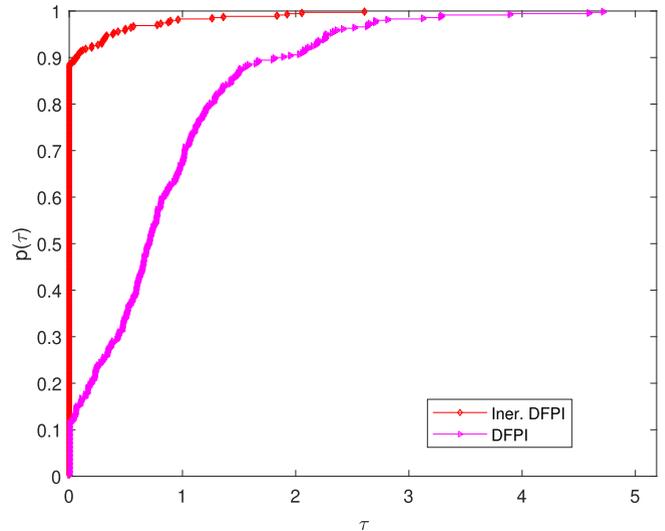


FIGURE 3. Performance profiles for the CPU time (in seconds).

- NFE: denotes the number of function evaluations
- CPUT: denotes the CPU time in seconds
- LNORM: denotes the final norm

V. CONCLUSION

In this paper, we suggested an inertial derivative-free method for solving nonlinear monotone operator equation. Based on the DFPI method, an inertial term was added to it in order to speed up its convergence. We used some mild assumptions to establish the global convergence of the proposed inertial method. To support the theoretical results, we perform some numerical experiments on some benchmark test problems with the proposed method and the DFPI. The results indicate that the proposed inertial method is faster than DFPI.

APPENDIX

See Tables 2–15.

ACKNOWLEDGMENT

The author Auwal Bala Abubakar would like to thank the Postdoctoral Fellowship from King Mongkut’s University of Technology Thonburi (KMUTT), Thailand. He also acknowledge with thanks, the Department of Mathematics and Applied Mathematics at the Sefako Makgatho Health Sciences University.

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