Modeling Drug Concentration Level in Blood Using Fractional Differential Equation Based on Psi-Caputo Derivative

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1. Introduction

To treat an infection from a human being or even from an animal, a suitable dose of medicine is substantial. Owing to the amount of the drug in the blood plasma decreasing with time, medicine must be given in multiple doses.

In phase I of clinical development, the time to achievement of steady state of a new regimen is routinely evaluated. The time to the achievability of the steady state is the time needed until the drug concentration is stable in the blood, i.e., does not display an increasing tendency by drug accumulation. If a drug is given at orderly dosing intervals, drug sediment from preceding doses is accumulated. Stabilization of the concentration occurs when the quantity of drug discarded during the dosing interval equals the amount that was given. In order to evaluate the time to achieve steady state, blood is sampled at a certain time point within each dosing interval see [1].

Following the drug concentrations at these time points [2] Jordan et al. proposed a model for the achievement of the steady state of the drug concentration in plasma. Authors of [3] proposed a model for the prediction of the “unbound brain-to-plasma” drug concentration ratio. Zhang et al. [4] studied the ratio of the drug concentration between tissues and plasma.

A simple and novel sensor was developed for the analysis of clinical doxorubicin (DOX) concentration based on the screen-printed electrode by evaluating the DOX concentration, see [5]. In [6] the authors evaluated the drug concentrations in postmortem blood samples where the value of concentrations slightly differs depending on the sample site. For more works on drug concentration in the blood, we refer the reader to the references [7–11].

Fractional calculus (F.C) helps to describe models and natural phenomena problems. Many researches have dedicated their work in this branch (see, e.g., previous studies [12–19]). The results obtained were significantly positive in
different fields of Medicine and Biology. The foundation of fractional calculus is laid on fractional integrals and derivatives. The efficiency of the fractional order model over the integer order is investigated by Bagley and Torvik [20]. Through fractional calculus, Djordjevic et al. [21] developed a rheological model of airway smooth muscle cells, which came as an alternative to the least square data fitting technique often used for this purpose. Recently, an application of fractional calculus to nanotechnology was proposed in [22]. These are just a few out of plenty examples of research works in which fractional calculus has proven its efficiency compared to existing classical approach.

This research article contributes to showing the power of mathematical modeling using fractional calculus. In particular, a class of fractional derivatives called $\psi$-Caputo, introduced by Almeida [23], has proven its efficiency in various applications including a recent study by Awadalla et al. [24]. A preliminary investigation on the topic of this study was carried out by us. The results of the said investigation are provided in this reference [25]. The main contribution of this work to the literature is the reduction or further mini- 

Definition 2 (see [9]). The Caputo derivative of order $\xi > 0$ of a function $\mathcal{H} : [a, b] \rightarrow \mathbb{R}$, is defined as

$$
\left( D^\xi_{0+} \mathcal{H} \right)(q) = \frac{1}{\Gamma(n - \xi)} \int_0^q (q - \theta)^{n-\xi-1} \mathcal{H}^{(n)}(\theta)d\theta, \quad n - 1 < \xi < n, \quad \xi \in \mathbb{N},
$$

where $n = [\xi] + 1$, $[\xi]$ is the integer part of $\xi$.

Definition 3 (see [2]). Let $\xi > 0$, $\mathcal{H} \in \mathcal{L}^1[a, b]$ and $\psi \in \mathcal{C}^1[a, b]$ is selected to be an increasing function with $\psi'(x) \neq 0$, $\forall x \in [a, b]$; then, the notation $\mathcal{J}^{\xi, \psi}_{0+} \mathcal{H}(q)$ represents the fractional integral of $\mathcal{H}$ with respect to another function $\psi$, and it is defined by

$$
\mathcal{J}^{\xi, \psi}_{0+} \mathcal{H}(q) = \frac{1}{\Gamma(\xi)} \int_0^q \psi'(\theta) (\psi(q) - \psi(\theta))^{\xi-1} \mathcal{H}(\theta)d\theta.
$$

The idea of integrating a function definition is known as $\psi$ - Caputo integral of the fractional integral is taken in the Caputo sense. This is used in the sequel for formulating the solution to the $\psi$ - Caputo fractional model.

Definition 4 (see [2]). Let $\xi > 0$ and $\mathcal{H}, \psi \in \mathcal{C}^n[a, b]$ where $\psi$ is an increasing function and $\psi'(x) \neq 0$, $\forall x \in [a, b]$. Then, $(\psi D^\xi_{0+} \mathcal{H})(q)$ denotes the fractional derivative of $\mathcal{H}$ with respect to $\psi$. $\psi$ - Caputo if the fractional derivative is taken in the Caputo sense, and it is given by

$$
\psi D^\xi_{0+} \mathcal{H}(q) = \frac{1}{\Gamma(n - \xi)} \int_0^q \psi'(\theta) (\psi(q) - \psi(\theta))^{n-\xi-1} \left( \frac{d}{d\theta} \right)^n \mathcal{H}(\theta)d\theta.
$$

Lemma 5 (see [2]). Let $\xi > 0$ and $n$ be a positive integer such that $\xi \in [n-1, n]$.

For every $\mathcal{H}, \psi \in \mathcal{C}^n[a, b]$, we have

$$
\psi D^\xi_{0+} \mathcal{H}(q) = \mathcal{H}(q) + \sum_{p=1}^{n-1} \frac{1}{\Gamma(p+1)} \int_0^q \psi'(\theta) \mathcal{H}(\theta)d\theta - \int_0^q \psi'(\theta) \mathcal{H}(\theta)d\theta.
$$

3. Pharmacokinetics and Drug Concentration Model

A brief definition and overview of pharmacokinetics are proposed in this section. To treat an infection from a human body, a suitable dose of medicine is substantial. Once a drug is administrated to an individual through intravenous injection, it has an initial concentration that decreases over time. The decrement appears as a result of metabolism and excretion. Pharmacokinetics is a branch of medicine that studies the dynamic (kinetics of drugs in a living body). Owing to the amount of the drug in the human body decreasing with time medicine must be given in multiple doses.

Two main streams of study exist in pharmacokinetics, the theoretical approach and the experimental approach.
The former approach focuses on the development of a pharmacokinetics (mathematical) model that predicts drug concentration levels in the blood over time. The latter method involves empirical development based on a biological sample, during which analytical methods for drugs and their metabolites are measured. In this case, it is required to have an adequate experimental setting for data collection and handling. This article focuses in the sequel on the development of a mathematical pharmacokinetics model. The entire process of absorption, distribution, metabolism, and elimination (ADME) of a drug is illustrated in the next figure as described in [26, 27].

Figure 1 represents the ADME process of a drug after it has been administered to a human. The process is governed by a change in concentration over time. The change rate can be denoted by $\frac{dY}{dq}$. More generally, let us denote by $Y$ the drug concentration in the body; then, the mathematical model describing the rate change is given by

$$\frac{dY}{dq} = -kY,$$  \hspace{1cm} (6)

where $k$ is a constant to be experimentally determined for each drug. If a patient is given an initial drug dose, $Y_0$, then, the drug level in his body at any time is the solution of the differential equation defined by Eq. (6), that is,

$$Y(q) = Y_0 e^{-kq}.$$  \hspace{1cm} (7)

The objective of this work is to prove the advantages of modeling drug concentration kinetics using fractional differential equations. Indeed, we will show empirically that modeling results using F.C are better than those obtained from classical calculus. The starting point is to build a fractional counterpart of Eq. (6). The said equation is built as follows

$$cD_0^\xi Y(q) = -kY(q), \quad \xi \in [0, 1], \quad Y(0) = Y_0.$$  \hspace{1cm} (8)

or simply

$$cD_0^\xi Y(q) = \mathcal{G}(q, Y(q)), \quad \xi \in [0, 1], \quad Y(0) = Y_0.$$  \hspace{1cm} (9)

The Lemma below is defined to introduce a general form of the solution to Eq. (9) representing drug concentration kinetics with initial condition.

**Lemma 6.** Let us consider $\mathcal{G}$, with the assumption that it is an integrable function, which is defined over $[0, T]$. It follows that the solution of the fractional differential equation given by Eq. (9) has a general form which can be expressed by the following integral equation

$$Y(q) = Y_0 + \frac{1}{T(\xi)} \int_0^q \psi'(\theta)(\psi(q) - \psi(\theta))^{\xi-1}\mathcal{G}(\theta, Y(\theta))d\theta.$$  \hspace{1cm} (10)

It is worth to highlight in Eq. (10) from Lemma 6 the presence of $\psi$-Caputo fractional integral.

**Proof.** Let us apply the operator $\mathcal{J}_0^\psi$ to both sides of Eq. (9) which leads to $Y(q) - Y_0 = \mathcal{J}_0^\psi \mathcal{G}(q, Y(q))$.

Equation (10) can be rewritten in the following form

$$Y(q) = Y_0 E_\xi[-k(\psi(q) - \psi(0))^\xi].$$  \hspace{1cm} (11)

where $E_\xi(q) = \sum_{n=0}^{\infty} \frac{(q^\xi)^n}{\Gamma(\xi, n+1)}$, $q \in \mathbb{R}_+$ is the Mittag-Leffler function.

In the application, Kernel functions are selected under the data distribution. There is not a steady rule for that. However, a linear kernel works well in many cases. Other commonly used kernel includes but is not limited to $\sqrt{u}$, log $u$.

### 4. Main Result of Psi-Caputo Drug Concentration Model

This section aims to investigate theoretical study around Eq. (9). The final goal is to build prove of the existence and the uniqueness of a solution to Eq. (9).

Let $C[0, T]$ be the space of real valued functions that are continuous on $[0, T]$ endowed with the norm of the uniform convergence: $\|Y\|_\infty = \sup_{q \in [0, T]}|Y(q)|$ for every $Y \in C[0, T]$. Then, $\mathcal{D} = (C[0, T], \|\cdot\|_\infty)$ is a Banach space.

An operator $\mathcal{Z} : \mathcal{D} \longrightarrow \mathcal{D}$ is defined and attached to the problem introduced by Eq. (9) can be built as

$$\mathcal{Z}(q) = \mathcal{Y}_0 + \frac{1}{T(\xi)} \int_0^q \psi'(\theta)(\psi(q) - \psi(\theta))^{\xi-1}\mathcal{G}(\theta, Y(\theta))d\theta.$$  \hspace{1cm} (12)

In what follows, the existence of a solution to Eq. (10) is proved followed by a proof of the uniqueness of the said solution. Before establishing the proof of the main results, let us first establish the following statements. Indeed, the statements are mathematical hypotheses that are used in sections dedicated to proofs.

**(A1)** The function $\mathcal{G} : [0, T] \times \mathbb{R}_+ \longrightarrow \mathbb{R}_+$ is continuous,

**Proof.** We apply the operator $\mathcal{J}_0^\psi$ to both sides of Eq. (9) leading to $Y(q) - Y_0 = \mathcal{J}_0^\psi \mathcal{G}(q, Y(q))$.

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**(A1)** The function $\mathcal{G} : [0, T] \times \mathbb{R}_+ \longrightarrow \mathbb{R}_+$ is continuous,

**(A2)** There exists $L_\mathcal{G} > 0$ such that,

$$|\mathcal{G}(q, Y_1) - \mathcal{G}(q, Y_2)| \leq L_\mathcal{G}|Y_1 - Y_2|, \quad \forall q \in [0, T],$$  \hspace{1cm} (14)

**(A3)** There exists a function $\mathcal{F} \in C([0, T], \mathbb{R}_+)$ and a nondecreasing function,

$$\mathcal{F} : \mathcal{R}_+ \longrightarrow \mathcal{R}_+ \text{ such that } |\mathcal{F}(q, Y)| \leq \mathcal{F}(q)|Y|, \quad \forall q, Y \in [0, T] \times \mathbb{R}_+.$$  \hspace{1cm} (15)
Proof. The proof of theorem 7 will be divided into several steps. The first step consists of showing that the operator $\mathcal{T} : \Phi \rightarrow \Phi$ maps bounded sets of $\Phi$ into bounded sets of $\Phi$. Let $\mathcal{B}_1 = \{ \gamma \in \Phi : \|\gamma\|_{\infty} \leq \lambda \}$ be a bounded set of $\Phi$. Then

$$
|\mathcal{T}\gamma| \leq |\gamma| + \frac{1}{\Gamma(\xi + 1)} \int_0^\infty \psi(\theta)(\gamma(\theta) - \psi(\theta))^{\xi-1} \mathcal{R}(\theta) \gamma(\|\gamma(\theta)\|_{\infty}) d\theta
$$

$$
\leq |\gamma| + \frac{1}{\Gamma(\xi + 1)} \int_0^\infty \psi(\theta)(\gamma(\theta) - \psi(\theta))^{\xi-1} \mathcal{R}(\theta) \gamma(\|\gamma(\theta)\|_{\infty}) d\theta
$$

$$
\leq |\gamma| + \|\mathcal{R}\|_{\infty} \lambda \left( \frac{1}{\Gamma(\xi + 1)} (\gamma(\theta) - \psi(\theta))^\xi \right). 
$$

(17)

Applying the supremum on $t$ on both sides of Eq. (17) leads to

$$
\|\mathcal{T}\gamma\|_{\infty} \leq |\gamma| + \|\mathcal{R}\|_{\infty} \lambda \left( \frac{1}{\Gamma(\xi + 1)} (\gamma(\theta) - \psi(\theta))^\xi \right). 
$$

(18)

The second step of this proof is to show that the operator $\mathcal{T} : \Phi \rightarrow \Phi$ maps bounded sets of $\Phi$ into equi-continuous sets of $\Phi$.

Let $q_1, q_2 \in [0, \mathcal{T}]$ with $q_1 < q_2$ and $\gamma \in \mathcal{B}_1$. The relation below holds as results of the assumptions (A1)-(A4)

$$
|\mathcal{T}\gamma(q_2) - \mathcal{T}\gamma(q_1)| 
\leq \lambda \left( \frac{1}{\Gamma(\xi + 1)} \int_0^\infty \psi(\theta) \left( (\gamma(q_2) - \psi(\theta))^{\xi-1} \right.
$$

$$
- (\gamma(q_1) - \psi(\theta))^{\xi-1} \mathcal{R}(\theta) d\theta
$$

$$
+ \frac{1}{\Gamma(\xi + 1)} \int_0^{q_2} \psi(\theta) \left( (\gamma(q_2) - \psi(\theta))^{\xi-1} \mathcal{R}(\theta) d\theta \right). 
$$

(19)

The right-hand side of Eq. (19) tends to zero as $q_1 \longrightarrow q_2$. That is $|\mathcal{T}\gamma(q_2) - \mathcal{T}\gamma(q_1)| \longrightarrow 0$ as $q_1 \longrightarrow q_2$.

It is worth observing that the right hand part of Eq. (19) does not depend on $\gamma \in \mathcal{B}_1$, this implies by Arzela-Ascoli theorem that $\mathcal{T}(\mathcal{B}_1)$ is completely continuous.

The third step of the proof requires one last intermediate step to complete the assumptions of the Leray-Schauder nonlinear alternative theorem. This consists of showing the boundedness of the set of all solutions to equation $\gamma = \delta \mathcal{T}$ ($\gamma$). Assume that $\gamma$ is a solution Eq. (9), then, it follows from Eq. (10) that

$$
|\gamma(q)| = \delta \mathcal{T}(\gamma(q)) \leq \delta \left( |\gamma| + \|\mathcal{R}\|_{\infty} \lambda \left( \frac{1}{\Gamma(\xi + 1)} (\gamma(\theta) - \psi(\theta))^\xi \right) \right)
$$

$$
\leq |\gamma| + \|\mathcal{R}\|_{\infty} \lambda \left( \frac{1}{\Gamma(\xi + 1)} (\gamma(\theta) - \psi(\theta))^\xi \right). 
$$

(20)

Inverting both sides of Eq. (20) and dividing them by R.H.S of Eq. (20) leads to the following relation

$$
\frac{|\gamma| + \|\mathcal{R}\|_{\infty} \lambda \left( \frac{1}{\Gamma(\xi + 1)} (\gamma(\theta) - \psi(\theta))^\xi \right)}{\|\gamma\|_{\infty}} \leq 1. 
$$

(21)
Recalling \((A_2)\), there exists a constant \(W > 0\), which is indeed such that \(W \neq \mathcal{Y}\). Moreover, let us construct the set \(\Omega = \{ \mathcal{Y} \in \Phi ; \| \mathcal{Y} \|_{\infty} < W \}\). It is obvious that the operator \(\mathcal{I} : \Omega \to \Phi\) is continuous and completely continuous. Based on the constructed \(\Omega\), there exists \(\mathcal{Y} \in \partial \Omega\) such that \(\| \mathcal{Y} \delta \mathcal{I}(\mathcal{Y}) \| < W\) for some \(\delta \in [0, 1]\). Consequently, by the nonlinear alternative of Leray-Schauder type, we deduce that \(\mathcal{I}\) has a fixed point \(\mathcal{Y} \in \Omega\) which is a solution to the problem defined by Eq. (10).

**Theorem 8.** Let us assume that conditions \((A_1)\) and \((A_2)\) hold. Moreover, if the condition

\[
\frac{\mathcal{L}_\mathcal{Y}(\psi(\mathcal{Y})) - \psi(0)}{1 - \| \mathcal{L}_\mathcal{Y}(\psi(\mathcal{Y})) - \psi(0) \|^2 < 1, \tag{22}
\]

holds; then, the problem defined by Eq. (9) has a solution which is unique. The said solution belongs to the interval \([0, \mathcal{T}]\).

**Proof.** Let us consider the operator \(\mathcal{I}\) defined in Eq. (12). Let us also define a ball

\[
\mathcal{B}_1 = \{ \mathcal{Y} \in \Phi; \| \mathcal{Y} \|_{\infty} \leq \varepsilon \}
\]

where \(\varepsilon = \sup_{0 \leq q \leq \mathcal{T}} | \mathcal{Z}(\mathcal{Y}) |\).

First, let us show that \(\mathcal{I} \mathcal{B}_1 \subset \mathcal{B}_1\). For any \(\mathcal{Y} \in \mathcal{B}_1, \rho \in [0, \mathcal{T}]\), and using Eq. (12), we have the following relation

\[
| \mathcal{I} \mathcal{Y}(\mathcal{Y}) | \leq | \mathcal{Y}_0 | + \frac{1}{\mathcal{L}_\mathcal{Y}(\psi(\mathcal{Y})) - \psi(0)} \int_0^\rho | \mathcal{Z}(\mathcal{Y}) | \psi(\mathcal{Y}) - \psi(0) | d\xi.
\tag{24}
\]

On the other hand,

\[
| \mathcal{Z}(\mathcal{Y}), \mathcal{Y}(\mathcal{Y}) | \leq | \mathcal{Z}(\mathcal{Y}), \mathcal{Y}(\mathcal{Y}) | - \mathcal{Z}(\mathcal{Y}), (0, 0) | + | \mathcal{Z}(\mathcal{Y}, 0) | \leq \mathcal{L}_\mathcal{Y}, | \mathcal{Y} |_{\infty} + \mathcal{M}_\mathcal{Y} \leq \mathcal{L}_\mathcal{Y}, \varepsilon + \mathcal{M}_\mathcal{Y}.
\tag{25}
\]

Substituting the appropriate fragment of equation in Eq. (24) by Eq. (25) implies a new relation which is given by

\[
| \mathcal{I} \mathcal{Y} |_{\infty} \leq | \mathcal{Y}_0 | + \frac{1}{\mathcal{L}_\mathcal{Y}(\psi(\mathcal{Y})) - \psi(0)} \mathcal{L}_\mathcal{Y}, \varepsilon + \mathcal{M}_\mathcal{Y} \leq \varepsilon.
\tag{26}
\]

Equation (26) is sufficient to conclude that \(\mathcal{I} \mathcal{B}_1 \subset \mathcal{B}_2\).

The second step of the proof is to show that the considered operator is a contraction mapping. For every \(\mathcal{Y}_1, \mathcal{Y}_2 \in \Phi\), the following relation holds.

\[
| \mathcal{I} \mathcal{Y}_1(\mathcal{Y}_1) - \mathcal{I} \mathcal{Y}_2(\mathcal{Y}_2) | \leq \frac{1}{\mathcal{L}_\mathcal{Y}(\psi(\mathcal{Y})) - \psi(0)} \int_0^\rho | \mathcal{Z}(\mathcal{Y}) | \psi(\mathcal{Y}) - \psi(0) | d\xi d\xi.
\tag{27}
\]

From Eq. (27), we deduce that \(\mathcal{I}\) is a contraction. By the Banach contraction mapping theorem, the problem defined by Eq. (9) has a unique solution. The said solution belongs to the interval \([0, \mathcal{T}]\).

## 5. Application Example

In this section, application examples are provided to support the theoretical work developed above. Data set obtained from real-life experiment were used. The classical method, simple fractional method, and kernel fractional method were used to fit the data set. Finally, a comparison of results is done to support theoretical findings.

### 5.1. First Experimental Data Set

This data set was retrieved from [28]. The author carried out an experiment in which he measured a drug concentration in (mg/L) over 6 hours of an antibiotic. A single dose of the said antibiotic was administered intravenously to a 50-kilogram woman. The dose level was 20 mg/kg. A scatter plot of the concentration data over time shows a decay. Three deterministic approaches were used to fit the data set. The first approach is what is referred to as the classical approach, in which the general solution is defined by Eq. (7). The second and third approaches are fractional differential method and kernel fractional differential method, respectively, which general solutions are given by Eq. (11), respectively, with \(\psi(x) = x\), trivial kernel, and \(\psi(x) \neq x\), pure kernel. The selected pure kernel here is linear \(\psi(x) = x + 1\). It was observed empirically that using any linear kernel \(\psi(x) = x + a\), with \(a \neq 0\), would produce a similar result to the case where \(\psi(x) = x + 1\) is used.

Table 1 summarises one hand best estimates of the parameters for both classical and fractional approaches. On the other hand, it displays the MSE of each method. It is observed that the fractional kernel method with \(\psi(x) = x + 1\) performed the best, followed by the fractional method with \(\psi(x) = x\) and lastly the classical method. It is worth highlighting consistency in the results. Indeed, the solution to the classical approach is a first order differential equation; therefore, one would expect the solution to its fractional counterparts to be such that \(\xi \in (0, 1) \cup (1, 2)\).

Figure 2 is the graph of the original data set, the fitted line is obtained from the classical model, and the fitted line is obtained from the fractional method with \(\psi(x) = x\). Both fitted lines overlap over each other at the beginning of the plot but show a difference toward the end. The fractional
method with $\psi(x) = x$ seems to be closer to the true data. MSE in Table 1 is an evidence.

Figure 3 is the graph of the original data set, the fitted line is obtained from the classical model, and the fitted line is obtained from the fractional method with $\psi(x) = x + 1$. Similar to Figure 2, a close look at the figure reveals that the fractional method with $\psi(x) = x + 1$ does the job better than the classical method. Moreover, recalling Figures 2 and 3 as well as Table 1, the ordinal classification (first: fractional method with $\psi(x) = x + 1$; second: fractional method with $\psi(x) = x$; and third: classical method) of the three methods used in this work becomes explicit.

5.2. Second Experimental Data Set. In this experiment, a newly developed drug was administrated to a patient. The administration was done through an IV injection. A sample of blood was taken regularly, and the drug plasma concentration was determined. The data set was retrieved from [29]. Similar experimental procedures to those from the first example are used. The best values of parameters as well as MSE of each method are consigned in the table below.

Table 2 summarises and displays the results of the second experiment. It is observed that the fractional kernel method with $\psi(x) = x + 1$ performed the best, followed by the fractional method with $\psi(x) = x$ and lastly the classical method. Moreover, the fractional order of derivatives is always such that $\xi \in (0, 1) \cup (1, 2)$, proving that the results are in line with the first-order differential equation. Hence, the results are consistent.

Figure 4 displays the original data, the classical solution, and the fractional with the kernel $\psi(x) = x$. The results in Table 2 are reflected by the fact that the fractional approach fits the original data points better than the classical approach does.

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Figure 4 displays the original data, the classical solution, and the fractional with the kernel $\psi(x) = x$. The results in Table 2 are reflected by the fact that the fractional approach fits the original data points better than the classical approach does.
Figure 5 is the graph of the original data set, the fitted line is obtained from the classical model, and the fitted line is obtained from the fractional method with $\psi(x) = x + 1$. A close check of the figure reveals that the fractional method with $\psi(x) = x + 1$ does the job better than the classical method.

6. Conclusion and Future Work

In this work, we studied the $\psi$-Caputo type of fractional differential equation. This derivative is the fractional analog of the so-called (fog)$^r$ derivative in classical calculus. The existence and uniqueness of the proposed method were discussed before the application examples. Experiment results show that the $\psi$-Caputo method which uses a pure kernel function performed the best, followed by a simple fractional approach and finally the classical method. The fractional order of derivative that allows to best fit the data is always such that $\xi \in (0, 1) \cup (1, 2)$, which is in line with the setup of the studied problem since the classical approach solution is a first-order differential equation. The experimental section has revealed the following results:

For the first data set, a psi-Caputo with the kernel $\psi = x + 1$ is the best approach as it yields a mean square error (MSE) of 0.04065. The second best is the simple fractional method whose MSE is 0.05814; finally, the classical approach is in the third position with an MSE of 0.07299.

For the second data set, a psi-Caputo with the kernel $\psi = x + 1$ is the best approach as it yields an MSE of 0.03482. The second best is the simple fractional method whose MSE is 0.04116 and, finally, the classical approach with an MSE of 0.048640.

In future works, we aim to investigate if the obtained results hold for all or most of existing fractional derivatives. We may also study properties that can help in the selection of a suitable kernel function. In the current study, the selection $\psi$ function was done randomly, on a try and error basis, until we found out that a family of linear functions could well do the job.

Data Availability

The data set used in application section is available through the url provided in [27].

Conflicts of Interest

The authors declare that they have no competing interests.

Authors’ Contributions

Each of the authors, M.A, Y.Y.Y, K.A, and N.G., contributed to each part of this work equally and read and approved the final version of the manuscript.

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