



Advanced Numerical Methods for Fractional-Order Differential Systems

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Abstract. Fractional-order differential systems have become very popular in the last few years because they can model memory and hereditary effects. However, existing numerical techniques for solving such systems still have certain limitations. We used generalized Caputo-type fractional derivatives for the Abel differential equation in normal form and for the four-dimensional Chen system to avoid such problems. We also used two different methods for their solutions: the adaptive predictor–corrector (P–C) method and the generalized Laplace decomposition method (\mathcal{T}_ρ DM). First, the methods are easy to use and give more accurate results than other methods. Second, the methods let you do calculations quickly without having to recalculate fractional sequences for different starting points. Thirdly, the methods are strong enough to accurately identify chaotic attractors and capture the system’s dynamics. Lastly, they are flexible and work well with computers, which makes them useful for many different scientific and engineering systems. A lot of numerical tests and comparisons with the Adams–Bashforth–Moulton (ABM) method show that the proposed methods work well, are reliable, and have real-world benefits.

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Introduction

Calculus with non-integers as the order is referred to as fractional calculus and now has a general application compared to standard integer forms of derivatives and integrals in several areas such as physics, engineering, applied mathematics, and others. [1–4]. It provides a versatile approach to describe phenomena such as diffusion, viscoelasticity, and control systems. Researchers have developed diverse methods to solve fractional differential equations, aided by advancements in computing and software tools [5–8]. These techniques, rooted in solid mathematical foundations, have applications in physics and engineering and areas like economics, biology, and management [9–16].

Many scientific and engineering sectors use chaotic system modeling articles [17–19], a trend that has grown in recent years. Many of these works address the challenge of incorporating chaotic systems into electrical circuit modeling for chaotic applications. Reliable forecasts are difficult due to the complexity of real-world phenomena and chaotic modeling. We can use phase portraits to analyze the effects of model parameters on system behavior, Lyapunov exponents, and chaotic and hyperchaotic tendencies.

Recent studies have advanced the numerical and analytical treatment of generalized Caputo-type fractional differential equations. Novel predictor–corrector schemes have been developed to enhance stability and accuracy [20, 21], while new approaches address long-term integration and error analysis [22, 23]. Extensions to multidimensional settings and non-uniform meshes further broaden applicability [24]. In parallel, theoretical progress has been made on stochastic and non-Lipschitz cases [25], and alternative methods such as the homotopy analysis method have been proposed [26]. These contributions collectively emphasize the growing importance of generalized Caputo-type derivatives in modeling complex dynamical systems, motivating the present study.

Fractional-order differential systems have attracted increasing attention over the past decades, due to their ability to capture memory and hereditary effects that classical integer-order models neglect [27–32]. Analytical approaches such as the Caputo fractional derivative, Riemann–Liouville fractional derivative, and other generalized definitions provide a solid theoretical foundation for formulating fractional-order dynamics [30–34]. Our goals are to enhance both accuracy and computational efficiency, and to demonstrate the methods’ capability to capture complex dynamics including chaotic attractors. The results confirm that the proposed strategies outperform classical approaches and are well-suited for a wide range of fractional-order dynamical systems [35–37].

Which offers advantages when it comes to modeling situations that occur in the actual world. The evidence shown in [38] demonstrates that there has been a growing interest in investigating the impact that memory modeling has on chaotic and hyperchaotic systems, which has revealed a new opportunity for research. It is essential to bring to your attention that even minute modifications to the initial conditions of chaotic systems can potentially reduce the occurrence of chaotic or hyperchaotic behavior. This section aims to provide an overview of existing publications on the topic. In particular, [39] delves into the chaotic behavior of the Chua circuit. In [40], the authors explore and substantiate the Lyapunov fractional exponent approach. Another alternative formulation is discussed in reference [41–46]; their primary focus revolves around Caputo derivatives, bifurcations, and Lyapunov analysis. On the contrary, references [47, 48] encompass a diverse spectrum of chaotic and hyperchaotic systems employing Caputo derivatives. Furthermore, amplitude control is instrumental in capturing dynamically symmetric systems, as elucidated in the reference [49]. The four-dimensional fractional-order Chen system with generalized Caputo-type derivatives and the canonical Abel differential equation are examined in this study. Solutions are achieved utilizing the generalized Laplace decomposition method (\mathcal{T}_ρ DM) and adaptive predictor-corrector (P-C) while comparing to the ABM scheme. The offered methods accurately capture chaotic attractors and match ABM results. These results show they can accurately numerically solve complex scientific and engineering models. The \mathcal{T}_ρ decomposition method (\mathcal{T}_ρ DM) [50, 51] combines the generalized Laplace transform \mathcal{T}_ρ with the standard Adomian method. It has been displayed by many mathematicians to solve many problems associated with generalized Caputo fractional derivatives. This method is much easier and has fewer mathematical calculations compared with different analytical methods. The results revealed the effectiveness and efficiency of the method. The novelty of this research lies in its innovative application of the adaptive (P-C) method and (\mathcal{T}_ρ DM) to solve the fractional Abel equation and the 4-D fractional-order Chen system, as well as its comparative analysis with the ABM. Additionally, it demonstrates the effectiveness of these methods and their utility in identifying chaos. This research can potentially advance numerical and analytical methods in science and engineering, specifically in dealing with complex, non-linear systems.

The paper is structured as follows: Section 2 displays basic definitions. Section 3 provides the adaptive (P-C) method. Section 4 discusses the numerical solution of the first kind of Abel differential equation and the 4-D fractional-order Chen system using the adaptive (P-C) scheme, including numerical results. Section 5 presents a logarithm of the (\mathcal{T}_ρ DM). The application of the (\mathcal{T}_ρ DM) to our problems is made in Section 6. Section 7 concludes the study.

1. Basic definitions

In this section, we present a short survey of operator derivatives, focusing primarily on the fractional types that play a key role in our analysis.

Definition 1. [52] For continuous functions f , the left-side generalized fractional integral (FI), denoted by $\mathbf{I}_{a+}^{\alpha,\rho} f(t)$, $\alpha > 0$, and $\rho > 0$, is given by

$$\mathbf{I}_{a+}^{\alpha,\rho} f(t) = \frac{\rho^{1-\alpha}}{\Gamma(\alpha)} \int_a^t s^{\rho-1} (t^\rho - s^\rho)^{\alpha-1} f(s) ds, \quad \alpha > 0, t > a. \quad (1)$$

for $m - 1 < \alpha \leq m$ where $m \in \mathbb{N}$.

Definition 2. For continuous functions f , the generalized fractional derivative (RLFD) denoted by ${}^R\mathbf{D}_{a+}^{\alpha,\rho} f(t)$, of order $\alpha > 0$ is given by

$${}^R\mathbf{D}_{a+}^{\alpha,\rho} f(t) = \frac{\rho^{\alpha-m+1}}{\Gamma(m-\alpha)} \left(t^{1-\rho} \frac{d}{dt} \right)^m \int_a^t s^{\rho-1} (t^\rho - s^\rho)^{m-\alpha-1} f(s) ds, \quad t > a \geq 0. \quad (2)$$

Definition 3. [53] For continuous functions f , the generalized fractional derivative of the Caputo type (CFD), denoted by ${}^C\mathbf{D}_{a+}^{\alpha,\rho} f(t)$, of order $\alpha > 0$ is given by

$${}^C\mathbf{D}_{a+}^{\alpha,\rho} f(t) = {}^R\mathbf{D}_{a+}^{\alpha,\rho} \left(f(x) - \sum_{n=0}^{m-1} \frac{f^{(n)}(a)}{n!} (x-a)^n \right) (t), \quad t > a \geq 0, \quad (3)$$

where $m = \lceil \alpha \rceil$ and $\rho > 0$. In case of $0 < \alpha \leq 1$.

$${}^C\mathbf{D}_{a+}^{\alpha,\rho} f(t) = \frac{\rho^\alpha}{\Gamma(1-\alpha)} \int_a^t (t^\rho - s^\rho)^{-\alpha} s^{1-\rho} f'(s) ds, \quad 0 < \alpha \leq 1, t > a \geq 0. \quad (4)$$

Definition 4. [49] The new generalized (CFD) operator, $\mathbf{D}_{a+}^{\alpha,\rho}$, $\alpha > 0$ is given by:

$$\mathbf{D}_{a+}^{\alpha,\rho} f(t) = \frac{\rho^{\alpha-m+1}}{\Gamma(m-\alpha)} \int_a^t s^{\rho-1} (t^\rho - s^\rho)^{m-\alpha-1} \left(s^{1-\rho} \frac{d}{ds} \right)^m f(s) ds, \quad t > a, \quad (5)$$

where $\rho > 0, a \geq 0$, and $m - 1 < \alpha < m$.

Definition 5. [54] if $f : [0, \infty] \rightarrow \mathbb{R}$, then the generalized Laplace transform of f is defined by

$$\mathcal{T}_\rho\{f(t)\} = \int_0^\infty e^{-\delta t^\rho} f(t) t^{\rho-1} dt. \quad (6)$$

The generalized Laplace transform of the generalized (CFD) $\mathbf{D}_0^{\alpha,\rho}$ is defined by

$$\mathcal{T}_\rho\{\mathbf{D}_0^{\alpha,\rho} f(t)\} = \delta^\alpha \mathcal{T}_\rho\{f(t)\} - \delta^{-1} f(0), \quad 0 < \alpha \leq 1. \quad (7)$$

2. Algorithm of the adaptive predictor-corrector method

This section presents the adaptive (P-C) method, an algorithm designed for the efficient numerical solution of initial value problems containing the generalized (CFD).

$$\mathbf{D}_{a+}^{\alpha,\rho} y(t) = f(t, y(t)), \quad t \in [0, T], \quad y^{(k)}(a) = y_0^k, \quad k = 0, 1, \dots, \lceil \alpha \rceil, \quad (8)$$

where $\mathbf{D}_{a+}^{\alpha,\rho}$ is CFD, for $m-1 < \alpha \leq m, a \geq 0, \rho > 0$ and $y \in C^m([a, T])$, the IVP (8) is equivalent, we get:

$$y(t) = u(t) + \frac{\rho^{1-\alpha}}{\Gamma(\alpha)} \int_a^t s^{\rho-1} (t^\rho - s^\rho)^{\alpha-1} f(s, y(s)) ds, \quad (9)$$

where

$$u(t) = \sum_{n=0}^{m-1} \frac{1}{\rho^n n!} (t^\rho - a^\rho)^n \left(x^{1-\rho} \frac{d}{dx} \right)^n y(x) \Big|_{x=a}. \quad (10)$$

Assuming that the function f has one solution on $[a, T]$, we partition the interval into N unequal subintervals $[t_k, t_{k+1}], k = 0, 1, \dots, N-1$ using mesh points.

$$t_0 = a, \quad t_{k+1} = (t_k^\rho + h)^{1/\rho}, \quad k = 0, 1, \dots, N-1, \quad (11)$$

where $h = \frac{T^\rho - a^\rho}{N}$. [54] $y_k, k = 0, 1, \dots, N$, then $y(t_j)$ and $y_j \approx y(t_j) (j = 1, 2, \dots, k)$, using the integral equation. $y_{k+1} \approx y(t_{k+1})$.

$$y(t_{k+1}) = u(t_{k+1}) + \frac{\rho^{1-\alpha}}{\Gamma(\alpha)} \int_a^{t_{k+1}} s^{\rho-1} (t_{k+1}^\rho - s^\rho)^{\alpha-1} f(s, y(s)) ds. \quad (12)$$

Now, substitution

$$z = s^\rho, \quad (13)$$

we get

$$y(t_{k+1}) = u(t_{k+1}) + \frac{\rho^{-\alpha}}{\Gamma(\alpha)} \int_{a^\rho}^{t_{k+1}^\rho} (t_{k+1}^\rho - z)^{\alpha-1} f(z^{1/\rho}, y(z^{1/\rho})) dz. \quad (14)$$

That is

$$y(t_{k+1}) = u(t_{k+1}) + \frac{\rho^{-\alpha}}{\Gamma(\alpha)} \sum_{j=0}^k \int_{t_j^\rho}^{t_{j+1}^\rho} (t_{k+1}^\rho - z)^{\alpha-1} f(z^{1/\rho}, y(z^{1/\rho})) dz. \quad (15)$$

Following that, an application of the trapezoidal quadrature method with respect to the weight function $(t_{k+1}^\rho - z)^{\alpha-1}$, we obtain the corrector formula to get a close approximation of the right-hand side of Eq. (15),

$$y(t_{k+1}) \approx u(t_{k+1}) + \frac{\rho^{-\alpha} h^\alpha}{\Gamma(\alpha + 2)} \sum_{j=0}^k a_{j,k+1} f(t_j, y(t_j)) + \frac{\rho^{-\alpha} h^\alpha}{\Gamma(\alpha + 2)} f(t_{k+1}, y(t_{k+1})) \quad (16)$$

where

$$a_{j,k+1} = \begin{cases} (k^{\alpha+1} - (k-\alpha)(k+1)^\alpha) & \text{if } j = 0 \\ (k-j+2)^{\alpha+1} + (k-j)^{\alpha+1} - 2(k-j+1)^{\alpha+1} & \text{if } 1 \leq j < k \end{cases} \quad (17)$$

Equation (14) is evaluated by substituting $y(t_{k+1})$ with the predictor $y^P(t_{k+1})$ using Eq. (16) where $f(z^{1/\rho}, y(z^{1/\rho}))$ is replaced by $f(t_j, y(t_j))$.

$$\begin{aligned} y^P(t_{k+1}) &\approx u(t_{k+1}) + \frac{\rho^{-\alpha}}{\Gamma(\alpha)} \sum_{j=0}^k \int_{t_j^\rho}^{t_{j+1}^\rho} (t_{k+1}^\rho - z)^{\alpha-1} f(t_j, y(t_j)) dz \\ &= u(t_{k+1}) + \frac{\rho^{-\alpha} h^\alpha}{\Gamma(\alpha+1)} \sum_{j=0}^k ((k+1-j)^\alpha - (k-j)^\alpha) f(t_j, y(t_j)). \end{aligned} \quad (18)$$

Then,

$$y_{k+1} \approx u(t_{k+1}) + \frac{\rho^{-\alpha} h^\alpha}{\Gamma(\alpha+2)} \sum_{j=0}^k a_{j,k+1} f(t_j, y_j) + \frac{\rho^{-\alpha} h^\alpha}{\Gamma(\alpha+2)} f(t_{k+1}, y_{k+1}^p). \quad (19)$$

In [24]. The proposed adaptive (P-C) method uses a non-uniform grid $t_{j+1} = (t_j^\rho + h_\rho)^{1/\rho} : j = 0, 1, \dots, N-1$, $t_0 = a$ and $h = \frac{T^\rho - a^\rho}{N}$, where N is natural. We cannot use the (P-C) technique to solve IVP defined with the generalized CFD if we employ a uniform grid, as mentioned in [55].

3. Applications

This section explores the applicability of the (P-C) approach for the numerical resolution of initial value issues, utilizing the suggested under-generalized Caputo-type derivatives. Considering this, we turned to numerical simulations to investigate potential solutions to our examples.

3.1. Problem 1

Consider the first kind of Abel differential equation in canonical form, nonhomogeneous equation with cubic nonlinearity [56]

$$\mathbf{D}_0^{\alpha,\rho} y(t) = \sin(t) - y(t)^3 \quad (20)$$

This is associated with the condition $y(0) = 0.5$. By using Eq. (19), the approximations y_{k+1} , and for $N \in \mathbb{N}$ and $T > 0$,

$$y_{k+1} \approx y_0 + \frac{a\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} \sum_{j=0}^k a_{j,k+1} (\sin(t_j) - y_j^3) + \frac{a\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} (\sin(t_{k+1}) - (y_{k+1}^k)^3) \quad (21)$$

where $h = \frac{T^\rho}{N}$ and $y_0 = 0.5$, then

$$y_{k+1} \approx 0.5 + \frac{a\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+1)} \sum_{j=0}^k ((k+1-j)^\alpha - (k-j)^\alpha) (\sin(t_j) - y_j^3) \quad (22)$$

The tables display solutions of Equation (20) using the adaptive (P-C) method under different settings to display the behavior and precision of the numerical method. Table 1 presents a comparison of solutions using different values of t , utilizing various step sizes of h , in addition to an ABM method solution as a reference. It can be observed from the table that the solutions gradually reduce as the step size is taken forward. Table 2 provides the solutions at $t = 0.1$ for several α, ρ . Table 3 depicts solutions at $t = 0.2$. For the same values of the step size and parameter combinations. These results show that the fractional order parameters influence the solution's stability and its convergence.

Table 1: Solutions of Equation (20), where $\alpha = 1, \rho = 1$.

| h | $t = 0.1$ | $t = 0.2$ | $t = 0.5$ |
|-------|-----------|-----------|-----------|
| 1/10 | 0.49889 | 0.50233 | 0.53928 |
| 1/20 | 0.49751 | 0.49978 | 0.53459 |
| 1/40 | 0.49686 | 0.49857 | 0.53237 |
| 1/80 | 0.49654 | 0.49798 | 0.53128 |
| 1/160 | 0.49638 | 0.49769 | 0.53075 |
| 1/320 | 0.49630 | 0.49755 | 0.53049 |
| ABM | 0.49283 | 0.49575 | 0.55589 |

Table 2: Solutions of Equation (20), where $t = 0.1$.

| h | $\alpha = 1, \rho = 0.9$ | $\alpha = 0.95, \rho = 0.8$ | $\alpha = 0.9, \rho = 1.2$ |
|-------|--------------------------|-----------------------------|----------------------------|
| 1/10 | 0.49876 | 0.49830 | 0.49856 |
| 1/20 | 0.49724 | 0.49622 | 0.49677 |
| 1/40 | 0.49651 | 0.49509 | 0.49568 |
| 1/80 | 0.49654 | 0.49442 | 0.49493 |
| 1/160 | 0.49598 | 0.49398 | 0.49432 |
| 1/320 | 0.49590 | 0.49363 | 0.49379 |
| 1/640 | 0.49585 | 0.49334 | 0.49327 |

Table 3: Solutions of Equation (20), where $t = 0.2$.

| h | $\alpha = 1, \rho = 0.9$ | $\alpha = 0.95, \rho = 0.8$ | $\alpha = 0.9, \rho = 1.2$ |
|-------|--------------------------|-----------------------------|----------------------------|
| 1/10 | 0.50259 | 0.50324 | 0.50243 |
| 1/20 | 0.49977 | 0.49962 | 0.49950 |
| 1/40 | 0.49843 | 0.49778 | 0.49788 |
| 1/80 | 0.49778 | 0.49679 | 0.49691 |
| 1/160 | 0.49746 | 0.49621 | 0.49625 |
| 1/320 | 0.49730 | 0.49584 | 0.49574 |
| 1/640 | 0.49722 | 0.49557 | 0.49530 |

Fig. 1 illustrates the curves and parametric plots obtained using the ABM method, and the different formal parameters tend to remain stable and periodic over the solution period. These are presented using parametric plots and curves slightly different from those in Fig. 2, and given the robust nature of the (P-C) method, this shows variations due to the adaptation. The adaptive (P-C) method and the ABM nearly coincide, supporting the adaptive method's accuracy in efficiently capturing the system's dynamics.

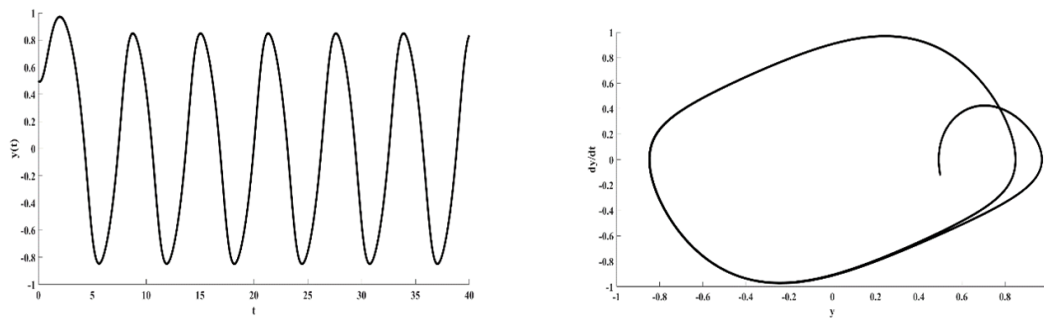


Figure 1: Curves and parametric plots using the ABM method.

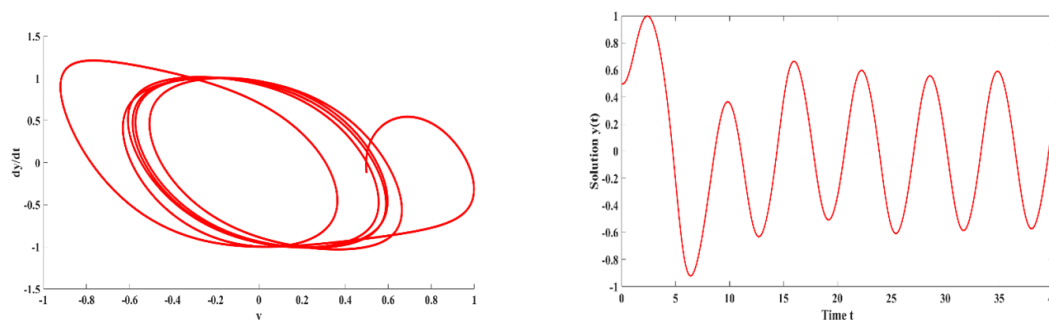


Figure 2: The curves and parametric plots using (P-C) schema when $(\alpha, \rho) = (1, 1)$.

3.2. Problem 2

Consider the following 4-D fractional-order Chen system: [49].

$$\begin{cases} D_0^{\alpha, \rho} x_1(t) = a(x_2 - x_1) \\ D_0^{\alpha, \rho} x_2(t) = bx_1 - x_1x_3 + cx_2 - x_4 \\ D_0^{\alpha, \rho} x_3(t) = x_1x_2 - dx_3 \\ D_0^{\alpha, \rho} x_4(t) = x_1 + k \end{cases} \quad (23)$$

When $a = 36, b = -16, c = 28, d = 3$, and $k = 0.5$, with $x_1(0) = 0, x_2(0) = 0, x_3(0) = 8$, and $x_4(0) = 6$. By using Eq. (19), the approximations $x_{1_{k+1}}, x_{2_{k+1}}, x_{3_{k+1}}$ and $x_{4_{k+1}}$, and for $N \in \mathbb{N}$ and $T > 0$,

$$\begin{aligned}
x_{1_{k+1}} &\approx x_{1_0} + \frac{a\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} \sum_{j=0}^k a_{j,k+1}a(x_{2_j} - x_{1_j}) + \frac{a\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} a(x_{2_{k+1}}^P - x_{1_{k+1}}^P) \\
x_{2_{k+1}} &\approx x_{2_0} + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} \sum_{j=0}^k a_{j,k+1}(bx_{1_j} - x_{1_j}x_{3_j} + cx_{2_j} - x_{4_j}) \\
&\quad + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} (bx_{1_{k+1}}^P - x_{1_{k+1}}^P x_{3_{k+1}}^P + cx_{2_{k+1}}^P - x_{4_{k+1}}^P) \\
x_{3_{k+1}} &\approx x_{3_0} + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} \sum_{j=0}^k a_{j,k+1}(x_{1_j}x_{2_j} - dx_{3_j}) + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} (x_{1_{k+1}}^P x_{2_{k+1}}^P - bx_{3_{k+1}}^P) \\
x_{4_{k+1}} &\approx x_{3_0} + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} \sum_{j=0}^k a_{j,k+1}(x_{1_j} + k) + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+2)} (x_{1_{k+1}}^P + k)
\end{aligned} \tag{24}$$

where $h = \frac{T^\rho}{N}$ and take value of initial condition

$$\begin{aligned}
x_{1_{k+1}} &\approx \frac{a\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+1)} \sum_{j=0}^k ((k+1-j)^\alpha - (k-j)^\alpha) a(x_{2_j} - x_{1_j}) \\
x_{2_{k+1}} &\approx \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+1)} \sum_{j=0}^k ((k+1-j)^\alpha - (k-j)^\alpha) (bx_{1_j} - x_{1_j}x_{3_j} + cx_{2_j} - x_{4_j}) \\
x_{3_{k+1}} &\approx 8 + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+1)} \sum_{j=0}^k ((k+1-j)^\alpha - (k-j)^\alpha) (x_{1_j}x_{2_j} - dx_{3_j}) \\
x_{4_{k+1}} &\approx 6 + \frac{\rho^{-\alpha}h^\alpha}{\Gamma(\alpha+1)} \sum_{j=0}^k ((k+1-j)^\alpha - (k-j)^\alpha) (x_{1_j} + k)
\end{aligned} \tag{25}$$

In Table 4, we provide a numerical solution using the adaptive (P-C) method to Eq. (20) when $\alpha = 1$, $\rho = 1$ and $t = 0.1$. In Table 5, we provide the numerical solution for the value of $\alpha = 0.95$, $\rho = 1$, and $t = 0.5$.

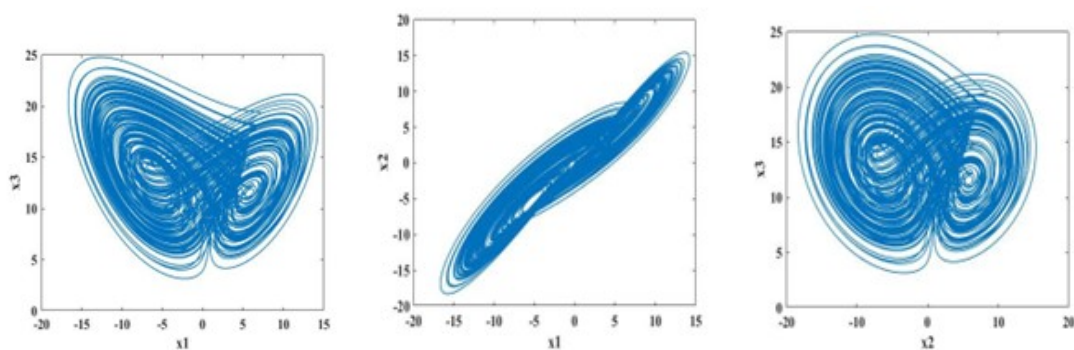
We analyze phase portraits to study the impact of the generalized Caputo-type fractional derivative on the system dynamics (Eq. (20)). Using fractional orders $\alpha = 0.96, 0.97, 0.98$, and 1 , chaotic behavior emerges at $t = 200$. Figures (5 - 8) display the $x_1 - x_3$, $x_1 - x_2$, and $x_2 - x_3$ attractors for these cases.

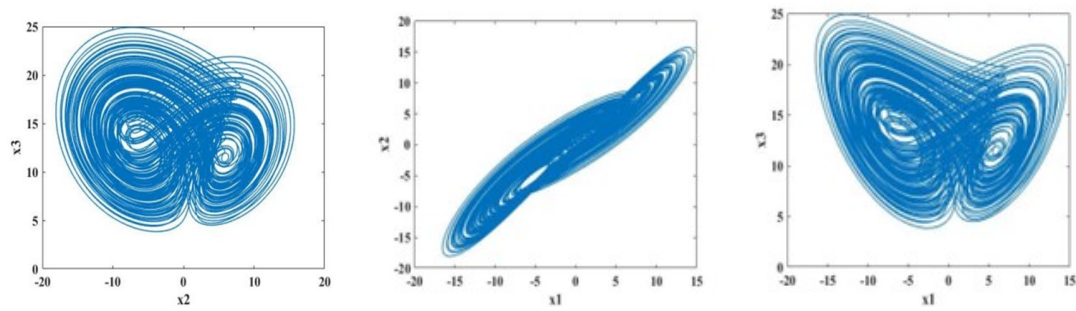
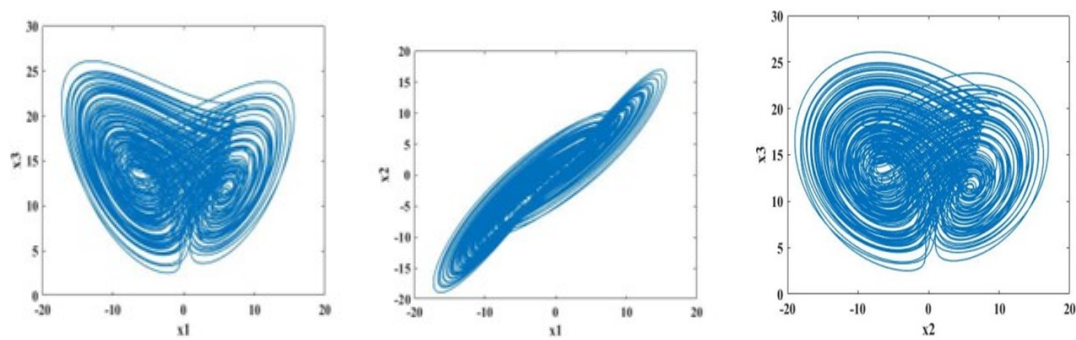
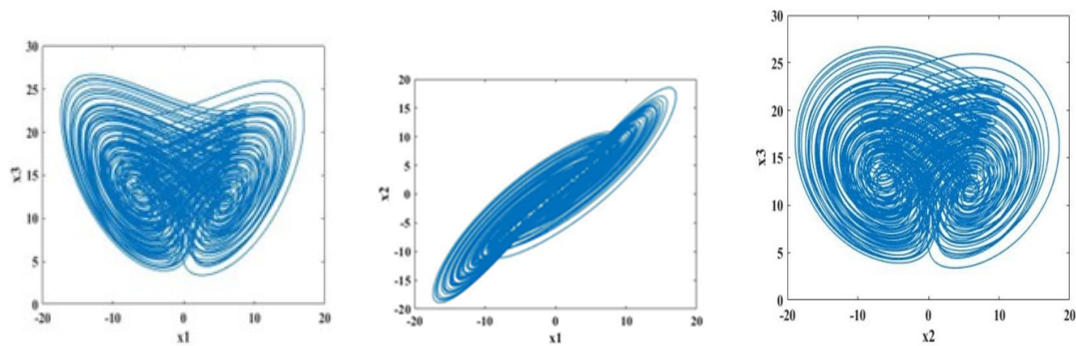
Table 4: Solutions of Equation (23) where $\alpha = 1$, $\rho = 1$

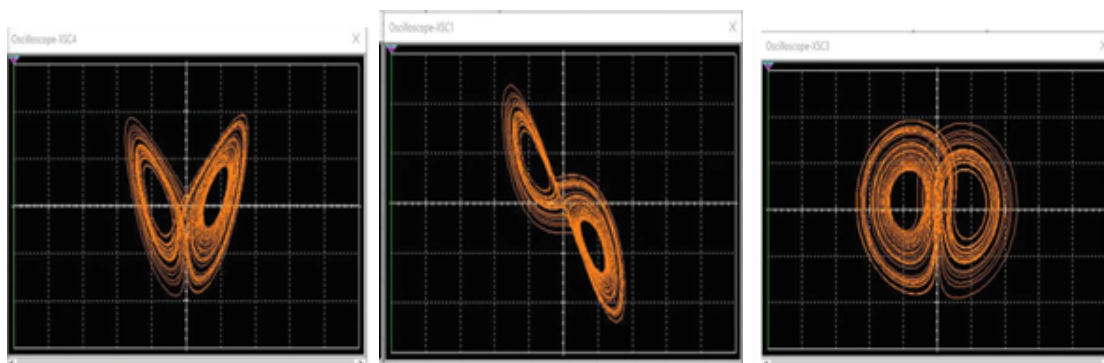
| t | x_1 | x_2 | x_3 | x_4 |
|------|-------------|-------------|------------|------------|
| 0.00 | 0.0 | 0.0 | 8.0 | 6.0 |
| 0.01 | -0.01022397 | -0.06749064 | 7.76586077 | 6.00491571 |
| 0.02 | -0.04060235 | -0.15215288 | 7.53633892 | 6.00967634 |
| 0.03 | -0.09006631 | -0.25354305 | 7.31370546 | 6.01403610 |
| 0.04 | -0.15798295 | -0.37223740 | 7.09790601 | 6.01780768 |
| 0.05 | -0.24415282 | -0.50923671 | 6.88897815 | 6.02080794 |
| 0.06 | -0.34880859 | -0.66597648 | 6.68707193 | 6.02285351 |
| 0.07 | -0.47261853 | -0.84434467 | 6.49247647 | 6.02375654 |
| 0.08 | -0.61669539 | -1.04670703 | 6.30565516 | 6.02332024 |
| 0.09 | -0.78261150 | -1.27593957 | 6.12729239 | 6.02133439 |
| 0.10 | -0.97242014 | -1.53546722 | 5.95835556 | 6.01757063 |

Table 5: Solutions of Equation (23), where $\alpha = 0.95$, $\rho = 1$.

| t | x_1 | x_2 | x_3 | x_4 |
|------|-------------|-------------|------------|------------|
| 0.00 | 0.0 | 0.0 | 8.0 | 6.0 |
| 0.01 | -0.01460575 | -0.07355130 | 5.92025254 | 4.62814279 |
| 0.02 | -0.05216391 | -0.15941269 | 5.50628735 | 4.47569747 |
| 0.03 | -0.10921573 | -0.26170607 | 5.20137134 | 4.39075850 |
| 0.04 | -0.18483585 | -0.38256715 | 4.94609561 | 4.33213396 |
| 0.05 | -0.27936101 | -0.52459541 | 4.72162850 | 4.28709078 |
| 0.06 | -0.39408408 | -0.69107296 | 4.51960152 | 4.24992067 |
| 0.07 | -0.53114673 | -0.88606622 | 4.33577357 | 4.21749171 |
| 0.08 | -0.69351942 | -1.11452870 | 4.16803272 | 4.18782509 |
| 0.09 | -0.88503361 | -1.38242209 | 4.01566038 | 4.15951848 |
| 0.10 | -1.11045120 | -1.69685657 | 3.87908994 | 4.13147199 |

Figure 3: Chaotic dynamics for $(\alpha, \rho) = (0.96, 0.7)$.

Figure 4: Chaotic dynamics for $(\alpha, \rho) = (0.97, 0.8)$.Figure 5: Chaotic dynamics for $(\alpha, \rho) = (0.98, 0.9)$.Figure 6: Chaotic dynamics for $(\alpha, \rho) = (1, 1)$.

Figure 7: The circuit generated results when $(\alpha, \rho) = (1, 1)$.

In Figures (3–6), we plot numerical solutions to Eq. (20) $(a, b, c, d, k) = (36, -16, 28, 3, 0.5)$, with the initial conditions $x_1(0) = 0, x_2(0) = 0, x_3(0) = 8$, and $x_4(0) = 6$. In Fig. 5, we show the circuit generated results for Eq. (20), when $(\alpha, \rho) = (1, 1)$. We display these figures using the adaptive (P-C) method when $T = 50$ and $N = 1000$ for some different values of the parameters α and ρ in Eq. (20). Furthermore, the importance of changing the α and ρ parameters in generalized Caputo fractional models lies in their capacity to capture a broad spectrum of system behaviors, adapt the model to specific applications, and facilitate model validation and optimization. This flexibility is valuable when dealing with complex and diverse real-world systems. Comparing the circuit simulation in 7 to numerical findings showed that they were in good agreement. Chaos theory has wide-ranging applications, from weather forecasting (where small changes in initial conditions can lead to drastically different weather patterns) to studying turbulent fluid dynamics, the behavior of financial markets, and even biological systems like the human heart's rhythm. It is worth noting that while chaotic systems are deterministic and governed by mathematical equations, they can still appear random and unpredictable over extended periods, making them a fascinating area of study and posing challenges in various fields. Chaos theory has deepened our understanding of the inherent complexity and unpredictability present in many natural and man-made systems. Refer to [55, 57–59] for further insights. Chaos can manifest in a variety of real-world systems, including coronary arteries within blood vessels [60] and even within cancer and tumor cells [61].

4. \mathcal{T}_ρ Decomposition Method (\mathcal{T}_ρ DM)

In this section, we present the algorithm of \mathcal{T}_ρ to deal with equations that have the (CFD). Consider the Initial value problem

$$\mathbf{D}_0^{\alpha, \rho} y(t) = f(t, y(t)), \quad \rho > 0, \quad 0 < \alpha \leq 1, \quad (26)$$

Rewire (26) in the following

$$\mathbf{D}_0^{\alpha, \rho} y(t) = f(t) + S(y(t)),$$

Where $f(t)$ is known linear part and $S(y(t))$ is a nonlinear part Taking \mathcal{T}_ρ and its inverse, we obtain

$$y(t) = P(t) + \mathcal{T}_\rho^{-1} \left[\frac{1}{\delta^\alpha} \mathcal{T}_\rho \{S(y(t))\} \right] \quad (27)$$

Where $P(t) = y_0 + \mathcal{T}_\rho^{-1} \left[\frac{1}{\delta^\alpha} \mathcal{T}_\rho \{f(t)\} \right]$ Consider the series expansion

$$y(t) = \sum_{n=0}^{\infty} y_n(t), \quad S(y(t)) = \sum_{n=0}^{\infty} L_n(t) \quad (28)$$

where L_n are the Adomian polynomials corresponding to S . Substituting Eq. (28) into Eq. (24) yields

$$\sum_{n=0}^{\infty} y_n(t) = P(t) + \mathcal{T}_\rho^{-1} \left[\frac{1}{\delta^\alpha} \mathcal{T}_\rho \left\{ S \left(\sum_{n=0}^{\infty} y_n(t) \right) \right\} \right]. \quad (29)$$

As a result, we have the recursive relation

$$y_0(\tau) = P(t), \quad (30)$$

$$y_{n+1}(\tau) = \mathcal{T}_\rho^{-1} \left[\frac{1}{\delta^\alpha} \mathcal{T}_\rho \{L_n(t)\} \right], \quad n \geq 0. \quad (31)$$

After P components, the truncated solution is

$$y^{[P]}(t) = \sum_{n=0}^P y_n(t) \quad (32)$$

5. Application (\mathcal{T}_ρ DM)

in this section, we display the solutions of problem1 and 2 by using \mathcal{T}_ρ DM to demonstrate its capability and efficiency. To substantiate these claims, we benchmark the results with (P-C) as a high-accuracy method.

Table 6: \mathcal{T}_ρ DM solutions of Equation (20), where $\alpha = 1, \rho = 1$, $\alpha = 0.9, \rho = 1.2$ and $\alpha = 1, \rho = 0.9$ respectively, together with the ABM method.

| t | $y(t)$ | $y(t)$ | $y(t)$ | $y(t)$ (ABM) |
|-----|------------|----------|----------|--------------|
| 0.0 | 0.50000000 | 0.5 | 0.5 | 0.50000000 |
| 0.1 | 0.49283965 | 0.495194 | 0.489829 | 0.49282671 |
| 0.2 | 0.49581033 | 0.498667 | 0.493661 | 0.49566222 |
| 0.3 | 0.50802144 | 0.510806 | 0.507845 | 0.50772079 |
| 0.4 | 0.52849733 | 0.531068 | 0.530572 | 0.52803985 |
| 0.5 | 0.55618490 | 0.558590 | 0.560347 | 0.56034700 |

Tables 6, 7, and 8 display the high efficiency results of the \mathcal{T}_ρ DM for both the Abel equation and the 4-D fractional Chen system. The results demonstrate strong consistency

Table 7: \mathcal{T}_ρ DM Solutions of Equation (23) where $\alpha = 1, \rho = 1$

| t | x_1 | x_2 | x_3 | x_4 |
|------|-------------|-------------|------------|------------|
| 0.00 | 0.0 | 0.0 | 8.0 | 6.0 |
| 0.01 | -0.01053361 | -0.06836528 | 7.76356602 | 6.00496467 |
| 0.02 | -0.04121716 | -0.15336438 | 7.53414660 | 6.00972220 |
| 0.03 | -0.09100584 | -0.25516654 | 7.31161424 | 6.01407664 |
| 0.04 | -0.15929223 | -0.37435081 | 7.09591955 | 6.01784018 |
| 0.05 | -0.24590100 | -0.51189428 | 6.88710762 | 6.02082868 |
| 0.06 | -0.35108370 | -0.66916040 | 6.68533439 | 6.02285719 |
| 0.07 | -0.47551353 | -0.84788718 | 6.49088303 | 6.02373547 |
| 0.08 | -0.62028005 | -1.05017548 | 6.30418030 | 6.02326349 |
| 0.09 | -0.78688399 | -1.27847725 | 6.12581293 | 6.02122700 |
| 0.1 | -0.97723200 | -1.53558383 | 5.95654400 | 6.01739300 |

Table 8: \mathcal{T}_ρ DM Solutions of Equation (23) where $\alpha = 0.95, \rho = 1$

| t | x_1 | x_2 | x_3 | x_4 |
|------|-------------|-------------|------------|------------|
| 0.00 | 0.0 | 0.0 | 8.0 | 6.0 |
| 0.01 | -0.01811237 | -0.09157316 | 7.69781898 | 6.00633965 |
| 0.02 | -0.06585216 | -0.20293349 | 7.42709690 | 6.01181555 |
| 0.03 | -0.13942618 | -0.33624535 | 7.17327700 | 6.01638560 |
| 0.04 | -0.23733389 | -0.49273276 | 6.93328192 | 6.01981814 |
| 0.05 | -0.35932110 | -0.67424636 | 6.70582162 | 6.02186336 |
| 0.06 | -0.50607992 | -0.88326294 | 6.49042558 | 6.02225709 |
| 0.07 | -0.67909657 | -1.12283235 | 6.28716065 | 6.02071449 |
| 0.08 | -0.88055485 | -1.39652456 | 6.09652515 | 6.01692204 |
| 0.09 | -1.11326677 | -1.70838245 | 5.91940659 | 6.01052941 |
| 0.1 | -1.38061856 | -2.06287971 | 5.75706686 | 6.00114154 |

with the adaptive (P-C) solutions obtained in Tables 2–5, confirming the efficiency of \mathcal{T}_ρ DM. The comparisons show that \mathcal{T}_ρ DM solutions are very close to those obtained by using the (P-C) and ABM scheme in Table 1. Overall, the results validate \mathcal{T}_ρ DM as a powerful method for generalized Caputo-type problems.

6. Discussion

The adaptive predictor-corrector method is extremely accurate; its result always lies very close to the result of the Adams–Bashforth–Moulton (ABM) method. Its precision allows safe reconstruction of dynamic behaviors, like the exact determination of chaotic attractors in the fractional-order Chen system. The above characteristic renders it exceptionally suitable to nonlinear dynamics and complex system modeling research, where observation of intricate system behaviors is of utmost concern. We examine in this pa-

per two highly effective numerical approaches to fractional-order systems with generalized (CFD): the (P-C) and \mathcal{T}_ρ DM methods. Both approaches were used to solve the canonical Abel differential equation and four-dimensional fractional-order Chen system to compare their inherent strengths and usability. The \mathcal{T}_ρ DM method, however, is easier to compute. It is not as accurate as the adaptive (P-C) method, but it's easier to calculate and doesn't require as much in the way of computing power, so it's better for quick simulations and situations where an approximate solution will suffice. Interestingly, the results of \mathcal{T}_ρ DM remain as very close to those of both ABM as well as the adaptive (P-C) solutions. This means that \mathcal{T}_ρ DM is nearly accurate in a wide range of applications. The comparison shows that both methods give solutions very close to the solutions that are found by standard methods. The flexible (P-C) method's ability to extract order from chaos very nicely complements the usability of \mathcal{T}_ρ DM. The implication is that the two methods can supplement one another: one supplies accuracy and chaos detection, and the other supplies ease of implementation of larger or easier simulations. This complementarity makes the flexibility of fractional-order modeling more powerful and enables these methods to be extended to a wider range of nonlinear systems. The work shows that the proposed methods are both effective and flexible. Their compatibility with traditional methodologies, coupled with innovative features such as chaos detection and diminished computational expense, underscores their significance for scientific and engineering numerical analyses. Future research may extend their application to additional complex systems, such as higher-dimensional fractional-order models and multi-physics challenges, thereby facilitating the development of sophisticated computational techniques in nonlinear dynamics. In this part, we employed generalized Caputo-type fractional derivatives and implemented two complementary methods: the adaptive predictor–corrector (P-C) scheme and the generalized Laplace decomposition method (\mathcal{T}_ρ DM). The choice of these methods is supported theoretically by their convergence, consistency, and stability properties, which are essential for accurately solving fractional differential equations with memory and hereditary effects. Numerically, we benchmarked the proposed methods against the classical Adams–Bashforth–Moulton (ABM) approach for the Abel differential equation and the four-dimensional Chen system. The comparison considered solution accuracy, computational efficiency, and the ability to capture complex dynamics, including chaotic attractors. Results demonstrate that the P-C and \mathcal{T}_ρ DM methods not only reduce computational cost by avoiding repeated evaluations of fractional sequences but also reliably reproduce the system's dynamical features. Therefore, the combination of theoretical justification and systematic numerical evaluation confirms that these methods provide an effective and robust framework for solving nonlinear fractional-order systems.

The study aims to develop robust numerical methods for fractional-order differential systems using generalized Caputo-type derivatives. We implement the adaptive predictor–corrector (P-C) method and the generalized Laplace decomposition method (\mathcal{T}_ρ DM) to handle nonlinear dynamics and chaotic behavior, demonstrated on the Abel equation and the four-dimensional Chen system. The combination of theoretical justification and numerical testing supports the effectiveness and applicability of the proposed methods.

The study is limited to two example systems with fixed fractional orders. Although the

methods accurately capture chaotic attractors, their performance for stiff, high-dimensional, or variable-order systems requires further investigation. Future work will extend the analysis to a broader class of fractional-order differential equations to fully assess the generality and robustness of the proposed approaches.

7. Conclusions

This study aims at solving the Abel differential equation in its standard form and the four-dimensional fractional-order Chen system with the use of the adaptive (P-C) method and the \mathcal{T}_ρ DM method. To assess the efficacy of such methods, a comprehensive comparative analysis was done against the existing ABM method. First, the suggested methods are very precise as they always give answers that are highly comparable to those given by the ABM method. Second, a numerical method using MATLAB was created to ensure that comparisons could be made more easily and to ensure compatibility of the methods with established computational techniques. Third, the adaptive (P-C) method shows a remarkable capacity to achieve complex dynamical behavior, such as precise identification of chaotic attractors, through realistic numerical evidence. Lastly, analytical results of the \mathcal{T}_ρ DM method are very close to ABM solutions, which is proof that it is robust and reliable. In general, these methods offer scientists and engineers useful and flexible tools for solving enormous types of models numerically and analytically. This enables more accurate and reliable simulations of complex fractional-order systems.

References

- [1] Rania Saadeh, Mohamed A Abdoon, Ahmad Qazza, Mohammed Berir, Fathelrhman EL Guma, Naseam Al-Kuleab, and Abdoelnaser M Degoot. Mathematical modeling and stability analysis of the novel fractional model in the caputo derivative operator: A case study. *Heliyon*, 10(5), 2024.
- [2] Mohamed A Abdoon and Abdulrahman BM Alzahrani. Comparative analysis of influenza modeling using novel fractional operators with real data. *Symmetry*, 16(9):1126, 2024.
- [3] Faeza Hasan, Mohamed A Abdoon, Rania Saadeh, Mohammed Berir, and Ahmad Qazza. A new perspective on the stochastic fractional order materialized by the exact solutions of allen-cahn equation. *International Journal of Mathematical, Engineering and Management Sciences*, 8(5):912, 2023.
- [4] Mawada Ali, Salem Mubarak Alzahrani, Rania Saadeh, Mohamed A Abdoon, Ahmad Qazza, Naseam Al-kuleab, and Fathelrhman EL Guma. Modeling covid-19 spread and non-pharmaceutical interventions in south africa: A stochastic approach. *Scientific African*, 24:e02155, 2024.
- [5] Behzad Ghanbari and Abdon Atangana. Some New Edge Detecting Techniques Based on Fractional Derivatives with Non-Local and Non-Singular Kernels. *Advances in Difference Equations*, 2020(1), Aug 2020.

- [6] Rashid Jan, Hakima Degaichia, Salah Boulaaras, Ziad Ur Rehman, and Salma Bahramand. Qualitative and Quantitative Analysis of Vector-Borne Infection through Fractional Framework. *Discrete and Continuous Dynamical Systems - S*, 0(0):0–0, 2024.
- [7] Tahar Bouali, Rafik Guefaifa, Rashid Jan, Salah Boulaaras, and Taha Radwan. Existence of Weak Solutions for the Class of Singular Two-Phase Problems with a ψ -Hilfer Fractional Operator and Variable Exponents. *Fractal and Fractional*, 8(6):329, May 2024.
- [8] Zakia Hammouch and Toufik Mekkaoui. Approximate Analytical Solution to a Time-Fractional Zakharov-Kuznetsov Equation. *International Journal of Physical Research*, 1(2), May 2013.
- [9] Mohamed A. Abdoon and Faeza Lafta Hasan. Advantages of the Differential Equations for Solving Problems in Mathematical Physics with Symbolic Computation. *Mathematical Modelling of Engineering Problems*, 09(01):268–276, Feb 2022.
- [10] Mohamed A. Abdoon, Faeza Lafta Hasan, and Nidal E. Taha. Computational Technique to Study Analytical Solutions to the Fractional Modified KDV-Zakharov-Kuznetsov Equation. *Abstract and Applied Analysis*, 2022:1–9, Jun 2022.
- [11] Mohamed A Abdoon, Rania Saadeh, Mohammed Berir, and Dalal Khalid Almutairi. Exploring chaotic dynamics in a modified fractional system with the atangana-baleanu operator. In *Advances in Computational Methods and Modeling for Science and Engineering*, pages 157–169. Elsevier, 2025.
- [12] Sana Abdulkream Alharbi, Mohamed A Abdoon, Abdoelnaser M Degoot, Reima Daher Alsemiry, Reem Allogmany, Fathelrhman EL Guma, and Mohammed Berir. Mathematical modeling of influenza dynamics: A novel approach with sveihr and fractional calculus. *International Journal of Biomathematics*, page 2450147, 2025.
- [13] Mohamed Elbadri and Tarig M Elzaki. New modification of homotopy perturbation method and the fourth-order parabolic equations with variable coefficients. *Pure Appl. Math. J*, 4(6):242–247, 2015.
- [14] Reem Allogmany, Nada A Almuallem, Reima Daher Alsemiry, and Mohamed A Abdoon. Exploring chaos in fractional order systems: A study of constant and variable-order dynamics. *Symmetry*, 17(4):605, 2025.
- [15] Athar I Ahmed, Mohamed Elbadri, Naseam Al-kuleab, Dalal M AlMutairi, Nidal E Taha, and Mohammed E Dafaalla. Chaos and bifurcations in the dynamics of the variable-order fractional rössler system. *Mathematics*, 13(22):3695, 2025.
- [16] Athar I Ahmed, Mohamed Elbadri, Abeer M Alotaibi, Manahil AM Ashmaig, Mohammed E Dafaalla, and Ilhem Kadri. Chaos and dynamic behavior of the 4d hyperchaotic chen system via variable-order fractional derivatives. *Mathematics*, 13(20):3240, 2025.
- [17] Mohamed Elbadri, Dalal M AlMutairi, DK Almutairi, Abdelgabar Adam Hassan, Walid Hdidi, and Mohamed A Abdoon. Efficient numerical techniques for investigating chaotic behavior in the fractional-order inverted rössler system. *Symmetry*, 17(3):451, 2025.
- [18] Mohamed Elbadri, Mohamed A Abdoon, Abdulrahman BM Alzahrani, Rania Saadeh, and Mohammed Berir. A comparative study and numerical solutions for the fractional

- modified lorenz–stenflo system using two methods. *Axioms*, 14(1):20, 2024.
- [19] Mohamed Elbadri, Mohamed A Abdoon, DK Almutairi, Dalal M Almutairi, and Mohammed Berir. Numerical simulation and solutions for the fractional chen system via newly proposed methods. *Fractal and Fractional*, 8(12):709, 2024.
- [20] S. M. Sivalingam and et al. A novel L1-Predictor-Corrector method for the numerical solution of the generalized-Caputo type fractional differential equations. *Mathematics and Computers in Simulation*, 220:462–480, 2024.
- [21] Zaid Odibat. Error analysis of the universal predictor–corrector algorithm for generalized fractional differential equations: Z. Odibat. *Journal of Applied Mathematics and Computing*, 71(3):4529–4548, 2025.
- [22] Enyu Fan, Changpin Li, and Zhiqiang Li. Numerical approaches to Caputo–Hadamard fractional derivatives with applications to long-term integration of fractional differential systems. *Communications in Nonlinear Science and Numerical Simulation*, 106:106096, 2022.
- [23] Zaid Odibat. On the numerical discretization of the fractional advection-diffusion equation with generalized Caputo-type derivatives on non-uniform meshes. *Communications on Applied Mathematics and Computation*, pages 1–19, 2024.
- [24] Dmitriy Tverdyi. Derivative of Gerasimov-Caputo Type by Multidimensional Levenberg-Marquardt. In *Computing Technologies and Applied Mathematics: CTAM 2024, Komsomolsk-na-Amure, Russia, October 07-11, 2024*, volume 500, page 159, 2025.
- [25] Xue Yang and Danfeng Luo. Averaging principle for Caputo-type generalized proportional fractional stochastic delay differential equations with non-Lipschitz coefficients. *Journal of Applied Mathematics and Computing*, pages 1–30, 2025.
- [26] Wafia Fafa, Zaid Odibat, and Nabil Shawagfeh. The homotopy analysis method for solving differential equations with generalized Caputo-type fractional derivatives. *Journal of Computational and Nonlinear Dynamics*, 18(2):021004, 2023.
- [27] Dumitru Baleanu, Hassan Kamil Jassim, and Maysaa Al Qurashi. Approximate analytical solutions of goursat problem within local fractional operators. *Journal of Nonlinear Science and Applications*, 9(6):4829–4837, 2016.
- [28] Hassan Kamil Jassim and Habeeb Kadhim. Fractional sumudu decomposition method for solving pdes of fractional order. *Journal of Applied and Computational Mechanics*, 7(1):302–311, 2021.
- [29] Hassan Kamil Jassim. A new approach to find approximate solutions of burger’s and coupled burger’s equations of fractional order. *TWMS Journal of Applied and Engineering Mathematics*, 2021.
- [30] Lamees K Alzaki and Hassan Kamil Jassim. The approximate analytical solutions of nonlinear fractional ordinary differential equations. *International Journal of Nonlinear Analysis and Applications*, 12(2):527–535, 2021.
- [31] HK Jassim, H Ahmad, A Shamaoon, and C Cesarano. An efficient hybrid technique for the solution of fractional-order partial differential equations. *Carpathian Mathematical Publications*, 13(3):790–804, 2021.
- [32] Hossein Jafari, Hassan Kamil Jassim, Maysaa Al Qurashi, and Dumitru Baleanu. On

- the existence and uniqueness of solutions for local fractional differential equations. *Entropy*, 18(11):420, 2016.
- [33] HK Jassim, J Vahidi, and VM Ariyan. Solving laplace equation within local fractional operators by using local fractional differential transform and laplace variational iteration methods. *Nonlinear Dynamics and Systems Theory*, 20(4):388–396, 2020.
 - [34] Dumitru Baleanu and Hassan Kamil Jassim. A modification fractional homotopy perturbation method for solving helmholtz and coupled helmholtz equations on cantor sets. *Fractal and Fractional*, 3(2):30, 2019.
 - [35] Ilhem Kadri, Rania Saadeh Saadeh, Dalal M. AlMutairi, Mohammed E. Dafaalla, Mohammed Berir, and Mohamed A. Abdoon. Analytical and numerical investigation of a fractional order 4d chaotic system via caputo fractional derivative. *European Journal of Pure and Applied Mathematics*, 18(3):6381, August 2025.
 - [36] Ilhem KADRI. Numerical approach to fractional model for dispersion, dissipation, and diffusion with a logistic reaction. *International Journal of Advances in Soft Computing and its Applications*, 17(3), 2025.
 - [37] Dumitru Baleanu, Hassan Kamil Jassim, and Maysaa Al Qurashi. Solving helmholtz equation with local fractional derivative operators. *Fractal and Fractional*, 3(3):43, 2019.
 - [38] Abdon Atangana and J.F. Gómez-Aguilar. Hyperchaotic Behaviour Obtained via a Nonlocal Operator with Exponential Decay and Mittag-Leffler Laws. *Chaos, Solitons & Fractals*, 102:285–294, Sep 2017.
 - [39] Ivo Petráš. A Note on the Fractional-Order Chua’s System. *Chaos, Solitons & Fractals*, 38(1):140–147, Oct 2008.
 - [40] Marius-F. Danca and Nikolay Kuznetsov. Matlab Code for Lyapunov Exponents of Fractional-Order Systems. *International Journal of Bifurcation and Chaos*, 28(05):1850067, May 2018.
 - [41] Karthikeyan Rajagopal, Sundarapandian Vaidyanathan, Anitha Karthikeyan, and Prakash Duraisamy. Dynamic Analysis and Chaos Suppression in a Fractional Order Brushless DC Motor. *Electrical Engineering*, 99(2):721–733, Oct 2016.
 - [42] Karthikeyan Rajagopal, Anitha Karthikeyan, and Prakash Duraisamy. Hyperchaotic Chameleon: Fractional Order FPGA Implementation. *Complexity*, 2017:1–16, 2017.
 - [43] Mamadou Diouf and Ndolane Sene. Analysis of the Financial Chaotic Model with the Fractional Derivative Operator. *Complexity*, 2020:1–14, Jun 2020.
 - [44] Wei-Ching Chen. Nonlinear Dynamics and Chaos in a Fractional-Order Financial System. *Chaos, Solitons & Fractals*, 36(5):1305–1314, Jun 2008.
 - [45] Karthikeyan Rajagopal, Akif Akgul, Sajad Jafari, Anitha Karthikeyan, Unal Cavusoglu, and Sezgin Kacar. An Exponential Jerk System, Its Fractional-Order Form with Dynamical Analysis and Engineering Application. *Soft Computing*, 24(10):7469–7479, Sep 2019.
 - [46] Ndolane Sene. Analysis of a Fractional-Order Chaotic System in the Context of the Caputo Fractional Derivative via Bifurcation and Lyapunov Exponents. *Journal of King Saud University - Science*, 33(1):101275, Jan 2021.
 - [47] Kolade M. Owolabi, José Francisco Gómez-Aguilar, G. Fernández-Anaya, J. E. Lavín-

- Delgado, and E. Hernández-Castillo. Modelling of Chaotic Processes with Caputo Fractional Order Derivative. *Entropy*, 22(9):1027, Sep 2020.
- [48] N. Sene. Mathematical Views of the Fractional Chua's Electrical Circuit Described by the Caputo-Liouville Derivative. *Revista Mexicana de Física*, 67(1 Jan-Feb):91–99, Jan 2021.
- [49] Zaid Odibat and Dumitru Baleanu. Numerical Simulation of Initial Value Problems with Generalized Caputo-Type Fractional Derivatives. *Applied Numerical Mathematics*, 156:94–105, Oct 2020.
- [50] M. Elbadri. An approximate solution of a time fractional Burgers' equation involving the Caputo-Katugampola fractional derivative. *Partial. Differ. Equ. Appl. Math.*, 8:100560, 2023.
- [51] N. Bhangale, K.B. Kachhia, and J.F. Gomez-Aguilar. A new iterative method with ρ -Laplace transform for solving fractional differential equations with Caputo generalized fractional derivative. *Eng. Comput.*, 38:2125–2138, 2022.
- [52] U.N. Katugampola. Existence and uniqueness results for a class of generalized fractional differential equations. Technical Report arXiv:1411.5229, arXiv, 2014.
- [53] Ricardo Almeida, Agnieszka B. Malinowska, and Tatiana Odziejewicz. Fractional Differential Equations With Dependence on the Caputo–Katugampola Derivative. *Journal of Computational and Nonlinear Dynamics*, 11(6), Sep 2016.
- [54] F. Jarad and T. Abdeljawad. A Modified Laplace Transform for Certain Generalized Fractional Operators. *Results in Nonlinear Analysis*, 1(2):88–98, 2018.
- [55] A. Abdoon, M. Elbadri, ABM. Alzahrani, M. Berir, and A. Ahmed. Analyzing the inverted fractional rössler system through two approaches: numerical scheme and lham. *Physica Scripta*, 99(11):115220, 2024.
- [56] K. Diethelm, N. Ford, and A. Freed. A predictor-corrector approach for the numerical solution of fractional differential equations. *Nonlinear Dyn.*, 29:3–22, 2002.
- [57] Mohamed A Abdoon. First integral method: a general formula for nonlinear fractional klein-gordon equation using advanced computing language. *American Journal of Computational Mathematics*, 5(2):127–134, 2015.
- [58] M. Elbadri, M.A. Abdoon, D.K. Almutairi, D.M. Almutairi, and M. Berir. Numerical Simulation and Solutions for the Fractional Chen System via Newly Proposed Methods. *Fractal Fract.*, 8:709, 2024.
- [59] F. Zhang, R. Chen, and X. Chen. Analysis of a Generalized Lorenz–Stenflo Equation. *Complexity*, 2017:1–6, 2017.
- [60] Chih-Jer Lin, Shyi-Kae Yang, and Her-Terng Yau. Chaos Suppression Control of a Coronary Artery System with Uncertainties by Using Variable Structure Control. *Computers & Mathematics with Applications*, 64(5):988–995, Sep 2012.
- [61] Awad El-Gohary. Chaos and Optimal Control of Cancer Self-Remission and Tumor System Steady States. *Chaos, Solitons & Fractals*, 37(5):1305–1316, Sep 2008.