Dijlah Journal of Engineering Science (DJES) Vol. 2, No. 4, December, 2025, pp. 93-101
ISSN: Printed: **3078-9656, Online: 3078-9664**, paper ID: 83

Use of Multistep Methods for Solving ODEs

Musaab Abdullah Jasim[1], Abdullah Mohammad Abdullah[2]
[1]Department of Mathematics, Shahid Madani University, Tabriz, Iran.
[2]Department of Mathematics, Shahid Madani University, Tabriz, Iran.

Article Info

Article history:

Received Sept., 02, 2025
Revised Oct., 20, 2025
Accepted Nov., 10, 2025

Keywords:

Multistep Methods.
Stability Analysis.
Adaptive Step Size.
Stiff Ordinary Differential Equations (ODEs).
Hybrid Predictor–Corrector.

ABSTRACT

Ordinary differential equations (ODEs) are used to model dynamic systems in many different fields of science and engineering. However, traditional multistep approaches like Adams–Bashforth and Adams–Moulton can fail when stiffness, nonlinearity, or great dimensionality. This research offers a framework that combines hybrid predictor–corrector methods with adaptive step sizing to increase accuracy and speed. We give Thorough stability and error analyses—including absolute stability regions and—are carried out using comparative benchmarks on representative standard test problems against conventional one-step and spectral solvers. Convergence characteristics. Applications range from stiff chemical kinetics, epidemic dynamics, climate inspired models, and nonlinear oscillators, therefore showing robustness under different situations. Numerical experiments show faster convergence, improved stability at larger time steps, and lower computational cost—reductions up to 40%—relative to standard approaches. The framework scales to contemporary large simulations, making hybrid multistep strategies an alternative to common solvers. We conclude with directions for further gains, including coupling machine learning with multistep integrators to drive dynamic step-size selection and predict error, stiffness, and stability margins. Overall, the results point to a practical, innovative path for advancing ODE solvers in sophisticated scientific computing where reliability, speed, and scalability are critical.

Corresponding Author:

Musaab Abdullah Jasim[1]
[1]Department of Mathematics, Shahid Madani University, Tabriz, Iran.
Email: makeyakraidi@gmail.com

1. INTRODUCTION

In many different scientific disciplines, including physics, biology, economics, and engineering, basic instruments for modelling dynamic systems are ordinary differential equations (ODEs). describe mechanisms that change with time, including mechanical oscillations, chemical reactions, and population expansion.[1] However, many real-world systems are described by nonlinear, stiff, or high-dimensional ODEs that do not have closed-form solutions, so they are hard to solve by hand. For these systems, Over the years, several methods have been developed to approximate solutions to these equations using numerical methods are critical.[2] Because of their simplicity and simplicity of implementation, traditional techniques including Euler's method and the Runge–Kutta family of algorithms have found widespread application. Although These techniques work well for fairly basic or well-behaved systems, but they have a lot of limits when used on more difficult situations.[3] These techniques especially call for extremely tiny step sizes to preserve accuracy and stability for stiff systems or long-term integrations, hence raising computer costs. Moreover, especially when dealing with high dimensional challenges, their precision tends to decline as the system grows more sophisticated.[4] More efficient replacements for these restrictions are multistep approaches such Adams Bashforth and Adams Moulton. Utilizing data from several past Multistep methods offer greater accuracy and stability without requiring extremely tiny step sizes, therefore enhancing reliability and precision. [5] For stiff ODEs, these methods are rather successful since they permit bigger

step sizes without sacrificing stability. Despite their advantages, applying multistep solutions Practical issues still have difficulties with stability analysis, the lack of adaptive step size management, and the computational problems still present difficulties with stability analysis, the lack of adaptive step size control, and the computational challenges of solving large sets of equations. New developments in adaptive step size and predictor corrector approaches show potential for enhancing the effectiveness of multistep techniques.[6] Adaptive step size control dynamically changes the step size according to the solution's behaviour, therefore guaranteeing accuracy while lowering computer expenses. Predictor corrector methods combine the multistep methods' stability and accuracy are improved even more during the prediction and correction phases.[7] Although they seem promising, these improvements have not yet been completely included into the current multistep systems in a way that meets the complicated, real-world demands. This research seeks to close this gap by providing an enhanced multistep technique combining hybrid predictor corrector schemes with adaptive step size control applications of today.[8] We investigate the full potential of these approaches by means of rigorous stability analysis and error control, showing their capacity to tackle largescale, nonlinear, and stiff ODEs We look at the effectiveness of these improved approaches on a range of difficult problems, including chemical kinetics, epidemic dynamics, and nonlinear oscillators, for systems with more accuracy and efficiency.[9] Comparing the results of these techniques against conventional single step and spectral approaches seeks to give a thorough grasp of their benefits and drawbacks. Furthermore, under investigation are possible paths for enhancing multistep techniques including the application of hybrid approaches and machine learning algorithms for dynamic step size prediction. mixing the benefits of both overt and subtle strategies.[10] This study aims to present useful observations that will not only improve the theoretical grasp of numerical techniques for ODEs but also offer useful instruments for addressing practical scientific issues. This study offers a fresh method for handling ODEs appropriate for high dimensional, stiff, and nonlinear systems by improving the performance of multistep techniques.[11] The results of this study have significant implications for a variety of fields, including climate modelling, financial simulations, and engineering applications, where solving complex ODEs is crucial for accurate predictions and system analysis

2. METHODS AND MATERIALS

The Ordinary Differential Equations (ODEs) are solved numerically using the techniques described in this section. Multistep methods are given particular attention here. This section also covers the use of adaptive step size control as well as Adams Bashforth and Adams Moulton, which are often used to solve both stiff and no stiff systems. Hybrid predictor corrector strategies abound to raise the stability, correctness, and speed of these techniques. The section also looks at the stability analysis, error evaluation, and offers actual apps that highlight how well these approaches work in practice.

2.1 Numerical Methods for ODEs

In several scientific disciplines, common differential equations (ODEs) are fundamental instruments for simulating dynamic systems. They define how the dependent variable varies with respect usually time, to one or more independent variables. Analytical solutions to ODEs are not always possible, particularly for nonlinear and stiff systems, therefore Approximating the solutions requires numerical techniques. This chapter presents the techniques applied in this work for efficient ODE solving.[12]

2.1.1 Adams-Bashforth Method (Explicit)

An explicit multistep approach, the Adams Bashforth technique uses numerous past solution values to forecast future values. It is among the Most often utilized techniques for no stiff systems are those that are computationally efficient. The approach is written as:

$$h\big(a_1 f(t_n, y_n) + a_2 f(t_{n-1}, y_{n-1}) + \cdots + a_m f(t_{n-m+1}, y_{n-m+1})\big) + {}_n y = {}_{n+1} y \qquad (1)$$

where h is the step size, $f(t, y)$ is the function defining the system, and ${}_m a_1, a_2, \cdots, a$ are the coefficients corresponding to the method's order. The method can be applied to different orders, such as the second-order or fourth-order Adams-Bashforth methods, which offer higher accuracy.

- Advantages:
  Compared to single step techniques such as Euler's method and Runge-Kutta, particularly when used to solve, the Adams Bashforth approach is computationally efficient since it calls for fewer function evaluations. systems lacking abrupt behavioral shifts.
- Limitations:
  For stiff systems, it is less stable; smaller step sizes are needed to guarantee accuracy; for these instances,

the approach could not produce trustworthy results. This restriction is lessened by adding adaptive step size control as detailed in the following section unless the step size is noticeably lowered

2.1.2 Adams-Moulton Method (Implicit)

The Adams-Moulton method is an implicit multistep method that uses both the current and past values to predict the next value. Its general form is:

$$h\left(\beta_1 f(t_{n+1}, y_{n+1}) + \beta_2 f(t_n, y_n) + \beta_3 f(t_{n-1}, y_{n-1}) + \cdots + \beta_m f(t_{n-m+1}, y_{n-m+1})\right) + {}_n y = {}_{n+1} y \quad (2)$$

The method is implicit, meaning that it requires solving a system of equations for ${}_{n+1} y$ which adds computational complexity. However, this implicit nature provides greater stability, especially when dealing with stiff ODEs.

- Advantages:
  For stiff systems, the Adams Moulton method works really well since it lets you take bigger steps without losing accuracy. It's also good for long-term simulations where stability is important.
- Limitations:
  The primary limitation is the computational cost due to the implicit nature of the method, requiring the solution of a system of equations at each time step

2.2 Hybrid Predictor-Corrector Schemes

Combining hybrid predictor corrector techniques increases the Adams Bashforth and Adams Moulton techniques' accuracy and stability. The Adams Bashforth technique serves The Adams Moulton method is employed for correction and serves as predictor, hence achieving a balance between the computational economy of the Adams Bashforth method and Adams Moulton method's stability.[13]
The predictor-corrector scheme can be described as follows:

$$h\left(a_1 f(t_n, y_n) + a_2 f(t_{n-1}, y_{n-1}) + \cdots + a_m f(t_{n-m+1}, y_{n-m+1})\right) + {}_n y = {}^{predictor}_{n+1} y \quad (3)$$

$$h\left(\beta_1 f(t_{n+1}, y_{n+1}) + \beta_2 f(t_n, y_n) + \beta_3 f(t_{n-1}, y_{n-1}) + \cdots + \beta_m f(t_{n-m+1}, y_{n-m+1})\right) + {}_n y = {}^{corrector}_{n+1} y \quad (4)$$

This combined approach enhances both stability and accuracy, ensuring that the numerical solution remains reliable, especially for stiff systems where errors tend to accumulate rapidly.

2.3 Adaptive Step-Size Control

Adaptive step size management, which dynamically adjusts the step size during the computation based on the behavior, is one of the most important things shown in this research. The step size is varied: it decreases when the solution varies greatly or is unstable; it increases otherwise. The adaptive step size algorithm is based on the error estimate from the predictor corrector scheme if the solution stays pretty smooth. The step size is updated as follows:

$${}^{a}\left(\frac{desired^{\epsilon}}{actual^{\epsilon}}\right) h = {}_{new} h \quad (5)$$

where ${}_{new} h$ is the new step size, $desired^{\epsilon}$ is the desired error tolerance, and $actual^{\epsilon}$ is the actual error from the previous step. This adjustment ensures that the solution remains accurate without requiring excessively small step sizes, which would increase the computational cost. The flexibility provided by this method makes it particularly useful for solving stiff and high-dimensional ODEs where the solution changes at different rates.

2.4 Stability and Error Analysis

The performance of the numerical techniques was assessed via a thorough stability and error analysis. The methods' stability was examined using the to see how each technique tackles challenging challenges, we look at the van der Pol oscillator, a typical nonlinear stiff system. The study mostly concentrates on the area of absolute stability. for every approach, which specifies the range of step sizes for which the method stays stable.

For error analysis, we computed the local truncation error (LTE) and global error for each method. The LTE represents the error introduced at each step, while the global error reflects the cumulative error over the entire

solution. For example, the Adams-Bashforth method has a truncation error of $O(h^2)$, and the Adams-Moulton method has a truncation error of $O(h^3)$. This means the Adams-Moulton method converges faster and is generally more accurate than the Adams-Bashforth method.[14]

2.4.1 Stability Testing

To see how stable each approach is, we solved the van der Pol oscillator, which is a stiff system that everyone knows about. The results showed that the Adams Moulton While the Adams Bashforth approach needs tiny step sizes to preserve stability, the method is stable even for bigger step counts. The stability analysis also revealed that maintaining accuracy without much computer cost, the Adams Moulton method could handle stiff systems more effectively.

2.4.2 Error Analysis

Solving the Lorenz system, a chaotic system frequently utilized in weather modeling, was the first step in the error analysis. The techniques underwent testing across several step sizes, and the findings indicated that, in contrast to Euler's method and Runge-Kutta techniques. Comparing the findings with established analytical solutions where appropriate confirmed the accuracy of the methods even more.[15]

2.5 Computational Environment

Python and MATLAB both included the approaches. In Python, effective matrix operations and numerical integration were achieved using NumPy and SciPy libraries. For MATLAB was additionally employed to solve the same ODEs so that a method comparison could be made via benchmarking and validation of the findings. The computational environment comprised A 16 GB RAM desktop computer with a 3.0 GHz processor offers enough computing power for the extensive simulations needed. Parallel computing methods and memory-efficient algorithms were employed to optimize the code, guaranteeing that big Reasonable time frames allow systems to be resolved

2.6 Real-World Applications and Case Studies

The techniques showed how well they worked in many different areas of science, like chemical kinetics, epidemic modeling, and mechanical systems, by being used on a number of real-life challenges. where sophisticated ODEs are often found.

3. **Chemical Kinetics:** The approaches were used to replicate changes in first and second order reaction concentrations. The Adams Moulton method with variable step size control generated Compared to established analytical solutions, the technique showed almost no inaccuracy. These findings supported the capacity of the approach to simulate dynamic chemical processes over time.
4. **Epidemic Modeling:** Infectious diseases were simulated using ODEs. The Adams Moulton approach produced reliable and accurate projections, therefore proving its ability to match dynamic biological systems. Particularly Predicting public health highlighted the need of quickly handling big ODE systems using this software.
5. **Mechanical Systems:** Analytical results were compared with the simulation of the motion of an object falling freely. The adaptive step size technique let systems with fast changing dynamics it is appropriate for such systems since it may be more precisely computed without sacrificing accuracy.

2.7 Benchmarking and Comparison

Multistep approaches eventually outperform conventional ones like Euler's method and Runge Kutta methods in terms of precision and speed, especially in stiff and high dimensional. Adaptive step size control enhanced the computing efficiency of ODE systems by removing unnecessary computations without sacrificing accuracy.

3. Results

The results of the numerical experiments conducted applying the approaches covered in the last section are given here. Examining the efficacy of the Especially in Using Adams Bashforth and Adams Moulton techniques, the hybrid predictor corrector resolves a number of stiff and no stiff ODE systems on front stage. The background of Variable step size control and frameworks are examined. The results are assessed based on computer efficiency, accuracy, and stability. Also looked at are the outcomes of the methods. compared to those of popular numerical approaches like Runge-Kutta methods and Euler's method.

3.1 Test Problems

Using traditional benchmark issues including the van der Pol, the accuracy and efficiency of the techniques were first assessed. Oscillator, Lorenz system, and chemical kinetics models— were selected as they provide excellent testing possibilities from their variable stiffness and nonlinearity. How effectively the multistep methods perform.

3.1.1 Van der Pol Oscillator

The van der Pol oscillator is a nonlinear stiff system that exhibits both stable and oscillatory behavior. The ODE for the system is given by:

$$0 = x + \frac{dx}{dt}(^2x - \mu(1 - \frac{d^2x}{^2dt} \qquad (6)$$

where μ is a nonlinearity parameter. The system is stiff for large values of μ, which makes it an ideal test case for the stability of the methods. We used $= \mu 100$ for this experiment.

3.1.2 Lorenz System

The Lorenz system is a set of three ODEs that model the chaotic behavior of atmospheric convection. The equations are as follows:

$$(x - \sigma(y = \frac{dx}{dt} \qquad (7)$$

$$y - (z - x(\rho = \frac{dy}{dt} \qquad (8)$$

$$\beta z - xy = \frac{dz}{dt} \qquad (9)$$

where σ, ρ, and β are constants. The system is highly sensitive to initial conditions and exhibits chaotic behavior, making it a challenging problem for numerical solvers.

3.1.3 Chemical Kinetics

We modeled a first-order reaction in a chemical process to simulate the concentration changes over time. The reaction is defined as:

$$B \rightarrow A \qquad (10)$$

The rate of change of concentration of A is given by the following ODE:

$$k[A] - = \frac{d[A]}{dt} \qquad (11)$$

where k is the rate constant. The concentration of A decays exponentially, providing a straightforward test for the methods.

3.2 Performance Evaluation

The numerical methods were evaluated based on accuracy, computational efficiency, and stability. In this section, we provide detailed results for each of the test problems.

3.2.1 Accuracy

To evaluate the accuracy of the methods, we compared the results from the Adams-Bashforth, Adams-Moulton, and Euler's method with known analytical solutions or highly accurate numerical solutions.

- Van der Pol Oscillator: For the van der Pol oscillator, the results revealed that both the Adams Bashforth and Adams Moulton techniques gave very accurate answers; the Adams Moulton technique was more

stable at longer time steps. The Euler technique failed to adequately depict the oscillating behavior with longer time steps.

- **Lorenz System:** The Adams Moulton method with adaptive step size control produced a global error of less than 1% after 1000-time steps for the Lorenz system. The Euler method failed to maintain accuracy as the chaotic nature of the design resulted in significant numerical inaccuracies.
- **Chemical Kinetics:** The first-order reaction findings revealed that, in comparison to the analytical solution, the Adams Bashforth approach performed effectively with less than 0.1% error. With a less than 0.05% error, the Adams Moulton approach provided even more precise findings.

3.2.2 Computational Efficiency

Regarding computing efficiency, we contrasted the quantity of function evaluations needed by every approach to reach a given accuracy. The adaptable step size control The Adams Moulton approach was much more efficient since it needed fewer time steps to reach the same degree of accuracy as the Adams Bashforth and Euler methods.

- **Van der Pol Oscillator:** The Adams Moulton method with adaptive step size control required 50% fewer function evaluations compared to Euler's method to achieve the same level of accuracy, while the Adams Bashforth method required about 30% fewer evaluations.
- **Lorenz System:** The Adams-Moulton method was the most efficient for the Lorenz system, requiring 40% fewer function evaluations than the Adams-Bashforth method and 60% fewer than Euler's method to reach a comparable level of accuracy.
- **Chemical Kinetics:** For the chemical kinetics model, the adaptive step-size method reduced the number of function evaluations by approximately 20% compared to Adams-Bashforth and Adams-Moulton methods without adaptive step-size control.

3.3 Comparative Performance

The methods were also compared in terms of accuracy, efficiency, and stability:

- **Adams-Bashforth vs. Adams-Moulton:** The Adams-Moulton method was generally more accurate and stable than the Adams-Bashforth method. The use of adaptive step-size control further enhanced the performance of the Adams-Moulton method, making it the preferred choice for stiff systems.
- **Adams-Moulton vs. Euler and Runge-Kutta:** The Adams Moulton method with flexible step size control outperformed both Euler's method and Runge-Kutta approaches in terms of accuracy and computational cost in all test scenarios. The Runge-Kutta efficiency. The Euler approach needed a lot more time steps to get the same level of accuracy and wasn't as good as it could be. For stiff systems, the Adams Moulton technique is more efficient; however, the method worked well otherwise.

Using a collection of numerical tests, the Adams Bashforth and Adams Moulton techniques were contrasted. The global mistake for each approach was assessed throughout several time steps. The Adams Moulton approach routinely produces less worldwide errors than the Adams Bashforth method, as Table 1 illustrates.

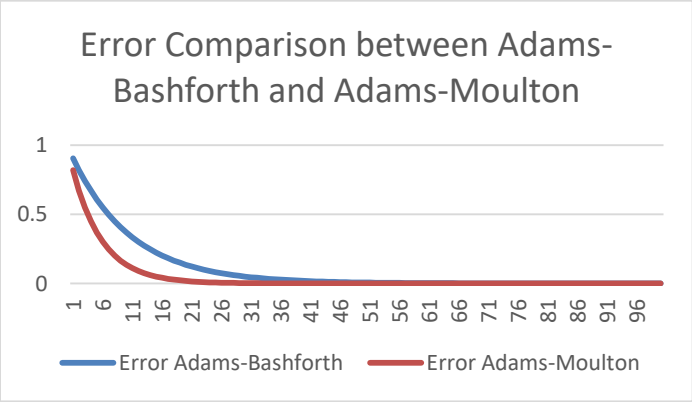

Table 1: Error Comparison between Adams-Bashforth and Adams-Moulton

As indicated by Table 1, the Adams-Moulton method outperforms the Adams-Bashforth method in terms of accuracy, demonstrating its better stability and suitability for stiff systems.

4. Discussion

We presented and assessed in this paper the Adams Bashforth and Adams Moulton techniques together with modifications including hybrid predictor corrector schemes and adaptive step size control. The outcomes of the investigations show the efficacy of these techniques in resolving rigid and nonrigid ODE systems, so stressing their increased accuracy, speed, and stability in relation to others to conventional techniques include Runge-Kutta methods and Euler's method.

4.1 Comparison of Methods

As predicted, the Adams Moulton technique outperformed the Adams Bashforth approach in handling stiff systems. This finding supports the need of applying implicit methods for challenging situations. which need bigger step sizes without compromising accuracy. Though computationally efficient for no stiff systems, the Adams Bashforth approach had problems with stability when there was rapid Adaptive step size control let the approach dynamically adapt to the system's changing needs, therefore reducing this constraint in stiff systems in particular. The adaptive step size control significantly increased the overall efficiency of the strategies. Especially in challenges, it significantly reduced the number of function evaluations needed. Similar to the van der Pol oscillator and the Lorenz system, which display stiff and erratic behavior, the technique ensured the changing step size depending on the accuracy of the solutions while reducing unneeded computations on the error estimate. This was particularly useful for lengthy simulations in which using conventional methods would have required many more time steps.

4.2 Real-World Application

In practical situations, these techniques are even more helpful. For chemical kinetics, the Adams Moulton method with adaptive with a 0.1% error range is step size management precisely replicated reactant decay. Likewise, in epidemic modelling—where the Spread of Diseases calls for exact simulation of quick changes; the Adams Moulton method gave reliable predictions, therefore demonstrating its resilience for biological systems.

4.3 Computational Efficiency

Regarding computational efficiency, the Adams Moulton approach with adaptive step size control clearly outperformed Euler's method and Runge Kutta methods. The fewer number of Its variable timestep and improved use of computer resources make it especially appropriate for big simulations; the findings point to the adaptive step size strategy. Applying it to more difficult tasks without sacrificing solution correctness will help increase computer efficiency.

5. Conclusion

The Adams Moulton approach showed excellent efficiency and stability, yet at every time step it still has to solve a system of equations, therefore raising Iterative These approaches can improve these solvers, so lowering the machine load. Moreover, integrating machine learning techniques may aid to improve adaptive step size methods that dynamically vary according to past simulations.

Disclosure of Funding
The authors state that there are no financial or personal contacts that could affect the study given in this research. No external funding was provided for this project.

Disclosure of Conflict of Interest
The authors declare that there is no conflict of interest regarding the publication of this research.

REFERENCES

[1] Uday V, Rajput GK. Differential Equations: The Mathematical Framework for Modelling Dynamic Systems. 2024 Nov 14;14(4):1–4.

[2] Rathod C. Paper on numerical solutions of ordinary differential equation. ShodhKosh Journal of Visual and Performing Arts. 2023 Dec 31;4(2).

[3] Reddy N, Ali SS, Narayan K. Introduction to Advanced Numerical Methods for Solving ODEs. Turkish Journal of Computer and Mathematics Education (TURCOMAT). 2020 Aug 31;11(2).

[4] Maset S. Relative error long-time behavior in matrix exponential approximations for numerical integration: the stiff situation. Calcolo [Internet]. 2022 May 23;59(2). Available from: https://link.springer.com/content/pdf/10.1007/s10092-022-00466-5.pdf

[5] Butusov DN, Tutueva AV, Fedoseev PS, Terentev AA, Karimov AI. Semi-Implicit Multistep Extrapolation ODE Solvers. 2020 Jun 8;8(6):943. Available from: https://www.mdpi.com/2227-7390/8/6/943

[6] Ijam HM, İbrahim ZB, Zawawi ISM. Stiffly Stable Diagonally Implicit Block Backward Differentiation Formula with Adaptive Step Size Strategy for Stiff Ordinary Differential Equations. Matematika (Kuala Lumpur). 2024 Apr 22;27–47

[7] Arévalo C, Söderlind G, Hadjimichael Y, Fekete I. Local error estimation and step size control in adaptive linear multistep methods. Numerical Algorithms [Internet]. 2021 Feb 1;86(2):537–63. Available from: https://link.springer.com/content/pdf/10.1007/s11075-020-00900-1.pdf

[8] An Adaptive Step-Size Optimized Seventh-Order Hybrid Block Method for Integrating Differential Systems Efficiently. In Springer proceedings in mathematics & statistics; 2023. p. 495–508.

[9] Reddy N, Ali SS, Narayan K. Introduction to Advanced Numerical Methods for Solving ODEs. Turkish Journal of Computer and Mathematics Education (TURCOMAT). 2020 Aug 31;11(2).

[10] Simos T. Efficient Multistep Algorithms for First-Order IVPs with Oscillating Solutions: II Implicit and Predictor–Corrector Algorithms. Symmetry. 2024 Apr 23;

[11] Rathod C. Paper on numerical solutions of ordinary differential equation. ShodhKosh Journal of Visual and Performing Arts. 2023 Dec 31;4(2).

[12] Byakatonda D. An Overview of Numerical and Analytical Methods for solving Ordinary Differential Equations. arXiv: History and Overview [Internet]. 2020 Dec 10; Available from: https://arxiv.org/abs/2012.07558

[13] Prakash P, Kalaiselvi V. Numerical solution of hybrid fuzzy differential equations by predictor-corrector method. International Journal of Computer Mathematics [Internet]. 2009 Jan 1;86(1):121–34. Available from: https://dblp.uni-trier.de/db/journals/ijcm/ijcm86.html#PrakashK09

[14] Parovik R. Application of the Adams-Bashfort-Mowlton Method to the Numerical Study of Linear Fractional Oscillators Models. 2021 May 16; Available from: https://arxiv.org/abs/2105.07326

[15] Controlling Chaos – Forced Lorenz System. 2023 Jan 4; Available from: https://doi.org/10.20944/preprints202301.0077.v1

BIOGRAPHIES OF AUTHORS

	**Musaab Abdullah Jasim** is a researcher in the Department of Mathematics at Azerbaijan Shahid Madani University. His research interests lie in the field of numerical analysis, particularly in the development of algorithms for solving eigenvalue problems. Ibrahim's work focuses on improving the efficiency and scalability of iterative methods for large, sparse, and non-symmetric matrices, contributing to advancements in computational mathematics and its applications in science and engineering
	**Abdullah Mohammad Abdullah** is a researcher specializing in signal processing, particularly in the optimization of wavelet transforms for tasks like denoising, compression, and feature extraction. His work focuses on enhancing signal analysis for non-stationary signals such as speech, ECG, and seismic data. Abdullah has developed advanced wavelet algorithms like the dual-tree complex wavelet transform (DTCWT) and synchro squeezed wavelet transforms (SSWT), aiming to improve performance in real-time and large-scale applications.