STM JOURNALS

Journal of
Software Engineering Tools & Technology Trends

ISSN: 2394-7292
Volume 13, Issue 1, 2026
January–April
DOI (Journal): 10.37591/JoSETTT

https://journals.stmjournals.com/josettt

Review JoSETTT

A Review of an Artificial Neural Network Based Single-Step Method for Solving Engineering Problems

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Abstract

Artificial neural networks (ANNs) have become one of the most powerful computational approaches for solving highly complex and nonlinear problems in science and engineering. Owing to their data-driven learning nature and strong approximation capabilities, ANNs are able to model intricate functional relationships that are often difficult to represent using traditional analytical techniques. Their ability to learn from data, identify hidden patterns, and adapt to varying problem conditions has made them an essential tool in advancing modern technology and scientific research across diverse application areas. This review focuses on the integration of ANN frameworks with fractional calculus–based numerical methods, specifically single-step Caputo-type, Atangana–Baleanu, and conformable fractional approaches, for the solution of nonlinear equations frequently encountered in engineering systems. These hybrid methodologies combine the theoretical strength of fractional operators with the learning efficiency of neural networks to improve solution accuracy and robustness. A comparative assessment of existing studies demonstrates that ANN-assisted fractional models consistently achieve superior performance when compared with conventional numerical techniques. Improvements are observed in terms of reduced approximation error, lower computational cost, and fewer iterations required for convergence. The findings highlight the effectiveness of neural network based strategies as reliable and efficient alternatives for solving complex nonlinear engineering problems, reinforcing their growing significance in computational modeling and applied mathematics.

Keywords: Artificial neural networks, Atangana–Baleanu fractional method, Caputo-type fractional derivative, computational modeling, conformable fractional method, nonlinear engineering problems, numerical analysis, single-step methods

INTRODUCTION

Artificial neural networks (ANNs) have become powerful computational tools for solving complex nonlinear problems in science and engineering. It mimics the information processing of the human brain by using interconnected neurons to learn and solve complex problems.

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Received Date: January 15, 2026
Accepted Date: January 22, 2026
Published Date: February 24, 2026

Citation: Shailja Agarwal. A Review of an Artificial Neural Network Based Single-Step Method for Solving Engineering Problems. Journal of Software Engineering Tools & Technology Trends. 2026; 13(1): 13–17p.

Their ability to model these complex patterns makes them useful across multiple domains and is valuable for advancing technology and scientific understanding, where numerical methods are used to train to solve complex mathematical problems. From an application perspective, ANNs are widely used in various areas of science and engineering.

In biomedical engineering [1], we have witnessed advancements in computational modeling and simulation largely driven by advances in artificial intelligence (AI) and machine learning (ML) techniques.

Among these, ANNs are widely used for solving complex and nonlinear problems because they can approximate nonlinear functions with high accuracy.

For differential equations in biomedical systems, ANN-based single-step methods are particularly promising owing to their flexibility, adaptability, and ability to learn complex patterns from data. Traditional numerical methods, such as the finite difference, finite element, and Runge–Kutta [2] approaches, often face difficulties with highly nonlinear or stiff biological problems. The single-step ANN approach overcomes these challenges by approximating derivatives and solutions directly in a single iteration, reducing the computational time, and improving the convergence. Applications include bioheat transfer, neural activity modeling, and cardiac electrophysiology, and these methods have demonstrated improved accuracy and efficiency compared to conventional techniques.

In mechanical engineering, structural mechanics [3] involves analyzing complex systems composed of different structural components, such as membranes and cables. Terahara et al. (2023) described the T-splines computational method applied to a wind-tunnel model of a disk-gap-band spacecraft parachute, demonstrating its effectiveness in handling 2D membranes and 1D cable connections with continuity and smoothness. Traditional numerical methods can address such multidimensional, nonlinear problems, but ANN-based single-step fractional methods provide an efficient alternative by approximating derivatives and solutions in a single iteration. These approaches improve accuracy, reduce computational time, and enhance convergence, making them suitable for analyzing complex structural mechanics problems such as vibrations, stress-strain modeling, and parachute deployment simulations.

In electrical and control engineering, ANN-based single-step fractional methods are increasingly being used for modeling and controlling complex systems. Power electronics form a fundamental component of smart grid infrastructures by supporting renewable energy source integration, efficient power generation and distribution, advanced grid control, and energy storage management [4]. These systems involve highly nonlinear dynamics and require fast and accurate solutions that can be efficiently handled using ANN-based approaches. Similarly, in vehicle control systems, Chen et al. (2023) [5] demonstrated how neural networks and fuzzy logic controllers can improve the lateral stability for distributed electric vehicles, ensuring smooth and safe operation even under challenging conditions such as low-adhesion roads. These examples demonstrate that ANN-based single-step methods are effective for real-time control, smart grids, automation, and vehicle stability analysis in complex electrical and control engineering systems.

In chemical and process engineering, ANN-based single-step fractional methods have been applied to model complex biochemical and chemical reaction systems. For example, Akgül and Khoshnaw (2020) [6] explored fractional-order derivatives in nonlinear enzyme inhibitor reaction models and demonstrated that these derivatives capture memory effects often overlooked by classical integer-order methods. Using a numerical scheme based on fractional calculus, this study efficiently approximated the solutions for complex nonlinear biochemical networks. Such ANN-based fractional approaches improve accuracy, convergence, and computational efficiency, making them valuable tools for simulating and analyzing chemical kinetics, nonlinear reaction-diffusion systems, and other complex process engineering problems.

Motivated by the above work, in this review paper, we focus on the study of ANN-based single-step fractional methods, including Caputo-type [7], Atangana–Baleanu [8, 9], and conformable approaches [10], and their applications in biomedical, mechanical, electrical, and chemical engineering problems. We highlight the computational frameworks, advantages, and performance of these methods in solving nonlinear equations, emphasizing their superior accuracy, reduced computational time, and improved convergence compared with traditional numerical techniques. By providing a comprehensive overview in this review, we demonstrate the potential of ANN-based single-step fractional methods as efficient and intelligent tools for addressing complex engineering challenges across multiple domains.

ARTIFICIAL NEURAL NETWORK BASED METHODS

Artificial neural networks are computational models that consist of multiple interconnected processing units organized in layered architectures, known as neurons. ANNs establish the relationship between the input and output data by iteratively adjusting the model parameters during training. To solve the differential equations, the ANN approximates the unknown solution function using weights and biases adjusted to minimize an error function derived from the governing equations.

In ANN-based numerical techniques, a trial solution is constructed using neural network functions that automatically satisfy the initial or boundary conditions. The learning process involves minimizing the residual error of the governing differential equation, typically using gradient-based optimization or evolutionary algorithms. Compared with traditional numerical schemes, ANN-based methods can handle complex geometries and nonlinearities without requiring mesh generation.

The single-step variant of ANN-based methods further enhances computational efficiency by obtaining the solution at each step independently, rather than relying on iterative multistep corrections. This approach has been successfully applied in various engineering contexts where real-time computation and adaptive learning are crucial.

SINGLE-STEP METHODS IN NUMERICAL MODELING

Single-step methods are numerical schemes that advance the solution of a differential equation from one point to the next using only the information from the current step. Classic examples include the Euler and Runge–Kutta methods [2]. When combined with ANNs, single-step techniques enable the network to predict the next state of the system directly from the current conditions, eliminating the need for multistep iterations and improving computational efficiency.

In recent studies, ANN-based single-step fractional methods, including Caputo-type, Atangana–Baleanu, and conformable approaches, have been formulated to solve nonlinear differential equations in engineering applications. These methods allow the ANN to approximate the solution while incorporating memory and non-local effects inherent in fractional derivatives. In engineering systems, the network is trained to minimize the difference between the predicted and theoretical derivatives and to efficiently learn the temporal evolution of complex processes such as diffusion, reaction kinetics, and electrophysiological behavior.

Comparative Analysis and Discussion

In comparison, ANN-based single-step fractional methods provide a flexible framework for solving nonlinear differential equations for various engineering applications. While traditional numerical methods often struggle with stiff or highly nonlinear systems, integrating fractional derivatives with ANN-based single-step approaches improves accuracy, convergence, and computational efficiency. Among these methods, the Caputo-type method is widely used and directly incorporates initial conditions. Atangana–Baleanu captures smoother memory effects with a non-singular kernel, and conformable methods offer computational simplicity for real-time applications. Each method has advantages and limitations, and the choice depends on the complexity of the problem, required accuracy, and computational resources shown in Table 1.

Limitations

Despite their growing success, ANN-based single-step fractional methods provide enhanced accuracy and computational efficiency compared to classical techniques; each fractional approach has specific limitations.

Caputo-type methods can be computationally expensive for long-time simulations owing to their memory-dependent nature.

Table 1. Comparison of fractional derivative methods in modeling and computation.

Method	Advantages	Limitations
Caputo-type fractional technique	• Well-established and widely used. • Directly incorporates initial conditions. • Suitable for many engineering problems.	• Computationally expensive for long-time simulations. • May require fine discretization for stiff problems.
Atangana–Baleanu (AB)	• Non-singular, non-local kernel reduces numerical instability. • Smooth memory effect modeling. • Better captures complex dynamics.	• Less widely used, fewer standard implementations. • Computationally becomes more complex than the simple Caputo in some cases.
Conformable fractional method	• Local derivative formulation simplifies computation. • Easier to implement in ANN-based single-step methods. • Reduces computational cost.	• May not capture long-memory effects accurately. • Less suitable for strongly non- local systems.

Atangana–Baleanu methods, although better at capturing smooth memory effects and reducing numerical instability, are less widely implemented and may require higher computational effort.

Conformable methods are computationally simple and easier to integrate with ANN frameworks; however, they may not fully capture long-memory or non-local effects in complex systems.

CONCLUSION AND FUTURE DIRECTIONS

This review highlights the ability of ANN-based single-step fractional methods, including Caputo-type, Atangana–Baleanu, and Conformable approaches, as efficient and adaptive tools for solving complex nonlinear equations in biomedical, mechanical, electrical, and chemical engineering applications. These methods offer significant advantages over traditional numerical schemes, including improved accuracy, computational efficiency, and the ability to handle nonlinearities without mesh generation. They have been successfully applied to bioheat transfer, structural mechanics, smart grid systems, vehicle control, and chemical reaction networks, demonstrating their versatility and effectiveness.

From the above comprehensive study and performance comparison, the Caputo-type is generally preferable for accuracy and versatility in engineering problems. Atangana–Baleanu is ideal when smooth memory effects and stability are critical. Conformability is recommended for problems that require fast computation with moderate accuracy.

Despite these strengths, challenges remain, including limited interpretability, computational costs, stability issues in stiff systems, and the need for careful network design and hyperparameter tuning. Future research should focus on hybrid modeling approaches, physics-informed neural networks (PINNs), transfer learning, uncertainty quantification, and explainable AI (XAI) to enhance robustness, transparency, and applicability. Overall, ANN-based single-step fractional methods represent a promising and powerful framework for addressing complex engineering problems and paving the way for intelligent, reliable, and scalable computational solutions across multiple domains.

Future research should combine the strengths of these methods while mitigating their limitations. Strategies include developing hybrid approaches that integrate Caputo, Atangana–Baleanu, and Conformable derivatives depending on problem requirements; improving numerical schemes for faster convergence; and exploring adaptive ANN architectures to efficiently handle complex, stiff, or nonlinear systems. Additionally, incorporating PINNs, transfer learning, uncertainty quantification, and explainable AI (XAI) can enhance robustness, transparency, and interpretability, making these methods more practical for real-world engineering applications in biomedical, mechanical, electrical, and chemical domains.

Acknowledgement

The authors are thankful to the reviewers for their valuable suggestions for improving this paper.

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