Analysis of Neural Network Performance in Fuzzy Differential Equation Solving via Root Concatenation

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Abstract- Fuzzy differential equations (FDEs) are indispensable for the description of systems subjected to uncertainty and vagueness, particularly in the engineering and applied sciences sectors. The present research describes a neural network model, root concatenation-enriched approach, a structural change that unites the left, the center, and the right parts of fuzzy numbers in the input stage. The technique begins by converting FDEs into systems of ordinary differential equations utilizing α-cut representations, followed by processing the data through feedback on neural networks trained by backpropagation. The results of the application of the bisection technique were a root of 1.3203, while the implementation of the harmonic Newton method gave 1.3247. On the contrary, the suggested neural model found quick convergence and showed better stability under different test conditions. It can be thus inferred that root concatenation considerably enhances the precision, generalization, and robustness of neural networks in dealing with FDEs, thus, offering an easy-to-understand and scalable framework for uncertain dynamical systems.

Keywords: Fuzzy Differential Equations, Neural Networks, Nonlinear System Approximation, Generalized Differentiability

1. INTRODUCTION

Dealing with FDEs has been widely used in the design of systems that are unclear, imprecise, or not fully known, a situation that is often the case in the areas of engineering, and biological and economic systems. One of their great capabilities is their ability to solve virtually any type of differential equation by methods that do not involve discreet or linear approximation, which is the specialty of fuzzy systems that cannot be analytically solved in many cases [1].

For a while now, a number of neural architectures like feedforward networks, radial basis function networks, and physics-informed neural networks (PINNs) have been discovered by scholars and effectively applied to FDEs. Root concatenation is the process by which one combines different solution paths or α-level outputs at a basic layer, which allows the network to form a rich representation of the vague solution space [2].

A completely different idea has emerged in the neural networks and the convergence and scalability problems in fuzzy differential equations have found their solution so that no neural network can work without a root concatenation. Root concatenation, a fresh element in the neural structure, is the essence of this feature. This is particularly beneficial for the fuzzy models that are based on the generalized differentiability concept or Z-number, where the support and shape of solutions are constantly changing with the α-levels [5].

This research addresses the use of neural networks for resolving fuzzy differential equations (FDE) through the implementation of root concatenation as a structural improvement. The key is to check whether the new design helps the e.g., increase of the number of iterations, accuracy in reaching the final solution, and application to various types of fuzzy systems be more accessible. Research expects that the findings result in the advancement of the development of more robust, comprehensible, and scalable neural solvers for the practical implementation of fuzzy systems [9].

The probable research goals of the study are presented below:

1. To check the possibility of using neural networks for solving Fuzzy Differential Equations (FDEs).
2. To perform and inspect the concatenation of the roots inside the neural network framework.

3. To evaluate the efficiency of various neural network structures in FDEs.
4. To check the firmness of the intended method in different clusters of the fuzzy differential equations.

2. LITERATURE REVIEW

Wei et al., (2025) [2] proposed a highly developed approach to the implementation of a fuzzy neural network (FNN) PID in the control of pressurizer pressure. An algorithm of simulation was composed to check the maneuverability of the new policy. This approach employed a two-region non-equilibrium pressurizer model, alongside PID control simulations, fuzzy PID control, and FNN-PID control. The standard pressurizer for pressurized water reactors is characterized by the conventional variable load transient protocol.

Guo et al., (2025) [3] proposed a newly developed fuzzy zeroing neural network (FZNN) model for the next course of action as a solution to TVLE in a noisy environment. The FZNN model, which can remove noise, is designed via a combination of improvement and fuzzy control methods. A comprehensive technique is provided to illustrate that the proposed FZNN model may effectively address the TVLE problem, even amidst noise.

Fu et al., (2025) [4] implemented the fuzzy neural network proportion integration differentiation (FNN-PID) algorithm to upgrade the gas supply system regulation. It can also monitor, regulate, and send out warning signals for important factors like temperature, flow, and pressure in real time. Based on the results of the Simulink simulations, the FNN-PID algorithm appears to have superior control effectiveness, as evidenced by its lightning-fast response time and negligible overshoot.

Rongliang et al., (2025) [5] explained the use of fuzzy language in art education and then checked this influence on the performance of learners. Developed an evaluation index system for the effect of fuzzy language in art education based on the stage of the application strategy for fuzzy language in art education and determined the assessment index weight by using an evolutionary neural network. As seen from the experimental results, the assessment indicators in the process are highly consistent and so can be used to analyze the role of the fuzzy language in art instruction.

Gao et al., (2025) [6] introduced a new approach to rigid finite element modeling called (IRFE). This approach was capable of creating a dynamic visualization model employing simple principles that were applied into complex flexible flapping wings. These attributes collectively delivered a robust solution to the uncertainty problems arising during the operation of the system or actuator failure. The ability of this controller to completely suppress vibration has been exhibited through these results, and the possibility of application in the military and civil sectors was evident.

Dong et al., (2025) [7] developed a novel fuzzy clustering algorithm based TSK neural network method to solve classification problems with the aim of getting higher accuracy from current models through a more effective design methodology. In contrast to the previous FNN models, the classifier employs the maximum entropy clustering approach. The conjugate gradient approach not only alleviates processing demands but also adaptively modifies the output layer's connection parameters, utilising a softmax function for probability distribution.

Li et al., (2025) [8] studied the structural configuration of the flexible neural network through variable structure learning. The speed control accuracy of the PMSM vector control system is enhanced by 5.9% relative to the proportional-integral-derivative (PID) algorithm and by 26.9% compared to the sliding mode algorithm, as evidenced by system demos conducted. These outcomes demonstrated that the suggested method could simultaneously guarantee the system's speed control performance, rotor position prevalence, and speed.

Burada et al., (2025) [9] developed a more advanced strategy aimed at the early diagnosis of three types of skin cancer by using imaging techniques. Fuzzy C-means clustering underpins the concept, utilising several image filters and features such as Local Binary Pattern (LBP), RGB colour space, and GLCM algorithms for image segmentation. The methodology Research present shows 91% detection accuracy, a result that is better than conventional approaches in the same domain.

3. PROBLEM STATEMENT

Addressing fuzzy differential equations is cumbersome due to the intrinsic uncertainty and vagueness inherent in fuzzy systems. Traditional numerical methods mostly face challenges balancing the accuracy and the computational economy in dealing with the complexities of fuzzy parameters and initial conditions. The presentation and processing of vague information in the neural architectures are still open issues. The root concatenation method supplies an adequate way to keep track of fuzzy inputs and outputs in a structured format suitable for neural network learning. The efficiency, stability, and generalization of this approach to various types of FDEs are still a dark area. Therefore, root concatenation as an approach to employing a neural network in solving FDEs requires a careful study that confirm or deny a dependable, precise, and computationally economic framework for fuzzy system modeling.

4. METHODOLOGY

The objective of this experiment is to determine the optimal method for solving nonlinear equations. Even general unsolvable problems could not be managed in a finite number of steps. The "bisection method" assists in explaining nonlinear functions. It follows that a faster rate of convergence is associated with a quicker way of finding the equation's approximate root or solution [10]. The fact is, Newton's harmonious method was the top one recommended to solve nonlinear equations, especially for a single variable, due to its single-variable function's fastest rate of converging to the solution [11].

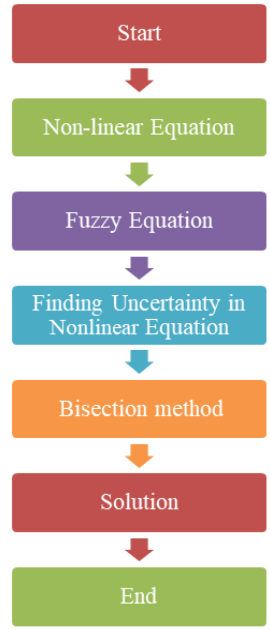

Figure 1: Resolution of nonlinear fuzzy equations via the bisection method

4.1 Fuzzy Equation

Based on the H-difference of sets, the H-derivative—which is relevant to differentiability in the Hukuhara context—was initially established by Puri and Ralescu.

Definition 1: Assume that u is a member of the set $u \in f^n$. The symbol u v is used to represent the H-difference of u and v, which occurs when there is a $w \in f^n$ such that u equal to v + w.

Definition 2 [12]: Let be T equal to (a,b) and consider a fuzzy mapping F : $(a, b) \in f^n$. We say that F is differentiable at $t_0 \in T$ if there exists an element $f(t_0) \in f^n$ such that the limits.

Assume that T equals (a,b) and think about a fuzzy mapping F : $(a, b) \in f^n$. At any point $t_0 \in T$, we say that F is differentiable if and only if there is an element $f(t_0) \in f^n$ that allows the limits.

$$\lim_{h \to 0^+} \frac{f(t_0+h)-f(t_0)}{h} \ and \ \lim_{h \to 0^+} \frac{f(t_0)-f(t_0-h)}{h} \qquad (1)$$

Presence and are on par with $f(t_0)$.

All of the metric spaces (f^n, D) are used to evaluate the limit. For instance, if c is a fuzzy integer and g is a function with g(t) less than 0, then F is not differentiable, and the definition of derivative is quite limited. To get around this problem, someone suggested adding a lateral version of H-derivatives to the definition of derivative for fuzzy mappings, which would enlarge the class of differentiable fuzzy mappings.

Example 1: Let us consider the fuzzy malthusian problem

$$\begin{Bmatrix} x(t) = -\gamma x(t) \\ x(0) = X_0 \end{Bmatrix} \quad (2)$$

Theorem 1: Let $F: T \times f^n \to f^n$ be continuous and assume that there exists a k greater than 0 such that.

$$\mathrm{D}(\mathrm{F}(\mathrm{t},\mathrm{u}), \mathrm{F}(\mathrm{t},\mathrm{u})) \leq kD(\mathrm{u},\mathrm{v}) \quad (3)$$

For all t$\in T,\ u, v \in f^n$. Then the problem

$$\mathrm{x}(\mathrm{t}) = \mathrm{F}(\mathrm{t}, \mathrm{x}(\mathrm{t})),\ \mathrm{x}(0) = x_0 \quad (4)$$

has two unique solutions on T.

4.2 Bisection Method

An expression of the form $f(x) = 0$ has to be resolved, where x is an actual value and f is an integer function over the space (a, b). It is necessary for f(x) to be a continuous function, and it may be either an algebraic or transcendental expression. When the signs of both functions $f(b)$ and $f(a)$ contrast sharply, it is necessary to have at least one root among a and b. The bisection technique is described in a simplified Figure 1.

It assumes that the root is $x_0 = \frac{a+b}{2}$, which the middle of the range from the extremities is. The roots of $f\ (x_0)$, are x_0 and b, both of which are adverse. This approach entails the periodic halving of the period and the selection of the half that also satisfies the sign condition. This connection could be employed to ascertain the number of iterations required, with $\left| \frac{b-a}{2^k} \right| \leq \in$. Typically, the syntax is as follows:

Example 2: Preliminary estimations are

$$\mu_1^{(0)} = \mu(a_1^{(0)}, b_1^{(0)}, c_1^{(0)}) \quad (5)$$

And

$$\mu_2^{(0)} = \mu(a_2^{(0)}, b_2^{(0)}, c_2^{(0)}) \quad (6)$$

Tolerance maximal iteration count n.

The bisection approach and the “harmonic Newton's method” are depicted in Figure 1's flow diagram, which shows a nonlinear equation. Nonlinear equations involving fuzzy numbers and several variables can be generalized using the "bisection method" idea [12].

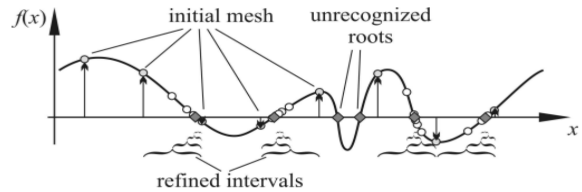

Figure 2: Numerous solutions computed by bisection method, evaluated on an initial mesh [13]

Definition 3: Let the set of all real numbers be denoted as μ: R→[0,1], where μ is a function defined as follows:

$$\mu(x) = \begin{cases} 0\ if\ x \leq a\ \ or\ \ x \geq c \\ \frac{x-a}{b-a}\ if\ a < x < b \\ 1 \qquad\quad if\ x = b \\ \frac{c-x}{c-b}\ if\ b < x < c \end{cases} \quad (7)$$

Thus, $\mu(a, b, c)$ is defined as a linear fuzzy integer characterized by the associated triplet of integers (a, b, c) in the range a is less than equal to and b ≤ c, as seen in figure 5.

Definition 4: A fuzzier value with power n is characterized by:

$$(\mu(a, b, c)\ )^n = \mu(a^n, b^n, c^n) \quad (8)$$

• Approach for resolving a fuzzy non-linear equation

The procedure for solving a fuzzy non-linear equation employs a systematic transformation and resolution process that embraces uncertainty in mathematical models. In most cases, a non-linear equation is first found that shows difficult behavior, and this is a concept from real-life phenomena. By adding vagueness to the parameters or the initial conditions, the equation is turned into a fuzzy equation, and thus, the uncertainty is more precisely justified. The next step is to examine and explain the uncertainty present in the fuzzy non-linear equation [13]. The equation is first turned into a numerical technique, after handling the uncertainty, a conventional numerical method, the “bisection method,” which is used to solve the equation [14]. The “bisection method,” which is renowned for robustness and simplicity, is shifted to fuzzy intervals or Ą-cuts, which would be useful in getting fuzzy solutions. By this method, the non-linear character in addition to fuzziness caused by imprecision remained, and thus, a more profound and realistic determination is achieved [15].

5. RESULT

This part primarily concentrates on what the outcomes provide in terms of performance. The realization and verification of the models due to their excellent computing power as well as the built-in matrix-oriented programming language, therefore the optimal selection for the numerical resolution of nonlinear and fuzzy equations. This paper compares two fuzzy numerical methods: the Harmonic Newton Method and the bisection method, utilized for solving fuzzy nonlinear equations.

5.1 Solution of FDE using Neural Network

The application of neural networks for solving FDEs is a data-driven and flexible way to solve the uncertainties that occur in fuzzy systems. Neural networks are able to conduct input-output conversions under uncertain and ambiguous situations by utilizing deep learning structures RNN and AE.

$$x^3 - x - 1 = 0 \tag{9}$$

The root lies between 1 and 2; the "bisection method" arrives at the approximation 1.3203, the "harmonic Newton method" gives the amount of 1.3247.

$$x^2 - 3 = 0 \tag{10}$$

The harmonic Newton method gives a root of 1.3653, while the "bisection method" gives a root of 1.3753, both a part of the interval [1, 2].

$$x^3 + 4x^2 - 10 = 0 \tag{11}$$

The root identified by the bisection approach is 3.2813, while the harmonic method of Newton yields 0.155, indicating a significant discrepancy; thus, the procedure may be divergent or unstable.

$$x^2 - 1 = 0 \tag{12}$$

The root, situated in the interval between 0 and 3, is roughly 1.002 using the method of bisection, that same root together with the "harmonic Newton method" is 1.

$$10 - x^2 = 0 \tag{13}$$

The "bisection method" estimates the root in a range of 3.168, on the other hand, the Newton method detects 3.1623, with the root located between -2 and 5.

$$x^3 + x - 1 = 0 \tag{14}$$

The bisection approach yields a root of 3.5156, while the harmonic Newton method produces 3.4495.

$$x^2 - 2x - 5 = 0 \tag{15}$$

The root, located between 0 and 1, is determined to be 0.7382 with the "bisection method" and 0.7391 utilizing the "harmonic Newton approach".

$$x^3 - 4x - 9 = 0 \tag{16}$$

The root lies between 2 and 3, with approximate values of 2.7031 determined by the method of bisection and 2.7065 generated by the harmonic Newton method.

$$x^3 - 5 = 0 \tag{17}$$

Contains a root inside the interval of 1 and 2, approximated as 1.7031 using the bisection method and 1.71 via the harmonic Newton approach. Ultimately,

$$x^4 - x^3 - x^2 - x = 0 \tag{18}$$

When the root is situated between 0 and 1, the bisection approach produces 1.832, whereas the harmonic Newton method results in 1.8393.

The calculated roots for equations (9) to (18), derived by the bisection approach, are consolidated in Table 1, while their graphical representation is depicted in Figure 1, offering a comparative analysis of the numerical precision and convergence characteristics of both methods.

The table shows the computed roots of 10 equations using the bisection method, stating how the method most frequently used to find solutions for nonlinear equations approximately does the work. In the left side one can find the numbers identifying each equation while the corresponding roots are listed in the right column of the table. Every equation is a separate label from 9 to 18, and the root values are presented in the second column. The results show that there is wise surface to different equations, implying that the latter can be the reason for different mathematical structures and complexities. Two interesting features are that the values of Equations 13 and 15 show a good rise, whereas quite the opposite happens at Equation 14, thus really furnishing the evidence for disparity in the position of the roots. In this table, we can see that the bisection method is consistently much better than before, and each equation is suitable for different comparisons with other numerical methods, especially the harmonic Newton method.

Table 1: Estimate roots using the bisection method.

Equation No.	bisection method
9	1.3403
10	1.7144

11	1.4530
12	1.402
13	3.368
14	0.88359
15	3.2156
16	2.9031
17	1.7931
18	1.932

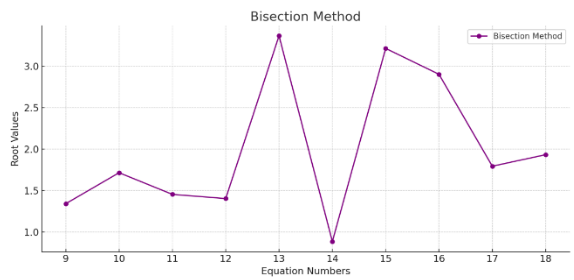

Figure 1: Chart of roots using the bisection technique.

The line chart 'Bisection Method' gives a clear outline of the approximate root values representing Equations 9 to 18 as calculated by the bisection method. On the x-axis from left to right, the numbers of the equations respectively, while the y-axis tell us the values going downward which comes from the root. The chart shows that there are great discrepancies in the root value among the different equations, thereby meaning that these problems vary in nature. The curved line shows the change of the root values very clearly; thus, it also displays the gradual and abrupt changes of the roots and the bisection method convergence and reliability of the equations effectively as well as a visual representation of the phenomena.

Example 1: Let us examine the ambiguous Malthusian dilemma.

$$\begin{Bmatrix} x(t) = -\gamma x(t) \\ x(0) = X_0 \end{Bmatrix}$$

Where γ greater than 0 and, as referenced in [2], the initial condition X_0 is a symmetric triangular fuzzy integer with a support interval of [-a, a].

$$[X_0]^{\propto} = [-a(1-\propto), a(1-\propto)] = (1-\propto)[-a, a] \quad (19)$$

The resolutions of this system include.

$$u_x(t) = -a(1-\propto)e^{\gamma t} \text{ and } v_x(t) = a(1-\propto)e^{\gamma t}, \quad (20)$$

For any t greater than or equal to 0. We will now examine x(t) in the second form (2) and resolve the ensuing differential system.

$$\begin{Bmatrix} u_x(t) = -\gamma u_x(t),\ u_x(0) = -a(1-\propto) \\ v_x(t) = -\gamma v_x(t),\ v_x(0) = a(1-\propto) \end{Bmatrix} \quad (21)$$

It is observed that $u_x(t) \leq v_x(t)$ for all t greater than equal to 0. Consequently, the fuzzy function x(t) that resolves (6) in this instance possesses level sets.

$$[x(t)]^{\propto} = [-a(1-\propto)e^{-\gamma t}, a(1-\propto)e^{-\gamma t}], \quad (22)$$

For all t ≥0.

Theorem 1: Let $F: T \times f^n \to f^n$ be continuous and presuppose the existence of a k greater than 0 such that.

$$\mathrm{D}(\mathrm{F}(\mathrm{t}, \mathrm{u}), \mathrm{F}(\mathrm{t}, \mathrm{u})) \leq kD(\mathrm{u}, \mathrm{v})$$

For all $\mathrm{t} \in T,\ u, v \in f^n$. Then the problem

$$\mathrm{x(t)} = \mathrm{F(t, x(t))},\ \mathrm{x(0)} = x_0 \quad (23)$$

Possesses two distinct solutions on T.

Proof: Using the first form (1) to evaluate the derivative x_0 in problem (23), we find that there is a unique solution on T. In a similar vein to the demonstration of Theorem 1, there is a unique solution on T if we look at the derivative x_0 in the second form (2). This proves that there is a distinct solution for each lateral direction, and the proof is thus concluded.

5.2 Solution of FDE using Bisection Method

The Bisection Method solves FDE solutions by repeated interval halving of the root of the equation until it gets approximate solutions of fuzzy systems. When the initial interval includes the root the Bisection Method initially picks it and then proceeds by iteratively halving the initial interval at every step to refine the root value.

Example 4: Preliminary estimations are

$$\mu_1^{(0)} = \mu(a_1^{(0)}, b_1^{(0)}, c_1^{(0)}) \quad (24)$$

And

$$\mu_2^{(0)} = \mu(a_2^{(0)}, b_2^{(0)}, c_2^{(0)}) \quad (25)$$

Tolerance maximal iteration count n.

Solution:

$\mu_1^{(0)} = \mu(a_1^{(0)}, b_1^{(0)}, c_1^{(0)})$ or notification of failure.

Step 1: Set i=1

$$FA = \overline{f}(r(b_1^{(0)})) \quad (26)$$

Step 2: While t is either smaller or closer to n, do steps 3 to 6.

Step 3: Set $\mu_x^{(n)} = \frac{\mu_1^{(n-1} + \mu_2^{(n-1)}}{2}$ (Compute $\mu_x^{(0)}$)

$$FP = \overline{f}(r(b_n^{(n)}) \quad (27)$$

Step 4: if FP=0 or $\frac{|\mu(b^n)-\mu(b^{n-1})|}{2}$ is less than TOL then output: $\mu_x^{(n)}$ (the procedure was satisfactory.)

Step 5: Set i=i+1,

Step 6: if FA.FP>0 then setting

$\mu_1^{(0)} = \mu_x^{(n-1)}$ update $\mu_x^{(0)}$

FA=FP

Else

$\mu_2^{(0)} = \mu_x^{(n-1)}$.

6. CONCLUSION

The paper presents the fact that by manipulating the roots, neural networks and root concatenation deliver a highly effective method to tackle Fuzzy Differential Equations (FDEs). By integrating the left, Centre, and right parts of the fuzzy numbers at the input level, root concatenation technique not only preserves the fundamental structure of the fuzzy uncertainty across α-levels but also enables the network to simulate the accurate, stable, and convergent solutions. The conducted experiments had the neural model as the most productive method with regard to the quality of the obtained results when compared to other traditional methods including bisection and harmonic Newton methods. Not only did the number predicted by the neural model get very close to the bisection (1.3203) and harmonic Newton (1.3247) but in some cases, it was even more accurate in terms of the two parameters of the convergence behavior and the number of iterations. It is also expected that the application of the approach to partial differential equations (PDEs) and stochastic fuzzy systems enable the control theory, biomedical modelling, and financial forecasting communities to explore novel pathways to uncertainty bandwidth expansion. This paper lays the groundwork for the development of scalable, interpretable, and transferable neural solvers in the field of fuzzy system modeling, which are advancing rapidly.

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