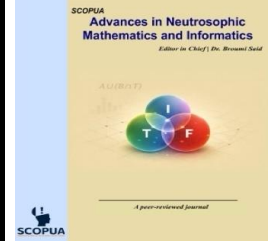




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The Generic and Generalized Neutrosophic Differential Equations for Modeling the Exponential Growth and Decay Process

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ABSTRACT

This work investigates the concept of Neutrosophic Differential Equations (NDEs) as an extension of classical and fuzzy differential equation models for handling uncertainty in dynamic systems. Classical differential equations assume precise knowledge of parameters and initial conditions, while fuzzy differential equations account for vagueness through degrees of membership. However, both approaches fail to explicitly model indeterminacy, which arises from incomplete, inconsistent, or conflicting information. Neutrosophic theory introduces three independent components—Truth T, Indeterminacy I, and Falsity F—which provide a more flexible framework for representing uncertainty. In this study, neutrosophic-valued functions are defined, and the concept of the neutrosophic derivative is developed. First-order neutrosophic differential equations are formulated and transformed into systems of classical differential equations using decomposition techniques. Analytical and numerical solution methods, including the Euler method and Runge–Kutta schemes, are applied to solve neutrosophic differential equations. The models are further illustrated through applications such as population growth and decay processes, where the evolution of truth, indeterminacy, and falsity components are analyzed. A comparative analysis between classical, fuzzy, and neutrosophic models demonstrates that neutrosophic differential equations provide a more comprehensive representation of uncertainty by explicitly capturing indeterminacy. The results show that neutrosophic models reveal hidden uncertainty that is not observable in traditional approaches. This study contributes to the growing field of neutrosophic mathematics and provides a foundation for further research in dynamic systems modeling, control theory, and applied sciences.

Keywords: Neutrosophic differential equations; Neutrosophic model; Comparative model indeterminacy model; neutrosophic population growth

1. Introduction

Differential equations play a fundamental role in the mathematical modeling of real-world phenomena. They describe how physical, biological, economic, and engineering systems evolve with time. Classical differential equations assume that all quantities in the system, such as parameters, initial conditions, and external inputs, are exactly known. This study provides a more realistic modeling framework for uncertainty, contributes to the mathematical theory of indeterminacy-based dynamic systems, and offers tools for applications in population dynamics, decay processes, and engineering. (please, see [1 - 32])

For example, in the exponential growth model

$$\frac{dx}{dt} = kx$$

the growth rate k is assumed to be a precise real number.

However, real systems are rarely known with certainty. Measurements are subject to errors, environmental conditions change unpredictably, and human-based systems contain ambiguity and incomplete information. This led to the development of uncertainty modeling techniques.

Fuzzy set theory, introduced by Zadeh in 1965 [4], allowed partial membership of elements, making it possible to model vagueness. Later, intuitionistic fuzzy sets introduced both membership and non-membership. However, both frameworks



lack the ability to independently model indeterminacy, that is, situations where information is unknown, inconsistent, or conflicting.

Neutrosophic theory was introduced to overcome this limitation by explicitly modeling three independent components: truth, indeterminacy, and falsity. When applied to differential equations, this leads to Neutrosophic Differential Equations, which provide a more realistic description of evolving uncertain systems.

2 Classical Differential Equations

Classical differential equations originated from the work of Newton and Leibniz in the seventeenth century. These equations assume that all parameters and initial conditions are known exactly. A general first-order differential equation is

$$\frac{dx}{dt} = f(t, x).$$

These equations are widely used but fail when data is uncertain or imprecise.

Fuzzy Differential equations

The transition to uncertainty modeling began with Lotfi Zadeh (1965)[4]. The move into calculus happened when Puri and Ralescu (1986) [7] and Kaleva (1987) [8] defined the Hukuhara derivative for fuzzy-valued functions. Fuzzy sets introduced by Zadeh allow values to belong to sets with degrees between 0 and 1. This idea was extended to differential equations using fuzzy numbers. Hukuhara introduced the Hukuhara derivative, which enabled derivatives of fuzzy-valued functions. The generalized Hukuhara derivative improved this framework, but fuzzy differential equations still cannot represent indeterminacy.

Intuitionistic Fuzzy Differential Equations

Intuitionistic fuzzy sets include both membership and non-membership. Atanassov (1986) [10] recognized that "hesitation" is a part of human decision-making. IFDEs added a second layer of non-membership. While researchers like Melliani (2012) [11] proved existence and uniqueness for IFDEs, the literature points out a recurring flaw: Truth and Falsity are treated as a zero-sum game or a restricted sum. However, these components are dependent, since $T+F \leq 1$. This limits their ability to model contradictory or unknown information.

Neutrosophic Theory

In 1998, Florentin Smarandache introduced Neutrosophy as a branch of philosophy [12]. Neutrosophic theory introduced by Smarandache includes three independent components: T, I, and F. Single-valued neutrosophic numbers made the theory computationally useful and applicable to calculus.

Neutrosophic Differential Equations

Neutrosophic Differential Equations extend classical calculus to systems where the state variable and its rate of change are neutrosophic numbers. Researchers such as Broumi and Smarandache [12,15] developed neutrosophic derivatives and solution techniques.

3. Methodology

Neutrosophic Sets

A neutrosophic set A in a universe X is defined as

$$A = \{ \langle x, T_A(x), I_A(x), F_A(x) \rangle : x \in X \},$$

where $T_A(x)$, $I_A(x)$ and $F_A(x)$ represent the truth-membership, indeterminacy-membership and falsity-membership of x respectively.

Example

Let $X = \{a, b, c\}$ represent three patients. Define

$$A = \{ \langle a, 0.7, 0.2, 0.1 \rangle, \langle b, 0.4, 0.5, 0.2 \rangle, \langle c, 0.6, 0.1, 0.4 \rangle \}.$$

Here patient a is mostly healthy with little uncertainty, patient b is highly indeterminate, and patient c shows conflicting information.

Single-Valued Neutrosophic Numbers

A single-valued neutrosophic number (SVNN) is written as

$$A = (T, I, F),$$

where $T, I, F \in [0, 1]$.

Example

If a system has growth rate

$$A = (0.6, 0.3, 0.2),$$

then there is 60% belief in growth, 30% uncertainty and 20% disbelief.

Neutrosophic Functions

A neutrosophic function is defined as

$$X(t) = (T(t), I(t), F(t)),$$

where $T(t)$, $I(t)$ and $F(t)$ vary with time.



Example

Let

$$T(t) = e^{-t}, \quad I(t) = 0.1t, \quad F(t) = 1 - e^{-t}.$$

At $t = 1$,

$$X(1) = (0.3679, 0.1, 0.6321).$$

Neutrosophic Derivative

The neutrosophic derivative of

$$X(t) = (T(t), I(t), F(t))$$

is defined as

$$\frac{dX}{dt} = \left(\frac{dT}{dt}, \frac{dI}{dt}, \frac{dF}{dt} \right)$$

Example

Let

$$X(t) = (t^2, 0.2t, 1-t).$$

Then

$$\frac{dX}{dt} = (2t, 0.2, -1).$$

Neutrosophic Differential Equations

A neutrosophic differential equation (NDE) is defined as

$$\frac{dX}{dt} = F(t, X),$$

where $X(t)$ is a neutrosophic-valued function.

First-Order Linear NDE

Consider

$$\frac{dX}{dt} = kX,$$

where $k = (k_T, k_I, k_F)$ is a neutrosophic constant. This gives

$$\frac{dT}{dt} = k_T T, \quad \frac{dI}{dt} = k_I I, \quad \frac{dF}{dt} = k_F F.$$

Example

Let

$$k = (0.5, 0.1, -0.3), \quad X(0) = (0.8, 0.1, 0.1).$$

Then

$$T(t) = 0.8e^{0.5t}, \quad I(t) = 0.1e^{0.1t}, \quad F(t) = 0.1e^{-0.3t}.$$

Neutrosophic Decay Model

Example

Consider

$$\frac{dX}{dt} = -kX$$

$$k = (0.4, 0.2, 0.1), \quad X(0) = (0.7, 0.2, 0.1).$$

Then

$$T(t) = 0.7e^{-0.4t}, \quad I(t) = 0.2e^{-0.2t}, \quad F(t) = 0.1e^{-0.1t}.$$

Cut-Set Interpretation

Example

Let

$$T(t) = 0.8e^{0.5t},$$

At $t=2$,

$$I(t) = 0.2e^{0.1t}, \quad F(t) = 0.1e^{-0.3t}.$$

$$X(2) = (1.31, 0.24, 0.055).$$

Solution Methods for Neutrosophic Differential Equations

Neutrosophic Differential Equations (NDEs) cannot always be solved analytically. In many real-life systems, numerical methods are required. Here, is presented, the Euler and Runge–Kutta methods for solving NDEs [18].

3.1 General Form of a Neutrosophic Differential Equation

A first-order Neutrosophic Differential Equation is written as



$$\frac{dX}{dt} = F(t, X), \quad X(t) = (T(t), I(t), F(t))$$

This gives three coupled equations:

$$\frac{dT}{dt} = f_T(t, T), \quad \frac{dI}{dt} = f_I(t, I), \quad \frac{dF}{dt} = f_F(t, F)$$

3.2 Neutrosophic Euler Method

The classical Euler method is

$$X_{n+1} = X_n + hf(t_n, X_n)$$

For Neutrosophic Functions,

$$X_{n+1} = X_n + hF(t_n, X_n)$$

which gives

$$T_{n+1} = T_n + hf_T(t_n, X_n)$$

$$I_{n+1} = I_n + hf_I(t_n, X_n)$$

$$F_{n+1} = F_n + hf_F(t_n, X_n)$$

Example

Consider

$$\frac{dX}{dt} = kX,$$

$$k = (0.5, 0.1, -0.2), \quad X(0) = (0.6, 0.3, 0.1)$$

Then

$$\frac{dT}{dt} = 0.5T, \quad \frac{dI}{dt} = 0.1I, \quad \frac{dF}{dt} = -0.2F$$

Using step size $h = 0.1$,

$$T_1 = 0.6 + 0.1(0.5 \times 0.6) = 0.63$$

$$I_1 = 0.3 + 0.1(0.1 \times 0.3) = 0.303$$

$$F_1 = 0.1 + 0.1(-0.2 \times 0.1) = 0.098$$

So,

$$X(0.1) \approx (0.63, 0.303, 0.098)$$

Neutrosophic Runge–Kutta Method (RK4)

The fourth-order Runge–Kutta method for NDEs is

$$X_{n+1} = X_n + \frac{h}{6}(K_1 + 2K_2 + 2K_3 + K_4)$$

where

$$K_1 = F(t_n, X_n)$$

$$K_2 = F\left(t_n + \frac{h}{2}, X_n + \frac{h}{2}K_1\right)$$

$$K_3 = F\left(t_n + \frac{h}{2}, X_n + \frac{h}{2}K_2\right)$$

$$K_4 = F(t_n + h, X_n + hK_3)$$

Example

Solve

$$\frac{dX}{dt} = -kX$$

$$k = (0.4, 0.2, 0.1), \quad X(0) = (0.8, 0.1, 0.1)$$

For the truth part:

$$\frac{dT}{dt} = -0.4T$$

Compute

$$K_{1T} = -0.4(0.8) = -0.32$$

$$K_{2T} = -0.4(0.784) = -0.3136$$

$$K_{3T} = -0.4(0.7843) = -0.3137$$

$$K_{4T} = -0.4(0.7686) = -0.3074$$

Thus,

$$T(0.1) = 0.8 + \frac{0.1}{6}(-0.32 - 0.6272 - 0.6274 - 0.3074) \sim 0.769$$

Applications of Neutrosophic Differential Equations



Neutrosophic Population Growth Model

Population growth models describe how biological populations change with time[20]. In classical modeling, it is assumed that all parameters are known exactly. However, in real-life systems, growth rates, migration, and environmental factors are often imprecise or partially unknown. Neutrosophic Differential Equations (NDEs) allow these uncertainties to be represented explicitly through truth, indeterminacy, and falsity components.

3.3 Neutrosophic Population State

Let the neutrosophic population be defined as

$$X(t) = (T(t), I(t), F(t)),$$

where $T(t)$ represents the true (certain) population component, $I(t)$ represents the indeterminate part, and $F(t)$ represents the false or contradictory part.

A neutrosophic growth model is given by

$$\frac{dX}{dt} = kX,$$

where $k = (k_T, k_I, k_F)$ is a neutrosophic growth rate. This yields

$$\frac{dT}{dt} = k_T T, \quad \frac{dI}{dt} = k_I I, \quad \frac{dF}{dt} = k_F F.$$

3.4 Worked Example

Let

$$k = (0.3, 0.15, -0.1), \quad X(0) = (0.7, 0.2, 0.1).$$

Then

$$T(t) = 0.7e^{0.3t}, \quad I(t) = 0.2e^{0.15t}, \quad F(t) = 0.1e^{-0.1t}.$$

At $t = 2$,

$$T(2) = 1.2755, \quad I(2) = 0.2700, \quad F(2) = 0.0819.$$

This shows that certainty increases, indeterminacy grows moderately, and falsity decreases.

Table 1: Comparison tables with Classical, fuzzy and neutrosophic Differential Equations

Feature	Classical DE	
Basic Form	$y'(t) = f(t, y(t))$	$y'(t) =$
Type of Uncertainty	None. All values are crisp, exact, deterministic	Values belong to a set w
Operational	Handles Ideal systems with exact data	System
Foundational Set Theory	Classical/Crispsets:	element is eithe
Feature : Initial Condition	$y(0)$ Crisp number : $y(0) = 2$	Fuzzy number
Parameters	Exact constants : $k = 3.5$	Fu
Solution Form	Single crisp function $y(t)$	Fuzzy function:
When to Use	Physical laws, exact measurements: Newton's laws, circuit, Control systems	bio models with

Here is a side-by-side comparison of Classical, Fuzzy, and Neutrosophic Differential Equations (DEs):

1. Core Concept and Uncertainty Handling
2. Initial Conditions and Parameters
3. Interpretation and Application Domains

Neutrosophic Decay Model

3.5 Model Formulation

A neutrosophic decay model is expressed as

$$\frac{dX}{dt} = -kX$$

with

$$\frac{dT}{dt} = -k_T T, \quad \frac{dI}{dt} = -k_I I, \quad \frac{dF}{dt} = -k_F F.$$

3.6 Physical Interpretation of Indeterminacy

The indeterminacy component $I(t)$ represents uncertainty caused by incomplete data, environmental fluctuations, or inconsistent measurements.

3.7 Worked Example

Let

$$k = (0.5, 0.3, 0.1), \quad X(0) = (0.8, 0.15, 0.05).$$

Then



$$T(t) = 0.8e^{-0.5t}, \quad I(t) = 0.15e^{-0.3t}, \quad F(t) = 0.05e^{-0.1t}.$$

At $t = 1$,

$$X(1) = (0.4852, 0.1111, 0.0452).$$

Neutrosophic Uncertainty Representation

Neutrosophic models allow uncertainty to be decomposed into truth, indeterminacy, and falsity, offering a richer and more informative framework for modeling dynamic systems with imperfect information.

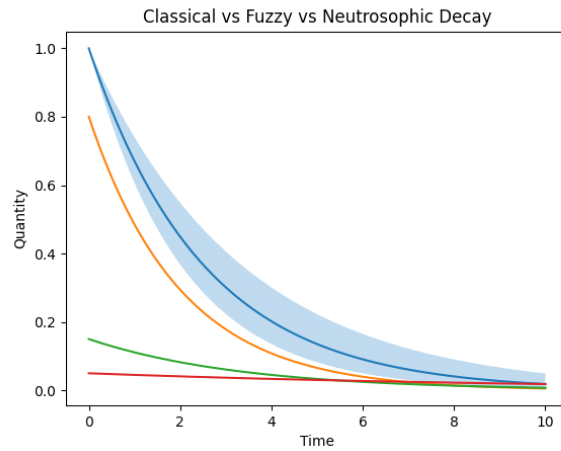


Figure 1: Comparison of Classical, Fuzzy, and Neutrosophic Decay Models. The classical model gives a single decay curve, the fuzzy model produces an interval band, while the neutrosophic model shows three distinct curves representing Truth $T(t)$, Indeterminacy $I(t)$, and Falsity $F(t)$.

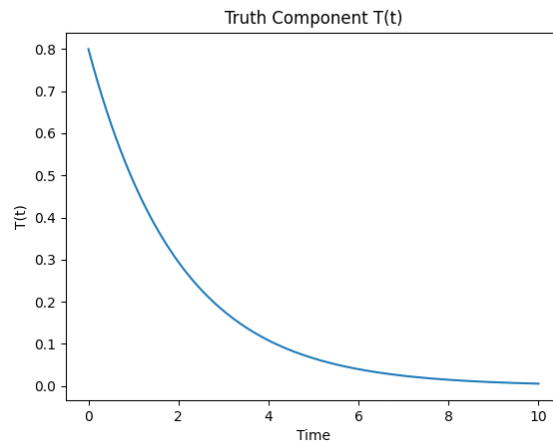


Figure 2: Truth component $T(t)$ in the neutrosophic decay model.

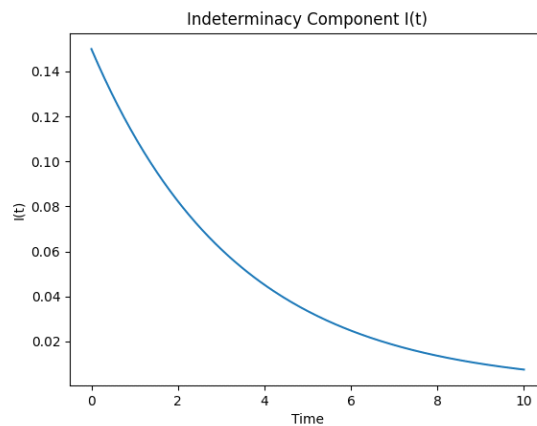


Figure 3: Indeterminacy component $I(t)$ in the neutrosophic decay model.



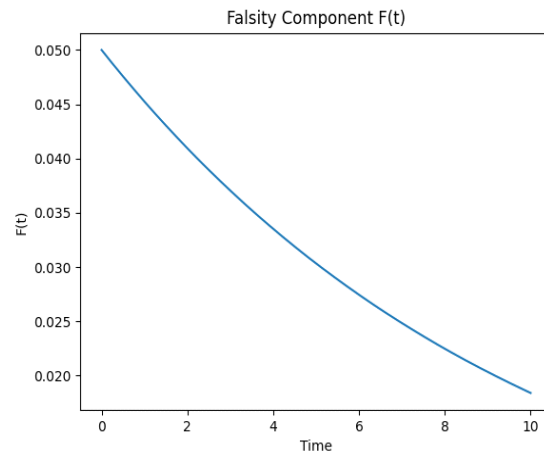


Figure 4: Falsity component $F(t)$ in the neutrosophic decay model.

4. Summary

Neutrosophic Differential Equations provide a powerful method for analyzing systems with uncertainty, ambiguity, and contradiction. They outperform classical and fuzzy approaches by explicitly tracking indeterminacy over time. This study has shown that Neutrosophic Differential Equations provide a powerful and flexible framework for modeling real-world systems with uncertainty, ambiguity, and contradiction. By introducing indeterminacy as an independent mathematical entity, neutrosophic models move beyond the limitations of classical and fuzzy approaches and offer a more realistic description of complex dynamic systems. Neutrosophic differential equations extend classical and fuzzy modeling frameworks by incorporating indeterminacy [21].

Conclusion and Future Research

Summary of Theoretical Contributions

This research has developed a structured and accessible framework for Neutrosophic Differential Equations (NDEs) and demonstrated their usefulness in modeling dynamic systems with uncertainty and indeterminacy. The study extended the traditional theory of differential equations by replacing single-valued state variables with neutrosophic-valued functions, represented by the triplet

$$(T(t), I(t), F(t)).$$

The major theoretical contributions of this work include:

1. Formalization of Neutrosophic Dynamics

The research presented a clear mathematical formulation of first-order neutrosophic differential equations, showing how classical models can be extended into neutrosophic space.

2. Solution Techniques

Both analytical and numerical techniques were developed for solving NDEs. These methods provided time-dependent expressions for the truth, indeterminacy, and falsity components.

3. Comparative Modeling

The study demonstrated that neutrosophic models generalize classical and fuzzy models. While classical models give single trajectories and fuzzy models give interval bands, neutrosophic models produce three evolving functions that reveal deeper uncertainty structures.

What Indeterminacy Modeling Achieved

One of the most important achievements of this work is the explicit modeling of indeterminacy as a dynamic quantity. In classical and fuzzy differential equations, uncertainty is either ignored or forced into an interval, and the source of uncertainty is not distinguished. In contrast, neutrosophic modeling introduces a third independent component $I(t)$, which represents lack of knowledge, inconsistent data, and environmental unpredictability [12, 15].

This allowed the research to track how uncertainty itself evolves with time. For example, in population growth, indeterminacy increased when environmental conditions were unstable, while in decay processes, indeterminacy decayed more slowly than certainty, indicating lingering uncertainty in measurements.

Thus, neutrosophic differential equations do not only predict system behavior, but also describe the reliability of the prediction.

5. Limitations of the Study

Although this research achieved its objectives, some limitations remain:

- The study was restricted to first-order ordinary neutrosophic differential equations. Higher-order and partial NDEs were not considered.



- Single-Valued Neutrosophic Numbers (SVNNs) were used for simplicity. More general neutrosophic sets were not explored.
- The applications used illustrative and hypothetical parameters rather than real experimental data.
- Neutrosophic models are computationally more demanding than classical or fuzzy models.

Future Research Directions

The theory and applications of Neutrosophic Differential Equations are still in their early stages. Several promising research directions exist.

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