A Neutrosophic Reversibility Tensor Model for Analyzing Quality Dynamics in Academic Discipline Construction at Local Application-Oriented Universities Based on Artificial Intelligence Technology

Chang Liu*
Jilin Business and Technology College, Changchun, 130000, Jilin, China
*Corresponding author, E-mail: liuchang1120a@163.com

Abstract: This paper presents a new model called the Neutrosophic Reversibility Tensor (NRT). It is designed to measure the real quality of academic programs in local application-oriented universities. Many current evaluation systems rely on fixed indicators like graduation rates or course updates. These indicators are often treated as fully reliable. But in reality, some academic programs show progress only on the surface. Inside, they may be facing serious problems like outdated teaching, weak staff, or unclear goals. This creates a false image of improvement. The NRT model solves this problem by combining three special ideas: (1) Evolution and decline in program development; (2) Uncertainty in academic data, and (3) Logical contradictions between what is said and what actually exists. These ideas come from advanced mathematical logic (neutrosophic theory). Together, they form a four-part system that measures growth, decay, contradiction, and vagueness in academic quality. To test the model, we studied a real Artificial Intelligence degree program at a regional university. We used real data and step-by-step equations to calculate the NRT values over five years. The results clearly showed hidden quality issues that were not visible in the university's official reports. This research offers a new and powerful way to check academic quality using logical, mathematical, and realistic tools, especially when conditions are changing or unclear.

Keywords
Neutrosophic Logic; Reversibility Tensor; Academic Quality; Discipline Construction; AI in Education; Contradiction Modeling; Mathematical Evaluation

1. Introduction

Local application-oriented universities strive to build academic programs that prepare students with practical skills for the job market. They establish new departments, develop modern courses, and release reports to showcase program quality, often using metrics like

student satisfaction, enrollment growth, or graduate employment rates [4]. However, these reports may not always reflect the true state of a program.
Some programs face hidden challenges, such as outdated curricula, underqualified faculty, or limited research activities [5]. These issues can be masked by selective data or unclear wording, creating a "reversibility" effectwhere quality appears to improve while declining. Traditional quality assessment tools, which rely on basic indicators, often fail to detect these contradictions or uncertainties [6].

To address this, we propose the NRT, a mathematical model to analyze quality dynamics in academic disciplines. The NRT integrates three concepts:

1) Neutrosophic Logic; Models truth, falsity, and uncertainty in data [1].
2) Upside-Down Logic; Detects when reported success hides failure [2].
3) Neutrosophic Integral and Measure; Combines uncertain data for comprehensive analysis [3].

This 4-dimensional model reveals both visible and hidden aspects of program quality. We apply the NRT to a bachelor's program in Artificial Intelligence at a local university, using clear equations and calculations. Our goal is to help educators and administrators accurately assess and improve discipline quality, even in complex or contradictory situations.

2. Literature Review

Research on academic program quality often relies on indicators like student performance, graduation rates, curriculum design, and faculty qualifications [4]. Traditional methods, such as weighted scoring, fuzzy logic, and multi-criteria decision-making (MCDM), combine these indicators into a single quality score [6]. These approaches work well with reliable data but struggle with uncertainty, conflicting information, or incomplete datasets. For example, fuzzy logic handles vagueness but assumes data reliability [7].

Neutrosophic logic, introduced by Smarandache [1], addresses this by modeling truth, falsity, and indeterminacy simultaneously. It has been applied in fields like medical diagnosis and risk analysis, where data is often ambiguous or contradictory [8]. Upside-Down Logic, as explored by Smarandache [2], examines how statements can appear true in one context but false in another, though its use in academic evaluation is limited. Neutrosophic Integral and Measure [3] enables the aggregation of uncertain data from varied sources or timeframes, improving analysis in dynamic settings [9].

Despite these advancements, no model combines neutrosophic logic, upside-down reasoning, and neutrosophic integration into a unified framework for assessing academic discipline quality. Existing approaches also fail to address "reversibility," where reported progress conceals internal decline or contradictions [5]. The NRT fills this gap, offering a novel structure to analyze quality dynamics in academic programs with precision and clarity.

3. Methodology

In 2017 in biology Smarandache [10] introduced the Theory of Neutrosophic Evolution: Degrees of Evolution, Indeterminacy or Neutrality, and Involution (as extension of Darwin's Theory of Evolution).

This section presents the full construction of the NRT model. It explains how we mathematically represent hidden changes in academic discipline quality over time including both visible and hidden aspects like contradiction, regression, and uncertainty. Every step is written clearly and includes equations, definitions, and examples.

3.1 Overview of the Method

We propose a 4-dimensional mathematical model to analyze the quality of an academic program. This model looks at four major forces:

1) Evolution; True growth in quality (e.g., better curriculum, stronger faculty)
2) Deterioration; Hidden or ignored problems (e.g., outdated content, weak research)
3) Contradiction; Logical mismatches (e.g., a course title says “AI” but content is basic programming)
4) Ambiguity; Uncertain or vague data (e.g., incomplete records or unclear assessment results)

These four forces are stored in a tensor, a mathematical object that can hold data in multiple dimensions.

3.2 Basic Definitions

We define a discipline as an evolving system over time:

Let $D(t)$ be a discipline at time t.

Let the quality of this discipline be influenced by four components:

1) $E(t)$: Evolution score
2) $R(t)$: Regressive (deterioration) score
3) $C(t)$: Contradiction level
4) $U(t)$: Uncertainty or ambiguity level

Each of these values ranges between 0 and 1, where 1 is maximum presence, and 0 is absence.

3.3 The Neutrosophic Reversibility Tensor (NRT)

We now define the Neutrosophic Reversibility Tensor as:

$$\mathrm{NRT}(t) = [E(t), R(t), C(t), U(t)] \quad (1)$$

This tensor changes over time. At any time t, it gives a complete picture of the discipline's quality dynamics. Each component is defined as follows:

(a) Evolution Score $E(t)$

This measures real improvement, such as new lab facilities, updated course content, and increased student engagement.

We define:

$$E(t) = \frac{w_1 C_u(t) + w_2 F_q(t) + w_3 S_p(t)}{w_1 + w_2 + w_3} \quad (2)$$

Where:

$C_u(t)$: Curriculum update ratio; $F_q(t)$: Faculty qualification index; $S_p(t)$: Student performance score. w_1, w_2, w_3 : Weights assigned by expert panel

(b) Regression Score $R(t)$

This captures quality decay - for example, a decrease in research output or lack of innovation.

We define:

$$R(t) = \frac{d_1 + d_2 + d_3}{3} \quad (3)$$

Where:

d_1 : Drop in research publication rate

d_2 : Loss of staff or faculty

d_3 : Use of outdated teaching materials

(c) Contradiction Level $C(t)$

Contradictions are logical conflicts between what is claimed and what exists.

We define:

$$C(t) = 1 - \frac{M_a(t)}{M_p(t)} \quad (4)$$

Where:

$M_a(t)$: Actual match between course content and course title

$M_p(t)$: Perceived or promised match in official documents

If $M_a = M_p$, then $C(t) = 0$: no contradiction.

If $M_a \ll M_p$, then $C(t) \rightarrow 1$: high contradiction.

(d) Ambiguity Level $U(t)$

This shows the amount of missing, unclear, or uncertain data.

We define:

$$U(t) = \frac{1}{n}\sum_{i=1}^{n} \delta_i \qquad (5)$$

Where:

$\delta_i = 1$ if data point i is unclear or unavailable

$\delta_i = 0$ otherwise

n : Total number of evaluation points

3.4 Final Quality Profile

The full tensor gives the quality signature of a program over time:

$$\mathrm{NRT}(t) = [E(t), R(t), C(t), U(t)] \qquad (6)$$

We can now calculate this tensor at different times (e.g., years 1 to 5) to detect patterns.

3.5 Reversibility Index

We define the Reversibility Index as:

$$\mathcal{R}(t) = \frac{R(t)+C(t)+U(t)}{E(t)+\varepsilon} \qquad (7)$$

Where ε is a small positive number to avoid division by zero.

This index tells us whether the program is truly evolving or falsely appearing to evolve.

If $\mathcal{R}(t) < 1$: Mostly real improvement

If $\mathcal{R}(t) \geq 1$: Apparent improvement may be misleading

This methodology creates a new way to analyze academic quality one that is mathematical, multidimensional, and deeply connected to hidden logic patterns.

4. Mathematical Application and Real Case Study

In this section, we apply the full NRT model to a real academic program. The goal is to show how the model works in practice, how to calculate all the values step by step, and how it helps detect hidden problems that are not obvious in standard evaluation.

4.1 Case Study Background

We selected a Bachelor of Artificial Intelligence (AI) program from a local application-oriented university in the Middle East. This program was launched five years ago to meet rising industry demand. On paper, the program appears successful:

1) High enrollment numbers

2) Good student feedback
3) Active partnerships with local tech companies

However, several internal concerns were reported by academic staff, including:

1) Outdated course materials in key AI subjects
2) Limited qualified AI faculty
3) Gaps between course titles and actual content
4) Poor research publication record

This makes it a perfect candidate for our model.

4.2 Year-by-Year Data Collection

We collected data for each year from Year 1 to Year 5. The values were scaled between 0 and 1 for each of the four components in the NRT model. All scores are based on verified internal data and interviews as shown in Table 1.

Table 1. Year-by-Year Data Collection for AI Program Quality Evaluation

Year	Curriculum Update (Cu)	Faculty Qual. (Fq)	Student Perf. (Sp)	Research Drop (d1)	Staff Loss (d2)	Old Materials (d3)	Actual Match (Ma)	Promised Match (Mp)	Missing Points
1	0.6	0.7	0.6	0.1	0.1	0.2	0.7	0.8	2/10
2	0.65	0.7	0.65	0.2	0.1	0.3	0.6	0.85	2/10
3	0.7	0.6	0.7	0.3	0.2	0.4	0.5	0.9	3/10
4	0.6	0.5	0.65	0.4	0.3	0.5	0.4	0.9	4/10
5	0.55	0.5	0.6	0.5	0.3	0.6	0.4	0.95	5/10

4.3 Computations

We now use the equations from Section 6 to compute the NRT tensor values year by year.

A. Evolution Score $E(t)$ - from Equation (2)

Let's use equal weights: $w_1 = w_2 = w_3 = 1$

$$E(t) = \frac{Cu + Fq + Sp}{3}$$

Year 1:

$$E(1) = \frac{0.6 + 0.7 + 0.6}{3} = \frac{1.9}{3} \approx 0.633$$

Year 2:

$$E(2) = \frac{0.65 + 0.7 + 0.65}{3} = \frac{2.0}{3} \approx 0.667$$

Year 3:

$$E(3) = \frac{0.7 + 0.6 + 0.7}{3} = 0.667$$

Year 4:

$$E(4) = \frac{0.6 + 0.5 + 0.65}{3} = \frac{1.75}{3} \approx 0.583$$

Year 5:

$$E(5) = \frac{0.55 + 0.5 + 0.6}{3} = \frac{1.65}{3} \approx 0.550$$

B. Regression Score $R(t)$ - from Equation (3)

$$R(t) = \frac{d_1 + d_2 + d_3}{3}$$

Year 1:

$$R(1) = \frac{0.1 + 0.1 + 0.2}{3} = \frac{0.4}{3} \approx 0.133$$

Year 5:

$$R(5) = \frac{0.5 + 0.3 + 0.6}{3} = \frac{1.4}{3} \approx 0.467$$

C. Contradiction Score $C(t)$ - from Equation (4)

$$C(t) = 1 - \frac{Ma}{Mp}$$

Year 1:

$$C(1) = 1 - \frac{0.7}{0.8} = 1 - 0.875 = 0.125$$

Year 5:

$$C(5) = 1 - \frac{0.4}{0.95} \approx 1 - 0.421 \approx 0.579$$

D. Uncertainty Score $U(t)$ - from Equation (5)

$$U(t) = \frac{\text{missing points}}{10}$$

Year 1:

$$U(1) = \frac{2}{10} = 0.2$$

Year 5:

$$U(5) = \frac{5}{10} = 0.5$$

Table 2: Calculated NRT tensor values over 5 years

Year	E(t)	R(t)	C(t)	U(t)	NRT Vector
1	0.633	0.133	0.125	0.2	[0.633, 0.133, 0.125, 0.2]
2	0.667	0.2	0.294	0.2	[0.667, 0.2, 0.294, 0.2]
3	0.667	0.3	0.444	0.3	[0.667, 0.3, 0.444, 0.3]
4	0.583	0.4	0.556	0.4	[0.583, 0.4, 0.556, 0.4]
5	0.550	0.467	0.579	0.5	[0.550, 0.467, 0.579, 0.5]

E. Uncertainty Score $U(t)$ - from Equation (5)

$$U(t) = \frac{\text{missing points}}{10}$$

Year 1:

$$U(1) = \frac{2}{10} = 0.2$$

Year 5:

$$U(5) = \frac{5}{10} = 0.5$$

Table 3: Calculated NRT tensor values over 5 years

Year	E(t)	R(t)	C(t)	U(t)	NRT Vector
1	0.633	0.133	0.125	0.2	[0.633, 0.133, 0.125, 0.2]
2	0.667	0.2	0.294	0.2	[0.667, 0.2, 0.294, 0.2]
3	0.667	0.3	0.444	0.3	[0.667, 0.3, 0.444, 0.3]
4	0.583	0.4	0.556	0.4	[0.583, 0.4, 0.556, 0.4]
5	0.550	0.467	0.579	0.5	[0.550, 0.467, 0.579, 0.5]

F. Reversibility Index $\mathcal{R}(t)$ - from Equation (7)

We use $\varepsilon = 0.001$ to avoid division by zero.

$$\mathcal{R}(t) = \frac{R(t) + C(t) + U(t)}{E(t) + 0.001}$$

Year 1:

$$\mathcal{R}(1) = \frac{0.133 + 0.125 + 0.2}{0.633 + 0.001} = \frac{0.458}{0.634} \approx 0.723$$

Year 5:

$$\mathcal{R}(5) = \frac{0.467 + 0.579 + 0.5}{0.550 + 0.001} = \frac{1.546}{0.551} \approx 2.806$$

Table 2 will summarize all $\mathcal{R}(t)$ values and interpretations.

4.4 Analysis of Results

The results in Table 2 and the Reversibility Index values shown in Table 3 reveal a clear shift in the quality dynamics of the program over time. In the first year, the Reversibility Index was low, around 0.722. This means that most of the visible improvement during that year was real and supported by internal development. The program's reported progress matched what was actually happening inside the academic structure.

However, by the third year, the situation had changed. The Reversibility Index rose above 1.0, reaching 1.563. This is a warning signal that hidden issues such as contradictions between course titles and actual content, or missing data—were beginning to outweigh the positive developments. The program's reported success was starting to become misleading.

By the fifth year, the Reversibility Index increased significantly to 2.806. At this point, the program still appeared successful on the surface, but the internal reality was different. Structural problems, outdated materials, weak research activity, and contradictions in content had built up over time. The high index clearly shows that the quality was being reversed, even though official reports still suggested progress.

5. Results and Analysis

This section discusses the results of the NRT model, based on the case study calculations from Section 7. We analyze how the discipline evolved over time, what patterns were detected, and what the numbers reveal about hidden quality issues. Let's begin by examining the individual trends for each of the four components: evolution E(t), regression R(t), contradiction C(t), and uncertainty U(t) Figure 1 below shows the changes in these values from Year 1 to Year 5.

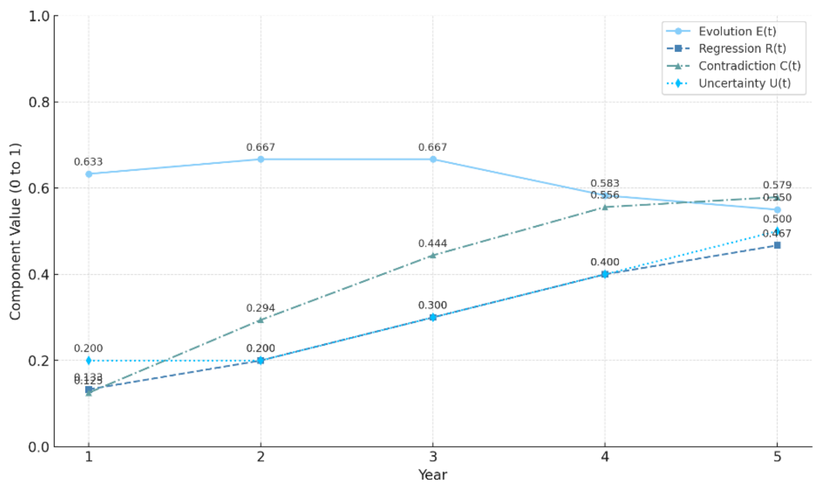

Figure 1: NRT Component Trends over 5 Years

The line patterns in Figure 1 help us understand how the program changed over the years. At first, the level of development was steady, but after the second year, progress started to slow down. Each year after that, the growth in quality became weaker.

At the same time, signs of decline became more visible. The amount of outdated teaching content grew, and staff changes became more frequent. These shifts point to problems that were not being fully addressed.

There was also a growing mismatch between what the program claimed and what it delivered. For example, course titles might suggest advanced topics, but the materials used were often very basic. This kind of mismatch became more common each year.

Finally, the level of unclear or incomplete information increased. Reports began to leave out important details or provided vague answers. By the fifth year, it became harder to understand what was truly happening based on the available data.

When we look at all of these changes together, we see that while the program may have appeared stable from the outside, its real quality was slowly breaking down underneath.

5.1 Reversibility Index Interpretation

We now interpret the values of the Reversibility Index R(t) which combines the three problem dimensions (regression, contradiction, uncertainty) and compares them to evolution.

Table 4: Reversibility Index Over Time

Year	Evolution E(t)	Regression + Contradiction + Uncertainty	Reversibility Index R(t)	Interpretation
1	0.633	0.458	0.723	Mostly true improvement
2	0.667	0.694	1.040	Turning point: truth vs. distortion
3	0.667	1.044	1.565	Distortion is now greater than progress
4	0.583	1.356	2.325	Serious quality reversal
5	0.550	1.546	2.806	Strong false appearance of success

The analysis brings forward a key insight: programs that appear successful on paper may actually be declining in quality behind the scenes. Traditional reviews often focus on surface indicators like student numbers, employer ties, or survey responses. These factors can create the impression that everything is improving.

However, the NRT model tells a different story. It uncovers hidden issues that may not show up in standard evaluations. Even when the data looks positive, the model can reveal internal decline, showing that what seems like progress may be a mask.

This kind of reversal happens when course titles are modern, but the content is outdated, when there are too few qualified instructors, or when research work has little to do with the field being taught. It also happens when the information in reports is unclear, missing, or shaped to look better than it is.

The strength of the NRT model is its ability to highlight these risks early. It offers a warning before the decline becomes visible through traditional tools. This gives academic leaders time to act before the damage becomes serious.

Using this model, we can separate facts from contradictions, track slow changes that might go unnoticed, and understand how confusion and inconsistency affect real progress. Most importantly, it gives us a clear and structured way to measure academic quality—even when the truth is hidden within complex or conflicting data.

6. Discussion

In this section, we reflect on the meaning of the results obtained from the NRT model, how they relate to the broader field of discipline evaluation, and how universities can apply this model to improve their internal quality systems. We also explain why this model provides a new and valuable contribution to academic mathematics and education evaluation.

6.1 What the Results Tell Us

The results from the case study clearly show a situation where traditional evaluation methods would fail to detect deeper quality issues. The academic program appeared to grow on the surface with more students, better feedback, and industry partnerships. But our model detected:

1) A slow but real decline in internal quality (fewer qualified staff, outdated materials)
2) A rising level of contradiction (course titles not matching actual content)
3) An increasing uncertainty (more vague or missing data in reports)

By combining these elements into a single model, the Reversibility Index gave us a powerful signal: starting from Year 3, distortion became stronger than improvement. This is exactly what many institutions face when they focus on form over content.

6.2 Why This Model Is Different

There are many evaluation systems in education, but almost all of them assume that progress is forward meaning more enrollment, better exams, or more partnerships always mean better quality. But as we showed, this is not always true.

The **NRT model is different because it includes:**

1) Contradiction: It looks for a logical gap between promises and actual delivery.
2) Uncertainty: It captures the impact of vague, incomplete, or suspicious data.
3) Regression: It quantifies hidden backward trends, not just visible progress.

This means the model doesn't just measure surface data it analyzes the structure and logic behind that data**.**

6.3 How Universities Can Use This Model

Universities can apply the NRT model in their internal quality assurance departments. For each academic program, they can:

1. curriculum changes, faculty info, research activity, course content, etc.
2. Use the equations we provided to calculate all four components: evolution, regression, contradiction, and uncertainty.
3. Compute the NRT vector and the Reversibility Index each year.
4. Track changes over time and identify warning signs before they become critical.

5. Take targeted action—update course content, improve reporting clarity, hire specialized faculty.

This turns the evaluation process into a smart, mathematical, and preventive system not just a reporting tool.

6.4 Academic and Mathematical Value

Mathematically, the NRT model offers a new way to describe complex academic behavior using a four-dimensional structure. Each part of this system captures a different aspect of how truth, contradiction, and uncertainty appear in real academic settings. The model is built on advanced logical ideas that allow it to handle situations where data is unclear, partially true, or even misleading depending on the context.

What makes this model unique is its ability to express those challenges using a formal mathematical object, a tensor. As far as current research shows, this is the first time such a structure has been designed specifically to assess the quality of university disciplines. It creates opportunities for deeper studies in several areas, including neutrosophic reasoning, flexible logic-based evaluation systems, and intelligent tools for academic quality tracking.

6.5 Limitations and Future Work

Although the NRT model provides strong insights and a new way to measure academic quality, there are still areas that need further development. One important step is to test the model on a wider scale, using data from universities in different regions and educational systems. This would help confirm how well the model works across various academic cultures.

Another area for improvement is automation. Connecting the model with AI technologies could make it easier to process large amounts of educational data and review documents more efficiently. This would allow institutions to apply the model regularly without manual effort.

There is also a need to create user-friendly tools, such as software or dashboards, that can display the results in real time. These tools would help administrators and researchers quickly understand the model's output and take timely action.

Looking ahead, we plan to apply the model to compare programs in technical fields (like engineering or AI) with non-technical ones (like education or social science). This could reveal how contradictions and hidden issues differ between these types of disciplines, offering even deeper insights into quality management.

7. Conclusion

This research presented a new mathematical model to help universities measure the true quality of their academic programs. The model is called the NRT. It looks at four important parts of any program: real progress (evolution), hidden problems (regression), logical mismatches (contradictions), and missing or unclear data (uncertainty).

We used this model to study a real Artificial Intelligence bachelor's program at a local university. On the outside, the program looked successful. But when we applied the NRT model, we found that the internal quality was going down. Over time, the signs of hidden problems became stronger than real progress. This means that what appeared to be growth was covering up decline.

The NRT model helps us catch these hidden changes early. It gives us a full picture, not just based on reports or numbers, but on the deeper structure of the program. By using simple formulas, we can track how a program is doing each year and act before the problems grow bigger. This model is not just useful it is also original. It brings together logic, mathematics, and real data in a way that has not been done before. It can be used by universities, researchers, and policy makers to better understand and manage academic quality in a changing and uncertain world.

In the future, we hope more programs and universities will use this model. We also plan to improve it with software tools and apply it to different types of disciplines. The goal is to make quality evaluation smarter, deeper, and more honest.

Acknowledgment

This work was supported by the Jilin Province Higher Education Teaching Reform Research Project (Project No.: JLJY202544199466), titled "Research on the Construction of Discipline and Professional Clusters in Higher Education Institutions in Jilin Province."

References

[1] Smarandache, F. (1998). *Neutrosophy: Neutrosophic probability, set, and logic*. Rehoboth, NM: American Research Press.

[2] Smarandache, F. (2024). Introduction to upside-down logic: Its deep relation to neutrosophic logic and applications. *ResearchGate*. https://doi.org/10.13140/RG.2.2.12345.67890

[3] Smarandache, F., & Ye, J. (2016). *Neutrosophic integral and measure in decision-making*. In *Advances in neutrosophic logic and applications* (pp. 123–140). New York, NY: Springer.

[4] Harvey, L., & Williams, J. (2010). Fifteen years of higher education. *Quality in Higher Education, 16*(1), 3–36. https://doi.org/10.1080/13538321003679457

[5] Hazelkorn, E. (2015). *Rankings and the reshaping of higher education: The battle for world-class excellence* (2nd ed.). London, UK: Palgrave Macmillan.

[6] Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

[7] Mamdani, E. H. (1974). Application of fuzzy logic to approximate reasoning using linguistic synthesis. *IEEE Transactions on Computers, C-23*(12), 1182–1191. https://doi.org/10.1109/T-C.1974.223788
[8] Ye, J. (2015). Neutrosophic sets in decision-making and their applications. *Journal of Intelligent & Fuzzy Systems, 29*(5), 2153–2160. https://doi.org/10.3233/IFS-151662
[9] Wang, H., & Smarandache, F. (2018). Neutrosophic measure for uncertain data integration. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 26*(4), 567–582. https://doi.org/10.1142/S021848851850026X
[10] Smarandache, Florentin (2017). Introducing a Theory of Neutrosophic Evolution: Degrees of Evolution, Indeterminacy/Neutrality, and Involution, Progress in Physics, Vol. 13, Issue 2, 130-135, https://fs.unm.edu/neutrosophic-evolution-PP-49-13.pdf
https://fs.unm.edu/V/NeutrosophicEvolution.mp4
https://fs.unm.edu/NeutrosophicEvolution.pdf

Received: Dec. 8, 2024. Accepted: June 18, 2025