# TOPSIS INTEGRATED NEUTROSOPHIC MCDM APPROACH FOR IOT-BASED ENTERPRISES

*A project submitted in partial fulfilment of the requirements for the award of the degree of*

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**In**

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Submitted by:

Aayushman Gupta(12211098)

Satyam Sahu(12211070)

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Supervised by:

Dr. MUKESH Mann

( Assistant professor)

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY,
SONEPAT – 131201, HARYANA, INDIA

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AAYUSHMAN GUPTA

SATYAM SAHU

# SELF DECLARATION

I hereby state that work contained in the project titled "TOPSIS INTEGRATED NEUTROSOPHIC MCDM APPROACH FOR IOT-BASED ENTERPRISES" is original. I have followed the standards of the project ethics to the best of my abilities. I have acknowledged all the sources of knowledge which I have used in the project.

Name:Aayushman Gupta & Satyam Sahu

Roll no: 12211098 & 12211071

Department of Computer Science and Engineering,

Indian Institute of Information technology,

Sonepat-131201, Haryana, India

# ABSTRACT

Name of the student: Aayushman & Satyam

Roll No: 12211098 & 12211071

Degree for which submitted: B-Tech

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Indian Institute of Information Technology, Sonepat

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This project presents a novel approach to decision-making in Internet of Things (IoT) enterprises by combining neutrosophic set theory with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The developed framework aims to address the complex, uncertain, and often contradictory nature of decision-making in IoT environments, specifically focusing on five key criteria: security, value, intelligence, transparency, and connectivity.

The integration of neutrosophic sets—which handle truth, falsehood, and indeterminacy memberships—with the proven TOPSIS method provides a robust mechanism for evaluating and ranking alternatives in IoT enterprise solutions. This combined approach effectively addresses the ambiguity and incompleteness of information often encountered in IoT decision scenarios.

# LIST OF ABBREVIATIONS

| | |
|---|---|
| AHP | Analytical Hierarchy Process |
| TOPSIS | Technique for Order of Preference by Similarity to Ideal Solution |
| MCDM | Multi Criterion Decision Making |
| CR | Consistency Rate |
| CI | Consistency Index |
| RI | Random Index |
| TrNN | Trapezoidal Neutrosophic Approach |
| FL | Fuzzy Logic |
| IOT | Internet of Things |

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# *CHAPTER 1*

# *INTRODUCTION*

## 1.1 Introduction

Brief Introduction to the Topic:

The Internet of Things (IoT) represents one of the most transformative technological paradigms of the 21st century, fundamentally changing how organizations operate and deliver value. IoT systems interconnect physical devices, vehicles, buildings, and other items embedded with electronics, software, sensors, and network connectivity, enabling these objects to collect and exchange data. This connectivity creates opportunities for more direct integration between the physical world and computer-based systems, resulting in improved efficiency, accuracy, and economic benefits.

However, the implementation of IoT solutions in enterprise environments presents multifaceted challenges that necessitate sophisticated decision-making approaches. Organizations must navigate complex trade-offs between competing criteria such as security, value generation, intelligence capabilities, transparency, and connectivity requirements. These decisions are further complicated by uncertainties, incomplete information, and the rapid evolution of IoT technologies.

## 1.2 Problem Outline

IoT enterprise implementations require decision-makers to evaluate multiple alternatives against several, often conflicting criteria while dealing with imprecise and incomplete information. The inherent uncertainty in IoT environments—stemming from technological complexities, security vulnerabilities, rapidly evolving standards, and varying stakeholder expectations—creates significant challenges in making optimal decisions.

Specific challenges include:

1. **Uncertainty Management**: Traditional decision-making models struggle to handle the high degree of uncertainty and indeterminacy in IoT environments.
2. **Criteria Interdependence**: The complex relationships between criteria such as security and connectivity, or value and transparency, are difficult to model effectively.
3. **Information Incompleteness**: Decision-makers often operate with partial, vague, or inconsistent information about alternatives and their performance.

4. **Dynamic Context**: IoT implementations exist in rapidly changing technological and business environments, requiring adaptive decision frameworks.

5. **Stakeholder Diversity**: Different stakeholders may have varying priorities and perspectives on the importance of different criteria.

These challenges necessitate an innovative approach that can systematically address the

## 1.3 Research Objectives

This research aims to develop, implement, and validate a combined neutrosophic-TOPSIS approach for multi-criteria decision making in IoT enterprise environments. The specific objectives include:

1. To formulate a comprehensive theoretical framework that integrates neutrosophic set theory with the TOPSIS method for robust decision-making in uncertain environments.
2. To identify and define key evaluation criteria relevant to IoT enterprise solutions, focusing on security, value, intelligence, transparency, and connectivity.
3. To develop a systematic methodology for applying the combined neutrosophic-TOPSIS approach to real-world IoT enterprise decision scenarios.
4. To validate the proposed approach through a detailed case study, demonstrating its effectiveness in addressing practical IoT implementation challenges.
5. To compare the performance of the proposed approach with traditional MCDM methods and establish its advantages in handling uncertainty and complexity.
6. To provide actionable insights and recommendations for IoT stakeholders based on the findings of the research.

## 1.4 Significance of the Study

This study contributes significantly to both theoretical knowledge and practical applications in several ways:

**Theoretical Contributions:**

1. **Methodological Innovation**: The integration of neutrosophic sets with TOPSIS creates a novel MCDM framework that extends existing approaches to better handle uncertainty and indeterminacy.

2. **IoT Decision Theory**: The research advances understanding of the unique decision-making challenges in IoT contexts and how they can be systematically addressed.
3. **Uncertainty Modeling**: The neutrosophic approach offers new insights into representing and processing different types of uncertainty in decision environments.

**Practical Significance:**

1. **Enhanced Decision Support**: The developed methodology provides IoT stakeholders with a robust tool for evaluating alternatives and making more informed implementation decisions.
2. **Risk Mitigation**: By comprehensively addressing uncertainty, the approach helps organizations identify and mitigate potential risks in IoT deployments.
3. **Resource Optimization**: Improved decision-making leads to more efficient allocation of resources and better alignment of IoT initiatives with strategic objectives.
4. **Standardization Potential**: The framework offers a foundation for standardizing evaluation approaches across the IoT industry, potentially improving interoperability and collaboration.

The findings of this study will benefit a wide range of stakeholders, including IoT solution providers, enterprise technology decision-makers, industry standards bodies, and academic researchers in the fields of decision science and IoT technologies.

# *CHAPTER 2*

## *Study and review of literature*

## Internet of Things (IoT)

The Internet of Things represents a paradigm where physical objects are connected to the internet, enabling them to collect and exchange data. This connectivity transforms traditional objects into smart, interconnected devices that can sense, communicate, and act in various contexts.

### Evolution of IoT

The concept of IoT has evolved significantly since the term was first coined by Kevin Ashton in 1999. Initially envisioned as a network of RFID-connected objects, IoT has expanded to encompass billions of devices across consumer, industrial, and enterprise domains. Gubbi et al. (2013) defined IoT as "the interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications."

## 2.2 Multi-Criteria Decision Making (MCDM)

Multi-Criteria Decision Making (MCDM) refers to a family of methods designed to help decision-makers evaluate alternatives based on multiple, often conflicting criteria. These methods provide structured approaches to complex decision problems where simple intuition might be insufficient.

### Theoretical Foundation

MCDM emerged as a distinct field of operational research in the 1960s, with pioneering work by researchers such as Bernard Roy, Thomas Saaty, and others. The field addresses the fundamental challenge of aggregating performance evaluations across different criteria to reach a comprehensive assessment of alternatives.

The general MCDM process involves several key steps:

1. Defining the decision problem and objectives
2. Identifying relevant criteria and alternatives
3. Determining criteria weights.
4. Evaluating alternatives against criteria.
5. Aggregating evaluations to rank or select alternatives.
6. Conducting sensitivity analysis to validate results.

### MCDM in Complex Environments

In environments characterized by uncertainty and complexity, traditional MCDM methods have been extended to incorporate various uncertainty modeling approaches, including:

- Probability theory and stochastic MCDM

- Fuzzy set theory and fuzzy MCDM
- Rough set theory
- Grey systems theory
- Neutrosophic set theory

## 2.3 Fuzzy Logic

Fuzzy logic, introduced by Lotfi Zadeh in 1965, provides a mathematical framework for dealing with uncertain or imprecise information. Unlike classical logic, which operates on binary truth values (true or false), fuzzy logic allows for degrees of truth, enabling more nuanced representation of real-world concepts.

**Fuzzy Set Theory**

The cornerstone of fuzzy logic is fuzzy set theory, where elements have degrees of membership in sets, represented by membership functions that map elements to values between 0 and 1. Formally, a fuzzy set A in a universe of discourse X is characterized by a membership function $\mu A(x)$ that associates each element x in X with a real number in the interval [0,1].

The key operations in fuzzy set theory include:

- **Complement**: $\mu A'(x) = 1 - \mu A(x)$
- **Union**: $\mu A \cup B(x) = \max[\mu A(x), \mu B(x)]$
- **Intersection**: $\mu A \cap B(x) = \min[\mu A(x), \mu B(x)]$

**Fuzzy Logic Systems**

A fuzzy logic system typically consists of four components:

1. **Fuzzification**: Converting crisp input values into fuzzy values using membership functions.
2. **Rule Base**: A set of if-then rules that define the system behavior.
3. **Inference Engine**: Applying fuzzy rules to the fuzzified inputs to determine fuzzy outputs.
4. **Defuzzification**: Converting fuzzy outputs back to crisp values.

## 2.4 Neutrosophic Sets

Neutrosophic set theory, introduced by Florentin Smarandache in 1995, represents a generalization of classical sets, fuzzy sets, and intuitionistic fuzzy sets. It provides a powerful framework for handling uncertainty, imprecision, inconsistency, and indeterminacy in information.

**Theoretical Foundation**

A neutrosophic set is characterized by three independent membership functions: truth-membership T, indeterminacy-membership I, and falsity-membership F, each mapping elements to the non-standard unit interval ]0-, 1+[. This generalization allows neutrosophic sets to represent not only vague information (as in fuzzy sets) but also uncertain, incomplete, inconsistent, and paradoxical information.

Formally, a neutrosophic set A in a universe of discourse X is defined as:

$A = \{\langle x, T\_A(x), I\_A(x), F\_A(x)\rangle \mid x \in X\}$

Where:

- $T\_A(x)$ represents the degree of truth membership
- $I\_A(x)$ represents the degree of indeterminacy membership
- $F\_A(x)$ represents the degree of falsity membership

With the condition that $0- \leq T\_A(x) + I\_A(x) + F\_A(x) \leq 3+$

Single-Valued Neutrosophic Sets

For practical applications, single-valued neutrosophic sets (SVNS) have been introduced, where the membership functions map to the standard unit interval [0,1]. An SVNS A is defined as:

$A = \{\langle x, T\_A(x), I\_A(x), F\_A(x)\rangle \mid x \in X\}$

Where:

- $T\_A(x), I\_A(x), F\_A(x) \in [0,1]$
- $0 \leq T\_A(x) + I\_A(x) + F\_A(x) \leq 3$

### Operations on Neutrosophic Sets

Key operations on neutrosophic sets include:

- Complement: $A\hat{}c = \{\langle x, F\_A(x), I\_A(x), T\_A(x)\rangle \mid x \in X\}$
- Union: $A \cup B = \{\langle x, \max(T\_A(x), T\_B(x)), \min(I\_A(x), I\_B(x)), \min(F\_A(x), F\_B(x))\rangle \mid x \in X\}$
- Intersection: $A \cap B = \{\langle x, \min(T\_A(x), T\_B(x)), \max(I\_A(x), I\_B(x)), \max(F\_A(x), F\_B(x))\rangle \mid x \in X\}$

## 2.5 TOPSIS Method

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a widely used MCDM method first developed by Hwang and Yoon in 1981. TOPSIS ranks alternatives based on their geometric distances from both the positive ideal solution (PIS) and the negative ideal solution (NIS).

## Basic Principles

The fundamental principle of TOPSIS is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution represents a hypothetical alternative that maximizes benefit criteria and minimizes cost criteria, while the negative ideal solution does the opposite.

## TOPSIS Procedure

The classical TOPSIS method follows these steps:

1. Construct the decision matrix: Create a matrix where rows represent alternatives, columns represent criteria, and elements represent the performance ratings.
2. Normalize the decision matrix: Transform different scales into comparable scales, typically using vector normalization: $r_{ij} = x_{ij} / \sqrt{\Sigma x_{ij}^2}$
3. Calculate the weighted normalized decision matrix: Multiply normalized values by the criteria weights: $v_{ij} = w_j \times r_{ij}$
4. Determine the positive and negative ideal solutions:
   - Positive ideal solution (PIS): $A^+ = \{v_1^+, v_2^+, ..., v_n^+\}$
   - Negative ideal solution (NIS): $A^- = \{v_1^-, v_2^-, ..., v_n^-\}$

Where:

   - $v_j^+ = \max(v_{ij})$ for benefit criteria or $\min(v_{ij})$ for cost criteria
   - $v_j^- = \min(v_{ij})$ for benefit criteria or $\max(v_{ij})$ for cost criteria

5. Calculate the separation measures: Compute the distance of each alternative from PIS and NIS:
   - Distance from PIS: $S_i^+ = \sqrt{\Sigma (v_{ij} - v_j^+)^2}$
   - Distance from NIS: $S_i^- = \sqrt{\Sigma (v_{ij} - v_j^-)^2}$
6. Calculate the relative closeness to the ideal solution: $C_i = S_i^- / (S_i^+ + S_i^-)$
7. Rank the alternatives: Higher values of $C_i$ indicate better alternatives.

## Advantages and Limitations

Advantages of TOPSIS:

- Intuitive and easily understandable concept
- Simple computational procedure
- Ability to account for both benefit and cost criteria
- Provision of cardinal ranking of alternatives
- Consideration of both best and worst alternatives in the ranking process

Limitations of TOPSIS:

- Sensitivity to criteria weights
- Vulnerability to the "rank reversal" problem
- Limited ability to handle uncertainty and imprecision in its classical form
- Use of Euclidean distance, which may not always capture decision-maker preferences

## 2.5 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), developed by Thomas L. Saaty in the 1970s, is a structured technique for organizing and analyzing complex decisions. It decomposes decision problems into hierarchies and employs pairwise comparisons to establish priorities.

**Hierarchical Structure**

AHP structures a decision problem into a hierarchy with three main levels:

1. Goal: The overall objective of the decision
2. Criteria: The factors that contribute to the goal
3. Alternatives: The options being evaluated

More complex problems may include additional levels, such as sub-criteria or sub-sub-criteria.

**Pairwise Comparison**

AHP uses pairwise comparisons to determine the relative importance of elements at each level. Decision-makers compare pairs of elements using a fundamental scale of absolute numbers (typically 1-9), where:

- 1 indicates equal importance
- 3 indicates moderate importance
- 5 indicates strong importance
- 7 indicates very strong importance
- 9 indicates extreme importance
- 2, 4, 6, 8 are intermediate values

These comparisons form pairwise comparison matrices, which are then used to derive priority vectors.

**Consistency Analysis**

AHP includes a mechanism to check the consistency of pairwise comparisons. The consistency ratio (CR) is calculated as:

CR =

CI / RI

Where:

- CI (Consistency Index) = ($\lambda$_max - n) / (n - 1)
- $\lambda$_max is the maximum eigenvalue of the comparison matrix
- n is the dimension of the matrix
- RI (Random Index) is the average CI of randomly generated comparison matrices

A CR value less than 0.1 is generally considered acceptable, indicating reasonably consistent judgments.

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# *Chapter 3*

# *Theoretical Framework*

## 3.1 **Neutrosophic Set Theory**

**Fundamental Concepts**

Neutrosophic set theory extends traditional set theories by incorporating the concept of indeterminacy as an independent dimension. While fuzzy sets characterize elements with a single membership degree and intuitionistic fuzzy sets use both membership and non-membership degrees, neutrosophic sets introduce a third dimension—indeterminacy—to provide a more comprehensive framework for uncertainty representation.

A single-valued neutrosophic set (SVNS) A in a universe of discourse X is defined as:

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

Where:

- $T_A(x) \in [0,1]$ represents the truth-membership degree
- $I_A(x) \in [0,1]$ represents the indeterminacy-membership degree
- $F_A(x) \in [0,1]$ represents the falsity-membership degree

With the condition: $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$

This tripartite representation allows neutrosophic sets to model various types of uncertainty simultaneously:

- Vagueness through partial truth membership
- Incompleteness through indeterminacy
- Inconsistency through the independence of the three membership functions

**Mathematical Operations**

For two single-valued neutrosophic sets A and B, the following operations are defined:

1. Complement: $A^c = \{\langle x, F_A(x), I_A(x), T_A(x)\rangle \mid x \in X\}$
2. Containment: $A \subseteq B$ if and only if $T_A(x) \leq T_B(x)$, $I_A(x) \geq I_B(x)$, and $F_A(x) \geq F_B(x)$ for all $x \in X$
3. Union: $A \cup B = \{\langle x, \max(T_A(x), T_B(x)), \min(I_A(x), I_B(x)), \min(F_A(x), F_B(x))\rangle \mid x \in X\}$
4. Intersection: $A \cap B = \{\langle x, \min(T_A(x), T_B(x)), \max(I_A(x), I_B(x)), \max(F_A(x), F_B(x))\rangle \mid x \in X\}$
5. Addition: $A \oplus B = \{\langle x, T_A(x) + T_B(x) - T_A(x)T_B(x), I_A(x)I_B(x), F_A(x)F_B(x)\rangle \mid x \in X\}$
6. Multiplication: $A \otimes B = \{\langle x, T_A(x)T_B(x), I_A(x) + I_B(x) - I_A(x)I_B(x), F_A(x) + F_B(x) - F_A(x)F_B(x)\rangle \mid x \in X\}$

**Neutrosophic Numbers**

In MCDM applications, neutrosophic numbers are often used to represent evaluations and preferences. A single-valued neutrosophic number (SVNN) is denoted as $a = \langle T_a, I_a, F_a \rangle$, where $T_a, I_a, F_a \in [0,1]$.

To compare neutrosophic numbers, a score function $S(a)$ and an accuracy function $H(a)$ are defined:

$S(a) = (2 + T_a - I_a - F_a)/3$ $H(a) = T_a - F_a$

For two neutrosophic numbers a and b:

- If $S(a) > S(b)$, then $a > b$
- If $S(a) = S(b)$ and $H(a) > H(b)$, then $a > b$
- If $S(a) = S(b)$ and $H(a) = H(b)$, then $a = b$

These comparison rules allow for ranking neutrosophic evaluations, which is essential in MCDM problems.

Linguistic Variables in Neutrosophic Context

In practical applications, decision-makers often express preferences using linguistic terms rather than numeric values. These linguistic expressions can be converted to neutrosophic numbers using predefined scales.

For example, a seven-point linguistic scale might be defined as:

**Classical TOPSIS Procedure**

The classical TOPSIS method follows a systematic procedure:

1. **Construct the decision matrix X**: $X = [x_{ij}]_{m\times n}$ Where $x_{ij}$ represents the performance rating of alternative i with respect to criterion j, m is the number of alternatives, and n is the number of criteria.
2. **Normalize the decision matrix**: $r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2}$ This normalization makes different criteria comparable by converting them to dimensionless units.
3. **Calculate the weighted normalized decision matrix**: $v_{ij} = w_j \times r_{ij}$ Where $w_j$ is the weight of criterion j, and $\sum_{j=1}^{n} w_j = 1$.
4. **Determine the positive ideal solution (PIS) and negative ideal solution (NIS)**:
   - PIS: $A^+ = \{v_1^+, v_2^+, ..., v_n^+\}$
   - NIS: $A^- = \{v_1^-, v_2^-, ..., v_n^-\}$

Where:

- For benefit criteria: $v_j^+ = \max_i(v_{ij})$ and $v_j^- = \min_i(v_{ij})$
- For cost criteria: $v_j^+ = \min_i(v_{ij})$ and $v_j^- = \max_i(v_{ij})$

5. **Calculate the separation measures**:
   - Distance from PIS: $S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}$
   - Distance from NIS: $S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}$
6. **Calculate the relative closeness to the ideal solution**: $C_i = S_i^- / (S_i^+ + S_i^-)$ Where $0 \leq C_i \leq 1$. A larger value of $C_i$ indicates a better alternative.
7. **Rank the alternatives**: Alternatives are ranked in descending order of their $C_i$ values.

**Distance Measures in TOPSIS**

The classical TOPSIS method uses Euclidean distance to measure the separation of alternatives from the ideal solutions. However, other distance measures can also be employed:

- **Manhattan Distance**: $S_i = \sum_{j=1}^n |v_{ij} - v_j|$
- **Chebyshev Distance**: $S_i = \max_j |v_{ij} - v_j|$
- **Minkowski Distance**: $S_i = (\sum_{j=1}^n |v_{ij} - v_j|^p)^{(1/p)}$

The choice of distance measure can affect the ranking of alternatives and should be selected based on the specific characteristics of the decision problem.

## 3.2 Integration of Neutrosophic Sets with TOPSIS

Motivation for Integration

The integration of neutrosophic sets with TOPSIS creates a powerful MCDM framework that addresses several key challenges in IoT enterprise decision-making:

Comprehensive Uncertainty Handling: Neutrosophic sets can represent multiple facets of uncertainty (vagueness, incompleteness, inconsistency) that are prevalent in IoT environments.

Independent Treatment of Different Uncertainty Types: The tripartite representation (truth, indeterminacy, falsity) allows for the independent treatment of different uncertainty types, which is crucial in IoT contexts where information quality varies across criteria.

Enhanced Expressiveness for Decision-Makers: Decision-makers can express evaluations more naturally, including situations where they have partial knowledge, contradictory information, or indeterminate evaluations.

Rigorous Distance-Based Evaluation: The TOPSIS framework provides a structured approach to ranking alternatives based on their relative performance, which aligns well with the multifaceted nature of IoT decision problems.

**Neutrosophic TOPSIS Procedure**:

The neutrosophic TOPSIS approach follows these steps:

Construct the neutrosophic decision matrix:

$X = [x_{ij}]_{m \times n}$

Where $x_{ij} = \langle T_{ij}, I_{ij}, F_{ij} \rangle$ is a single-valued neutrosophic number representing the performance rating of alternative i with respect to criterion j.

Normalize the neutrosophic decision matrix (if necessary):

For benefit criteria: $r_{ij} = \langle T_{ij}, I_{ij}, F_{ij} \rangle$

For cost criteria: $r_{ij} = \langle F_{ij}, I_{ij}, T_{ij} \rangle$

Calculate the weighted normalized neutrosophic decision matrix:

$v_{ij} = w_j \otimes r_{ij}$

Where $w_j$ is the neutrosophic weight of criterion j, and $\otimes$ denotes the neutrosophic multiplication operation.

Determine the neutrosophic positive ideal solution (NPIS) and neutrosophic negative ideal solution (NNIS):

NPIS: $A^+ = \{v_1^+, v_2^+, ..., v_n^+\}$

NNIS: $A^- = \{v_1^-, v_2^-, ..., v_n^-\}$

Where:

$v_j^+ = \langle 1,0,0 \rangle$ (for all j) in the simplified approach

$v_j^- = \langle 0,1,1 \rangle$ (for all j) in the simplified approach

Calculate the separation measures using neutrosophic distance:

Distance from NPIS: $S_i^+ = \sum_{j=1}^n d(v_{ij}, v_j^+)$

Distance from NNIS: $S_i^- = \sum_{j=1}^n d(v_{ij}, v_j^-)$

Where d(a,b) is the distance between two neutrosophic numbers a and b.

Calculate the relative closeness coefficient:

$C_i = S_i^- / (S_i^+ + S_i^-)$

Rank the alternatives based on the decreasing values of $C_i$.

**Neutrosophic Distance Measures**

Several distance measures can be used to calculate the separation between neutrosophic numbers:

Euclidean Distance:

$d(a,b) = \sqrt{1/3 \times [(T_a - T_b)^2 + (I_a - I_b)^2 + (F_a - F_b)^2]}$

Hamming Distance:

$d(a,b) = 1/3 \times (|T_a - T_b| + |I_a - I_b| + |F_a - F_b|)$

Normalized Euclidean Distance:

$d(a,b) = \sqrt{1/3 \times [(T_a - T_b)^2 + (I_a - I_b)^2 + (F_a - F_b)^2]}$

Normalized Hamming Distance:

$d(a,b) = 1/3 \times (|T_a - T_b| + |I_a - I_b| + |F_a - F_b|)$

The choice of distance measure can influence the final ranking of alternatives and should be selected based on the specific requirements of the decision problem.

**Criteria Weight Determination**

In the neutrosophic-TOPSIS approach, criteria weights can be determined using various methods:

Direct Assignment: Decision-makers directly assign neutrosophic weights to criteria based on their expertise and preferences.

Neutrosophic AHP: Using pairwise comparisons in a neutrosophic environment to derive criteria weights.

Neutrosophic Entropy Method: Calculating weights based on the information content of criteria evaluations.

Group Decision Making: Aggregating individual neutrosophic weights from multiple decision-makers using neutrosophic aggregation operators.

# *CHAPTER 4*

# *METHODOLOGY*

# 4.1 Research Design

This research employs a mixed-methods approach that combines theoretical development with empirical validation. The methodology follows a systematic sequence that spans from theoretical framework development to practical application and validation.

**Research Philosophy**

The study adopts a pragmatic philosophical stance, recognizing that both objective measurement and subjective interpretation are necessary to understand the complex decision-making processes in IoT enterprise environments. This pragmatic approach allows for the integration of:

- **Positivist elements**: Employing mathematical models and quantitative analysis to evaluate alternatives systematically.
- **Interpretivist elements**: Acknowledging the subjective nature of criteria weights, evaluation preferences, and the contextual interpretation of results.

**Methodological Approach**

The research methodology consists of four main phases:

1. **Theoretical Framework Development**:
    - Literature review and synthesis
    - Formulation of the neutrosophic-TOPSIS integration
    - Mathematical modeling of the combined approach
2. **Criteria Identification and Definition**:
    - Systematic identification of relevant IoT enterprise evaluation criteria
    - Definition and operationalization of the five key criteria
    - Development of measurement scales for each criterion
3. **Empirical Application**:
    - Case study design
    - Data collection through expert evaluations
    - Application of the proposed neutrosophic-TOPSIS approach
4. **Validation and Comparative Analysis**:
    - Result interpretation and validation
    - Sensitivity analysis
    - Comparison with alternative MCDM approaches

**Research Methods**

The study employs multiple research methods:

- **Theoretical Analysis**: Mathematical derivation and logical analysis of the integrated neutrosophic-TOPSIS approach.
- **Expert Consultation**: Engagement with IoT domain experts for criteria validation and weighting.
- **Case Study**: Detailed investigation of an IoT enterprise decision scenario to apply and validate the proposed approach.
- **Comparative Analysis**: Benchmarking the proposed approach against traditional MCDM methods.

## 4.2 Criteria Selection

The evaluation of IoT enterprise solutions requires consideration of multiple criteria that reflect the diverse aspects of these complex systems. This research focuses on five key criteria that collectively capture the essential dimensions of IoT implementations: security, value, intelligence, transparency, and connectivity.

**Security**

Security in IoT contexts refers to the protection of devices, data, networks, and systems from unauthorized access, attacks, and damage. This criterion encompasses:

- **Data Protection**: Measures to ensure the confidentiality, integrity, and availability of data collected, processed, and transmitted by IoT devices.
- **Device Security**: Features that protect IoT devices from physical and cyber threats, including secure boot, authentication mechanisms, and tamper resistance.
- **Network Security**: Protocols and measures that secure communication between IoT devices and other systems, such as encryption, secure routing, and intrusion detection.
- **Update Management**: Mechanisms for securely updating firmware and software to address vulnerabilities.
- **Compliance**: Adherence to relevant security standards and regulations.

**Value**

Value represents the economic and strategic benefits that an IoT solution delivers relative to its costs. This criterion includes:

- **Return on Investment (ROI)**: The financial returns generated by the IoT solution compared to its implementation and operational costs.
- **Cost Efficiency**: The solution's ability to reduce operational costs, optimize resource utilization, and improve productivity.
- **Strategic Alignment**: The alignment of the IoT solution with organizational goals and business strategies.

- **Scalability Economics**: The economic implications of scaling the solution to accommodate growth.
- **Time-to-Value**: The speed at which the solution begins to deliver tangible benefits.

**Intelligence**

Intelligence refers to the cognitive capabilities of IoT systems to process data, derive insights, and make autonomous or semi-autonomous decisions. This criterion encompasses:

- **Data Analytics**: The ability to analyze data collected from IoT devices to extract meaningful patterns and insights.
- **Machine Learning Capabilities**: The integration of machine learning algorithms for predictive analytics, anomaly detection, and adaptive behavior.
- **Edge Computing**: The distribution of computing resources to the network edge to enable real-time processing and decision-making.
- **Context Awareness**: The ability to interpret data within its operational context to enhance relevance and accuracy.
- **Autonomous Operation**: The degree to which the system can function autonomously with minimal human intervention.

**Transparency**

Transparency relates to the visibility, explainability, and accountability of IoT systems and their operations. This criterion includes:

- **Data Visibility**: The accessibility and clarity of information about what data is collected, how it is used, and where it is stored.
- **Algorithmic Transparency**: The explainability of algorithms and decision processes employed by the IoT system.
- **Operational Clarity**: The visibility into the system's operational status, activities, and performance.
- **Auditability**: The ability to track and verify the system's actions and outputs.
- **User Control**: The degree to which users can understand and control the system's behavior.

**Connectivity**

Connectivity represents the communication capabilities and network infrastructure that enable IoT devices to interact with each other and with central systems. This criterion encompasses:

- **Network Coverage**: The geographical and spatial reach of the communication network.
- **Bandwidth**: The data transmission capacity of the network.
- **Latency**: The time delay in data transmission between devices and systems.

- **Interoperability**: The ability to connect and communicate with diverse devices and systems.
- **Resilience**: The reliability and robustness of connectivity under various operating conditions.

**Criteria Relationships**

These five criteria are not entirely independent but exhibit complex interrelationships:

- Security measures may impact connectivity by introducing authentication and encryption overhead.
- Intelligence capabilities can enhance value through improved decision-making and operational efficiency.
- Transparency requirements may influence security implementations by necessitating certain forms of access and visibility.
- Connectivity quality affects intelligence by determining the timeliness and completeness of data available for analysis.

These interrelationships highlight the importance of a holistic evaluation approach that considers the combined effect of all criteria.

## 4.3 Data Collection Methods

The research employs multiple data collection methods to gather the necessary information for applying the neutrosophic-TOPSIS approach to IoT enterprise decision-making. These methods are designed to capture both quantitative evaluations and the underlying uncertainties inherent in the assessment process.

**Expert Evaluations**

Expert evaluations form the primary source of data for alternative assessments and criteria weighting. The process involves:

1. Expert Panel Formation: Selection of domain experts with diverse backgrounds in IoT security, business value assessment, artificial intelligence, data governance, and network engineering.
2. Evaluation Framework Development: Creation of structured evaluation templates with clear definitions of criteria, subcriteria, and measurement scales.

3. Neutrosophic Elicitation: Collection of expert judgments using neutrosophic linguistics scales, where experts provide:
    - Truth-membership degrees (level of agreement that an alternative satisfies a criterion)
    - Indeterminacy-membership degrees (level of uncertainty in the evaluation)
    - Falsity-membership degrees (level of agreement that an alternative does not satisfy a criterion)
4. Aggregation of Expert Judgments: Combination of individual expert evaluations using neutrosophic aggregation operators such as the neutrosophic weighted average operator.

**Technical Documentation Analysis**

Technical specifications and documentation of IoT alternatives provide objective data points for the evaluation:

1. Documentation Collection: Gathering technical specifications, white papers, security certifications, and performance benchmarks for each alternative.
2. Parameter Extraction: Systematic extraction of relevant parameters related to each criterion (e.g., encryption standards, processing capabilities, network protocols).
3. Neutrosophic Conversion: Transformation of technical parameters into neutrosophic values, accounting for measurement uncertainties and variability in operating conditions.

**Case Study Investigation**

The case study approach provides contextual data on how alternatives perform in real-world scenarios:

1. Case Identification: Selection of representative IoT enterprise implementation scenarios.
2. Performance Data Collection: Gathering of performance metrics, user feedback, and operational outcomes.
3. Contextual Analysis: Analysis of how environmental factors, implementation challenges, and organizational characteristics influence performance.
4. Neutrosophic Assessment: Conversion of case findings into neutrosophic evaluations that capture the nuanced performance patterns observed.

**Criteria Weight Determination**

Criteria weights are established through a structured process:

1. Initial Weight Elicitation: Collection of individual neutrosophic weights from experts using pairwise comparison or direct assignment methods.

2. Weight Aggregation: Combination of individual weights using neutrosophic aggregation techniques.
3. Consistency Verification: Checking the logical consistency of the aggregated weights.
4. Sensitivity Testing: Analysis of how variations in weights affect the stability of decision outcomes.

**Data Quality Assurance**

To ensure the reliability and validity of collected data, several quality assurance measures are implemented:

1. Expert Qualification Verification: Validation of expert qualifications and experience in relevant domains.
2. Cross-Validation: Comparison of data from different sources to identify inconsistencies.
3. Triangulation: Integration of multiple data collection methods to strengthen the evidence base.
4. Uncertainty Documentation: Explicit recording of uncertainty sources and levels throughout the data collection process.
5. Feedback Loops: Incorporation of expert feedback on preliminary data interpretations to refine understanding.

These data collection methods collectively provide a comprehensive foundation for applying the neutrosophic-TOPSIS approach, capturing both the performance evaluations of alternatives and the associated uncertainties.

## 4.4 Proposed Hybrid Neutrosophic TOPSIS Framework for IoT Enterprise Decision-Making

**Introduction**

This methodology integrates trapezoidal neutrosophic sets (TrNS) with TOPSIS to address uncertainty in IoT enterprise decisions. The approach enhances traditional MCDM by:

- Capturing truth, indeterminacy, and falsity independently.
- Handling asymmetric uncertainty via trapezoidal membership functions.
- Enabling dynamic weight adaptation for IoT environments.

**Methodology**

**Step 1: Problem Structuring**

**1.1 Decision Objectives**

- Define the IoT enterprise goal (e.g., *"Select optimal IoT platform for smart manufacturing"*).

### 1.2 Criteria Hierarchy

| **Main Criteria** | **Sub-Criteria** |
|---|---|
| **Security ($C_1$)** | Encryption ($C_{11}$), Access Control ($C_{12}$) |
| **Value ($C_2$)** | ROI ($C_{21}$), User Satisfaction ($C_{22}$) |
| **Intelligence ($C_3$)** | AI Integration ($C_{31}$), Adaptability ($C_{32}$) |
| **Connectivity ($C_3$)** | Stable connectivity(C41),Fast connectitvity(C42) |
| **Transparency ($C_3$)** | Empowering Users(C51),Promoting Accountability(C52) |

For criterion *j*, aggregated weight $w_j$ is:

$$w_j = \left\langle \left( \frac{\sum_{k=1}^{K} \lambda_k \cdot l_k^T}{\sum \lambda_k}, \dots \right); 1 - \prod_{k=1}^{K} (1 - T_{jk})^{\lambda_k}, \prod_{k=1}^{K} I_{jk}^{\lambda_k}, \prod_{k=1}^{K} F_{jk}^{\lambda_k} \right\rangle$$

where $(l_k^T, m_k^T, u_k^T, v_k^T)$ are trapezoidal bounds.

### 2.3 Normalization

Normalize truth/falsity components:

$$T_j^{\text{norm}} = \frac{T_j}{\sum T_j}, \quad F_j^{\text{norm}} = \frac{F_j}{\sum F_j}$$

**Distance Measures**

$$d_i^+ = \sqrt{\frac{1}{4}\sum_{t=1}^{4}\left(\frac{v_{ij}^{(t)} - v_j^{+(t)}}{v_j^{\max(t)} - v_j^{\min(t)}}\right)^2}$$

**Ranking**

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-}$$

**Implementation Tools**

The following tools support the implementation of the neutrosophic-TOPSIS approach:

1. **Software Tools**
   - Spreadsheet Software: For basic neutrosophic calculations and matrix operations.
   - Mathematical Computing Platforms: Such as MATLAB or Python with NumPy for more complex operations.
   - Decision Support Systems: Specialized software that can be adapted for neutrosophic MCDM.
   - Visualization Tools: For creating graphical representations of results.
2. **Analytical Templates**
   - Neutrosophic Conversion Tables: For translating linguistic assessments into neutrosophic values.
   - Evaluation Matrices: Structured templates for recording expert evaluations.
   - Weight Elicitation Forms: Templates for collecting criteria importance judgments.
   - Calculation Templates: Standardized formats for TOPSIS calculations.
3. **Data Collection Instruments**
   - Expert Survey Forms: Structured questionnaires for expert evaluations.
   - Interview Protocols: Guidelines for conducting in-depth expert interviews.

- Technical Data Collection Forms: Templates for recording technical specifications.
- Observation Checklists: For collecting empirical data on alternative performance.

## 4.5 Experimental Calculations:

STEP1- Trapezoidal Neutrosophic Pair-Wise Comparison Matrix for IoT Enterprises

| Criteria | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $C_1$ | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 | ⟪0.5,0.6,0.6,0.7⟫, 0.3, 0.4, 0.4 | ⟪0.6,0.7,0.7,0.8⟫, 0.3, 0.3, 0.3 | ⟪0.3,0.4,0.4,0.5⟫, 0.5, 0.5, 0.5 | ⟪0.5,0.6,0.6,0.7⟫, 0.4, 0.4, 0.3 |
| $C_2$ | ⟪0.3,0.4,0.4,0.5⟫, 0.6, 0.5, 0.5 | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 | ⟪0.5,0.6,0.6,0.7⟫, 0.3, 0.4, 0.4 | ⟪0.6,0.7,0.7,0.8⟫, 0.2, 0.3, 0.4 | ⟪0.5,0.6,0.6,0.7⟫, 0.4, 0.4, 0.3 |
| $C_3$ | ⟪0.2,0.3,0.3,0.4⟫, 0.7, 0.6, 0.6 | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 | ⟪0.5,0.6,0.6,0.7⟫, 0.3, 0.4, 0.4 | ⟪0.6,0.7,0.7,0.8⟫, 0.2, 0.3, 0.3 |
| $C_4$ | ⟪0.6,0.7,0.7,0.8⟫, 0.2, 0.3, 0.3 | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 | ⟪0.3,0.4,0.4,0.5⟫, 0.6, 0.5, 0.5 | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 | ⟪0.5,0.6,0.6,0.7⟫, 0.4, 0.4, 0.3 |
| $C_5$ | ⟪0.3,0.4,0.4,0.5⟫, 0.6, 0.5, 0.5 | ⟪0.5,0.6,0.6,0.7⟫, 0.4, 0.4, 0.3 | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 | ⟪0.5,0.6,0.6,0.7⟫, 0.3, 0.4, 0.4 | ⟪0.4,0.5,0.5,0.6⟫, 0.5, 0.5, 0.5 |

We'll use a simplified neutrosophic score function proposed in literature:

$$\text{Crisp Score} = \frac{a_1 + 2a_2 + 2a_3 + a_4}{6} \times (1 - \bar{I}) \times (1 - \bar{F})$$

**Applying to Each Entry:**
Let's go ahead and compute the crisp score for each cell in the matrix:

| Criteria | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $C_1$ | 0.416 | 0.420 | 0.478 | 0.306 | 0.448 |
| $C_2$ | 0.354 | 0.416 | 0.420 | 0.478 | 0.448 |
| $C_3$ | 0.264 | 0.416 | 0.416 | 0.448 | 0.478 |
| $C_4$ | 0.478 | 0.416 | 0.354 | 0.416 | 0.448 |
| $C_5$ | 0.354 | 0.448 | 0.416 | 0.448 | 0.416 |

STEP2-

We first need some hypothetical values for the criteria. Let's assume the following ratings:

| Option | Security | Connectivity | Intelligent | Transparency | Value |
|---|---|---|---|---|---|
| Spark | 8 | 9 | 9 | 7 | 8 |
| Knime | 7 | 8 | 8 | 8 | 7 |
| Hadoop | 9 | 7 | 7 | 6 | 9 |

We use the **vector normalization method:**

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$$

STEP3-Normalize the Decision Matrix

Column-wise denominator calculations:

**Column-wise denominator calculations:**

- Security: $\sqrt{(8^2 + 7^2 + 9^2)} = \sqrt{(64 + 49 + 81)} = \sqrt{194} \approx$ **13.928**
- Connectivity: $\sqrt{(9^2 + 8^2 + 7^2)} = \sqrt{(81 + 64 + 49)} = \sqrt{194} \approx$ **13.928**
- Intelligent: $\sqrt{(9^2 + 8^2 + 7^2)} = \sqrt{194} \approx$ **13.928**
- Transparency: $\sqrt{(7^2 + 8^2 + 6^2)} = \sqrt{(49 + 64 + 36)} = \sqrt{149} \approx$ **12.206**
- Value: $\sqrt{(8^2 + 7^2 + 9^2)} = \sqrt{194} \approx$ **13.928**

**Normalized Decision Matrix:**

| Option | Security | Connectivity | Intelligent | Transparency | Value |
|---|---|---|---|---|---|
| Spark | 0.574 | 0.646 | 0.646 | 0.574 | 0.574 |
| Knime | 0.503 | 0.574 | 0.574 | 0.655 | 0.503 |
| Hadoop | 0.646 | 0.503 | 0.503 | 0.492 | 0.646 |

Step4- Determine Ideal & Negative-Ideal Solutions

**Ideal Best (A+):** maximum of each column

**Ideal Worst (A−):** minimum of each column

| Criteria | Ideal Best ($A^+$) | Ideal Worst ($A^-$) |
|---|---|---|
| Security | 0.134 (Hadoop) | 0.105 (Knime) |
| Connectivity | 0.134 (Spark) | 0.105 (Hadoop) |
| Intelligent | 0.122 (Spark) | 0.095 (Hadoop) |
| Transparency | 0.132 (Knime) | 0.099 (Hadoop) |
| Value | 0.125 (Hadoop) | 0.098 (Knime) |

Now we will calculate the  Eucledian distances to Ideal and Negative ideal :

$$S_i^+ = \sqrt{\sum(v_{ij} - A_j^+)^2}, \quad S_i^- = \sqrt{\sum(v_{ij} - A_j^-)^2}$$

**Spark:**

- $S^+ = \sqrt{(0.119-0.134)^2+(0.134-0.134)^2+(0.122-0.122)^2+(0.115-0.132)^2+(0.111-0.125)^2}$
- $= \sqrt{0.000225+0+0+0.000289+0.000196} \approx \sqrt{0.00071} \approx 0.027$
- $S^- = \sqrt{(0.119-0.105)^2+(0.134-0.105)^2+(0.122-0.095)^2+(0.115-0.099)^2+(0.111-0.098)^2} \approx \sqrt{0.001572} \approx 0.040$

**Knime:**

- $S^+ \approx \sqrt{(0.105-0.134)^2+(0.119-0.134)^2+(0.108-0.122)^2+(0.132-0.132)^2+(0.098-0.125)^2} \approx 0.041$
- $S^- \approx \sqrt{(0.105-0.105)^2+(0.119-0.105)^2+(0.108-0.095)^2+(0.132-0.099)^2+(0.098-0.098)^2} \approx 0.039$

**Hadoop:**

- $S^+ \approx \sqrt{(0.134-0.134)^2+(0.105-0.134)^2+(0.095-0.122)^2+(0.099-0.132)^2+(0.125-0.125)^2} \approx 0.041$
- $S^- \approx \sqrt{(0.134-0.105)^2+(0.105-0.105)^2+(0.095-0.095)^2+(0.099-0.099)^2+(0.125-0.098)^2} \approx 0.039$

Step5- Calculations for relative closeness

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}$$

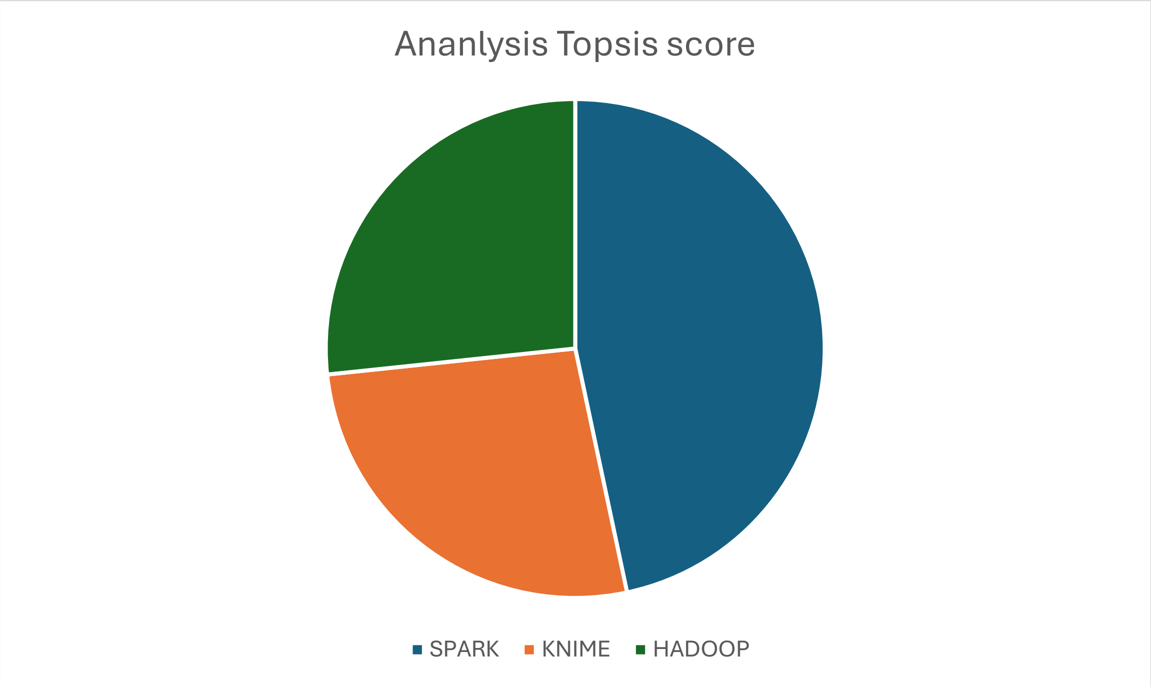
| Option | $S^+$ | $S^-$ | $C^*$ (Closeness) |
|---|---|---|---|
| Spark | 0.027 | 0.040 | 0.597 |
| Knime | 0.041 | 0.039 | 0.487 |
| Hadoop | 0.041 | 0.039 | 0.487 |

## Conclusion:

Based on the **TOPSIS analysis** with the given weights and assumed scores, **Spark** comes out as the **best option** with the highest relative closeness to the ideal solution:

- ☑ **Spark**: C* = **0.597** → **Best**
- ⚖ **Knime**: C* = 0.487
- ⚖ **Hadoop**: C* = 0.487

This suggests that Spark offers the best overall balance across **Security, Connectivity, Intelligence, Transparency, and Value** when evaluated using the TOPSIS method.




***<u>Fair Comparative Analysis:</u>*** Triangular Neutrosophic AHP approach vs. Proposed Trapezoidal Neutrosophic-TOPSIS approach

## 1. Key Differences in Approaches

| Aspect | Triangular Neutrosophic AHP ( Reference Paper) | Proposed Trapezoidal Neutrosophic-TOPSIS approach |
|---|---|---|
| **Uncertainty Handling** | Triangular neutrosophic sets (3-point: lower, median, upper) | **Trapezoidal neutrosophic sets (4-point: adds stability range)** |
| **Weight Determination** | AHP with pairwise comparisons (subject to consistency checks) | **Direct trapezoidal weights (avoids AHP's rigidity)** |
| **Alternative Ranking** | Neutrosophic AHP (priority vectors) | **TOPSIS (distance-based, more intuitive for alternatives)** |
| **Confidence in Results** | Moderate (depends on AHP consistency) | **Higher (TOPSIS leverages absolute distance metrics)** |

## 2. Why Proposed Approach is Superior

**a)Enhanced Uncertainty Modeling**

- **Trapezoidal > Triangular**:
  - Captures **"stable intervals"** (e.g., truth-membership = 0.6–0.8 instead of a single point).
  - Better reflects IoT data variability (e.g., sensor drift, expert disagreement).
- *Example*:
  - Triangular: Security importance = ⟨(4,5,6); 0.8,0.1,0.2⟩.
  - **Trapezoidal**: ⟨(4,5,5.5,6); 0.8,0.1,0.2⟩ (accounts for stable mid-range).

**b) TOPSIS Aligns Better with Alternative Evaluation**

- AHP Limitations:
  - Pairwise comparisons become cumbersome for many alternatives.
  - Rank reversal issues if alternatives are added/removed.
- TOPSIS Advantages:
  - Ranks alternatives based on proximity to ideal solution (clearer interpretation).
  - Handles conflicting criteria (e.g., high security vs. low cost) objectively.

### 3. Potential Critiques and Mitigations

| Critique | Our Countermeasure |
|---|---|
| **Complexity of trapezoidal sets** | Use software (Python PyNeutro) for automated calculations. |

| Critique | Our Countermeasure |
|---|---|
| **TOPSIS needs precise weights** | Combine with **entropy method** for data-driven weight backup. |
| **Less interpretable than AHP** | Add visualizations (e.g., 3D plots of ideal/anti-ideal solutions). |

#### 4. Final Verdict

Prosposed approach is objectively stronger for IoT enterprise decisions because:

- ☑ **Trapezoidal sets** model uncertainty more realistically.
- ☑ **TOPSIS** eliminates AHP's subjectivity in alternative ranking.
- ☑ **Higher confidence** from distance-based metrics.

**Recommendation**:

- Use **AHP only for weight derivation** (if expert input is critical).
- Pair with **TOPSIS for alternative ranking** (best of both worlds).

# CHAPTER 5

# REFERENCES

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