

Intuitionistic Fuzzy TOPSIS-Based Hardware Selection for Industrial Robots Under Conflicting Quantitative Criteria

Dr. Naziya Parveen Faquddin

Department of Mathematics,
Dr. Rafiq Zakaria College for Women, Navkhanda, Chh. Sambhajinagar

Abstract - Selecting the optimal industrial robot in modern manufacturing presents a complex Multi-Criteria Decision-Making (MCDM) challenge due to conflicting technical specifications, economic constraints, and expert hesitation. While traditional fuzzy logic addresses vagueness via membership degrees, it fails to account for non-membership and uncertainty in human judgment. This paper presents a structured **Intuitionistic Fuzzy TOPSIS (IF-TOPSIS)** framework to resolve industrial robot hardware selection.

Key Words: Industrial Robots, Robot Selection, Intuitionistic Fuzzy Sets, IF-TOPSIS, MCDM, Hesitation Degree, Automation.

1. INTRODUCTION

Industrial automation relies heavily on selecting the right robotic hardware to maximize productivity, operational efficiency, and product quality. Industrial robots carry out diverse tasks ranging from high-precision electronic assembly to heavy material handling, making equipment selection a critical driver of manufacturing performance.

However, selecting robotic hardware involves navigating major trade-offs among conflicting criteria:

- **Payload vs. Efficiency:** High payload capacity requires larger structural footprints and higher energy consumption.
- **Precision vs. Investment:** Superior accuracy and repeatability significantly increase procurement and long-term maintenance costs.
- **Reach vs. Performance:** Extending the working reach radius often compromises structural rigidity or operational speed.

Traditional Multi-Criteria Decision-Making (MCDM) tools rely on exact, crisp numerical values. Standard Fuzzy Set Theory (FST) improves upon crisp models by evaluating membership degrees (μ). However, in real-world engineering evaluations, decision-makers

frequently exhibit hesitation due to incomplete data or dynamic operational requirements.

To address these limitations, this study utilizes **Intuitionistic Fuzzy Sets (IFS)** integrated with the **Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)**. By incorporating membership (μ), non-membership (ν), and hesitation (π) parameters, the proposed **IF-TOPSIS** framework enables decision-makers to evaluate complex technical trade-offs while explicitly modeling expert uncertainty.

The remainder of this paper is organized as follows: Section 2 outlines the mathematical preliminaries of Intuitionistic Fuzzy Sets; Section 3 details the IF-TOPSIS methodology; Section 4 demonstrates a step-by-step numerical application; and Section 5 concludes the paper.

2. PRELIMINARIES

2.1 Intuitionistic Fuzzy Sets (IFS)

Let X be a fixed universe of discourse. An Intuitionistic Fuzzy Set A in X is defined by Atanassov as:

$$A = \{ \{x, \mu_A(x), \nu_A(x)\} \mid x \in X \}$$

where $\mu_A(x): X \rightarrow [0,1]$ defines the degree of membership and $\nu_A(x): X \rightarrow [0,1]$ defines the degree of non-membership of $x \in X$ to the set A , subject to the condition:

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1, \quad \forall x \in X$$

2.2 Degree of Hesitation

For each element $x \in X$, the intuitionistic fuzzy hesitation degree $\pi_A(x)$ (representing uncertainty or lack of knowledge) is calculated as:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x), \quad \text{where } 0 \leq \pi_A(x) \leq 1$$

An Intuitionistic Fuzzy Number (IFN) is concisely written as $\alpha = (\mu_\alpha, \nu_\alpha, \pi_\alpha)$.

2.3 Operations on Intuitionistic Fuzzy Numbers

Given two IFNs $\alpha_1 = (\mu_1, \nu_1)$ and $\alpha_2 = (\mu_2, \nu_2)$, and a scalar $\lambda > 0$:

- Addition ($\oplus$):**

$$\alpha_1 \oplus \alpha_2 = (\mu_1 + \mu_2 - \mu_1\mu_2, \nu_1\nu_2)$$

- Multiplication ($\otimes$):**

$$\alpha_1 \otimes \alpha_2 = (\mu_1\mu_2, \nu_1 + \nu_2 - \nu_1\nu_2)$$

- Scalar Multiplication:**

$$\lambda\alpha_1 = (1 - (1 - \mu_1)^\lambda, \nu_1^\lambda)$$

2.4 Distance Measurement

Using the Normalized Euclidean Distance proposed by Szmidt and Kacprzyk, the distance $d(\alpha_1, \alpha_2)$ between two IFNs $\alpha_1 = (\mu_1, \nu_1, \pi_1)$ and $\alpha_2 = (\mu_2, \nu_2, \pi_2)$ is defined as:

$$d(\alpha_1, \alpha_2) = \sqrt{\frac{1}{2}[(\mu_1 - \mu_2)^2 + (\nu_1 - \nu_2)^2 + (\pi_1 - \pi_2)^2]}$$

3. INTUITIONISTIC FUZZY TOPSIS METHODOLOGY

The IF-TOPSIS evaluation process follows these algorithmic steps:

- Construct Evaluation Matrix:** Gather expert ratings as IFNs $\tilde{a}_{ij} = (\mu_{ij}, \nu_{ij}, \pi_{ij})$ for alternative i under criterion j .

- Normalize Decision Matrix ($\tilde{R}$):**

- For Benefit Criteria (B):** $\tilde{r}_{ij} = (\mu_{ij}, \nu_{ij}, \pi_{ij})$

- For Cost Criteria (C):** Swap membership and non-membership values:

$$\tilde{r}_{ij} = (\nu_{ij}, \mu_{ij}, \pi_{ij})$$

- Calculate Weighted Normalized Matrix ($\tilde{V}$):** Multiply weighted criteria $\tilde{w}_j = (\mu_{wj}, \nu_{wj})$ with normalized ratings $\tilde{r}_{ij}$:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j = (\mu_{ij}\mu_{wj}, \nu_{ij} + \nu_{wj} - \nu_{ij}\nu_{wj})$$

- Identify Intuitionistic Fuzzy Ideal Solutions:**

- Intuitionistic Fuzzy Positive Ideal Solution (IFPIS, A^*):**

$$A^* = (\mu^*, \nu^*, \pi^*) = (1, 0, 0)$$

- Intuitionistic Fuzzy Negative Ideal Solution (IFNIS, A^-):**

$$A^- = (\mu^-, \nu^-, \pi^-) = (0, 1, 0)$$

- Compute Separation Distances (d_i^*, d_i^-):**

$$d_i^* = \sum_{j=1}^n d(\tilde{v}_{ij}, A^*), \quad d_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, A^-)$$

- Calculate Relative Closeness Coefficient (CC_i):**

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}$$

Rank alternatives in descending order based on CC_i .

4. NUMERICAL APPLICATION

Three robot candidates (R_1, R_2, R_3) are evaluated across three criteria:

- C_1 (Purchase Cost):** Non-Beneficial (Cost) — Weight $\tilde{w}_1 = (0.7, 0.2, 0.1)$
- C_2 (Payload Capacity):** Beneficial — Weight $\tilde{w}_2 = (0.8, 0.1, 0.1)$
- C_3 (Repeatability / Precision):** Non-Beneficial (Cost) — Weight $\tilde{w}_3 = (0.6, 0.3, 0.1)$

Step 1: Formulate Decision Matrix ($\tilde{D}$)

Performance assessments expressed as IFNs (μ, ν, π) :

Robot	C1: Cost (Cost)	C2: Payload (Benefit)	C3: Repeatability (Cost)
R_1	(0.3, 0.6, 0.1)	(0.8, 0.1, 0.1)	(0.4, 0.5, 0.1)

Robot	C1: Cost (Cost)	C2: Payload (Benefit)	C3: Repeatability (Cost)
R_2	(0.7,0.2,0.1)	(0.5,0.4,0.1)	(0.2,0.7,0.1)
R_3	(0.5,0.4,0.1)	(0.7,0.2,0.1)	(0.3,0.6,0.1)
Weights ($\tilde{w}_j$)	(0.7,0.2,0.1)	(0.8,0.1,0.1)	(0.6,0.3,0.1)

Step 2: Normalize Decision Matrix ($\tilde{R}$)

Applying transformation rules ($\mu \leftrightarrow \nu$ for Cost criteria C_1 and C_3):

Robot	C1 (Cost Normalized)	C2 (Benefit Normalized)	C3 (Cost Normalized)
R_1	(0.6,0.3,0.1)	(0.8,0.1,0.1)	(0.5,0.4,0.1)
R_2	(0.2,0.7,0.1)	(0.5,0.4,0.1)	(0.7,0.2,0.1)
R_3	(0.4,0.5,0.1)	(0.7,0.2,0.1)	(0.6,0.3,0.1)

Step 3: Compute Weighted Normalized Matrix ($\tilde{V}$)

Using $\tilde{v}_{ij} = (\mu_r \mu_w, \nu_r + \nu_w - \nu_r \nu_w)$ and $\pi = 1 - \mu - \nu$:

Robot	C1 Weight: (0.7,0.2,0.1)	C2 Weight: (0.8,0.1,0.1)	C3 Weight: (0.6,0.3,0.1)
R_1	(0.42,0.44,0.0)	(0.64,0.19,0.0)	(0.30,0.58,0.0)

Robot	C1 Weight: (0.7,0.2,0.1)	C2 Weight: (0.8,0.1,0.1)	C3 Weight: (0.6,0.3,0.1)
R_2	(0.14,0.76,0.0)	(0.40,0.46,0.0)	(0.42,0.44,0.0)
R_3	(0.28,0.60,0.0)	(0.56,0.28,0.0)	(0.36,0.51,0.0)

Step 4: Calculate Separation Distances (d_i^*, d_i^-)

Distance to IFPIS $A^* = (1,0,0)$ and IFNIS $A^- = (0,1,0)$:

Formula: $d(\tilde{v}_{ij}, A^*)$

$$= \sqrt{\frac{1}{2}[(\mu - 1)^2 + (\nu - 0)^2 + (\pi - 0)^2]}$$

Distance Computations:

1. Robot 1 (R_1):

$$d(v_{11}, A^*) = 0.424, \quad d(v_{12}, A^*) = 0.280, \quad d(v_{13}, A^*) = 0.509 \Rightarrow \mathbf{d_1^* = 1.213}$$

$$d(v_{11}, A^-) = 0.435, \quad d(v_{12}, A^-) = 0.638, \quad d(v_{13}, A^-) = 0.354 \Rightarrow \mathbf{d_1^- = 1.427}$$

2. Robot 2 (R_2):

$$d(v_{21}, A^*) = 0.627, \quad d(v_{22}, A^*) = 0.447, \quad d(v_{23}, A^*) = 0.424 \Rightarrow \mathbf{d_2^* = 1.498}$$

$$d(v_{21}, A^-) = 0.208, \quad d(v_{22}, A^-) = 0.457, \quad d(v_{23}, A^-) = 0.435 \Rightarrow \mathbf{d_2^- = 1.100}$$

3. Robot 3 (R_3):

$$d(v_{31}, A^*) = 0.528, \quad d(v_{32}, A^*) = 0.342, \quad d(v_{33}, A^*) = 0.468 \Rightarrow \mathbf{d_3^* = 1.338}$$

$$\begin{aligned} d(v_{31}, A^-) &= 0.323, \quad d(v_{32}, A^-) \\ &= 0.563, \quad d(v_{33}, A^-) = 0.398 \Rightarrow \mathbf{d_3^-} \\ &= \mathbf{1.284} \end{aligned}$$

Step 5: Compute Closeness Coefficients (CC_i) and Rankings

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}$$

Final IF-TOPSIS Results Summary

Robot Alternative	d_i^* (Distance to Ideal)	d_i^- (Distance to Anti-Ideal)	Closeness Coefficient (CC_i)	Final Rank
R_1	1.213	1.427	0.541	1
R_3	1.338	1.284	0.490	2
R_2	1.498	1.100	0.423	3

Discussion

Alternative R_1 is selected as the optimal choice ($CC_1 = 0.541$). While R_2 features lower repeatability errors, R_1 demonstrates superior overall satisfaction across payload capacity (C_2) and cost (C_1), maintaining low non-membership degrees that yield the closest overall proximity to the ideal solution.

5. CONCLUSION

This study successfully applied an Intuitionistic Fuzzy TOPSIS (IF-TOPSIS) framework to resolve the industrial robot hardware selection problem under conflicting criteria. By incorporating non-membership (ν) and hesitation (π) degrees alongside standard membership (μ), the proposed approach effectively models uncertainty and expert judgment hesitation inherent in major equipment procurement decisions. The numerical analysis proves that IF-TOPSIS provides a transparent,

objective, and mathematically reliable decision-support system for manufacturing managers. Future research can extend this work by incorporating dynamic weighting methods or integrating Pythagorean Fuzzy Sets (PFS) for higher variance domains.

References

- Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 20(1), 87–96.
- Boran, F. E., Genç, S., Kurt, M., & Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Systems with Applications*, 36(8), 11363–11368.
- P. N. Kamble and Naziya Parveen (2022). Extended TOPSIS and VIKOR methods-based on a new distance measure of intuitionistic fuzzy number, *Artificial intelligence and sustainable computing*, springer nature, Singapore Pte Ltd, 495-510.
- Naziya Parveen and P. N Kamble (2021). An Extension of TOPSIS for group decision making in Intuitionistic Fuzzy environment, *Mathematical Foundation of Computing*, American Institute of Mathematical Science, 4(1), 61-71.
- Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, 114(1), 1–9.
- Chu, T. C., & Lin, Y. C. (2003). A fuzzy TOPSIS method for robot selection. *The International Journal of Advanced Manufacturing Technology*, 21(4), 284–290.
- Devi, K. (2011). Extension of VIKOR method in intuitionistic fuzzy environment for robot selection. *Expert Systems with Applications*, 38(11), 14163–14168.
- Hwang, C. L., & Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Applications*. Springer-Verlag.
- Narayana Moorthy, S., Geetha, S., Rakkiyappan, R., & Joo, Y. H. (2019). Interval-

valued intuitionistic hesitant fuzzy entropy-based VIKOR method for industrial robots' selection. Expert Systems with Applications, 121, 28–37.

10. Parameswaran, R., Kumar, S. P., & Saravanakumar, K. (2015). An integrated fuzzy MCDM based approach for robot selection considering objective and subjective criteria. Applied Soft Computing, 26, 31–41.

11. Szmidt, E., & Kacprzyk, J. (2000). Distances between intuitionistic fuzzy sets. Fuzzy Sets and Systems, 114(3), 505–518.

12. Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338–353.