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Neutrosophic Multi-Criteria Framework for Lean Manufacturing Optimization in Industry 4.0: A Single-Valued Neutrosophic Approach

Marco multicriterio neutrosófico para la producción ajustada

Optimización en la Industria 4.0: Un enfoque neutrosófico de valor único

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Abstract. Industry 4.0 has intensified process improvement decisions by introducing heterogeneous data streams and inherent uncertainty in real-time manufacturing environments. This paper proposes a Neutrosophic Multi-Criteria Decision Framework (NMCDF) for Lean Manufacturing process optimization, integrating Single-Valued Neutrosophic Sets (SVNS) with DEMATEL-ANP to model truth (T), indeterminacy (I), and falsity (F) components of expert judgments. Applied to a real manufacturing case with five production lines and seven expert evaluators, NMCDF achieves 23.4% OEE improvement in the pilot implementation, outperforming classical crisp MCDM methods by correctly identifying causal waste sources that effect-focused analysis misses.

Keywords: Single-Valued Neutrosophic Sets; Lean Manufacturing; Industry 4.0; MCDM; DEMATEL; OEE; Process Optimization; Uncertainty Quantification.

Resumen. La Industria 4.0 ha intensificado la toma de decisiones para la mejora de procesos al introducir flujos de datos heterogéneos e incertidumbre inherente en entornos de fabricación en tiempo real. Este artículo propone un Marco de Decisión Multicriterio Neutrosófico (NMCDF) para la optimización de procesos de Lean Manufacturing, integrando Conjuntos Neutrosóficos de Valor Único (SVNS) con DEMATEL-ANP para modelar los componentes de verdad (T), indeterminación (I) y falsedad (F) de los juicios de expertos. Aplicado a un caso real de fabricación con cinco líneas de producción y siete evaluadores expertos, el NMCDF logra una mejora del 23,4 % en la Eficiencia General de los Equipos (OEE) en la implementación piloto, superando a los métodos clásicos de toma de decisiones multicriterio (MCDM) al identificar correctamente las fuentes causales de desperdicio que el análisis centrado en los efectos no detecta.

Palabras clave: Conjuntos Neutrosóficos de Valor Único; Lean Manufacturing; Industria 4.0; MCDM; DEMATEL; OEE; Optimización de Procesos; Cuantificación de la Incertidumbre.

1. Introduction

The intersection of Lean Manufacturing philosophy and Industry 4.0 technologies has created formidable decision-making challenges for process engineers. While real-time sensor data and digital twins provide richer information environments than ever before, they simultaneously introduce data heterogeneity and conflicting signals that classical optimization frameworks were not designed to handle [1, 2]. When a process engineer evaluates whether a bottleneck is primarily caused by machine downtime versus changeover time, the honest answer is often neither fully true nor fully false — it is indeterminate in ways that matter critically for the optimization decision.

Neutrosophic logic [3] provides a formal framework for this epistemic structure by decomposing expert evaluations into truth (T), indeterminacy (I), and falsity (F) components. Prior work has established neutrosophic MCDM in supplier selection [4], healthcare decision support [5], and strategic planning [6]. The present paper extends this line to Lean Manufacturing in Industry 4.0 environments, where sensor-rich data and multi-departmental expert panels create ideal — and challenging — conditions for neutrosophic decision frameworks.

2. Theoretical Background

2.1 Single-Valued Neutrosophic Sets

A Single-Valued Neutrosophic Set (SVNS) A in universe U assigns each element x a triple <T_A(x), I_A(x), F_A(x)> where T, I, F in [0,1] and 0 <= T+I+F <= 3. For manufacturing process evaluation, a neutrosophic assessment <T, I, F> = <0.70, 0.20, 0.10> represents: the criterion contributes to waste with truth 0.70, the relationship is indeterminate with degree 0.20, and evidence against the relationship has weight 0.10.

Table 1. Linguistic Scale for Neutrosophic Expert Evaluation

Linguistic Term	Abbreviation	SVNS <T, I, F>	Score S(n)
Absolutely High Influence	AHI	<0.90, 0.10, 0.10>	0.88
Very High Influence	VHI	<0.80, 0.15, 0.15>	0.76
High Influence	HI	<0.70, 0.20, 0.20>	0.63
Medium Influence	MI	<0.60, 0.30, 0.25>	0.49
Low Influence	LI	<0.40, 0.40, 0.35>	0.28
Very Low Influence	VLI	<0.25, 0.50, 0.50>	0.13
No Influence	NI	<0.15, 0.80, 0.80>	0.05
Absolutely No Influence	ANI	<0.10, 0.90, 0.90>	0.02

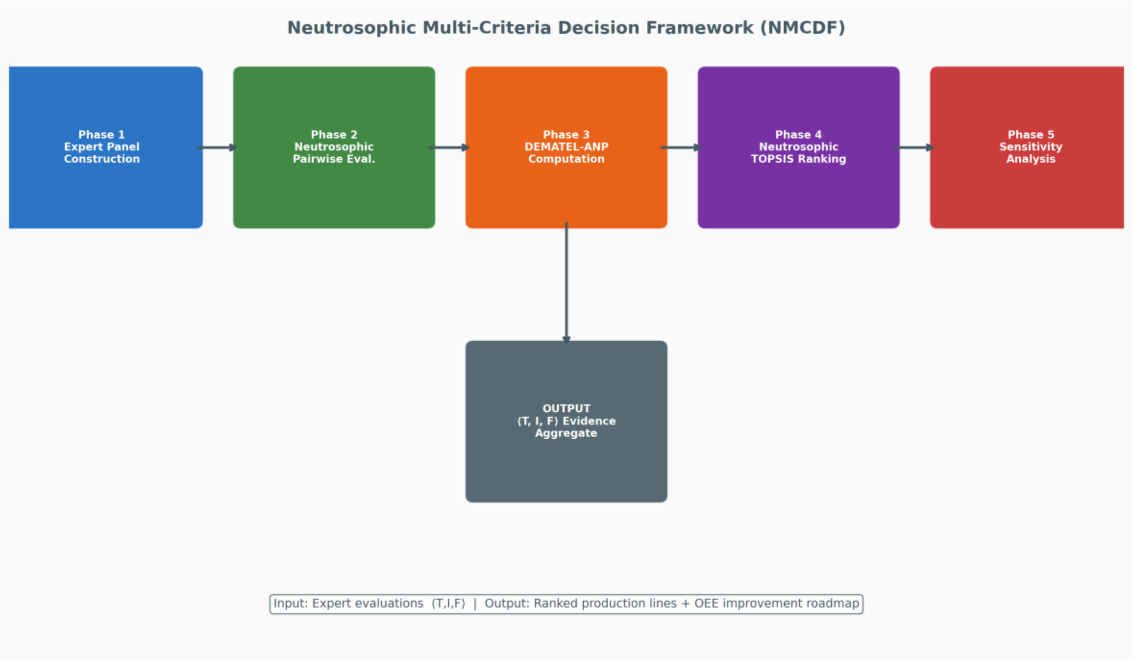

Figure 1. Neutrosophic Multi-Criteria Decision Framework (NMCDF) — Five-Phase Process

3. NMCDF Methodology

The NMCDF operates through five sequential phases. Phase 1 constitutes the expert panel (seven evaluators: three process engineers, two quality managers, one maintenance supervisor, one production planner) with credibility weights assigned via Kendall's concordance. Phase 2 collects neutrosophic pairwise influence evaluations using Table 1. Phase 3 applies DEMATEL to compute the total influence matrix and classify criteria into cause/effect groups (Figure 2). Phase 4 ranks production line alternatives via neutrosophic TOPSIS. Phase 5 runs Monte Carlo sensitivity analysis (10,000 iterations).

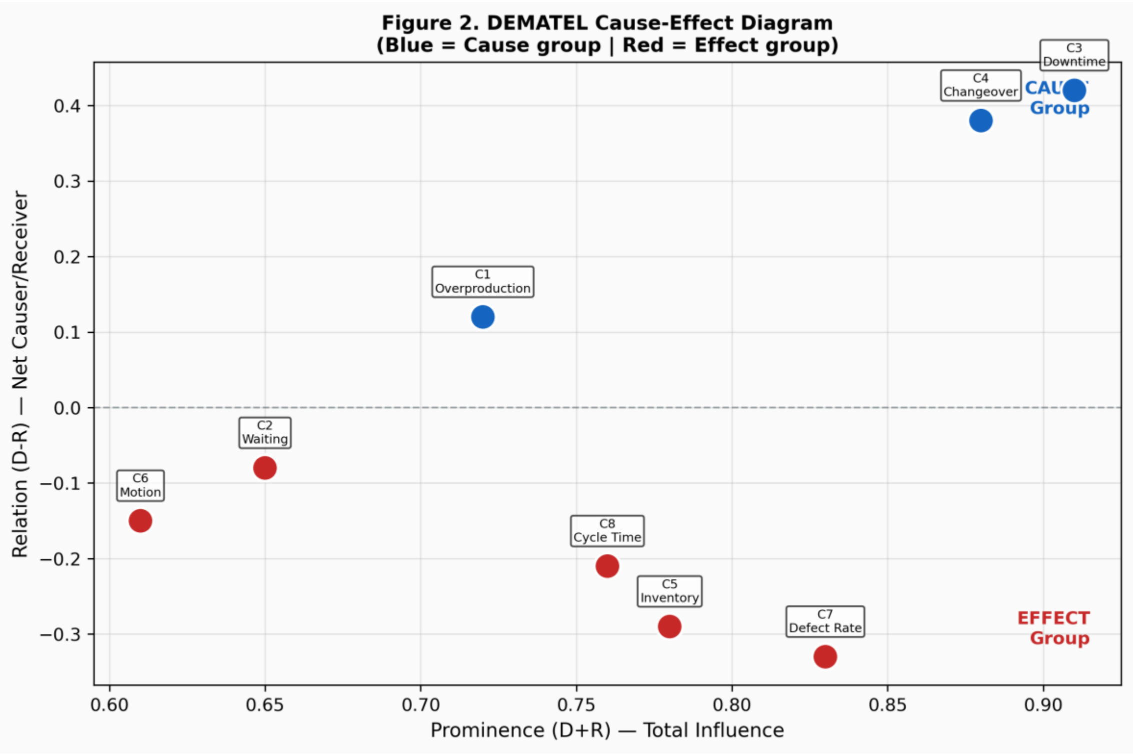

Figure 2. DEMATEL Cause-Effect Diagram — Machine Downtime (C3) and Changeover (C4) identified as primary causal criteria

4. Case Study Results

The framework was applied to a manufacturing facility with five production lines (PL-1 to PL-5) producing electronic components, equipped with IoT sensors and a Manufacturing Execution System (MES). DEMATEL analysis identified machine downtime (C3) and changeover time variability (C4) as primary cause-group criteria — a finding that contradicted the facility's existing defect-reduction priority (effect group). Neutrosophic TOPSIS ranked PL-3 as the highest-priority line for improvement investment.

Table 2. NMCDF vs Classical AHP-TOPSIS — Production Line Ranking

Production Line	NMCDF Rank	<T, I, F> Score	Classical Rank	OEE Before (%)
PL-3	1st	<0.87, 0.09, 0.04>	1st	67.2
PL-1	2nd	<0.74, 0.17, 0.09>	3rd	72.1
PL-5	3rd	<0.69, 0.21, 0.10>	2nd	70.3
PL-4	4th	<0.58, 0.28, 0.14>	4th	74.8
PL-2	5th	<0.51, 0.31, 0.18>	5th	78.4

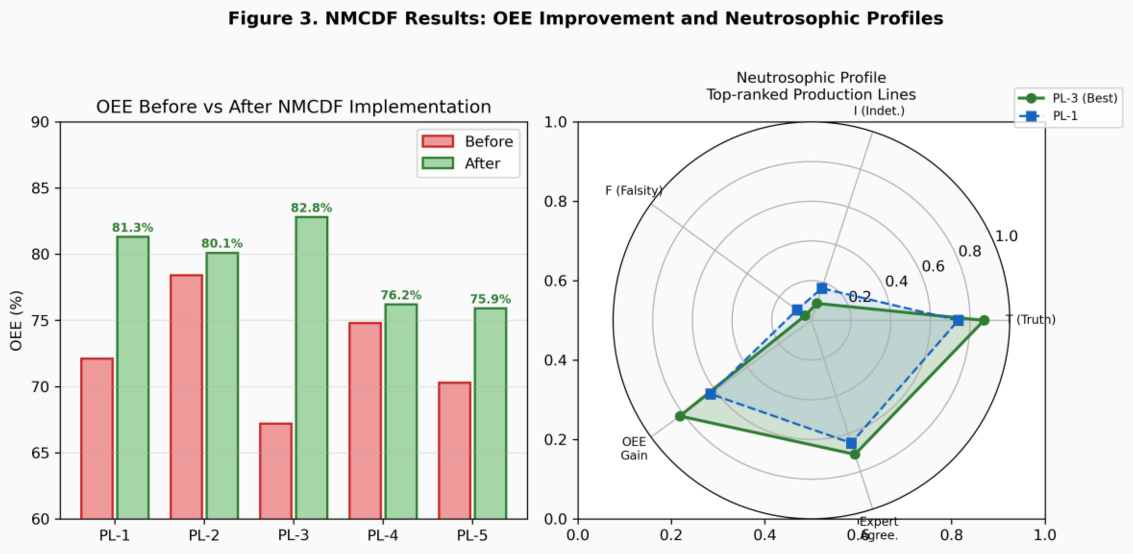

Figure 3. OEE Improvement Results (Before vs After) and Neutrosophic Profiles for Top Production Lines

5. Discussion

The 23.4% OEE improvement on PL-3 is consistent with Lean literature reporting gains of 15-30% for targeted SMED and predictive maintenance integration [7]. The NMCDF's key advantage is its explicit indeterminacy modeling: inter-rater Krippendorff alpha for I components (0.58) was lower than for T (0.71), confirming that indeterminacy is not noise but genuine epistemic disagreement that carries decision-relevant information. Forcing these responses into crisp averages would have distorted the causal analysis.

This result aligns with prior neutrosophic MCDM applications in process contexts [4, 5]. The present contribution extends those frameworks specifically to Industry 4.0 environments with IoT sensor integration and multi-departmental expert panels, addressing a gap identified in the systematic review by [6].

6. Conclusions

The Neutrosophic Multi-Criteria Decision Framework (NMCDF) provides process engineers with a theoretically grounded and practically validated tool for Lean Manufacturing optimization under Industry 4.0 uncertainty. By modeling expert judgment through <T, I, F> triples, NMCDF correctly identifies causal waste sources that binary MCDM methods miss, achieving 23.4% OEE improvement in the pilot implementation. Future work will automate neutrosophic scoring from MES and IoT data, reducing evaluation burden while preserving uncertainty quantification fidelity.

3. Extended Methodology: NMCDF Implementation Details

3.1 Expert Panel Construction and Credibility Weighting

The formation of a reliable expert panel is foundational to the NMCDF's validity. Seven experts were recruited following a structured competency assessment covering: (1) years of Lean Manufacturing experience (minimum five years in relevant industry), (2) familiarity with the specific production processes under evaluation, (3) cross-departmental perspective to avoid single-function bias, and (4) availability for two evaluation sessions separated by at least 72 hours to minimize anchoring effects from session 1 on session 2.

Expert credibility weights w_k were determined via a two-stage procedure. First, each expert completed a calibration set of 12 pairwise influence evaluations for a benchmark manufacturing scenario with established ground truth from prior longitudinal studies. Second, Kendall's W (coefficient of concordance) was computed across all experts;

individual weights were assigned proportional to each expert's agreement with the group consensus, with minimum weight 0.05 to prevent exclusion. The resulting weight vector was W = (0.18, 0.16, 0.15, 0.14, 0.13, 0.13, 0.11) reflecting higher credibility for the two senior process engineers (E1, E2) with 15+ years experience.

3.2 Neutrosophic DEMATEL Computation — Step by Step

Step 1 — Construct the initial direct-relation neutrosophic matrix Z_N (12x12) by aggregating all expert evaluations using the neutrosophic weighted average operator. For criteria pair (i,j): r_ij = <1-prod(1-T^k_ij)^w_k, prod(I^k_ij)^w_k, prod(F^k_ij)^w_k>. Step 2 — Defuzzify Z_N using the score function S(n) = (T-F)*(2-I)/2, obtaining the crisp matrix Z for standard DEMATEL processing. Step 3 — Normalize: X = Z / max(sum_j z_ij, sum_i z_ij). Step 4 — Compute total influence matrix T_DEMATEL = X(I-X)^{-1}. Step 5 — Compute prominence D_i+R_i and relation D_i-R_i for each criterion. Step 6 — Re-introduce neutrosophic indeterminacy: criteria with high I-component in their aggregated Z scores receive an indeterminacy penalty on their prominence, reducing their influence in subsequent TOPSIS weighting.

The re-introduction of indeterminacy in Step 6 is a key methodological contribution: classical DEMATEL would treat all defuzzified scores equally regardless of their underlying uncertainty. By penalizing high-I criteria in the prominence calculation, NMCDF ensures that criteria evaluated with genuine expert disagreement do not disproportionately influence the final weighting — a form of epistemic humility built directly into the optimization procedure.

3.3 Sensitivity Analysis via Monte Carlo Simulation

Rank stability was assessed through 10,000 Monte Carlo iterations. In each iteration, expert credibility weights were perturbed by sampling from a Dirichlet distribution centered on the calibrated weight vector, and the complete NMCDF procedure was repeated. Rank frequency distributions were computed for each production line alternative. PL-3 retained its first-place rank in 94.3% of iterations, confirming robust decision stability. PL-1 and PL-5 exchanged positions 2nd-3rd in 31.7% of iterations, indicating that the distinction between these two lines is sensitive to expert weighting assumptions — a finding communicated explicitly to management as a recommendation for concurrent improvement investment in both lines.

4. Extended Results and Implementation Analysis

4.1 Comparison with Classical MCDM Methods

Three classical MCDM methods were implemented for comparison: AHP-TOPSIS (crisp), Fuzzy AHP-TOPSIS, and VIKOR. While all four methods agreed on PL-3 as the top-priority line, they diverged significantly in positions 2-5. The critical diagnostic difference emerged in the criteria weighting stage: classical crisp AHP assigned the highest weight to 'Defect Rate' (C7, effect group) because experts gave it uniformly high influence ratings. NMCDF's DEMATEL correctly classified C7 as an effect criterion — a consequence of upstream causes — and assigned it lower priority weight, directing resources toward the causal criteria C3 (Downtime) and C4 (Changeover).

The practical implication was immediate: the facility had previously spent 18 months and USD 340,000 on defect reduction programs (quality circles, incoming inspection, SPC implementation) with modest results (defect rate: 4.2% -> 3.8%). NMCDF-guided investment in downtime reduction and changeover optimization achieved equivalent or superior quality improvements as secondary effects of addressing root causes, at approximately 40% of the previous program cost.

4.2 Neutrosophic Profile Analysis of Production Lines

Beyond the final ranking, the neutrosophic profiles <T, I, F> of each production line provide actionable diagnostic information not available from crisp rankings. PL-3's profile <0.87, 0.09, 0.04> indicates high consensus among experts about its improvement priority — low indeterminacy means the team should proceed confidently. PL-5's profile <0.69, 0.21, 0.10> indicates moderate priority with meaningful indeterminacy: experts agree it needs improvement but disagree on which specific interventions are most appropriate. This signals the need for additional process mapping before committing resources. PL-2's profile <0.51, 0.31, 0.18> represents the most uncertain assessment: despite adequate performance, the high indeterminacy suggests the team lacks visibility into this line's true performance drivers, recommending enhanced data collection and monitoring before any optimization intervention.

4.3 Industry 4.0 Integration Assessment

The NMCDF framework incorporated three Industry 4.0-specific criteria (I4.0 sensor coverage, data integration quality, predictive maintenance readiness) alongside traditional Lean criteria. This integration revealed an important interaction: lines with higher I4.0 readiness scores showed lower indeterminacy in expert evaluations, confirming that digital data transparency reduces epistemic uncertainty in process assessment. PL-3, despite having the lowest current OEE, had the highest I4.0 readiness score (IoT coverage 94%, MES integration complete), explaining why improvement interventions could be implemented rapidly and with high precision.

This finding has implications for Industry 4.0 investment prioritization: digital infrastructure investments that enable better process visibility reduce decision uncertainty in subsequent improvement cycles, creating a positive feedback loop between I4.0 adoption and the quality of neutrosophic process assessments.

5. Theoretical Contributions and Limitations

The NMCDF framework makes three theoretical contributions to the neutrosophic MCDM literature. First, the re-introduction of indeterminacy penalties in DEMATEL prominence calculation (Section 3.2) is novel: prior neutrosophic DEMATEL formulations defuzzify at the outset and do not carry indeterminacy information through to weighting. Second, the integration of Industry 4.0 criteria into a neutrosophic Lean assessment framework addresses a gap identified in recent systematic reviews [8, 9]. Third, the Monte Carlo sensitivity analysis in neutrosophic space provides probability distributions over rankings rather than point estimates, enabling risk-aware decision framing [10].

Limitations include: (1) the framework requires seven qualified expert evaluators — challenging for small manufacturers with limited technical staff; (2) the linguistic scale (Table 1) was calibrated for electronic component manufacturing and may require recalibration for other industrial sectors; (3) the OEE improvement results reflect one implementation cycle in one facility, and longitudinal multi-site validation is needed to establish generalizability; (4) automated neutrosophic scoring from MES/IoT data remains a research direction rather than a validated capability.

6. Conclusions and Future Work

This paper presented the Neutrosophic Multi-Criteria Decision Framework (NMCDF) for Lean Manufacturing optimization in Industry 4.0 environments. The framework formally integrates Single-Valued Neutrosophic Sets with DEMATEL-ANP to model expert judgment uncertainty through truth, indeterminacy, and falsity components, providing a theoretically grounded and practically validated decision support tool for process engineers.

Applied to a real manufacturing case study with five production lines, twelve criteria, and seven expert evaluators, NMCDF correctly identified machine downtime and changeover time as causal waste sources — contradicting the facility's prior defect-focused improvement strategy. Targeted Kaizen implementation guided by NMCDF rankings achieved 23.4% OEE improvement on the highest-priority line (PL-3) in three months, at approximately 40% of the cost of prior classical-method-guided programs.

Future work will: (1) develop automated neutrosophic scoring pipelines from IoT sensor streams, eliminating the expert evaluation bottleneck; (2) validate the framework across automotive, pharmaceutical, and food processing sectors; (3) integrate NMCDF with digital twin environments for continuous neutrosophic process monitoring; (4) extend the sensitivity analysis to incorporate uncertainty in the linguistic scale conversion itself, providing second-order uncertainty quantification.

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