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OPTIMIZING SUPPLY CHAIN EFFICIENCY WITH FUZZY CRITIC-EDAS

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Abstract
In today's dynamic and complex global business landscape, effective supply chain network (SCN) management is critical for achieving competitive advantage and sustainability. This study presents an innovative methodology that leverages the fuzzy CRITIC (CRiteria Importance Through Intercriteria Correlation) and EDAS (Evaluation based on Distance from Average Solution) techniques to enhance the efficiency of SCNs. By integrating both quantitative and qualitative factors, the approach effectively navigates uncertainties and imprecise data in supply chain operations. The fuzzy CRITIC-EDAS method's application in a case study showcases its utility in optimizing SCN configurations for improved efficiency, cost savings, and risk reduction. The results offer a valuable decision support tool for supply chain management, promising to boost competitiveness and sustainability in an unpredictable market.
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Key Words: Production Supply Chain Networks, Fuzzy CRITIC-EDAS Method, Efficiency Optimization, Decision Support Tool, Risk Mitigation

1. INTRODUCTION

In the contemporary global landscape of corporate operations, the strategic orchestration and governance of industrial SCN are recognized as paramount for entities aspiring to thrive amidst intense competition and rapid flux. A continual reassessment of supply chain strategies is necessitated by the global expansion of markets, technological advancements, and shifts in consumer preferences. Within this context, the efficacious refinement of SCN configurations has surfaced as a critical determinant of organizational prosperity and enduring stability. Comprising a complex nexus of interconnected activities, entities, and resources, SCN facilitates the seamless transit of goods, information, and capital from the initial suppliers to the end consumers. Decisions regarding the structuring and governance of these networks bear significant repercussions, influencing key performance indicators such as cost efficiency, completion timeliness, adaptability, and resilience. Furthermore, it is imperative to acknowledge the substantial impact of supply chain management decisions on the environmental footprint of enterprises, especially in the current era of heightened sustainability awareness.

Historically, the optimization of SCN has relied on diverse mathematical and analytical models, predominantly favouring quantitative parameters and deterministic data. However, it must be recognized that supply chain systems are frequently beset by uncertainties, imprecise information, and qualitative factors, challenging the efficacy of conventional optimization approaches in practical applications. In response to the growing demand for resilient and versatile decision support systems, this manuscript introduces an innovative methodology, amalgamating the CRITIC and EDAS methods. The fusion of fuzzy CRITIC-EDAS unites the strengths of Multi-Criteria Decision-Making (MCDM) and Fuzzy Logic (FL), thereby accommodating both quantitative and qualitative dimensions in the evaluation and selection of

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SCN configurations [1]. The integration of fuzziness within this methodology addresses the ambiguity and subjectivity inherent in decision-making processes, rendering it aptly suited to the dynamic and uncertain nature of contemporary supply chain environments.

In industrial SCN, FL has been identified as an integral component, effectively addressing uncertainties, imprecise data, and qualitative factors prevalent in real-world supply chain scenarios. Vulnerabilities in SCN to various uncertainties, such as demand fluctuations, lead-time variances, and unforeseen outages, are acknowledged. FL has been employed to model and manipulate data that is uncertain and imprecise, thus enabling decision-makers to derive well-informed decisions under conditions of limited precision and clarity. It is highlighted that precise numerical values for numerous variables may be elusive, underscoring the necessity of FL in supply chain optimization. The process of SCN optimization is illuminated, revealing its occasional need to balance conflicting objectives. FL's role in facilitating multi-objective decision-making, through the accommodation of diverse criteria and their respective levels of significance, is emphasized. This functionality is crucial for optimizing trade-offs among various goals, especially when considering competing interests such as cost reduction, minimization of lead times, and risk mitigation. Furthermore, the essential qualities of flexibility and adaptability in supply chains, required to effectively respond to dynamic market conditions, are underscored. FL is portrayed as a catalyst for adaptive decision-making, empowering decision-makers to adjust parameters and criteria in accordance with evolving conditions, ensuring SCN alignment with strategic objectives. It is asserted that FL is important in optimizing production SCN, aiding in the modelling, analysis, and optimization of complex systems within uncertain and qualitative environments. The integration of FL into decision-making processes is presented as a means for firms to achieve more resilient and flexible SCN architectures, enhancing their capability to navigate the intricacies of the modern business landscape.

The utilization of the CRITIC methodology in Multi-Criteria Decision-Making (MCDM) scenarios is discussed, emphasizing its role in evaluating the relative importance of various assessment criteria. Introduced by Diakoulaki et al. [2], the CRITIC approach is grounded in the principle of deriving insights about the relative importance of variables through the analysis of inter-criteria correlations. The application of inter-criteria correlation is acknowledged across diverse academic disciplines, including engineering, economics, administration, ecological science, and related fields. In these contexts, the evaluation of multiple alternatives, considering multiple criteria and assigning weights to these criteria to ascertain their relative importance, is recognized as a crucial task [3]. The applicability of the CRITIC methodology across various domains, including pavement condition assessment [4], dynamic visual analytical approach for crime transformation [5], pontoon bridge selection [6], turning process [7], and modelling ethical behaviours [8], is highlighted, demonstrating its versatility and relevance.

Introduced by Keshavarz et al. [9], the Evaluation based on Distance from Average Solution (EDAS) method marked a significant advancement in the realm of MCDM techniques. This novel methodology was developed with the specific aim of serving as a bespoke ranking technique adept at navigating complex decision-making scenarios, which necessitate the prioritization of multiple alternatives amidst a plethora of diverse factors. A distinguishing feature of the EDAS method, setting it apart from alternative approaches, is its unique normalizing technique. The overarching goal of the EDAS method is to identify the most optimal choice, employing an average solution-based normalization process. Within this process, both positive and negative deviations from the mean value are utilized to evaluate the performance of each alternative, thereby determining its respective ranking. Applications of the EDAS methodology are observed in diverse domains, encompassing the assessment of bioenergy production methods [10], robotics [11], and the evaluation of aviation services [12].

The structure of this manuscript is delineated as follows. A comprehensive exposition of the principal criteria pertinent to SCN is provided in Section 2. Section 3 elucidates the fuzzy CRITIC-EDAS approach, while Section 4 presents an in-depth case study, replete with numerical examples, to illustrate the efficacy of the proposed methodology. Finally, Section 5 offers a succinct synthesis of the key insights gleaned from the investigation.

2. KEY CRITERIA IN SCN

Optimizing the structure of production SCN constitutes a complex task, necessitating the meticulous evaluation of various variables to ensure optimal operational efficiency and effectiveness of the network. In this endeavour, a myriad of criteria, encompassing both quantitative and qualitative dimensions, is imperative. Each of these factors is instrumental in delineating the most apt configuration of the supply chain. Critical factors are encompassed in the structuring optimization of production SCN.

2.1 Customer service levels

Paramountcy is afforded to customer satisfaction within supply chain management, necessitating alignment of the supply chain network's design with customer expectations and preferences. A pivotal role is played by the network's proficiency in meeting customer service level requirements, which encompasses timely deliveries and product availability. These factors are integral to ensuring a positive consumer experience and maintaining customer loyalty, underscoring the importance of supply chain efficiency.

2.2 Scalability and flexibility

The dynamic nature of business landscapes and market dynamics necessitates a supply chain network capable of adapting its size and operations. Assessment in this domain involves evaluating the network's responsiveness to demand fluctuations, product offer changes, and shifts in market priorities. Such adaptability not only ensures resilience against operational challenges but also fosters a proactive stance towards industry trends, enhancing the network's flexibility and responsiveness.

2.3 Technology and information systems

The integration of advanced technology and information systems is crucial for performance enhancement in supply chain management. This encompasses the application of data analytics, real-time visibility, and seamless information sharing across supply chain partners. These technologies aid in decision-making, resource allocation, and improvement of transparency and communication, contributing to a more adaptable and productive supply chain.

2.4 Quality control and product integrity

Maintaining product quality and integrity throughout the supply chain is imperative. This involves stringent quality control measures, adherence to safety regulations, and maintenance of product quality. Upholding these standards is essential for brand reputation protection, risk minimization, and legal compliance, underscoring their role in ensuring long-term supply chain performance and sustainability.

2.5 Cost efficiency

Cost reduction is a primary driver of supply chain network optimization, hinging on strategic location of suppliers, manufacturing plants, and distribution centres. Additionally, inventory management optimization plays a key role in minimizing holding, warehousing, and carrying costs. Achieving cost efficiencies bolsters financial performance and enhances the supply chain network' s resilience and competitive edge.

2.6 Lead time reduction

The reduction of lead times is vital for meeting customer needs and enhancing operational efficiency. Strategies for achieving this objective include strategic location selection and implementation of efficient manufacturing and distribution procedures, ensuring prompt adaptation to market conditions and mitigating inventory shortage risks.

3. FUZZY CRITIC-EDAS METHOD

FL is identified as a pivotal element in the optimization of industrial SCN configurations, addressing the prevalent issues of uncertainty and imprecision inherent in supply chain management. The multifaceted and complex nature of supply chains often entails the management of uncertain variables, thereby diminishing the effectiveness of traditional optimization methods. To harness the benefits of FL, the fuzzy CRITIC-EDAS method is given, assuming there are n alternatives, denoted as $\mathrm{A} = \{\mathrm{A}_1, \dots, \mathrm{A}_i, \dots, \mathrm{A}_n\}$ $(n \geq 2)$ and $P = \{P_1, \dots, P_j, \dots, P_m\}$ $(m \geq 2)$ that comprise the finite set of m criteria.

The fuzzy CRITIC-EDAS is delineated through several distinct steps, as described below.

Algorithm

Step 1: Obtain the fuzzy decision matrix from the decision-makers (DMs) as $\Omega = (\zeta_{ij})_{n\times m}$.

Step 2: The CRITIC approach can be employed to estimate the weights of criteria.

Step 2.1:

Eqs. (1) and (2) are employed to normalize the positive and negative attributes of the decision matrix, respectively:

$$T_{ij} = \frac{\zeta_{ij} - \zeta_i^-}{\zeta_i^+ - \zeta_i^-} \tag{1}$$

$$T_{ij} = \frac{\zeta_{ij} - \zeta_i^+}{\zeta_i^- - \zeta_i^+} \tag{2}$$

Step 2.2: The correlation coefficient (CC) between the attributes is calculated by Eq. (3).

$$\rho_{jt} = \frac{\sum_{i=1}^{m} \left(T_{ij} - \bar{x}_j\right)(T_{it} - \bar{x}_t)}{\sqrt{\sum_{i=1}^{m} \left(T_{ij} - \bar{x}_j\right)^2 \sum_{i=1}^{m} (T_{it} - \bar{x}_t)^2}};\ j = 1, \dots, n,\ \ t = 1, \dots, p \tag{3}$$

where, ρ_{jt} is the CC between j^{th} and t^{th} attributes, $\bar{x}_j$ and $\bar{x}_t$ display the mean of j^{th} and t^{th} attributes, while $\bar{x}_j$ and $\bar{x}_t$ are computed from Eq. (4).

$$\bar{x}_j = \frac{1}{n}\sum_{i=1}^{m} T_{ij};\ j = 1, \dots, n \tag{4}$$

Step 2.3: The standard deviation for every attribute is calculated by Eq. (5).

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{m} \left(T_{ij} - \bar{x}_j\right)^2};\ j = 1, \dots, n \tag{5}$$

Then, the index Γ_j is calculated using Eq. (6).

$$\Gamma_j = \sigma_j \sum_{t=1}^{n} \left(1 - \rho_{jt}\right);\ j = 1, \dots, n \tag{6}$$

Step 2.4: The process of calculating attribute weights is carried out by employing Eq. (7).

$$w_j = \frac{\Gamma_j}{\sum_{j=1}^{n} \Gamma_j};\ j = 1, \dots, n \tag{7}$$

Step 3: Subsequently, the average solution (*N*) for every feature is calculated utilizing Eq. (8).

$$N_j = \frac{\sum_{i=1}^{m} T_{ij}}{m};\ j = 1, \dots, n \tag{8}$$

Step 4: Assess the magnitudes of both positive and negative deviations from the mean answer. The calculation of positive distances from average (*Z*) and negative distances from average (λ) for positive qualities is determined by Eqs. (9) and (10), respectively.

$$Z_{ij} = \frac{\max\left(0, \left(T_{ij} - N_j\right)\right)}{N_j};\ i = 1, \dots, m,\ \ j = 1, \dots, n \tag{9}$$

$$\lambda_{ij} = \frac{\max\left(0, \left(N_j - T_{ij}\right)\right)}{N_j};\ i = 1, \dots, m,\ \ j = 1, \dots, n \tag{10}$$

In addition, the *Z* and λ values of the negative attributes are determined using Eqs. (11) and (12).

$$Z_{ij} = \frac{\max\left(0, \left(N_j - T_{ij}\right)\right)}{N_j};\ i = 1, \dots, m,\ \ j = 1, \dots, n \tag{11}$$

$$\lambda_{ij} = \frac{\max\left(0, \left(T_{ij} - N_j\right)\right)}{N_j};\ i = 1, \dots, m,\ \ j = 1, \dots, n \tag{12}$$

Step 5: Calculate the weighted positive distances from average (C_i) and weighted negative distances from average (B_i) using Eqs. (13) and (14), respectively.

$$C_i = \sum_{j=1}^{n} Z_{ij} \cdot w_j;\ i = 1, \dots, m \tag{13}$$

$$B_i = \sum_{j=1}^{n} \lambda_{ij} \cdot w_j;\ i = 1, \dots, m \tag{14}$$

Step 6: Evaluate the weighted normalized positive distances from average (*L*) and weighted normalized negative distances from average (*N*) by using Eqs. (15) and (16), respectively.

$$L_i = \frac{C_i}{\max_i(C_i)};\ i = 1, \dots, m \tag{15}$$

$$N_i = \frac{B_i}{\max_i(B_i)};\ i = 1, \dots, m \tag{16}$$

Step 7: The appraisal score for each choice is calculated using the Eq. (17).

$$M_i = \frac{1}{2}\left(L_i + N_i\right);\ i = 1, \dots, m \tag{17}$$

Step 8: The final ranking of the alternatives is established by sequencing the evaluation scores in descending order.

Fig. 1 provides a graphical representation of the fuzzy CRITIC-EDAS method.

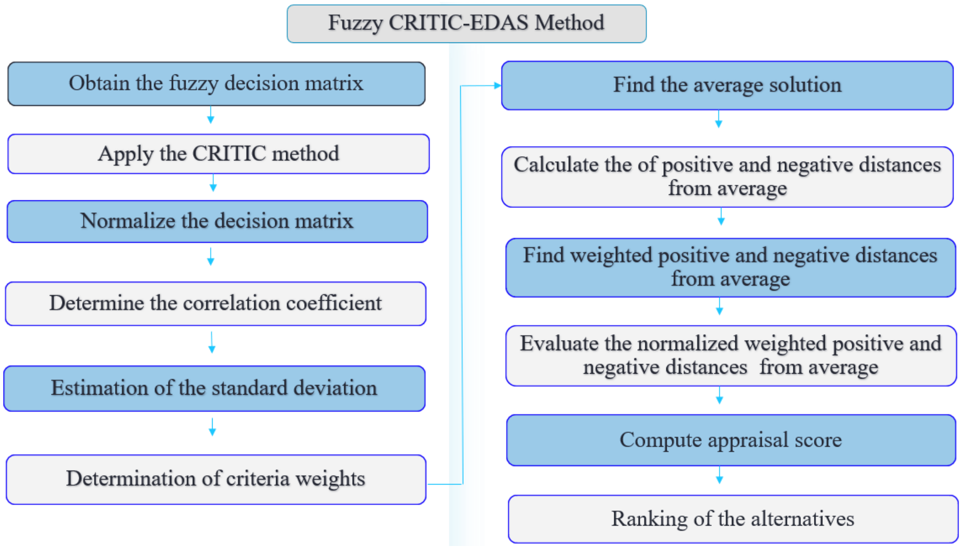

Figure 1: Flow of the fuzzy CRITIC-EDAS method.

4. CASE STUDY

The principal aim of the case study presented herein is the analytical evaluation and enhancement of the production SCN structure for Automax, a leading multinational manufacturing entity, has embarked on this inquiry to fortify its competitive position, reduce expenditures, and augment overall operational efficiency. This investigation encompasses an assessment of ten distinct network configurations, with each being appraised on the basis of six criteria to discern the configuration that epitomizes efficiency and cost-effectiveness. Historical and operational data from a myriad of sources, inclusive of Automax, its suppliers, and distribution centres, have been meticulously gathered. Ten unique SCN configurations, each varying in the number of production plants, distribution centres, and the integration of third-party logistics providers, have been subsequently formulated. These configurations, deliberately crafted, span a spectrum from cost-centric to customer-centric networks, thereby providing a comprehensive array of options for evaluation. In this intricate process, customer service levels, scalability and flexibility, technology and information systems, quality control and product integrity, cost efficiency, and lead time reduction have been established as the pivotal criteria. The configurations are assessed with the intention of illuminating the optimal SCN structure for Automax, thereby facilitating the company's navigation through its progressively complex operational landscape. This endeavour aims not only at optimizing the production SCN structure but also at providing Automax with a robust framework that aligns seamlessly with its evolving business imperatives. In doing so, it is anticipated that the study will yield valuable insights, contributing significantly to the corpus of knowledge in supply chain management and offering practical implications for Automax and similar entities in the manufacturing sector.

4.1 Problem statement

Ten distinct alternatives, represented as companies, are given as A = {A_1, A_2, A_3, …, A_{10}} and the criteria are represented by $P = \{P_1, P_2, \ldots, P_6\}$, wherein P_1 – customer service levels, P_2 – scalability & flexibility, P_3 – technology & information systems, P_4 – quality control & product integrity, P_5 – cost efficiency, and P_6 – lead time reduction. The overarching objective is to elucidate the supplier that most adeptly balances these parameters.

Algorithm

Step 1: Obtain the fuzzy decision matrix from the DMs as $\Omega = (\zeta_{ij})_{n\times m}$. Alternatives and criteria are listed in Table I.

Table I: Fuzzy decision matrix.

Alternatives	**Criteria**					
	P_1	P_2	P_3	P_4	P_5	P_6
A_1	0.250	0.650	0.550	0.950	0.350	0.850
A_2	0.350	0.555	0.200	0.800	0.350	0.650
A_3	0.800	0.300	0.850	0.550	0.200	0.750
A_4	0.600	0.550	0.800	0.300	0.900	0.250
A_5	0.550	0.900	0.750	0.200	0.300	0.800
A_6	0.550	0.900	0.750	0.250	0.350	0.800
A_7	0.350	0.550	0.500	0.550	0.650	0.250
A_8	0.550	0.650	0.300	0.350	0.750	0.550
A_9	0.850	0.850	0.250	0.650	0.800	0.950
A_{10}	0.250	0.350	0.700	0.450	0.350	0.350

Step 2.1: Determine the normalized decision matrix by applying Eqs. (1) and (2), as presented in Table II.

Table II: Normalized decision matrix.

1	0.4167	0.4615	0	0.2143	0.1429
0.8333	0.5750	1	0.2000	0.2143	0.4286
0.0833	1	0	0.5333	0	0.2857
0.4167	0.5833	0.0769	0.8667	1	1
0.5	0	0.1538	1	0.1429	0.2143
0.5	0	0.1538	0.9333	0.2143	0.2143
0.8333	0.5833	0.5385	0.5333	0.6429	1
0.5	0.4167	0.8462	0.8000	0.7857	0.5714
0	0.0833	0.9231	0.4000	0.8571	0
1	0.9167	0.2308	0.6667	0.2143	0.8571

Step 2.2: Evaluate the *CC* between the attributes, as given in Table III.

Table III: *CC* values between the attributes.

1	0.2169	0.0837	-0.3035	-0.2656	0.3958
.2169	1	-0.2020	-0.2636	-0.1734	0.5376
.0837	-0.2020	1	-0.5026	0.3502	-0.1699
-0.3035	-0.2636	-0.5026	1	0.1602	0.2633
-0.2656	-0.1734	0.3502	0.1602	1	0.3869
.3958	0.5376	-0.1699	0.2633	0.3869	1

Step 2.3: The standard deviation for each attribute is calculated using Eq. (5). Subsequently, the index Γ_j is derived by employing Eq. (6), as delineated in Table IV.

Table IV: The index (Γ).

Γ_1	Γ_2	Γ_3	Γ_4	Γ_5	Γ_6
1.7099	1.7174	2.0316	1.8393	1.6112	1.3184

Step 2.4: Attribute weights are ascertained utilizing Eq. (7), and the values are presented in Table V.

Table V: Weights of the attributes.

Criteria					
w_1	w_2	w_3	w_4	w_5	w_6
0.1672	0.1679	0.1986	0.1798	0.1575	0.1289

Step 3: In this step, Eq. (8) is used to determine the average solution (*N*) of each attribute, as given in Table VI.

Table VI: Average solution.

Average values					
N_1	N_2	N_3	N_4	N_5	N_6
0.5100	0.6255	0.5650	0.5050	0.5000	0.6200

Step 4: Evaluate the positive and negative distances from the average solution (see Table VII and VIII).

Table VII: The positive distances from average solution.

Alternatives	**Criteria**					
	P_1	P_2	P_3	P_4	P_5	P_6
A_1	0.5098	0	0.0265	0	0	0
A_2	0.3137	0.1127	0.6460	0	0	0
A_3	0	0.5204	0	0	0	0
A_4	0	0.1207	0	0.4059	0.8000	0.5968
A_5	0	0	0	0.6040	0	0
A_6	0	0	0	0.5050	0	0
A_7	0.3137	0.1207	0.1150	0	0.3000	0.5968
A_8	0	0	0.4690	0.3069	0.5000	0.1129
A_9	0	0	0.5575	0	0.6000	0
A_{10}	0.5098	0.4404	0	0.1089	0	0.4355

Table VIII: The negative distances from average solution.

Alternatives	**Criteria**					
	P_1	P_2	P_3	P_4	P_5	P_6
A_1	0	0.0392	0	0.8812	0.3000	0.3710
A_2	0	0	0	0.5842	0.3000	0.0484
A_3	0.5686	0	0.5044	0.0891	0.6000	0.2097
A_4	0.1765	0	0.4159	0	0	0
A_5	0.0784	0.4388	0.3274	0	0.4000	0.2903
A_6	0.0784	0.4388	0.3274	0	0.3000	0.2903
A_7	0	0	0	0.0891	0	0
A_8	0.0784	0.0392	0	0	0	0
A_9	0.6667	0.3589	0	0.2871	0	0.5323
A_{10}	0	0	0.2389	0	0.3000	0

Step 5: The values of *C* and *B* were found by using Eqs. (13) and (14), respectively. They are provided in Table IX.

Step 6: In this step, the weighted normalized positive and negative distances from average were computed by Eqs. (15) and (16), respectively. They are presented in Table X.

Step 7: The appraisal score for each alternative was computed by Eq. (17) and given in Table XI.

Table IX: Weighted positive and weighted negative distances from average solution.

C_1	0.0905	B_1	0.2601
C_2	0.1997	B_2	0.1585
C_3	0.0874	B_3	0.3328
C_4	0.2962	B_4	0.1121
C_5	0.1086	B_5	0.2523
C_6	0.0908	B_6	0.2365
C_7	0.2196	B_7	0.0160
C_8	0.2417	B_8	0.0197
C_9	0.2053	B_9	0.2920
C_{10}	0.2349	B_{10}	0.0947

Table X: Weighted normalized positive and negative distances from average.

N_1	0.7815	L_1	0.3055
N_2	0.4764	L_2	0.6742
N_3	1.0000	L_3	0.2950
N_4	0.3369	L_4	1.0000
N_5	0.7579	L_5	0.3667
N_6	0.7106	L_6	0.3066
N_7	0.0481	L_7	0.7419
N_8	0.0592	L_8	0.8159
N_9	0.8772	L_9	0.6929
N_{10}	0.2846	L_{10}	0.7930

Table XI: The appraisal scores.

M_1	0.5435
M_2	0.5753
M_3	0.6475
M_4	0.6684
M_5	0.5623
M_6	0.5086
M_7	0.3950
M_8	0.4375
M_9	0.7850
M_{10}	0.5388

Step 8: The final ranking is given as:

$$A_9 > A_4 > A_3 > A_2 > A_5 > A_1 > A_{10} > A_6 > A_8 > A_7$$

4.2 Comparison analysis

In this analysis, the proposed methodology undergoes evaluation and comparison with established methodologies. Table XII below delineates the final rankings and comparative outcomes, illustrating the distinctions between the suggested approach and existing methods with respect to efficacy and authenticity enhancement. Additionally, a graphical representation is provided in Fig. 2.

Table XII: Comparison analysis of the proposed approach.

Method	Ranking of alternatives
Fuzzy TOPSIS [13]	$A_9 > A_4 > A_3 > A_2 > A_5 > A_{10} > A_1 > A_6 > A_7 > A_8$
Fuzzy VIKOR [14]	$A_9 > A_4 > A_3 > A_5 > A_2 > A_1 > A_{10} > A_6 > A_8 > A_7$
Fuzzy MOORA [15]	$A_9 > A_4 > A_3 > A_2 > A_8 > A_1 > A_{10} > A_7 > A_5 > A_6$
Proposed approach	$A_9 > A_4 > A_3 > A_2 > A_5 > A_1 > A_{10} > A_6 > A_8 > A_7$

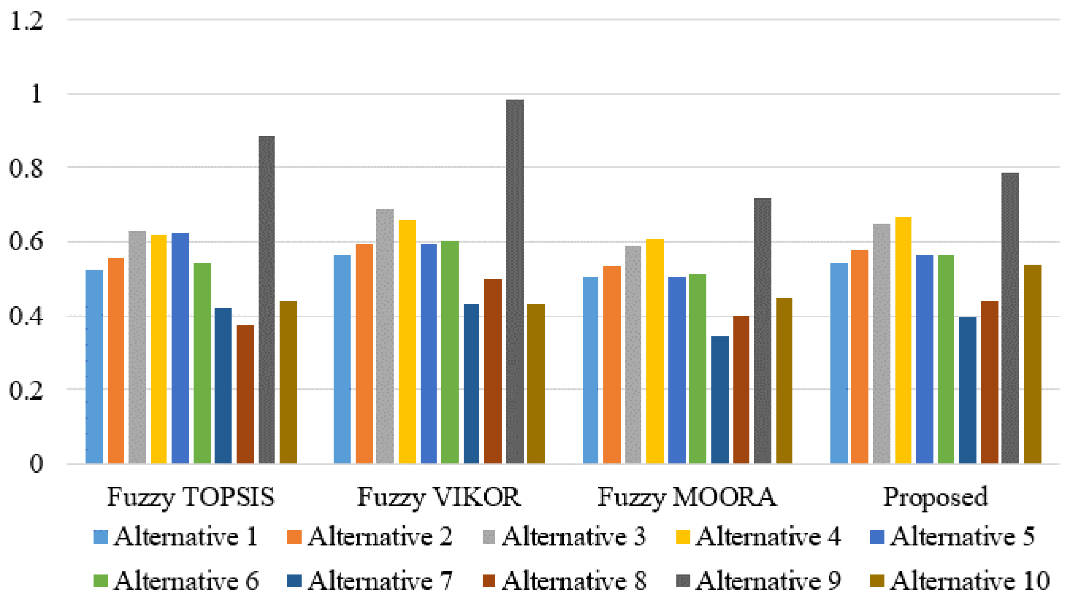

Figure 2: Ranking of alternatives with different methods.

5. CONCLUSION

The fusion of fuzzy CRITIC and EDAS methodologies has culminated in the development of a sophisticated instrument, transcending traditional boundaries in decision-making domains. The acknowledgment and incorporation of fuzziness reflect the inherent uncertainty and imprecision prevalent in real-world supply chain scenarios. This innovative approach not only facilitates a thorough evaluation of supply chain configurations but also equips decision-makers with the versatility necessary to navigate complex, multifaceted optimization challenges.

Through empirical application to a specific case analysis, the efficacy of the fuzzy CRITIC-EDAS methodology in identifying an optimal SCN configuration has been demonstrated. The resulting structure, meticulously optimized for peak efficiency, cost reduction, and risk alleviation, serves as a tangible testament to the practical utility and relevance of this method in real-world contexts.

The contribution of this work extends beyond theoretical constructs, providing a valuable decision support tool for practitioners. In an era marked by globalization, rapid technological advancements, and escalating environmental concerns, the ability to make informed and flexible supply chain decisions is paramount. This study introduces a viable strategy, enabling organizations to navigate and thrive in the ever-evolving global marketplace.

The aspiration for the future is to see the principles and methodologies delineated in this study continue to exert influence over the field of supply chain management. Embracing innovative strategies and a commitment to data-driven decision-making positions organizations at the forefront of competitiveness and sustainability. It is fervently hoped that this research acts as a catalyst, spurring further exploration, implementation, and refinement of groundbreaking strategies in supply chain management. The ultimate goal is to forge a future marked by enhanced adaptability, efficiency, and resilience.

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REFERENCES

[1] Cano, J. A.; Gomez-Montoya, R. A.; Cortes, P.; Campo, E. A. (2021). MRP systems considering fuzzy capacity, lead times and inventory availability, *International Journal of Simulation Modelling*, Vol. 20, No. 1, 29-39, doi:10.2507/IJSIMM20-1-538

[2] Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. (1995). Determining objective weights in multiple criteria problems: the CRITIC method, *Computers & Operations Research*, Vol. 22, No. 7, 763-770, doi:10.1016/0305-0548(94)00059-H

[3] Ordu M. (2022). A simulation-based decision-making approach to evaluate the returns on investments, *International Journal of Simulation Modelling*, Vol. 21, No. 3, 441-452, doi:10.2507/IJSIMM21-3-609

[4] Elmansouri, O.; Alossta, A.; Badi, I. (2022). Pavement condition assessment using pavement condition index and multi-criteria decision-making model, *Mechatronics and Intelligent Transportation Systems*, Vol. 1, No. 1, 57-68, doi:10.56578/mits010107

[5] Chaudhary, N.; Thakur, H. K.; Dwivedi, R. (2022). A dynamic visual analytical approach for crime – transformation to better decision making, *Journal of Logistics, Informatics and Service Science*, Vol. 9, No. 1, 367-404, doi:10.33168/LISS.2022.0122

[6] Tešić, D.; Božanić, D.; Milić, A. (2023). A multi-criteria decision-making model for pontoon bridge selection: an application of the DIBR II-NWBM-FF MAIRCA approach, *Journal of Engineering Management and Systems Engineering*, Vol. 2, No. 4, 212-223, doi:10.56578/jemse020403

[7] Trung, D. D.; Thinh, H. X. (2021). A multi-criteria decision-making in turning process using the MAIRCA, EAMR, MARCOS and TOPSIS methods: a comparative study, *Advances in Production Engineering and Management*, Vol. 16, No. 4, 443-456, doi:10.14743/apem2021.4.412

[8] Zainal, M.; Al-Eideh, B. M. (2021). Modeling ethical decision-making behaviors through using information index, *Journal of System and Management Sciences*, Vol. 11, No. 2, 15-28, doi:10.33168/JSMS.2021.0202

[9] Keshavarz Ghorabaee, M.; Zavadskas, E. K.; Olfat, L.; Turskis, Z. (2015). Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS), *Informatica*, Vol. 26, No. 3, 435-451, doi:10.15388/Informatica.2015.57

[10] Abdel-Basset, M.; Gamal, A.; Chakrabortty, R. K.; Ryan, M. (2021). Development of a hybrid multi-criteria decision-making approach for sustainability evaluation of bioenergy production technologies: a case study, *Journal of Cleaner Production*, Vol. 290, Paper 125805, 19 pages, doi:10.1016/j.jclepro.2021.125805

[11] Ashraf, S.; Rehman, N.; Hussain, A.; AlSalman, H.; Gumaei, A. H. (2021). q-rung orthopair fuzzy rough Einstein aggregation information-based EDAS method: applications in robotic agrifarming, *Computational Intelligence and Neuroscience*, Vol. 2021, Paper 5520264, 27 pages, doi:10.1155/2021/5520264

[12] Ghorabaee, M. K.; Amiri, M.; Zavadskas, E. K.; Turskis, Z.; Antucheviciene, J. (2017). A new hybrid simulation-based assignment approach for evaluating airlines with multiple service quality criteria, *Journal of Air Transport Management*, Vol. 63, 45-60, doi:10.1016/j.jairtraman.2017.05.008

[13] Visagan, A.; Ganesh, P. (2022). Parametric optimization of two point incremental forming using GRA and TOPSIS, *International Journal of Simulation Modelling*, Vol. 21, No. 4, 615-626, doi:10.2507/IJSIMM21-4-622

[14] Więckowski, J.; Kizielewicz, B.; Shekhovtsov, A.; Sałabun, W. (2023). How do the criteria affect sustainable supplier evaluation? – A case study using multi-criteria decision analysis methods in a fuzzy environment, *Journal of Engineering Management and Systems Engineering*, Vol. 2, No. 1, 37-52, doi:10.56578/jemse020102

[15] Jhodkar, D.; Khan, A.; Gupta, K. (2021). Fuzzy-MOORA based optimization of machining parameters for machinability enhancement of titanium, *Mathematical Modelling of Engineering Problems*, Vol. 8, No. 2, 189-198, doi:10.18280/mmep.080204