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SUPPLY CHAIN PERFORMANCE EVALUATION USING THE SCOR® MODEL AND FUZZY-TOPSIS

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Research Paper

Abstract: *The monitoring of SC development offers several benefits, including the evaluation of progress, identification of achievements, enhancement of understanding of crucial business processes, and identification of potential future challenges. This study introduces an innovative approach to evaluate the efficiency of a supply chain (SC) by using the performance metrics of the SCOR® model and employing the fuzzy-TOPSIS technique. The strategy provided in this study involves evaluating and comparing the overall performance of 10 different supply chain alternatives in a demonstration scenario. This study introduces a novel approach that combines the SCOR model with fuzzy TOPSIS to facilitate the assessment of supply chain performance. The Supply Chain Operations Reference (SCOR) model serves as a benchmarking tool, facilitating the comparison of a firm's performance with other businesses that are organized within the supply chain. The proposed approach offers numerous advantages over alternative approaches. These advantages include the capability to conduct benchmarking against other supply chains (SCs), the fuzzy TOPSIS method requiring minimal judgments for parameterization, thereby enhancing the agility of the decision-making process, the ability to evaluate multiple alternatives simultaneously, and the elimination of the ranking reversal issue. The fuzzy TOPSIS method enables the measurement of metrics and probability of alternatives using language phrases that are described by fuzzy numbers. The potential for evaluating numerous alternatives and measurements concurrently is boundless, distinguishing it from other methodologies such as AHP and TOPSIS. The proposed method was implemented in MATLAB and subsequently applied to an illustrative scenario. These findings demonstrate the appropriateness of this concept.*

Keywords: *Benchmarking; Supply chain; Fuzzy TOPSIS; SCOR® model; Performance evaluation.*

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1. Introduction

Supply chains include manufacturers, merchants, warehouses, suppliers, transporters, and other businesses. The activities are the combination of planning, implementing, controlling, and regulating all activities related to the movement of resources and the transformation of commodities from the stage of raw materials to the final consumer (Khan, Yu, Rehman Khan, & Yu, 2019). By manufacturing and distributing items in the appropriate quantity, to the right location, at the right time, and in a sustainable manner, SC management aims to reduce total costs while giving value to customers and other stakeholders (Lohman, Fortuin, & Wouters, 2004).

Performance assessment may be stated as quantitative and/or qualitative evaluation of the efficacy and productivity pertaining to a procedure or activity (Cuthbertson & Piotrowicz, 2011). Evaluation of the efficacy and efficiency of an SC requires measures relating to a variety of performance targets, including cost, agility, responsiveness, adaptability, and sustainability. The benefits of monitoring the progress of SC performance include measuring progress, recognising successes, enhancing awareness of critical business processes, detecting potential difficulties, and offering insight into potential future improvement activities (Ahi & Searcy, 2015). Nonetheless, this evaluation is a difficult task owing to its transversal nature involving several parties, which contributes greatly to a number of obstacles, such as the distribution of data, absence of consistency, and insufficiency (Ahi & Searcy, 2015; Lohman, Fortuin, & Wouters, 2004).

Selecting the appropriate action to enhance SC performance is contingent on the SC's evaluation. This evaluation enables the development of operational plans based on the analysis of the performance gap between actual and intended performance. The SCOR® (Supply Chain Operations Reference) model is a conceptual model created by the Supply Chain Council to facilitate supervision and assessment of SC performance (ASCM, 2022). The SCOR® model offers a standardised set of SC performance metrics that are broadly embraced by managers in a variety of industries. SCOR® is a benchmarking tool that allows organisations that utilise the SCOR® model's performance measures to compare their level of performance to those of other supply chain-organised businesses. Benchmarking measures facilitate the establishment of attainable goals to support strategic decisions (ASCM, 2022).

Combining the SCOR® performance measurement model with quantitative methodologies has been researched as a means to help management assessment on a growing scale. Several strategies incorporating artificial intelligence and multi-criteria evaluation (Moharamkhani, Bozorgi-Amiri, & Mina, 2017) have been investigated for such applications. Fuzzy-TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is a method which can provide several advantages for evaluating SC performance (Ho, Feng, Lee, & Yen, 2012). This method uses language evaluations from management to evaluate supply chain performance and the ranking of indicators (Dehghani, Khaleghi, & Sanzighi, 2019).

The SCOR model proposes various attributes and metrics that can be employed to measure supply chain efficacy. The SCOR model emphasises the fundamental attributes of the supply chain, including reliability, responsiveness, agility, cost, and assets (Divsalar, Ahmadi, & Nemati, 2020; Marques Perez, Rodríguez Mañay, & Guaita Pradas, 2022). The selection of performance indicators is influenced by multiple perspectives, dimensions, and criteria. Assessing the significance of these metrics poses a decision-making dilemma that necessitates the simultaneous consideration of several elements. The Analytical Hierarchy Process (AHP) (Saleheen & Habib, 2023) and the Analytical Network Process (ANP) (Kamble, Mor, & Belhadi, 2023) are among the various methodologies available for evaluating the level of suitability of supply chain performance measures. The system comprises multiple components or facets that collaborate to ensure the safe and efficient movement of individuals and goods. The implementation of a robust measurement system is crucial for ensuring the efficiency and efficacy of the business supply chain system, thus contributing to the overall performance of the organization (Panudju, Marimin, Raharja, & Nurilmala, 2023). It is imperative for every organisation engaged in the supply chain to establish a performance measurement system for each individual procedure to enhance its levels of responsiveness and productivity. These instruments ensure the attainment of their objectives and the ongoing enhancement of their processes. The main purpose of information systems within the supply chain is to fulfil strategic goals such as enhancing performance, enabling information sharing among different stakeholders, and, notably, formulating business strategies that can effectively compete in the market (Kunrath, Dresch, & Veit, 2023; Tripathi & Talukder, 2023). The fundamental components of supply chain architecture encompass three essential elements of operational flexibility: organizational capabilities, information systems (IT), and operations. To effectively monitor and analyse key performance indicators, it is imperative for companies to showcase these requisite talents (Oktaviani & Asrol, 2022).

The integration of performance appraisals into supply chain operations has attracted significant attention from both scholars and practitioners. The completion of this section is crucial to facilitate the attainment of supply chain objectives and effectively address any associated obstacles (Djatna et al., 2020; Panudju et al., 2023). There are numerous factors to be considered when proposing a theoretical framework for assessing performance. Several models are commonly used in business analyses. These models include Data Evolved Analysis (DEA), activity-based costing (Jaiswal & Samuel, 2022), balanced score cards (Asrol, Marimin, Machfud, & Yani, 2018), and the Supply Chain Operation Reference (SCOR) model, which is widely utilized (Tutuhatunewa, Ririmasse, & Noya, 2023).

This study examines the objectives and significance of the supply chain performance assessment process, which exerts a substantial influence on the activities of all participants within the supply chain. The utilisation of this planning methodology is applicable in conjunction with SCOR, a framework endorsed by the Supply Chain Council. The Supply Chain Operations Reference (SCOR) model has the potential to be applied across various industries to identify, quantify, restructure, and enhance supply chain operations (Asrol & Syahruddin, 2022; Panudju et al., 2023). The SCOR framework is categorised into four distinct levels: Level 1 encompasses an enterprise framework that encompasses various aspects such as planning, procurement, manufacturing, and distribution. Level 2 encompasses fundamental business processes. Level 3 provides guidance for making supply chain decisions, whereas Level 4 focuses primarily on key performance indicators in the implementation phase. Furthermore, to assess the efficacy of the supply chain, it is important to initially ascertain the many business activities that are implicated (Kamble, Mor, & Belhadi, 2023; Panudju & Nurilmala, 2022).

In this respect, this study provides a novel method for assessing supply chain effectiveness in light of the SCOR® model's performance metrics and the Fuzzy-TOPSIS technique. MATLAB was used to implement the proposed method, which was then applied to an example situation. The remainder of this paper is structured as follows. Part 2 concerns the theoretical foundation of the SC performance assessment, SCOR®, and the fuzzy TOPSIS approach. Section 3 discusses the suggested method for evaluating SC performance and its implementation in a specific instance. Section 4 concludes with findings and suggestions for future research.

2. Material and Method

2.1 Supply Chain Performance Measurement

Various studies are included in the study on supply chain performance evaluation, such as metrics conceptual frameworks (Pires & Aravechia, 2001; Tripathi & Talukder, 2023), identify the most metrics frequently used (Marques Perez, Rodríguez Mañay, & Guaita Pradas, 2022), and supporting the performance review process with quantitative models (Majhi et al., 2021). To address the complexity and unpredictability of SC performance and decision-making, a number of quantitative models have been created. Figure I provides a summary of research that offers systems based on the combination of SCOR® measures and quantitative methodologies to enable the evaluation of SC performance, categorised by single or mixed methods. Combined approaches suggest hybridisation or the sequential use of two or more techniques.

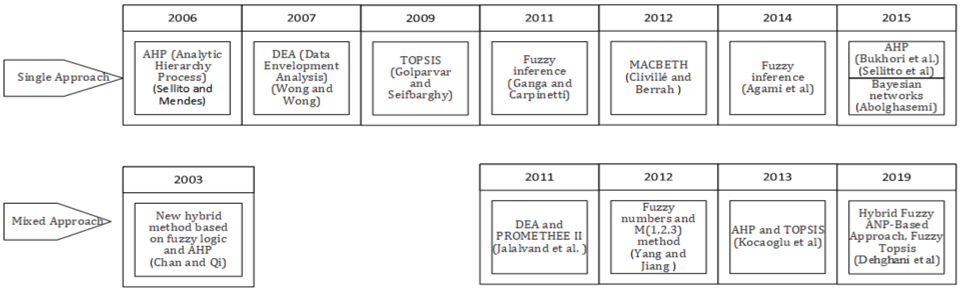

Fig. 1. Roadmap of Quantitative Models

Although the numerical methods mentioned in figure 1 have contributed to the evaluation of SC performance, the majority of the technique-related methods have limitations. Importantly, these methodologies for evaluating SC performance must permit the subtraction of indicators without compromising the consistency of the results. The ranking reversal problem impacts models based on AHP (Figueira et al.; Sinoimeri & Teta, 2023), and TOPSIS (Chakraborty, 2022) when extra measurements or alternatives are introduced. Techniques for evaluating SC performance should also address uncertainty (Yusianto & Hardjomidjojo, 2020). Nevertheless, DEA-based models (Moazeni, Shirani, & Hejazi, 2023) and TOPSIS (Moharamkhani, Bozorgi-Amiri, & Mina, 2017) cannot cope with imperfect data and ambiguous information, which is necessary for evaluating the performance of SC.

Utilising comparative techniques, such as AHP (Bukhori, Widodo, & Ismoyowati, 2015; Figueira et al.) and MACBETH (Clivillé & Berrah, 2012), are appropriate methods for addressing qualitative criteria and subjective judgments. However, these strategies restrict the number of measurements and options that may be assessed concurrently. Saaty (1990) a dvises limiting the number of measurements to be examined using pair-wise comparisons in order not to jeopardise the consistency of human judgment.

The incorporation of language variables defined by fuzzy numbers is another strategy often employed to deal with qualitative metrics and subjective evaluations (Abolghasemi, Khodakarami, & Tehranifard, 2015; Asrol, Yani, & Taira, 2020; Ayyildiz & Taskin, 2022).

In such techniques, fuzzy number classification serves as the primary tool for assessing unpredictability. As the parameters of the attribute values may be selected to best represent the language phrases that each decision maker evaluates available options, the membership functions are linguistically adaptive in terms of different performance metrics, and the membership functions can more accurately reflect the language phrases (Gul & Ak, 2021).

Out of the various techniques rooted in fuzzy set theory, fuzzy TOPSIS emerges as the most suitable option due to its ability to accommodate a wide range of assessed performance measures and alternatives. This feature enables the comparison of performance outcomes across different supply chains (SCs) without encountering any ranking reversal issues. Despite these advantages and numerous applications, few studies have been published that combine the fuzzy SCOR model to improve SC performance (Junior, Osiro, & Carpinetti, 2014).

2.2 SCOR® model

The SCOR® model was established to outline business activities associated with all steps of meeting customer expectations. The reference model (version 14.0) was predicated on six fundamental management processes: planning, sourcing, making, delivering, returning, and empowering. The performance part of the SCOR® model shows hierarchical assesment indicators associated with five qualities. SCOR ® level measurements concentrate on the following performance characteristics (ASCM, 2022):

- Reliability and quality: the capacity to accomplish duties as anticipated. Common dependability criteria include on-time delivery, proper amount, and right quality.
- Responsiveness: How quickly a supply chain delivers things to the client.
- Agility: the capacity to adjust to external factors and market changes to achieve or preserve competitiveness.
- Costs: operational supply chain expenses. This comprises expenditures for man, materials, management, and movement.
- Asset management: The capacity to utilise assets efficiently. Supply chain portfolio management solutions include inventory reduction.

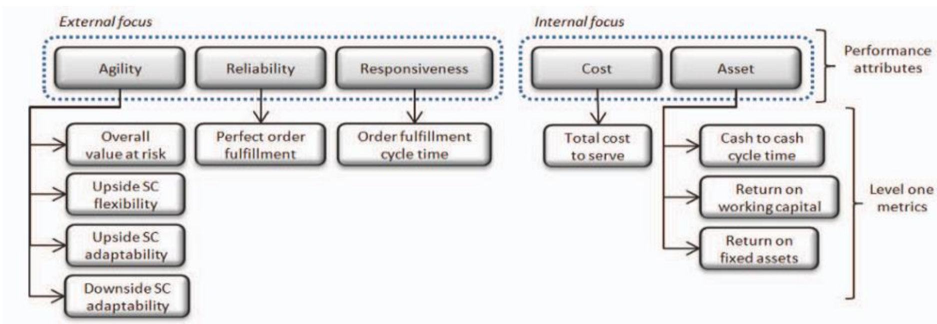

Fig. 2 Performance measures recommended for SC assessment based on SCOR®.

The SCOR model specifies a three-tiered framework for the metrics. Figure 2 depicts the hierarchy of level 1 with five quality metrics. According to the recommendations put forth by the Supply Chain Council, it is advisable to incorporate a minimum of one indicator for each performance component inside scorecards. This practice is advocated in order to foster equitable decision-making processes. Their creation, as well as the links between their causes makes it feasible to examine supply chain performance from several perspectives (ASCM, 2022).

Using the SCOR® benchmarking tool, companies utilising the SCOR® model's performance metrics may compare their results with those of other businesses in the supply chain. The benchmarking procedure with SCOR® may be carried out as follows: (1) identify supply chains; (2) assess external- internal performance; (3) benchmark against relevant companies; (4) develop competitive needs; and (5) determine the value of change (ASCM, 2022).

Fuzzy set theory-based solutions may deal with the uncertainty of evaluations better than conventional methods because they are meant to replicate human judgment and reasoning (Chan & Qi, 2003). This section discusses the methodology employed in this study.

2.3 Fuzzy-TOPSIS

The fuzzy set concept has been utilised to facilitate decisions based on ambiguous data (Zadeh, 1965). It provides a vocabulary for qualitatively representing variables via linguistic words and numerically fuzzy sets, together with their appropriate membership functions (Junior, Osiro, & Carpinetti, 2014). Chen (2000) presented the Fuzzy- TOPSIS technique in order to solve challenges regarding group decision making in unpredictable circumstances.

In the Fuzzy-TOPSIS technique, the decision makers, *Dr* (*r =1,..., k*), employ linguistic variables to assess the weights of the criteria (or metrics) and alternatives. The variable $\tilde{w}_j^r$ specifies the weight of the j^{th} criteria presented by the rth decision maker, $C_j = (j = l, \dots, m)$. Similarly, $\tilde{x}_{ij}^r$ describes the rates of the r^{th} option, $A_i = (i = l, \dots, m)$, according to criteria j specified by the r^{th} decision maker (Junior, Osiro, & Carpinetti, 2014). This approach includes the following steps:

The criteria weights and alternative weights provided by k stakeholders, as shown by equations 1 and 2:

$$\tilde{W}_j = \frac{1}{k}\left[\tilde{W}_j^1 + \tilde{W}_j^2 + \cdots + \tilde{W}_j^k\right] \quad (1)$$

$$\tilde{X}_j = \frac{1}{k}\left[\tilde{X}_{ij}^1 + \tilde{X}_{ij}^r + \cdots + \tilde{X}_{ij}^k\right] \quad (2)$$

Assemble the fuzzy decision matrix of options (D) and criterion (W), as shown in Equations 3 and 4.

$$\tilde{D} = \begin{array}{c} A_1 \\ A_i \\ A_n \end{array} \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{1j} & \tilde{x}_{1m} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \tilde{x}_{nj} & \tilde{x}_{nm} \end{bmatrix} \quad (3)$$

$$\tilde{W} = [\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_m] \quad (4)$$

Normalisation of the fuzzy matrices of decisions (D) of the alternatives with exponential transformation of scale. The equation 5 is for the normalized fuzzy decision matrix R. The calculation of the normalised decision matrix is dependent on the criteria type. For the benefit criteria, equation 6 represents the normalised decision matrix. Alternatively, the normalised choice matrix for the cost criteria is given by Equation 7 (linguistic phrases in the lower portion of the scale suggest better rates).

$$\tilde{R} = [\tilde{r}_{ij}]_{m\ x\ n} \qquad (5)$$

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right) \qquad (6)$$

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right) \qquad (7)$$

Compute the weighted normalized decision matrix, $\tilde{V}$, by multiplying the weights of the evaluation criteria, $\widetilde{w}_j$, by the elements $\tilde{r}_{ij}$ of the normalized fuzzy decision matrix.

$$\tilde{V} = [\tilde{v}_{ij}]_{m\ x\ n} \qquad (8)$$

where $\tilde{V}_{ij}$ is given by equation 9.

$$\tilde{V}_{ij} = \tilde{r}_{ij} * \widetilde{w}_j \qquad (9)$$

Equations 10 and 11 show how to determine the Fuzzy Positive Ideal Solution (FPIS-A+) and the Fuzzy Negative Ideal Solution (FPIS- A-).

$$A^+ = (\tilde{V}_1^+, \tilde{V}_j^+, \dots, \tilde{V}_m^+) \qquad (10)$$

$$A^- = (\tilde{V}_1^-, \tilde{V}_j^-, \dots, \tilde{V}_m^-) \qquad (11)$$

Where $\tilde{V}_j^+ = (1,1,1)$ dan $\tilde{V}_j^- = (0,0,0)$.

Compute the distance d_i^+ and d_i^- of each alternative from respectively $\tilde{V}_j^+$ and $\tilde{V}_j^-$ according to equations 12 and 13.

$$d_i^+ = \sum_{j=1}^{n} dv\,(\tilde{V}_{ij}, \tilde{V}_j^+) \qquad (12)$$

$$d_i^- = \sum_{j=1}^{n} dv\,(\tilde{V}_{ij}, \tilde{V}_j^-) \qquad (13)$$

Where $d(\,.\,,.)$ represents the distance between two fuzzy numbers according to the vertex method. For triangular fuzzy numbers, this is expressed as in Equation 14.

$$\mathrm{d}\,(\tilde{x},\tilde{z}) = \sqrt{\frac{1}{3}\,[(l_x - l_z)^2 + (m_x - m_z)^2 + (u_x - u_z)^2]} \qquad (14)$$

Compute the closeness coefficient, CCi, according to Equation 15.

$$CC_i = {d_i^-}\big/{(d_i^+ + d_i^-)} \qquad (15)$$

We define the ranking of the alternatives according to the closeness coefficient, CCi, in decreasing order. The best alternative was closest to FPIS and farthest from FNIS.

3. Results and Discussion

3.1. The SC Performance Evaluation Proposed Model

Figure 3 shows the suggested methodology to assist the SC performance assessment. It can be applied to assess the effectiveness of various business divisions or supply networks within the same organisation. Alternatively, it may be implemented by various organisations with the objective of comparing performance supply chains within a similar sector. The adopted set of metrics for SC assessment consisted of all Level 1 measures from the SCOR® model.

The metrics and units of measurement (Table 2) were selected for SC performance evaluation in accordance with SCOR® models (ASCM, 2022).

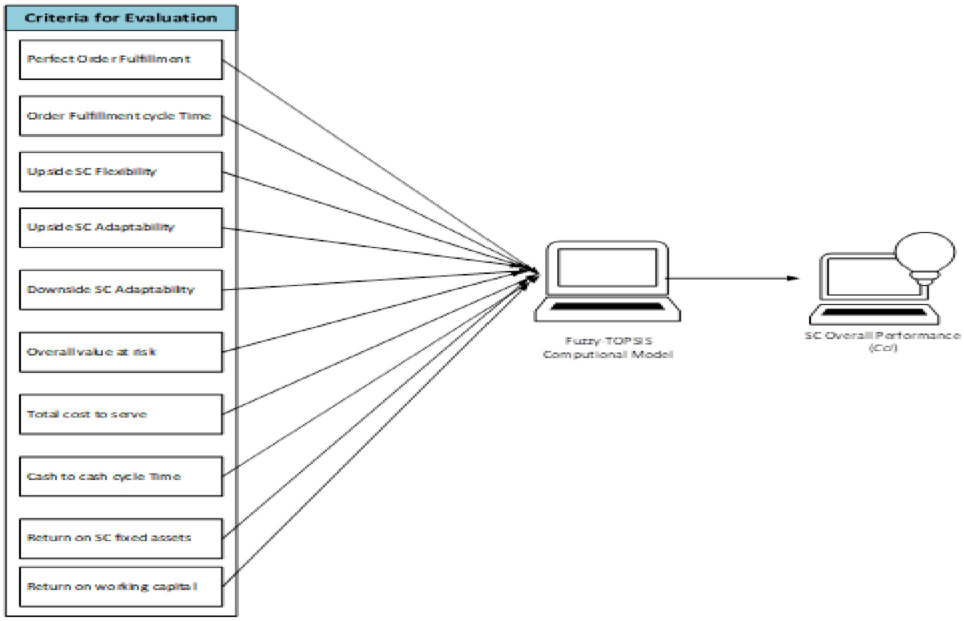

Fig. 3. Conceptual model for assessing Supply Chain performance.

Table 2. SCOR® based metrics models

Ci	Description	Unit
C_1	Proportion of orders that fulfill delivery with complete documentation and no damage.	%
C_2	Cycle time for order fulfillment: The typical cycle duration continually attained when fulfilling client orders. This cycle time begins with the receipt of each individual order and concludes with customer acceptance.	Days
C_3	Positive SC flexibility: days required to achieve an unexpected 20% increase in supplied quantities.	Days
C_4	SC adaptability plus: achievable 30-day supply quantity increase cap at the highest level.	%
C_5	A drawback of SC flexibility is the reduction of desired quantities 30 days before to delivery without any impact on costs or inventories.	%
C_6	The chance of risk events multiplied by the financial impact of risk occurrences that could potentially affect any crucial SC operations results in the overall value at risk.	$
C_7	Total cost of service is the sum of all direct and indirect costs incurred in providing clients with goods and services.	Rp
C8	Cash-to-cash cycle time is the time it takes for an investment to return to a business after being used to purchase raw materials.	Days
C9	Return on Assets: This metric measures the profit a company makes from the money it invests in supply chain fixed assets. These are the fixed assets used in the processes of planning, sourcing, making, delivering, and returning.	%
C10	ROI as the ratio of investment of working capital and supply chain revenue.	%

This plan should involve SC managerial decision-making from logistics, procurement, product development, and assurance. Based on their understanding of the SC's business operations and historical data, decision makers may assess option expenses. They must also quantify the indicators' relative values based on the supply chain manager's competitive strategy. Lean businesses should prioritise cost and reliability. Emphasise adaptability and agility KPIs when using agile: The execution of the suggested method necessitates the creation of a fuzzy TOPSIS-based computational model. With the support of external IT specialists, fuzzy TOPSIS might be deployed as an information strategy.

Furthermore, because of its convenience of use, internal implementation is possible by the institution using a digital worksheet, provided developers understand the fundamentals of fuzzy variables and associated algebraic operations. The decision maker can help in the parameterisation of the fuzzy TOPSIS model by selecting the appropriate language phrases for SC assessment and weighting the metrics. In addition, they may parameterise the fuzzy integers associated with each linguistic phrase.

3.2. Application example

An exemplary application of the model was constructed. The authors determined the definitions of the language phrases, metric weights, and scores of the SC assessed. In this example, the objective is to assess and categorize the 10 supply chains performance (*A1*, *A2*,…, *A10*).

The weights and supply chain rates of the metrics were evaluated based on the linguistic phrases presented in Tables 3 and 4, respectively. Triangular fuzzy numbers were employed to designate the attributes of the metrics' weights and alternative rates (Chen, 2000).

Table 3. The weights scale metrics

Linguistic Terms	Fuzzy Triangular Number
Less Importance (LI)	(0.10, 0.10, 0.25)
Mildly Important (MI)	(0.10, 0.25, 0.50)
Important (I)	(0.25, 0.50, 0.75)
Very Important (VI)	(0.50, 0.75, 1.00)
Absolutely Important (AI)	(0.75, 1.00, 1.00)

Table 4. Supply Chain Performance Scale

Linguistic Terms	Fuzzy Triangular Number
Very Low (VL)	(1.00, 1.00, 2.50)
Low (L)	(1.00, 2.50, 5.00)
Medium (M)	(2.50, 5.00, 7.50)
High (H)	(5.00, 7.50, 10.0)
Very High (VH)	(7.50, 10.0, 10.0)

The authors' linguistic evaluations of supply chain rates are shown in Table 5. Noting that grades C2, C6, C7, and C8 were modelled as cost criteria is important. This indicates that the phrases in the lower scale is used to imply higher scores. The weights assigned to each statistic are listed in Table 6.

Table 5. The Evaluated Supply Chains Rates

	C _1	C _2	C _3	C _4	C _5	C _6	C _7	C _8	C _9	C _10
A_1	H	VL	VH	VH	VH	VL	VL	VL	H	VH
A_2	M	M	H	VH	H	M	M	L	VH	H
A_3	VH	L	VH	L	L	VL	L	VL	H	M
A_4	H	VL	H	VH	H	H	L	VL	H	VH
A_5	M	VL	M	L	M	M	L	M	H	M
A_6	VH	VL	VH	VH	VH	VL	VL	VL	VH	VH
A_7	H	VL	H	L	L	M	VL	L	H	H
A_8	H	VL	M	M	H	L	M	L	M	M
A_9	M	M	M	M	M	L	M	M	H	M
A_10	H	L	L	H	H	L	VL	L	VL	VL

Table 6. The Evaluated Criteria Weights

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10
Wi	AI	AI	I	I	I	AI	AI	I	VI	AI

The SC rates presented in Table 5 were subjected to a transformation process utilizing the fuzzy TOPSIS model, resulting in the representation of these rates as fuzzy triangular numbers. The triangular numbers under consideration, which constitute the fuzzy decision matrix, are listed in Table 6. These data were standardised using Equation 5 and weighted using Equation 8. Table 7 displays the normalised decision matrix and Table 8 displays the weighted normalised decision matrix.

Table 7. Normalized Fuzzy Decision Matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10
A_1	(0.50, 0.75, 1.00)	(0.40, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.40, 1.00, 1.00)	(0.40, 1.00, 1.00)	(0.40, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)
A_2	(0.25, 0.50, 0.75)	(0.13, 0.20, 0.40)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.13, 0.20, 0.40)	(0.13, 0.20, 0.40)	(0.20, 0.40, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)
A_3	(0.75, 1.00, 1.00)	(0.20, 0.40, 1.00)	(0.75, 1.00, 1.00)	(0.10, 0.25, 0.50)	(0.10, 0.25, 0.50)	(0.40, 1.00, 1.00)	(0.20, 0.40, 1.00)	(0.40, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
A_4	(0.50, 0.75, 1.00)	(0.40, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.10, 0.13, 0.20)	(0.20, 0.40, 1.00)	(0.40, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.75, 1.00, 1.00)
A_5	(0.25, 0.50, 0.75)	(0.40, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.10, 0.25, 0.50)	(0.25, 0.50, 0.75)	(0.13, 0.20, 0.40)	(0.20, 0.40, 0.20)	(0.13, 0.20, 0.40)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
A_6	(0.75, 1.00, 1.00)	(0.40, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.40, 1.00, 1.00)	(0.40, 1.00, 1.00)	(0.40, 1.00, 1.00)	(0.75, 1.00, 1.00)	(0.75, 1.00, 1.00)
A_7	(0.50, 0.75, 1.00)	(0.40, 1.00, 1.00)	(0.50, 0.75, 1.00)	(0.10, 0.25, 0.50)	(0.10, 0.25, 0.50)	(0.13, 0.20, 0.40)	(0.40, 1.00, 1.00)	(0.20, 0.40, 1.00)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)
A_8	(0.50, 0.75, 1.00)	(0.40, 1.00, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.50, 0.75, 1.00)	(0.20, 0.40, 1.00)	(0.13, 0.20, 0.40)	(0.20, 0.40, 1.00)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)
A_9	(0.25, 0.50, 0.75)	(0.13, 0.20, 0.40)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.25, 0.50, 0.75)	(0.20, 0.40, 1.00)	(0.13, 0.20, 0.40)	(0.13, 0.20, 0.40)	(0.50, 0.75, 1.00)	(0.25, 0.50, 0.75)
A_10	(0.50, 0.75, 1.00)	(0.20, 0.40, 1.00)	(0.10, 0.25, 0.50)	(0.50, 0.75, 1.00)	(0.50, 0.75, 1.00)	(0.20, 0.40, 0.20)	(0.40, 1.00, 0.13)	(0.20, 0.40, 1.00)	(0.10, 0.10, 0.25)	(0.10, 0.10, 0.25)

Table 8. Fuzzy Decision Matrix Weighted and Normalized

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10
A_1	(0.38, 0.75, 1.00)	(0.30, 1.00, 1.00)	(0.19, 0.50, 0.75)	(0.19, 0.50, 0.75)	(0.19, 0.50, 0.75)	(0.30, 1.00, 1.00)	(0.30, 1.00, 1.00)	(0.10, 0,50, 0.75)	(0.25, 0.56, 1.00)	(0.56, 1.00, 1.00)
A_2	(0.19, 0.50, 0.75)	(0.10, 0.20, 0.40)	(0.13, 0.38, 0.75)	(0.19, 0.50, 0.75)	(0.13, 0.38, 0.75)	(0.10, 0.20, 0.40)	(0.10, 0.20, 0.40)	(0.05, 0.20, 0.75)	(0.38, 0.75, 1.00)	(0.38, 0.75, 1.00)
A_3	(0.56, 1.00, 1.00)	(0.15, 0.40, 1.00)	(0.19, 0.50, 0.75)	(0.03, 0.13, 0.38)	(0.03, 0.13, 0.38)	(0.30, 1.00, 1.00)	(0.15, 0.40, 1.00)	(0.10, 0.50, 0.75)	(0.25, 0.56, 1.00)	(0.19, 0.50, 0.75)
A_4	(0.38, 0.75, 1.00)	(0.30, 1.00, 1.00)	(0.13, 0.38, 0.75)	(0.19, 0.50, 0.75)	(0.13, 0.38, 0.75)	(0.08, 0.13, 0.20)	(0.15, 0.40, 1.00)	(0.10, 0.50, 0.75)	(0.25, 0.56, 1.00)	(0.56, 1.00, 1.00)
A_5	(0.19, 0.50, 0.75)	(0.30, 1.00, 1.00)	(0.06, 0.25, 0.56)	(0.03, 0.13, 0.38)	(0.06, 0.25, 0.56)	(0.10, 0.20, 0.40)	(0.15, 0.40, 0.20)	(0.03, 0.10, 0.30)	(0.25, 0.56, 1.00)	(0.19, 0.50, 0.75)
A_6	(0.56, 1.00, 1.00)	(0.30, 1.00, 1.00)	(0.19, 0.50, 0.75)	(0.19, 0.50, 0.75)	(0.19, 0.50, 0.75)	(0.30, 1.00, 1.00)	(0.30, 1.00, 1.00)	(0.10, 0.50, 0.75)	(0.38, 0.75, 1.00)	(0.56, 1.00, 1.00)
A_7	(0.38, 0.75, 1.00)	(0.30, 1.00, 1.00)	(0.13, 0.38, 0.75)	(0.03, 0.13, 0.38)	(0.03, 0.13, 0.38)	(0.10, 0.20, 0.40)	(0.30, 1.00, 1.00)	(0.05, 0.20, 0.75)	(0.25, 0.56, 1.00)	(0.38, 0.75, 1.00)
A_8	(0.38, 0.75, 1.00)	(0.30, 1.00, 1.00)	(0.06, 0.25, 0.56)	(0.06, 0.25, 0.56)	(0.13, 0.38, 0.75)	(0.15, 0.40, 1.00)	(0.10, 0.20, 0.40)	(0.05, 0.20, 0.75)	(0.13, 0.38, 0.75)	(0.19, 0.50, 0.75)
A_9	(0.19, 0.50, 0.75)	(0.10, 0.20, 0.40)	(0.06, 0.25, 0.56)	(0.06, 0.25, 0.56)	(0.06, 0.25, 0.56)	(0.15, 0.40, 1.00)	(0.10, 0.20, 0.40)	(0.03, 0.10, 0.30)	(0.25, 0.56, 1.00)	(0.19, 0.50, 0.75)
A_10	(0.38, 0.75, 1.00)	(0.15, 0.40, 1.00)	(0.03, 0.13, 0.38)	(0.13, 0.38, 0.75)	(0.13, 0.38, 0.75)	(0.15, 0.40, 0.20)	(0.30, 1.00, 0.13)	(0.05, 0.20, 0.75)	(0.05, 0.08, 0.25)	(0.08, 0.10, 0.25)

According to Chen (2000), the Fuzzy Positive Ideal Solution (FPIS, A^+) and the Fuzzy Negative Ideal Solution (FNIS, A^-) were defined as

$$A^+ = \begin{bmatrix} (1.0,1.0,1.0),(1.0,1.0,1.0),(1.0,1.0,1.0),(1.0,1.0,1.0),(1.0,1.0,1.0), \\ (1.0,1.0,1.0),(1.0,1.0,1.0),(1.0,1.0,1.0),(1.0,1.0,1.0),(1.0,1.0,1.0) \end{bmatrix}$$

$$A^- = \begin{bmatrix} (0.0,0.0,0.0),(0.0,0.0,0.0),(0.0,0.0,0.0),(0.0,0.0,0.0),(0.0,0.0,0.0), \\ (0.0,0.0,0.0),(0.0,0.0,0.0),(0.0,0.0,0.0),(0.0,0.0,0.0),(0.0,0.0,0.0) \end{bmatrix}$$

The distance d_i^+ and d_i^- of the rates of each alternative from A^+ to A^-, calculated according to equation 12, 13, and 14 by using vertex method, presented in Tables 9 and 10.

Table 9. FPIS per option

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10	d_i^+
A_1	.390	.405	.570	.570	.570	.405	.405	.613	.502	.254	4.523
A_2	.570	.778	.638	.570	.638	.778	.778	.732	.390	.390	5.144
A_3	.254	.602	.570	.839	.839	.405	.602	.613	.502	.570	5.103
A_4	.390	.405	.638	.570	.638	.866	.602	.613	.502	.254	5.078
A_5	.570	.405	.739	.839	.739	.778	.759	.864	.502	.570	5.868
A_6	.254	.405	.570	.570	.570	.405	.405	.613	.390	.254	3.939
A_7	.390	.405	.638	.839	.839	.778	.405	.732	.502	.390	4.792
A_8	.390	.405	.739	.739	.638	.602	.778	.732	.638	.570	5.261
A_9	.570	.778	.739	.739	.739	.602	.778	.864	.502	.570	6.139
A_10	.391	.602	.839	.638	.638	.759	.644	.732	.881	.863	5.769

Table 10. FNIS per option

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10	d_i^-
A_1	.754	.836	.533	.533	.533	.836	.836	.525	.679	.880	4.862
A_2	.533	.266	.490	.533	.490	.266	.266	.450	.754	.754	4.125
A_3	.880	.629	.533	.230	.230	.836	.629	.525	.679	.533	4.258
A_4	.754	.836	.490	.533	.490	.146	.629	.525	.679	.880	4.250
A_5	.533	.836	.358	.230	.358	.266	.273	.185	.679	.533	3.276
A_6	.880	.836	.533	.533	.533	.836	.836	.525	.754	.880	5.837
A_7	.754	.836	.490	.230	.230	.266	.836	.450	.679	.754	4.716
A_8	.754	.836	.358	.358	.490	.629	.266	.450	.490	.533	4.323
A_9	.533	.266	.358	.358	.358	.629	.266	.185	.679	.533	2.981
A_10	.754	.629	.230	.490	.490	.273	.609	.450	.154	.162	3.536

Table 9 shows the total performance of each SC alternative using the closeness coefficient (*Cci*). The overall CCi performance for each SC result was A6 > A1 > A4 > A3 > A7 > A8 > A2 > A5 > A10 > A9. Since alternative 6 had the highest performance, its business process appeared to be better managed than that of the other alternatives. In this regard, managers of other supply chains should identify and evaluate the SC's management practices for continual development.

Table 11. Each Alternative SCOR Closeness Coefficient

Alternative	CCi	Rank
A_1	.597	2nd
A_2	.434	7th
A_3	.496	4th
A_4	.521	3rd
A_5	.386	8th
A_6	.617	1st
A_7	.483	5th
A_8	.453	6th
A_9	.377	10th
A_10	.378	9th

3.3 Discussion

The proposed solution facilitates the evaluation of supply chain performance by allowing managers to assess various perspectives. This was achieved by providing a comprehensive analysis of the disparity between the intended and realised performance for each SCOR® level indicator. Subsequently, managers have the ability to formulate strategic initiatives aimed at enhancing the outcomes of the indicators that indicate suboptimal performance. By employing the recommended system, managers can evaluate the effectiveness of their strategies, thereby enhancing the proactive nature of the target organisation in its endeavour to achieve enhanced performance outcomes. The measures of the evaluation system under consideration are susceptible to modification by managers over time. The proposed system integrates many measurements associated with multiple performance dimensions, such as dependability, agility, responsiveness, cost, and asset management, in contrast to the frameworks proposed by Nathania and Desrianty (2023).

The application of the metrics suggested by the Supply Chain Council leads to enhanced integration, standardisation, and alignment of performance measures at various levels of the supply chain. Consistent with prior literature, this study employs a combination of SCOR® measures and mathematical modelling techniques, as described by Liu and Liu (2017). In contrast to the fuzzy inference model established by Ayyildiz and Taskin (2022), the proposed technique does not require manual judgment from domain expertise. A significant limitation of the proposed performance evaluation method is the challenge of acquiring sufficient information to facilitate the learning process of ANFIS models. Thus far, the aforementioned challenge has hindered the implementation of the proposed approach in practical settings (Dias & Ierapetritou, 2017; Lima-Junior & Carpinetti, 2017). One limitation of the system is the constraint imposed by the number of fuzzy partitions and input variables utilised in each ANFIS model.

The number of inference rules will exhibit a positive correlation with the number of partitions employed, as the utilisation of many partitions will yield a multitude of potential partition combinations. In this particular case, it may be imperative to augment the number of training samples employed to refine the topological parameters. Additionally, there is potential for the system's output to be compromised, thereby affecting its reliability. According to Jaiswal and Samuel (2022) and Kamble, Mor, and Belhadi (2023), information models that are based on the Supply Chain Operations Reference (SCOR) framework require fewer iterations for updating their adaptive parameters compared to models that utilise neural network systems. The utilisation of SCOR models offers the advantage of facilitating the identification of decision rules that contribute to the observed outcomes. In addition, these models enhance the transparency and comprehensibility of the techniques employed to compute the performance values of the output variables. Operations managers may exhibit greater confidence in decision-making processes aimed at enhancing supply chain performance if the information provided by the decision rules is presented in a more comprehensive manner. An additional benefit is the simplicity of the mathematical model, which facilitates its utilisation and does not necessitate advanced technological expertise. This feature enhances usability, particularly for aquaculture practitioners operating in the field. Dias and Ierapetritou (2017) assert that a majority of contemporary enterprises utilise a collection of information technology (IT) applications to oversee and manage their supply chains. Regrettably, the integration of these programs is rarely observed. Consequently, data pertaining to different phases of the decision-making process are commonly maintained in distinct organizational units. Hence, it can be argued that stakeholders involved in supply chain management are faced with a dearth of comprehensive information, which hinders their ability to make informed and prudent decisions (Dias & Ierapetritou, 2017).

4. Conclusion

This research offers a novel evaluation method for supply chains that uses a combination of SCOR® and fuzzy-TOPSIS performance metrics. To show the suitability of this idea, it was utilised to assess the comprehensive performance of ten alternative supply chains, it is imperative to conduct a thorough evaluation in a demonstration scenario. The proposed method offers the following advantages:

- In contrast to other comparative techniques, such as AHP (Asrol & Syahruddin, 2022; Figueira et al., 2020), TOPSIS (Moharamkhani, Bozorgi-Amiri, & Mina, 2017), MACBETH (Clivillé & Berrah, 2012), and DEA (Jalalvand et al., 2011; Peng Wong & Yew Wong, 2007), the fuzzy-TOPSIS method allows language phrases defined by fuzzy numbers to measure metrics and the probability of alternatives. Unlike AHP-based models when an additional alternative is included in the evaluation process, the ranking reversal problem is avoided.

- Unlike fuzzy inference, the fuzzy TOPSIS approach without parameterising determination rules (Moharamkhani, Bozorgi-Amiri, & Mina, 2017) leads to its ease of use, adaptibility, and capacity to examine the decision process;

- An further benefit of employing fuzzy TOPSIS is in its ability to evaluate an unlimited number of alternatives and metrics concurrently, which distinguishes it from competitive methodologies like AHP (Dehghani, Khaleghi, & Sanzighi, 2019; Figueira et al.) and MACBETH (Clivillé & Berrah, 2012; Zhang, Wei, & Wei, 2022), when the quantity of choices is limited by the cognitive ability of individuals to engage in simultaneous comparative evaluation.

- The SCOR® model's defined metrics help integrate and communicate SC evaluations and enable worldwide benchmarking to drive continuous improvement.

In contrast, the disadvantages of using Fuzzy-TOPSIS are as follows.

- Greater computing complexity. Once utilising the criteria of cost, the normalisation process (as in equation 7) results in a narrow range of proximity coefficient values. Even though option A6 performed exceptionally well across all criteria, the calculated closeness coefficient of 0.619% did not exhibit a significant proximity to the desired or optimal solution. Nonetheless, this issue with the SCOR®-Fuzzy-TOPSIS approach may be resolved by normalising all CC_i values to the greatest CC_i value.

Finally, proposals for future studies include expanding the suggested technique to incorporate SCOR® level 2 and 3 performance criteria. In addition, future research might employ the suggested methodology to conduct worldwide supply chain benchmarking utilising the SCOR® database.

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