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A SUSTAINABLE SUPPLIER SELECTION IN GREEN SUPPLY CHAIN FRAMEWORK USING FUZZY TOPSIS METHOD

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Abstract. Today's growing awareness of environmental preservation and social responsibilities, the idea of sustainability is evolving into a fundamental guiding principle for many industrial sectors. The value of the green supply chain (GSC) can be maximised through supplier selection (SS) to keep the business sustainable and profitable. A multi-criteria decision-making (MCDM) is the most desirable technique for choosing electric vehicle from a variety of options. The objective of this study is to create the testing process correlate with the analytical hierarchy process (AHP) and the technique for ordering performance by similarity to ideal solution (TOPSIS) that will be useful for performers in the vehicle company select the best electric vehicle in fuzzy surroundings where, subjectivity and ambiguity are handled by Parameterized triangular fuzzy numbers for linguistic values. The electric vehicle selection problem's structure is analysed using the AHP, and the weights criteria are determined. The fuzzy TOPSIS approach is then used to calculate the resultant ranking.

1. Introduction

Most of manufacturing companies participating in supply networks, judgements about supplier selection are a crucial part of Logistics and production control. Finding the best option from all conceivable options is the method of solving decision-making challenges. Many authors strive to reduce the cost and carbon emissions of supply chain in the multi-purpose approach of the GSC network (Zhang et al., 2020). The environmental quality that is linked to supply chain activities is significantly influenced by carbon dioxide em1ission throughout the entire system of supply chain. It is the main cause of climate change. Supply chain managers are too concerned with effectiveness and client satisfaction in order to maximise economic gain, which wastes additional resources and creates more unneeded waste, adding to the environmental pressure. Supply chain costs and carbon emissions are inversely correlated in the context of a green supply chain operation that takes greening costs into account. Even though the decision-makers could have their own preferences for cost-cutting or environmental conservation, it is advisable to assess the two aspects equally in a plan for a green supply chain network. This will enable the economic and environmental conservation to coexist in harmony. Green training (GT) practises in businesses play a role and have benefited the green supply in some ways (Zhu, 2022). The study looks at the

Key words and phrases. green supplier selection; Electric vehicle; TOPSIS; Linguistic variables; Triangular fuzzy number; MCDM; sustainability.

complexity of green innovation, different pricing strategies used by the players, the level of green innovation, and marketing initiatives run by a centralised manufacturer. For green products, according to research, as Compared to a supply chain with just one channel or two channels is more effective (Pal et al., 2023).

The focus of recent research on MCDM strategies for GSCM has been on supplier selection concerns. According to (Uygun and Dede, 2016), an integrated fuzzy MCDM-based model techniques is suggested for assessing GSCM effectiveness of organisations for example green purchasing, layout, logistics, improvement, and reverse shipping. (Ghosh et al., 2021) used the TOPSIS technique to answer the problem, which is the same as the outcome of both the GRA and COPRAS methods. They considered three organisations, namely the service organisation, manufacturing organisation, and process organisation. To choose suppliers and distribute orders in the green supply chain, two-stage integrated strategy based on the Fuzzy AHP and multiple-objective MILP was created by (Ebrahim et al., 2021). (Nag and Helal, 2016) concentrated on a MCDM problem that covers both numerical and qualitative criteria pertinent to the choice of suppliers for a medicine distributor in the case where there are several global suppliers engaged. The four main criteria—economic, social, environmental, and technical dimensions—were considered by (Wei et al., 2023) using 14 sub-criteria. Then, a thorough decision-making framework based on fuzzy MCDM using the best-worst method (BWM). (Awasthi et al. 2010) presented a fuzzy multicriteria approach that includes 12 criteria for assessing suppliers' environmental performance. The fuzzy density is owned by the criterion of "production cost," according to weighted findings from a framework (Wu et al., 2020) established to choose the best green suppliers of electric vehicle charging facilities (EVCF). An assessment approach built around AHP and TOPSIS was generated by (Dadeviren et al., 2009) in order to support the players in the defence industry choose the appropriate weapon in a hazy setting where subjectivity and ambiguity are addressed by linguistic values specified by triangular fuzzy numbers.

A triangular fuzzy number-based fuzzy decision matrix was created by (To and Kritchanchai, 2022) and provided for the criterion and individual criteria. The measurements for the sub and main criteria, as well as the DMs' judgements, will be combined in the subsequent stage after the fuzzy decision matrix has been established. To determine the score and choose the three providers for this section based on the primary and supporting criteria, the Fuzzy TOPSIS was used. (Memari et al., (2019) developed an intuitive fuzzy TOPSIS technique to choose the top resilient provider for a maker of car parts that considers nine criteria and thirty sub-criteria. The suggested method offers a trustworthy answer for sustainable sourcing choices and a precise sustainable rating of providers that is proven by a real-world case study. A thorough technique for choosing the best offer made by several suppliers in the Para pharmaceutical business has been developed by (Kirytopoulos et al., 2008). Additionally, the supplier selection procedure is modified to reflect the enterprise cluster structure that governs how the case study's particular industry operates in the decision-making process.

A supply chain's potential to be environmentally sustainable is mostly dependent on the members' purchasing practises. Most earlier models had a strong emphasis on quality, cost, and lead time, etc. but did not place enough emphasis on carbon emission when evaluating suppliers. Members of the supply chain are under increasing pressure to lower their supply chain's carbon emissions recently. This study uses fuzzy multi-objective linear programming and fuzzy-AHP to propose a holistic plan for choosing the suitable vendor in distribution system and solving the problem of carbon emissions. First, Fuzzy AHP (FAHP) analyse the measurements of various components. Demand, cost, supply, proportion of shipments made late, and emissions of greenhouse gases are the criteria that (Shaw et al., 2012) took into consideration.

To choose a resilient supplier in a production system, (Pramanik et al., 2017) create a quantitative method that manages conflicts between various decision-makers and evaluates supplier performance. A novel strategy for choosing the best supplier has been put forth in this paper that integrates FAHP and TOPSIS. Planning for Quality Function Deployment (QFD) is utilised to integrate the resilience criterion and the manufacturer's essential criteria during the selection process. (Chamodrakas, et al., 2010) described a novel method for supplying decision support that would deal with these issues. In order to narrow down the range of prospective providers for supplier pre-qualification, the author first suggested using a satisficing strategy. In contrast, we now present a modified, rating-scale version of the FPP method for supplier evaluation at the end of the process. (Khoshfetrat et al., 2020) utilising the AHP methodology, inflation, fuzzy uncertainty, and risk were considered when developing an integrated sustainable system for ordering and supplier allocation. For the facility placement selection problem of a textile industry, (Erturul et al., 2008) discussed a comparison study of fuzzy TOPSIS and AHP approaches. A broader definition of excellence was used by (Cheraghi et al., 2004) to develop supplier selection criteria that considered both traditional performance factors (quality, price, delivery, and service) as well as unconventional, dynamic ones (supply chain executives, immediately communication, and process improvement). A comparison study of the crisp and fuzzy TOPSIS algorithms for supplier selection was reported by (Sevkli et al., 2010). In order to pick a supplier of reverse logistics, (Kannan et al., 2009) created a MCGDM model in a fuzzy environment employing ISM and fuzzy TOPSIS. When choosing a vendor, (Junior et al., 2014) offered an analysis of Fuzzy AHP and TOPSIS approaches.

Supplier selection Conventional criteria: A crucial aspect of SS is the selection of the criteria. According to Govindan et al. (2015), GSS calls for combining traditional supplier selection techniques with procedures pertaining to GSCM elements. Cost, value, and shipping were mostly identified as the prevailing and most often used SS criteria between 1966 and 1990 in most of the earlier study. Following a thorough analysis of the literature, three distinct temporal periods may be identified. In the early 1980s, the primary goal of organisations was to maximise profits or generate revenue, hence "Product price" or "Cost" replaced other criteria as the decisive factor in SS. Delivery and customer demand were then considered in the early 1990s, and finally, the emphasis was changed to "Flexibility," "Reliability," and "Service level" (Orji et al., 2014). Quality, Price, and delivery continue to be the most significant Traditional norms in SS, according to a summary of conventional criteria in the literature (Memari, et al., 2019). After carefully examining conventional criteria, (Luthra et al., 2017) concluded that "On-time delivery," "Service level," and "Production capacity" are superior to different conservative standards. It is evident that traditional criteria like quality, price, and delivery have the highest research concentration among all criteria.

Criterion for choosing green suppliers: In addition to Traditional norms, GSSC has been extensively utilised in contemporary GSS-related research. The GSS process is increasingly being required to consider social, economic, and operational criteria in addition to environmental criteria as awareness of environmental deterioration grows (Ghosh et al.,2022; Wei et al., 2023). According to a literature review by (Govindan et al., 2015), the Environmental Management System (EMS) was the GSS criterion that was most frequently utilised. EMS, green image, green design, environmental expertise, pollution creation, and Recycling are a few of the most used environmental, social, and operational GSSC criteria. Other frequently used criteria include Resource consumption and Health and Safety Measures.

The environmental quality, which is linked to supply chain activities, is now significantly influenced by carbon dioxide emissions along the entire supply chain. Recent research by (Ghosh et al., 2021) in the context of GSS identified "Total CO2 emission" as the most important factor for eco-friendly sourcing practises. To fulfil the prerequisites for the environment, both the environmental implications of EVCS development and use on the local environment and the environmental advantages associated with the promotion and development of electric vehicles must be considered. A fuzzy multi-criterion technique was created by (Govindan, et al., 2013) based on an idea of three-bottom line, which combines economic, social, and ecological benefits for evaluating the sustainability performance of a supplier.

Fuzzy TOPSIS method: (Chen, 2000) presented the Fuzzy TOPSIS technique to address MCDM issues in the presence of uncertainty. The managers assess the weights of conditions and the ratings of different possibilities using linguistic components.

Let us assume that $(a_{ijk}, b_{ijk}, c_{ijk})$ is a fuzzy triangular number indicates the weight of standards i chosen by DM k.
(i) Indicated by Eqs. (1.1), (1.2), and (1.3), respectively, are the aggregate weights $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$ of the criteria and ratings of options provided by k decision makers:

$$a_{ij} = min_k\{a^k_{i\,j}\} \tag{1.1}$$

$$b_{ij} = k\sqrt{\Pi_{r=1}^{k} b_{i\,j}^{k}} \tag{1.2}$$

$$c_{ij} = max_k\{c_{i\,j}^{k}\} \tag{1.3}$$

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(ii)Assume that aij assigns the alternative $A_i(i = 1..., n)$relation's rate to combined weights of the DMs' standards. A combined fuzzy matrix for decision criteria, M, could be produced using the equation (1.4) below.

$$\begin{bmatrix} X_{11} & ... & X_{1n} \\ : & : & : \\ X_{m1} & ... & X_{mn} \end{bmatrix} \tag{1.4}$$

(iii) Use a linear scale transformation to normalise the fuzzy decision matrix of the potential choices. The following formula yields the normalised form of fuzzy decision matrix R:

$$R = [q_{ij}]mn \tag{1.5}$$

$$qij = (\frac{a_{ij}}{c_j*}, \frac{b_{ij}}{c_j*}, \frac{c_{ij}}{c_j*}) \tag{1.6}$$

and $\mathrm{c}_j* = max_i = c - i_j$(benefit criteria)

$$qij = (\frac{a_j-}{c_{ij}}, \frac{a_j-}{b_{ij}}, \frac{a_j-}{a_{ij}}) \tag{1.7}$$

$and\ \mathrm{a}_j- = min_i = a_{ij}$(cost criteria)

(iv) To construct the weighted normalised decision matrix, V, the weights of the rating parameters should be multiplied by the components of normalised fuzzy form of matrix,q_{ij}.

$$V = [v_{ij}]_{m\times n} \tag{1.8}$$

$$Where \quad v_{ij} = q_{ij}w_j \tag{1.9}$$

(v) Fuzzy Negative Ideal Solution (FNIS, $\mathrm{A}^-)andFuzzyPositiveIdealSolution$ $(FPIS,\ A^+)$ are defined in accordance with Equations(1.10)and(1.11).

$$A^+ = v_1^+, v_2^+, \ldots...v_n^+ \tag{1.10}$$

$$where\ \mathrm{v}_j^+ = max_i v_{ij3}$$

$$A^- = v_1^-, v_2^-, \ldots...v_n^- \tag{1.11}$$

$$where\ \mathrm{v}_j- = max_i\{v_{ij1}\}$$

(vi) Calculate the distances $d_j^+$and $d_i^-$of each potential choice from v_j^+ and v_j^-,respectively, using Equations (1.12) and (1.13).

$$d_j^+ = \sum_j d(v_{ij}, v_j^+) \tag{1.12}$$

$$d_i^- = \sum_j d(v_{ij}, v_j^-) \tag{1.13}$$

where d is the vertex method's measurement of the separation between two fuzzy integers. This is written as Eq. (1.14) for triangular fuzzy numbers (TFN).

$$d(x, y) = \sqrt{1/3[(a1 - a2)2 + (b1 - b2)2 + (c1–c2)2]} \tag{1.14}$$

(vii) Next, we apply the method to each possibility to determine the Closeness Coefficient cci.

$$cc_i = (d_i^-)/(d_i^- + d_i^+) \tag{1.15}$$

(viii) Describe the order in which the options are ranked based on the close-ness coefficient, CCi. The optimum option is located between the FPIS and the FNIS.

Application case in the electric vehicle industry:

A supplier of metallic parts used in various gearbox cables must be chosen by a maker of gearbox cables for electric vehicles. Five possible suppliers were compared against six decision criteria in order to choose the best option. A team of personnel from the quality and procurement departments of the business, used linguistic assessments to evaluate possible suppliers according to each criterion. The following criteria were established by the decision-makers:

Here, three criteria are benefit or maximizing criteria as C1, C2 and C3. Three are reducing criteria C4, C5 and C6.

- Quality (C1): relates to after-sale service quality, quality management, and conformance quality.
- Supplier profile (C2): relates to the financial stability and reputation of suppliers.
- Agility (C3): related to fluctuating demand and production of new products.
- Price (C4): concerning the purchase price.
- Delivery (C5): relates to reliability and timing of delivery.
- Carbon emission (C6): related to the reduction of carbon emissions.

Fuzzy TOPSIS application:

Using language expressions, the decision-makers ranked possibilities and evaluated relative weight of requirements. According to (Chen, 2000), the linguistic values of these variables were denoted by fuzzy triangular numbers (TFN) showing in

Tables 1 and 2. Table 3 includes a list of the selection procedure involved three individuals as well as their linguistic assessments of the weights of the factors and order of the possibilities. The linguistic elements in Table 3 are used to produce TFN. Table 4 lists the TFN's parameters because of averaging the assessments in Table 3 to reflect the fuzzy decision matrix. Tables 5 and 6 respectively display the matrix of normalised fuzzy decisions and the decision matrix that is weighted and normalised.

The FNIS (A-) and FPIS (A+) both characterised as (Table 7):

A+ = [(0.16,0.46,0.9), (0.16,0.40,0.9), (0.27,0.64,0.9), (0.10,0.33,0.9), (0.06,0.23,0.9), (0.1,0.26,0.9)]

A- =[(0.03,0.16,0.49), (0.16,0.40,0.9), (0.05,0.33,0.70), (0.05,0.11,0.30), (0.03,0.11,0.30), (0.05,0.08,0.13)]

Distances between each alternative's scores and an A+ and A- in relation to each criterion given by Table 8 and Table 9 respectively. According to Eqs. (12), (13) and (14), Table 10 shows the distances di+ and di- of each alternative's ratings from A+ and A-.

Table 1
Fuzzy decision matrix that is weighted and normalised.

ligustic variable	Triangular fuzzy Number
Absolutely important (AI)	(0.7,0.8,0.9)
Very important (VI)	(0.5,0.6,0.7)
Important (I)	(0.3,0.4,0.5)
Moderate importance (MI)	(0.1,0.2,0.3)
Low importance (LI)	(0.1,0.1,0.1)

Table 2
Language scale to assess the evaluations of the substitute providers.

ligustic variable	Triangular fuzzy Number
Very High (VH)	(7,8,9)
High (H)	(5,6,7)
Good (G)	(3,4,5)
Low (L)	(1,2,3)
Very low (VL)	(1,1,1)

Table 3
Different decision makers' linguistic ratings of the competing suppliers.

DM	C1	C2	C3	C4	C5	C6
DM1						
Al	H	L	G	VH	VL	G
A2	G	G	H	L	H	L
A3	L	H	G	H	H	G
A4	VH	H	VH	VH	G	VH
A5	G	VL	H	L	H	G
Weight	AI	I	VI	AI	VI	VI
DM2						
Al	G	H	G	L	G	G
A2	H	VL	G	H	H	G
A3	VH	G	H	G	G	H
A4	H	VH	VH	G	VH	VH
A5	G	H	L	VL	H	G
Weight	I	AI	VI	VI	AI	VI
DM3						
Al	H	G	H	H	G VL	
A2	H	VH	G	L	H	H
A3	G	G	H	VH	H	L
A4	VH	VH	VH	H	G	VH
A5	VL	H	H	G	H	G
Weight	VI	I	AI	VI	I	AI

Table 4
Combined ratings of the alternate providers

Criteria	C1	C2	C3	C4	C5	C6
A1	(3,5.24,7)	(1,3.63,7)	(3,4.93,7)	(1,4.57,9)	(1,2.52,5)	(1,2.52,5)
A2	(3,5.24,7)	(1,3.71,9)	(3,4.57,7)	(1,2.88,7)	(5,6,7)	(1,3.63,7)
A3	(1,4,9)	(3,4.57,7)	(3,5.24,7)	(3,5.76,9)	(3,5.24,7)	(1,3.63,7)
A4	(5,7.26,9)	(5,7.26,9)	(5,8,9)	(3,5.76,9)	(3,5.04,9)	(7,8,9)
A5	(1,2.52,5)	(1,3.30,7)	(1,4.16,7)	(1,2,5)	(5,6,7)	(3.4,5)
Weight	(0.3,0.58,0.9)	(0.3,0.5.0.9)	(0.5,0.72,0.9)	(0.5,0.66,0.9)	(0.3,0.57,0.9)	(0.5,0.66,0.9)

Table 5
Matrix of normalised fuzzy decisions

Criteria	C1	C2	C3	C4	C5	C6
A1	(0.33,0.58,0.78)	(0.11,0.40,0.78)	(0.33,0.55,0.78)	(0.11,0.22,1)	(0.20,0.40,1)	(0.20,0.40,1)
A2	(0.33,0.58,0.78)	(0.11,0.35,1)	(0.33,0.51,0.78)	(0.14,0.35,1)	(0.14,0.17,0.20)	(0.14,0.27,1)
A3	(0.11,0.44,1)	(0.33,0.51,0.78)	(0.33,0.58,0.78)	(0.11,0.17,0.33)	(0.14,0.19,0.33)	(0.14,0.27,1)
A4	(0.55,0.81,1)	(0.55,0.81,1)	(0.55,0.89,1)	(0.11,0.17,0.33)	(0.11,0.20,0.33)	(0.11,0.12,0.14)
A5	(0.11,0.28,0.55)	(0.11,0.37,0.78)	(0.11,0.46,0.78)	(0.20,0.50,1)	(0.14,0.17,0.20)	(0.20,0.25,0.33)

Table 6
Fuzzy decision matrix that is weighted and normalised

Criteria	C1	C2	C3	C4	C5	C6
A1	(0.1,0.34,0.70)	(0.03,0.10,0.70)	(0.16,0.40,0.70)	(0.05,0.14,0.9)	(0.06,0.23,0.9)	(0.1,0.26,0.9)
A2	(0.1,0.34,0.70)	(0.03,0.17,0.9)	(0.16,0.40,0.70)	(0.07,0.23,0.9)	(0.04,0.09,0.18)	(0.07,0.18,0.9)
A3	(0.03,0.25,0.9)	(0.09,0.25,0.70)	(0.16,0.42,0.70)	(0.05,0.11,0.30)	(0.04,0.10,0.30)	(0.07,0.18,0.9)
A4	(0.16,0.46,0.9)	(0.16,0.40,0.9)	(0.27,0.64,0.9)	(0.05,0.11,0.30)	(0.03,0.11,0.30)	(0.05,0.08,0.13)
A5	(0.03,0.16,0.49)	(0.03,0.18,0.70)	(0.05,0.33,0.70)	(0.10,0.33,0.9)	(0.04,0.09,0.18)	(0.10,0.16,0.30)

Table 7
Determine the FPIS and FNIS:

Criteria	C1	C2	C3	C4	C5	C6
A+	(0.16,0.46,0.9)	(0.16,0.40,0.9)	(0.27,0.64,0.9)	(0.10,0.33,0.9)	(0.06,0.23,0.9)	(0.1,0.26,0.9)
A-	(0.03,0.16,0.49)	(0.16,0.40,0.9)	(0.05,0.33,0.70)	(0.05,0.11,0.30)	(0.03,0.11,0.30)	(0.05,0.08,0.13)

Table 8
Distances between each alternative's scores and an A+ in relation to each criterion

Criteria	C1	C2	C3	C4	C5	C6
A1	0.0334	0.0848	0.0633	0.0223	0.00	0.00
A2	0.0334	0.0402	0.0721	0.0062	0.3108	0.0042
A3	0.0352	0.0389	0.0580	0.2374	0.2166	0.3624
A4	0.00	0.00	0.00	0.2372	0.2166	0.3624
A5	0.1587	0.0607	0.1065	0.00	0.3108	0.2136

Table 9
Distances between each alternative's grade and an A- in relation to each criterion

Criteria	C1	C2	C3	C4	C5	C6
A1	0.0469	0.0848	0.0098	0.2083	0.2167	0.3624
A2	0.0469	0.0402	0.0079	0.2163	0.0086	0.3483
A3	0.1017	0.0389	0.0166	0.00	0.0001	0.3483
A4	0.1587	0.00	0.1065	0.00	0.00	0.00
A5	0.00	0.0607	0.00	0.2372	0.0086	0.0218

Table 10
The rankings, closeness coefficients, and distances between possibilities to the optimal solutions, both positive and negative.

Criteria	Distance di+	Distance di-	Closeness coefficients (CCi)	Rank
A1	0.2028	0.9289	0.8208	1
A2	0.4669	0.6903	0.5965	2
A3	0.5913	0.5056	0.4609	3
A4	0.8162	0.2652	0.2452	5
A5	0.8503	0.3283	0.2785	4

Conclusion: When performance metrics are difficult to convey using crisp values in the procedure of deciding, the use of linguistic factors in choice issues is quite helpful. The major goal of this study is to suggest a methodology for assessing supplier organisations according to their GSCM performances. The findings show that suppliers ranked determined by significance their efficacy evaluations, shown in Table 10 of the Fuzzy TOPSIS technique. This work can ascertain the ranking order as well as the evaluation state of all potential suppliers using the closeness coefficient (Table 10). In this problem Supplier A1 found the rank 1 because its CCi 0.8208 which is greater than others. And Supplier A4 found the rank 5 because its CCi 0.2452 is lowest. Importantly, the suggested method offers more impartial data for supplier selection and assessment in GSCM.

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