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AN OPTIMISATION MODEL FOR SUSTAINABLE MULTI-COMMODITY TRANSPORTATION PLANNING

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Abstract. This paper aims to establish a supply chain model that significantly reduces economic and environmental costs. It comprises all activities related to procurement, production, and distribution planning. The proposed multi-objective multi-commodity optimisation model deals with the four conflicting objectives of reducing costs and emissions and choosing top-priority suppliers and the most efficient vehicles. We apply an integrated AHP (analytic hierarchy process) and TOPSIS (technique for order preference by similarity to an ideal solution) technique to determine the weights of suppliers, depending on three indices of criteria, alternatives, and raw material. This paper proposes a cross-efficiency evaluation method using data envelopment analysis (DEA) to ensure that the cross-evaluation of different types of vehicles for evaluating peers is as consistent as possible. The mutually contradictory objectives give rise to several Pareto-optimal solutions. The optimal compromise solutions are found using a lexicographic goal programming technique. We present a real-world case to demonstrate the effectiveness of the proposed methodology, followed by numerical comparisons and additional insights.

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1. Introduction and theoretical underpinning

A supply chain consists of amenities and logistics operations that execute material procurement planning, process the materials into finished goods, and distribute the finished goods to customers *via* different stages [7]. Supply chain management is a vital part of a business process, and it requires a great deal of skill and expertise to maintain the relationships between all the channels. As consumers and organisations become concerned about the harmful effects of external trade and logistics on a supply chain, demand for sustainable supply chains rises, which requires managing resources, knowledge, direct investment, coordination, and collaboration between its members. At the same time, it needs all sustainable objectives that emanate from triple bottom-line management, such as economic, social, and environmental perspectives, to be met.

Keywords. Sustainable supply chain, multi-objective optimisation, multi-commodity transportation, mixed-integer decision problem, TOPSIS technique, DEA technique.

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As a result of the excessive consumption of natural resources, global warming, carbon emissions, and climate change, sustainability has been seen as an essential criterion for enhancing economic and social competitiveness in the market. Companies like the Ford Motor Company, Adidas, Nike, Sony, and many more have taken steps to boost their sustainability [3]. Because of the dire consequences of greenhouse gas (GHG) emissions, the sustainability challenges in production and distribution networks urge a shift from a profit-based economy to an environmentally friendly business world [36]. Human beings release about 50 000 mega-tonnes of CO_2 equivalents [79]. It is a major reason behind the climate change that the world is currently witnessing. More than 50% of the world's GHG emissions emanate from eight essential supply chains [17]. Therefore, *decarbonisation* of various supply chain components is vital for achieving climate stability. However, Zhang *et al.* [82] identified a few common challenges to supply chain decarbonisation, including high upfront expenditures, a lack of awareness, a lack of expertise, a resistant mindset, a lack of support from supply chain partners, and uncertainty over return on investments. They proposed a multi-stakeholder approach to address these concerns.

For a long time, businesses in developing nations have worked to improve their competitiveness by achieving supply chain sustainability through various initiatives, including developing information systems, creating flexible networks, and adopting cutting-edge technologies [37]. Due to various societal, regulatory, and competitive constraints, businesses are increasingly being pushed to emphasise the social and environmental effects of their supply chain operations. It is essential for a company's success in cost management, providing high-quality experiences for consumers, and being ready to confront both obstacles and possibilities [47]. Sustainable supply chain principles include incorporating sustainability considerations into all aspects of the supply chain, reducing waste and emissions, developing sustainable products and services, and promoting ethical and socially responsible business practices [55]. Additionally, it entails cooperation and communication between all parties involved in the supply chain, including suppliers, manufacturers, retailers, and customers, and it can provide businesses with several advantages, including increased productivity, lower costs, a better reputation, and a reduction in social and environmental risks [2].

The environmental effects caused by a supply chain are emissions from vehicles during transportation, emissions from production, emissions during procurement, toxic waste, etc. Thus, transportation planning has an underlying influence on the overall performance of a supply chain. It contributes significantly to the total supply chain cost and is one of the primary concerns. Therefore, it is essential to consider green objectives and environmental issues in distribution operations in addition to economic goals. Green logistics, which seeks to enhance environmental sustainability in the transportation sector by decreasing fossil fuel consumption, has been a broad research topic in recent years [29]. Green logistics can be defined as the evolution of traditional logistics that emphasises the performance of logistics activities in an environmentally friendly manner in order to realise logistical and economic development while conserving resources and preserving the environment [81]. Demand for sustainable energy vehicles, such as those powered by batteries, hydrogen, and bio-diesel, is increasing daily and has been strongly supported by the transportation sector. These alternative fuel vehicles reduce a carbon footprint on the environment, and as a result of the government's encouraging policies, the market for these vehicles is expanding even faster and is contributing to creating a more sustainable future globally.

Optimisation models have been of great interest in supply chain operations. A multi-period equilibrium model for a supply chain network with a network of freight carriers to reduce the pollution produced by each polluter over a multi-period planning horizon was developed and evaluated by Saberi [69]. Sarkar *et al.* [71] developed a three-layer supply chain model to reduce supply chain costs by considering variable and fixed transportation and carbon emission costs. Durmaz and Bilgen [26] proposed a multi-objective mixed-integer linear programming model to maximise profit and minimise the total distance between poultry farms and biogas facilities. Resat and Unsal [66] proposed a mixed-integer linear multi-objective mathematical model to minimise cost and time and maximise sustainability. Lagoudis and Shakri [40] developed a multi-attribute problem to minimise carbon emissions across the different echelons of the supply chain. A multi-objective and multi-period optimisation model for the resilience and sustainable supply chain was proposed by Zamanian *et al.* [80] to analyse a real case study of the natural gas supply chain. The integrated three-objective linear programming optimisation model has been designed and applied by Bortolini *et al.* [14] to manage modern supply chain networks to accomplish the goal of sustainability. Various models have been developed to optimise overall supply chain management costs through effective transportation planning [35,42,48,51,53]. A multi-commodity transportation problem is a generalised problem that is beneficial for industries that deal with shipping more than one type of product. A large body of literature focuses on multi-commodity [38,56,61]. There is a need for transportation professionals to maximise the efficiency of vehicles, which is an essential requirement for a strong relationship between the various stages of a supply chain. The efficiency of a vehicle is described by multiple parameters, such as cost, fuel efficiency, safety, and carbon emissions. Gupta *et al.* [30] maximised the efficiency scores of vehicles on various routes of the given transportation network using inputs and outputs considered critical in the industrial sector employing data envelopment analysis (DEA). Li *et al.* [43] used a revised DEA framework to test the performance of bus routes within a public transport network. The majority of efficiency evaluation models have some drawbacks because they measure simple efficiency; these drawbacks can be treated using cross-efficiency [23]. It is based on the concept of peer review and the efficiencies determined for each decision-making unit (DMU) using optimal weighting from the rest of the DMUs. Omrani *et al.* [60] proposed a combination of cross-efficiency DEA and a cooperative game approach to evaluate the energy efficiency of transportation sectors. A wealth of literature is available on using alternative fuel vehicles to enhance green logistics management in the supply chain industry [5,24,59,64].

Apart from the issues discussed above, the current trend in globalisation and the steadily more competitive environment have driven companies to develop successful strategies for supplier selection. As suppliers are the first element of a supply chain, the success of supplier selection has a continuing effect on the performance of the entire supply chain, enhancing its productivity and profit. The expectations of a customer-focused market cannot be fulfilled just by selecting suppliers based on the cost criterion alone; several other requirements must be met, such as quality, warranty, and delivery time. As a result, selecting the best alternative among multiple prospective suppliers is subject to several criteria that may be tangible or intangible, and the decision-maker must analyse and evaluate qualitative and quantitative aspects, resulting in a multi-criteria problem [78]. These criteria may conflict; therefore, it is vital to consider a trade-off between them to select the best supplier. Ho *et al.* [33] produced an excellent analysis of the multi-criteria decision-making (MCDM) literature concerning the assessment and selection of suppliers. The literature on the selection of suppliers refers to various methods, such as the analytic hierarchy process (AHP), linear weighting methods, the analytic network process (ANP), the technique for order preference by similarity to ideal solution (TOPSIS), and DEA. Literature on supplier selection using these MCDM methods includes Beikkhakhian *et al.* [13], Hatami-Marbini *et al.* [32], Naveen Jain and Upadhyay [57], Željko Stević *et al.* [75] and Rasmussen *et al.* [65].

Based on the literature reviewed herein, we identified the following research gaps that the proposed study will address.

1.1. Research gaps

First, in the realm of supply chain optimisation, existing literature has primarily focused on a limited subset of processes. This narrow scope raises concerns about the consistency and practicality of the results when applied to the broader spectrum of supply chain activities. A significant research gap emerges, therefore, from the need to address these inconsistencies.

Second, another noteworthy research gap revolves around the simultaneous selection of efficient suppliers and vehicles for facilitating the logistical movement of supply chain activities. Surprisingly, this critical aspect has not been explored in prior studies, leaving an uncharted territory in supply chain optimisation.

Third, the integration of AHP and TOPSIS techniques has predominantly been limited to only two indices. The absence of studies employing the three-indices technique, which holds considerable importance in decision-making, highlights a research gap within the field.

Fourth, cross-efficiency, a concept that offers significant advantages in supply chain operations, remains an unexplored dimension. While researchers have traditionally computed simple vehicle efficiency, the potential benefits and implications of cross-efficiency in vehicle selection and performance evaluation (discussed later in this study) have not been examined so far.

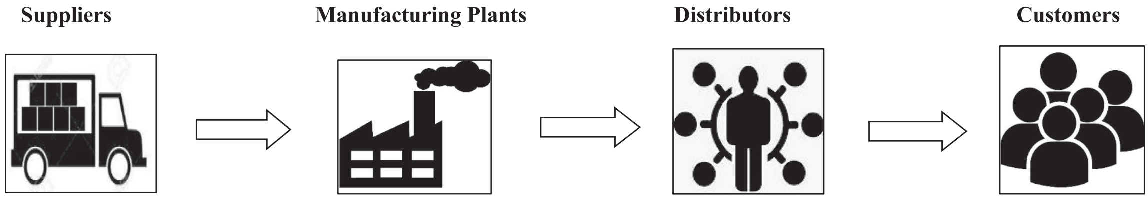

Figure 1. Problem concept diagram.

Lastly, there is a dearth of research that effectively combines qualitative and quantitative data for managing supply chain operations. This gap highlights an opportunity to bridge the divide between theory and practical application, offering a more comprehensive and holistic approach to supply chain management.

1.2. Focus of the present study

Motivated by the research gaps mentioned above, we propose specific innovations to make decision-making in supply chain operations more effective. As we know, there are various stages in a supply chain; it is essential to optimise every step. The proposed integrated decision model boosts productivity and streamlines supply chain operations. Here, we attempt to manage the flow of goods, from the procurement of raw materials through the delivery of finished goods to customers. The proposed supply chain model, therefore, consolidates three significant types of decisions, classified as strategic decisions (the selection of suppliers and vehicle type based on various parameters), tactical decisions (production status), and operational decisions (satisfaction of customer demand and coordination of the logistic network). This study proposes a three-stage optimisation framework for multi-commodity transportation planning in a sustainable supply chain. Different raw materials are primarily transported from different suppliers to different manufacturing plants, where different products are manufactured using different raw materials. After that, different manufactured products are transported to distributors and are finally transported to customers. A diagram of the concept of the problem is shown in Figure 1.

In stage 1, we apply an integrated AHP-TOPSIS technique to prioritise suppliers based on sustainability criteria. This technique has an advantage over the individual uses of AHP and TOPSIS. AHP allows decision-makers with several competing requirements to find a consensus in decision-making, and TOPSIS is used to measure alternative scores. Stage 2 uses a cross-efficiency method to choose vehicles with maximum efficiency. For most literature, supplier selection and determining vehicle efficiency are the final research results/outcomes. In the current study, these results are obtained independently and considered further to optimise them; therefore, the work presented here is unique. In stage 3, the results of stages 1 and 2 are adapted to formulate two separate objective functions that are maximised and two other objective functions that are minimised. Therefore, this study provides an integrated approach for *decarbonisation* of the supply at both the supplier and the logistical level.

1.3. Contribution of this research to the existing literature

The prominent features are compared with existing research on supply chains, shown in Table 1, to emphasise the achievement of this research. Some of the significant additions of this research to the existing literature are mentioned below.

This study contributes to the existing literature by extending the single-objective supply chain problem to a multi-objective supply chain problem in a systematic context, building upon references such as Maiyar *et al.* [48], Mogale *et al.* [53], Islam *et al.* [35], Lee *et al.* [42], and others.

TABLE 1. Comparison with existing literature.

Literature	MO	MC	VT	VC	VE	SS	SI	Approach
Sarrafha *et al.* [72]	√	√	×	×	×	×	×	Multi-objective biogeography based optimisation
Mogale *et al.* [53]	×	×	√	√	×	×	×	Chemical reaction optimisation algorithm
Alavidoost *et al.* [6]	√	√	×	×	×	√	×	Non-dominated sorting genetic algorithm
Cao *et al.* [15]	√	×	√	×	×	×	√	Hybrid global criterion method
Mondal and Roy [54]	√	√	√	√	×	×	√	Augmented weighted Tchebycheff method
Liaqait *et al.* [44]	√	×	√	√	×	√	√	Multi-phase holistic decision support framework
Tirkolaee *et al.* [77]	√	×	√	√	×	√	√	Multi-objective grey wolf optimisation algorithm
Babaei *et al.* [10]	√	×	√	×	×	×	√	Chance-constrained programming
Proposed research	√	√	√	√	√	√	√	Goal programming

Notes. Acronyms – MO: Multi-objective, MC: Multi-commodity, VT: Vehicle types, VC: Vehicle capacity, VE: Vehicle cross-efficiency, SS: Supplier selection and SI: Sustainability issues.

Additionally, it advances the single-commodity supply chain problem to a multi-commodity supply chain problem, expanding upon the work of Mogale *et al.* [53], Cao *et al.* [15], Liaqait and Becker [44], Tirkolaee *et al.* [77], Babaei *et al.* [10], and related references.

The study further adds to the research on comparing the efficiency of various types of vehicles using the DEA approach ([18, 25, 30, 43, 51], and related references), taking into account cross-efficiency for different transportation options. This approach maximises the total cross-efficiency score for sustainable transportation system selection.

In the context of multi-objective supply chain problems [6,10,15,44,54,72,77], the study advances the literature with an integrated model, which produces compromise solutions for the objective functions (minimising the overall cost incurred in the supply chain process, minimising the total emissions from the selected vehicles, maximising the priority weights of the different suppliers, and maximising the cross-efficiency score of different vehicle types). These objectives have not been commonly measured together.

The inclusion of several real-world restrictions along with the traditional supply and demand constraints of suppliers, manufacturers, distributors, and customers in the present study enhances the literature relating to supply chain problems ([6, 10, 15, 44, 53, 54, 72, 77], and related references). Additional restrictions are constraints on vehicle capacity, the number of vehicles available, and production, which are significant in real-world sustainable supply chain problems.

Lastly, the study enhances the literature on the use of AHP and TOPSIS techniques for selecting sustainable suppliers ([11, 13, 67], and related references) by applying an integrated AHP-TOPSIS technique for the sustainable selection of suppliers of different types of raw materials.

1.4. Organisation of the paper

This paper is presented in the following way. Section 2 discusses sustainable supply chains, the DEA cross-efficiency technique, and the integrated AHP-TOPSIS technique. Section 3 formulates the multi-objective, multi-commodity optimisation model for a sustainable supply chain. Section 4 illustrates the solution approach. In Section 5, a real-world case study validates the proposed multi-objective, multi-commodity optimisation model. Section 6 presents the managerial benefits. Finally, Section 7 concludes the paper.

2. Sustainable supply chain

Organisations must incorporate sustainable practices in every process, including procurement, manufacturing, and distribution; hence, goods and services should be provided in a way that does not affect the environment, does not reduce mineral resources, and does not lead to social inequality. Therefore, we aim to establish a sustainable supply chain, considering various real-world restrictions. The first step in fulfilling this objective is to select suppliers satisfying all three sustainability parameters. Moreover, realistically, a supplier's performance is not the same for all the raw materials it provides; therefore, consider that a supplier's priorities may change for different raw materials. Secondly, we require sustainability in delivering goods at every supply chain point. Thus, vehicle selection plays a significant role in achieving the goal of sustainable transportation. Alternative fuel sources such as hydrogen, electricity, biodiesel, ethanol, and natural gas are available for sustainable vehicles. Vehicles using alternative fuel sources have their strengths and weaknesses. Hence, evaluating the cross-efficiency of each vehicle type is a prerequisite for sustainable transportation selection.

2.1. Integrated AHP-TOPSIS supplier assessment

AHP is a popular MCDM technique designed by Saaty [68], which helps in decision-making analysis. The significance of AHP is that it quantifies the weights of all available alternatives. It can deal effectively with substantial and insubstantial criteria in the presence of objective and/or subjective judgements given by distinct entities in pair-wise comparisons to complete the decision-making process [68]. In some instances, the pair-wise comparison of alternatives results in an unmanageable number. The TOPSIS technique can overcome this situation, resulting in a final ranking. TOPSIS, presented by Hwang and Yoon [34], can select the alternative nearest to the positive ideal solution and farthest from the negative ideal solution. It is a simple, rational, and understandable concept. However, it does not provide for weight elicitation or checking for the consistency of judgments. In AHP, decision-makers assign weight values to different attributes, causing a bias in the selection procedure. They allocate a good score for some specific criteria and, at the same time, a poor score for others. The aggregation property of AHP addresses this behaviour but results in the loss of detailed and vital information [46]. However, the closer a solution comes to the positive ideal solution in the TOPSIS model, the further it moves away from the negative ideal solution, the more optimal it becomes. Consequently, the TOPSIS method needs an effective method like AHP that estimates the effectiveness of different objective attributes [16]. Therefore, TOPSIS integrated with AHP satisfies the entirety of the MCDM procedure, managing both the objective and subjective aspects [16]. Hence, an integrated AHP-TOPSIS technique is implemented to identify the ideal supplier to take advantage of both methods. This paper, therefore, introduces an integrated AHP-TOPSIS technique for supplier evaluation. The procedure for implementing the AHP-TOPSIS technique is described below.

Step 1. Consider decision matrices having δ criteria and m alternatives for b type of raw materials. For the first type of raw material, the decision matrix is represented as:

$$\begin{bmatrix} \lambda_{111} & \lambda_{121} & \dots & \dots & \lambda_{1\delta 1} \\ \lambda_{211} & \lambda_{221} & \dots & \dots & \lambda_{2\delta 1} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \lambda_{m11} & \lambda_{m21} & \dots & \dots & \lambda_{m\delta 1} \end{bmatrix},$$

where, $\lambda_{i\theta 1}$ is the value of the ith alternative for the θth criterion for the first type of raw material. Similarly, we can generate matrices for each type of raw material, $a = 1, 2, \dots, b$.

Step 2. Calculate the normalised decision matrices, which can be found as:

$$r_{i\theta a} = \frac{\lambda_{i\theta a}}{\sqrt{\sum_{i=1}^{m} \lambda_{i\theta a}^2}}, \qquad \theta = 1, 2, \dots, \delta;\ a = 1, 2, \dots, b. \tag{2.1}$$

Step 3. Relative benefits of individual criteria that follow the AHP matrix for a pair-wise comparison are determined. The pair-wise comparison matrix is generated by applying the Saaty nine-point preference scale. The scale values 1, 3, 5, 7, and 9 exhibit equal priority, low priority, high priority, very high priority, and absolute priority, respectively. The intermediate values 2, 4, 6, and 8 represent in-between preferences. Additionally, the association of the two criteria resembles the reflexive characteristics of the defined scale. In other words, if the value of X is three times more significant than the other criterion Y, then at that point Y is correspondingly 1/3 times as significant as X.

Consider the $\delta \times \delta$ pair-wise comparison matrix:

$$\begin{bmatrix} 1 & \mu_{12} & \dots & \dots & \mu_{1\delta} \\ \mu_{21} & 1 & \dots & \dots & \mu_{2\delta} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \mu_{\delta 1} & \mu_{\delta 2} & \dots & \dots & 1 \end{bmatrix}.$$

The diagonal components in the matrix are equivalent to themselves, each having a similar value, thus $\mu_{\theta\eta} = 1$, where $\theta = \eta, \theta, \eta = 1, 2, \dots, \delta$. The values above and below the diagonal reflect the relative significance of the θth criterion compared to the ηth criterion. Therefore, $\mu_{\theta\eta} = \frac{1}{\mu_{\eta\theta}}$ for $\theta \neq \eta$.

The normalised matrix is obtained to determine the significance level of each considered criterion. Let ω_θ denote the significance level for the θth criterion; then,

$$\omega_\theta = \frac{\sum_{\eta=1}^{\delta} \frac{\mu_{\theta\eta}}{\sum_{\theta=1}^{\delta} \mu_{\theta\eta}}}{\delta}, \qquad \theta = 1, 2, \dots, \delta. \tag{2.2}$$

The consistency ratio (CR) is calculated to verify the accuracy of the evaluation given by the pairwise comparison matrix. Calculate the CR according to the following steps:

I Determine the matrix eigenvalue ($\lambda_{\max}$).

II Compute the consistency index (CI) as $\mathrm{CI} = \frac{\lambda_{\max} - \delta}{\delta - 1}$.

III Then, evaluate the value of CR as $\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}$,
where RI is a random consistency index that primarily depends on the matrix order. When the value of CR is below the 0.10 threshold, it is considered acceptable to determine the significance of the criterion.

Step 4. The weighted normalised matrix $v_{i\theta a}$ has been created by multiplying the weight w_θ with every column of the matrix $r_{i\theta a}$. Hence,

$$v_{i\theta a} = w_\theta r_{i\theta a}. \tag{2.3}$$

Step 5. Determine the positive ideal solution and negative ideal solution expressed as:

$$v^+ = \left\{ \left(\max_i \sum_a v_{i\theta a} | \theta \in \theta' \right), \left(\min_i \sum_a v_{i\theta a} | \theta \in \theta'' \right) | i = 1, 2, \dots, m \right\}, \tag{2.4}$$

$$= \left\{ v_1^+, v_2^+, \dots, v_\delta^+ \right\}, \tag{2.5}$$

$$v^- = \left\{ \left(\min_i \sum_a v_{i\theta a} | \theta \in \theta' \right), \left(\max_i \sum_a v_{i\theta a} | \theta \in \theta'' \right) | i = 1, 2, \dots, m \right\}, \tag{2.6}$$

$$= \left\{ v_1^-, v_2^-, \dots, v_\delta^- \right\}, \tag{2.7}$$

where $\theta' = (\theta = 1, 2, \dots, \delta) | \theta$ corresponds to the benefit criterion and $\theta'' = (\theta = 1, 2, \dots, \delta) | \theta$ corresponds to the cost criterion.

Step 6. Compute the separation distance between alternatives.

The separation distance of each alternative from the positive ideal solution is defined as:

$$S_i^+ = \sqrt{\sum_{\theta=1}^{\delta} \sum_a \left(v_{i\theta a} - v_\theta^+ \right)^2}, \qquad i = 1, 2, \dots, m. \tag{2.8}$$

The separation distance of each alternative from the negative ideal solution is defined as:

$$S_i^- = \sqrt{\sum_{\theta=1}^{\delta} \sum_a \left(v_{i\theta a} - v_\theta^-\right)^2}, \qquad i = 1, 2, \ldots, m. \tag{2.9}$$

Step 7. The relative closeness to the ideal solution is computed as:

$$C_i = \frac{S_i^-}{\left(S_i^+ + S_i^-\right)}, \qquad i = 1, 2, \ldots, m. \tag{2.10}$$

Step 8. The alternatives are ranked based on the C_i values.

2.1.1. Supplier selection criteria

An extensive search has been conducted through publications and an open search engine literature survey to prepare a detailed list of criteria for the sustainable assessment of suppliers. The selected criteria are economic: price, quality, rejection ratio, flexibility, and logistics costs; environmental: resource consumption, recycling, and air pollution; and social: safety practices, the annual number of accidents, and staff training. Quality, flexibility, recycling, safety practices, and staff training are benefit criteria, and price, logistic costs, resource consumption, air pollution, and the annual number of accidents are cost criteria. The selected criteria are explained below.

I Price [52]: the price paid for purchasing raw materials from suppliers occupies a special role in choosing a suitable supplier. The pricing parameters include unit price, pricing conditions, exchange rates, taxes, and discounts. Price is, therefore, the primary consideration when selecting a supplier, and as a result, procurement costs must be minimised to maximise supply chain efficiency.

II Quality [52]: given the intense global competition, quality has emerged as one of the key elements that directly influences supplier selection. Quality describes a product or service's ability to consistently fulfill customer expectations and the supplier's ability to adhere to quality criteria, including material, dimensions, design, and durability. Numerous techniques can be used to evaluate the quality, including process capability indices, continuous improvement activities, certifications, the ability to handle erroneous quality, reliability, rate of rejects, yield rate, and rate of loss functions [1]. Hence, the most crucial factor in supplier selection is the quality level of the procured items, and efforts are made to manage this with a proactive and collaborative approach.

III Flexibility [8]: this is characterised as an ability to adjust to changing circumstances, help maintain process continuity, and react quickly to changes. It even assists in responding to supply chain disruptions, demand shifts, and external market fluctuations. It is identified as a key component to ensure companies can address the threats and opportunities created by changing phenomena and environmental complexity. The ability to quickly flex their supply chain is essential for many firms to succeed and acquire a competitive advantage.

IV Logistics cost [52]: the logistics cost includes charges for the movement of goods across the country using various transportation methods. It also includes fuel costs, inventory costs, and packaging costs. Companies need to manage their logistics to maintain a balance between cost and performance and manage time effectively. It is essential to regularly assess a company's logistical strategy so that the appropriate steps can be taken to resolve any shortcomings effectively.

V Resource consumption [39]: the utilisation of non-renewable resources determines the criteria for resource consumption. Resource consumption may apply to water, energy, or oil usage. Suppliers should struggle to reduce the over-consumption of resources. The main reasons for recognising this criterion as a significant factor for supplier selection are the scarcity of natural resources, governmental regulation, and social responsibility for environmental preservation.

VI Recycling capability [28]: recycling is a method by which waste materials are transformed into usable materials and products. It seeks to achieve environmental sustainability by eliminating the waste of precious materials and reducing the consumption of fresh raw materials. Furthermore, recycling tends to boost the overall brand perception of an organisation. Hence, suppliers should improve their recycling behaviour.

VII Air pollution [9]: this refers to toxins that are detrimental to human health being emitted into the environment. Reducing air pollution when procuring raw materials from suppliers is the ultimate goal of organisations. Additionally, in response to environmental concerns, the government imposes stringent rules to minimise carbon emissions and encourages businesses to choose suppliers who promote environmental sustainability. This criterion may also assist organisations in gaining a competitive advantage and improving their reputation [4].

VIII Safety practices [49]: ensuring employees work in a safe environment is mandatory to avoid interruptions in the supply chain. Companies need to be more careful when reviewing their supplier base to prevent unjustified issues caused by a lack of safety measures that not only impact the business but also the reputation of the brand [49]. Suppliers are required to keep improving their safety practices and to modify them when new threats arise.

IX The annual number of accidents [31]: to prevent accidental injuries, workers should be provided with safety equipment and training. Facilitating the safe transport and movement of stock from suppliers reduces the risk of accidents. Statistics from incident investigations worldwide have progressively shown that most accidents have involved third-party suppliers. Therefore, businesses need procedures and frameworks for choosing, screening, controlling, and persuading suppliers in terms of their ability to prevent and mitigate these accidents. These factors might be included in the bidding process to improve supplier performance [31].

X Staff training [12]: staff training is important to expand employees' knowledge base so that they can perform their jobs better. They should be trained to ensure they give the level of service that clients expect. Training gives employees a greater understanding of their responsibilities, benefiting the organisation. This criterion aids in achieving the goal of increasing overall value to the buyer and fostering deep, long-lasting connections between buyers and suppliers [76].

2.2. Cross-efficiency evaluation of vehicles

DEA, a widely recognised data-driven performance evaluation technique [19, 83, 84], has proven effective across various disciplines and industries, streamlining decision-making processes [20, 74]. Furthermore, in view of Charles *et al.* [21], DEA can be categorised as a prescriptive analytics-oriented technique, as it assists in offering recommendations to enhance the efficiency of DMUs by identifying the best practice frontier.

Cross-efficiency is a powerful tool for evaluations by DMUs. It is based on the principle of peer review. The cross-efficiency evaluation by each DMU is performed in two steps: first, the optimal weights derived by the DMU alone are used to calculate self-assessed efficiency; second, the optimal weights chosen by other DMUs are used to calculate peer-assessed efficiencies [45]. The significant qualities of a cross-efficiency assessment include obtaining a unique order ranking by the DMUs, excluding impractical weight structures without preempting any weight limitations, and effective differentiation between the best and worst performers among the DMUs.

The ideal input-oriented DEA model is as follows [22]:

$$\text{Max} \sum_{r=1}^{R} u_r y_{rp}$$

subject to:

$$\sum_{r=1}^{R} u_r y_{rj} - \sum_{i=1}^{I} v_i x_{ij} \leq 0, \qquad j = 1, 2, \ldots, J,$$

$$\sum_{i=1}^{I} v_i x_{ip} = 1,$$

$$u_r, v_i \geq \epsilon, \qquad i = 1, 2, \ldots, I;\ r = 1, 2, \ldots, R,$$

where $j, (j = 1, 2, \ldots, J)$ is the index of DMUs, $i, (i = 1, 2, \ldots, I)$ and $r, (r = 1, 2, \ldots, R)$ is the index of inputs and outputs, respectively. x_{ij} is the ith input value for the jth DMU, y_{rj} is the rth output value for the jth DMU, u_r is the weight of the output r, v_i is the weight of the input i. Lastly, ϵ is a positive infinitesimal value. The weights of output and input are calculated by applying this model, which further maximises the efficiency of DMU p. The optimal weights are represented by $*$. The cross-efficiency of those DMUs (evaluated by DMU p) is the efficiency of other DMUs, which are evaluated by using optimal weights of DMU p. The cross-efficiency of DMU q is determined as follows [50]:

$$e_{pq} = \frac{\sum_{r=1}^{R} u_r^* y_{rq}}{\sum_{i=1}^{I} v_i^* x_{iq}}. \tag{2.11}$$

The cross-efficiency of the jth DMU determined by the ith DMU is represented by e_{ij}, which has been used to obtain a cross-efficiency matrix denoted by $E = (e_{ij}), i, j = 1, 2, \ldots, J$. A qth DMU cross-efficiency score is found by calculating the average of the qth column as:

$$\bar{e}_q = \frac{1}{J} \sum_{p=1}^{J} e_{pq}. \tag{2.12}$$

2.2.1. Inputs and outputs to obtain cross-efficiency of vehicles

The inputs and outputs used for estimating the cross-efficiency of each vehicle type have been carefully selected based on an extensive review of publications such as Falsini *et al.* [27] and Leal *et al.* [41]. These selected inputs and outputs are explained below:

Inputs

Fuel cost: vehicles mainly depend on expensive liquid hydrocarbons emitting many greenhouse gases. Hence, using alternative fuels such as natural gas or bio-diesel saves money and reduces climate change.
Use of sustainable fuel: sustainable fuels such as electricity and hydrogen are low carbon-emitting fuels used to reduce harmful environmental impacts. Using sustainable fuels reduces air pollution and the amount of imported oil, contributing to sustainable transport and energy independence.

Outputs

Fuel efficiency: this measures how far a vehicle can move per unit of fuel. Fuel-efficient vehicles use less fuel and produce less pollution. This is the most authentic evaluation of a vehicle's performance.
Carbon emissions: carbon emissions from vehicles significantly cause global warming. The amount of carbon emitted by a vehicle depends on several factors: the type of fuel, the fuel economy, and the number of miles driven per year. Additionally, the carbon emissions from a fully-loaded vehicle differ from those from an empty vehicle. Hence, the two different outputs are considered, corresponding to the vehicle with a full load and in an empty state.
Safety: safety measures evaluate the likelihood that customers are involved in an accident. Accidents can often be avoided with proper safety precautions. Therefore, the importance of transportation safety cannot be overlooked.

3. The integrated multi-objective multi-commodity optimisation model

This section introduces the integrated multi-objective multi-commodity optimisation model for a supply chain that follows a sustainable approach. The closeness coefficients for the suppliers and the cross-efficiency of the vehicles, which were explained in the previous section, are assessed and integrated with the other two objectives of cost and emission reduction, demonstrating the novelty of the suggested model. The proposed supply chain model addresses four conflicting objectives. The first objective is to minimise the overall supply chain cost. This total cost comprises the cost of transporting raw materials and products from one phase of the supply chain to another, the fixed cost of hiring vehicles, the production cost incurred at the manufacturing plants, the ordering cost of the suppliers, and the inventory cost incurred at the distributors. The second objective is to minimise vehicle emissions by requiring them to meet sustainability criteria. The third objective is framed by maximising the supplier weights obtained using an integrated AHP-TOPSIS technique. Supplier selection is performed using an evaluation of sustainability based on economic, environmental, and social parameters. The fourth objective is to maximise each vehicle type's cross-efficiency score calculated by applying the DEA technique, considering various inputs and outputs. These four objectives are directly or indirectly connected. The objective efficiency of vehicles directly affects the emissions objective, and the objective corresponding to supplier selection directly impacts the cost objective. However, costs and emissions are negatively correlated. Minimising costs would lead to an increase in emissions, and *vice versa*. The multi-objective multi-commodity optimisation model presented here includes many necessary restrictions on raw material supply, production, distributor and customer demand, vehicle capacity, and availability. The notations for the proposed model are explained in Table 2.

3.1. Objective functions

- **Total cost**: it comprises the transportation cost, the manufacturing cost, the ordering cost, and the storage cost. The transportation cost is calculated in three stages. The first journey is from supplier i to manufacturing plant j, the second is from manufacturing plant j to distributor k, and the last is from distributor k to customer r. Each stage includes two kinds of costs: a variable cost and a fixed cost. The variable cost is determined by multiplying the transportation cost for each unit and each unit of distance by the number of units transported and the distance between the source and the destination. The fixed cost is determined by multiplying the vehicle's hiring cost with a corresponding binary variable for that route. Mathematically, the cost function is stated as:

$$\begin{aligned}\text{Min } Z_1 = &\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\sum_{h=1}^{t}\sum_{a=1}^{b}(x_{ijha}c'_{ha})d_{ij} + \sum_{h=1}^{t} f_h V^1_{ijh}\alpha_{ijh}\right] \\ &+ \sum_{j=1}^{n}\sum_{k=1}^{l}\left[\sum_{h=1}^{t}\sum_{p=1}^{q}(y_{jkhp}c_{hp})d'_{jk} + \sum_{h=1}^{t} f_h V^2_{jkh}\beta_{jkh}\right] \\ &+ \sum_{k=1}^{l}\sum_{r=1}^{s}\left[\sum_{h=1}^{t}\sum_{p=1}^{q}(z_{krhp}c_{hp})d''_{kr} + \sum_{h=1}^{t} f_h V^3_{krh}\gamma_{krh}\right]\sum_{j=1}^{n}\sum_{p=1}^{q}(v_{jp}A_{jp}) \\ &+ \sum_{i=1}^{m}\sum_{a=1}^{b}\left(\sum_{j=1}^{n}\sum_{h=1}^{t} x_{ijha}O_{ia}\right) + \sum_{k=1}^{l}\sum_{p=1}^{q}(B_{kp}H_{kp}). \end{aligned} \tag{3.1}$$

- **Total emissions from vehicles**: minimising transportation-related emissions is the second objective of the model. The emissions of CO_2 depend on the distance covered by the vehicle, the weight carried by the vehicle, the average speed of the vehicle, and the road quality. The formula given in Pan *et al.* [63] is used here to calculate the CO_2 emissions, subject to two assumptions: (a) the average speed is 80 km/h, and (b) the road gradient is not considered. As a result, the final CO_2 emissions function is given as:

$$\begin{aligned}\text{Min } Z_2 = &\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{h=1}^{t}\sum_{a=1}^{b} d_{ij}V^1_{ijh}\left[\left(E^h_{\text{full}} - E^h_{\text{empty}}\right)\frac{x_{ijha}w'_a}{W_h} + E^h_{\text{empty}}\alpha_{ijh}\right] \\ &+ \sum_{j=1}^{n}\sum_{k=1}^{l}\sum_{h=1}^{t}\sum_{p=1}^{q} d'_{jk}V^2_{jkh}\left[\left(E^h_{\text{full}} - E^h_{\text{empty}}\right)\frac{y_{jkhp}w_p}{W_h} + E^h_{\text{empty}}\beta_{jkh}\right]\end{aligned}$$

Table 2. Notations.

Indices	
i	Index of suppliers ($i = 1, 2, \ldots, m$)
j	Index of manufacturing plants ($j = 1, 2, \ldots, n$)
k	Index of distributors ($k = 1, 2, \ldots, l$)
r	Index of customers ($r = 1, 2, \ldots, s$)
h	Index of vehicles ($h = 1, 2, \ldots, t$)
p	Index of products ($p = 1, 2, \ldots, q$)
a	Index of raw materials ($a = 1, 2, \ldots, b$)
Decision variables	
x_{ijha}	Number of units of raw material a carried by vehicle type h from supplier i to manufacturing plant j
y_{jkhp}	Number of units of product p carried by vehicle type h from manufacturing plant j to distributor k
z_{krhp}	Number of units of product p carried by vehicle type h from distributor k to customer r
α_{ijh}	1, if vehicle type h is used for transportation from supplier i to manufacturing plant j; 0 otherwise
β_{jkh}	1, if vehicle type h is used for transportation from manufacturing plant j to distributor k; 0 otherwise
γ_{krh}	1, if vehicle type h is used for transportation from distributor k to customer r; 0 otherwise
V^1_{ijh}	Number of vehicle type h used for transportation from supplier i to manufacturing plant j
V^2_{jkh}	Number of vehicle type h used for transportation from manufacturing plant j to distributor k
V^3_{krh}	Number of vehicle type h used for transportation from distributor k to customer r
v_{jp}	Quantity of product p produced at manufacturing plant j
Parameters	
S_{ia}	Capacity of supplier i for raw material a
I_{kp}	Demand of product p at distributor k
D_{rp}	Demand of product p at customer r
O_{ia}	Ordering cost per unit of raw material a from supplier i
H_{kp}	Storage cost per unit of product p at distributor k
w_p	Per unit weight of product p
w'_a	Per unit weight of raw material a
A_{jp}	Production cost of product p at manufacturing plant j
u_{ap}	Amount of raw material a required to produce per unit of product p
W_h	Weight capacity of vehicle type h
f_h	Fixed cost of hiring vehicle type h
c_{hp}	Transportation cost per unit distance per unit of product p using vehicle type h
c'_{ha}	Transportation cost per unit distance per unit of raw material a using vehicle type h
d_{ij}	Distance between supplier i and manufacturing plant j
d'_{jk}	Distance between manufacturing plant j and distributor k
d''_{kr}	Distance between distributor k and customer r
n_h	Number of available vehicle type h
B_{kp}	Number of units of product p stored by distributor k
R_i	Priority of supplier i
e_h	Efficiency of vehicle type h
E^h_{full}	Emission per unit distance in full load by vehicle type h
E^h_{empty}	Emission per unit distance in empty state by vehicle type h

$$+\sum_{k=1}^{l}\sum_{r=1}^{s}\sum_{h=1}^{t}\sum_{p=1}^{q} d''_{kr} V^3_{krh} \left[\left(E^h_{\text{full}} - E^h_{\text{empty}} \right) \frac{z_{krhp} w_p}{W_h} + E^h_{\text{empty}} \gamma_{krh} \right]. \tag{3.2}$$

- **Aggregated closeness coefficient of suppliers**: the aggregated closeness coefficient is a benefit criterion for choosing suppliers, as indicated by their priorities, which are decided through the integrated AHP-TOPSIS technique. The objective function maximises the total closeness coefficient, selecting top-positioned suppliers for supplying raw materials. Mathematically, the aggregated closeness coefficient is stated as:

$$\text{Max } Z_3 = \sum_{i=1}^{m} R_i \sum_{j=1}^{n}\sum_{h=1}^{t}\sum_{a=1}^{b} x_{ijha}. \tag{3.3}$$

- **Aggregated cross-efficiency score**: the aggregated cross-efficiency score is a benefit criterion utilised for choosing efficient vehicles. The cross-efficiency score function facilitates the effective differentiation between the best and the worst performers among the vehicle types. Mathematically, the aggregated cross-efficiency score function is stated as:

$$\text{Max } Z_4 = \sum_{h=1}^{t} e_h \left[\sum_{i=1}^{m}\sum_{j=1}^{n} \alpha_{ijh} + \sum_{j=1}^{n}\sum_{k=1}^{l} \beta_{jkh} + \sum_{k=1}^{l}\sum_{r=1}^{s} \gamma_{krh} \right]. \tag{3.4}$$

3.2. Constraints

- **Raw material supply constraint**: the aggregate number of units of raw material carried by all vehicles from the supplier to the manufacturing plants must be less than or equal to the capacity of the supplier:

$$\sum_{j=1}^{n}\sum_{h=1}^{t} x_{ijha} \leq S_{ia}, \qquad i = 1, 2, \ldots, m;\ a = 1, 2, \ldots, b. \tag{3.5}$$

- **Distributor demand constraint**: the aggregate number of units of the product acquired by a distributor and delivered by all vehicles from distinct manufacturing plants must be greater than or equal to the demand of that distributor:

$$\sum_{j=1}^{n}\sum_{h=1}^{t} y_{jkhp} \geq I_{kp}, \qquad k = 1, 2, \ldots, l;\ p = 1, 2, \ldots, q. \tag{3.6}$$

- **Customer demand constraint**: the aggregate number of units of the product acquired by a customer and delivered by all vehicles from distinct distributors must be greater than or equal to the demand of that customer:

$$\sum_{k=1}^{l}\sum_{h=1}^{t} z_{krhp} \geq D_{rp}, \qquad r = 1, 2, \ldots, s;\ p = 1, 2, \ldots, q. \tag{3.7}$$

- **Production constraint**: the aggregate number of units of each product carried by all vehicles from a manufacturing plant to distinct distributors must be less than or equal to the quantity of that product manufactured at that manufacturing plant:

$$\sum_{k=1}^{l}\sum_{h=1}^{t} y_{jkhp} \leq v_{jp}, \qquad j = 1, 2, \ldots, n;\ p = 1, 2, \ldots, q. \tag{3.8}$$

- **Balancing constraint**: the number of units of raw material carried by all vehicles to a manufacturing plant from all suppliers must be greater than or equal to the number of units of raw material used to produce the number of units of product transported from that manufacturing plant to all the distributors by all vehicles:

$$\sum_{i=1}^{m}\sum_{h=1}^{t} x_{ijha} \geq \sum_{k=1}^{l}\sum_{h=1}^{t}\sum_{p=1}^{q} y_{jkhp}u_{ap}, \qquad j=1,2,\ldots,n;\; a=1,2,\ldots,b. \tag{3.9}$$

The number of units of product carried by all vehicles to a distributor from all manufacturing plants must be greater than or equal to the number of units of product carried by all vehicles from that distributor:

$$\sum_{j=1}^{n}\sum_{h=1}^{t} y_{jkhp} \geq \sum_{r=1}^{s}\sum_{h=1}^{t} z_{krhp}, \qquad k=1,2,\ldots,l;\; p=1,2,\ldots,q. \tag{3.10}$$

– **Vehicle capacity constraints**: the total weight conveyed by any vehicle type, whether moved from a supplier to all manufacturing plants, from a manufacturing plant to all distributors, or a distributor to all customers, must not exceed the capacity of that vehicle type:

$$\sum_{j=1}^{n}\alpha_{ijh}\sum_{a=1}^{b} x_{ijha}w'_a \leq W_h\sum_{j=1}^{n} V^1_{ijh}, \qquad i=1,2,\ldots,m;\; h=1,2,\ldots,t \tag{3.11}$$

$$\sum_{k=1}^{l}\beta_{jkh}\sum_{p=1}^{q} y_{jkhp}w_p \leq W_h\sum_{k=1}^{l} V^2_{jkh}, \qquad j=1,2,\ldots,n;\; h=1,2,\ldots,t \tag{3.12}$$

$$\sum_{r=1}^{s}\gamma_{krh}\sum_{p=1}^{q} z_{krhp}w_p \leq W_h\sum_{r=1}^{s} V^3_{krh}, \qquad k=1,2,\ldots,l;\; h=1,2,\ldots,t. \tag{3.13}$$

– **Vehicle availability constraint**: the number of vehicles of any given vehicle type utilised in the transportation system of the supply chain must not exceed the availability of that specific vehicle type:

$$\sum_{i=1}^{m}\sum_{j=1}^{n} V^1_{ijh}\alpha_{ijh} + \sum_{j=1}^{n}\sum_{k=1}^{l} V^2_{jkh}\beta_{jkh} + \sum_{k=1}^{l}\sum_{r=1}^{s} V^3_{krh}\gamma_{krh} \leq n_h, \qquad h=1,2,\ldots,t. \tag{3.14}$$

– **Association of decision variables and corresponding binary variables**: this signifies that if $\sum_{a=1}^{b} x_{ijha} > 0$, then $\alpha_{ijh} = 1$, otherwise 0; if $\sum_{p=1}^{q} y_{jkhp} > 0$, then $\beta_{jkh} = 1$, otherwise 0; and if $\sum_{p=1}^{q} z_{krhp} > 0$, then $\gamma_{krh} = 1$, otherwise 0. The equations describing this association are written as

$$\alpha_{ijh} \leq \sum_{a=1}^{b} x_{ijha} \leq \alpha_{ijh}M, \qquad i=1,2,\ldots,m; j=1,2,\ldots,n;\; h=1,2,\ldots,t \tag{3.15}$$

$$\beta_{jkh} \leq \sum_{p=1}^{q} y_{jkhp} \leq \beta_{jkh}M, \qquad j=1,2,\ldots,n; k=1,2,\ldots,l;\; h=1,2,\ldots,t \tag{3.16}$$

$$\gamma_{krh} \leq \sum_{p=1}^{q} z_{krhp} \leq \gamma_{krh}M, \qquad k=1,2,\ldots,l; r=1,2,\ldots,s;\; h=1,2,\ldots,t. \tag{3.17}$$

where M is a sufficiently large number.

– **Integer and binary restrictions on decision variables**: the requisite restrictions are expressed as follows: $x_{ijha}, y_{jkhp}, z_{krhp}, v_{jp}, V^1_{ijh}, V^2_{jkh}, V^3_{krh} \geq 0$ and integer, $\alpha_{ijh}, \beta_{jkh},\ \gamma_{krh} \in \{0,1\}$,

$$\begin{aligned} &i=1,2,\ldots,m; j=1,2,\ldots,n;\; k=1,2,\ldots,l; r=1,2,\ldots,s;\\ &h=1,2,\ldots,t; p=1,2,\ldots,q; a=1,2,\ldots,b. \end{aligned} \tag{3.18}$$

The objective functions (3.1)–(3.4) and the constraints (3.5)–(3.18) constitute the final integrated multi-objective multi-commodity optimisation model ($M1$).

4. Solution methodology

Multi-objective problems consist of two or more objectives that are conflicting in nature. Either the optimal values are not attained simultaneously or, if one objective is achieved, the other(s) complete satisfaction is undermined [62]. Therefore, a set of compromise solutions known as Pareto-optimal solutions are attained instead of a single optimal solution. Different approaches to solving multi-objective problems exist, such as the weighted sum method, goal programming, and the ϵ-constraint method. Goal programming is a mathematical programming technique that manages multiple objectives; a satisfactory solution is derived rather than optimal. This paper applies the lexicographic goal programming (LGP) technique, which accomplishes multiple goals simultaneously to make appropriate decisions [62]. A set of attributes is considered to solve the problem by LGP, corresponding to which a target value is determined. Next, two types of deviation variables, negative deviation variables (representing underachievement of a goal) and positive deviation variables (representing over-achievement of a goal), are introduced. Finally, the undesirable deviation variables are prioritised in order of importance, and then, for each attribute, these deviations are minimised. The general model of LGP is given as:

$$
\begin{aligned}
\text{Min } Z = & \left(p_1\left(d_1^-, d_1^+\right), p_2\left(d_2^-, d_2^+\right), \ldots, p_k\left(d_k^-, d_k^+\right)\right) \\
\text{subject to } & \sum_{j=1}^{n} a_{ij}x_{ij} + d_i^- - d_i^+ = b_i, && i = 1,2,\ldots,m, \\
& x_{ij}, d_i^-, d^+ =_i \geq 0, && i = 1,2,\ldots,m;\ j = 1,2,\ldots,n,
\end{aligned}
$$

where p_i such that $(p_1 \gg p_2 \gg p_3 \ldots \gg p_k)$ is the priority of the ith deviational variable in the objective function, k denotes the priorities, m are the objectives, and n are the decision variables.

Assume that X is a feasible region of the model $(M1)$. Applying the LGP approach, the model $(M1)$ is described by various levels that are defined according to the priority of the objective functions. Since the model $(M1)$ has four objective functions, we define four levels. Let us suppose that arbitrary priorities are assigned to the four objective functions as explained below:

Level 1. The first priority objective function is included in level 1. The objective function of the aggregated cross-efficiency score (Z_4) is assumed to have first priority, as explained in equation (3.4). The model for level 1 is defined as follows:

$$
\begin{aligned}
\text{Min} = & \; d_4^- \\
\text{subject to } & \sum_{h=1}^{t} e_h \left[\sum_{i=1}^{m}\sum_{j=1}^{n}\alpha_{ijh} + \sum_{j=1}^{n}\sum_{k=1}^{l}\beta_{jkh} + \sum_{k=1}^{l}\sum_{r=1}^{s}\gamma_{krh}\right] + d_4^- = A_4, \\
& x \in X,
\end{aligned}
$$

where parameter A_4 is the aspiration level in respect of the first prioritised objective function.
Suppose that Z_4^* is the value of Z_4 attained by solving the level 1 model. If Z_4^* attains the aspiration level A_4, then we move to level 2; otherwise, this is considered to be a compromise solution, and the values of the other objective functions are found from the solution of the level 1 model, and we do not proceed further. Note that if there is no alternate optimal solution to the level 1 model, we do not proceed to subsequent levels, and a compromise solution is obtained. The same holds for the models at the subsequent levels.

Level 2. The second priority objective function is included in level 2. The objective function of the aggregated closeness coefficient of suppliers (Z_3) is assumed to have a second priority, as explained in equation (3.3).

The model for level 2 is defined as follows:

$$\begin{aligned} &\text{Min} = d_3^- \\ \text{subject to} \quad &\sum_{i=1}^{m} R_i \sum_{j=1}^{n} \sum_{h=1}^{t} \sum_{a=1}^{b} x_{ijha} + d_3^- = A_3, \\ &Z_4 = Z_4^*, \quad x \in X, \end{aligned}$$

where the parameter A_3 is the aspiration level in respect of the second prioritised objective function. Suppose that Z_3^* is the value of Z_3 attained by solving the level 2 model. If Z_3^* attains the aspiration level A_3, then we move to level 3; otherwise, this is considered to be a compromise solution, and the values of the other objective functions are found from the solution of the level 2 model, and we do not proceed further.

Level 3. The third priority objective function is included in level 3. The objective function of total emissions from vehicles (Z_2) is assumed to have a third priority, as explained in equation (3.2). The model for level 3 is defined as follows:

$$\begin{aligned} &\text{Min} = d_2^+ \\ \text{subject to} \quad &\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{h=1}^{t} \sum_{a=1}^{b} V_{ijh}^1 d_{ij} \left[\left(E_{\text{full}}^h - E_{\text{empty}}^h\right) \frac{x_{ijha} w_a'}{W_h} + E_{\text{empty}}^h \alpha_{ijh} \right] \\ &+ \sum_{j=1}^{n} \sum_{k=1}^{l} \sum_{h=1}^{t} \sum_{p=1}^{q} V_{jkh}^2 d_{jk}' \left[\left(E_{\text{full}}^h - E_{\text{empty}}^h\right) \frac{y_{jkhp} w_p}{W_h} + E_{\text{empty}}^h \beta_{jkh} \right] \\ &+ \sum_{k=1}^{l} \sum_{r=1}^{s} \sum_{h=1}^{t} \sum_{p=1}^{q} V_{krh}^3 d_{kr}'' \left[\left(E_{\text{full}}^h - E_{\text{empty}}^h\right) \frac{z_{krhp} w_p}{W_h} + E_{\text{empty}}^h \gamma_{krh} \right] - d_2^+ = A_2, \\ &Z_3 = Z_3^*, \quad Z_4 = Z_4^*, \quad x \in X, \end{aligned}$$

where parameter A_2 is the aspiration level for the third prioritised objective function. Suppose that Z_2^* is the value of Z_2 attained by solving the level 3 model. If Z_2^* attains the aspiration level A_2, then we move to level 4; otherwise, this is considered to be a compromise solution, and the value of the other objective function is found from the solution of the level 3 model, and we do not proceed further.

Level 4. The fourth priority objective function is included in level 4. The objective function of the total cost (Z_1) is assumed to have a fourth priority, as explained in equation (3.1). The model for level 4 is defined as follows:

$$\begin{aligned} &\text{Min} = d_1^+ \\ \text{subject to} \quad &\sum_{i=1}^{m} \sum_{j=1}^{n} \left[\sum_{h=1}^{t} \sum_{a=1}^{b} (x_{ijha} c_{ha}') d_{ij} + \sum_{h=1}^{t} f_h V_{ijh}^1 \alpha_{ijh} \right] \\ &+ \sum_{j=1}^{n} \sum_{k=1}^{l} \left[\sum_{h=1}^{t} \sum_{p=1}^{q} (y_{jkhp} c_{hp}) d_{jk}' + \sum_{h=1}^{t} f_h V_{jkh}^2 \beta_{jkh} \right] \\ &+ \sum_{k=1}^{l} \sum_{r=1}^{s} \left[\sum_{h=1}^{t} \sum_{p=1}^{q} (z_{krhp} c_{hp}) d_{kr}'' + \sum_{h=1}^{t} f_h V_{krh}^3 \gamma_{krh} \right] + \sum_{j=1}^{n} \sum_{p=1}^{q} (v_{jp} A_{jp}) \\ &+ \sum_{i=1}^{m} \sum_{a=1}^{b} \left(\sum_{j=1}^{n} \sum_{h=1}^{t} x_{ijha} O_{ia} \right) + \sum_{k=1}^{l} \sum_{p=1}^{q} (B_{kp} H_{kp}) - d_1^+ = A_1, \\ &Z_2 = Z_2^*, \quad Z_3 = Z_3^*, \quad Z_4 = Z_4^*, \quad x \in X, \end{aligned}$$

where the parameter A_1 is the aspiration level in respect of the fourth prioritised objective function.

Let us suppose that Z_1^* is the value of Z_1 attained by solving the level 4 model. Finally, Z_1^*, Z_2^*, Z_3^*, and Z_4^* are the optimal/compromise values of the four objective functions defined in model $M1$. The priorities can be altered according to the decision-maker's preference, and the corresponding levels are defined to find the compromise values of the four objective functions.

5. Case study

This section examines a real-life supply chain case study at Ctflomag (a pseudonym), a global leader in smartphones, consumer electronics, and semiconductors. Its supply network is the foundation of its business, and the firm's success may be ascribed in part to effective supply chain management. Supply chain management is a challenging field, but because the success of a brand is highly reliant on it, firms like Ctflomag go to great lengths to make their supply networks as flexible, integrated, and flawless as possible. Through strategic supply chain management, Ctflomag aims to achieve cost competitiveness and operational efficiency while focusing on sustainability. They manage their supply chain activities by focusing on the economic, social, and environmental elements.

- Economic: Ctflomag's supply chain management strategy aims to provide an all-encompassing competitive advantage in cost, delivery, quality, technology, and human resources to maximise collaboration, speed, and efficiency with its suppliers and build a corporate system that allows for sustainable growth.
- Environmental: Ctflomag primarily works with Eco-Partner-certified suppliers to maintain an environmentally sustainable supply chain. This ensures that the environmental effects of components, raw materials, and manufacturing processes can be assessed and managed. Ctflomag began using sustainable manufacturing best practices in 2004, and its manufacturing process focuses on making goods sustainable from the planning stage forward through eco-friendly design.
- Social: Ctflomag also ensures that suppliers follow international standards and regulations in human rights management, work environment, ethics, and conflict mineral issues, intending to establish an open and transparent management accountability system that involves all stakeholders throughout the supply chain.

The supply chain in the electronic industry is highly complicated and comprises multiple procedures. The first step is to select the suppliers of raw materials with the goal of sustainability and choose the best supplier based on different parameters. Choosing sustainable suppliers is deemed to play an essential role in the success of the company Ctflomag as a dominant player in the global market. This stage is completed by evaluating suppliers based on the data collected through interviews and obtained by an organisation's procurement team. The second step is producing electronic items from the raw materials supplied by the suppliers, attempting to maintain a low cost of production. Production planning is laborious because of the unavoidable lack of commitment by the customers to make a decision early enough about quantity, delivery time, product classification, etc. To deal with these issues, a production manager is employed to compile all the relevant and necessary information collected from records and coordinate with the suppliers and retailers. The third step is distributing products from the manufacturers to the distributors and ultimately to the customers. The vehicles used for distribution play a crucial role in ensuring an environmentally sustainable process, and this is the biggest obstacle in logistics planning. The evaluation of vehicle efficiency is thus essential to accomplish the objective of sustainable transportation planning. The cross-efficiency of vehicles is evaluated based on data collected by the logistics manager through questionnaires. The proposed model in this section addresses the challenges in the electronic industry mentioned above.

Transportation planning, as we know, plays a vital role in a sustainable supply chain. Therefore, the ABC logistics company took over responsibility for managing the logistics of the company Ctflomag. The logistics manager coordinates the transport systems between suppliers, manufacturers, distributors, and customers. The individual in charge of material resources for the company selects three suppliers, namely Daeducic Electronics (S_1), Daeyong Electronics (S_2), and AAC Technologies Holdings (S_3), to supply three types of raw material,

Table 3. Supplier's capacity.

Suppliers	Capacity (no. of units)		
	a_1	a_2	a_3
S_1	8000	7500	12 500
S_2	10 000	9750	8250
S_3	9500	12 000	17 750

Table 4. Manufacturing plant's capacity.

Manufacturing plants	Capacity (no. of units)			
	p_1	p_2	p_3	p_4
P_1	450	630	550	375
P_2	525	340	450	625

namely PVC (a_1), LDPE (a_2), and HDPE (a_3) to two manufacturing plants situated at Noida-Location-1 (P_1) and Noida-Location-2 (P_2). These manufacturing plants manufacture four types of products, Mobile Phones (p_1), LED (p_2), Refrigerators (p_3), and Dishwashers (p_4), under the supervision of the production planner. These finished products are transported to four distributors, ABC Warehouse (D_1), ABT Electronics (D_2), M & A Distributors (D_3), and Mega Electronics (D_4), under the supervision of the logistics executive. These four distributors sell directly to six customers: Venzon (C_1), Best Buy (C_2), Telekom (C_3), Telctronix (C_4), Apple (C_5), and ABCL Inc. (C_6). Five different types of vehicles, a diesel vehicle (V_1), a compressed natural gas vehicle (V_2), a bio-diesel vehicle (V_3), an electric vehicle (V_4), and a hybrid vehicle (V_5), are used to transport raw materials and products at each stage of supply chain discussed above.

To use the proposed model, we consulted the organisation's management, which formed a committee of ten members from various departments, such as the logistics, production, and sales departments, to provide the necessary data. The data obtained are summarised in the following tables. The capacity of the three suppliers to supply the three different types of raw materials to the different manufacturing plants is given in Table 3. The manufacturing capacity of the two manufacturing plants for the four types of products is given in Table 4. The demand and number of units stored by the four distributors for the four types of products are given in Table 5. The demand of the six customers for the four types of products is given in Table 6. The per-unit ordering costs of the three types of raw materials from the different suppliers are given in Table 7. The per-unit production costs of the four types of products by the different manufacturing plants are given in Table 8. The per-unit storage costs of the four types of products at the different distributors are given in Table 9. The per-unit transportation costs for the four types of products and the three types of raw materials carried by the distinct vehicle types are given in Table 10. The per-unit requirements of the three types of raw materials for manufacturing the distinct product types are given in Table 11. The distances (in kilometers) between the suppliers and the manufacturing plants are given in Table 12. The distances (in kilometers) between the manufacturing plants and the distributors are given in Table 13. The per-unit weights of the different product types are given in Table 14. The distances (in kilometers) between the distributors and the customers are given in Table 15. The per-unit weights of the different raw material types are given in Table 16. The capacity of the different types of vehicles, the fixed cost of hiring them, the available number, the emissions with a full load, and the emissions in an empty state are given in Table 17.

TABLE 5. Distibutor's demand and number of units stored.

Distributors	p_1		p_2		p_3		p_4	
	Demand (no. of units)	No. of units stored	Demand (no. of units)	No. of units stored	Demand (no. of units)	No. of units stored	Demand (no. of units)	No. of units stored
D_1	150	10	120	25	200	10	155	15
D_2	125	12	190	10	100	20	175	17
D_3	130	15	140	15	145	15	170	16
D_4	165	11	110	20	120	15	140	18

TABLE 6. Customer's demand.

Customers	Demand (no. of units)			
	p_1	p_2	p_3	p_4
C_1	87	69	86	105
C_2	74	82	72	76
C_3	63	74	72	83
C_4	67	86	83	66
C_5	59	87	90	82
C_6	60	85	69	69

TABLE 7. Ordering costs.

Suppliers	Ordering cost of raw material (Rs.)		
	a_1	a_2	a_3
S_1	150	210	175
S_2	140	215	170
S_3	151	200	160

TABLE 8. Production costs.

Manufacturing plants	Production cost (Rs.'00)			
	p_1	p_2	p_3	p_4
P_1	110	150	130	215
P_2	115	145	120	200

5.1. AHP-TOPSIS evaluation of suppliers

The suppliers are prioritised based on criteria representing economic, environmental, and social concerns, as defined in Section 2.1. The procurement team for the organisation approved these criteria, and we documented their preferences through interviews with 36 interview questions built based on prior work and the literature review. The interviews were performed in person, and the data were collected and compiled for review. The hierarchy of suppliers was then obtained and is shown in Figure 2.

Using the integrated AHP-TOPSIS technique, as discussed in Section 2.1, we follow the following steps:

Table 9. Storage costs.

Distributors	Storage cost (Rs.)			
	p_1	p_2	p_3	p_4
D_1	8	5	9	7
D_2	5	3	7	5
D_3	7	4	8	6
D_4	6	5	7	7

Table 10. Transportation costs.

Vehicle types	Transportation cost (Rs.)						
	p_1	p_2	p_3	p_4	a_1	a_2	a_3
V_1	15	14	19	18	9	7	6
V_2	10	16	17	14	10	11	8
V_3	12	13	16	12	8	4	8
V_4	11	15	16	15	9	8	7
V_5	18	20	22	23	14	13	11

Table 11. Consumption of raw material (no. of units).

Raw material types	Product types			
	p_1	p_2	p_3	p_4
a_1	9	6	10	8
a_2	10	12	9	4
a_3	11	10	6	5

Table 12. Distance between suppliers and manufacturing plants (km).

Suppliers	Manufacturing plants	
	P_1	P_2
S_1	95	70
S_2	86	93
S_3	74	65

Table 13. Distance between manufacturing plants and distributors (km).

Manufacturing plants	Distributors			
	D_1	D_2	D_3	D_4
P_1	85	92	76	69
P_2	73	65	84	57

TABLE 14. Product weight.

Product types	Weight (grams)
p_1	400
p_2	600
p_3	500
p_4	450

TABLE 15. Distance between distributors and customers (km).

Distributors	Customers					
	C_1	C_2	C_3	C_4	C_5	C_6
D_1	43	20	19	17	48	24
D_2	50	47	26	22	16	33
D_3	39	39	21	39	44	47
D_4	26	42	30	42	38	15

TABLE 16. Raw material weight.

Raw material types	Weight (grams)
a_1	20
a_2	24
a_3	26

TABLE 17. Vehicle details.

Vehicle types	Capacity (Kilograms)	Fixed cost (Rs.)	Number of vehicles	Emission in full load (gram/km)	Emission in empty state (gram/km)
V_1	800	2000	25	118.2	102.4
V_2	500	2400	16	105.6	98.6
V_3	700	2800	8	96.8	83.5
V_4	400	1800	30	19.6	8.7
V_5	900	3200	12	44.6	30.2

Step 1. The performance matrices $\lambda_{i\theta a}$ are considered.

Step 2. The normalised decision matrix $r_{i\theta a}$, as explained by equation (2.1), is obtained and is shown in Table 18.

Step 3. The pair-wise comparison matrix is considered for all the criteria, and the importance degree w_θ is obtained with the help of equation (2.2), as shown in Table 19.

Step 4. The weighted normalised matrix $v_{i\theta a}$, as explained by equation (2.3), is shown in Table 20.

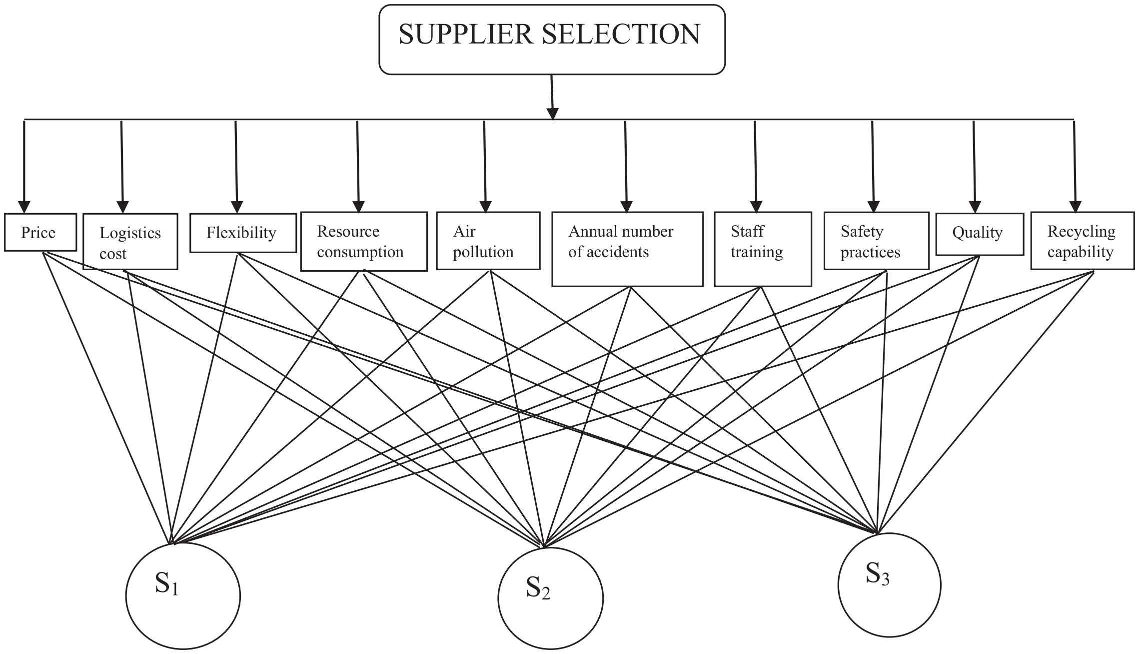

FIGURE 2. Supplier prioritisation.

TABLE 18. Normalised decision matrix.

Raw material types	Suppliers	Criteria									
a_1	S_1	0.603	0.704	0.597	0.709	0.534	0.848	0.558	0.352	0.575	0.527
	S_2	0.551	0.352	0.398	0.354	0.427	0.424	0.544	0.616	0.633	0.738
	S_3	0.577	0.616	0.696	0.61	0.729	0.318	0.627	0.704	0.518	0.421
a_2	S_1	0.476	0.505	0.398	0.565	0.602	0.425	0.423	0.643	0.379	0.425
	S_2	0.563	0.303	0.895	0.589	0.695	0.596	0.355	0.595	0.53	0.596
	S_3	0.676	0.808	0.199	0.577	0.393	0.681	0.833	0.482	0.758	0.681
a_3	S_1	0.473	0.493	0.425	0.545	0.502	0.456	0.564	0.471	0.674	0.769
	S_2	0.718	0.563	0.681	0.562	0.737	0.57	0.63	0.596	0.49	0.513
	S_3	0.51	0.663	0.596	0.622	0.454	0.684	0.534	0.649	0.552	0.385

Step 5. The positive and negative ideal solutions are obtained through equations (2.5) and (2.7), respectively, and are shown in Table 21.

Step 6. The separation distance of each alternative from the positive and negative ideal solutions is obtained from the expressions (2.8) and (2.9) and is shown in Table 22.

Step 7. The relative closeness coefficients of different suppliers obtained from equation (2.10) are shown in Table 23.

TABLE 19. Weights of criteria.

θ	1	2	3	4	5	6	7	8	9	10
w_θ	0.108	0.243	0.052	0.068	0.092	0.191	0.161	0.025	0.029	0.016

TABLE 20. Weighted normalised decision matrix.

Raw material types	Suppliers	Criteria									
a_1	S_1	0.065	0.171	0.031	0.048	0.049	0.162	0.09	0.009	0.017	0.008
	S_2	0.059	0.085	0.021	0.024	0.039	0.081	0.088	0.015	0.018	0.012
	S_3	0.062	0.15	0.036	0.041	0.067	0.061	0.101	0.018	0.015	0.007
a_2	S_1	0.051	0.123	0.021	0.038	0.055	0.081	0.068	0.016	0.011	0.007
	S_2	0.061	0.074	0.047	0.04	0.064	0.114	0.057	0.015	0.05	0.009
	S_3	0.073	0.196	0.01	0.039	0.036	0.13	0.134	0.012	0.022	0.011
a_3	S_1	0.051	0.12	0.022	0.037	0.046	0.087	0.09	0.012	0.02	0.012
	S_2	0.078	0.137	0.035	0.038	0.068	0.109	0.101	0.015	0.014	0.008
	S_3	0.055	0.161	0.031	0.042	0.042	0.131	0.086	0.016	0.016	0.006

TABLE 21. Positive and negative ideal solutions.

Positive ideal solution		Negative ideal solution	
v_1^+	0.167	v_1^-	0.198
v_2^+	0.507	v_2^-	0.296
v_3^+	0.103	v_3^-	0.074
v_4^+	0.102	v_4^-	0.124
v_5^+	0.145	v_5^-	0.171
v_6^+	0.127	v_6^-	0.048
v_7^+	0.246	v_7^-	0.321
v_8^+	0.046	v_8^-	0.037
v_9^+	0.047	v_9^-	0.053
v_{10}^+	0.029	v_{10}^-	0.024

TABLE 22. Separation distances.

Separation distance from positive ideal solution		Separation distance from negative ideal solution	
S_1^+	0.772	S_1^-	0.634
S_2^+	0.823	S_2^-	0.654
S_3^+	0.71	S_3^-	0.58

Table 23. Relative closeness coefficients.

Suppliers	Relative closeness to the ideal solution
S_1	0.5644
S_2	0.4378
S_3	0.5695

Table 24. Input and output data for DEA analysis.

	Parameters	Vehicle types				
		V_1	V_2	V_3	V_4	V_5
Input	Fuel cost (Rs)	66.08	45.20	55	21	52
	Use of sustainable fuel	0	1	1	1	1
Output	Fuel efficiency (per km)	50	30	40	10	48
	Carbon emission in full load (gram/km)	118.2	105.6	96.8	19.6	44.6
	Carbon emission in empty state (gram/km)	102.4	98.6	83.5	8.7	30.2
	Safety	8	2	6	7	6

5.2. Cross-efficiency evaluation of vehicles

As mentioned above, the vehicle types are assessed on sustainability parameters to determine their strengths and weaknesses. The cross-efficiency scores are calculated utilising several inputs and outputs. The inputs and outputs are selected based on positive and negative criteria influencing transportation decisions. The team's preferences from the logistics department were recorded based on a specifically designed questionnaire using a 7-point verbal scale. Since the necessary data were both objective and subjective, we chose the accompanying inputs and outputs mentioned in Table 24.

The inputs concerning the use of sustainable fuels are expressed as a binary variable that takes the value one if a sustainable fuel is used 0 otherwise. The safety output parameter is measured on a 10-point scale, where ten corresponds to maximum safety, and one corresponds to minimum safety. To obtain a cross-efficiency score, the simple efficiency of the vehicles is first obtained from the CCR model [22]. The simple efficiency scores for the vehicles are shown in Table 25. The matrix E, which represents the cross-efficiency of vehicle j evaluated by vehicle i, is obtained with the help of equation (2.11), as explained in Section 2.2.

$$\begin{array}{c} \\ e_1^* \\ e_2^* \\ e_3^* \\ e_4^* \\ e_5^* \end{array} \begin{array}{c} \begin{array}{ccccc} e_1 & e_2 & e_3 & e_4 & e_5 \end{array} \\ \begin{bmatrix} 1 & 0.877 & 0.961 & 1 & 0.893 \\ 1 & 1 & 0.965 & 0.855 & 1 \\ 1 & 1 & 0.968 & 0.995 & 0.934 \\ 1 & 1 & 0.868 & 0.872 & 0.962 \\ 1 & 1 & 0.974 & 0.895 & 1 \end{bmatrix} \end{array}.$$

The cross-efficiency scores of the vehicle types shown in Table 26 are obtained by averaging each column of the matrix E, as explained in equation (2.12).

5.3. The trade-off solutions of sustainable supply chain

The multi-objective multi-commodity optimisation model formulated in Section 3 is solved as follows: Inserting the values from Tables 5, 7–10, 12–14, and 17 in equation (3.1) helps in the development of the first objective

TABLE 25. Simple efficiency scores.

Vehicle types	Simple efficiency score
V_1	1.0
V_2	1.0
V_3	0.968
V_4	0.985
V_5	0.998

TABLE 26. Cross-efficiency scores.

Vehicle types	Cross-efficiency score
V_1	1.0
V_2	0.9754
V_3	0.9472
V_4	0.9234
V_5	0.9578

function. Inserting the values from Tables 12–14 and 15–17 in equation (3.2) helps develop the second objective function. Inserting the values of the closeness coefficient mentioned in Table 23 in equation (3.3) helps develop the third objective function. Inserting the cross-efficiency scores mentioned in Table 26 in equation (3.4) helps develop the fourth objective function. The raw material supply constraint (3.5) is formulated using the data from Table 3. The distributor and customer demand constraints (3.6) and (3.7) are formulated by utilising the data from Tables 5 and 6. The production and balancing constraints (3.8)–(3.10) can be easily obtained. The vehicle capacity and vehicle availability constraints (3.11)–(3.14) are formulated by utilising the data in Table 17. The other constraints (3.15)–(3.17) are relationship constraints between decision variables and binary variables, and the integrability assumption is mentioned in equation (3.18). We formulate the model and apply the LGP method explained in Section 4 to solve for distinct cases of the formulated model leading to trade-off solutions, as presented in Table 27.

Each solution presented in Table 27 is an Pareto-optimal solution. In Case I, we observe that Z_4 and Z_3 achieve their aspiration values, but compromise solutions are obtained for Z_1 and Z_2. In Case II, the interchanging priority of Z_1, Z_2, and Z_3 significantly impact the solution. In this case, only Z_4 attains its aspiration level; the other objective functions have compromise values, but the values of Z_1 and Z_2 are indeed closer to their aspiration levels than they are in Case I. Keeping Z_1 at second priority in Case III improves the solutions for Z_1 and Z_2 but degrades the value of Z_3. Interchanging the priority of Z_2 and Z_3 in Case IV does not produce any real change in the solution. Similarly, other cases can be analysed in which changes in the priority of the objective functions lead to a different solution set every time. Hence, the observed solutions validate the proposed model.

The different trade-offs between the four objective functions regarding the solutions presented in Table 27 are shown in Figures 3 and 4. Figure 3 depicts the trade-off between four objective functions when considering two at a time. From Figures 3a, 3b, and 3d, it is evident that the values of Z_1, Z_2, and Z_3 fluctuate with changes in their assigned priorities in different scenarios. Regardless of the priorities assigned to them, the values of Z_1, Z_2, and Z_3 exhibit an inverse relationship with Z_4. Conversely, in Figures 3c, 3e and 3f, the

Table 27. Distinct solutions.

Cases	Objective function	Z_1	Z_2	Z_3	Z_4
	Aspiration levels	28 074 190	3 069 358	39 848	48.064
	Priorities of objective function	Compromise values			
Case I	I: Z_4; II: Z_3; III: Z_1; IV: Z_2	72 197 590	5 269 016	39 848	48.064
Case II	I: Z_4; II: Z_2; III: Z_3; IV: Z_1	37 321 680	4 199 440	17 246.94	48.064
Case III	I: Z_4; II: Z_1; III: Z_3; IV: Z_2	28 074 190	3 594 519	16 921.22	48.064
Case IV	I: Z_4; II: Z_1; III: Z_2; IV: Z_3	28 074 190	3 586 015	16 921.22	48.064
Case V	I: Z_3; II: Z_2; III: Z_4; IV: Z_1	75 930 330	4 870 297	39 848	20.38
Case VI	I: Z_3; II: Z_1; III: Z_2; IV: Z_4	72 197 590	5 269 016	39 848	20.427
Case VII	I: Z_2; II: Z_1; III: Z_3; IV: Z_4	35 575 540	3 069 357	17 227.33	14.491
Case VIII	I: Z_2; II: Z_3; III: Z_1; IV: Z_4	35 823 000	3 069 357	17 240.92	14.491
Case IX	I: Z_2; II: Z_4; III: Z_3; IV: Z_1	35 823 000	3 069 357	17 240.92	48.064

value of Z_4 remains constant until case 4, gradually decreasing as its priority decreases. Figure 4 presents a three-dimensional visualisation of the trade-off between all four objective functions when considering three at a time. Figure 4a demonstrates that, as priority increases, the values of Z_1 and Z_2 decrease while the value of Z_3 increases, supporting the validity of the proposed model. Similar insights can be derived from the other figures.

From the above discussion, it can be noted that simultaneous optimisation of all four objectives is not attainable. However, applying the suggested approach achieves the economic, environmental, and social objectives of Ctflomag to the greatest extent possible. If the manager prioritises selecting a sustainable supplier and vehicle cross-efficiency, he will pursue Case I. However, if only the cross-efficiency of the vehicle is prioritised, Case II would be considered. If the manager needs some cost improvement with vehicle cross-efficiency, then Case III will be an option. Similarly, it is possible to consider other cases as per the manager's preferences. Hence, the behaviour of the proposed model has been examined using the case study provided and found to be beneficial to the company. Similarly, other organisations may implement the proposed model to achieve sustainability in their supply chains.

5.4. Trade-off solutions for radical changes

The following test cases address the utility of the various objective functions in the cost-savings of the proposed model, taking Table 27 as a baseline solution. The revised values of the various objective functions for Cases A, B, and C are shown in Table 28.

- Case A: the cross-efficiency score objective function is dropped, and the cost objective function is given the lowest priority in Case II of Table 27. As a result, the total cost and quantity of emissions increase. However, the objective function of the closeness coefficient of suppliers, which is the highest priority, is heading towards optimality. It can be seen that if the efficiency score objective function is dropped, inefficient vehicles are selected for some routes, which leads to an increase in the emissions function.
- Case B: the cross-efficiency score objective function is dropped, and the cost objective function is given the highest priority in Case III of Table 27. This results in the achievement of the aspiration value for the cost objective function but leads to an increase in the value of the emissions objective function. Further, the objective function of the closeness coefficient of suppliers shifts further away from its aspiration value.
- Case C: the emissions objective function is dropped, and the closeness coefficient of suppliers is given the highest priority in Case VIII of Table 27. This results in the achievement of the aspiration value of the objective function of the closeness coefficient of suppliers. However, because of the elimination of the emissions function, the total cost heads towards optimality; the sustainability restriction is ignored, whereas the total efficiency score objective function decreases.

Table 28. Modified solutions.

	Objective function	Z_1	Z_2	Z_3	Z_4
	Aspiration levels	28 074 190	3 069 358	39 848	48.064
Cases	Priorities of objective function	Compromise values			
Case A	I: Z_3; II: Z_2; III: Z_1	7 593 030	4 870 297	39 848	–
Case B	I: Z_1; II: Z_3; III: Z_2	28 074 190	4 853 940	14 266	–
Case C	I: Z_3; II: Z_1; III: Z_4	30 824 100	–	39 848	12.34

Table 29. Numerical comparison.

	Objective functions			
	Z_1 (min)	Z_2 (min)	Z_3 (max)	Z_4 (max)
Tirkolaee *et al.* [77]	50 448 330	2 779 652	–	–
Proposed model	37 504 190	3 002 504	–	–
Mehlawat *et al.* [51]	641 070	–	–	37.808
Proposed model	588 490	–	–	48.064
Niakan *et al.* [58]	19 941 920	2 697 555	–	–
Proposed model	20 026 780	2 148 858	–	–

Furthermore, several other cases can be constructed by dropping the other objective functions specified in the proposed model and giving different priorities to the various objective functions to see the effects. Consequently, all the objective functions defined in the proposed model are significant for cost-savings.

5.5. Critical findings of the paper

This section presents the critical findings of the proposed multi-objective multi-commodity optimisation model by comparing it numerically to the results for existing models in the literature. Table 29 provides a quantitative comparison of the proposed model with the closely related existing models to explain its validity.

I Comparison with [77]: in order to compare our proposed model with the approach of Tirkolaee *et al.*, we evaluate the model of Tirkolaee *et al.* using the numerical data from this paper. Some adjustments are needed to both models to bring them to the same basis. One of the major adjustments to the proposed model is to drop the index of the different types of products since the comparative paper is not multi-commodity. Since the proposed model is a single-period model, the planning period index has been removed from the comparative paper. Here, the emission objective function and the cost objective function's values are compared.
Using the model of Tirkolaee *et al.*, the minimal cost value is 50 448 330, and the minimum emissions value is 2 779 652, but the suggested model produces a cost of 37 504 190 and emissions of 3 002 504. As can be observed, the suggested model generates emissions that are marginally greater than those produced by Tirkolaee *et al.*'s model, but the total cost differs significantly. The cost of sustainable results is something that organisations are willing to pay a little bit more for, but if the cost is too high, they might not be as willing to spend as much. Thus, the above result demonstrates the proposed approach's more practical applicability.

II Comparison with [51]: in order to compare our proposed model with the approach of Mehlawat *et al.*, we evaluate the model of Mehlawat *et al.* using the numerical data from this paper. Some adjustments are needed to both models to bring them to the same basis. One of the major adjustments to the proposed model is to drop the index of the different types of raw materials and different types of products since the comparative paper is not multi-commodity. The values of the cost objective function and the efficiency-score objective function are compared here.

Applying Mehlawat *et al.*'s approach, the minimum cost value is 641 070, and the maximum value for efficiency is 37.808, while the proposed model generates a cost of 588 490 and an efficiency of 48.064. It can be seen that the proposed model provides a better solution to both the objective functions (lower costs and greater efficiency). Mehlawat *et al.*'s approach evaluated simple efficiency, while the proposed approach evaluates cross-efficiency so that a higher efficiency score is obtained. The above results, therefore, justify the proposed approach.

III Comparison with [58]: to compare our proposed model with the approach followed by Niakan *et al.*, we evaluate their model using the numerical data from this paper. Some modifications are required for both models to bring them to the same standard. One of the key adjustments to the proposed model is to reduce it from a three-stage supply chain problem to a two-stage supply chain problem since the comparative paper is a two-stage supply chain problem. The values of the cost objective function and the emissions objective function are compared here.

Applying Niakan *et al.*'s approach, the minimum cost value is 19 941 920, and the minimum emissions value is 2 697 555, while the proposed model generates a cost of 20 026 780 and emissions of 2 148 858. It can be seen that the proposed model produces a cost slightly higher than Niakan *et al*'s model, but that the emissions are much lower. Organisations do not mind paying slightly higher costs to minimise pollution. Hence, the above result illustrates the utility of the proposed approach.

6. Managerial benefits

This research has some managerial benefits, which are presented in this section. The paper aims to develop a sustainable supply chain model that experts recognise as meeting requirements. It can provide competitive advantages through improved efficiency and market differentiation. Supply chain management strives to make environmentally sustainable choices to reduce the environmental consequences of the supply chain, which may include industrial waste, water contamination, deforestation, hazardous air emissions, and long-term damage to ecosystems. The main factors cited for implementing sustainable supply chain management are customer expectations, top management commitment, managers' moral and ethical values, reputation management, and economic and operational benefits, whereas cost concerns, structural and strategic constraints, supplier and customer issues, and a lack of efficient regulations were cited as major roadblocks [70]. Despite these challenges, companies continue to implement sustainability practices to protect the environment. Companies that aim for sustainability have market advantages such as enhanced brand visibility, the ability to attract more environmentally conscious customers, improved productivity, and quality. This implies that, after the initial costs, sustainability investments will substantially help reduce long-term expenses.

Minimal costs and effective response strategies are important if companies are to become front runners. The multi-objective model that we have developed tries to minimise total costs, including the transportation costs, ordering costs, production costs, and inventory costs of the various raw materials and products. The proposed model manages the supply chain to achieve a consistently successful performance. Effective supply chains make it possible for a business to be more efficient in achieving customer satisfaction goals at the lowest cost. The proposed model helps control, speed up product flow, and reduce supply chain costs by optimising the usage of fixed assets within the supply chain, such as manufacturing plants, warehouses, and vehicles.

The transportation network is the backbone of the supply chain. It is important for every organisation, as it links the organisation to its suppliers and customers. The distribution of raw materials for production and the distribution of finished products for consumption depends solely on transportation. Prioritising various vehicles according to sustainability criteria aids in gaining a realistic understanding of their utility in achieving specified objectives [30]. The supply chain is required to have the most convenient, effective, and economical means of transportation that benefit customers' loyalty. An efficient transport system contributes to economic prosperity and brings benefits not only to service quality but also to the company's competitiveness. However,

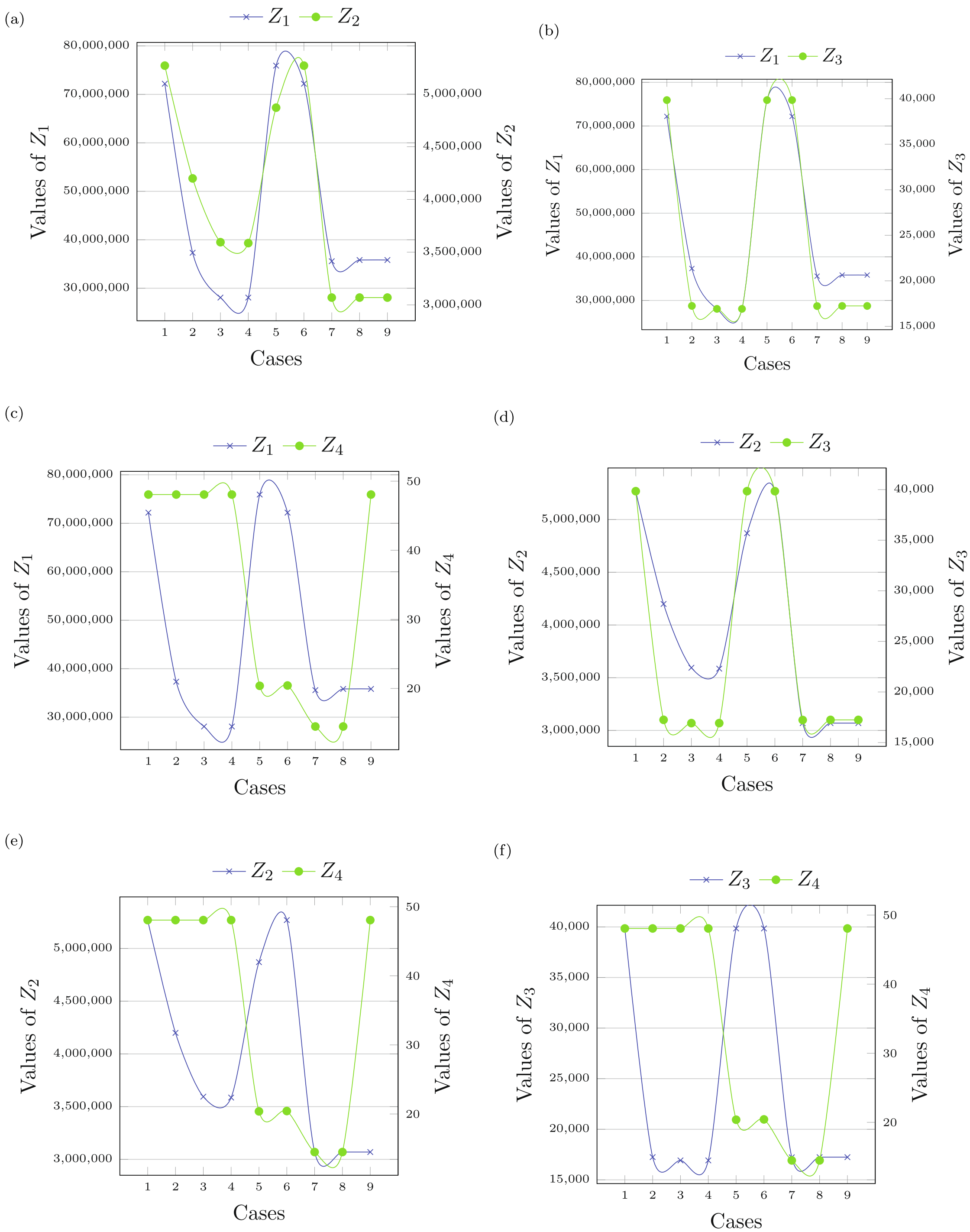

FIGURE 3. Tradeoff between the values of each pair of objectives. (a) Trade-off between Z_1 and Z_2. (b) Trade-off between Z_1 and Z_3. (c) Trade-off between Z_1 and Z_4. (d) Trade-off between Z_2 and Z_3. (e) Trade-off between Z_2 and Z_4. (f) Trade-off between Z_3 and Z_4.

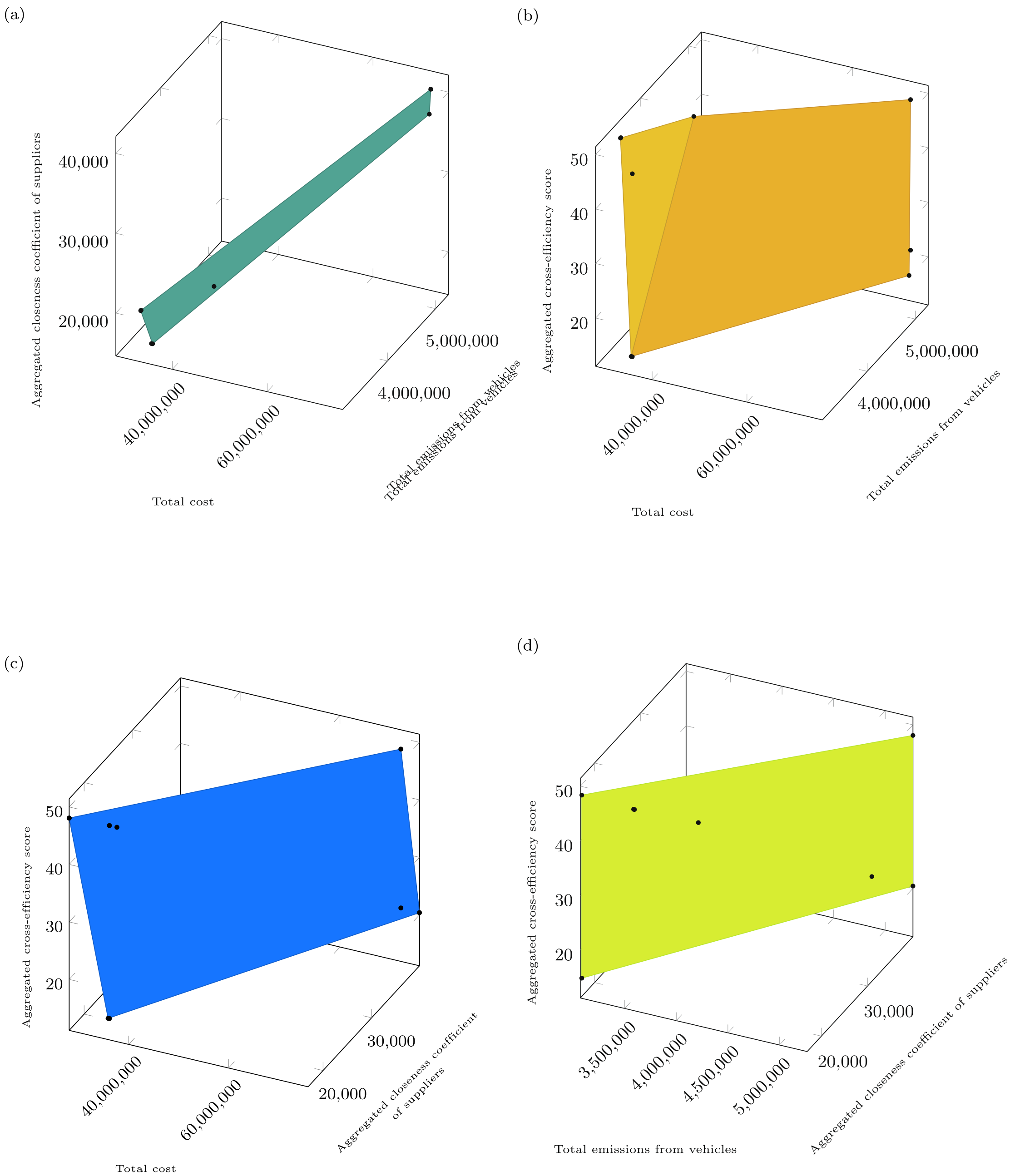

FIGURE 4. Three dimensional visualisation for each combination of objective function values. (a) Z_1, Z_2, and Z_3. (b) Z_1, Z_2, and Z_4. (c) Z_1, Z_3, and Z_4. (d) Z_2, Z_3, and Z_4.

transportation can be hazardous as it causes environmental pollution, accidental injury, and death. Hence, the proposed optimisation model minimises the emissions from vehicles and simultaneously maximises the efficiency of vehicles. The model enables supply chain managers to plan a transportation network that emphasises more efficient alternatives.

A supplier in business serves as a bridge between the producer and the consumer, ensuring proper communication among them and ensuring that the stock is of good quality. The role of a supplier in business is crucial, as customers expect a certain level of quality. Furthermore, suppliers must be flexible and reliable and must manage relationships so a business can ensure the efficient supply of products. The last objective of the proposed model is to maximise the priorities of suppliers; these priorities are strategically chosen according to various criteria such as price, quality, and flexibility. Different weights are given to these factors according to their importance to the business. The proposed integrated AHP-TOPSIS technique significantly increases the efficiency of the decision-making process in supplier selection. The selection of the most suitable supplier is important, as inefficient suppliers can damage the company's brand.

Multi-objective problems are essential for decision-making, as they analyse all the trade-offs between conflicting objectives. The multi-objective optimisation problem presented in this paper aims to minimise the total cost and emissions from vehicles and simultaneously maximise the efficiency of vehicles and the priorities concerning suppliers. The four objectives are conflicting in nature. Hence, a compromise solution to the problem is obtained by applying the lexicographic goal programming technique.

Sustainable transport systems entail policies, technologies, and other activities that improve system efficacy while minimising detrimental effects on the environment and social life [73]. For companies, transportation planning plays a crucial role in allowing meaningful reductions to operational costs and enhancing profitability. Efficient transportation planning allows the supply chain to operate smoothly. The proposed model applies to any manufacturing company wishing to develop a sustainable supply chain, and it benefits the company in several ways, including by reducing overall operating costs, enhancing customer satisfaction, taking care of social responsibility, reducing its carbon footprint, minimising energy usage, and retaining organisational competence. The developed model is better than the existing models in the literature as it enables the organisation to make decisions while considering multiple factors, such as cost reduction, emissions reduction, sustainable supplier selection, and use of efficient vehicles, simultaneously. Further, it strengthens transportation planning, allowing businesses to be sustainable and prosperous in a competitive market. Managers in manufacturing companies can adapt the results obtained to plan, identify, evaluate, analyse, and interpret all the operations involved in the supply chain to provide a strategic solution to logistical bottlenecks. The suggested model is a multi-objective mixed-integer non-linear programming problem, and there are several approaches available in the literature to solve it, making it easy to implement in practice. The challenges faced when using the model are during the collection of data concerning the selection of suppliers since much of the data is subjective. There are also some limitations in the established model since it does not consider volatility in fuel prices, increased customer expectations, the hiring and retention of drivers, or increased enforcement complexities. The proposed model could be used as a practical tool in various industries. One example might be the automotive industry, which has high costs and, at the same time, demands sustainability. The automotive industry needs realistic solutions because of globalisation, changes in production processes, market demands, and many other factors. Internal and external factors require managers in the automotive supply chain to minimise costs, optimise production and distribution, and select appropriate suppliers. The increasing competition in the automobile industry means that the given model can be of great benefit to car manufacturers.

7. Conclusion and future work

The supply chain is considered the most challenging segment to make sustainable, but it is also one of the critical segments. With the growing awareness of sustainability issues in society, improvements in sustainability within supply chains are strongly supported by customers. The focus of this paper is the environmental impact of logistics. Additionally, the paper aims to establish an optimisation model to facilitate strategic decision-making.

The proposed model is helpful for any organisation, as it can provide benefits in several ways. The organisation can benefit by reducing its expenditures, increasing its revenue, reducing carbon emissions, selecting sustainable suppliers, and using vehicles effectively. Embedding sustainability efforts in the organisation's supply chain is costly but has a positive impact on business performance in the long term. The performance of the supply chain is enhanced by the selection of sustainable suppliers and the efficient use of the transportation system. An integrated AHP-TOPSIS technique and cross-efficiency DEA evaluation are applied to accomplish this objective.

The lexicographic goal programming technique solves the proposed multi-objective optimisation model. The purpose of using this technique is to take account of different priorities assigned to the objectives by the decision-maker. The company can apply the solution obtained from the specified objective functions to restructure its supply chain and increase overall productivity with cost savings. It enables users to construct numerous scenarios for long-term analysis. Finally, the real-world case study is a substantial addition to the description of the proposed approach and permits superior comprehension of the proposed model.

Our current study has some shortcomings that could be the focus of future research. The study primarily deals with a deterministic problem, but it may be more practical to explore uncertain environments. Furthermore, due to technological constraints, the number of facilities addressed in the case study is quite limited, which might be increased further by building a software code for the suggested model. In future work, we may further consider broadening the research on sustainable supply chains to incorporate recycling. Emphasising waste management for sustainable development is vital, as it not only reduces costs but can also confer a competitive advantage to companies.

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The authors confirm that they have adhered to publication ethics and assert that this work is original and has not been previously published.

Informed consent

All authors consented to the publication.

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