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Integrated Supplier Selection and Inventory-Controlled Order Allocation via Fractional Programming

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ABSTRACT

Objective: The Supply chain plays a key role in adapting the organization to variable conditions and an uncertain future. The selection of appropriate suppliers can significantly increase the competitiveness and ability of a business in the market. One of the essential factors in supply chain optimization is controlling and managing inventory cost. This paper aims to simultaneously optimize supplier selection and order allocation while considering inventory control using a fractional programming approach.

Methodology: The methodology integrates quantitative analytical techniques in a multi-phase approach. First, the most frequent supplier selection criteria are identified with a literature review. The Delphi method was used to select the supplier selection criteria. In the next step, fuzzy Shannon entropy determines criterion weights. Then, fuzzy EDAS calculates supplier performance scores. Finally, fractional programming facilitates supplier selection and order allocation.

Results: The most frequent supplier selection criteria were extracted from the literature review. In the Delphi technique, experts ultimately agreed on six key criteria: price, quality, delivery, flexibility, responsiveness, and financial stability. The results of the Shannon entropy analysis indicate that flexibility, with a weight of 0.20, holds the highest relative importance among the criteria. The suppliers score obtained from the fuzzy EDAS method is used as one of the parameters of the mathematical model.

Conclusion: The proposed hybrid MADM approach and mathematical model have been validated using empirical data obtained from Sirjan Steel Company. The result shows that the hybrid MADM approach and fractional programming have high accuracy in selecting the best supplier.

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Introduction

Different conditions and diversity of supplier evaluation criteria in supplier selection have been necessary in supply chains because procurement costs constitute a significant part of costs in many industries. Many criteria can be considered in supplier selection, such as quality, price, delivery performance, and distance to the buyer (Çabuk & Erol, 2019) Manufacturing industries continuously strive to optimize operating costs to enhance profitability, as the production process involves multiple cost components, including procurement and inventory costs.. Procurement costs are incurred while purchasing raw materials or products; inventory costs are required to store raw materials and products in the warehouse. A manufacturer usually has several suppliers with different requirements, such as product price, transportation cost, maximum capacity to supply the product, product defect rate, and product late delivery rate. This means that procurement cost can be optimized by selecting the optimal supplier or, in a more advanced technique, determining the optimal order quantity for each supplier (Sutrisno et al., 2022).

The success of an organization depends on its ability to create a reliable and effective supply chain. This decision is critical for a business to enter the global and competitive market (Akbari Arbatan et al., 2025). In addition, all levels of the supply chain must operate as an integrated and coordinated system to achieve sustainability in the industry (Ghasemi et al., 2025). Supply management of strategic items can have a significant impact on a company's profits, so raw materials must be sourced from appropriate suppliers in the correct quantities, at competitive prices, according to the delivery schedule to ensure that the final products are delivered on time and meet high-quality standards (Alejo-Reyes et al., 2021).

The selection of appropriate suppliers is critical to a company's success. The complexity of supply and the rapid change of the global market have forced companies to focus on risk reduction. Risk reduction is significant for strategic items because it significantly affects overall supply chain performance. Among the diverse activities within the supply chain, the procurement of raw materials and components is considered a strategic function, as it offers significant opportunities for cost reduction across the entire supply chain. In most industries, the costs associated with raw materials and components constitute a substantial proportion of the overall product cost. For example, in high-tech companies, purchased services and materials account for 80% of the total product cost (Ventura et al., 2013). The selection of appropriate suppliers can increase the competitiveness of a business. In most industries, the main cost of a product depends on the cost of raw materials and components. The supply of raw materials and its inventory control can play a key role in the efficiency and effectiveness of a business and have a direct impact on its cost reduction, profitability, and flexibility (Rabieh et al., 2016)

Previous studies have incorporated risk factors into supplier selection. However, these studies do not simultaneously consider uncertainty and risk factors regarding delivery delays, poor quality, and disruptions. Furthermore, these studies do not accurately consider risk factors and the integration of disruption risk reduction strategies through inventory management. Studies on supplier selection have been conducted using multi-criteria decision-making (MCDM) approaches, including the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). However, although these methods can consider different types of criteria, a stand-alone MCDM method cannot correctly evaluate supplier selection and accurately represent the nature of disruptions, and manage their effects on parameters that change dynamically according to the nature of the disruptions (Saputro et al., 2023).

Supplier selection and order allocation (SSOA) are fundamental decisions in supply chain management that are often studied through deterministic models, multi-objective optimization, and multi-criteria decision-making (MCDM) techniques. According to a review article (Nguyen et al., 2024), numerous studies have been conducted in the field of supplier selection and order allocation. However, according to Table 3 of this article, which categorizes the studies in this field based on the operations research techniques used, no fractional programming studies were found. Also, a search in the Scopus citation database with the keywords "supplier selection" and "order allocation" in the title and "fractional planning" in the title, abstract, or keywords did not find any articles. Fractional programming has been used in supply chain literature to optimize ratios such as total return on capital (W. Ali et al., 2025) and the total cost per unit (Joshi & Gupta, 2011), However, its application to supplier selection and order allocation has been investigated to a limited extent. Given the potential of fractional models in supply chain-related assessments, this paper applies fractional planning to the supplier selection and order allocation problem by introducing an integrated framework.

To fill the research gap based on the literature, this study considers two problems in supplier selection. First, fuzzy Shannon entropy and fuzzy EDAS are used to incorporate the uncertainty of decision-makers in their perception when determining the weight of criteria and evaluating suppliers, respectively. Second, the main innovation is the application of fractional programming to the supplier selection and order allocation problem, enabling the optimization of ratios rather than absolute values. In this study, the supplier score obtained from the fuzzy EDAS method is considered as one of the parameters of the mathematical model. In fact, the output of the fuzzy EDAS is considered as the input of the mathematical model. This study aims to select suppliers for strategic items by incorporating qualitative and quantitative criteria, accounting for uncertainty in decision-makers' judgments, and integrating the process with inventory management. The proposed optimization model is a multi-objective model that maximizes the total purchase value and minimizes the total costs (purchase, inventory, and transportation costs). In order to achieve these goals, the research questions are: 1- What are the supplier selection criteria in the steel industry? 2- What is the weight of the criteria using the fuzzy Shannon entropy method? 3- How is the supplier score calculated using the fuzzy EDAS method? 4- Using the fractional programming approach, what is the mathematical model for allocating orders to selected suppliers? The article continues with the research background, methodology, findings, conclusions, and suggestions.

Literature Background

A supply chain consists of processes, activities, and entities creating, producing, distributing, and delivering consumer goods and services. It includes suppliers, manufacturers, distributors, retailers, and various intermediaries that work together to ensure the smooth flow of products from source to consumer (Miar et al., 2024). A supply chain is a network that encompasses people, resources, activities, and all stages of the process by which a product reaches the customer from the primary producer. The transfer of inputs to the production center for the production stage, the preparation of the product, and then its delivery to the final consumer, dealing with external factors such as waste and residue after the product is produced, are all components of the supply chain process (Güneri & Deveci, 2023).

In the supplier selection, companies identify, screen, evaluate, and analyze potential suppliers to ensure alignment with strategic objectives and operational requirements. Choosing the appropriate supplier affects the purchasing cost and helps supply chain managers achieve effective operational performance. Supplier selection has been widely studied in supply chain, operations management, operations research, etc. The traditional method of selecting suppliers focuses only on price, but in the modern method, the focus is on quality, quantity, technology, order-to-delivery time, service, etc (Agrawal, 2022). The selection of appropriate suppliers is a key success factor for any manufacturing or service business because it significantly reduces purchasing costs, increases customer satisfaction, and improves competitive ability. In this context, the supplier selection process is considered one of the most critical activities in procurement and supply management, and it is recognized as a key managerial responsibility. The selection of appropriate suppliers is not an easy decision because it requires the simultaneous consideration of quantitative (e.g., cost) and qualitative (e.g., environmental responsibility) criteria that are generally in conflict with each other (Alegoz & Yapicioglu, 2019).

Supplier selection significantly influences the purchasing process. Appropriate selection of suppliers has become vital because it improves industrial companies' competitive advantages. In this regard, selecting the best suppliers affects the quality and price of the final product and increases customer satisfaction. However, supplier selection is complex because several criteria must be considered, such as prices, volume discounts, reliability, and quality. Therefore, companies explore and implement various decision-making methods and models to select the most suitable final suppliers (Alejo-Reyes et al., 2020).

Literature Review

Traditional models often focus on short-term efficiency and ignore supplier development as a critical strategy for improving sustainable performance, hence (Dai et al., 2025) proposed an integrated decision-making framework that integrates supplier selection, supplier development, and order allocation into a comprehensive approach to strategic sourcing. This framework uses a two-stage robust optimization model to effectively align short-term performance with long-term goals (Hayati et al., 2025). A four-stage framework was proposed for planning sustainable supplier selection and order allocation. The goal of this model is to minimize the total purchasing cost, the probability of product defects, and the environmental impact, while maximizing the total value of the allocated order. (Rezaie et al., 2025) a new data-driven approach was proposed based on data mining and decision-making methods by focusing on the problem of supplier selection and order allocation with prominent features such as resilience, circular economy, and customer-oriented dimensions. The results show that cost, quality, waste management, service level, and resilience are the most desirable indicators. The proposed model identifies the best suppliers and determines the optimal location for constructing facilities. In addition, the results confirm the efficiency and validity of the developed data-driven approach. Also, the sensitivity analysis results show that with the increase of the demand parameter, the total cost and the supply chain resilience increased, while the service level decreased. (Wang et al., 2025) investigate sustainability in supplier selection and order allocation problem under parameter uncertainty. This study aims to balance four conflicting objectives of cost, carbon dioxide emissions, social impacts, and the overall value of suppliers. In the proposed model, priority levels reflect decision-makers' preferences. At the same time, sets of internal and external uncertainties are incorporated to manage the multiplicity of uncertainty sources effectively. The results highlight the model’s ability to balance conflicting objectives while maintaining resilience to uncertainty and provide significant value for sustainable supply chain management. Also, the sensitivity analysis results show that with the increase of the demand parameter, the total cost and the supply chain resilience increased, while the service level decreased. (Ye et al., 2024) combine the theories of sustainable and resilient supply chains with the principles of risk management and carbon emission reduction in a framework for supplier selection. They introduced a specialized decision-making model for the food industry by employing the Delphi method, fuzzy analytic hierarchy process, and fuzzy multi-objective programming. The proposed framework ensures supply chain sustainability and aligns with sustainable development goals, improving supply chain efficiency and competitiveness. (Jafari-

Raddani et al., 2024) proposed a three-stage method for sustainable supplier selection and order allocation. In the first stage, fuzzy AHP and TOPSIS methods were employed to determine the criteria weights and rank sustainable suppliers accordingly. Suppliers with acceptable performance in the field of sustainability were selected. The future demand value was predicted using polynomial regression in the second stage. In the third step, a mathematical programming model is formulated considering a new policy in the quality standard. Efficient solutions are obtained by solving a multi-objective and multi-period stochastic integer mixed model using the LP criterion. (H. Ali et al., 2023) proposed an integrated approach for global supplier selection and order allocation in the context of developing an environmentally friendly supply chain under data uncertainty. In this approach, after determining the weight of supplier evaluation criteria with fuzzy analytic hierarchy process and ranking suppliers with fuzzy TOPSIS, the results are used in a multi-choice goal programming model that includes multi-objective levels to allocate the optimal order quantity to global suppliers. (Kaur & Prakash Singh, 2021) proposed a model for evaluating suppliers based on criteria aligned with the Industry 4.0 environment, utilizing Data Envelopment Analysis (DEA) for performance assessment and applying FAHP-TOPSIS for prioritization. The risk associated with each supplier is calculated. This paper also proposes a Mixed Integer Program to optimize the allocation of multi-period and multi-item orders to suppliers to minimize the overall cost and disruption risk. (Alegoz & Yapicioglu, 2019) developed a hybrid approach based on fuzzy TOPSIS, fuzzy trapezoidal AHP type 2, and goal programming. This approach simultaneously considers qualitative and quantitative criteria, considers the specific requirements of each case, such as capacity constraints, package size constraints, and quantity discounts, and finally determines not only the suitable supplier for cooperation but also performs the order allocation. The results indicate that this approach effectively identifies a trade-off among conflicting criteria and generates an order allocation that satisfies all relevant constraints.

(Abtahi & feili, 2024) proposed a hybrid approach for supplier selection and order allocation to improve quality performance and use multi-criteria decision-making methods. The main objective of this research is to develop a comprehensive method, including the SWARA technique, for evaluating quality criteria, goal planning, and sensitivity analysis for optimal supplier selection (Khosroabadi et al., 2024). Bayesian networks have been utilized to address disruptions in supplier selection and their impact on supplier–manufacturer relationships and customer demand. This study incorporates inflation rates to forecast and mitigate demand uncertainties. Furthermore, a bi-objective mixed-integer stochastic programming model has been employed to enhance geographical diversification and minimize total cost while accounting for supplier reliability.

(Keshavarz-Ghorabaee, 2024) proposed a multi-objective model based on group decision making and interval-valued Pythagorean fuzzy sets for the supplier selection and order allocation problem. (AmirSalami & Alaei, 2023) proposed a hybrid approach of fuzzy multi-criteria decision making and bi-objective mathematical modeling for the problem of green supplier selection and order allocation. (Hooshmandi Maher et al., 2014) have investigated uncertainty in supply chain planning by considering the multi-criteria nature of the problem of supplier selection and order allocation. (Teymouri et al., 2020) proposed a mixed zero-one nonlinear model for order allocation to suppliers, multi-product pricing with uncertain demand, and supplier discount offer by expanding the newsagent problem, which the response surface methodology technique and genetic algorithm have solved.

Materials and Methods

This study aligns with the positivist paradigm because it adopts quantitative methods. From a research objective standpoint, the study is classified as applied research. In terms of data type, it falls within the category of quantitative research, and regarding data collection, it utilizes a descriptive-survey approach with a cross-sectional design. The data were analyzed using fuzzy multi-criteria decision-making (MCDM) methods and fractional mathematical programming. Specifically, the most frequent supplier selection criteria are identified through a literature review. The Delphi method was used to select supplier selection criteria; fuzzy Shannon entropy was applied to determine the weights of these criteria; fuzzy EDAS (Evaluation based on Distance from Average Solution) was utilized to assess and score suppliers, and fractional mathematical modeling was implemented to allocate orders to the selected suppliers. The supplier scores derived from the fuzzy EDAS method were employed as input for the mathematical model.

Selection of key criteria: The Delphi method is a structured process for gathering and synthesizing expert knowledge, typically conducted through iterative rounds of questionnaires distributed among a panel of specialists, with controlled feedback on responses (Güneri & Deveci, 2023). In this study, to obtain expert insights on supplier evaluation criteria, the opinions of 11 professionals from the steel industry were obtained. The profiles of these experts are presented in Table 1.

Table 1. Expert Profiles

Expert Code	Position	Job Responsibility	Supply Chain Experience (Years)	Industry Experience (Years)	Education
1	Purchasing Planning Manager	Identification and evaluation of suppliers	8	15	B.Sc. in Industrial Engineering
2	Procurement Supervisor	Product purchasing operations	10	16	M.Sc.
3	Commercial Supervisor	Oversight of purchase and sales contracts	7	20	M.Sc.
4	Contracts Manager	Tender management and contractor selection	22	22	Ph.D.
5	Foreign Purchasing Manager	Management of foreign purchases	7	13	B.Sc.
6	Contracts Supervisor	Reviewing the terms and conditions of contracts	10	20	B.Sc.
7	Purchasing Planning Officer	Supplier database review	7	13	M.Sc.
8	Purchasing Planning & Support Manager	Purchasing planning	5	30	B.Sc.
9	Commercial Officer	Coordination of commercial operations	5	7	M.Sc. in Mechanical Engineering
10	Planning Officer	Supplier identification	4	8	M.Sc. in Mechanical Engineering
11	Equipment Manufacturing Inspector	Equipment serviceability testing	8	15	B.Sc.

The concept of entropy, introduced by Shannon and Weaver in 1947, has been widely applied in decision-making processes. Shannon entropy is an effective tool for accurately determining criteria weights by analyzing subjective and objective expert opinions. It can generate relative weights (Ojadi et al., 2023). To calculate criteria weights by means of the Shannon entropy, given by the distance between triangular fuzzy numbers, the fuzzy data is converted into set-level data through the level of confidence interval limits. The following outlines the steps of the fuzzy Shannon entropy method (Shang et al., 2022):

Step 1: Defining the decision matrix. In this step, the evaluation of m alternatives $(\mathrm{i} = 1,2,3, \dots m)$ is performed in the matrix X with respect to n evaluation criteria $j = (1,2,3 \cdots n)$. The alternatives are suppliers.

$$X = \begin{bmatrix} X_{11} & X_{12} & X_{1j} & X_{1n} \\ X_{21} & X_{22} & X_{2j} & X_{2n} \\ \dots & \dots. & X_{ij} & \dots. \\ X_{m1} & X_{m2} & X_{mj} & X_{mn} \end{bmatrix} (i = 1,2,3, \dots m), j = (1,2,3 \cdots n) \tag{1}$$

Step 2: Assume that the triangle fuzzy number is $\tilde{A} = [l, m, u]$, take the α-level set with $\alpha \in [0,1]$ Moreover, the confidence level interval can be obtained as follows.

$$\tilde{A}\alpha = [(\widetilde{x_{ij}})_{\alpha}^{L}, (\widetilde{x_{ij}})_{\alpha}^{U}] = [(m-l)\alpha + l, -(u-m)\alpha + u] \tag{2}$$

Step 3: Normalization of the elements of the decision matrix with Eq. (3).

$$p_{ij}^{L} = \frac{x_{ij}^{L}}{\sum x_{ij}^{u}}, \quad P_{ij}^{u} = \frac{x_{ij}^{u}}{\sum x_{ij}^{u}}, i = 1,2, \dots, n; \ \ j = 1,2, \dots, m \tag{3}$$

Step 4: Calculation of min and max anti-entropy values for each criterion.

$$h_{j}^{L} = min\left\{-\frac{1}{ln\,n}\Sigma P_{ij}^{L}\, ln\, P_{ij}^{L}, -\frac{1}{ln\,n}\Sigma P_{ij}^{u}\, ln\, P_{ij}^{u}\right\}, j = 1, \dots, m \tag{4}$$

$$h_{j}^{u} = max\left\{-\frac{1}{ln\,n}\Sigma P_{ij}^{L}\, ln\, P_{ij}^{L}, -\frac{1}{ln\,n}\Sigma P_{ij}^{u}\, ln\, P_{ij}^{u}\right\}, j = 1, \dots, m \tag{5}$$

Step 5: Calculate the diversification interval values of d_j^L and d_j^u.

$$d_j^L = 1 - h_j^u, d_j^u = 1 - h_j^L, j = 1, \dots, m \tag{6}$$

Step 6: Calculate the criteria weights' upper and lower limits with Eq. (7).

$$w_j^L = \frac{d_j^L}{\sum d_j^u}, \qquad w_j^u = \frac{d_j^u}{\sum d_j^L} \tag{7}$$

Step 7: Calculate the average value w_j and standardize it to obtain the objective criteria weights (w_j).

$$w_j = \frac{w_j^L + w_j^u}{2}, \qquad w_o = \frac{w_j}{\sum w_j} \tag{8}$$

Supplier Ranking: (Keshavarz Ghorabaee et al., 2015) introduced the EDAS method. The EDAS method, which can consider conflicting criteria, has been used in many MCDM problems. This method calculates the difference between the alternatives and the average solution (AV) based on two distance measures, namely positive distance from average (PDA) and negative distance from average (NDA). The steps of fuzzy EDAS are presented as follows:

Step 1: Defining the decision matrix. In this step, the evaluation of m alternatives $(i = 1,2,3, \dots m)$ is performed in the matrix X with respect to n evaluation criteria $j = (1,2,3 \cdots n)$. The alternatives are suppliers.

$$X = \begin{bmatrix} X_{11} & X_{12} & X_{1j} & X_{1n} \\ X_{21} & X_{22} & X_{2j} & X_{2n} \\ \dots & \dots. & X_{ij} & \dots. \\ X_{m1} & X_{m2} & X_{mj} & X_{mn} \end{bmatrix} (i = 1,2,3, \dots m) , j = (1,2,3 \cdots n) \tag{9}$$

Step 2: Calculate the average solutions with respect to each criterion.

$$AV = [\widetilde{av}_j]_{n\times m} \quad \widetilde{av}_j = \frac{1}{k}\pi_{p=1}^{k}\tilde{X}_{ij} \tag{10}$$

Step 3: In this step, the matrices of positive distance from average (PDA) and negative distance from average (NDA) are calculated according to the type of criteria (beneficial and non-beneficial criteria), shown as follows:

$$PDA = [\widetilde{pda}_j]_{n\times m}$$

$$NDA = [\widetilde{nda}_j]_{n\times m}$$

$$\widetilde{pda}_j = \begin{cases} \dfrac{\psi(\tilde{x}_{ij} - \widetilde{av}_j)}{k(\widetilde{av}_j)} & if\ j \in B \\ \dfrac{\psi(\widetilde{av}_j - \tilde{x}_{ij})}{k(\widetilde{av}_j)} & if\ j \in N \end{cases} \tag{11}$$

$$\widetilde{nda}_j = \begin{cases} \dfrac{\psi(\widetilde{av}_j - \tilde{x}_{ij})}{k(\widetilde{av}_j)} & if\ j \in B \\ \dfrac{\psi(\tilde{x}_{ij} - \widetilde{av}_j)}{k(\widetilde{av}_j)} & if\ j \in N \end{cases} \tag{12}$$

In Eq (11-12), the function (ψ) is defined as Eq (13) to find the maximum between a trapezoidal fuzzy number and zero.

$$\psi(\tilde{A}) = \begin{cases} \tilde{A} & if\ k(\tilde{A}) > 0 \\ \tilde{0} & if\ k(\tilde{A}) \le 0 \end{cases} \tag{13}$$

Step 4: The weighted sum of positive and negative distances for all alternatives is calculated in Eq. (14-15).

$$\widetilde{sp}_i = \pi_{j=1}^{m}\left(\widetilde{w}_j \times \widetilde{pda}_j\right) \tag{14}$$

$$\widetilde{sn}_i = \pi_{j=1}^{m}\left(\widetilde{w}_j \times \widetilde{nda}_j\right) \tag{15}$$

Step 5: The normalized values of $\widetilde{sp}_i$ and $\widetilde{sn}_i$ calculations are performed for all alternatives, Eq (16-17).

$$n\widetilde{sp}_i = \frac{\widetilde{sp}_j}{max_i(k(\widetilde{sp}_j))} \tag{16}$$

$$n\widetilde{sn}_i = 1 - \frac{\widetilde{sn}_i}{max_i\left(k(\widetilde{sn}_j)\right)} \tag{17}$$

Step 6: The appraisal score ($\widetilde{as}_i$) for all alternatives is calculated in Eq. (18).

$$\widetilde{as}_i = \frac{1}{2}(n\widetilde{sp}_i + n\widetilde{sn}_i) \tag{18}$$

The supplier score obtained from the fuzzy EDAS method is used as one of the parameters of the mathematical model.

Mathematical Modeling with Fractional Programming Approach: Mathematical modeling is a decision-making tool mainly used to solve optimization problems. In an optimization model, one or more objective functions to minimize (or maximize) with respect to some constraints are formulated. Supplier selection and inventory management problems in the supply chain can be solved using the mathematical optimization approach (Sutrisno, Sonarseh, & Vidwati, 2022). Fractional programming optimizes the ratio of two functions subject to some specified conditions and is applied in management, engineering, finance, and economics. Charnes and Cooper (1962) proposed optimization with linear fractional functions, which is called the fractional programming problem (FPP) (Abd El-Wahed Khalifa et al., 2022). This study presents a multi-objective optimization model with a fractional programming approach (including maximizing the total purchase value and minimizing the total costs) by considering uncertainty in decision makers' judgments and integrating it with the order allocation and inventory control problem.

Table 2. Input parameters and decision variables

Notation	Description
Indices	
j	Index for item
g	Index for supplier
Parameters	
d_j	Excepted annual demand of item j
a_j	External failure costs per unit for imperfect item j
O_j	Order costs of item j
h_j	Holding costs per unit for a perfect item
h'_j	Holding costs per unit for an imperfect item
sr_j	Space required for each item j
ss_g	Score of supplier g (result of EDAS method)
ms_j	Warehouse capacity of item j
f_g	Fixed annual contractual costs of the supplier g
p_g	Fixed transportation costs of supplier g
r_g	Transportation costs per kilometer of supplier g
m_g	Distance of supplier g
c_{jg}	Purchasing costs per unit of supplier g
k_{jg}	Rate of imperfect quality of item j for supplier g
b_{jg}	Annual supply capacity of item j from supplier g
LTD_{jg}	Demand for item j in the lead time of supplier g
Decision variables	
X_g	If supplier j is selected, 1; otherwise, 0
Y_{jg}	Purchase amount allocated for item j to supplier g
Q_{jg}	Order quantity for item j to supplier g

The optimization model includes two objective functions: maximize total value and minimize total costs. In supplier selection, the total value of purchase (TVP) means the company's long-term value. Instead of focusing on monetary values, TVP emphasizes the advantage of every unit purchased allocated to the selected suppliers. Since the sourcing experiences of purchasing each unit can affect the willingness to purchase and perceptions towards a company's suppliers, TPV is calculated based on the purchase amount (y_{jg}) and the supplier score (ss_g), (Eq.19).

$$MAX\ Z_1\ (TVP) = \sum_j \sum_g ss_g Y_{jg} \tag{19}$$

The total cost function is the sum of all costs and includes contract and purchasing costs (Eq.20), inventory costs (Eq.21), transportation costs (Eq.22), external failure costs, and holding costs for imperfect items (Eq.23) (Saputro et al., 2023).

$$MinZ_2(TC) = \sum_g f_g X_g + \sum_j \sum_g c_{jg} Y_{jg} \tag{20}$$

$$+\sum_j \sum_g \frac{o_j Y_{jg}}{Q_{jg}(1-k_{jg})} + \sum_j \sum_g h_j \left(\frac{Q_{jg}(1-k_{jg})}{2} - LTD_{jg}\right) \tag{21}$$

$$+\sum_j \sum_g \frac{(p_g + r_g\, m_g) Y_{jg}}{Q_{jg}(1-k_{jg})} \tag{22}$$

$$+\sum_j \sum_g a_j Y_{jg} k_{jg} + \sum_j \sum_g h'_j\, Q_{jg}\, k_{jg} \tag{23}$$

The main constraints regard capacity and demand fulfillment. (Eq.24) ensures that the order allocated to the selected suppliers (Y_{jg}) must satisfy the demand for item j.

$$\sum_{g=1} Y_{jg} = d_j \qquad \forall j \in J \tag{24}$$

Due to the suppliers' capacity constraint, the order allocation (Y_{jg}) should not exceed their capacity (b_{jg}), (Eq.25).

$$\sum_{j=1} Y_{jg} \le b_{jg}\, X_g \quad \forall g \in G \tag{25}$$

The total space required for the item must be equal to or less than the maximum warehouse capacity for that item (Eq.26).

$$\sum_{g=1} sr_j\, Q_{jg} <= ms_j \qquad \forall j \in J \tag{26}$$

Finally, constraint (27) represents non-negativity and a binary decision variable.

$$y_{jg} \ge 0,\ Q_{jg} \ge 0,\quad X_g = 0\ or\ 1, \qquad \forall j \in J,\ \forall g \in G \tag{27}$$

In this model, the inventory and transportation costs are fractional functions that should be transformed into non-fractional. A typical transformation technique is the Charnes-Cooper method, which transforms the objective function from a fractional form to a linear form. In this study, the Charnes-Cooper transformation is applied.

Z_{jg}: This variable is the product of $\frac{1}{Q_{jg}}$ and Y_{jg}. This change transforms the mathematical model from fractional mode to linear, and Eqs. 21 and 22 are changed. The objective function Z_2 is reformulated as follows.

$$min\,Z_{\,2}(TC): \sum_{g} f_g x_g + \sum_j \sum_g c_{jg}\, Y_{jg} + \sum_j \sum_g \frac{o_j\, z_{jg}}{(1-k_{jg})} + \sum_j \sum_g h_j \left(\frac{Q_{jg}(1-k_{jg})}{2} - LTD_{jg}\right) + \sum_j \sum_g \frac{(p_g + r_g m_g) z_{jg}}{(1-k_{jg})} + \sum_j \sum_g a_j\, Y_{jg}\, k_{jg} + \sum_j \sum_g h'_j\, Q_{jg}\, k_{jg}$$

One common approach to solving multi-objective optimization problems is assigning weights to the objectives. By aggregating the weighted objectives, a unified objective function is formulated (Mehregan, 2016). In this model, based on expert consensus:

$w_{z2} = 4w_{z1}$ and $w_{z2} + w_{z1} = 1$

Then the final formulation of the model is presented as follows:

$$MAX(Z) = 0.2\,(Z_{\,1}) + 0.8\,(Z_{\,2})$$

$$MAX\ (Z) = \sum_j \sum_g (0.2)\,(ss_g\, y_{jg}) + \left(-\sum_g (0.8)\left(f_g\, x_g\right) - \sum_j \sum_g (0.8)\left(c_{jg}\, Y_{jg} + \frac{o_j\, z_{jg}}{(1-k_{jg})} + h_j\left(\frac{Q_{jg}(1-k_{jg})}{2} - LTD_{jg}\right) + \frac{(p_g + r_g\, m_g) z_{jg}}{(1-k_{jg})} + a_j\, Y_{jg}\, k_{jg} + h'_j\, Q_{jg}\, k_{jg}\right)\right.$$

subject to

$$\sum_{g=1} Y_{jg} = d_j \qquad \forall j \in J$$

$$\sum_{j=1} Y_{jg} \le b_{jg}\, x_g \quad \forall g \in G$$

$$\sum_{g=1} sr_j\, Q_{jg} \le ms_j \qquad \forall j \in J$$

$$Y_{jg} \ge 0, \qquad Q_{jg} \ge 0, \quad X_g = 0\ or\ 1, \qquad \forall j \in J, \qquad \forall g \in G$$

Results

A literature review in the field of supplier selection shows that the most frequent criteria for supplier selection are: price, quality, delivery criteria, flexibility, after-sales service, financial stability, product reliability or performance, technology, reputation, responsiveness, collaboration, quality assurance, discount opportunities, custom manufacturing, and geographical location. Then, the Delphi technique was used to select the most important criteria. The experts (Table 1) finally agreed on the six criteria. Table 3 presents the criteria selected by the experts. The second column of the table references that these criteria have previously been employed for supplier evaluation.

Table 3. Selected Criteria in Delphi

Criteria	Refrences
Price	(Chakraborty et al., 2023), (Ghafoori & Abdallah, 2025), (Erdebilli et al., 2023), (Güneri & Deveci, 2023), (Manik, 2023), (Ayough et al., 2023), (Modares et al., 2023), (İlbaş et al., 2023), (Agrawal, 2022)
Quality	(Chakraborty et al., 2023), (Erdebilli et al., 2023), (Güneri & Deveci, 2023), (Manik, 2023), (Wei & Zhou, 2023), (Paul et al., 2022), (Leong et al., 2022), (Zandieh et al., 2018).
Delivery	(Chakraborty et al., 2023), (Erdebilli et al., 2023), (Manik, 2023), (Ayough et al., 2023), (Modares et al., 2023), (İlbaş et al., 2023), (Agrawal, 2022), (Rezaei et al., 2020), (Pereira et al., 2019)
Flexibility	(Chakraborty et al., 2023), (Dai et al., 2025), (Manik, 2023), (Gunawan et al., 2025), (Leong et al., 2022), (Pérez-Domínguez et al., 2020), (Rezaei et al., 2020), (Zandieh et al., 2018)
Financial stability	(Leong et al., 2022), (Lahdhiri et al., 2022), (Kim & Ahn, 2020), (Zandieh et al., 2018), (Ganguly et al., 2019), (Yazdani et al., n.d.), (Koganti et al., 2019)
Responsiveness	(Chakraborty et al., 2023), (Leong et al., 2022), (Ziquan et al., 2021)

Price: Suppliers must adopt a competitive pricing strategy in global competition. Such a strategy should ensure the timely delivery of products that meet specified quality and quantity requirements (Güneri & Deveci, 2023). Considering the highly competitive nature of the steel industry and the substantial cost of raw materials, which significantly influences the final product cost, raw material prices must remain competitive and aligned with prevailing market conditions.

Quality: This criterion is defined as the supplier's capability to fulfill and maintain established quality specifications consistently (Paul et al., 2022). In the steel industry, the quality of raw materials is a critical determinant of the final product's integrity, the operational efficiency of production lines, and the minimization of costs associated with rework or production interruptions.

Delivery: Strict compliance with the delivery schedule is critical for maintaining optimal inventory levels, thereby ensuring the efficiency and continuity of all production processes (Paul et al., 2022).

Flexibility refers to the supplier's ability to respond quickly to changing demands concerning delivery, volume, and product design. It can be considered a tool for dealing with environmental uncertainties (Paul et al., 2022).

Responsiveness: The supplier's ability to respond to demands despite market fluctuations in the shortest possible time (Davoudabadi et al., 2020).

Financial stability: This criterion is commonly used to assess the financial performance of an individual, institution, or economy and refers to the ability to generate positive and growing cash flow (Leong et al., 2022). Large-scale investment, large volumes of raw materials, and continuous supply are essential requirements of the steel industry. Collaboration with financially stable suppliers is essential to reduce the company's operational and commercial risks.

Weighting of criteria: Fuzzy Shannon entropy is applied to calculate the criteria's weights by following the steps outlined below (Shang et al., 2022):

In the first step, define the decision matrix with fuzzy numbers (Table 4).

Table 4. Fuzzy Decision Matrix

Supplier	Price	Quality	Delivery	Flexibility	Responsiveness	Financial stability
1	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)
2	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(5, 7, 9)
3	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)
4	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	(7, 9, 9)	(7, 9, 9)
5	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)
6	(1, 3, 5)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)
7	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)
8	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)
9	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)
10	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)
11	(3, 5, 7)	(7, 9, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)

Then, the confidence level interval is calculated with (Eq.2), and the interval decision matrix is defined (Table 5).

Table 5. Interval Decision Matrix

Supplier	Price	Quality	Delivery	Flexibility	Responsiveness	Financial stability
1	(5.8, 8.2)	(7.8, 9)	(7.8, 9)	(5.8, 8.2)	(7.8, 9)	(7.8, 9)
2	(5.8, 8.2)	(5.8, 8.2)	(5.8, 8.2)	(3.8, 6.2)	(7.8, 9)	(5.8, 8.2)
3	(7.8, 9)	(7.8, 9)	(7.8, 9)	(7.8, 9)	(7.8, 9)	(7.8, 9)
4	(5.8, 8.2)	(7.8, 9)	(7.8, 9)	(5.8, 8.2)	(7.8, 9)	(7.8, 9)
5	(5.8, 8.2)	(5.8, 8.2)	(5.8, 8.2)	(5.8, 8.2)	(7.8, 9)	(5.8, 8.2)
6	(1.8, 4.2)	(3.8, 6.2)	(1.8, 4.2)	(1.8, 4.2)	(1.8, 4.2)	(3.8, 6.2)
7	(5.8, 8.2)	(5.8, 8.2)	(1.8, 4.2)	(3.8, 6.2)	(3.8, 6.2)	(5.8, 8.2)
8	(5.8, 8.2)	(5.8, 8.2)	(1.8, 4.2)	(1.8, 4.2)	(3.8, 6.2)	(3.8, 6.2)
9	(3.8, 6.2)	(5.8, 8.2)	(5.8, 8.2)	(3.8, 6.2)	(3.8, 6.2)	(3.8, 6.2)
10	(1.8, 4.2)	(3.8, 6.2)	(5.8, 8.2)	(1.8, 4.2)	(5.8, 8.2)	(1.8, 4.2)
11	(3.8, 6.2)	(7.8, 9)	(3.8, 6.2)	(5.8, 8.2)	(5.8, 8.2)	(5.8, 8.2)

In the next step, the elements of the decision matrix were normalized with (Eq.3). Then, the min and max anti-entropy values for each criterion were calculated with (Eq.4-5), and the diversification interval values of d_j^L and d_j^u computed with (Eq.6). Next, the upper and lower limits of criteria weights were calculated with (Eq.7). Finally, the average value w_j calculated and standardized to obtain the objective criteria weights by (Eq.8). The criteria weights are shown in Table 6.

Table 6. Weight of Criteria

criteria	Price	Quality	Delivery	Flexibility	Responsiveness	Financial stability
w_o	0.184	0.13	0.178	0.206	0.144	0.158

The scores of suppliers are calculated through the fuzzy EDAS method to write the objective function (Z_1) that maximize TPV. In this method, the AV value is calculated based on the fuzzy decision matrix (Eq.10)

Table 7. Average Solution (AV)

Price	Quality	Delivery	Flexibility	Responsiveness	Financial stability
(4.09, 6.09, 7.9)	(5.36, 7.36, 8.63)	(4.27, 6.27, 7.72)	(3.53, 5.54, 7.36)	(5, 7, 8.9)	(4.64, 6.63, 8.09)

The positive distance from the average (PDA) and the negative distance from the average (NDA) are calculated with (Eq.11-12). Then (PDA) and (NDA) are defuzzified through the Minkowski method. In the next step, $\widetilde{sp}_i$, $\widetilde{sn}_i$, $\widetilde{nsp}_i$ and $\widetilde{nsn}_i$are calculated for all suppliers with (Eq.14-17). The final score of the suppliers ($\widetilde{as}_i$) computed with (Eq.18). This score is used as one of the parameters of the optimization model

Table 8. score of the suppliers ($\widetilde{as}_i$)

Supplier	$\widetilde{as}$
1	0.857
2	0.505
3	0.893
4	0.857
5	0.630
6	0.359
7	0.346
8	0.168
9	0.551
10	0.417
11	0.698

The mathematical model has been validated using empirical data from Sirjan Steel Company, and the decision variable values have been specified. The proposed model has been solved through the LNGO 11 software. The results show suppliers No. 5, 6, 10, and 11 are selected. In other words $X_5 = X_6 = X_{10} = X_{11} = 1\ and\ X_g = 0$ for other g.

Other decision variable values are shown in Table 9.

Table 9. decision variable values

Supplier No	(Y_{1g})	(Q_{1g})	(z_{1g})	Supplier No	(Y_{2g})	(Q_{2g})	(z_{2g})
1	0	0	0	1	0	0	0
2	0	0	0	2	0	0	0
3	0	0	0	3	0	0	0
4	0	0	0	4	0	0	0
5	0	0	0	5	700	350	2
6	2996	749	4	6	0	0	0
7	0	0	0	7	0	0	0
8	0	0	0	8	0	0	0
9	0	0	0	9	0	0	0
10	2004	668	3	10	0	0	0
11	0	0	0	11	3000	750	4

Conclusion

The proposed supplier selection model is specifically designed to address the inventory control challenges within a company in the steel industry. At the same time, maximize the total purchase value (TPV) and minimize the total costs (TC), including inventory costs (cost of holding healthy items and ordering costs), transportation costs, cost of holding imperfect items, and external failure costs.

This paper's methodological innovation uses fractional programming and fuzzy multi-criteria decision-making techniques in supplier selection and order allocation, considering inventory costs. This hybrid method is designed to handle the uncertainty and complexity inherent in supplier selection processes by simultaneously incorporating objective and subjective criteria, order allocation, and inventory control. The Charnes-Cooper transformation method has been used to solve fractional optimization, and two objective functions have been converted to a unified objective with a weighting method.

Fuzzy entropy methods are also applied to weight the criteria, and the supplier's score is calculated with fuzzy EDAS. Supplier evaluation is measured against six key criteria: price, quality, delivery, flexibility, responsiveness, and financial stability. Flexibility and responsiveness are qualitative and subjective, while the other criteria are measurable and objective. The fuzzy Shannon entropy method results show that the flexibility criterion with a weight of 0.206 has the highest weight, and the quality criterion with a weight of 0.13 has the lowest weight. The results of the fuzzy EDAS method have also been used as one of the parameters in an optimization model for supplier selection and order allocation. The proposed model evaluates and selects suppliers based on their ability to optimize inventory control and meet specific requirements.

Empirical data of a company active in the steel industry has been used to validate the proposed model. The results of this study increase the overall performance of the supply chain by providing an applied approach that is compatible with the steel industry. Considering qualitative and quantitative factors in supplier selection and optimizing procurement strategies for steel manufacturers sets a precedent for future research in supplier management in different industries.

This study is applied research in supplier selection, considering inventory control, and can be used in other manufacturing companies. Future research suggests that other MCDM methods, which are less commonly used, should be applied. Also, the mathematical model can consider discount conditions or use fuzzy goal programming.

Data Availability Statement

Data available on request from the author.

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Ethical considerations

The author have witnessed the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy.

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Conflict of interest

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