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Order Allocation Model and Supplier Evaluation in Textile Industry with Fuzzy OPA and RAFSI Methods

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ABSTRACT

Increasing competition, accelerating production processes, and dynamic market conditions are forcing companies to make strategic decisions. Effective management of contract supply production processes is essential in the textile sector to promptly meet customer demands while ensuring high quality and affordability. In this context, choosing the best subcontractor is crucial for a company seeking a competitive advantage. Factors such as supplier capacity, quality of workmanship, timely delivery, and cost efficiency have a direct impact on the performance of textile companies. During the supplier evaluation process, factors such as sustainability criteria, efficiency, speed, and quality should be taken into account. This study proposes a decision-support methodology for evaluating subcontractors in textile companies that outsource manufacturing. The methodology incorporates a two-tiered Pareto analysis to identify focus product groups, fuzzy multi-criteria decision-making techniques for subcontractor assessment, and mathematical modelling approaches for capacity allocation. A real case study is presented to identify the most profitable product groups via Pareto analysis, to evaluate subcontractors through the Fuzzy-based Ordinal Priority Approach (OPA) and the Ranking of Alternatives by Functional Mapping of Criteria Sub-Intervals to Single Intervals (RAFSI) method, and a mixed-integer programming model for scheduling orders to subcontractors' production plans. The proposed approach enhances the effectiveness of the supplier selection process and offers a practical framework for strategic decision-making in contract manufacturing in similar industrial settings.

1. Introduction

The textile industry is one of the most labor-intensive sectors, serving as a cornerstone of industrialization and contributing significantly to the economic development of emerging countries. The textile industry, as part of the apparel supply chain, provides a wide range of production capabilities [1]. To remain competitive in the global market, companies must satisfy customer demands on time by considering order quantity, price, quality, and cost. To effectively manage operations through these factors, many companies prefer to collaborate with contract

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manufacturers. Turkey has positioned itself as a strong contract manufacturing hub in the textile industry, supplying products to numerous global brands. Due to the preference of international firms for Business-to-Business sales strategies in Turkey, partnerships with domestic corporate textile companies have become increasingly common in practice. This advancement has raised the emphasis on quality standards in production processes and contributed significantly to the growth and competitiveness of the textile and apparel sectors [2].

Effective supply chain management hinges on the strategic selection of contract suppliers. The appropriate selection of suppliers allows companies to respond rapidly and flexibly to demand while maintaining product quality, delivery quality, and reliable performance[3]. Furthermore, collaborating with suitable suppliers helps minimize operational risks and enhance customer satisfaction, thereby strengthening the company's competitive advantage. Therefore, the supplier selection process should consider factors beyond cost, adopting a broader, multi-dimensional evaluation approach that effectively addresses the inherent uncertainties of supply networks. This evolution toward fuzzy-based methodologies and sustainability-oriented criteria reflects the textile industry's growing recognition that supplier relationships represent strategic partnerships requiring robust decision support systems capable of managing ambiguity while advancing long-term organizational resilience and sustainability goals. The uncertainty in supplier evaluation criteria complicates the scoring and decision-making process. In the literature, the main sources of uncertainty are classified as demand, capacity, cost, delivery time, quality, and disruptions [4]. Researchers have developed various methods to address this uncertainty, with fuzzy techniques being among the most commonly used in supplier or subcontractor firms.

Fuzzy Multi-Criteria Decision Making (MCDM) methods facilitate supplier selection and evaluation processes using linguistic variables, also allowing uncertain data to be converted into quantitative values. Fuzzy MCDM approaches have proven to yield reliable and practical results under conditions of ambiguity, as demonstrated in the literature. They support decision-making by maximizing profit, minimizing costs, and improving efficiency, contributing to effective resource use at both strategic and operational levels [5].

The organization of this study is as follows: Section 2 presents a review of the literature on supplier evaluation and selection, with a particular focus on applications in the textile industry. Section 3 details the proposed methodology, outlining the four-step framework for supplier selection and order allocation. Section 4 presents a real-world case study to demonstrate the practical implementation of the framework. Section 5 offers managerial insights based on the analysis, and Section 6 concludes the study by summarizing key findings and implications.

2. Recent literature

With the continuous escalation of customer expectations, global enterprises face increasing challenges in enhancing and optimizing their supply chains to effectively respond to evolving consumer demands. These challenges are compounded by pressures from global competition, the spread of enterprise information systems, and shorter product life cycles, which result in increasingly complex supply chains and a greater need for more sophisticated management methods [6]. As customer expectations increase, businesses must not only meet these demands but also anticipate future trends to maintain their competitive advantage. This requires leveraging technological advances such as Artificial Intelligence, Internet of Things, and Blockchain to enhance supply chain visibility, efficiency, and responsiveness. By strategically developing relationships with suppliers who adopt these innovative approaches, businesses can build resilient supply chains capable of withstanding global competition and technological disruption. Table 1 examines decision-making methodologies used in the literature for subcontractor manufacturer and supplier selection in the textile industry.

Table 1
Supplier Selection in Textile Industry

Study	Weighting Method	Scoring Method	Uncertainty
Nazam *et al.,* [7]	Fuzzy AHP	Fuzzy TOPSIS	✓
Guo *et al.,* [8]	Direct fuzzy weighting	Fuzzy Axiomatic Design	✓
Gören and Şenocak [9]	MACBETH	Taguchi Loss functions	×
Gündüz and Gündüz [10]	Direct fuzzy weighting	Fuzzy TOPSIS	✓
Wang and Cheng [11]	Fuzzy AHP	Fuzzy TOPSIS	✓
Guarnieri and Trojan [12]	AHP	ELECTRE-TRI	×
Tayyab and Sarkar [13]	Direct fuzzy weighting	Interactive weighted FGP	✓
Karamaşa *et al.,* [14]	SAW	ROV	×
Rahman *et al.,* [15]	SWARA	WASPAS	×
Ulutaş *et al.,* [16]	Grey Best-Worst Method	Grey Weighted Sum-Product	✓
Dinh et al., [17]	NA	Association Rule Mining	×
Lin *et al.,* [18]	Fuzzy Delphi method	Fuzzy DEMATEL	✓
Sheikh *et al.,* [19]	Fuzzy AHP	Fuzzy AHP	✓
This study	Fuzzy OPA	Fuzzy RAFSI	✓

ROV: Range of Value Method, TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution, MACBETH: Measuring Attractiveness by a Categorical Based Evaluation Technique, AHP: Analytic Hierarchy Process, DEMATEL: Decision-Making Trial and Evaluation Laboratory, WASPAS: Weighted Aggregated Sum Product Assessment, ELECTRE: Elimination and Choice Translating Reality, FGP: Fuzzy Goal Programming

The concept of fuzziness is applied in many fields to address uncertainty in evaluations, and it has been particularly beneficial in decision-making processes in industries like textiles. Methods such as the AHP and the TOPSIS have been widely adopted, both in their standard forms and in variations that incorporate fuzzy logic. Wang and Cheng proposed a comprehensive multicriteria decision-making model specifically designed for the garment industry that integrates sustainability considerations. Their approach combines fuzzy AHP for criteria weighting with the TOPSIS for supplier evaluation [11]. Gündüz and Şimşek Gündüz addressed the inherent fuzziness in decision-making by applying fuzzy set theory to supplier selection for a textile manufacturer in Denizli. Their work emphasizes the value of expressing criteria ratings and weights through linguistic variables, culminating in a closeness coefficient calculation that enables effective supplier performance ranking using Fuzzy TOPSIS [10].

Recent literature reveals a growing emphasis on incorporating sustainability and resilience considerations into textile supply chain management frameworks. Guo *et al.,* [8] specifically focused on green supplier evaluation in global apparel manufacturing by developing a methodological framework based on the triple bottom line principle. Their approach incorporated comprehensive literature review, field investigation, and policy analysis to establish a green supplier evaluation criterion hierarchy, complemented by a fuzzy multi-criteria decision-making model [8]. Lin *et al.,* [18] made significant contributions by identifying six aspects and eighteen criteria related to supply chain disruption and resilience strategy attributes. Their research employed both fuzzy Delphi and DEMATEL methods, revealing that supply risk, flexible business strategies, and collaborative strategies form causal factors, while human issues, transportation failure, and preventive resilience strategies constitute effect factors. This comprehensive framework provides valuable guidance for adapting to disturbances with minimal performance impact [18].

Overall, fuzzy multiple criteria decision-making methods have been widely recognized for their effectiveness in evaluating suppliers within the textile industry. However, despite their extensive application, there remains a noticeable gap in the literature regarding the use of less common fuzzy techniques—such as the Fuzzy Ordinal Priority Approach (Fuzzy OPA) and the Ranking of Alternatives by Functional Mapping of Criteria Sub-Intervals to a Single Interval (RAFSI)—specifically within the context of textile supplier evaluation.

3. The proposed methodology

This study presents a comprehensive, four-step supplier selection and order allocation framework designed to optimize procurement decisions through a systematic analytical approach. The proposed framework is illustrated in Figure 1.

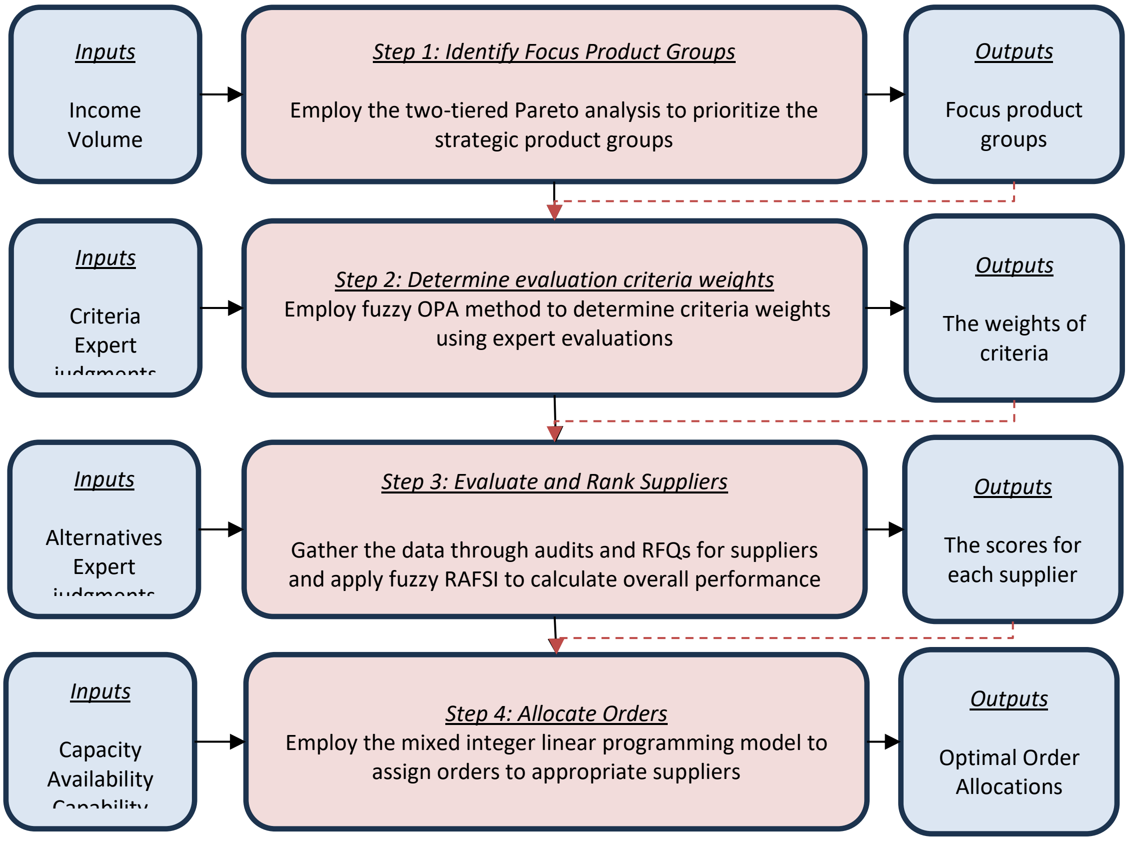

Fig. 1. Proposed Supplier Selection and Order Allocation Framework

The proposed methodology integrates multiple decision-making techniques to address the complex challenges faced by procurement professionals in today's dynamic supply chain environment. Beginning with focus product group determination through two-tiered Pareto analysis, the framework proceeds to develop a multi-criteria evaluation structure weighted via fuzzy OPA method. Supplier performance is then evaluated using the fuzzy RAFSI method, generating quantitative supplier scores that reflect organizational priorities. Finally, these scores are incorporated into a mathematical optimization model that allocates orders across the supplier portfolio while respecting capacity constraints and ensuring risk diversification. By combining multi-criteria decision-making methods with advanced mathematical programming, this framework offers procurement managers a robust, data-driven approach to subcontractor supplier selection that balances performance objectives with operational constraints and strategic risk considerations.

3.1 Two-tiered Pareto Analysis

The Pareto principle, also known as the "80-20 rule", originated from the research of Vilfredo Pareto who investigated the imbalance of wealth distribution in Italy around 1906 and proposed a statistical model with a continuous probability distribution of an unbounded random variable. He proposed a statistical model based on a continuous probability distribution for an unbounded random variable; however, since income distributions involve a finite population and discrete income levels, the Pareto model can only serve as an approximation [20]. Nonetheless, if there exists a probability distribution that satisfies the generalized 80/20 law, then it must be the Pareto distribution with pareto index is greater than 1. The term "Pareto's law" was first introduced by Juran, who distinguished between the contributions of the "vital few" and the "trivial many" [20]. The Pareto principle states that 80% of the effects of all events originate from 20% of the causes [21].

The first step of the proposed methodology involves employing Pareto Analysis to discern key product categories for prioritizing improvement initiatives, highlighting significant impact of a limited number of critical areas on overall outcomes. For pareto analysis, we use a two-phase approach: first, broad categories are analyzed to identify high-impact product groupings, and then these groups are broken down further to allow for thorough analysis and planning.

3.2 Fuzzy Ordinal Priority Approach

Several fuzzy multi-criteria decision-making methods have been proposed in the literature to evaluate a countable number of criteria in the presence of uncertainty and imprecision [22]. The broad spectrum of fuzzy sets employed in these methods provides the enrichment of mathematical decision analysis framework that can represent uncertainty and imprecision, particularly in human judgment.

In this study, we employed the Ordinal Priority Approach proposed by Ataei *et al.,* [23], which offers a promising foundation for methodological extensions in multi-criteria decision making. This approach serves as the foundation for the criteria weighing mechanism in this study's comprehensive supplier selection and order allocation framework. Several studies in the literature have enhanced the OPA method by extending its application to various types of fuzzy sets [22, 24-27].

OPA Method, establishes a systematic group decision making approach where experts are first prioritized based on their knowledge or experience in the respective field. Each expert provides a ranking for attributes/ alternatives with the flexibility to provide input only in areas where they possess sufficient knowledge. The main innovation of the approach lies in its mathematical formulation: a deterministic linear programming model that simultaneously determines weights for all decision elements without relying on traditional analytical requirements like normalization processes, comparison matrices, or linguistic variable transformations [23].

The fuzzy trigonometric based OPA method proposed by Deveci *et al.,* [22] has been employed for weight determination, as it offers a more effective representation of uncertainty compared to the crisp OPA [22].

The steps of fuzzy trigonometric based OPA are summarized as follows:

Let $\upsilon_j = \{\upsilon_1, \upsilon_2, \ldots, \upsilon_n\}$ define the set of criteria and $E_l = \{E_1, E_2, \ldots, E_m\}$ define the set of experts.

Step 1. The linguistic terms included in Table 2 are used to gather expert evaluations.

Table 2
Fuzzy terms for criteria assessments (Deveci *et al.,*, [22])

Linguistic terms	Linguistic values of fuzzynumbers
High (H)	(6.5,7.5,8.5)
Very high (VH)	(7.5,8.5,9.5)
Absolutely High (AH)	(8.5,9.0,10.0)
Medium-low (ML)	(3.5,4.5,5.5)
Equal (E)	(4.5,5.5,6.5)
Medium- high (MH)	(5.5,6.5,7.5)
Low (L)	(2.5,3.5,4.5)
Very low(VL)	(1.5,2.5,3.5)
Absolutely low (AL)	(1.0,1.5,2.5)

We construct the evaluation matrix $\tilde{\mathcal{A}} = [\tilde{a}_{ij}]_{n\times m}$ with $\tilde{a}_{ij} = (a_{ij}^L, a_{ij}^M, a_{ij}^U)$ fuzzy numbers.

Step 2. To aggregate the evaluations of experts, we employed a simplified formulation of fuzzy weighted geometric average operator. $B = [\tilde{b}_i]$, the aggregated weight vector, is determined by

$$\tilde{b}_i = \begin{pmatrix} \sum_{j=1}^{m} a_{ij}^L \frac{2}{\pi} \arcsin \prod_{j=1}^{m} \left(\frac{\sin \pi\, (a_{ij}^L}{\sum_{j=1}^{m} a_{ij}^L} \right)^m, \\ \sum_{j=1}^{m} a_{ij}^M \frac{2}{\pi} \arcsin \prod_{j=1}^{m} \left(\frac{\sin \pi\, (a_{ij}^M}{\sum_{j=1}^{m} a_{ij}^M} \right)^m, \\ \sum_{j=1}^{m} a_{ij}^U \frac{2}{\pi} \arcsin \prod_{j=1}^{m} \left(\frac{\sin \pi\, (a_{ij}^U}{\sum_{j=1}^{m} a_{ij}^U} \right)^m \end{pmatrix} \tag{1}$$

Step 3. The final ranking of the criteria is described by $w_{i'}^{(1)}, w_{i'}^{(2)}, \dots, w_{i'}^{(n)}$ where $w_{i'}^{(r)}$ denotes the i'th criterion assigned rth rank. To determine the weights of the criteria, the fuzzy linear programming model is formulated as in Equations (2-13):

$$Max\ \Omega^{(L)} + \Omega^{(M)} + \Omega^{(U)} \tag{2}$$

$$\frac{\min_{1\le i\le n} b_i^L}{b_i^U} \left(w_i^{L,r} - w_i^{U,r+1} \right) \ge\ \Omega^{(L)} \tag{3}$$

$$\frac{\min_{1\le i\le n} b_i^M}{b_i^M} \left(w_i^{M,r} - w_i^{M,r+1} \right) \ge\ \Omega^{(M)} \tag{4}$$

$$\frac{\min_{1\le i\le n} b_i^L}{b_i^L} \left(w_i^{U,r} - w_i^{L,r+1} \right) \ge\ \Omega^{(U)} \tag{5}$$

$$\frac{\min_{1\le i\le n} b_i^L}{b_i^U} \left(w_i^{L,r} \right) \ge\ \Omega^{(L)} \tag{6}$$

$$\frac{\min_{1\le i\le n} b_i^L}{b_i^m} \left(w_i^{m,r} \right) \ge\ \Omega^{(m)} \tag{7}$$

$$\frac{\min_{1\le i\le n} b_i^L}{b_i^L} \left(w_i^{U,r} \right)\ \ge \Omega^{(U)} \tag{8}$$

$$\sum_{i=1}^{n} w_i^L = 0.8 \tag{9}$$

$$\sum_{i=1}^{n} w_i^M = 1.0 \tag{10}$$

$$\sum_{i=1}^{n} w_i^U = 1.2 \tag{11}$$

$$w_i^L \leq w_i^M \leq w_i^U \tag{12}$$

$$w_i^L, w_i^M, w_i^U \geq 0 \tag{13}$$

The objective function aims to maximize the sum of the lower, modal and upper bounds of satisfaction levels which ensures a balanced adjustment of the fuzzy weights while encouraging a consistent ranking across the fuzzy intervals. Equation (3) ensures that the lower bound of the weight of the rth ranked criterion is greater than or equal to the upper bound of the next rank using a scaling factor derived from the corresponding fuzzy $\tilde{b}_i$ values. Equation (4) enforces that the modal value of the weight for the rth ranked criterion is greater than or equal to the modal value of the criterion ranked $r+1$, thereby maintaining the consistency of the ranking in terms of central estimates. Equation (5) ensures that the upper bound of the weight for a higher-ranked criterion is larger than the lower bound of the next ranked criterion, preserving ordinal consistency across the fuzzy bounds. Equations (6) – (8) ensure that the lower, modal, and upper bounds of each criterion's weight meet or exceed their respective satisfaction thresholds, using appropriate scaling factors derived from the fuzzy boundary values. The sum of the lower, modal, and upper bounds of the criteria's weights is normalized to 0.8, 1.0, and 1.2, respectively, in Equations (9) – (11). This ensures that the total importance of each fuzzy range remains within predefined limits while maintaining consistency in the aggregation of criteria. Equation (12) guarantees consistency in weight representation by maintaining the logical order of fuzzy numbers for each criterion. All fuzzy weights elements are guaranteed to be non-negative by Equation (13). Upon solving the fuzzy linear model in Equations (2)-(13), the resulting fuzzy vector represents the weights assigned to each criterion.

3.3 Fuzzy RAFSI approach

A fuzzy trigonometric-based extension of the RAFSI model was proposed by Deveci *et al.,* [22] to address decision-making problems involving uncertainty. The steps of the method are presented in this section.

Step 1. The linguistic evaluations are collected from a set of decision makers in respect to each criterion and transformed into fuzzy values using Table 2 to construct the assessment matrix E of decision maker l.

Step 2. To aggregate the experts' evaluations consistently, a simplified version of the fuzzy weighted geometric average operator was utilized, as described in Equation 1. The aggregated evaluation matrix $C = \left[\tilde{c}_{ij}\right]_{n\times k}$ is constructed, where n corresponds to the total number of criteria, k to the number of evaluated alternatives and $\left(c_{ij}^L, c_{ij}^M, c_{ij}^U\right)$ to the fuzzy representation of $\tilde{c}_{ij}$.

Step 3. The score matrix, denoted by $S = \left[s_{ij}\right]_{n\times k}$, including the score values of each alternative under each criterion are computed using the aggregated evaluation matrix, as specified in Equation (14).

$$S = \left[s_{ij}\right]_{n\times k} = \left[\frac{c_{ij}^L + 4c_{ij}^M + c_{ij}^U}{6}\right]_{n\times k} \tag{14}$$

Step 4. Decision makers specify two values for each criterion: an ideal value (s_i^*) and a non-ideal value (s_i^-), ensuring that for benefit-type criteria, the ideal value surpasses the non-ideal value, and for cost-type criteria, the ideal value is smaller than the non-ideal value. The RAFSI Method maps all entries of the matrix into criteria intervals into criterion-specific intervals using the range $[s_i^-, s_i^*]$ for benefit-type criteria and $[s_i^*, s_i^-]$ for cost-type criteria. The RAFSI method transforms all criteria into a common interval by generating a sequence of values within a defined range. Depending on the criterion's nature, the mapping is applied accordingly: for benefit-type criteria $(i \in \mathcal{B})$, the minimum value is assigned to the lower bound and the maximum to the upper bound; for cost-type criteria $(i \in \mathcal{C})$, the mapping is reversed to maintain consistency in the evaluation scale. After determination of sub-intervals $[\rho_{1,}\, \rho_{2v}]$, the matrix S is standardized using transformation function f, defined in Equation (15-16). represents the criteria range. This yields the standardized decision matrix $Y = [y_{ij}]$ following the application of the function to each element s_{ij}.

$$(\rho_1 < \rho_2 < \rho_3 < \dots < \rho_{2v-1} < \rho_{2v} \tag{15}$$

$$f(s_{ij}) = \frac{\rho_{2\hbar} - \rho_1}{s_i^* - s_i^-} p_{ij} + \frac{s_i^* \rho_1 - s_i^- \rho_{2\hbar}}{s_i^* - s_i^-}, \tag{16}$$

Step 5. The normalized decision matrix $(Z = [z_{ij}])$ is computed using the arithmetic mean (η) for benefit-type criteria and the harmonic mean (λ) for cost-type criteria using Equation (17).

$$z_{ij} = \begin{cases} \dfrac{y_{ij}}{2\eta} & if\ i \in \mathcal{B} \\ \dfrac{\lambda}{2y_{ij}} & if\ i \in \mathcal{C} \end{cases} \tag{17}$$

where the normalized matrix's elements are displayed by $z_{ij} \in [0, 1]$.

Step 6. The overall score R_j for each alternative j is computed as the weighted sum of the normalized scores z_{ij} of each criterion i, as presented in Equation (18).

$$R_j = \sum_{i=1}^{n} w_i z_{ij} \tag{18}$$

3.4 Order allocation model

This section introduces a mixed-integer programming formulation for the order allocation model, providing an effective quantitative method that incorporates both limitations on resources and supplier overall rankings. This model focuses on solving the problem of assigning orders to the schedules of subcontractor manufacturers. It considers parameters related to the suppliers' capabilities and available capacities, considering their classification, category, supply management division (SMD), and domain (e.g., gender-dependent).

In the proposed model, let I denote the set of orders, where each order is identified by an index $i \in I$. The set J represents the available suppliers or workshops, indexed by $j \in J$. The planning horizon is divided into a set of days T, with each day represented by $t \in T$. For each supplier j, a subset of feasible working days is defined as $T_j, t \subseteq T$, indicating the specific days on which that supplier j is available to process orders. Furthermore, for each order i, we define $J_i \subseteq$ J as the subset of suppliers that are capable of processing order i, i.e., those for which the processing time can be calculated, and the order is feasible to produce.

The parameters and decision variables are defined in Table 3. The processing time d_{ij} represents the number of days required to complete order i at supplier j, provided that supplier j is eligible to process that order. It is computed as the ratio of the order's demand quantity to the supplier's capacity and varies across suppliers. If supplier j is not eligible—due to mismatched

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technical requirements—d_{ij} is undefined. For normalization purposes, parameter P is defined as an upper bound on the total processing effort. Specifically, P represents the worst-case total processing time, obtained by summing the maximum processing time for each order across all eligible suppliers. It is used to normalize the second term of the objective function, ensuring comparability with the first component.

Table 3
Notation

Parameters	Definition
w_{jt}	binary parameter indicating whether supplier j is available to operate on day t
d_{ij}	the processing time (in days) required to complete order i at supplier j
b_i	the earliest day on which order i can start production
r_j	RAFSI score of supplier j
D_i	Due date of order i
P	Total processing time
Decision Variables	**Definition**
x_{ij}	binary variables equal to 1 if order i is assigned to supplier j, and 0 otherwise.
y_{ijt}	binary variables equal to 1 if order i is being processed by supplier j on day t, and 0 otherwise.
s_i	start time of order i representing the day on which its production begins.
c_i	completion time of order i representing the day on which its production is finished.

The objective function of the proposed order-supplier assignment model, given in Equation (19), balances two competing goals where the first term aims to maximize supplier quality by using the RAFSI scores and the second term effectively minimizes completion times across all orders which is normalized by total processing time to ensure proper scaling between the two objectives.

$$Max \sum_{i=1}^{N}\sum_{j=1}^{M} r_j x_{ij} - \sum_{i=1}^{N}\sum_{j=1}^{M} \frac{c_i}{P} \tag{19}$$

The constraints of the model are summarized as in the following.

$$\sum_{j\in J_i} x_{ij} = 1 \qquad \forall i \in I \tag{20}$$

$$\sum_{i\in I}\sum_{j\in J} y_{ijt} \leq x_{ij} \qquad \forall t \in T \tag{21}$$

$$\sum_{t=1}^{T} y_{ijt} = d_{ij} x_{ij} \qquad \forall i \in I, \forall j \in J \tag{22}$$

$$s_i + \sum_{j\in J_i} d_{ij} x_{ij} \leq c_i \qquad \forall i \in I \tag{23}$$

$$c_i \leq D_i \qquad \forall i \in I \tag{24}$$

$$s_i \geq b_i \qquad \forall i \in I \tag{25}$$

$$y_{ijt} \leq w_{jt}\, x_{ij} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{26}$$

$$\begin{gathered} t + 1 - M(1 - y_{ijt}) \leq s_i + d_{ij} x_{ij} \\ t \geq s_i - M(1 - y_{ijt}) \end{gathered} \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{27}$$

$$y_{ijt}, x_{ij} \in \{0,1\},\ s_i, c_i \in \mathbb{Z}^+ \qquad \forall i \in I, \forall j \in J, \forall t \in T \tag{28}$$

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Equation (20) ensures that each order can be assigned to only one supplier. Constraint (21) ensures that processing days align with supplier assignments by requiring that, for each period t, orders are only processed by suppliers officially assigned to them. Constraint (22) guarantees that the processing spans exactly the required number of days when a supplier is assigned. Equation (23) defines the relationship between the completion time and the start time for each order, ensuring that the completion time of an order accounts for its processing duration on the assigned supplier. Equations (24) and (25) define the due date constraint and the ready date constraint for each order, respectively, ensuring that production does not start before the order is ready and is completed no later than its due date. Equation (26) imposes the supplier's availability constraint, ensuring that each order assigned to a supplier is scheduled only on days within that supplier's availability. Equation (27) ensures that the days on which an order is processed are limited to the designated start day and carried out only on consecutive days. This is achieved by using the Big-M approach to maintain consistency between the start and completion times of the processing days. Equation (28) provides the definitions of the decision variables used in the model, including assignment and timing variables essential for representing the planning process.

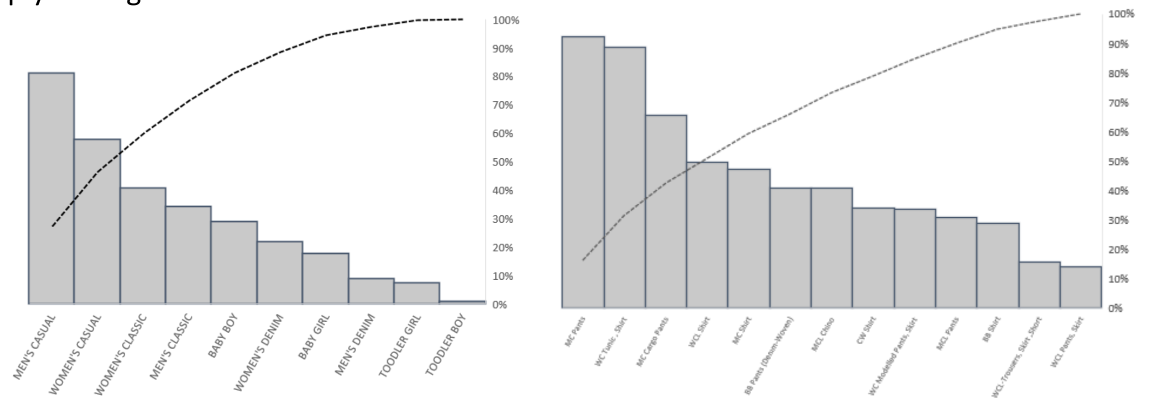
4. Application

Within the scope of the application of the proposed methodology, the supplier selection and capacity planning problem of a clothing brand in Türkiye was examined. Effective capacity planning directly influences quality, deadline performance, customer responsiveness, and overall satisfaction.

4.1 Application of Two-tiered Pareto Analysis

Strategic prioritization of high-impact product groups, based on metrics such as order frequency, quantity, and diversity, plays a critical role in optimizing overall system efficiency. We applied a two-tiered Pareto analysis to identify product categories and supply management strategies that most significantly influence profitability, utilizing net profitability data as the primary input.

First, a Pareto analysis was performed on all supply management divisions (SMD). In the initial stage of the Pareto analysis, five SMDs were chosen from the Men, Women, and Baby categories. In the second stage of Pareto analysis, the selected 5 SMDs were divided into supply groups (with classification details) and Pareto analysis was repeated. As a result, supply groups formed inside the supply management sub-division.



(a) (b)

Fig. 2. Two-tiered Pareto analysis: a) SMDs b) supply groups

Figure 2a illustrates the Pareto distribution of net profitability across main SMDs. The grey bars represent individual category contributions, while the red cumulative line indicates the aggregated percentage of total profitability. The analysis demonstrates that a limited number of categories—

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Men's Casual, Women's Casual, Women's Classic, Men's Classic, Baby Boy —generate the majority of the profitability, aligning with the Pareto principle. These high-impact categories should be prioritized in supply chain and inventory management strategies to maximize overall system efficiency. Figure 2b presents a more detailed, second-tier Pareto analysis across product subcategories. The subcategories for Women's Casual Shirts, Men's Casual Pants, Men's Cargo Pants, Women's Classic Shirts, Men's Casual Shirts and Baby Boy Pants emerge as the most profitable. Similar to the first-tier analysis, a small number of subcategories account for a disproportionately high percentage of total profits.

As a result of the Pareto analysis calculations, key suppliers engaged in active contract manufacturing within the supply chain have been identified as focal points. A total of 17 suppliers will be considered in the subsequent analysis.

4.2 Application of Fuzzy Trigonometric OPA Method

In this study, the criteria were defined based on both a comprehensive review of relevant literature and previous decision-making factors, supplemented by practical experience. In contract manufacturing environments, supplier evaluation involves a range of criteria, including company culture, working history, lessons learned from past issues, and findings from internal assessments and research. Additional criteria derived from these insights have also been incorporated into the model. Within the scope of supplier selection, 6 main criteria have been determined and classified in accordance with quality performance, ability to produce different products, overtime capability, reliability, economic incentives and supplier class.

The *Repair Rate-Quality Performance metric (C1)* measures production issues across daily, weekly, monthly, seasonal, and annual bases. Organizations establish threshold values for this key indicator, making it one of the most critical factors in supplier performance evaluation. Responsiveness Criterion refers to a supplier's ability to react quickly and effectively to changing demands, production challenges, and unexpected issues which can significantly impact on-time delivery performance in textile manufacturing, particularly for subcontracted production.

The *Flexibility - Ability to Produce Different Product Classifications metric (C2)* refers to a supplier's competence in manufacturing various product classifications. High-performance suppliers can maintain consistent quality not only with basic products but also with complex or more detailed items within the same classification. They demonstrate continuity by performing equally well when assigned different product groups than their usual specialty.

The *Flexibility –Overtime Capability metric (C3)* demonstrates flexibility during tight periods such as seasonal transitions, in-season order management, urgent holiday orders, and fast track production strategies. Suppliers who readily accept these working conditions and view them as teamwork are always preferred partners in the supply chain [28].

The *Reliability metric (C4)* refers to the track record of past collaborations and history of successful partnerships. It assesses whether suppliers adhere to all applicable laws and regulations, produce products that meet or exceed expectations, and maintain a disciplined work environment.

The *Economic Incentives metric (C5)* refers to the financial advantages suppliers receive based on their geographical location within government-supported development zones. This metric assesses how regional incentives influence a supplier's cost structure, competitive pricing ability, and long-term economic sustainability relative to suppliers in less-incentivized regions. Turkey is divided into six development regions for investment incentives [29]. Region 1, the most developed, receives minimal support, while incentives increase progressively through regions 2 to 5. Region 6, the least developed, benefits from the most comprehensive support, including tax reductions and social security contributions. Notably, key incentives such as interest rate subsidies are absent in regions 1 and 2 but are available from region 3 onward. Likewise, the rates and durations of tax relief, investment contribution, and employment incentives rise substantially toward region 6.

The *Supplier Class & Risk Classification metric (C6)* classifies suppliers into performance and risk-based tiers (5-Star, Platinum, Gold, Silver, Conditional, and Risky-New) based on engagement evaluations such as quality audits, social compliance, child labor checks, occupational health and safety, disciplinary procedures and warehouse inspection results. These classifications offer a preliminary insight into supplier reliability and maturity. This classification of suppliers enables a better understanding and management of supply chain risk profiles, supporting informed sourcing and collaboration decisions.

The comprehensive expert evaluations for each criterion evaluation are shown in Table 4, which presents the expert opinions that serve as the basis for the supplier selection procedure.

Table 4
Input of 5 expert ratings for each criterion

Criteria	Expert A	Expert B	Expert C	Expert D	Expert E
C1	AH	AH	VH	H	AH
C2	E	ML	AH	H	H
C3	E	ML	AH	H	VH
C4	VH	H	VH	H	E
C5	MH	E	MH	H	E
C6	L	ML	E	VL	ML

The aggregated values ($\tilde{b}_i$), each criterion's final ranking (r_i) and the fuzzy importance weights $\tilde{w}_i$ are presented in Table 5.

Table 5
Findings from the application of fuzzy OPA Method

Criteria	$\tilde{b}_i$	r_i	$\tilde{w}_i$
C1	(7.8539, 8.5777, 9.5801)	1	(0.2800,0.3066,0.4000)
C2	(5.6129, 6.5878, 7.6170)	4	(0.0986,0.1365,0.1599)
C3	(5.7745, 6.7533, 7.7869)	3	(0.1599,0.1870,0.2071)
C4	(6.3882, 7.4051, 8.4174)	2	(0.2071,0.2424,0.2800)
C5	(5.2447, 6.2534, 7.2597)	5	(0.0544,0.0872,0.0986)
C6	(2.8931, 3.9518, 4.9839)	6	(0.0000,0.0404,0.0544)

In this section, the weight values of six main criteria used in supplier selection were calculated: *Repair Rate - Quality Performance* was identified as the most critical factor, reflecting its direct impact on production efficiency and product standards. *Reliability* and *Overtime Capability* followed in importance, emphasizing the need for consistent partnerships and operational flexibility under pressure. *Ability to Produce Different Product* ranked fourth, highlighting the advantage of suppliers capable of handling various classifications. *Economic Incentives* and *Supplier Class & Risk Classification*, while still relevant, were given lower priority due to their more indirect influence on immediate production outcomes. This prioritization framework aligns with both strategic objectives and operational realities of contract manufacturing environments.

4.3 Application of Fuzzy Trigonometric RAFSI Method

Based on the Pareto analysis, key suppliers involved in active contract manufacturing within the supply chain have been identified. Seventeen alternative suppliers have been identified, each with their own advantages and disadvantages, operating in a sector without workforce-based automation. The best supplier will be evaluated based on six criteria outlined in Section 4.2. The list of suppliers provided in Table 6 presents a comprehensive overview of the clothing supply chain structure, categorizing seventeen suppliers across five main Supply Managements and their respective supply groups. While these suppliers possess the capability to manufacture any product within their designated product management segment, they demonstrate expertise and competence in the specific supply groups mentioned in Table 6. This organization facilitates a clear understanding of supplier distribution throughout the various clothing categories within the supply network.

Table 6
Supplier Distribution Based on SMDs and Supply Group Specializations

Supply Management Divisions	Respective Supply Groups	Suppliers
Baby Boy (BB)	BB Pants (Denim,Woven)	Supplier 1, Supplier 2
Men's Casual (MC)	MC Shirt	Supplier 3, Supplier 4
	MC Cargo Pant	Supplier 5, Supplier 6
	MC Pants	Supplier 7
Men's Classic (MCL)	MCL Chino	Supplier 8, Supplier 9
Women's Casual (WC)	WC Shirt	Supplier 10, Supplier 11
	WC Tunic, Shirt	Supplier 12, Supplier 13
Women's Classic (WCL)	WCL Modelled Pants, Skirt	Supplier 14, Supplier 15
	WCL Tunic, Shirt	Supplier 16, Supplier 17

To support the systematic supplier evaluation process, Table 7 provides a comprehensive collection of expert evaluations, with each possible supplier evaluated against all criteria.

Table 7
The linguistic assessments of 5 decision makers evaluating suppliers across six criteria

Suppliers	C1	C2	C3
Supplier 1	H; VH; AH; H; VH	E; VH; MH; H; E	H; VH; AH; AH; VH
Supplier 2	H; VH; AH; H; VH	AH; VH; AH; AH; VH	ML; L; E; MH; E
Supplier 3	ML; E; MH; ML; E	E; VH; MH; H; VH	AL; VL; L; AL; VL
Supplier 4	H; VH; AH; H; VH	E; VH; MH; H; E	H; VH; AH; AH; VH
Supplier 5	H; VH; AH; H; VH	E; VH; MH; H; E	H; VH; AH; AH; VH
Supplier 6	H; VH; H; VH; VH	H; VH; AH; H; VH	H; VH; AH; AH; VH
Supplier 7	H; VH; AH; H; VH	H; VH; AH; H; VH	H; VH; AH; AH; VH
Supplier 8	H; VH; AH; H; VH	AH; VH; AH; AH; VH	ML; L; E; MH; E
Supplier 9	H; VH; AH; H; VH	E; VH; MH; H; E	H; VH; AH; AH; VH
Supplier 10	MH; ML; E; ML; E	H; VH; AH; H; VH	AL; VL; L; AL; VL
Supplier 11	E; MH; E; MH; ML	H; VH; AH; H; VH	ML; L; E; MH; E
Supplier 12	AH; H; VH; AH; H	E; VH; MH; H; E	H; VH; AH; AH; VH
Supplier 13	E; MH; E; MH; ML	H; VH; AH; H; VH	H; VH; AH; AH; VH
Supplier 14	H; VH; AH; H; VH	H; VH; AH; H; VH	ML; L; E; MH; E
Supplier 15	H; VH; AH; H; VH	H; VH; AH; H; VH	H; VH; AH; AH; VH
Supplier 16	AH; H; VH; AH; H	E; VH; MH; H; E	H; VH; AH; AH; VH
Supplier 17	E; MH; E; MH; ML	E; VH; MH; H; E	ML; L; E; MH; E

Table 7
Continued

Suppliers	C4	C5	C6
Supplier 1	VH; AH; H; VH; AH	H; VH; AH; AH; VH	ML; E; E; ML; E
Supplier 2	VH; AH; H; VH; AH	ML; L; E; MH; E	H; VH; AH; H; VH
Supplier 3	VH; AH; H; VH; AH	L; VL; L; ML; VL	H; VH; AH; H; VH
Supplier 4	E; MH; E; MH; ML	H; VH; AH; AH; VH	H; VH; AH; H; VH
Supplier 5	VH; AH; H; VH; AH	H; VH; AH; AH; VH	H; VH; AH; H; VH
Supplier 6	VH; AH; H; VH; AH	H; VH; AH; AH; VH	H; VH; AH; H; VH
Supplier 7	VH; AH; H; VH; AH	H; VH; AH; AH; VH	ML; E; E; ML; E
Supplier 8	L; E; MH; E; MH	H; VH; AH; AH; VH	H; VH; AH; H; VH
Supplier 9	E; MH; E; MH; ML	H; VH; AH; AH; VH	ML; E; E; ML; E
Supplier 10	VH; AH; H; VH; AH	AL; VL; E; AL; VL	H; VH; AH; H; VH
Supplier 11	VH; AH; H; VH; AH	AL; VL; L; AL; VL	H; VH; AH; H; VH
Supplier 12	E; MH; E; MH; ML	H; VH; AH; AH; VH	H; VH; AH; H; VH
Supplier 13	L; E; MH; E; MH	H; VH; AH; AH; VH	H; VH; AH; H; VH
Supplier 14	VH; AH; H; VH; AH	ML; L; E; MH; E	H; VH; AH; H; VH
Supplier 15	VH; AH; H; VH; AH	E; VL; AH; E; MH	H; VH; AH; H; VH
Supplier 16	VH; AH; H; VH; AH	ML; L; E; MH; E	H; VH; AH; H; VH
Supplier 17	VH; AH; H; VH; AH	VH; VH; AH; AH; VH	H; VH; AH; H; VH

The aggregated evaluation matrix C is obtained, presented in Table 8, using fuzzy weighted geometric average operator described in Equation (1).

Table 8
The aggregated evaluations of suppliers across six criteria

Suppliers	C1	C2	C3	C4	C5	C6
Supplier 1	8.176	6.594	8.480	8.480	8.480	5.074
Supplier 2	8.176	8.796	4.984	8.480	4.984	8.176
Supplier 3	5.245	7.195	2.172	8.480	3.211	8.176
Supplier 4	8.176	6.594	8.480	5.645	8.480	8.176
Supplier 5	8.176	6.594	8.480	8.480	8.480	8.176
Supplier 6	8.084	8.176	8.480	8.480	8.480	8.176
Supplier 7	8.176	8.176	8.480	8.480	8.480	5.074
Supplier 8	8.176	8.796	4.984	5.364	8.480	8.176
Supplier 9	8.176	6.594	8.480	5.645	8.480	5.074
Supplier 10	5.245	8.176	2.172	8.480	2.365	8.176
Supplier 11	5.645	8.176	4.984	8.480	2.172	8.176
Supplier 12	8.270	6.594	8.480	5.645	8.480	8.176
Supplier 13	5.645	8.176	8.480	5.364	8.480	8.176
Supplier 14	8.176	8.176	4.984	8.480	4.984	8.176
Supplier 15	8.176	8.176	8.480	8.480	5.335	8.176
Supplier 16	8.270	6.594	8.480	8.480	4.984	8.176
Supplier 17	5.645	6.594	4.984	8.480	8.696	8.176

Table 9 displays the score matrix together with the related ideal and non-ideal values.

Table 9
The score matrix, ideal and non-ideal values for each criterion

Suppliers	C1	C2	C3	C4	C5	C6
Supplier 1	8.176	6.594	8.480	8.480	8.480	5.074
Supplier 2	8.176	8.796	4.984	8.480	4.984	8.176
Supplier 3	5.245	7.195	2.172	8.480	3.211	8.176
Supplier 4	8.176	6.594	8.480	5.645	8.480	8.176
Supplier 5	8.176	6.594	8.480	8.480	8.480	8.176
Supplier 6	8.084	8.176	8.480	8.480	8.480	8.176
Supplier 7	8.176	8.176	8.480	8.480	8.480	5.074
Supplier 8	8.176	8.796	4.984	5.364	8.480	8.176
Supplier 9	8.176	6.594	8.480	5.645	8.480	5.074
Supplier 10	5.245	8.176	2.172	8.480	2.365	8.176
Supplier 11	5.645	8.176	4.984	8.480	2.172	8.176
Supplier 12	8.270	6.594	8.480	5.645	8.480	8.176
Supplier 13	5.645	8.176	8.480	5.364	8.480	8.176
Supplier 14	8.176	8.176	4.984	8.480	4.984	8.176
Supplier 15	8.176	8.176	8.480	8.480	5.335	8.176
Supplier 16	8.270	6.594	8.480	8.480	4.984	8.176
Supplier 17	5.645	6.594	4.984	8.480	8.696	8.176
Ideal	8.270	8.796	8.480	8.480	8.696	8.176
Non-ideal	5.245	6.594	2.172	5.364	2.172	5.074

Table 10 shows the normalized decision matrix, derived by Equation (17), which normalizes the assessment scores to allow for proper comparisons across all criteria and alternatives in the supplier selection process. R_j values were calculated using Equation (18).

Table 10
Normalized decision matrix and R_j

Suppliers	C1	C2	C3	C4	C5	C6	R_j
Supplier 1	0.460	0.428	0.401	0.462	0.407	0.617	0.446
Supplier 2	0.460	0.476	0.292	0.462	0.559	0.513	0.441
Supplier 3	0.388	0.441	0.204	0.462	0.690	0.513	0.407
Supplier 4	0.460	0.428	0.401	0.394	0.407	0.513	0.427
Supplier 5	0.460	0.428	0.401	0.462	0.407	0.513	0.443
Supplier 6	0.458	0.463	0.401	0.462	0.407	0.513	0.447
Supplier 7	0.460	0.463	0.401	0.462	0.407	0.617	0.451
Supplier 8	0.460	0.476	0.292	0.387	0.407	0.513	0.411
Supplier 9	0.460	0.428	0.401	0.394	0.407	0.617	0.430
Supplier 10	0.388	0.463	0.204	0.462	0.777	0.513	0.417
Supplier 11	0.398	0.463	0.292	0.462	0.800	0.513	0.438
Supplier 12	0.463	0.428	0.401	0.394	0.407	0.513	0.427
Supplier 13	0.398	0.463	0.401	0.387	0.407	0.513	0.409
Supplier 14	0.460	0.463	0.292	0.462	0.559	0.513	0.440
Supplier 15	0.460	0.463	0.401	0.462	0.539	0.513	0.458
Supplier 16	0.463	0.428	0.401	0.462	0.559	0.513	0.456
Supplier 17	0.398	0.428	0.292	0.462	0.400	0.513	0.402

Upon analysis of the results, the highest performing suppliers are S15 (0.458), S16 (0.456), and S7 (0.451). These suppliers have demonstrated superior performance compared to others within the established criteria framework. Mid-level performance is observed for suppliers S1 (0.446), S6 (0.447), S5 (0.443), and S2 (0.441), who also present competitive values. The lowest performing suppliers are identified as S17 (0.402), S3 (0.407), and S13 (0.409).

Overall, the relatively narrow range of total values (0.402-0.458) among suppliers indicates that all suppliers meet a certain quality standard. This situation provides decision-makers with various alternatives for strategic supplier selection. This study makes a significant contribution to rational and evidence-based decision-making processes in supply chain management.

4.4 Application of Order Allocation Model

In this study, a mixed integer linear programming model has been developed to optimize the assignment of orders to suitable suppliers and the timing of production processes to improve supply chain management in the textile industry. The model has a very detailed structure that considers the multidimensional fit between supplier and product features, capacity constraints, production times and delivery dates.

The main purpose of the proposed model is twofold: on the one hand, to maximize the RAFSI performance scores of suppliers and to make a quality-oriented assignment; on the other hand, to increase the total production efficiency by minimizing completion times of orders. In this way, both the use of high-performance suppliers is increased, and the service level is increased by complying with customer delivery times.

In the model, each order is allowed to be assigned to only one supplier, and a high level of match is required between the assigned supplier and the order's production category, classification and supplier domain. This emphasizes that quality compliance between the product and supplier is a critical factor in improving supply chain performance and ensures quality product output.

The developed model also takes into account operational requirements such as daily production capacity, supplier working days, order start time and order completion time. In particular, the start date of each order cannot be earlier than the earliest start date, while the completion date must definitely not exceed the delivery date. The model was implemented in Python (version 3.13.1) and solved using the Gurobi Optimizer (version 12.0.1) via the Gurobipy interface. Assignment decisions were modeled using binary variables, while scheduling decisions were represented with integer variables. For the 20 orders considered in the first 15 days of the order allocation plan, the resulting schedule is illustrated in Figure 3.

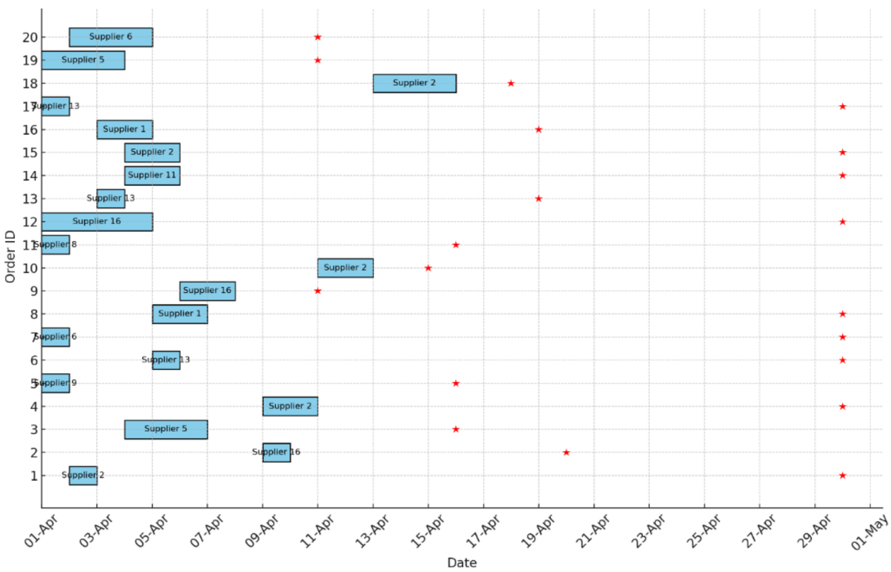

Fig. 3. Order allocation with assigned suppliers and due dates

Figure 3 shows the supplier to which each order was assigned as a result of the optimization model, the start and end days of production, delivery dates, processing time and the RAFSI scores of the relevant supplier. According to the solution results, each order was assigned to the suppliers that were found most suitable for it and had high RAFSI scores, and the production times were planned to be completed before the delivery dates.

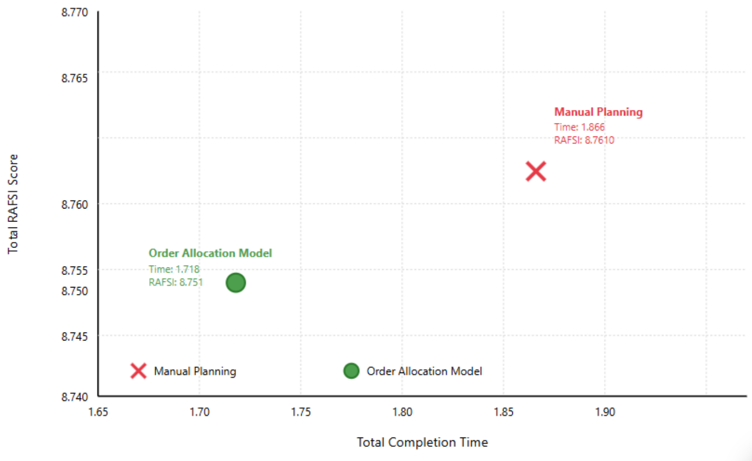

Fig. 4. Order allocation model and manual planning: A comparison of Pareto

As shown in Figure 4, to evaluate the accuracy and effectiveness of the model, the objective function value obtained from the developed optimization model was compared with that derived from the traditional manual planning method. The objective function value calculated from manual planning was 6.8948, whereas the output of the mathematical model was 7.0330. These results indicate that the developed model provides higher efficiency and quality in the planning process and, in addition, generates direct outputs in accordance with all constraints and objectives without the need for individual manual control.

The model achieved approximately 2.0% better performance compared to the manual method by optimizing order-to-supplier assignments, production scheduling, and resource utilization. Thus, it has been demonstrated that the model can serve as an important tool for improving operational efficiency and supporting decision-making systems.

Furthermore, it has been observed that the model provides a significant performance improvement compared to manual assignment methods, particularly in cases where order and supplier diversity is high. In conclusion, this optimization model is presented as a powerful tool that systematically and efficiently manages order allocation in the textile industry.

5. Managerial Insights

In today's increasingly competitive business environment, organizations are forced to make rapid decisions, while the accuracy and timeliness of these decisions remain critically important. Businesses often must make decisions that attempt to achieve multiple, sometimes conflicting objectives simultaneously [30,31]. Tactical decisions, such as contractor or supplier selection, carry significant strategic implications for organizational performance. When these decisions are aligned with a broader strategic viewpoint, they contribute more effectively to long-term goals. Integrating scientific and data-driven methods into the supplier selection process empowers managers with objective criteria, leading to more informed, consistent, and impactful decisions that enhance operational efficiency and competitive advantage.

By using Pareto analysis, managers can prioritize high-impact problems, ensuring that resources are allocated to areas that will yield the greatest return. It also supports strategic focus on high-profit product groups, enabling more informed decision-making and efficient performance improvement. By incorporating multiple criteria in the evaluation process and using holistic approaches in assessment of factors including production flexibility, overtime capability, quality, reliability, and the optimization of subjective judgments through mathematical models help managers make more informed decisions [32]. The use of fuzzy OPA in determining criteria weights successfully combines subjective expert opinions with mathematical consistency. This represents a successful adaptation of OPA's fuzzy extension to the textile industry [22,23].

From a managerial perspective, a striking insight is the digitalization and automation of decision-making processes. It is critically important to integrate computer-aided systems into decision processes, develop structures that work in conjunction with performance evaluation systems, and design processes that save labour and time. This transformation allows managers to devote more time to strategic issues while increasing operational efficiency.

6. Conclusions

This study addresses the supplier selection problem for a textile company engaged in contract manufacturing. The company works with suppliers based on product group specifications and characteristics for its manufacturing needs. Following an initial Pareto analysis, the study proceeded with 17 suppliers. The effectiveness of the methodology is demonstrated by the consistency between mathematically determined supply groups and those having the largest supplier pool and highest loading volume across the company.

6 main criteria were considered for supplier selection, identified through comprehensive literature review and practical experience. The study presents a new fuzzy logic-based methodology for data-driven supplier selection in the textile industry. This model provides decision-makers with objective criteria weights and dynamic ranking capabilities, conferring competitive advantages. Fuzzy OPA and RAFSI methods were employed, and supplier evaluation results were analyzed.

Supplier S15 achieved the highest score, largely due to its superior quality and flexible working principles. Conversely, supplier S17 ranked lowest, indicating opportunities for improvement in quality and flexibility domains.

The study aimed to implement a more systematic approach within the company using numerical data and scientific methods to analyze these data. Transforming this model into a computer-aided system that integrates with the company's performance evaluation system would both expedite the supplier selection process and reduce labor time expenditure.

These results have supported the modeling of placement decisions under specific constraints and have facilitated optimized outcomes.

The study is limited to 17 suppliers of a single company. However, as it encompasses suppliers from different geographical regions, various product types, and different supply management approaches, the findings can be generalized across supply management contexts.

The model is easily adaptable under different supplier profiles, order types and operational conditions and is suitable for use as a strategic decision support system. Future studies aim to develop more flexible versions where new orders arrive in a dynamic environment; capacities may change during production or supplier performances may be updated over time.

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Conflicts of Interest
The authors declare no conflicts of interest.

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