
SUBCONTRACTOR SELECTION IN A TEXTILE COMPANY USING AN INTEGRATED FUZZY MCDM BASED APPROACH

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Abstract

Several studies have addressed subcontractor selection problem to date. However, most of them considered subcontractor selection in construction industry and other fields have been disregarded. In order to fill this gap, this study focuses on selecting the best subcontractor under fuzzy environment for a Turkish textile company. The case problem is considered as a multiple criteria decision making (MCDM) problem and a hybrid methodology combining Fuzzy Preferences Programming (FPP) Method and Graph Theoretical Matrix Approach (GTMA) is proposed for the solution. In the application, the FPP is used to model the interrelations and interdependences among attributes and the GTMA is utilized to choose the best subcontractor for the company under consideration. The obtained results reveal that the devised methodology can successfully tackle with any type of MCDM problems as well as subcontractor selection.

Keywords: Subcontractor selection; Fuzzy decision-making; Fuzzy Preferences Programming Method (FPP); Graph Theoretical Matrix Approach (GTMA)

JEL Classification: C44, D81, L24

BULANIK ÇKKV TABANLI BÜTÜNLEŞİK BİR YAKLAŞIM KULLANARAK BİR TEKSTİL FİRMASI İÇİN TAŞERON SEÇİMİ

Öz

Günümüze kadar taşeron seçimi problemini ele alan birçok çalışma yapılmıştır. Ancak, bu çalışmalar çoğunlukla inşaat sektörüne odaklanmış ve diğer sektörler göz ardı edilmiştir. Literatürdeki bu boşluk dikkate alınarak bu çalışmada Türkiye’de faaliyet gösteren bir tekstil firması için en iyi taşeron işletme seçimi problemi ele alınmıştır. Seçim problemi bir çok kriterli karar verme (ÇKKV) problemi olarak kabul edilerek çözüm amacıyla Bulanık Tercih Programlama Yöntemi (Fuzzy Preferences Programming (FPP) Method) ve Çizge Teorisi Matris Yaklaşımı (Graph Theoretical Matrix Approach-GTMA) yöntemini birleştiren bütünleşik bir metodoloji önerilmiştir. Uygulamanın ilk aşamasında değerlendirme kriterleri arasındaki karşılıklı ilişkileri ve içsel bağımlılıkları ölçmek için FPP yöntemi kullanılmış, daha sonra en iyi taşeronu seçmek için GTMA yönteminden yararlanılmıştır. Elde edilen sonuçlar, önerilen metodolojinin taşeron seçimi yanında diğer ÇKKV problemlerinin çözümünde de faydalanılabilecek bir yaklaşım olduğunu ortaya koymaktadır.

Anahtar Kelimeler: Taşeron seçimi, Bulanık karar verme, Bulanık Tercih Programlama Yöntemi, Çizge Teorisi Matris Yaklaşımı

JEL Sınıflandırması: C44, D81, L24

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1. Introduction

Subcontracting is fruitful for main contractors as they can keep their companies balanced and agile and can enjoy subcontractors' specialization (Arditi and Chotibhongs 2005:867). How to evaluate and select the most appropriate subcontractor is a vital decision to be made for outsourced-type manufacturers seeking to survive in today's fierce competition environment. Therefore, a scientific decision making process including a rational and systematic algorithm is required to increase the success rate of outsourcing.

Chai et al. (2013) carried out a brief literature survey concerning the methods used in supplier selection and grouped those methods under three categories as: (i) multi-criteria decision-making (MCDM) techniques, (ii) mathematical programming techniques and (iii) artificial intelligence techniques. There are also some studies which handled the subcontractor selection problem using statistical techniques.

Subcontractor selection is a complicated decision-making problem since various quantitative and qualitative, usually conflicting criteria have to be taken into account to achieve the best one among feasible alternatives. Hence, optimal subcontractor selection can inherently be considered as a MCDM problem. However, the available information regarding the subcontractor evaluation criteria usually involves imprecise and vague data. In addition, the judgments and preferences of decision makers (DMs) are ambiguous and vague, thus cannot be modeled with crisp numbers. Zadeh (1965) introduced the fuzzy set theory to cope with ambiguity and vagueness involved in human judgment. Using linguistic variables, which are composed of a finite set of linguistic terms and whose meaning is a fuzzy subset in a universe of discourse, is a more practical approach (Doukas et al., 2007:845).

Several studies have addressed subcontractor selection problem to date. However, most of them handled subcontractor selection in construction industry and other fields are disregarded. The textile industry is one of the basic and visible industries of the world economy. Since there has been a fierce competition in the clothing market in recent years, textile firms should have a systematic and scientific supplier evaluation process. Choosing the best subcontractor will lead to decrease in costs, increase in profit and quality improvement. Therefore, the main motivation of this study is to propose a methodology to select the best subcontractor among eligible alternatives for a manufacturing company operating in Turkish textile industry.

Recently, Rajaeian et al. (2017) performed a systematic literature review of MCDM approaches used in outsourcing domain which concluded that most of the researchers executed hybrid MCDM approaches in order to strengthen their studies. Therefore, this study proposes a hybrid methodology incorporating Fuzzy Preferences Programming (FPP) method and Graph Theoretical Matrix Approach (GTMA). In the case application, the FPP is used to determine the importance ratings of the attributes and then the GTMA is utilized to choose the best subcontractor for the company under consideration. To the best of our knowledge, this combination has not been yet exploited in MCDM literature.

The rest of the paper is organized in the following way. A brief literature research on subcontractor selection is given in Section 2. Section 3 provides the algorithms of the FPP method and the GTMA. The real case application is presented in Section 4. Finally, the paper concludes in Section 5.

2. Literature Review on Subcontractor Selection

There exist many studies published over the past decades that have contributed to the field of subcontractor selection using MCDM methods. Analytic Hierarchical Process (AHP) and Analytical Network Process (ANP) (Saaty, 1980; 1996) are probably the most preferred MCDM techniques for subcontractor selection problem.

Bianchini (2018) provides a two-phase AHP and the technique for order preference by similarity to ideal solution (TOPSIS) approach for the selection of the best third-party logistics (3PL) partner. After the description of the selection criteria of 3PL providers that are determined by company management, the weights of criteria are calculated by applying the AHP method. The TOPSIS method is then employed to achieve the final ranking results. Polat et al. (2017) proposed an integrated fuzzy MCDM approach, which uses fuzzy AHP and fuzzy TOPSIS for the most appropriate rail supplier problem. In the suggested approach, fuzzy AHP was used to analyze the structure of the supplier selection problem and to determine the weights of the criteria, and the fuzzy TOPSIS method was employed to rank the alternative suppliers. Tavana et al. (2016) developed an integrated intuitionistic fuzzy AHP, FPP and SWOT methods for outsourcing reverse logistics. Firstly, the relevant criteria and sub-criteria were identified using a SWOT analysis. Then, Intuitionistic Fuzzy AHP was used to evaluate the relative importance weights among the criteria and the corresponding sub-criteria. These relative weights were then implemented in a novel extension of Mikhailov's FPP method to produce local weights for all criteria and sub-criteria. Finally, these local weights are used to assign a global weight to each sub-criterion and create a ranking.

Zhuang et al. (2017) suggested the hybrid use of the AHP and GTMA for solving the problem of selecting the best paper shredder product from a pool of alternatives. The AHP is used to calculate the criteria weights and then the GTMA is utilized for the alternative prioritizing phase. Agrawal et al. (2016) introduced a combined framework incorporating balanced scorecard and graph theoretic approach in order to make an outsourcing decision in reverse logistics. In the first stage of the application, a sustainable balanced scorecard is developed for the selection of attributes and in the second phase, a graph theoretic approach is run to select the best alternative. Mohaghar et al. (2014) proposed a new technique combining DEMATEL and GTMA methods for supplier selection in an Iranian industrial company. Then, the results were compared to TOPSIS and VIKOR methods.

The works of and Dobos and Vörösmarty (2018) and Ip et al. (2004) can be categorized under mathematical programming approach to supplier selection problem while those of Shabanpour et al. (2017), Fallahpour et al. (2016), Abbasianjahromi et al. (2014) can be categorized under artificial intelligence approach.

2.1 Gaps Identified Through Literature

The literature survey reveals that only a few previous studies investigating the subcontractor selection model used the FPP or GTMA methods, which means the interaction of evaluation criteria is disregarded. In addition, the interdependence among attributes is another neglected issue in the existing papers. Taking into account the void of the subcontractor selection literature mentioned above, the hybrid use of the FPP-GTMA is proposed in this study. In doing so, the merits of the two techniques are enjoyed.

The FPP method (Mikhailov, 2004) reduces the prioritization problem to a fuzzy programming problem that can easily be solved as a standard linear program. It can easily overcome with missing judgments and provides a meaningful indicator for measuring the level of group satisfaction and group consistency. The GTMA was originated from combinatorial mathematics and has some desirable properties such as "competence to model criteria interactions" and "skill to generate hierarchical models" for modeling and solving complex decision making problems (Baykaşoğlu, 2014:573). It can incorporate the interrelationship among different variables and supplies a synthetic score for the whole system. Besides, it considers directional relationship and interdependence among variables (Rajesh et al., 2013:51).

3. Methodology

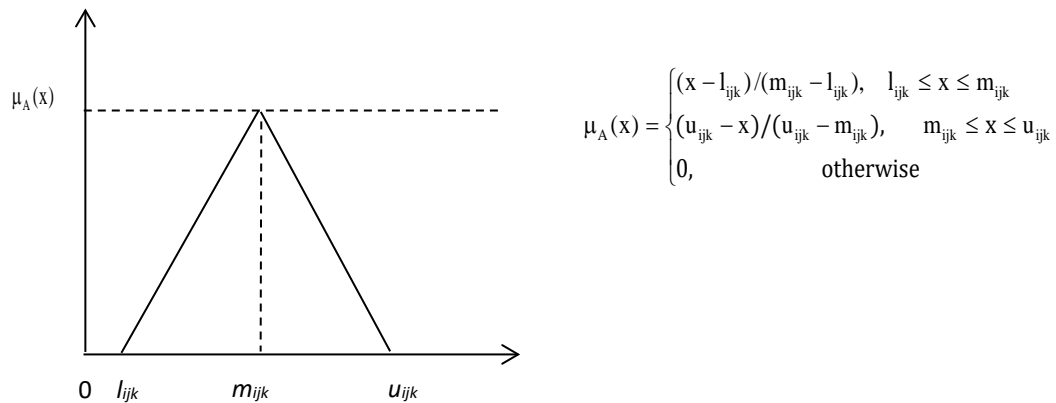
In this section a brief summary of the methods utilized in the application is provided.

3.1 The Fuzzy Preference Programming Method

The FPP method was developed by Mikhailov and Singh (1999) and later improved by Mikhailov (2000; 2002; 2003; 2004) in an effort to derive priorities from pairwise comparison matrices of the AHP. The method is based on a geometrical representation of the prioritization process as an intersection of fuzzy hyperlines and determines the values of the priorities corresponding to the point with the highest measure of intersection.

The procedure of the proposed FPP is briefly outlined below (Mikhailov, 2000; 2002; 2003; 2004). Consider a group of K DMs ($k=1,2,\dots,K$) assess n elements (clusters, criteria, sub-criteria, or alternatives) at the same level of the hierarchy. Assume each DM provides a set of $m_k \leq n(n-1)/2$ incomplete fuzzy comparison matrices $A_k = \{\tilde{a}_{ijk} \mid i=1,2,\dots,n-1, j=2,3,\dots,n, k=1,2,\dots,k\}$ $i=1,2,\dots,n-1, j=2,3,\dots,n, j > i$, which is represented as TFNs, $\tilde{a}_{ijk} = (l_{ijk}, m_{ijk}, u_{ijk})$ (Fig. 1).

Figure 1: A Triangular Fuzzy Number and Membership Function



Then, the prioritization problem is to obtain priority vector (weights) $w = (w_1, w_2, \dots, w_n)^T$ from A_i where w_i represents the relative importance weight of n elements. Mikhailov (2003) developed a FPP method which derives crisp priority vectors from fuzzy numbers by applying alpha-cuts (α -level sets) before comparisons and hence avoiding the final fuzzy scores that other methods obtain. The α -cuts concept is used in this method so as to convert the fuzzy judgments into interval judgments.

For a given α -cut, each fuzzy judgment a_{ijk} can be transformed into an interval set $a_{ijk} = \{l_{ijk}(\alpha), u_{ijk}(\alpha)\}$ where

$$\begin{aligned} l_{ijk}(\alpha) &= l_{ijk} + \alpha * (m_{ijk} - l_{ijk}) \\ u_{ijk}(\alpha) &= u_{ijk} - \alpha * (u_{ijk} - m_{ijk}) \end{aligned} \quad (1)$$

If the interval judgments are consistent, a priority vector $w = (w_1, w_2, \dots, w_n)^T$ is obtained by FPP, which satisfies,

$$l_{ijk}(\alpha) \leq \frac{w_i}{w_j} \leq u_{ijk}(\alpha) \quad (2)$$

For inconsistent judgments a crisp priority vector is derived by the FPP method which approximately satisfies,

$$\begin{aligned}
I_{ijk}(\alpha) &\lesssim \frac{w_i}{w_j} \lesssim u_{ijk}(\alpha) \\
\text{st.} & \\
-w_i + w_j I_{ijk}(\alpha) &\lesssim 0 \\
w_i - w_j u_{ijk}(\alpha) &\lesssim 0
\end{aligned} \tag{3}$$

where \lesssim implies "fuzzy less or equal to".

The above set of $2m$ fuzzy constraints can be given in a matrix form as

$$R_w \lesssim 0 \tag{4}$$

where the matrix $R \in \mathfrak{R}^{2m \times n}$.

The k th row of Eq.(4) represents a fuzzy linear constraint and can be characterized by a linear membership function of the type

$$\mu_k(R_k w) = \begin{cases} 1 - \frac{R_k(w)}{d_k}, & R_{ijk}(w) \leq d_k \\ 0, & R_{ijk}(w) \geq d_k \end{cases} \tag{5}$$

where d_k is a tolerance parameter assigned by the DM which indicates the permitted interval of approximate satisfaction of the crisp quality $R_k w \leq 0$. The solution to the group prioritization problem is hinged on two assumptions. The first assumption calls for the existence of a non-empty fuzzy feasible area \tilde{P} , which is expressed as an intersection of the whole fuzzy constraints characterized by the following membership function:

$$\mu_{\tilde{P}}(W) = [\text{Min}\{\mu_1(R_1 W), \mu_2(R_2 W), \dots, \mu_{2m}(R_{2m} W)\} \mid w_1 + w_2 + \dots + w_n = 1] \tag{6}$$

If the initial interval judgments are inconsistent a non-empty fuzzy feasible area can be acquired by adjusting "large enough" tolerance parameters. The second assumption of the FPP approach is that there is always a maximizing solution w^* on the simplex which has a maximum degree of membership λ^* (consistency index) in \tilde{P} such that,

$$\lambda^* = \mu_{\tilde{P}}(W^*) = \text{Max}[\text{Min}\{\mu_1(R_1 W), \mu_2(R_2 W), \dots, \mu_{2m}(R_{2m} W)\} \mid w_1 + w_2 + \dots + w_n = 1] \tag{7}$$

By defining a new variable λ that measures the maximum degree of membership of a given priority vector in the fuzzy feasible area \tilde{P} and using Eqs. (4) and (7), the problem of obtaining a maximizing solution can be denoted as the following linear programming:

$$\begin{aligned}
&\text{Maximize } \lambda \\
&\text{subject to } d_k \lambda + R_k w \leq d_k \\
&\sum_{i=1}^n w_i = 1 \quad w_i > 0, \quad i = 1, 2, \dots, n, \quad k = 1, 2, \dots, 2m.
\end{aligned} \tag{8}$$

The optimal solution to the Model (8) is a vector (w^*, λ^*) where w^* denotes the maximum degree of membership in the feasible area and λ^* is a consistency index measuring the level of satisfaction. In case the interval comparison judgments are consistent, then $\lambda^* \geq 1$. Otherwise, for inconsistent judgments the consistency index λ^* takes a value between 0 and 1 that depends on the degree of inconsistency and the values of the tolerance (deviation) parameters d_k . A negative value of λ^* indicates that the fuzzy judgments are strongly inconsistent and the solutions ratios are outside the extended intervals. The tolerance parameters should be taken large enough to assure

the non-emptiness of the feasible area \tilde{P} and a positive value of λ^* . As the DM usually has no preferences regarding his/her individual pairwise comparison judgments, it is plausible to set tolerance parameters equal to 1. It is evident that if $d = 1$, the scope of the feasible area \tilde{P} encompasses the whole simplex line $w_1 + w_2 = 1$ and ensures non-emptiness of the \tilde{P} even if we have many inconsistent judgments. It should be noted that equal values of whole deviation parameters do not have an impact on the solution value of w^* .

For instance, the solution of the two-dimensional prioritization problems at each α -level can be provided by solving the following linear programming model (9).

$$\begin{aligned} & \text{Maximize } \lambda \\ & \text{subject to } d_1\lambda + w_1 - u_{12}(\alpha)w_2 \leq d_1 \\ & \quad d_2\lambda - w_1 + l_{12}(\alpha)w_2 \leq d_2 \\ & \quad w_1 + w_2 = 1 \quad w_i > 0, \quad i = 1, 2 \end{aligned} \quad (9)$$

Executing the proposed FPP method by α -cuts a sequence of crisp priorities are achieved as:

$$W(\alpha) = (w_1(\alpha), (w_2(\alpha)), \dots, (w_n(\alpha)))^T, \quad l = 1, \dots, L, \quad 0 = \alpha_1 < \alpha_2 < \dots < \alpha_L = 1.$$

The relative importance of all attributes depends on the level of α . The value of the priorities under different α -levels might be quite different. A small value of α indicates high level of uncertainty and correspondingly less reliable priorities while a large value provides more precision of the interval chosen. The value of α can be exploited as a weighting factor of the solutions, hence aggregated values of the priorities can be obtained by a weighted sum of the type

$$W_j = \frac{\sum_{l=1}^L \alpha_l w_j}{\sum_{l=1}^L \alpha_l} \quad (10)$$

3.2 Graph Theoretical Matrix Approach (GTMA)

Let V be a finite nonempty set and let $E \subseteq V \times V$. The pair (V, E) is called a directed graph (or digraph) on V , where V is the set of vertices or nodes, and E is its set of directed edges or arcs. Then a digraph can be denoted as $G = (V, E)$ (Baykaşoğlu, 2009:479). Graph theory has served as a fruitful vehicle in modeling of systems, network analysis, functional representation, conceptual modeling etc. In addition, it can efficiently tackle with the problems of structural relationship by synthesizing the interrelationship among different variables and provides a synthetic score for the whole system (Rao, 2007). The graph theoretical methodology is comprised of three phases as digraph representation, matrix representation and permanent function representation.

3.2.1 Digraph Representation

A digraph is used to represent the factors and their interdependences in terms of nodes and edges. In an undirected graph no direction is assigned to the edges in the graph, while directed graphs or digraphs have directional edges (Grover et al. 2004:4040). The digraph consists of a set of nodes $N = \{n_i\}$ with $i=1, 2, \dots, M$ and a set of directed edges $E = \{C_{ij}\}$. A node n_i represents i -th selection attribute and edges represent the interdependence (relative importance) among the attributes. The total of nodes, M , is equal to the number of attributes considered for the system. If a node i has relative importance over another node j , then a directed edge or arrow is drawn from node i to node j (i.e. α_{ij}). If node j is having relative importance over i , then a directed edge or arrow is drawn from node j to node i (α_{ji}) (Koulouriotis and Ketipi 2011:11903).

3.2.2 Matrix Representation

When the system is large, its corresponding graph is complex and this complicates its understanding visually. Matrix representations help to model the digraph mathematically. The

matrix approach is beneficial in analyzing the graph/digraph models expeditiously to obtain the system function and index to meet the objectives (Rao, 2007).

3.2.3 Permanent Representation

Permanents were developed in 1812 simultaneously by Binet and Cauchy (Minc 1978). The permanent is a standard matrix function and is used in combinatorial mathematics. The permanent function is nothing but the determinant of a matrix but considering all the determinant terms as positive terms. By utilizing permanents no negative sign will appear in the expression and hence no information will be lost (Rao, 2006:1102).

Let $\xi = (a_{ij})$ be an $m \times n$ matrix, $m \leq n$. The permanent of ξ , written as $Per(\xi)$ is defined as:

$$Per(\xi) = \sum_{\sigma} a_{1\sigma(1)} a_{2\sigma(2)} \dots a_{m\sigma(m)} \quad (11)$$

where the summation extends over all one-to-one functions from $\{1, \dots, m\}$ to $\{1, \dots, n\}$. The sequence $a_{1\sigma(1)}, \dots, a_{m\sigma(m)}$ is referred to a diagonal of ξ and the product $a_{1\sigma(1)} \dots a_{m\sigma(m)}$ is a diagonal product of ξ . Thus, the permanent of ξ is the sum of all diagonal products of ξ . Ryser formula given in Eq. (12) is generally conducted for computing permanent of matrices.

$$Per(\xi) = (-1)^n \sum_{S \subseteq \{1, \dots, n\}} (-1)^{|S|} \prod_{i=1}^n \sum_{j \in S} a_{ij} \quad (12)$$

where the sum is over all subsets of $\{1, \dots, n\}$ and $|S|$ is the number of elements in S (Baykaşoğlu, 2014:481).

3.3 The Proposed Evaluation Framework for Subcontractor Selection

The algorithm of the proposed methodology is explained in a step by step manner in order to facilitate a better understanding.

Step -1. Identify subcontractor selection attributes that affect the decision and short-list the subcontractor alternatives on the basis of the identified attributes satisfying the requirements. Then, the graph representation of the attributes (criteria) and their interdependencies are created to enable a better comprehension of the MCDM problem. The subcontractor digraph models the subcontractor selection criteria and their interrelationship. The number of nodes must be equal to the number of attributes considered. The magnitude of the edges and their directions will be determined from the relative importance between the attributes (a_{ij}).

Step-2. Constitute evaluation matrix of the alternatives. Matrix representation of the subcontractor selection digraph gives one-to-one representation. This matrix will be an $M \times M$ matrix with diagonal elements of D_i and off-diagonal elements of a_{ij} . D_i is the score of an alternative with respect to criterion i that can be attained from available or estimated data. When quantitative values of the attributes are available, normalized values of an attribute assigned to the alternatives are calculated by v_j/v_i , where v_i is the measure of the attribute for the i -th alternative and v_j is the measure of the attribute for the j -th alternative which has the maximum value among the alternatives. This ratio is valid for beneficial attributes only. In the case of a non-beneficial attribute (e.g. total costs involved) whose lower measures are desirable, the normalized values assigned to the alternatives are calculated by v_j/v_i . In this case v_j is the measure of the attribute for the j -th alternative which has the minimum value among the considered alternatives.

When quantitative value is not available, then a ranked value judgment on a fuzzy conversion scale is adopted (Rao, 2009:6983). By exploiting fuzzy set theory, the value of the attributes (D_i) can be first expressed as the following matrix form.

$$\xi = \begin{bmatrix} D_1 & a_{12} & a_{13} & \dots & \dots & a_{1n} \\ r_{21} & D_2 & a_{23} & \dots & \dots & a_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & \dots & \dots & D_n \end{bmatrix} \quad (13)$$

The relative importance (or interaction) between criteria are specified by conducting the proposed FPP approach.

Step-3. Calculate final ratings of the alternatives. The permanent of the evaluation matrices of the alternatives, per (ξ), is defined as the subcontractor selection criteria function and gives the rating for the alternatives. Per (ξ) can be calculated via Eq.(11). An expanded version of that equation is given in Eq.(14). Per(ξ) must be computed for each alternative and ranked in a descending order. The alternative with the highest per (ξ) value is the best alternative (Baykaşoğlu, 2009:482).

$$\begin{aligned} \text{Per}(\xi) &= \prod_{i=1}^M D_i + \sum_{i,j,\dots,M} (a_{ij}a_{ji})D_k D_1 \dots D_M + \sum_{i,j,\dots,M} (a_{ij}a_{jk}a_{ki} + a_{ik}a_{kj}a_{ji})D_1 D_m \dots D_M \\ &+ \left\{ \sum_{i,j,\dots,M} (a_{ij}a_{ji})(a_{kl}a_{lk})D_m D_n \dots D_M + \sum_{i,j,\dots,M} (a_{ij}a_{jk}a_{kl}a_{li} + a_{il}a_{lk}a_{kj}a_{ji})D_{m_n} \dots D_M \right\} \\ &+ \left[\sum_{i,j,\dots,M} (a_{ij}a_{ji})(a_{kl}a_{lm}a_{mk}a_{km}a_{ml}a_{lk})D_n D_o \dots D_M + \sum_{i,j,\dots,M} (a_{ij}a_{jk}a_{kl}a_{lm}a_{mi} + a_{im}a_{ml}a_{lk}a_{kj}a_{ji})D_n D_o \dots D_M \right] + \dots \end{aligned} \quad (14)$$

The utilization of the matrix permanent concept provides better appreciation of the attributes as it includes all possible structural components of the attributes and their relative importance (Darvish et al., 2009:615; Attri et al., 2013).

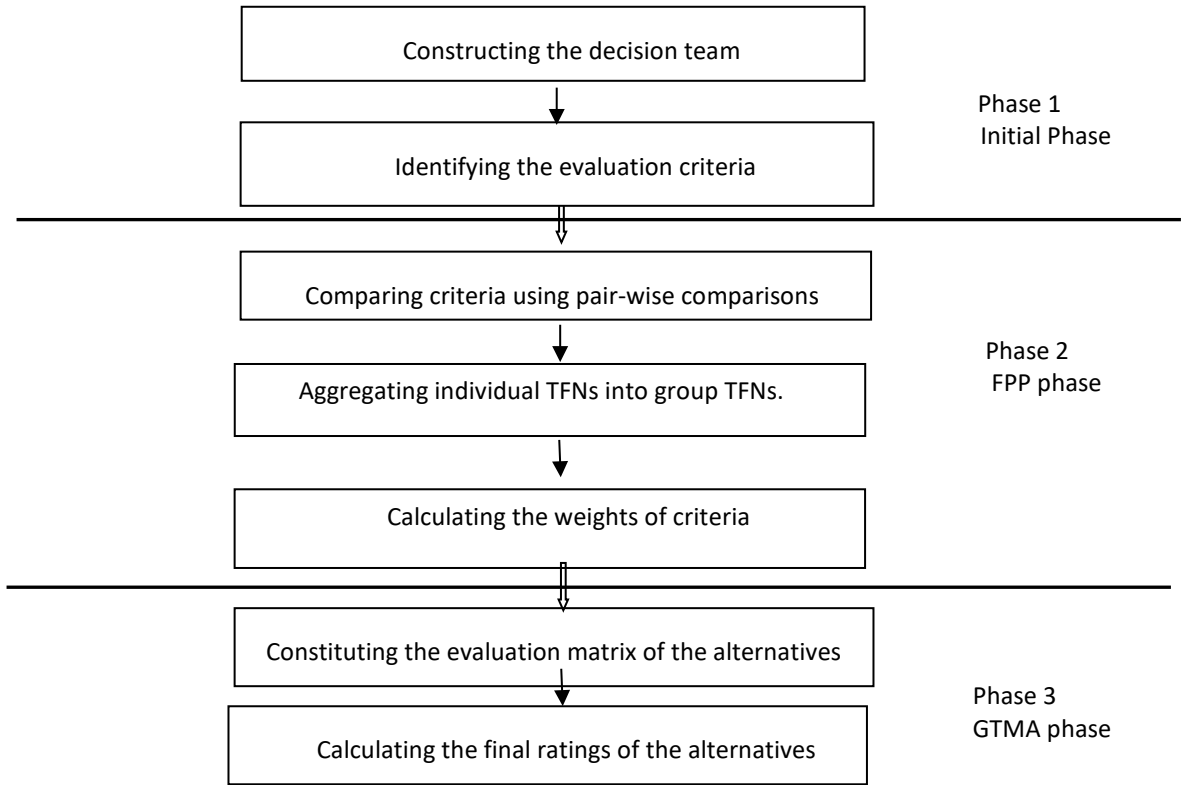
4. Case Study

The contribution of the Turkish textile industry to the world textile and ready-made clothing production is about 4%, ranking the 8th country worldwide. The Turkish sector is the second largest supplier in Europe and ranks the 5th globally in textile yarn and fiber production (Öztürk et al., 2015:117). The textile companies in Turkey used to supply clothes that are ready to be used in sewing production, but nowadays most of them buy cotton (raw material), then they are send for thread production, after the clothes are prepared they are sent for dyeing and finally the clothes are ready for sewing. The main reason why textile firms outsource those operations is reducing costs (Cebeci, 2009:8901).

The company considered is operating in the Turkish textile industry and has three manufacturing plants in different provinces of Turkey. The company has a monthly production capacity between 500.000 and 550.000 high quality pieces of clothing and household textiles with more than 2000 employees in total. The company commissions 40% of its products to subcontractors in order to remain flexible, gain competitive advantage and build close and long-term relationships with suppliers. Since the optimal subcontractor selection problem is quite complicated to deal with, the firm decided to use a scientific method. Initially, a decision committee including four managers of purchasing, operations, logistics and finance departments coded as (DM₁,...,DM₄), was constituted. The DMs were chosen according to their expertise and seniority. Then, the team adopted to perform hybrid use of the FPP and GTMA in the decision making process.

The hierarchical representation of the decision problem is exhibited in Figure 2.

Figure 2: The Flowchart of the Presented Methodology



The stepwise solution procedure of the case decision problem in line with the Section 3.3 is explained in detail below.

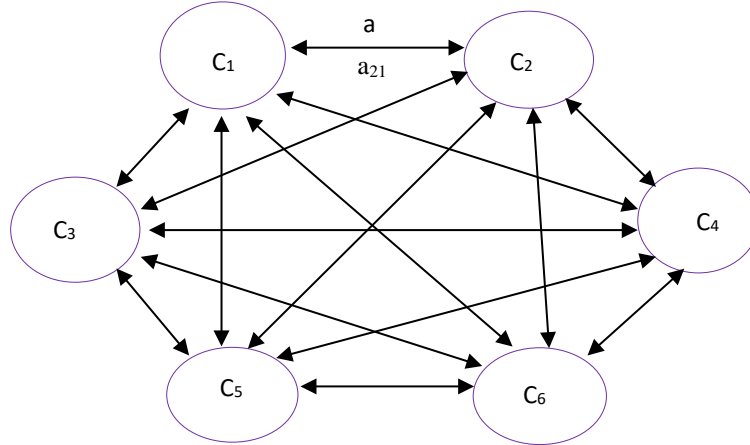
Step-1. The committee determined six attributes that affects the optimal subcontractor selection based on their expertise and past experiences. The evaluation criteria determined are exhibited in Table 1.

Table 1: Decision Criteria Used for the Subcontractor Selection

Criteria	Definition
Manufacturing capability (C ₁)	The subcontractor's ability to provide the orders with the required quality and quantity in a timely manner and meeting fluctuations in demand
Quality control systems (C ₂)	Input control system and commitment for preventing quality failures
Delivery (C ₃)	Compliance of order delivery with due date and order cycle time
Cost (C ₄)	Total cost of outsourcing activities
Financial strength (C ₅)	Financial stability of the supplier in the long-run and flexibility in billing and payment conditions
Past performance (C ₆)	Failure to have contracts completed and past customer relationship

Besides, four subcontractors (S_1, \dots, S_4) that successfully had passed the screening process specified as eligible alternatives. The interdependencies of the determined attributes are portrayed via the digraph shown in Figure 3. As mentioned above, the nodes in the digraph represent criteria and the interaction among criteria is represented by edges.

Figure 3: Subcontractor Selection Attributes Digraph



Step-2. In order to form the matrix representation of the subcontractor selection digraph, the relative importance of criteria were computed thanks to the proposed FPP approach. The decision team used the linguistic variables and corresponding TFNs shown in Table 2 for pairwise comparisons of the attributes (Cebeci, 2009).

Table 2: Linguistic Variables for Importance Weight of Each Criterion

Linguistic variables	Triangular fuzzy numbers	Inverse of TFN
Equally important	(1, 1, 1)	(1, 1, 1)
Weakly important	(1, 3, 5)	(1/5, 1/3, 1)
Fairly important	(3, 5, 7)	(1/7, 1/5, 1/3)
Very strongly important	(5, 7, 9)	(1/9, 1/7, 1/5)
Absolutely important	(7, 9, 9)	(1/9, 1/9, 1/7)

The obtained fuzzy comparison judgments are displayed in Table 3.

Because of the reciprocal property, only the upper-right triangular parts of these matrices are shown. In order to aggregate individual TFNs depicted in Table 3 into group TFNs, basic arithmetic mean is employed. Then, the fuzzy comparison judgments were converted to interval judgments using Eq.(1).

By performing the linear programming model (8) for $\alpha = (0, 0.3, 0.5, 0.7, 1)$ levels, the relative weights of the evaluation criteria were elicited as listed in Table 4.

Table 3: Fuzzy Pairwise Comparisons of the Criteria

Goal	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
DM ₁						
C ₁	(1, 1, 1)	(1, 3, 5)	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)	(7, 9, 9)
C ₂		(1, 1, 1)	(3, 5, 7)	(1, 3, 5)	(7, 9, 9)	(5, 7, 9)
C ₃			(1, 1, 1)	(1/5, 1/3, 1)	(1, 3, 5)	(1, 3, 5)
C ₄				(1, 1, 1)	(5, 7, 9)	(1, 3, 5)
C ₅					(1, 1, 1)	(1/5, 1/3, 1)
C ₆						(1, 1, 1)
DM ₂						
C ₁	(1, 1, 1)	(1, 1, 1)	(3, 5, 7)	(3, 5, 7)	(7, 9, 9)	(5, 7, 9)
C ₂		(1, 1, 1)	(3, 5, 7)	(3, 5, 7)	(7, 9, 9)	(5, 7, 9)
C ₃			(1, 1, 1)	(1/5, 1/3, 1)	(1, 3, 5)	(1, 3, 5)
C ₄				(1, 1, 1)	(3, 5, 7)	(1, 3, 5)
C ₅					(1, 1, 1)	(1/5, 1/3, 1)
C ₆						(1, 1, 1)
DM ₃						
C ₁	(1, 1, 1)	(1, 3, 5)	(3, 5, 7)	(1/5, 1/3, 1)	(5, 7, 9)	(5, 7, 9)
C ₂		(1, 1, 1)	(1, 3, 5)	(1/7, 1/5, 1/3)	(3, 5, 7)	(3, 5, 7)
C ₃			(1, 1, 1)	(1/7, 1/5, 1/3)	(1, 3, 5)	(1, 3, 5)
C ₄				(1, 1, 1)	(7, 9, 9)	(7, 9, 9)
C ₅					(1, 1, 1)	(1, 1, 1)
C ₆						(1, 1, 1)

Table 4: The Priorities of the Decision Attributes at Each α -Level

α -cuts	w ₁	w ₂	w ₃	w ₄	w ₅	w ₆	λ
0	0.3646	0.2604	0.1146	0.1562	0.0521	0.0521	0.9583
0.3	0.3592	0.2853	0.1075	0.1458	0.0511	0.0511	0.9515
0.5	0.3562	0.2996	0.1031	0.1404	0.05	0.05	0.9476
0.7	0.3745	0.2825	0.1059	0.1332	0.052	0.052	0.9393
1	0.4036	0.2554	0.1094	0.1236	0.054	0.054	0.9275

Since all judgments are of equal importance and in order not to affect the solution value of w^* , all tolerance parameters were set equal while executing the model. It is seen that the value of the consistency index λ is slightly smaller than 1 and takes positive values between 0 and 1 for all α -cuts. This indicates that the corresponding interval judgments for these α -levels are very weakly inconsistent. However, all the solution ratios are within the extended interval bounds and satisfy

$$I_{ijk}(\alpha) \lesssim \frac{w_i}{w_j} \lesssim u_{ijk}(\alpha). \text{ Afterwards, Eq. (10) was run to obtain the aggregated values of the}$$

priorities. Eventually, the weight vector of the attributes is calculated as:

$$W = (0.3806; 0.2754; 0.1069; 0.1323; 0.0524; 0.0524)^T.$$

As seen, manufacturing capability (C₁) and quality control systems (C₂) emerged as the most important criteria according to the proposed FPP method. When the number of considered criteria is large enough, the formation of interrelation matrix by DMs would be complicated. In addition, the possibility of the inconsistent judgments will increase accordingly.

Alternatively, all information regarding attributes' interrelations can be extracted from the weights of the attributes. In doing so, the complexity of the process would be decreased and reliability of given information would be increased (Koulouriotis and Ketipi, 2011:11904). In order

to construct the interrelation matrix, pairwise comparisons of the weights of the attributes with respect to each other were carried out. For example, the element a_{ij} shows the division of the weight of attribute i to the cumulative weight of attribute i and j , where $a_{ij} + a_{ji} = 1$, for normalization issue. By doing so, the interrelation matrix is acquired as shown in Table 5.

Table 5: The Interrelation Matrix

Attributes	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
C ₁	1	0.580	0.781	0.742	0.879	0.879
C ₂	0.420	1	0.720	0.675	0.840	0.840
C ₃	0.219	0.280	1	0.447	0.671	0.671
C ₄	0.258	0.325	0.553	1	0.716	0.716
C ₅	0.121	0.160	0.329	0.284	1	0.5
C ₆	0.121	0.160	0.329	0.284	0.5	1

For instance, the entry of 0.580 (C₁-C₂) is computed as follows:

$$(C_1-C_2) = 0.3806 / (0.3806 + 0.2754) = 0.580, \quad \text{then } (C_2-C_1) = 1 - 0.580 = 0.420$$

The following stage is the construction of the rating matrix for each subcontractor. For this purpose, the decision team evaluated the four subcontractors with respect to the attributes using the fuzzy scale displayed in Table 6.

Table 6: Linguistic Variables for Ratings

Linguistic variables	Triangular fuzzy numbers
Very poor (VP)	(0, 0, 2)
Poor (P)	(1, 2, 3)
Medium poor (MP)	(2, 3.5, 5)
Fair (F)	(4, 5, 6)
Medium good (MG)	(5, 6.5, 8)
Good (G)	(7, 8, 9)
Very good (VG)	(8, 10, 10)

The ratings of the DMs are depicted in Table 7.

Table 7: DMs' Ratings for Each Subcontractor

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
DM ₁						
S ₁	(5, 6.5, 8)	(4, 5, 6)	(8, 10, 10)	(7, 8, 9)	(5, 6.5, 8)	(7, 8, 9)
S ₂	(7, 8, 9)	(5, 6.5, 8)	(5, 6.5, 8)	(7, 8, 9)	(4, 5, 6)	(5, 6.5, 8)
S ₃	(4, 5, 6)	(5, 6.5, 8)	(7, 8, 9)	(8, 10, 10)	(5, 6.5, 8)	(7, 8, 9)
S ₄	(5, 6.5, 8)	(7, 8, 9)	(5, 6.5, 8)	(5, 6.5, 8)	(7, 8, 9)	(5, 6.5, 8)
DM ₂						
S ₁	(7, 8, 9)	(5, 6.5, 8)	(5, 6.5, 8)	(5, 6.5, 8)	(7, 8, 9)	(5, 6.5, 8)
S ₂	(5, 6.5, 8)	(7, 8, 9)	(8, 10, 10)	(5, 6.5, 8)	(4, 5, 6)	(7, 8, 9)
S ₃	(5, 6.5, 8)	(4, 5, 6)	(7, 8, 9)	(7, 8, 9)	(4, 5, 6)	(7, 8, 9)
S ₄	(4, 5, 6)	(7, 8, 9)	(7, 8, 9)	(5, 6.5, 8)	(7, 8, 9)	(4, 5, 6)
DM ₃						
S ₁	(5, 6.5, 8)	(5, 6.5, 8)	(7, 8, 9)	(7, 8, 9)	(5, 6.5, 8)	(7, 8, 9)
S ₂	(7, 8, 9)	(5, 6.5, 8)	(8, 10, 10)	(7, 8, 9)	(4, 5, 6)	(5, 6.5, 8)
S ₃	(5, 6.5, 8)	(7, 8, 9)	(5, 6.5, 8)	(8, 10, 10)	(4, 5, 6)	(7, 8, 9)
S ₄	(4, 5, 6)	(5, 6.5, 8)	(8, 10, 10)	(5, 6.5, 8)	(7, 8, 9)	(5, 6.5, 8)

In order to aggregate individual TFNs into group TFNs, a fuzzy weighted triangular averaging operator were applied as explained below. Let $\tilde{D}_{jt} = (l_{jt}, m_{jt}, u_{jt})$, $j = 1, 2, \dots, n$; $t = 1, 2, \dots, k$ be the rating given to D_j by DM_t . The aggregated value of \tilde{D}_j assessed by the team of k DMs is denoted by the following Eq.(15),

$$\tilde{D}_j = \tilde{D}_{j1} \otimes c_1 \oplus \tilde{D}_{j2} \otimes c_2 \oplus \dots \oplus \tilde{D}_{jk} \otimes c_k \quad (15)$$

In Eq. (15), c_1, c_2, \dots, c_k are the importance weights allocated to DMs based on their expertise, where $c_1 + c_2 + \dots + c_m = 1$. Because the judgments of the DMs are of equal importance, $c_1 = c_2 = c_3 = 1/3$ is set.

For instance, the fuzzy aggregation of the rating of the first alternative \tilde{D}_1 with respect to first criterion C_1 was computed as follows:

$$\tilde{D}_1 = (5, 6.5, 8) \otimes 1/3 \oplus (7, 8, 9) \otimes 1/3 \oplus (5, 6.5, 8) \otimes 1/3 = (5.67, 7, 8.33)$$

The remaining fuzzy judgments were aggregated in this manner. Then, these aggregated values were normalized as mentioned above. Herein, the attribute cost was treated as a non-beneficial attribute. In an effort to elicit the best non-fuzzy performance (BNP) values, the center of area (COA) method, which is a simple and practical method was performed for defuzzification. The COA method's BNP value for TFNs is formulated as below (Chang et al., 2009:7365):

$$\text{BNP} = d(\tilde{D}_i) = l_i + \frac{(m_i - l_i) + (u_i - l_i)}{3} \quad (i = 1, 2, \dots, n) \quad (16)$$

The aggregated rating matrix is presented in Table 8.

Table 8: The Aggregated Rating Matrix

	C_1	C_2	C_3	C_4	C_5	C_6
S_1	0.756	0.641	0.798	0.719	0.728	0.790
S_2	0.821	0.664	0.833	0.719	0.519	0.728
S_3	0.641	0.705	0.762	0.607	0.568	0.852
S_4	0.590	0.821	0.712	0.875	0.852	0.617

Next, the evaluation matrix are created for each alternative. For example, the matrix of the first subcontractor alternative (S_1) is displayed below.

$$\xi_1 = \begin{bmatrix} 0.756 & 0.580 & 0.781 & 0.742 & 0.879 & 0.879 \\ 0.420 & 0.641 & 0.720 & 0.675 & 0.840 & 0.840 \\ 0.219 & 0.280 & 0.798 & 0.447 & 0.671 & 0.671 \\ 0.258 & 0.325 & 0.553 & 0.719 & 0.716 & 0.716 \\ 0.121 & 0.160 & 0.329 & 0.284 & 0.728 & 0.5 \\ 0.121 & 0.160 & 0.329 & 0.284 & 0.5 & 0.790 \end{bmatrix}$$

The matrices of the remaining three alternatives are formed in a similar manner.

Step-3. In order to achieve the final ratings of alternatives, the permanent values of the evaluation matrices of each alternative obtained in the previous step have been calculated via Eq. (14). MATLAB software is exploited for the computations. The ranking of the *per* (ξ) values of the alternatives in the descending order is given in Table 9.

Table 9: Permanent Values and Ranking

Subcontractor	Per (ξ) value	Ranking
S ₁	9.537	1
S ₄	9.50	2
S ₂	8.947	3
S ₃	8.461	4

Consequently, since S₁ has occurred as the alternative with the highest *per* (ξ) value it should be selected as the optimal subcontractor under these conditions. The overall ranking is S₁> S₄> S₂> S₃.

4.1 Comparison with MCDM methods

For benchmarking purpose, the results of the proposed framework are compared with fuzzy AHP and fuzzy TOPSIS, well-known MCDM techniques.

4.1.1 Comparison with classical fuzzy AHP

In this sub-section, the attributes' weights calculated by the FPP method are compared with the results of Chang's (1996) extent analysis method (EAM). Performing the procedure of the EAM and using the fuzzy pairwise comparisons of the attributes in Table 3, the weights were obtained as: manufacturing capability (0.477), quality control systems (0.291), delivery (0.005), cost (0.227), financial strength (0.000) and past performance (0.000). As seen, the ranking order of the attributes with respect to importance weights is similar with the proposed FPP method. However, the EAM assigned a zero value of weight to the criteria "financial strength" and "past performance", which is irrational and means that those criteria have no effect in the decision process. Using the suggested FPP method, such unreasonable condition is circumvented. In addition, the proposed FPP approach employed simpler arithmetic operations than the EAM when calculating the importance weights of the criteria.

4.1.2. Comparison with fuzzy TOPSIS

Fuzzy ANP and fuzzy DEMATEL are alternative MCDM approaches to deal with interactions among criteria. However, these methods are based on pairwise comparisons while DMs rate the alternatives directly in the proposed GTMA. Therefore, the results of the GTMA were compared with the fuzzy TOPSIS developed by Chen (2000) in which the alternatives are rated directly, as well. While applying the procedure of the fuzzy TOPSIS, the criteria weights computed by the FPP were used. The closeness coefficients and ranking of the alternatives are presented in Table 10.

Table 10: The Results of the Fuzzy TOPSIS Method

	d_i^*	d_i^-	CC_i
S ₁	4.873	0.694	0.125
S ₂	4.847	0.749	0.134
S ₃	4.889	0.664	0.120
S ₄	4.937	0.651	0.117

According to Table 10, the ranking of the suppliers from the best to the worst is S₂> S₁> S₃> S₄ while it is S₁> S₄> S₂> S₃ for the GTMA method. As seen, the results of the two methods are different, as they have distinct algorithms. The TOPSIS method does not consider the interactions and interdependencies among criteria unlike the GTMA approach. Thus, it can be concluded that the ranking of the alternatives obtained through the GTMA is more powerful.

5. Conclusions

One of the main risks that may be faced during outsourcing process is inappropriate subcontractor selection, which can have a significant influence on the success of the firms. In this

study, combined use of the FPP method and GTMA is proposed in an attempt to select the best subcontractor. A real case application is presented to illustrate the validity and applicability of the proposed method in a Turkish textile company. The application results reveal that the devised methodology can successfully overcome subcontractor selection problem. The main contributions of the suggested methodology can be summarized as follows. The presented hybrid methodology is a valuable decision support tool for the companies since it incorporates the full support of the management to involve their experiences concerning the business processes of their firms and thus eliminate the biases in the selection procedure of the appropriate supplier. Besides, the proposed model provides to managers the opportunity of easily assigning their judgments to the hierarchical structure. The devised FPP method can extract priorities from fuzzy pairwise comparison judgments and does not require the construction of fuzzy comparison matrices of skewed reciprocal elements. Besides, it can obtain crisp priorities and does not need an additional ranking procedure while other prioritization methods in the literature provide a fuzzy priority vector or multiple crisp priority vectors, which require an additional aggregation method or a fuzzy ranking method. In addition, it has a natural indicator for the inconsistency of the DMs' judgments that measures the degree of satisfaction whereas similar methods require further analysis to check consistency. The suggested GTMA can take into account any number of qualitative and quantitative attributes of MCDM problems concurrently and presents a systematic approach for transformation of qualitative factors to quantitative values. Moreover, it can incorporate the interdependencies of attributes unlike most of the other MCDM techniques; in addition, the computational procedure of the GTMA is very simple compared to ANP, DEMATEL and fuzzy integral approaches which can also incorporate the interdependencies of the decision criteria. The application of the GTMA in MCDM field is relatively new and to the best of our knowledge, this paper is the first one in the literature employing the integrated use of the proposed FPP-GTMA methodology as a decision support tool. As for future studies, the proposed approach can be applied to any type of fuzzy MCDM problems including the interdependencies of decision criteria. Besides, several combinations of attributes and scenarios could be carried out in order results to be more robust. In addition, the developed framework is viable for the evaluation of bids where there are conflicting objectives.

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