FUZZY DATA ENVELOPMENT ANALYSIS-BASED DECISION APPROACHES FOR SUPPLIER EVALUATION AND SELECTION

(TEDARİKÇİ DEĞERLENDİRME VE SEÇİMİNDE BULANIK VERİ ZARFLAMA ANALİZİ BAZLI KARAR VERME YAKLAŞIMLARI)

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LIST OF SYMBOLS

AIDEA	:	Augmented Imprecise DEA
AR-IDEA	:	Assurance Region Imprecise DEA
AHP	:	Analytic Hierarchy Process
ANP	:	Analytic Network Process
CEM	:	Cross Efficiency Matrix
CCR	:	Charnes, Cooper & Rhodes
CWA	:	Common Weights Analysis
DEA	:	Data Envelopment Analysis
DELPHI	:	Documentation and Exchange of Lively and Pure Homeopathic Information
DEMATEL	:	Decision Making Trial and Evaluation Laboratory
DM	:	Decision Maker
DMU	:	Decision Making Unit
GA	:	Genetic Algorithm
GSCM	:	Green Supply Chain Management
LP	:	Linear Programming
MCDM	:	Multi Criteria Decision Making
MOLP	:	Multi Objective Linear Programming
NDEA	:	Network DEA
OR	:	Operations Research
QFD	:	Quality Function Deployment
SCM	:	Supply Chain Management
TFN	:	Triangular Fuzzy Number
TOPSIS	:	Technique Ordered Preference by Similarity to the Ideal Solution
VIKOR	:	Viekriterijumsko Kompromisno Rangiranje

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ABSTRACT

Supply Chain Management (SCM) is the active management of supply chain activities to maximize customer value and achieve a sustainable competitive advantage. SCM includes product development, sourcing, production, logistics and information systems and it is based on physical flows such as transformation, movement and storage and the information flows by which the long-term plans and daily controls are supported.

Supplier selection problem is one of the most essential and critical part of supply chain management. The firms identify their own requirements and perform studies to evaluate their supplier candidates in order to find the most suitable supplier(s) or partner(s) to them. Companies also employ these studies to measure regularly the performance of their already existing suppliers. In the realization of this process they rely on different factors. In the literature many researchers are focused on determining the supplier selection criteria. These criteria may differ from sector to sector and within the context of this study ten supplier selection criteria related to the textile sector are explained and utilized. The reputation, price/cost, quality, location, reliability, delivery, service, responsiveness, technical capability and relationship are the criteria that are used.

The existence of the multiple criteria, makes the supplier selection problem appropriate to be dealt with Multi Criteria Decision Making (MCDM) techniques. MCDM is a division of a general class of Operations Research (OR) models which deal with decision problems under the presence of a multiple decision criteria. In the literature there are several studies that employed an MCDM method or combined different MCDM methodologies to approach supplier selection problem in different areas.

In this thesis, Decision Making Trial and Evaluation Laboratory (DEMATEL) method and Data Envelopment Analysis (DEA) method are employed together and articles

focused on supplier selection problem employing these methods are provided as a literature review part.

DEMATEL is a method that originally developed by the Science and Human Affairs Program of the Battelle Memorial Institute between 1972 and 1979 for studying the complex and intertwined problematic group. It is being widely employed to determine the cause and the effect relationship among the evaluation criteria and to derive interrelationship among factors. In the thesis, three decision makers (DM) are asked to evaluate interrelationship among these criteria, and the aggregation of their evaluation is taken into consideration to fill the first matrix of DEMATEL. Using a threshold value, the criteria that will be involved in DEA are determined.

DEA, first proposed by Charnes, Cooper and Rhodes (CCR) (1978), is a non-parametric method identifying an efficiency frontier that is used for measuring efficiency of Decision Making Units (DMUs) which is calculated as the maximum of a ratio weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity. In the literature, many extensions of DEA that are proposed in order to improve its discriminating power, or logical structure in eliminating false candidates which overweight or ignore totally some factors, are provided as a literature review.

DEA mainly considers the crisp data. However, in real-life problems such as supplier selection, the decision makers confront with vagueness and uncertainty while evaluating their suppliers and they prefer to use linguistic terms. Within the context of this study, an introduction to fuzzy concepts is made and the concepts that are explained are used in the fuzzy DEA.

Fuzzy DEA, is an extension of DEA which incorporates imprecision in DEA. In the present study, the alternative fuzzy DEA methodologies are explained and the articles that are employed fuzzy DEA in supplier selection problem are examined. Two different fuzzy DEA methodologies basing on six different α-cuts are applied into the thesis problem for obtaining the efficiency results of twelve supplier alternatives and the results are compared. In addition, a single input, multiple output model is solved and a ranking methodology is applied.

Briefly, this study combines DEMATEL and (fuzzy) DEA for a supplier selection problem in textile sector. The results are yield to only two efficient DMUs, thus any extended fuzzy DEA model that increases the discriminating power is not required. The decision makers are expressed that the results were consistent with their working-principles and they were already considering to extend the contracts with efficient DMUs.

ÖZET

Tedarik Zinciri Yönetimi, müşteri değerini arttırmak ve sürdürülebilir rekabet avantajı sağlamak için kurumların yönettiği tüm tedarik zinciri aktivitelerini; ürün geliştirmeyi, satın almayı, üretimi, lojistik ve bilgi sistemlerini kapsar. Dönüştürme, nakliye ve depolama gibi fiziksel akışları temel alırken aynı zamanda uzun vadeli ilişkilerini desteklediği ve günlük rutin kontrollerini sağladığı bilgi akışlarını da kullanır.

Tedarikçi seçimi, tedarik zinciri yönetiminin en önemli ve kritik problemlerinden biridir. Firmalar, kendi ihtiyaçlarını belirleyerek, kendilerine en uygun tedarikçileri bulmak için alternatifleri değerlendiren çalışmalar gerçekleştirirler. Aynı zamanda mevcut tedarikçileri periyodik olarak değerlendirmek için bu çalışmaları kullanırlar ve bu süreçte değişik ölçütlere dayanırlar. Literatürde birçok araştırmacının tedarikçi seçimi ölçütlerinin tespiti konusunda çalıştığı görülmektedir. Bu ölçütler sektörden sektöre değişkenlik gösterebilmektedir ve bu çalışma kapsamında tekstil sektörü ile ilgili on ölçüt seçilerek açıklanmıştır. Bu ölçütler; itibar, fiyat/maliyet, kalite, lokasyon, güvenilirlik, teslimat, servis, cevap verebilirlik, teknik yeterlilik ve ilişkinin gücü ’dür.

Birden çok ölçütün var olması sebebi ile tedarikçi seçimi problemi Çok Ölçütlü Karar Verme tekniklerinin kullanımı açısından uygun bir ortama sahiptir. Çok Ölçütlü Karar Verme, karar verme problemlerinde birden çok faktörün olması durumunda kullanılan Yöneylem Araştırması modellerinden biridir. Literatürde değişik sektörlerden tedarikçi seçimi problemleri için Çok Ölçütlü Karar Verme yöntemlerini kullanan ve değişik yöntemlerini bütünleştiren birçok yayın mevcuttur.

Bu tez kapsamında, Çok Ölçütlü Karar Verme yöntemlerinden DEMATEL ve Veri Zarflama Analizi kullanılmıştır. Aynı zamanda tedarikçi seçimi probleminde bu yöntemleri kullanan yayınlara yer verilmiştir.

DEMATEL, 1972 ve 1979 yılları arasında karışık ve sarmal problem gruplarının çözümü için geliştirilen bir yöntemdir. Ölçütler arası sebep ve sonuç ilişkilerini matrisler üzerinden incelemek için sıklıkla kullanılmaktadır. Bu tez kapsamında, üç karar vericiden ölçütler arası ilişkileri puanlayarak değerlendirmeleri istenmiştir. Devamında üç karar vericinin skorları birleştirilerek DEMATEL'in ilk matrisi oluşturulmuştur ve DEMATEL yönteminin adımları takip edilerek ölçüt ilişki ve ağırlıklarına ulaşılmıştır. Eşik değer yardımı ile Veri Zarflama Analizi yöntemine dâhil edilecek ölçütler filtrelenmiştir.

Veri Zarflama Analizi 1978 yılında Charnes, Cooper ve Rhodes tarafından geliştirilen, parametrik olmayan ve etkinlik sınırı belirleyerek Karar Verme Birimlerinin etkinlik değerlerini hesaplayan bir yöntemdir. Etkinlik değeri çıktıların ağırlıklı toplamının girdilerini ağırlıklı toplamına bölünmesi ile ifade edilir. Literatürde, Veri Zarflama Analizinin seçici özelliğini arttırmak ve mantıksal gücünü (bazı karar verme birimlerinin azami etkinlik değerine ulaşmak için bazı ölçüt ağırlıklarını sıfırlaması veya fazla ağırlıklandırılması gibi durumlar) iyileştirmek üzere, ağırlık kısıtları eklemek, çapraz karşılaştırmalar yapmak, ortak ağırlık kullanmak gibi birçok geliştirmeleri yapılmıştır. Bu tez kapsamında temel çalışmalara yer verilmiştir.

Veri Zarflama Analizi genellikle kesin sayılar üzerinde kullanılmaktadır. Fakat tedarikçi seçimi gibi gerçek hayat problemlerinde, karar vericiler belirsizlik ve karasızlık ile karşı karşıya kalmaktadırlar. Bu sebeple, genellikle tedarikçileri değerlendirirken sözel terimleri kullanmayı tercih etmektedirler. Bu çalışma kapsamında, bulanık küme kavramına giriş yapılmış ve Veri Zarflama Analizinde kullanımına yer verilmiştir.

Bulanık Veri Zarflama Analizi, Veri Zarflama Analizi modeline bulanık sayıları dâhil eden bir yöntemdir. Bu çalışmada, alternatif bulanık veri zarflama analizi modelleri açıklanmış ve tedarikçi seçimi probleminde bulanık veri zarflama analizi kullanan yayınlara yer verilmiştir. İki değişik bulanık veri zarflama analizi yöntemi altı farklı değişik α- kesim seviyesinde uygulanmış ve on iki tedarikçi alternatifi için etkinlik değerleri hesaplanmıştır ve sonuçlar karşılaştırılmıştır. Ek olarak, tek girdi çok çıktılı bir problem için bir model kurulmuş ve sıralama yöntemi uygulanarak tedarikçi alternatifleri değerlendirilmiştir.

Kısaca, bu çalışmada tekstil sektöründe faaliyet gösteren bir kurumun tedarikçi seçimi problemine DEMATEL ve (bulanık) Veri Zarflama Analizini birlikte kullanarak yaklaşılmaktadır. Sonuçlar yalnızca iki etkin karar verme birimi sağladığı için veri zarflama analizinin ayırt edici gücünü arttıran herhangi bir ek model gerekmemiştir. Karar vericiler, sonuçların çalışma prensipleri ile tutarlı olduğunu belirtmişler ve etkin karar verme noktaları ile kontrat sürelerini uzatmayı düşündüklerini beyan etmişlerdir.

1. INTRODUCTION

Supply chain management (SCM) is the conduct of resources, information and assets as they move in a process from supplier to manufacturer to wholesaler to retailer to consumer. SCM involves coordinating and integrating the flows both within and among the enterprises. Firms in order to build a competitive infrastructure, leverage worldwide logistics, synchronize supply with demand and measure their performance and above all to create net value and increase their profit, design, plan execute, control and monitor their supply chain activities.

Undoubtedly, supplier selection process constitutes the core of the SCM. The firms according to their business' priorities and strategy, evaluate different supplier alternatives. First of all, the companies have to determine have many suppliers they need, the excess of it would create difficulties for controlling and satisfying them and the lack of it would hinder the production or the delivery. Their choice is dependent on a wide range of a factors such as cost, quality, service, reliability (Dickson, 1966; Weber at al. 1991). In general, they place emphasis on previous experience and past performance with the service/product to be purchased, and care the ability of suppliers to meet capacity requirements and to follow delivery schedule predefined. The financial stability and technical support availability are surplus, the willingness to participate as a partner in developing and optimizing design and a long-term relationship of supplier is really important. The suppliers must possess all the regulatory requirements and quality system registration. The low operational, managerial and communication costs would be advantage for suppliers. The firms for appraise the suppliers examine their financial reports, visit them with a management team, confirm their quality system status and discuss with other consumers served by the supplier Multi Criteria Decision Making (MCDM) is a sub-discipline of operations research that concerned with structuring and solving decision and planning problems involving multiple criteria. The main purpose of MCDM is to choose the "best" alternative or a set of desirable alternatives. MCDM techniques may be employed separately or they can be combined depending on the problem type. In the literature there are numerous articles that employed MCDM techniques in supplier selection problems due to its multi criteria framework (Karsak & Dursun, 2016). Besides, many researchers integrated different MCDM methodologies for the same problem.

One of these MCDM techniques is DEMATEL, which uses the structural modeling technique to identify the possible interdependence among the criteria in a system by constructing diagraphs to show the causal relationships and the strengths of influence among the criteria. It is mostly integrated with different MCDM tools, as a first step for filter or order the existing factors. This thesis proposes to integrate DEMATEL with DEA for determining the criteria that will be involved in DEA model.

DEA is one of the MCDM techniques that used in different engineering problems including supplier selection problem. It proposes an “efficiency” concept defined as the maximum of a ratio weighted outputs to weighted inputs that calculated for each Decision Making Unit (DMU) subject to the similar ratios for every DMU be less than or equal to unity. Since two decades, many extensions of DEA are proposed to sort out false efficient DMUs or increasing the discriminating power of DEA.

For selecting the right supplier, certainty and deterministic information is not always available and there arise certain kind of uncertainty associated with linguistic information or intuitive information while evaluating the alternatives. Existence of vagueness and imprecision in criteria, encouraged the academicians to integrate fuzzy concepts in DEA, and by this way different fuzzy DEA methodologies are developed (Sengupta, 1992). The two of them are employed and compared within the thesis for supplier selection problem.

The purpose of this thesis is to propose a decision making approach to attempt the solution of a supplier selection problem. In particular, the focus is on the integration of different MCDM models, which incorporate imprecise and subjective information inherent in the supplier evaluation process, to class the supplier alternatives as efficient-ones and inefficient-ones and even more to propose a ranking among them. The rest of this study is organized as follows. In section 2, a brief description of DEA is presented and the existing work addressing the supplier selection with the DEA method is reviewed. Section 3 describes the fuzzy DEA methodology, its extensions and reveal the supplier selection problems dealt with fuzzy DEA. In section 4, DEMATEL technique which is used to filter the excessive criteria is presented and the studies that employed DEMATEL are provided. The application of the described methodology, the comparison of the models and the analysis of the results are illustrated in section 5.

2. DATA ENVELOPMENT ANALYSIS

2.1. PRELIMINARIES OF DATA ENVELOPMENT ANALYSIS

DEA is a non-parametric linear programming-based technique employed as a decision making technique in comparing the efficiency of DMUs such as health services, local authority departments, education departments, factories, banks and also a decision help for selection problems (Karsak & Ahiska, 2007). DEA is first proposed by Charnes et al. (1978) and they based their study on productive efficiency (Farrell, 1957). The efficiency measure obtained as the maximum of a ratio weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity (Charnes, Cooper, & Rhodes, 1978). Their first proposed model is a nonlinear programming formulation of an ordinary fractional programming model and due to its' non convex structure it needs to be linearized. The input driven CCR model is as follows while (2.1) is in a nonlinear form and (2.2) is linearized.

$$\max E_{j_0} = \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}$$

subject to (2.1)

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad \forall j,$$

$$u_r, v_i \geq \varepsilon, \qquad \forall r, i.$$

where E_{j_0} is the efficiency score of the evaluated DMU, u_r is the weight assigned to output *r*, v_i is the weight assigned to input *i*, y_{rj} is the quantity of output *r* generated and x_{ij} is the amount of input *i* consumed by DMU *j*, respectively, and ε is a small positive scalar.

$$\max E_{j_0} = \sum_{r=1}^{s} u_r \, y_{rj_0}$$

subject to (2.2)

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \quad \forall j,$$

$$u_r, v_i \geq \varepsilon, \quad \forall r, i.$$

The conventional DEA model known as CCR model possess several shortcomings. Firstly, this model has to be solved for all DMUs which means *n* LP for *n* DMU. Furthermore, all DMUs are allowed to weight their inputs and outputs, in their own favor to maximize their efficiency scores, which allows complete weight flexibility, which may result to ignore totally some input or outputs, or extreme weighting of best inputs or outputs (Braglia & Petroni, 2010). In addition, the major drawback of traditional model is its poor discriminatory power. It dichotomizes DMUs as “efficient” with efficiency score of 1, and DMUs with efficiency score less than 1 are called as “inefficient”.

In the DEA literature several approaches are proposed in order to deal with these limitations. For computational savings, common-weight DEA-based models can be utilized which require only one LP model to reach efficiency scores of all the DMUs (Karsak & Ahiska, 2005). For increasing the discriminating power of DEA, minimax efficiency model, which minimizes maximum deviation from efficiency, is proposed and a discriminating parameter *k* is added for identifying the best DMU (Karsak & Ahiska, 2007).

$$\min M - k \sum_{j \in EF} d_j ,$$

subject to (2.3)

$$M - d_j \geq 0, \qquad \forall j,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \qquad \forall j,$$

$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1,$$

$$u_r, v_i, d_j \geq 0, \qquad \forall r, i, j.$$

Minsum efficiency is another model proposed for increasing the discriminating power of DEA, in which the objective is to minimize the total deviation from efficiency. (Li & Reeves, 1999). The model is as follows.

$$\min \sum_{j=1}^{n} d_j$$

subject to (2.4)

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \qquad \forall j,$$

$$u_r, v_i, d_j \geq 0, \qquad \forall r, i, j.$$

Another mathematical technique that is employed for dealing the self-appraisal evaluation of DEA, is cross-efficiency analysis. Cross-efficiency is calculated by using set of weights of inputs and outputs for each of the other DMUs and this calculation is repeated for each DMU constructing a matrix which is called Cross Efficiency Matrix (CEM) (Sexton et al. 1986).

Table 2.1. Cross Efficiency Matrix

	Rated DMU						
Rating DMU	1	2	3	4	5	6	Averaged appraisal of peers
1	$\mathbf{E_{11}}$	E_{12}	E_{13}	E_{14}	E_{15}	E_{16}	A_1
2	E_{21}	$\mathbf{E_{22}}$	E_{23}	E_{24}	E_{25}	E_{26}	A_2
3	E_{31}	E_{32}	$\mathbf{E_{33}}$	E_{34}	E_{35}	E_{36}	A_3
4	E_{41}	E_{42}	E_{43}	$\mathbf{E_{44}}$	E_{45}	E_{46}	A_4
5	E_{51}	E_{52}	E_{53}	E_{54}	$\mathbf{E_{55}}$	E_{56}	A_5
6	E_{61}	E_{62}	E_{63}	E_{64}	E_{65}	$\mathbf{E_{66}}$	A_6

Averaged appraisal by peers (peer appraisal)

In this matrix, simple efficiencies are in diagonal and E_{34} is the cross-efficiency accorded DMU-4 using DMU-3's weights. A_k and e_k are averaged without the leading diagonal, which is self-appraisal. In the standard DEA model, an efficient DMU weights a spread of both inputs and outputs to achieve efficiency while another DMU may weight only a single input and a single output (Doyle & Green, 1994). This DMU is called Maverick DMU and Maverick Index is calculated by the following formulation.

$$M_k = (E_{kk} - e_k)/e_k \tag{2.5}$$

The aggressive cross-efficiency model is as follows.

$$\min \quad \sum_{r=1}^{s} u_r \left(\sum_{\substack{j=1 \\ j \neq 0}}^{n} y_{rj} \right)$$

subject to (2.6)

$$\sum_{i=1}^{m} v_i \left(\sum_{\substack{j=1 \\ j \neq 0}}^{n} x_{ij} \right) = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj_0} - E_{kk}^{*} \sum_{i=1}^{m} v_i x_{ij_0} = 0,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad \forall j, \qquad j \neq 0,$$

$$u_r, v_i \geq \varepsilon, \qquad \forall r, i.$$

where E_{kk}^{*} is the CCR efficiency of DMU_0 derived from the CCR model. The aggressive cross-efficiency model leads to choosing input and output weights, which yield the maximum efficiency for a DMU under evaluation, while minimizing the other DMUs' cross efficiencies. Another model that is widely used on DEA is benevolent cross-efficiency formulation, it is based on maximizing the efficiency of a DMU evaluated, while maximizing the other DMUs' cross-efficiencies (Doyle & Green, 1994). The model is as:

$$\max \quad \sum_{r=1}^{s} u_r \left(\sum_{\substack{j=1 \\ j \neq 0}}^{n} y_{rj} \right)$$

subject to (2.7)

$$\sum_{i=1}^{m} v_i \left(\sum_{\substack{j=1 \\ j \neq 0}}^{n} x_{ij} \right) = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj_0} - E_{kk}^{*} \sum_{i=1}^{m} v_i x_{ij_0} = 0,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, \qquad \forall j, \qquad j \neq 0,$$

$$u_r, v_i \geq \varepsilon, \qquad \forall r, i.$$

Besides these models, Cook et al. (1996) presented a framework for incorporating ordinal data factors into the classical DEA model. They defined

$$y_{rl}(n) = \begin{cases} 1, if\ project\ n\ is\ rated\ in\ l^{th}\ place\ on\ the\ r^{th}\ ordinal\ output \\ 0, otherwise \end{cases}$$

and

$$\delta_{il}(n) = \begin{cases} 1, if\ project\ n\ is\ rated\ in\ l^{th}\ place\ on\ the\ i^{th}\ ordinal\ output \\ 0, otherwise \end{cases}$$

They proposed the model given below where, ORD_1 and ORD_2 represent the sets of ordinal outputs and inputs, respectively, while $CARD_1$ and $CARD_2$ represent the sets of numerical outputs and inputs (Cook et al. 1996).

$$\max \mu Y_0 + \sum_{r \in ORD} W_r^1 \gamma_r \,(0)$$

subject to (2.8)

$$vX_0 + \sum_{i \in ORD_2} W_i^2 \delta_i \,(0) = 1$$

$$\mu Y_n + \sum_{r \in ORD_1} W_i^1 \gamma_r \,(n) - vX_n - \sum_{i \in ORD_2} W_i^2 \delta_i \,(n) \leq 0, n = 1, \dots, N,$$

$$\mu_r \geq \varepsilon, r \in CARD_1$$

$$V_i \geq \varepsilon, i \in CARD_2$$

$$\{W_r^1, W_i^2\} \in \varphi$$

Including weight restriction constraints in traditional DEA model in order to increase the weight dispersion and discriminating power has been also a commonly used method (Wong & Beasley, 1990). However, it is always discussed how to constrain the weights without violating the objectivity of DEA (Braglia & Petroni, 2010). Braglia et al. (2010) used the model presented in Dyson et al. (1988), in which they restrict the weights in such a way that each weight is decreed to be greater than $\gamma\%$ of the corresponding average weight obtained by the LP models (Dyson & Thanassoulis, 1988). For instance:

$$k_1 = (\gamma / 100) * \sum_{k=1}^{s} a_{k,1} / s \qquad (2.9)$$

Where $\alpha_{k,1}$ is the weight of output 1 assigned by DMU *k* in the LP Model and *s* is the number of DMUs for each an LP Model will be solved. Thanks to this approach, they avoided to insert subjective judgements on a DEA model which is highly objective. Their model is as:

$$\max E_j = \sum_{k=1}^{m} u_k y_{kj}$$

subject to (2.10)

$$\sum_{i=1}^{n} v_i x_{ij} = 1,$$

$$\sum_{k=1}^{m} u_k y_{kj} - \sum_{i=1}^{n} v_i x_{ij} \leq 0, \qquad \forall j$$

$$u_k \geq k_k, \qquad \forall k$$

$$v_i \geq z_i, \qquad \forall i \,.$$

2.2. DEA IN SUPPLIER SELECTION

Supplier selection, owing to a variety of uncontrollable factors affecting the decision is a complicated process and the most appropriate selection is highly crucial (Braglia & Petroni, 2000). For this review, the publications were identified throughout database “Web of Science”, consulting works published until May 2016. To consult the database, the key words “supplier selection” and “DEA” are searched in topic. Articles found are given in their chronological order. Firstly, Braglia et al. (2000) employed cross-efficiency in DEA for ranking suppliers in bottling industry. Liu et al. (2000) applied DEA in evaluating the overall performance of suppliers for a firm that manufactures agricultural and construction equipment. Forker & Mendez (2001) employed DEA using cross-efficiency for benchmarking to determine best peer suppliers. Narashiman et al. (2001) used efficiencies derived from the DEA model in identifying suppliers clusters in a telecommunication company. Further, Talluri & Sarkis (2002) presented a methodological extension of DEA by improving the discriminatory power of an existing variable returns to scale model for the supplier performance evaluation and monitoring process. Garfamy (2006) employed DEA to measure the overall performances of suppliers based on total cost of ownership concept. Seydel (2006) incorporated weight constraints into CCR and ranked the available suppliers, employing 7-point scale for the subjective ratings of the qualitative criteria. Similarly, Saen (2007) used ordinal data to measure the qualitative attributes and employed DEA for selecting the best suppliers in the presence of both cardinal and ordinal data. Lately, Saen (2008) introduced a decision making approach based on super-efficiency analysis, to rank suppliers in the presence of volume discount offers. Ross & Buffa (2009) for each supplier limited the weighted sum of the output criteria by the weighted sum of the input performance factors of the buyer and the purchase control variables for that supplier, and they investigated the effects of buyer performance on supplier performance. Wu & Blackhurst (2009) incorporating a range of virtual standards and adding weight restriction in DEA, developed a supplier evaluation and selection methodology for a communication and aviation electronics company. Saen (2010) depicting the supplier selection process through a DEA model proposed a method for selecting the best suppliers in the presence of weight restrictions and dual-role factors. Shirouyehzad et al. (2011) used DEA to evaluate the vendors' efficiency for a pipe manufacturing company. Nourizadeh et al. (2013) proposed a cross-efficiency DEA model which enable to consider non-discretionary inputs, in supplier selection context. Mohaghor et al. (2013) integrated fuzzy VIKOR and assurance region-DEA for ranking suppliers of an LPG manufacturer. Talluri et al. (2013) employed cross-efficiency analysis in DEA fora telecommunication company in categorizing their supply base into groups for effective supplier rationalization.

Man et al. (2014) considered the competition between the suppliers and presented game cross-efficiency which is based on DEA to assess supplier performance. This method can set a unique efficiency and it is pareto solution. Wang & Li (2014) improved Nash bargaining game DEA model adopting common weights and applied it to the third party logistics service provider evaluation. Azadi et al. (2014) proposed two DEA approaches to find targets for two-stage network structures of public transportation service providers. Dobos & Vörösmarty (2014) examined the extension of the vendor evaluation methods with environmental, green issues by dividing the criteria in two manners: the traditional (managerial) and environmental (green) factors. They used composite indicators (CI) to study the extension of traditional supplier selection methods with environmental factors and to choose the mentioned weight system, they applied DEA with the common weights analysis (CWA) method.

Recently, Tavassoli et al. (2015) proposed a new network DEA (NDEA) model in the presence of zero data and developed a novel super-efficiency formulation of NDEA using input saving and output surplus concepts to rank suppliers of an airline industry. Shi et al. (2015) used CCR and super-efficiency DEA model as a benchmark for identifying green suppliers of a well-known manufacturer of home appliances. Mahdiloo et al. (2015) used linear goal programming to integrate technical, environmental and eco-efficiency objectives into a multiple objective linear programming (MOLP) DEA model and applied it for Hyundai Steel Company and its suppliers. Jain et al. (2015) proposed Genetic Algorithm (GA) based approach for weight restrictions which incorporates a dual role factor and organizational hierarchy in decision-making which is able to generate a common set of weights and Decision Making Unit (DMU) specific weight restrictions simultaneously. They applied their model to an automobile spare parts manufacturer supplier selection problem.

Table 2.2. DEA in Supplier Selection

Author(s)	Year	Journal	Method	Sector
Braglia & Petroni	2000	International Journal of Physical Distribution & Logistics Management	cross-efficiency	bottling industry
Liu, Ding & Lall	2000	Supply Chain Management: An International Journal	simplified DEA	agricultural-construction
Forker & Mendez	2001	International Journal of Operations & Production Management	cross-efficiency	electronics
Narashiman, Talluri & Mendez	2001	Journal of Supply Chain Management	DEA - clustering	telecommunication
Talluri & Sarkis	2002	International Journal of Production Research	BCC	government regulators
Garfamy	2006	Journal of Enterprise Information Management	CCR	hypothetical
Seydel	2006	Industrial Management + Data Systems	weight restrictions	sole-sourcing
Saen	2007	European Journal of Operational Research	cardinal-ordinal data	numerical-example
Saen	2008	International Journal of Advanced Manufacturing Technology	super-efficiency	numerical-example
Ross & Buffa	2009	International Journal of Production Research	dyadic DEA	information technology
Wu & Blackhurst	2009	International Journal of Production Research	weight restrictions	telecommunication
Saen	2010	Applied Mathematical Modelling	weight restrictions	numerical-example
Shirouyehzad et al.	2011	International Business Research	CCR	pipe-manufacturer
Nourizadeh, Mahdiloo, & Saen	2013	International Journal of Shipping and Transport Logistics	cross-efficiency	numerical-example
Mohaghor, Fathi, & Jafarzadeh	2013	International Journal of Industrial Engineering: Theory, Applications and Practice	AR-DEA-Fuzzy VIKOR	LPG manufacturer
Talluri, Decampos & Hult	2013	Decision Sciences Journal	cross-efficiency	telecommunication
Man et al.	2014	Applied Mathematics & Information Sciences	cross-efficiency	numerical example
Wang & Li	2014	Expert Systems with Applications	Nash bargaining DEA	logistics
Azadi et al.	2014	Transportation Research Part E	CCR	transportation
Dobos & Vörosmarty	2014	International Journal of Production Economics	common weight DEA	numerical example
Tavassoli, Saen, & Faramarzi	2015	Expert Systems	Network DEA	airline industry
Shi et al.	2015	Information Technology Management	super-efficiency	home appliances
Mahdiloo, Saen, & Lee	2015	International Journal of Production Economics	MOLP-DEA	automotive industry
Jain et al.	2015	Expert Systems with Applications	Genetic Alghoritm-DEA	automotive industry

3. FUZZY DEA

3.1. BASIC CONCEPTS OF FUZZY SET THEORY

Classical sets are sets with crisp boundaries. Usually an ordinary set (a classical or crisp set) is called a collection of objects which have some properties distinguishing them from other objects which do not possess these properties (Czogola & Leski, 2000). However, in real-life problems, certainty and deterministic information is not always available and there exist certain kind of uncertainty associated with linguistic information or intuitive information. For instance, while the data quality is “good”, or the transparency of an optical element is “acceptable” (Ross T. J., 2010). Moreover, let consider the proposition that an individual is “old”. Since the term “old” has various interpretations for each-one, it cannot precisely determined the age(s) at which a person is “old” versus the age(s) at which a person is not considered to be “old”. For dealing that kind of uncertainty, imprecision, ambiguity in other words fuzziness, fuzzy sets are mostly used. A fuzzy set is a class of objects with a continuum of grades of membership, which ranges between 0 and 1 (Zadeh, 1965). The membership function involves the mathematical representation of membership in a set. A fuzzy number is a convex, normalized fuzzy set whose membership function is at least segmentally continuous and has the functional value at least one element. An example fuzzy number is given in Figure 3.1.

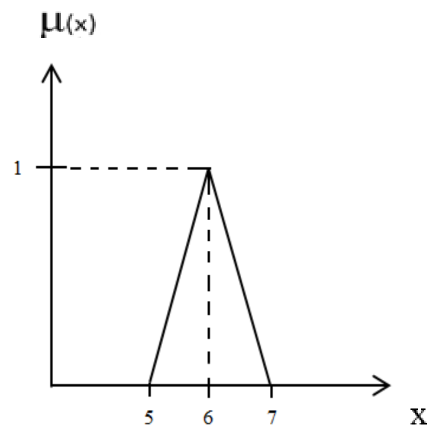

Figure 3.1: A triangular fuzzy number

Two notations for a fuzzy set $\tilde{A}$ with the universe of discourse, *X*, which is discrete and finite and Y, which is continuous and infinite, are as follows.   x

$$\tilde{A} = \left\{ \frac{\mu_{\tilde{A}}(x_1)}{x_1} + \frac{\mu_{\tilde{A}}(x_2)}{x_2} + \ldots \right\} = \left\{ \sum_i \frac{\mu_{\tilde{A}}(x_i)}{x_i} \right\} \tag{3.1}$$

$$\tilde{A} = \left\{ \int \frac{\mu_{\tilde{A}}(y)}{y} \right\} \tag{3.2}$$

A normal fuzzy set is a fuzzy set, whose membership function has at least one element *x* in the universe with a membership value that is equal to unity, while a subnormal fuzzy set is a fuzzy set, whose membership function has no element *x* in the universe with a membership value that is equal to unity. If the elements *x*, *y* and z in a fuzzy set $\tilde{A}$ has a relation such that *x* < *y* < *z*, which implies that $\mu_{\tilde{A}}(y) \geq \min[\mu_{\tilde{A}}(x), \mu_{\tilde{A}}(z)]$, then $\tilde{A}$ is a convex fuzzy set and the maximum value of a membership function is said to be the height of a fuzzy set $\tilde{A}$, which is denoted by the following formulation (Ross, 2010).

$$hgt(\tilde{A}) = \max\{\mu_{\tilde{A}}(x)\} \tag{3.3}$$

3.2. FUZZY SET OPERATIONS

For the fuzzy set operations, let $\tilde{A}$, $\tilde{B}$ and $\tilde{C}$ be fuzzy set on the universe *X*. For an element *x* on the universe, union, intersection and complement operations are represented respectively as (Zadeh, 1965).

$$\mu_{\tilde{A}\cup\tilde{B}}(x) = \mu_{\tilde{A}}(x) \vee \mu_{\tilde{B}}(x) \tag{3.4}$$

$$\mu_{\tilde{A}\cap\tilde{B}}(x) = \mu_{\tilde{A}}(x) \wedge \mu_{\tilde{B}}(x) \tag{3.5}$$

$$\mu_{\overline{\tilde{A}}}(x) = 1 - \mu_{\tilde{A}}(x) \tag{3.6}$$

- The core of a membership function contains elements *x* of the universe such that $\mu_{\tilde{A}}(x) = 1$.
- The support of a membership function involves elements *x* of the universe such that $\mu_{\tilde{A}}(x) > 0$.
- The boundaries of a membership function consists of elements *x* of the universe such that $0 < \mu_{\tilde{A}}(x) < 1$.
- The crossover points of a membership function includes elements *x* of the universe such that $\mu_{\tilde{A}}(x) = 0.5$(Ross, 2010).

For the arithmetic operations, fuzzy numbers are represented by their α - cuts, which are a subject of interval analysis of classical mathematics. Let Θ denote any of the main four operations " +, -, $\times$, / ", $[a,b]\times[d,e] = \{f \times g \mid a \le f \le b, d \le g \le e\}$, except $[a,b]/[d,e]$ when $0 \in [d,e]$, Thus the result of an operations on closed intervals is a closed interval as follows:

$$[a,b]+[d,e]=[a+b,b+e] \tag{3.7}$$

$$[a,b]-[d,e]=[a-b,b-e] \tag{3.8}$$

$$[a,b]\times[d,e]=[\min(ad,ae,bd,be),\max(ad,ae,bd,be)] \tag{3.9}$$

$$[a,b]/[d,e]=[\min(\frac{a}{d},\frac{a}{e},\frac{b}{d},\frac{b}{e}),\max(\frac{a}{d},\frac{a}{e},\frac{b}{d},\frac{b}{e})],0 \notin [d,e] \tag{3.10}$$

Properties of operations are as.

Let $A=[a_1,a_2]$, $B=[b_1,b_2]$, $C=[C_1,C_2]$, $0=[0,0]$, $1=[1,1]$

- Commutativity $$\begin{cases} A+B=B+A \\ A\times B=B\times A \end{cases} \tag{3.11}$$
- Associativity $$\begin{cases} (A+B)+C=A+(B+C) \\ (A\times B)\times C=A\times(B\times C) \end{cases} \tag{3.12}$$
- Identity $$\begin{cases} A=0+A=A+0 \\ A=1\times A=A\times 1 \end{cases} \tag{3.13}$$

- Subdistributivity $A \times (B + C) \subseteq A \times B + A \times C$ (3.14)
- Distributivity, If $\forall b \in B, c \in C, b \times c \geq 0, \Rightarrow A \times (B + C) = A \times B + A \times C$ (3.15)
- $0 \in A - A, \quad 1 \in A / A, \quad 0 \notin A$ (3.16)
- Inclusion monotonicity, If $A \subseteq E, B \subseteq F \Rightarrow \begin{cases} A + B \subseteq E + F \\ A - B \subseteq E - F \\ A \times B \subseteq E \times F \\ A / B \subseteq E / F \end{cases}$ (3.17)

3.3. AGGREGATION OF FUZZY NUMBERS

In order to expand the classical fuzzy arithmetic general aggregation operators are introduced as special functions defined on the space of all fuzzy subsets of some universe X (Takaci, 2003). An illustration of fuzzy aggregation is as follows.

Let $\tilde{A}$ and $\tilde{B}$ be 2 fuzzy triangular numbers (*a*,*b*,*c*) and (*d*,*e*,*f*), respectively. Their aggregated values are calculated as:

$$\left(1/2 \times (a + d), \quad 1/2 \times (b + e), \quad 1/2 \times (c + f)\right) \tag{3.18}$$

For illustration, Let $\tilde{A}$ and $\tilde{B}$ be 2 fuzzy triangular numbers (2,3,4) and (4,5,6), respectively and $\tilde{C}$ be their aggregation. These three triangular fuzzy numbers are illustrated as follows.

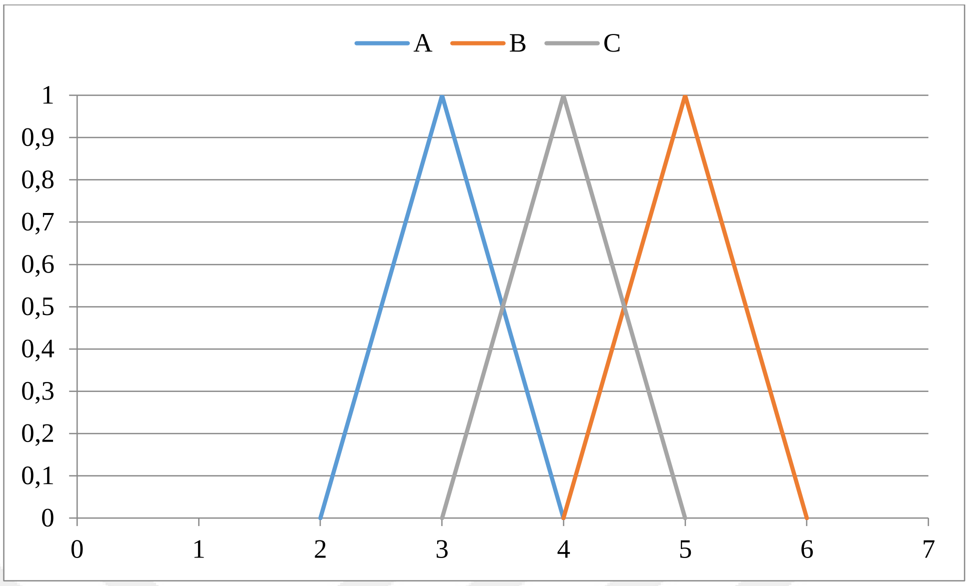

Figure 3.2 Fuzzy Aggregation

3.4. GENERAL CONCEPTS ON FUZZY DEA

In the previous sections we provided a general background about DEA Method and its extensions. Even if conventional DEA is totally suitable with crisp inputs and outputs, where the observed data set provides vague and imprecise knowledge about the generating process, use of the fuzzy measures and fuzzy mathematical programs in the DEA models is inevitable (Sengupta, 1992). Over the past decade, many researchers built imprecise DEA models enhancing traditional DEA by enabling to handle risk, uncertainty and imprecision (Karsak & Dursun, 2014). To the best of our knowledge Hatami et al. (2011), provided the only review on fuzzy DEA, presenting a classification scheme. They presented a taxonomy by classifying fuzzy DEA into four primary categories, namely, the tolerance approach of Sengupta (1992), the α-level based approach, the fuzzy ranking approach and the possibility approach (Hatami et al. 2011).

In the tolerance approach, input and output coefficients are considered as deterministic, but the inequality or equality signs are fuzzified (Sengupta, 1992). The main advantage of this approach that the decision maker is not forced into a precise formulation, and can attach different degree of importance to violations of different constraints (Kahraman & Tolga, 1998).

In the α-level based approach, a membership function is built on the premise that each fuzzy input and output varies between risk free and impossible bounds, and these bounds are incorporated into a membership function μ. The efficiency scores are computed for different values of the membership function allowing to observe variations in the efficiency performance of each individual DMU as the degree of fuzziness changes (Triantis & Girod, 1998). The main idea is to convert the fuzzy CCR model into a crisp linear programming model, thereby transforming the problem into an interval problem. This can be done by comparing the equality or inequality of two intervals, or by defining a variable in the interval which satisfy the constraints and maximizes the efficiency score (Saati et al. 2002). The formulation of an α-cut fuzzy DEA model is as follows.

$$\max E = \sum_{r=1}^{s} \bar{y}_{rp}$$

subject to (3.19)

$$\sum_{i=1}^{m} \bar{x}_{ip} = 1$$

$$\sum_{r=1}^{s} \bar{y}_{rj} - \sum_{i=1}^{m} \bar{x}_{ij} \leq 0$$

$$v_i(\alpha x_{ij}^m + (1-\alpha)x_{ij}^l) \leq \bar{x}_{ij} \leq v_i(\alpha x_{ij}^m + (1-\alpha)x_{ij}^u) \qquad \forall i, j,$$

$$u_r(\alpha y_{rj}^m + (1-\alpha)y_{rj}^l) \leq \bar{y}_{rj} \leq u_r(\alpha y_{rj}^m + (1-\alpha)y_{rj}^u) \qquad \forall i, j,$$

$$u_r, v_i \geq 0 \qquad \forall i, r.$$

In this formulation $\alpha \in (0,1]$ is a parameter. $\tilde{x}_{ij} = (x^l, x^m, x^u)$ and $\tilde{y}_{ij} = (y^l, y^m, y^u)$ are fuzzy triangular numbers and $\bar{x}_{ij} = v_i \hat{x}_{ij}$, $\bar{y}_{rj} = u_r \hat{y}_{rj}$ where $\hat{x}_{ij} \in \left[\alpha x_{ij}^m + (1-\alpha)x_{ij}^l, \alpha x_{ij}^m + (1-\alpha)x_{ij}^u\right]$ and $\hat{y}_{rj} \in \left[\alpha y_{rj}^m + (1-\alpha)y_{rj}^l, \alpha y_{rj}^m + (1-\alpha)y_{rj}^u\right]$.

Another approach for improving the differential capabilities of DEA is the ranking approach. In conventional DEA literature the ranking of DMUs are done by cross-efficiency matrix, by super-efficiency method or by combining MCDM techniques with the DEA (Adler et al. 2002). In fuzzy DEA area, the ranking approach is first developed by Guo & Tanaka (2001). They used comparison rules of fuzzy numbers and by predefining possibility levels, they proposed a fuzzy CCR model in which fuzzy equalities and inequalities are converted into crisp constraints (Guo & Tanaka, 2001). Their model is as follows.

$$\max_{v} v^t c_0$$

subject to (3.20)

$$v^t x_0 - (1-h)v^t c_0 = 1-(1-h)e,$$
$$v^t x_0 + (1-h)v^t c_0 \leq 1+(1-h)e,$$
$$v \geq 0.$$

Where h is the predetermined possibility level, input is a symmetric fuzzy triangular number with center x_0 and spread c_0. In addition $e = \max_i (c_i / x_i)$.

Considering the results of (3.20), they propose;

$$\max u^t y_0 - (1-h)u^t d_0$$

subject to (3.21)

$$v^t c_0 \geq g_0$$
$$v^t x_0 - (1-h)v^t c_0 = 1-(1-h)e,$$
$$v^t x_0 + (1-h)v^t c_0 \leq 1+(1-h)e,$$
$$u^t y_j - (1-h)u^t d_j \leq v^t x_j - (1-h)v^t c_j \qquad \forall j,$$
$$u^t y_j + (1-h)u^t d_j \leq v^t x_j + (1-h)v^t c_j \qquad \forall j,$$
$$u \geq 0,$$
$$v \geq 0.$$

Where g_0 is the result of (3.20), and similarly to input, y_j is the center of output and d_j is its spread.

Another ranking approach fuzzy DEA model is based on using the efficiency frontier. To rank DMUs, for each DMU the lower level of inputs and upper level of outputs are compared by the inner part of the efficiency frontier (Saati et al. 2002). The model is as:

$$\min z = \theta$$

subject to (3.22)

$$\theta(\alpha x_{ip}^{m} + (1-\alpha)x_{ip}^{l}) \geq \sum_{j=1}^{n} \lambda_j (\alpha x_{ij}^{m} + (1-\alpha)x_{ij}^{u}) \qquad \forall i,$$

$$\alpha y_{rp}^{m} + (1-\alpha)y_{rp}^{u}) \leq \sum_{j=1}^{n} \lambda_j (\alpha y_{rj}^{m} + (1-\alpha)y_{rj}^{l}) \qquad \forall r,$$

$$\lambda_j \geq 0 \qquad \forall j.$$

A fuzzy variable is associated with a possibility distribution (Zadeh, 1978). The possibility approach is based on this principle. In the possibility approach, by optimistic and pessimistic point of views, fuzzy constraints are treated as fuzzy events. By using possibility, credibility and necessity measures the efficiencies are obtained (Lertworasirikul et al. 2003).

3.5. LITERATURE REVIEW OF FUZZY DEA IN SUPPLIER SELECTION

Supplier selection is the process by which firms identify, evaluate, and contract with suppliers and it is one of the most critical activities of supply chain management. For reducing costs, improving corporate competiveness, increasing profit and ensuring sustainability, the firms have to take correct decisions and make the right choice. In the literature many papers are focused on identifying the supplier selection criteria (Dickson, 1966; Lehmann & O'Shaughnessy, 1974; Wilson, 1994; Kannan & Tan, 2002). Different non-deterministic analytical methods such as stochastic/fuzzy optimization techniques, multi-criteria decision-making (MCDM) methods and metaheuristic methods are proposed for supplier selection (Karsak & Dursun, 2016).

However, there exist only limited articles that employing fuzzy DEA in supplier selection problem and even less studies who integrates different methods with fuzzy DEA. For this review, the publications were identified throughout database "Web of Science", consulting works published until May 2016. To consult the database, the key words "supplier selection" and "fuzzy DEA" are searched in topic. Articles found are given in their chronological order. Wu et al. (2007), for dealing the imprecise data, and discriminatory power of traditional DEA to rank the efficient suppliers, introduced a 'virtual best' DMU by selecting the best values of each criterion and included to LP changing the efficient frontier of the model. Their model named as Augmented Imprecise DEA (AIDEA) (Wu et al. 2007). Saen (2008), highlighting the existence of a priori judgments on supplier selection problem and considering simultaneously weight restrictions and imprecise data proposed an assurance region-imprecise DEA (AR-IDEA) (Saen, 2008). The assumption of classical supplier selection models is based on the principle that suppliers consume common inputs to supply common outputs. However in many applications some suppliers do not comprehensively consume common inputs to comprehensively supply common outputs (Saen, 2009a) for that reason he proposed an interval DEA model for selecting non-homogenous suppliers. He improved his model by developing a nondiscretionary factors-imprecise DEA (NF-IDEA) model, in presence of the non-discretionary factors, ordinal and cardinal data and weight restrictions (Saen, 2009a). Azadeh et al. (2010) for three types of supplier selection model presented a decision making scheme which are under certainty DEA; under uncertainty fuzzy DEA, where they used α-cut method in five levels for α, to convert fuzzy DEA into interval programming and under probabilistic conditions; Chance Constraint DEA for two levels of probabilities (Azadeh & Alem, 2010). In DEA, it is generally assumed that all outputs are "positive". However, such an assumption is not always true because outputs may be "negative." (Saen, 2010). In the presence of such undesirable outputs in supplier selection problem Saen (2010) proposed a new fuzzy DEA methodology. Ahmady et al. (2013) for identifying the best supplier without any weight restrictions or cross-efficiency matrix, proposed a DEA approach with double frontiers. Recently, Mirhedayatian et al. (2014) proposed a novel network DEA model evaluating green supply chain management. Their model considers undesirable outputs, dual-role factors and fuzzy data simultaneously. Lately, Azadi et al. (2015) developed an integrated non-radial DEA model for sustainable supplier selection and they measured effectiveness, efficiency and productivity in fuzzy context.

In addition, some authors integrated fuzzy DEA with other methods. Kuo et al. (2010) integrated fuzzy AHP and fuzzy DEA for a supplier selection problem of an auto lighting company. They used fuzzy AHP to define the weight range of indicators' weight and these weights are integrated with fuzzy DEA. Recently, Karsak & Dursun (2014) incorporated QFD and fuzzy DEA with imprecise data in a medical supplier selection problem. They calculated lower and upper bounds of the suppliers' attributes and used them as weight restrictions in the DEA model .

Table 3.1. Fuzzy DEA in Supplier Selection

Author(s)	Year	Journal	Method
Wu et al.	2007	International Journal of Manufacturing Technology and Management	AIDEA
Saen	2008	International Journal of Advanced Manufacturing Technology	AR-IDEA
Saen	2009	Journal of Advances in Management Research	INTERVAL DEA
Saen	2009	Journal of the Operational Research Society	NF-IDEA
Azadeh & Alem	2010	Expert Systems with Applications	Chance Constraint DEA
Saen	2010	International Journal of Advanced Manufacturing Technology	undesirable outputs
Ahmady et al.	2013	International Journal of Logistics Research and Applications	double frontiers
Mirhedayatian et al.	2014	International Journal of Production Economics	network DEA
Azadi et al.	2015	Computers & Operations Research	non radial DEA
Kuo, Lee & Hu	2010	Production Palnning & Control	Fuzzy AHP - Fuzzy DEA
Karsak & Dursun	2014	Expert Systems with Applications	QFD - Fuzzy DEA

As can be observed from the Table 3.1. since one decade, there are only limited articles that are employed Fuzzy DEA in supplier selection problem and just two studies are integrated different MCDM techniques with fuzzy DEA.

4. DEMATEL METHOD

4.1. PRELIMINARIES OF DEMATEL METHOD

Decision-making trial and evaluation laboratory method (DEMATEL) is originally developed by the Science and Human Affairs Program of the Battelle Memorial Institute of Geneva between 1972 and 1976 (Fontela & Gobus, 1976). DEMATEL method uses the structural modeling technique to identify the possible interdependence among the criteria in a system by constructing diagraphs to show the causal relationships and the strengths of influence among the criteria (Yang & Tzeng, 2011). The computational procedures of DEMATEL method are summarized into the following four major steps;

Step 1: Computation of the average matrix by scores, *A*. The direct influence between any two factors is evaluated by each expert by an integer scale of 0, 1, 2, 3 and 4 representing ‘‘no influence’’, ‘‘low influence’’, ‘‘medium influence’’, ‘‘high influence’’ and ‘‘very high influence’’, respectively. Where, the notation of x_{ij} indicates the degree to which the decision maker evaluate factor *i* affects factor *j*. For $i = j$, the diagonal elements are set to zero, indicating no influence. For each decision maker, a $n \times n$ non-negative matrix can be established as $X^k = \left[x_{ij}^k\right]$, where *k* is the number of decision makers, with $1 \le k \le H$ and *n* is the number of criteria (Wu & Tsai, 2011). Therefore, $X^1, X^2, X^3, ..., X^H$ are the matrices of *H* decision makers. To incorporate all evaluations from *H* decision makers, the average matrix $A = \left[a_{ij}\right]$ is constructed as follows:

$$a_{ij} = \frac{1}{H}\sum_{k=1}^{H} x_{ij}^k \tag{4.1}$$

Step 2: Calculation of the normalized initial direct influence matrix, *D* by normalizing the average matrix *A*, in which all principal diagonal elements are equal to 0.

$$D = s \times A \tag{4.2}$$

where

$$s = \min\left[1/\max_{1\le i\le n}\sum_{j=1}^{n}\left|a_{ij}\right|, 1/\max_{1\le i\le n}\sum_{i=1}^{n}\left|a_{ij}\right|\right] \tag{4.3}$$

As the sum of each row *j* of matrix *A* represents the direct effects of each criterion on others, $\max_{1\le i\le n}\sum_{j=1}^{n} a_{ij}$ is the maximum direct influence. Similarly, as the sum of each column *I* of matrix *A* represents the direct effects on criterion *I*, $\max_{1\le i\le n}\sum_{j=1}^{n} a_{ij}$ represents the one most influenced by other criteria. The positive scalar *s* is equal to the larger of the two extreme sums. Matrix *D* is obtained by dividing each element of *A* by *s*. Each element d_{ij} of matrix *D* lies between 0 and 1 (Kuo, Hsu, & Li, 2015).

Step 3: Derivation of the total relation matrix *T*, where *I* is the identity matrix. Define *r* and *c* be $n \times 1$ and $1 \times n$ vectors representing the sum of rows and sum of columns of the total relation matrix *T*, respectively. Suppose r_i be the sum of i^{th} row in matrix *T*, then r_i summarizes both direct and indirect effects given by criterion I to the other criterion. If c_j denotes the sum of j^{th} column in matrix *T*, then c_j shows both direct and indirect effects by criterion *j* from the other criteria. When $j = i$, the sum $(r_i + c_j)$ shows the total effects given and received by criterion *i*. Thus, $(r_i + c_j)$ indicates the degree of importance for criterion *I* in the entire system. On the contrary, the difference $(r_i - c_j)$ represents the net effect that criterion I contributes to the system. Specifically, if $(r_i - c_j)$ is positive, criterion *I* is a net cause, while criterion *I* is a net receiver or result if $(r_i - c_j)$ is negative (Lee, Yen, & Tsai, 2008).

$$T = D \times (I - D)^{-1} \tag{4.4}$$

Step 4: Set up a threshold value to obtain the digraph. Since matrix T provides information on how one criterion affects another, it is necessary for a decision maker to set up a threshold value to filter out some negligible effects. In doing so, only the effects greater than the threshold value would be chosen and shown in digraph. The digraph can be acquired by mapping the dataset of $(r+c, r-c)$ (Wu & Tsai, 2011).

4.2. LITERATURE REVIEW OF DEMATEL IN SUPPLIER SELECTION

Since that Supply Chain Management (SCM) practices have flourished, supplier selection problem came into prominence. DEMATEL method is widely used to determine the relationship between criteria, generating the relationship diagrams between them and also to find key factor criteria to evaluate. For this review, the publications were identified throughout database "Web of Science", consulting works published until May 2016. To consult the database, the key words "supplier selection" and "DEMATEL" are searched in topic. Articles found are given in their chronological order. Lee (2008) presented an integrated decision-making process that could cope with the interdependencies among criteria using DEMATEL and demonstrated how to lessen the number of first suggested suppliers for applicable to more simple ANP methodology step. Chang et al. (2011) pioneered to use fuzzy DEMATEL method to find influential factors in selecting SCM suppliers in the electronic industry. Wu & Tsai (2011) applied DEMATEL method for evaluating suppliers in auto spare parts industry. Dalalah et al. (2011) utilized modified fuzzy DEMATEL model to deal with the influential relationship between the evaluation criteria and proposed a TOPSIS model to evaluate the criteria for the selection of cans supplier. Büyüközkan & Çiftçi (2012) integrated fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS in a Green Supply Chain Management (GSCM) problem for evaluating suppliers in the automotive industry.

Wu & Tsai (2012) integrated AHP and DEMATEL methods to improve suppliers' performance for both short-term and long-term in automotive industry. Kiani et al. (2013) employed fuzzy DEMATEL method to examine the influential logistical criteria of green supply chains. Hsu et al. (2013) used the DEMATEL approach to recognize the influential criteria of carbon management in green supply chain for improving the overall performance of suppliers in terms of carbon management. Liou et al. (2014) combined DEMATEL and ANP methods to develop the structure of the relationships among the criteria and the criteria weights and used fuzzy integral to aggregate the gaps using the weights obtained from the DANP in the airline industry. Recently, Wang (2015) aggregated the performance scores of Business Intelligence via fuzzy DELPHI and then conducted fuzzy DEMATEL to recognize the causalities between marketing requirements and technical attributes and employed fuzzy AHP to recommend optimal Business Intelligence Systems. Kuo et al. (2015) proposed a novel hybrid MCDM method to evaluate green suppliers in the electronics industry. They used DEMATEL ANP to determine both the importance of evaluation criteria in selecting suppliers and the causal relationships between them and evaluated the environmental performances of suppliers and to obtain a solution under each evaluation criterion by VIKOR. Keskin (2015) proposed an integrated model for supplier selection and evaluation quality. She used fuzzy DEMATEL in the first step to compute the interactions between the evaluation criteria and the criteria weight, and then performances of suppliers are assessed using both the criteria weights obtained at the first stage and fuzzy c-means clustering algorithm by classifying the vendors according to their performances. Ultimately, Liou et al. (2016) used DEMATEL technique which structures the relationships among criteria and via DEMATEL and ANP methods are used to obtain influential weights of the criteria.

Table 4.1. DEMATEL in Supplier Selection

Author(s)	Year	Journal	Method	Sector
Lee	2008	Korean Business Education Review	DEMATEL-ANP	numerical example
Chang, Chang, & Wu	2011	Expert Systems with Applications	fuzzy DEMATEL	electronic industry
Wu & Tsai	2011	Applied Mathematics and Computation	DEMATEL	automotive industry
Dalalah et al.	2011	Expert Systems with Applications	fuzzy DEMATEL - TOPSIS	cans supplier
Büyüközkan & Çifçi	2012	Expert Systems with Applications	fuzzy DEMATEL - fuzzy ANP- fuzzy TOPSIS	automotive industry
Wu & Tsai	2012	International Journal of Systems Science	AHP - DEMATEL	automotive industry
Kiani, et al.	2013	Polish Journal of Environmental Studies	fuzzy DEMATEL	logistics
Hsu, Kuo, Chen, & Hu	2013	Journal of Cleaner Production	DEMATEL	electronic industry
Liou, Chuang, & Tzeng	2014	Information Sciences	DEMATEL-ANP	airline industry
Wang	2015	Computers & Industrial Engineering	fuzzy DELPHI - fuzzy DEMATEL -fuzzy AHP	business intelligence systems
Kuo, Hsu, & Li	2015	Sustainability	DEMATEL ANP - VIKOR	electronic industry
Keskin	2015	International Journal of Production Research	fuzzy DEMATEL - fuzzy clustering algorithm	glass industry
Liou et al.	2016	International Journal of Production Research	DEMATEL-ANP	electronic industry

5. APPLICATION

5.1. SUPPLIER SELECTION IN TEXTILE SECTOR

A supply chain is the congregation of the suppliers, manufacturers, retailers and logistic services in order to reach to customers in a more productive way. The fast-changing nature of the competitive sector, increasing offer and product spectrum, globalized economy, progress of the technology force the companies to select their suppliers in a more selective route and the firms have to be evaluate many different criteria. Supplier selection process is mainly based on reducing costs and the purchasing risk, increasing general value to the customer and strengthen the collaboration between buyers and suppliers (Monczka et al. 1998). The selection problem has been a study focus of academicians and researchers have applied both qualitative and quantitative approaches. Dickson (1966) presented 23 criteria such as price/cost, quality, delivery, service, technical capability, production facilities and capacity, relationship, amount of past business, geographical location, financial position, warranties and claim policies, environmental issues, flexibility, management and organization, reliability, risk, lead time, performance history, product/service design, research and development, training aids, manufacturing capability and profitability; he determined that quality, delivery time and performance history were the most important factors for supplier selection. Later, Weber et al. (1991) introduced 10 criteria for supplier selection problem which are price, delivery, quality, production capability, geographic location, technical capability, management and organization, reputation and position in industry, financial position and performance history, from which dedicated that price, delivery, quality and location were the most important criteria. Wilson (1994) divided supplier selection studies as descriptive and prescriptive and classified in five categories such as performance, economic, integrative, adaptive and legalistic. She underlined the shift in the relative importance of selection criteria, and that total product cost which includes price, quality, service and use of the product took great attention.

5.2. CRITERIA SELECTION AND EVALUATION

In this study, it is addressed to a supplier selection problem of a company in textile sector which needs to evaluate its 12 alternative suppliers. Firstly, throughout a deep survey of existing supplier selection problem literature, the existing criteria are determined. Afterwards, with the three decision makers' consensus ten key criteria already existing in Weber et al. (1991) and Dickson (1966) related to the sector are selected to evaluate. The selected criteria are as follows:

Table 5.1. Supplier Selection Criteria

C1	REPUTATION
C2	PRICE/COST
C3	QUALITY
C4	LOCATION
C5	RELIABILITY
C6	DELIVERY
C7	SERVICE
C8	RESPONSIVENESS
C9	TECHNICAL CAPABILITY
C10	RELATIONSHIP

- Reputation

This criterion is based on the perception of the supplier on the market, it is based on the interaction of supplier with his supply chain environment. Any illicit case or scandal affects strongly this criterion.

- Price/Cost

The price/cost criterion includes all the elements associated with the purchase including purchase price, logistic services, taxes, operational costs. Low-cost suppliers are preferred.

- Quality

Being a brand that address to high-end market, quality assessment is a key factor for the company. Quality of suppliers is evaluated considering product, time, employee triangle. Mostly, when the company is content about its suppliers' quality, does not consider to alternate them, even other advantages on the market may exist.

- Location

Geographical location of the main plant and storages are important for the firm. The closeness aggrandizes all the other dimension of the collaboration and decrease the lead-time.

- Reliability

Reliability factor affects mutual trust between the firm and suppliers, which are called as partners in nowadays supply chain management understanding. The delay on the delivery, the failures on the product, the lack of the communication affect negatively this factor. Financial status of the supplier is also relevant to this factor.

- Delivery

The follow of the predefined delivery schedule is employed to appraise this criterion. The delays and wrecked or missing products affect directly the delivery scores of suppliers.

- Service

The service includes all the steps after purchase, including technical support, supportive call-center, and collaboration in case of a problem or malfunction.

- Responsiveness

Responsiveness is defined as the ability of the suppliers to respond purposefully and within an appropriate timeframe to firm requests or changes in the marketplace.

- Technical Capability

Technical capability is measured by compliance with quantity, compliance with due date and quality standards. The production abilities and facilities of suppliers, their production capacities influence this factor.

- Relationship

Relationship includes ease of the communication and the negotiability. Languages, business customs and cultural suitability are the races of this factor.

Later on, the decision makers are asked to evaluate all criteria for each supplier alternative. They were unable to express their preferences precisely and the evaluations are expressed in linguistic terms. These linguistic terms are expressed as triangular fuzzy numbers because they are easy to manage from the computational point of view. (Bevilacqua, Ciarapica, & Giaccheta, 2006). Linguistic scale that is used is $U = \{ \; VL, L, M, H, VH \; \}$ where *VL* is very low, *L* is low, *M* is medium, *H* is high and *VH* is very high where VL: (0, 1, 2), L: (2, 3, 4), M: (4,.5,6), H: (6,7,8), VH: (8,9,10). This scale due to the its' complete symmetric structure can be used with the DEA model that will be employed.

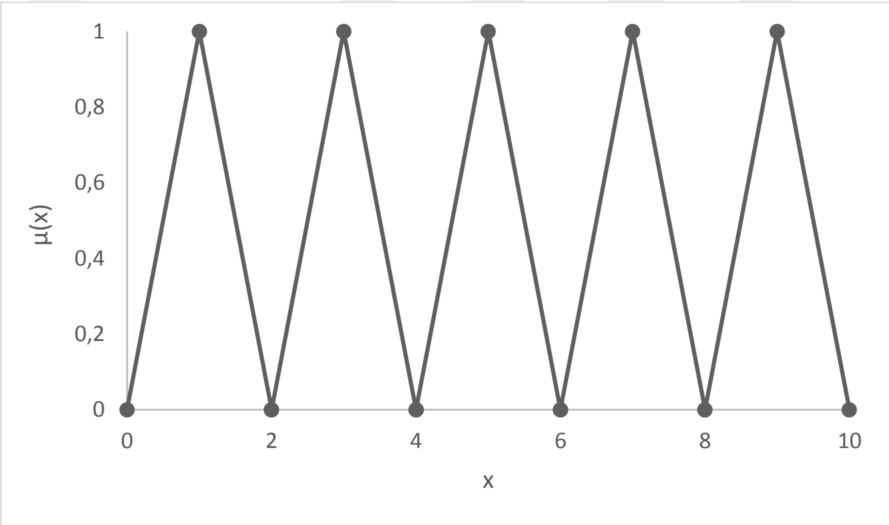

Figure 5.1. A linguistic term set where VL: (0,1,2), L: (2,3,4), M: (4,5,6), H: (6,7,8), VH: (8,9,10)

Each supplier is evaluated with this linguistic scale by three decision makers, and aggregated weights of all the criteria are computed using arithmetic fuzzy aggregation. For instance, (VL,VL,L) is aggregated as follows where three is the number of decision makers:

$$\left(1/3 \times (0+0+2), \quad 1/3 \times (1+1+3), \quad 1/3 \times (2+2+4)\right) = (0.67, 1.67, 2.67)$$

Table 5.2. Evaluation of Suppliers for 10 Criteria by three Decision Makers

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Sup1	(VL,VL,L)	(H,M,H)	(L,L,M)	(VH,H,H)	(VL,VL,VL)	(VL,VL,VL)	(M,L,L)	(L,L,L)	(VL,L,VL)	(M,L,M)
Sup2	(VH,VH,H)	(L,M,M)	(M,M,M)	(H,H,H)	(M,M,M)	(M,H,M)	(M,M,M)	(H,H,H)	(M,H,M)	(VL,VL,M)
Sup3	(M,L,M)	(VH,H,VH)	(L,L,M)	(M,M,M)	(L,L,L)	(VL,L,L)	(L,L,M)	(M,L,L)	(L,M,H)	(VL,M,VL)
Sup4	(H,H,H)	(VL,L,M)	(L,M,M)	(H,M,M)	(M,M,M)	(H,H,H)	(L,M,H)	(H,M,H)	(L,M,M)	(L,M,M)
Sup5	(M,M,M)	(VH,VH,VH)	(H,H,M)	(L,L,L)	(L,L,L)	(VL,L,L)	(L,M,M)	(L,H,L)	(H,VH,H)	(L,M,M)
Sup6	(VH,VH,VH)	(M,H,H)	(VH,VH,H)	(M,M,L)	(VH,VH,H)	(M,L,H)	(VH,H,VH)	(H,H,H)	(H,VH,H)	(H,VH,VH)
Sup7	(M,H,H)	(L,M,L)	(L,L,M)	(L,M,M)	(L,L,M)	(L,VL,M)	(L,M,M)	(M,L,M)	(L,H,M)	(M,M,L)
Sup8	(VH,VH,VH)	(M,H,H)	(M,M,M)	(VL,VL,VL)	(H,M,H)	(L,L,L)	(H,H,H)	(H,M,VH)	(H,H,M)	(H,H,H)
Sup9	(M,M,M)	(M,M,M)	(M,M,H)	(H,VH,VH)	(M,H,H)	(H,H,H)	(M,H,VH)	(M,H,H)	(L,H,M)	(H,VH,H)
Sup10	(H,M,M)	(H,M,H)	(H,VH,VH)	(H,VH,VH)	(H,H,H)	(M,M,H)	(M,VH,H)	(L,H,M)	(H,VH,H)	(H,VH,VH)
Sup11	(M,H,H)	(L,H,M)	(M,H,M)	(L,L,L)	(L,H,M)	(H,H,H)	(L,M,M)	(M,M,M)	(L,H,M)	(L,L,M)
Sup12	(H,H,H)	(L,VL,M)	(H,H,H)	(VL,VL,VL)	(H,VH,H)	(VH,VH,VH)	(L,M,H)	(H,M,VH)	(L,H,H)	(H,VH,H)

Table 5.3. Aggregated Values of Supplier Evaluation

	C1	C2	C3	C4	C5
SUP1	(0.67,1.67,2.67)	(5.33.6.33.7.33)	(0.67,1.67,2.67)	(6.67,7.67,8.67)	(0,1,2)
SUP2	(7.33,8.33,9.33)	(3.33,4.33,5.33)	(4,5,6)	(6,7,8)	(4,5,6)
SUP3	(3.33,4.33,5.33)	(7.33,8.33,9.33)	(2,3,4)	(4,5,6)	(2,3,4)
SUP4	(6,7,8)	(1.33,2.33,3.33)	(3.33,4.33,5.33)	(4.67,5.67,6.67)	(4,5,6)
SUP5	(4,5,6)	(8,9,10)	(5.33,6.33,7.33)	(2,3,4)	(2,3,4)
SUP6	(8,9,10)	(5.33,6.33,7.33)	(7.33,8.33,9.33)	(2.67,3.67,4.67)	(7.33,8.33,9.33)
SUP7	(5.33,6.33,7.33)	(2.67,3.67,4.67)	(2.67,3.67,4.67)	(3.33,4.33,5.33)	(2.67,3.67,4.67)
SUP8	(8,9,10)	(5.33,6.33,7.33)	(4,5,6)	(0,1,2)	(5.33,6.33,7.33)
SUP9	(4,5,6)	(4,5,6)	(4.67,5.67,6.67)	(7.33,8.33,9.33)	(5.33,6.33,7.33)
SUP10	(4.67,5.67,6.67)	(5.33,6.33,7.33)	(7.33,8.33,9.33)	(7.33,8.33,9.33)	(6,7,8)
SUP11	(5.33,6.33,7.33)	(4,5,6)	(4.67,5.67,6.67)	(2,3,4)	(4,5,6)
SUP12	(6,7,8)	(1.33,2.33,3.33)	(6,7,8)	(0,1,2)	(6.67,7.67,8.67)

	C6	C7	C8	C9	C10
SUP1	(0,1,2)	(1.33,2.33,3.33)	(2,3,4)	(0.67,1.67,2.67)	(3.33,4.33,5.33)
SUP2	(4.67,5.67,6.67)	(4,5,6)	(6,7,8)	(4.67,5.67,6.67)	(0.67,1.67,2.67)
SUP3	(1.33,2.33,3.33)	(2,3,4)	(2.67,3.67,4.67)	(4,5,6)	(0.67,1.67,2.67)
SUP4	(6,7,8)	(4,5,6)	(5.33,6.33,7.33)	(3.33,4.33,5.33)	(3.33,4.33,5.33)
SUP5	(1.33,2.33,3.33)	(3.33,4.33,5.33)	(3.33,4.33,5.33)	(6.67,7.67,8.67)	(3.33,4.33,5.33)
SUP6	(4,5,6)	(7.33,8.33,9.33)	(6,7,8)	(6.67,7.67,8.67)	(7.33,8.33,9.33)
SUP7	(2,3,4)	(3.33,4.33,5.33)	(3.33,4.33,5.33)	(4,5,6)	(3.33,4.33,5.33)
SUP8	(2,3,4)	(6,7,8)	(6,7,8)	(5.33,6.33,7.33)	(6,7,8)
SUP9	(6,7,8)	(6,7,8)	(5.33,6.33,7.33)	(4,5,6)	(6.67,7.67,8.67)
SUP10	(4.67,5.67,6.67)	(6,7,8)	(4,5,6)	(6.67,7.67,8.67)	(7.33,8.33,9.33)
SUP11	(6,7,8)	(3.33,4.33,5.33)	(4,5,6)	(4,5,6)	(2.67,3.67,4.67)
SUP12	(8,9,10)	(4,5,6)	(6,7,8)	(4.67,5.67,6.67)	(6.67,7.67,8.67)

5.3. APPLICATION OF DEMATEL

Afterwards, the direct influence between any two criteria is evaluated by each decision maker via an integer scale going from “0”to “4” where “0” represents ‘‘no influence’’ and “4” represents “very high influence” and average matrix, *A* is computed.

Table 5.4. Decision Maker #1 Direct Influence Evaluation Among Criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	1	2	0	2	0	2	2	3	3
C2	0	0	3	0	1	0	3	0	2	3
C3	1	4	0	0	3	2	2	1	2	2
C4	1	1	0	0	0	2	2	1	0	2
C5	0	2	2	0	0	1	1	0	0	3
C6	0	2	2	0	2	0	2	0	1	2
C7	1	2	3	0	2	2	0	0	0	2
C8	0	2	2	0	1	2	1	0	1	1
C9	2	2	2	0	1	2	2	1	0	1
C10	0	2	2	0	2	2	3	0	1	0

As is provided in Table 5.4. C1 has high influence on C10, controversially C10 has no influence at all on C1, in other saying C1 is not influenced by C10. Similarly, C2’s effect on C3 is medium and C3 affects highly C2 due to non-symmetric structure of DEMATEL.

Table 5.5. Decision Maker #2 Direct Influence Evaluation Among Criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	3	4	0	2	2	3	2	2	2
C2	0	0	3	0	1	1	2	0	0	1
C3	0	4	0	0	3	2	2	0	2	3
C4	2	2	1	0	2	2	3	0	0	2
C5	0	2	1	0	0	2	1	0	1	2
C6	0	2	2	0	2	0	2	0	1	2
C7	0	3	3	0	3	2	0	0	2	4
C8	2	2	2	0	1	1	1	0	0	1
C9	0	2	3	0	2	2	2	0	0	1
C10	0	2	3	0	2	3	3	0	2	0

Table 5.6. Decision Maker #3 Direct Influence Evaluation Among Criteria

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	3	2	0	3	2	3	1	2	2
C2	2	0	4	2	2	2	3	1	1	3
C3	3	4	0	1	2	1	2	1	2	3
C4	0	2	1	0	0	2	1	0	0	1
C5	2	3	0	0	0	0	1	0	1	2
C6	1	2	1	2	2	0	2	0	0	2
C7	1	3	3	0	3	2	0	0	1	3
C8	2	2	2	0	2	1	2	0	1	1
C9	2	1	2	0	1	1	1	0	0	1
C10	2	3	3	1	2	2	3	0	1	0

Table 5.7. Average Matrix, *A*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0.000	2.333	2.667	0.000	2.333	1.333	2.667	1.667	2.333	2.333
C2	0.667	0.000	3.333	0.667	1.333	1.000	2.667	0.333	1.000	2.333
C3	1.333	4.000	0.000	0.333	2.667	1.667	2.000	0.667	2.000	2.667
C4	1.000	1.667	0.667	0.000	0.667	2.000	2.000	0.333	0.000	1.667
C5	0.667	2.333	1.000	0.000	0.000	1.000	1.000	0.000	0.667	2.333
C6	0.333	2.000	1.667	0.667	2.000	0.000	2.000	0.000	0.667	2.000
C7	0.667	2.667	3.000	0.000	2.667	2.000	0.000	0.000	1.000	3.000
C8	1.333	2.000	2.000	0.000	1.333	1.333	1.333	0.000	0.667	1.000
C9	1.333	1.667	2.333	0.000	1.333	1.667	1.667	0.333	0.000	1.000
C10	0.667	2.333	2.667	0.333	2.000	2.333	3.000	0.000	1.333	0.000

Normalized initial direct influence matrix, D is calculated by normalizing the average matrix A, *b*y formula (4.3), $s = 0.0476$ and D is by formula (4.2) then the total relation matrix, T is derived by formula (4.4).

Table 5.8. Normalized initial direct influence matrix. D

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0.000	0.111	0.127	0.000	0.111	0.063	0.127	0.079	0.111	0.111
C2	0.032	0.000	0.159	0.032	0.063	0.048	0.127	0.016	0.048	0.111
C3	0.063	0.190	0.000	0.016	0.127	0.079	0.095	0.032	0.095	0.127
C4	0.048	0.079	0.032	0.000	0.032	0.095	0.095	0.016	0.000	0.079
C5	0.032	0.111	0.048	0.000	0.000	0.048	0.048	0.000	0.032	0.111
C6	0.016	0.095	0.079	0.032	0.095	0.000	0.095	0.000	0.032	0.095
C7	0.032	0.127	0.143	0.000	0.127	0.095	0.000	0.000	0.048	0.143
C8	0.063	0.095	0.095	0.000	0.063	0.063	0.063	0.000	0.032	0.048
C9	0.063	0.079	0.111	0.000	0.063	0.079	0.079	0.016	0.000	0.048
C10	0.032	0.111	0.127	0.016	0.095	0.111	0.143	0.000	0.063	0.000

Table 5.9. The total relation matrix. T

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0.090	0.351	0.350	0.029	0.303	0.223	0.326	0.107	0.227	0.324
C2	0.101	0.202	0.326	0.053	0.222	0.177	0.283	0.041	0.145	0.281
C3	0.143	0.407	0.230	0.045	0.307	0.230	0.296	0.061	0.207	0.332
C4	0.094	0.217	0.168	0.019	0.149	0.185	0.215	0.034	0.072	0.207
C5	0.076	0.234	0.175	0.018	0.108	0.134	0.164	0.017	0.098	0.223
C6	0.072	0.251	0.225	0.050	0.219	0.108	0.227	0.019	0.110	0.237
C7	0.105	0.332	0.329	0.028	0.290	0.228	0.185	0.027	0.153	0.324
C8	0.117	0.250	0.240	0.020	0.191	0.163	0.197	0.023	0.113	0.192
C9	0.119	0.243	0.259	0.021	0.197	0.182	0.216	0.039	0.086	0.198
C10	0.103	0.313	0.311	0.041	0.260	0.239	0.307	0.026	0.163	0.193

The study continues with defining r and c as n x 1 and 1 x n vectors representing the sum of rows and sum of columns of T, respectively where r_i denotes the sum of i^{th} row in matrix T and c_j denotes the sum of j^{th} column in matrix T. When $j = i$, $(r_i + c_j)$ is regarded as the degree of importance for criterion i in the entire system (Wu et al. 2011). In addition, these values are normalized by

$$(r_i + c_j) / \sum_{i=j} (r_i + c_j), \qquad \forall i = j. \tag{5.1}$$

The summarized table is given in the following table:

Table 5.10. Degrees of Importance and Normalized Values of Criteria

	r(i)+c(j)	normalized r(i) + c(j)	r(i)-c(j)
C1	3.352	0.095	1.310
C2	4.629	0.132	-0.967
C3	4.872	0.139	-0.356
C4	1.683	0.048	1,033
C5	3.495	0.099	-0,999
C6	3.388	0.096	-0,350
C7	4.416	0.126	-0,415
C8	1.901	0.054	1,113
C9	2.933	0.083	0,186
C10	4.469	0.127	-0,555
Σ	35.138	1.000	1.309

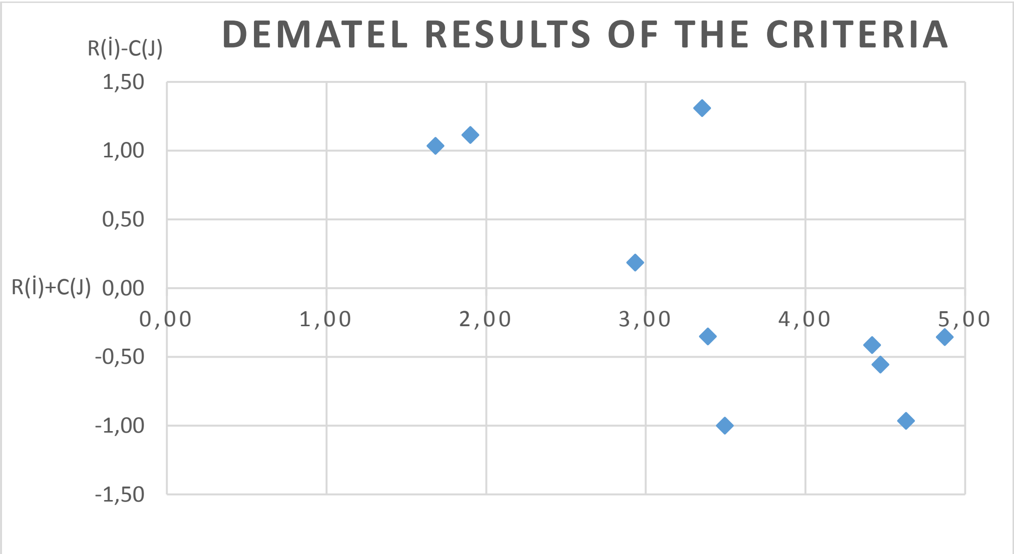

Figure 5.2 The DEMATEL Diagraph

The weight results of the criteria set is as follows.

Table 5.11. Criteria Weights

C1	REPUTATION	0.095
C2	PRICE/COST	0.132
C3	QUALITY	0.139
C4	LOCATION	0.048
C5	RELIABILITY	0.099
C6	DELIVERY	0.096
C7	SERVICE	0.126
C8	RESPONSIVENESS	0.054
C9	TECHNICAL CAPABILITY	0.083
C10	RELATIONSHIP	0.127

5.4. SINGLE-INPUT SINGLE-OUTPUT DEA MODEL

As a threshold value "0.13" is selected in order to construct a single-input single-output model where *C2* and *C3* are taken into consideration as input and output, respectively. Guo & Tanaka (2001) DEA model is employed to data set given in Table 5.3. for six different possibility level (h).

$$\max_{v} v^t c_0$$

subject to (5.2)

$$v^t x_0 - (1-h) v^t c_0 = 1 - (1-h) \times 0.25,$$

$$v^t x_0 + (1-h) v^t c_0 \leq 1 + (1-h) \times 0.25,$$

$$v \geq 0.$$

$$\max u^t y_0 - (1-h)u^t d_0$$

subject to (5.3)

$$\begin{aligned}
& v^t c_0 \geq g_0 \\
& v^t x_0 - (1-h)v^t c_0 = 1-(1-h)\times 0.25, \\
& v^t x_0 + (1-h)v^t c_0 \leq 1+(1-h)\times 0.25, \\
& u^t y_j - (1-h)u^t d_j \leq v^t x_j - (1-h)v^t c_j, \\
& u^t y_j + (1-h)u^t d_j \leq v^t x_j + (1-h)v^t c_j \qquad \forall j, \\
& u \geq 0, \\
& v \geq 0.
\end{aligned}$$

Efficiency results are derived via formula given below where the (E_L, E, E_U) is the lower efficiency, efficiency and upper efficiency, respectively.

$$E = \frac{u^{*t} y_0}{v^{*t} x_0} \tag{5.4}$$

$$E_L = \frac{u^{*t}(y_0 - d_0(1-h))}{v^{*t}(x_0 + c_0(1-h))} \tag{5.5}$$

$$E_U = \frac{u^{*t}(y_0 + d_0(1-h))}{v^{*t}(x_0 - c_0(1-h))} \tag{5.6}$$

Table 5.11. Fuzzy Efficiency Results, *h=0*

h=0	*g*	W_L	W	W_U
DMU1	0.11	0.02	0.06	0.11
DMU2	0.17	0.17	0.26	0.4
DMU3	0.08	0.05	0.08	0.12
DMU4	0.43	0.22	0.41	0.89
DMU5	0.07	0.12	0.16	0.21
DMU6	0.11	0.22	0.3	0.39
DMU7	0.21	0.13	0.22	0.38
DMU8	0.11	0.12	0.18	0.25
DMU9	0.14	0.17	0.25	0.37
DMU10	0.11	0.22	0.3	0.39
DMU11	0.14	0.17	0.25	0.37
DMU12	0.43	0.4	0.67	1.33

Table 5.12. Fuzzy Efficiency Results, *h=0.2*

h=0.2	*g*	W_L	W	W_U
DMU1	0.12	0.03	0.06	0.11
DMU2	0.19	0.2	0.29	0.41
DMU3	0.09	0.06	0.09	0.13
DMU4	0.43	0.28	0.46	0.83
DMU5	0.08	0.14	0.18	0.22
DMU6	0.12	0.26	0.32	0.4
DMU7	0.23	0.16	0.24	0.38
DMU8	0.12	0.14	0.19	0.26
DMU9	0.16	0.21	0.28	0.39
DMU10	0.12	0.26	0.32	0.4
DMU11	0.16	0.21	0.28	0.39
DMU12	0.43	0.49	0.74	1.26

Table 5.13. Fuzzy Efficiency Results, *h=0.4*

h=0.4	*g*	W_L	*W*	W_U
DMU1	0.13	0.04	0.07	0.11
DMU2	0.2	0.24	0.31	0.41
DMU3	0.1	0.07	0.1	0.13
DMU4	0.43	0.34	0.5	0.77
DMU5	0.09	0.16	0.19	0.23
DMU6	0.13	0.3	0.35	0.42
DMU7	0.24	0.19	0.27	0.37
DMU8	0.13	0.17	0.21	0.26
DMU9	0.17	0.25	0.31	0.39
DMU10	0.13	0.3	0.35	0.42
DMU11	0.17	0.25	0.31	0.39
DMU12	0.43	0.59	0.81	1.19

Table 5.14. Fuzzy Efficiency Results, *h=0.6*

h=0.6	*g*	W_L	*W*	W_U
DMU1	0.14	0.06	0.08	0.1
DMU2	0.21	0.29	0.34	0.4
DMU3	0.1	0.09	0.11	0.13
DMU4	0.43	0.42	0.55	0.72
DMU5	0.1	0.18	0.21	0.23
DMU6	0.14	0.35	0.39	0.43
DMU7	0.25	0.23	0.29	0.36
DMU8	0.14	0.2	0.23	0.27
DMU9	0.18	0.29	0.33	0.39
DMU10	0.14	0.35	0.39	0.43
DMU11	0.18	0.29	0.33	0.39
DMU12	0.43	0.71	0.88	1.13

Table 5.15. Fuzzy Efficiency Results, *h=0.8*

h=0.8	*g*	W_L	W	W_U
DMU1	0.15	0.07	0.08	0.1
DMU2	0.22	0.33	0.36	0.39
DMU3	0.11	0.1	0.11	0.12
DMU4	0.43	0.51	0.58	0.66
DMU5	0.1	0.21	0.22	0.24
DMU6	0.15	0.39	0.42	0.44
DMU7	0.26	0.28	0.32	0.35
DMU8	0.15	0.23	0.25	0.27
DMU9	0.19	0.33	0.36	0.39
DMU10	0.15	0.39	0.42	0.44
DMU11	0.19	0.33	0.36	0.39
DMU12	0.43	0.84	0.94	1.06

Table 5.16. Fuzzy Efficiency Results, *h=1*

h=1	*g*	W_L	W	W_U
DMU1	0.16	0.09	0.09	0.09
DMU2	0.23	0.38	0.38	0.38
DMU3	0.12	0.12	0.12	0.12
DMU4	0.43	0.62	0.62	0.62
DMU5	0.11	0.23	0.23	0.23
DMU6	0.16	0.44	0.44	0.44
DMU7	0.27	0.33	0.33	0.33
DMU8	0.16	0.26	0.26	0.26
DMU9	0.2	0.38	0.38	0.38
DMU10	0.16	0.44	0.44	0.44
DMU11	0.2	0.38	0.38	0.38
DMU12	0.43	1	1	1

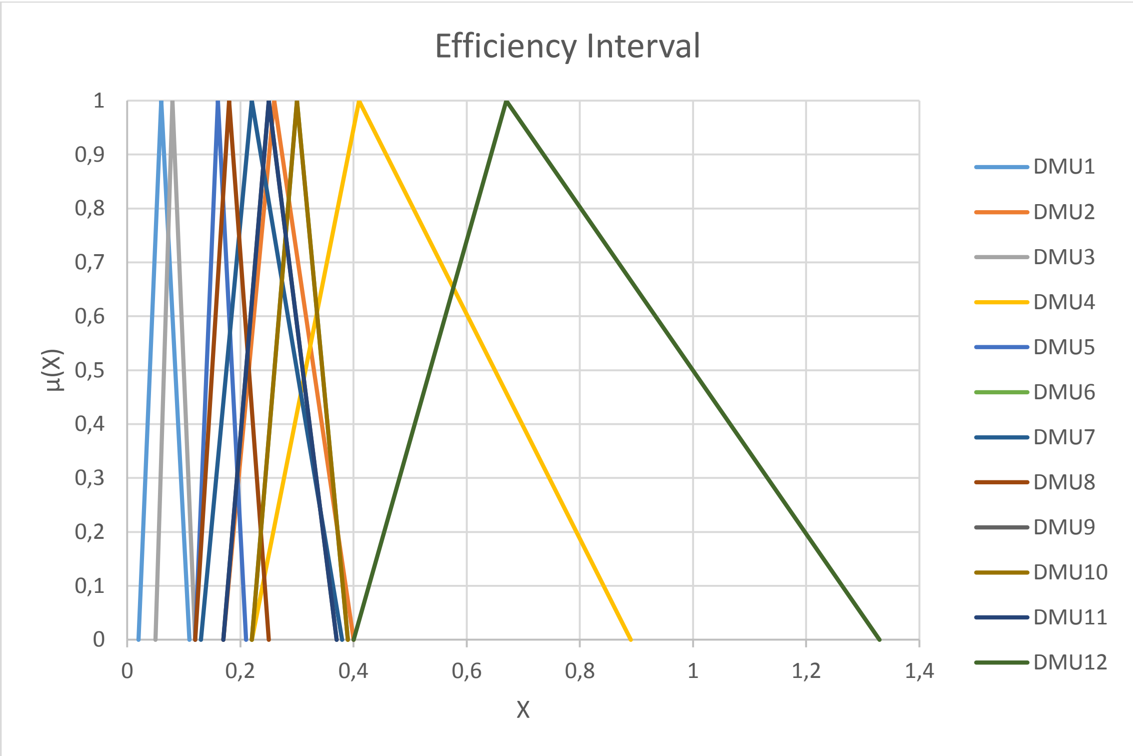

Figure 5.3. Efficiency Results of (5.3) for *h=0*

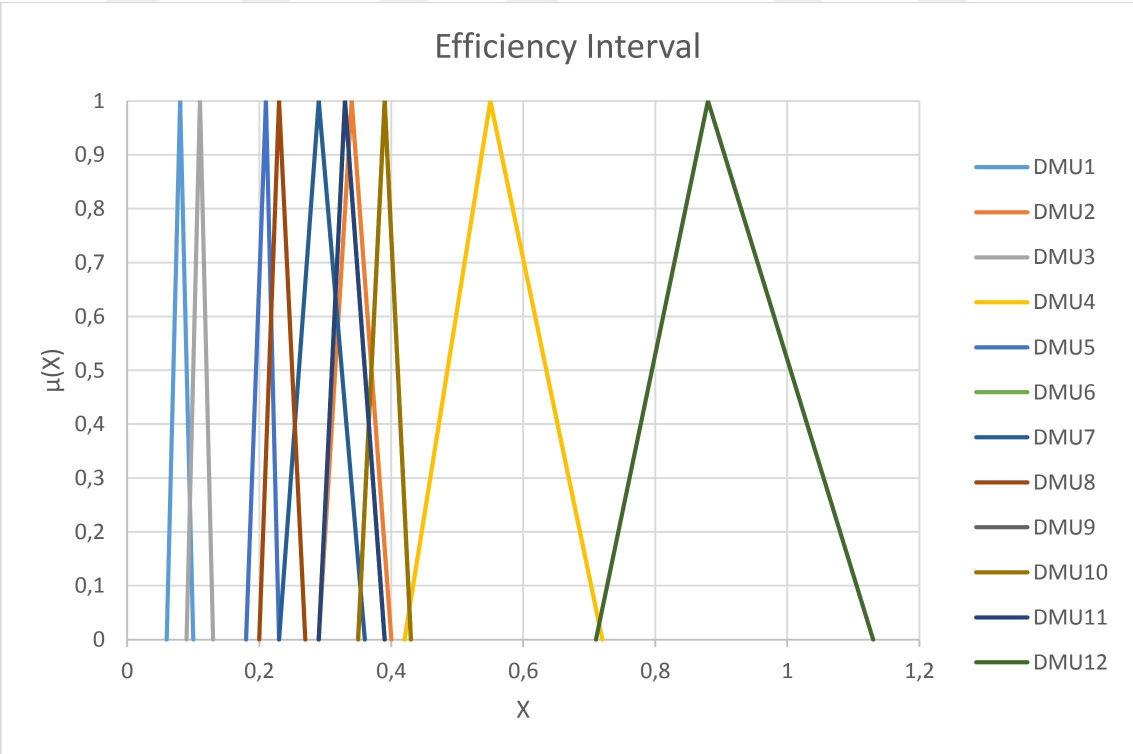

Figure 5.4. Efficiency Results of (5.3) for h=0.6

As is illustrated in the Table 5.11. to Table 5.16 for different *h* levels, there is just one *h*-possibilistic D efficient DMU (PD DMU) which is Supplier 12. It is provided also in Figure 5.3. and in figure 5.4. that efficiencies are intervals in asymmetric triangular fuzzy numbers format for *h* levels, and take crisp values only for $h=1$.

It can be noted that Guo & Tanaka. (2001) model is based on comparison of the intervals and is not able to rank alternative suppliers for $h \neq 1$, just the top of the triangles can be compared. Even more needs two linear programming models, and valid only for symmetric fuzzy numbers which is not always the case.

For further research, Saati et al. (2002) model is used. The model needs only a single LP to solve and eliminates Guo & Tanaka (2001) in tackling asymmetric fuzzy numbers.

$$\max E = \bar{y}_p$$

$$\begin{aligned}
&\text{subject to} && (5.7)\\
&\bar{x}_p = 1 \\
&\bar{y}_j - \bar{x}_j \leq 0 \\
&v(\alpha x_j^m + (1-\alpha)x_j^l) \leq \bar{x}_j \leq v(\alpha x_j^m + (1-\alpha)x_j^u) && \forall j, \\
&u\ (\alpha y_j^m + (1-\alpha)y_j^l) \leq \bar{y}_j \leq u(\alpha y_j^m + (1-\alpha)y_j^u) && \forall j, \\
&u, v \geq 0
\end{aligned}$$

The results of (5.7) for the same data set is as:

Table 5.17. Efficiency Results of Model (5.7)

α	0	0.2	0.4	0.6	0.8	1
SUP1	0.278	0.225	0.181	0.144	0.113	0.088
SUP2	1	0.829	0.687	0.568	0.468	0.384
SUP3	0.303	0.255	0.213	0.177	0.146	0.120
SUP4	1	1	1	1	0.791	0.619
SUP5	0.509	0.439	0.378	0.324	0.276	0.234
SUP6	0.972	0.833	0.713	0.609	0.518	0.438
SUP7	0.971	0.786	0.637	0.515	0.415	0.333
SUP8	0.625	0.529	0.447	0.377	0.316	0.263
SUP9	0.925	0.778	0.652	0.546	0.455	0.377
SUP10	0.972	0.833	0.713	0.609	0.518	0.438
SUP11	0.925	0.778	0.652	0.546	0.455	0.377
SUP12	1	1	1	1	1	1

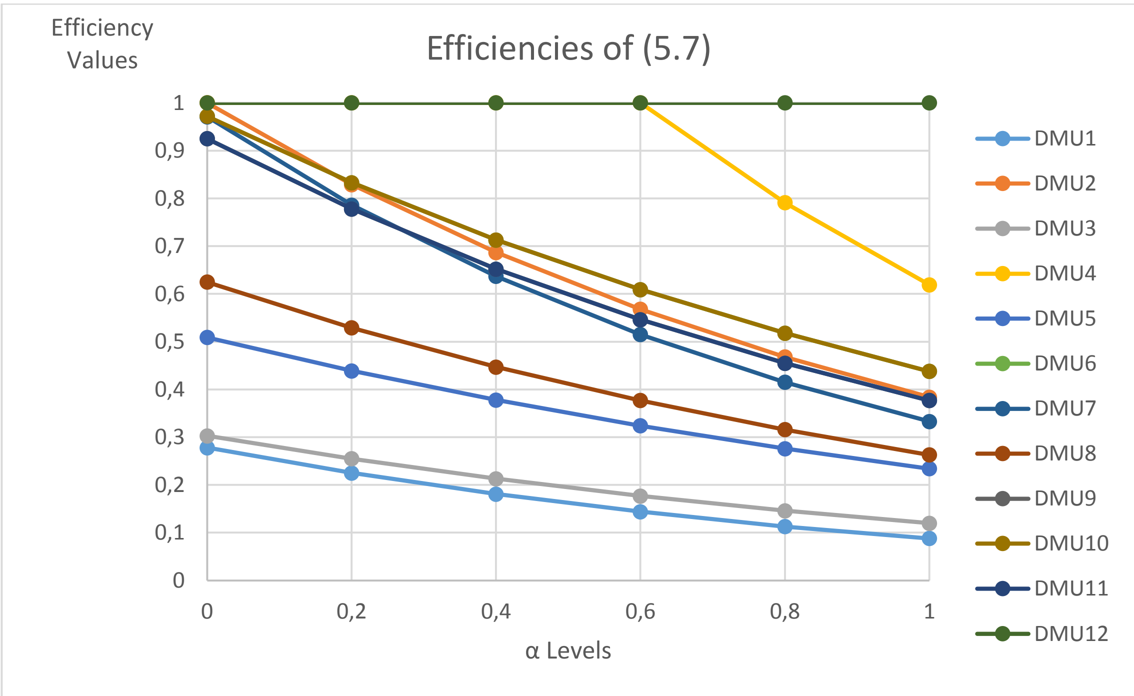

Figure 5.5. Efficiency Results of (5.7)

As can be observed in the Table 5.17. and Figure 5.5. efficiency values are precise and in a decreasing order, while α is increasing. Another advantage of this model, is that it needs only a single linear programming model to solve. The main advantage of this model is to have a deterministic efficiency value instead of an interval efficiency comparing to model (5.3).

5.5. SINGLE-INPUT MULTIPLE-OUTPUT MODEL

For differentiate the study, the criteria amount that will be involved in DEA wanted to be increased, and for that reason, the new threshold value of DEMATEL is determined as “0.10” such that *C7* and *C10* are added in the model. Besides for illustrating the ability of the alternative model an asymmetric linguistic scale employed by Karsak & Dursun (2014) is adapted.

$$\max E = \sum_{r=1}^{3} \bar{y}_{rp}$$

subject to (5.8)

$$\bar{x}_p = 1$$

$$\sum_{r=1}^{3} \bar{y}_{rj} - \bar{x}_j \leq 0$$

$$v(\alpha x_j^m + (1-\alpha)x_j^l) \leq \bar{x}_j \leq v(\alpha x_j^m + (1-\alpha)x_j^u) \qquad \forall j,$$

$$u_r(\alpha y_{rj}^m + (1-\alpha)y_{rj}^l) \leq \bar{y}_{rj} \leq u_r(\alpha y_{rj}^m + (1-\alpha)y_{rj}^u) \qquad \forall r, j,$$

$$u_r, v \geq 0 \qquad \forall i.$$

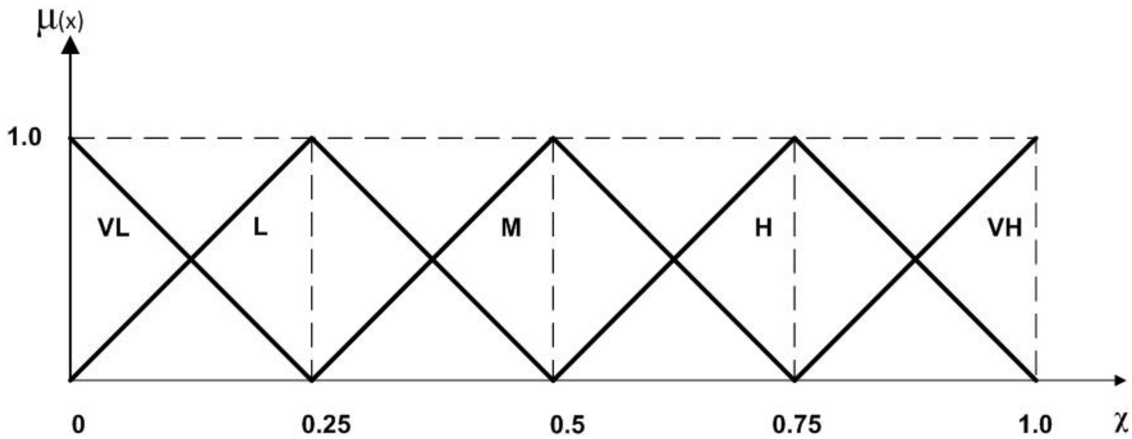

Figure 5.6. A linguistic term set where VL: (0, 0, 0.25), L: (0, 0.25, 0.5), M: (0.25, 0.5, 0.75), H: (0.5, 0.75, 1), VH: (0.75, 1, 1)

Table 5.18. Aggregated Values of Supplier Evaluation

	C1	C2	C3	C4	C5
Sup1	(0,0.08,0.33)	(0.41,0.66,0.91)	(0.08,0.33,0.58)	(0.58,0.83,1)	(0,0,0.25)
Sup2	(0.66,0.91,1)	(0.16,0.41,0.66)	(0.25,0.5,0.75)	(0.5,0.75,1)	(0.25,0.5,0.75)
Sup3	(0.16,0.41,0.66)	(0.66,0.91,1)	(0.08,0.33,0.58)	(0.25,0.5,0.75)	(0,0.25,0.5)
Sup4	(0.5,0.75,1)	(0.08,0.25,0.5)	(0.16,0.41,0.66)	(0.33,0.58,0.83)	(0.25,0.5,0.75)
Sup5	(0.25,0.5,0.75)	(0.75,1,1)	(0.41,0.66,0.91)	(0,0.25,0.5)	(0,0.25,0.5)
Sup6	(0.75,1,1)	(0.41,0.66,0.91)	(0.66,0.91,1)	(0.16,0.41,0.66)	(0.66,0.91,1)
Sup7	(0.41,0.66,0.91)	(0.08,0.33,0.58)	(0.08,0.33,0.58)	(0.16,0.41,0.66)	(0.08,0.33,0.58)
Sup8	(0.75,1,1)	(0.41,0.66,0.91)	(0.25,0.5,0.75)	(0,0,0.25)	(0.41,0.66,0.91)
Sup9	(0.25,0.5,0.75)	(0.25,0.5,0.75)	(0.33,0.58,0.83)	(0.66,0.91,1)	(0.41,0.66,0.91)
Sup10	(0.33,0.58,0.83)	(0.41,0.66,0.91)	(0.66,0.91,1)	(0.66,0.91,1)	(0.5,0.75,1)
Sup11	(0.41,0.66,0.91)	(0.25,0.5,0.75)	(0.33,0.58,0.83)	(0,0.25,0.5)	(0.25,0.5,0.75)
Sup12	(0.5,0.75,1)	(0.08,0.25,0.5)	(0.5,0.75,1)	(0,0,0.25)	(0.58,0.83,1)
	C6	C7	C8	C9	C10
Sup1	(0,0,0.25)	(0.16,0.41,0.66)	(0,0.25,0.5)	(0,0.08,0.33)	(0.16,0.41,0.66)
Sup2	(0.33,0.58,0.83)	(0.25,0.5,0.75)	(0.5,0.75,1)	(0.33,0.58,0.83)	(0.08,0.16,0.41)
Sup3	(0,0.16,0.41)	(0.08,0.33,0.58)	(0.08,0.33,0.58)	(0.25,0.5,0.75)	(0.08,0.16,0.41)
Sup4	(0.5,0.75,1)	(0.25,0.5,0.75)	(0.41,0.66,0.91)	(0.16,0.41,0.66)	(0.16,0.41,0.66)
Sup5	(0,0.16,0.41)	(0.16,0.41,0.66)	(0.16,0.41,0.66)	(0.58,0.83,1)	(0.16,0.41,0.66)
Sup6	(0.25,0.5,0.75)	(0.66,0.91,1)	(0.5,0.75,1)	(0.58,0.83,1)	(0.66,0.91,1)
Sup7	(0.08,0.25,0.5)	(0.16,0.41,0.66)	(0.16,0.41,0.66)	(0.25,0.5,0.75)	(0.16,0.41,0.66)
Sup8	(0,0.25,0.5)	(0.5,0.75,1)	(0.5,0.75,0.91)	(0.41,0.66,0.91)	(0.5,0.75,1)
Sup9	(0.5,0.75,1)	(0.5,0.75,0.91)	(0.41,0.66,0.91)	(0.25,0.5,0.75)	(0.58,0.83,1)
Sup10	(0.33,0.58,0.83)	(0.5,0.75,0.91)	(0.25,0.5,0.75)	(0.58,0.83,1)	(0.66,0.91,1)
Sup11	(0.5,0.75,1)	(0.16,0.41,0.66)	(0.25,0.5,0.75)	(0.25,0.5,0.75)	(0.08,0.33,0.58)
Sup12	(0.75,1,1)	(0.25,0.5,0.75)	(0.5,0.75,0.91)	(0.33,0.58,0.83)	(0.58,0.83,1)

Table 5.19. Efficiency Results of (5.8)

α	0	.2	.4	.6	.8	1
SUP1	1	1	1	.797	.503	.311
SUP2	1	1	1	1	1	.610
SUP3	1	.904	.673	.465	.295	.181
SUP4	1	1	1	1	1	1
SUP5	1	.924	.702	.496	.323	.220
SUP6	1	1	1	1	1	.689
SUP7	1	1	1	1	1	.621
SUP8	1	1	1	1	.874	.568
SUP9	1	1	1	1	1	.750
SUP10	1	1	1	1	.855	.568
SUP11	1	1	1	1	.681	.410
SUP12	1	1	1	1	1	1

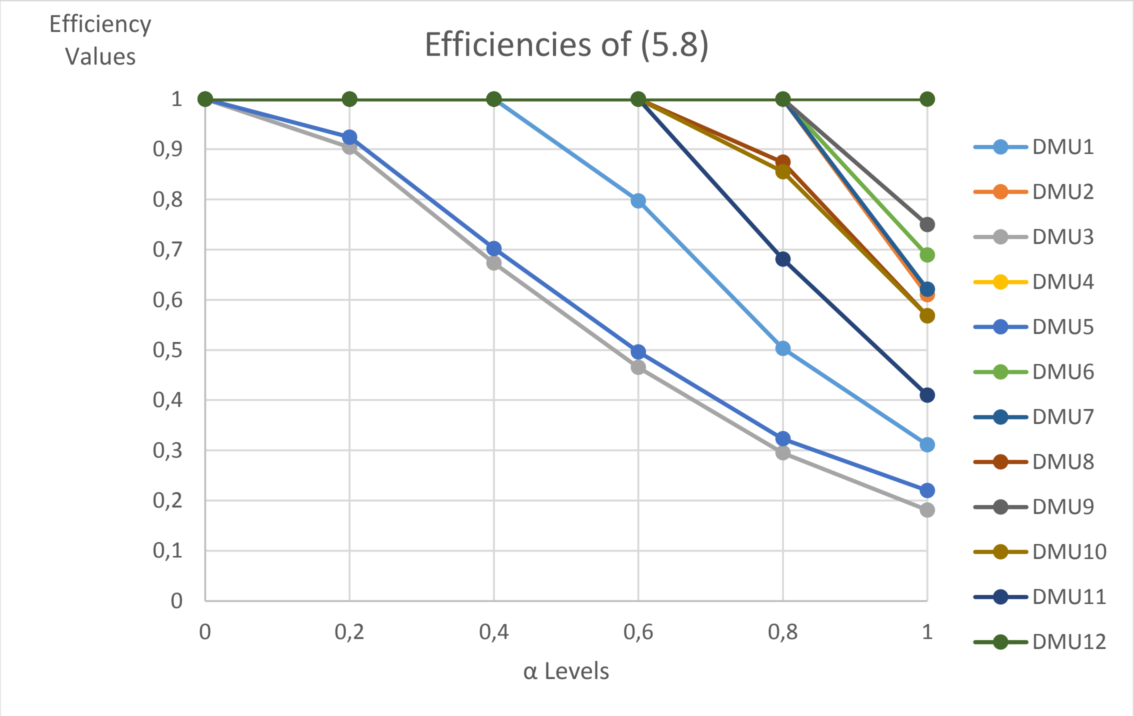

Figure 5.7. Efficiency Results of (5.8)

As can be observed from the Table 5.19. and the Figure 5.7. the discriminating power of this model is highly low, for minor α values, since for $\alpha = 0$ all DMUs are efficient and multiple efficient DMU exists for different α levels. This is because the obtained optimizing point provides in the best situation for each DMU. For that reason, a ranking model given in (5.8) will be applied.

$$\min z = \theta$$

subject to (5.9)

$$\theta(\alpha x_p^m + (1-\alpha)x_p^l) \geq \sum_{j=1}^{12} \lambda_j (\alpha x_j^m + (1-\alpha)x_j^u)$$

$$\alpha y_{rp}^m + (1-\alpha)y_{rp}^u) \leq \sum_{j=1}^{12} \lambda_j (\alpha y_{rj}^m + (1-\alpha)y_{rj}^l) \qquad \forall r,$$

$$\lambda_j \geq 0 \qquad \forall j.$$

The calculated efficiencies are as:

Table 5.20. Ranking Results of (5.9)

α	0	.2	.4	.6	.8	1
SUP1	2.220	1.606	1.170	.797	.503	.311
SUP2	6.463	4.038	2.664	1.694	1.019	.610
SUP3	1.212	.904	.673	.465	.295	.181
SUP4	12.926	7.438	4.681	2.885	1.698	1
SUP5	1.401	1.032	.734	.496	.323	.220
SUP6	3.363	2.586	2.015	1.478	1.014	.689
SUP7	11.375	5.684	3.316	1.940	1.095	.621
SUP8	3.363	2.502	1.881	1.328	.874	.568
SUP9	5.188	3.622	2.596	1.781	1.159	.750
SUP10	3.193	2.390	1.793	1.272	.855	.568
SUP11	4.022	2.659	1.758	1.116	.681	.410
SUP12	14.822	8.197	4.863	2.885	1.698	1

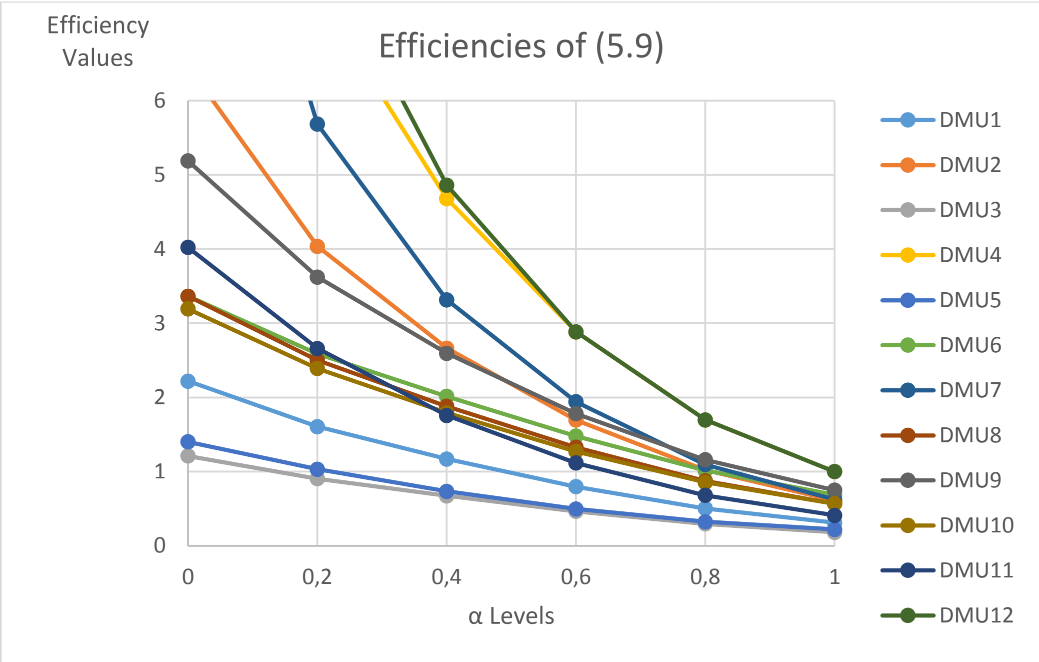

Figure 5.8. Efficiency Results of (5.9)

As can be observed from Table 5.20. and Figure 5.8. the ranking model allows to rank all DMUs for each α level. For $\alpha = 0$ DMU4 and DMU12 are the only efficient DMUs while in the previous model all DMUs were efficient. For $\alpha = 1$, similarly to previous model DMU4 and DMU12 remained the only efficient-ones.

6. CONCLUSION

In this thesis, two different fuzzy DEA models are applied and compared for the evaluation of the efficiency of twelve suppliers with fuzzy inputs and fuzzy outputs. Firstly, the general DEA studies are presented and the major drawbacks of classical DEA are illustrated. Then the papers that improved DEA with common-weights, weight restrictions, cross-efficiencies, minimum distance studies, are presented. Classical DEA studies ignore the interrelationship among criteria, and the existence of the to many criteria in a problem blocks the dispersion of input-output weights. Many papers are proposed adding weight restriction to deal with that problem which is criticized to being subjective, however no-one ever before considered to add an elimination step of excessive criteria to DEA.

In order to eliminate the excessive criteria of the existing problem, DEMATEL method is used. DEMATEL shows the causal relationships and the strengths of influence among the criteria by constructing a pairwise comparison matrix. The results of DEMATEL are used to determine the inputs and outputs that will be involved in DEA.

Additionally, the decision makers preferred to score the suppliers with linguistic terms, due to the vagueness of data, fuzzy theory is introduced. The background studies of fuzzy DEA are examined and the existing articles that approached to supplier selection problem with fuzzy DEA are reviewed. Because of their compatibility two fuzzy DEA model are selected to apply to the existing problem.

In Guo & Tanaka (2001) model which is based on the comparison of the intervals, efficiencies are obtained in a triangular fuzzy number format. As the h values increases, for all the DMUs the center of the fuzzy efficiency escalates while the width of efficiency tightens. For $h=1$ the width of the efficiencies is equal to 0, in short no longer a fuzzy triangular number, but a single point. The results belonging to all the different *h* levels, are yield to a single efficient DMU which is supplier 12.

In Saati et al. (2002) model, the obtained optimizing point provides the best situation for each DMU. Therefore, the efficiency value that are obtained are higher than Guo & Tanaka (2001) model. In addition, it needs only one single LP to solve while Guo & Tanaka (2001) model needs two LP. When the α values are increased, the efficiency results decrease. The efficiencies are in the crisp number format and for α values lower or equal to 0.6 there are only two efficient DMUs which are supplier 4 and supplier 12. For α =0.8 and α =1, similarly to the other model the unique efficient DMU is supplier 12. Another advantage of this model is that allows to deal with asymmetric fuzzy numbers comparing to Guo & Tanaka (2001) model.

For demonstrating the ability of Saati et al. (2002) model to deal with asymmetric fuzzy numbers the fuzzy scale is differentiated. In addition, decreasing the threshold-value utilized on DEMATEL, the output amounts that will be involved on model are increased. Therefore, the problem turned into a single input and multiple output problem. Increasing the output amount yield to a multiple efficient DMUs, as is expected from the DEA structure. For instance, while α =0 all the DMUs are efficient and for α = 0.2 and α = 0.4, 10 DMUs are efficient. The real discrimination only acquired while α =1 with 2 efficient DMUs (supplier 4 and supplier 12).

For increasing the low discriminating power of the model, a ranking DEA model is utilized and the efficiency value of DMUs are re-calculated. The efficiencies are decreased by increasing α . As is already expected, for all the different α values DMU4 and DMU12 remained on the top, and also as the only efficient-ones while α =1.

This study, integrating DEMATEL as an excessive criteria elimination tool with DEA, encourages future research to combine different methodologies with DEA, which is still an untouched area. It can be commented as an alternative to incorporating weight restrictions into DEA which is often criticized for violating the objectivity of DEA. Apart from that, contributes to the literature, with three different literature reviews focused on supplier selection problem with the used methodologies.

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