Lecture Notes in Electrical Engineering 349

Mitsuo Gen
Kuinam J. Kim
Xiaoxia Huang
Yabe Hiroshi
Editors

Industrial Engineering, Management Science and Applications 2015

Springer

Editors
Mitsuo Gen
Tokyo University of Science
Tokyo
Japan

Kuinam J. Kim
Department of Convergence Security
Inst. of Creative Advanced Tech.,
Sci. and Engg.
Kyonggi University
Suwon-si
Korea

Xiaoxia Huang
University of Science and Technology
Beijing (USTB)
Beijing
China

Yabe Hiroshi
Tokyo University of Science
Tokyo
Japan

ISSN 1876-1100 ISSN 1876-1119 (electronic)
Lecture Notes in Electrical Engineering
ISBN 978-3-662-47199-9 ISBN 978-3-662-47200-2 (eBook)
DOI 10.1007/978-3-662-47200-2

Library of Congress Control Number: 2015938793

Springer Heidelberg New York Dordrecht London

Printed on acid-free paper

Springer-Verlag GmbH Berlin Heidelberg is part of Springer Science+Business Media
(www.springer.com)

Organizing Committee

General Chairs

Mitsuo Gen	Fuzzy Logic Systems Institute and Tokyo University of Science, Japan
Xiaoxia Huang	University of Science and Technology Beijing, China
Kuinam J. Kim	Institute of Creative Advanced Technologies, Science and Engineering, Republic of Korea
Yabe Hiroshi	Tokyo University of Science, Japan

Steering Committee

Nikolai Joukov	Chair of IEEE CS STCOS, USA
Borko Furht	Florida Atlantic University, USA
Bezalel Gavish	Southern Methodist University, USA
Kin Fun Li	University of Victoria, Canada

Publicity Chairs

Dan (Dong-Seong) Kim	University of Canterbury, New Zealand

Workshop Chairs

Kuinam J. Kim	Kyonggi University, Republic of Korea
Donghwi Lee	University of Colorado, USA

Financial Chairs

Kyoungho Choi	Institute of Creative Advanced Technologies, Science and Engineering, Republic of Korea

Program Chairs

Adel Hejaaji	Engineering Services Management Limited [ESM LTD] ESSEX, UK

Organizers and Supporters

Institute of Creative Advanced Technologies, Science and Engineering (iCatse)
Chinese Management Science Society (CMSS)
Korean Industry Security Forum (KISF)
Korea Information Assurance Society (KIAS)
Kyonggi University
University of Science and Technology Beijing
Tokyo University of Science
River Publishers

Program Committee

Chil-Chyuan Kuo	Ming Chi University of Technology, Taiwan
Suksan Prombanpong	King Mongkut's University of Technology Thonburi, Thailand
Ramayah Thurasamy	Universiti Sains Malaysia, Malaysia
Siana Halim	Petra Christian University, Indonesia
Yves De Smet	Université Libre de Bruxelles, Belgium
Marco Aiello	University of Groningen, The Netherlands
Catalina Lucía Alberto	Universidad Nacional de Córdoba, Argentina
Llewellyn C.M. TANG	University of Nottingham Ningbo China, China
M. Birasnav	New York Institute of Technology, USA
Enslin Johannes van Rooyen	Tshwane University of Technology, South Africa
Supachart Iamratanakul	Kasetsart University, Thailand
Luciana Hazin Alencar	Universidade Federal de Pernambuco, Brazil
Jui-Sheng Chou	National Taiwan University of Science and Technology, Taiwan
Shimpei Matsumoto	Hiroshima Institute of Technology, Japan
Ahm Shamsuzzoha	University of Vaasa, Finland
Minghai Jiao	Northeastern University, China
Masaharu Tsujimoto	Tokyo Institute of Technology, Japan

Ahm shamsuzzoha	Sultan Qaboos University, Oman
Seren OZMEHMET TASAN	Dokuz Eylul University, Turkey
Yoshinobu Tamura	Yamaguchi University, Japan
António Grilo	Faculdade de Ciências e Tecnologia da Universidade Nova de Lisboa, Portugal
Fabrizio Maria Maggi	University of Tartu, Estonia
V. Cruz Machado	Universidade Nova de Lisboa, Portugal
Md Mamun Habib	Universiti Utara Malaysia, Malaysia
Kittisak Jermsittiparsert	Rangsit University, Thailand
Adel Hejaaji	Engineering Services Management Limited [ESM LTD] ESSEX, UK
Ulrich Reimer	University of applied sciences St. Gallen, Switzerland
Hardeep Singh	Ferozepur College of Engg & Technology, India
Fatemeh Almasi	Amirkabir University of Technology (Tehran polytechnic), Iran
Yiliu Liu	Norwegian University of Science and Technology, Norway
Ryo HARUNA	Kanazawa Gakuin University, Japan
Ilias Santouridis	Technological Educational Institute (TEI) of Thessaly, Greece
Purit Thanakijkasem	King Mongkut's University of Technology Thonburi, Thailand
Chun-Cheng Lin	National Chiao Tung University, Taiwan
Michel ALDANONDO	Toulouse University - Mines Albi -, France
Jinho Lee	Korea Naval Academy, Republic of Korea
Mojahid F. Saeed Osman	King Fahd University of Petroleum and Minerals, Saudi Arabia
Wasawat Nakkiew	Advanced Manufacturing Technology Research Center (AMTech), Chiang Mai University, Thailand
Somlak Wannarumon KIELAROVA	Naresuan University, Thailand
Jaekyung Yang	Chonbuk National University, Republic of Korea
Suprakash Gupta	Indian Institute of Technology (B H U), India
Alejandro Escudero-Santana	Universidad de Sevilla, Spain
RIKA AMPUH HADIGUNA	Andalas University, Indonesia
Andreas Dewald	University of Erlangen, Germany
Kit Fai Pun	The University of the West Indies, West Indies
Abdol S. SOOFI	University of Wisconsin-Platteville, USA
El-Houssaine AGHEZZAF	Ghent University, Belgium
Chompoonoot Kasemset	Chiang Mai University, Thailand
Ana Paula Ferreira Barroso	Universidade Nova de Lisboa, Portugal
Virgínia Helena Arimateia de Campos Machado	Universidade Nova de Lisboa, Portugal
Antonio Ruiz Molina	University of Malaga, Spain

Contents

Fuzzy Multi-objective Supplier Selection Problem: Possibilistic Programming Approach

Dicky Fatrias*, Ahmad Syafruddin Indrapriyatna, and Difana Meilani

Dept. of Industrial Engineering, Andalas University
Kampus limau Manis, Padang (25163), West Sumatera – INDONESIA
dicky@ft.unand.ac.id, ahmadsyaf@ft.unand.ac.id,
difana@ft.unand.ac.id

Abstract. In this paper, a multi-objective mathematical model is developed in fuzzy environment in which the vagueness in aspiration level of objectives and data imprecision regarding the selection criteria and related constraints are considered simultaneously as a source of fuzziness. In the model, such data imprecision is presented based on the estimation of its possibility distribution to better capture the uncertainty. Finally, a fuzzy solution methodology is constructed by the aid of weighted additive aggregation function to derive optimal solution. As preliminary investigation, we report that the proposed model is more flexible and convenient than the previous models whose imprecise parameters are treated as a given single estimated value.

1 Introduction

To remain competitive in a dynamically global market, the need to improve efficiency has prompted enterprises to seek opportunity to reduce costs while continuously improve their operation. Within the purchasing function, one of the key activities to achieve this goal is by selecting the appropriate supplier(s). In essential, supplier selection problem is a multi-criteria decision making within which criteria may be defined in quantitative and qualitative dimensions. Dickson [1] was the first to identify several criteria which are the most considered criteria in a practical supplier selection where quality, on-time delivery, performance history, warranty policy, and production facility/capacity of supplier were on the top five ranked in the list. A recent survey by Olson and Wu [2] study reported that cost, quality, and time response are major criteria that consistently appear for supplier selection.

The issue of considering uncertainty in supplier selection problem has received a great deal of concern in the field of supply chain management. This complexity in supplier selection stems from imprecise preferences of the decision maker (DM) regarding the aspiration level of decision objective and/or the imprecise nature of decision criteria and constraints. While the usefulness of stochastic approach has been documented, it is not always applicable in coding the information regarding the

* Corresponding author.

M. Gen et al. (eds.), *Industrial Engineering, Management Science and Applications 2015,*
Lecture Notes in Electrical Engineering 349, DOI: 10.1007/978-3-662-47200-2_56

imprecision of data and vagueness of goals. To avoid this drawback, the fuzzy approach is employed for modeling uncertain parameters. Moreover, it is frequently emphasized in the literature that fuzzy approach has had a great impact in preference modeling and multi-objective problem and has helped bring optimization techniques closer to the users' needs [3].

A number of studies have been devoted to examining supplier selection methods. Quantitative techniques have become increasingly applied recently. A comprehensive review of numerous quantitative techniques used for supplier selection has been done by [4].

This paper focuses on fuzzy multi-objective linear programming (fuzzy MOLP) to deal with supplier selection problem. Kumar et al. [5] developed a fuzzy multi-objective integer programming approach for supplier selection problem subject to constraints including buyer's demand and suppliers' capacity, and derived an optimal solution using max-min operator (Zimmermann's approach). To evaluate the performance of the model, they perform sensitivity analysis on the order allocation and objective function by changing the degree of uncertainty in supplier capacity. Amid et al. [6] solved fuzzy MOLP supplier selection problem by applying weighted additive aggregation function to facilitate an asymmetric fuzzy decision making technique. Since they found the performance of such a method is not adequate to support decision making process, α-cut approach is then proposed to improve the resulted achievement level. Later on, Amid et al. [7] applied weighted max-min aggregation function in supplier selection problem and compared the performance of the proposed approach with max-min operator and weighted additive aggregation function. They found that the ratio of achievement level of objectives matches the ratio of the objectives weight. Yucel & Guneri [8] proposed a new method of weights calculation in fuzzy MOLP supplier selection. Recent study by Arikan [9] developed a modified augmented max-min aggregation function that originally proposed by Lai dan hwang ([10],[11]) to solve fuzzy multi-objective supplier selection problem by considering a preference of the decision maker(s) (DMS) in determining the desired minimum achievement level of fuzzy objectives. The performance of the proposed approach is then is compared with the original augmented max-min and the weighted additive aggregation function in solving the test problem in Yucel & Guneri [8]'s study. The study reported that while the modified augmented max-min outperforms the weighted additive in terms of the achievement level of fuzzy objectives, it shows insignificant improvement in performance when compared to the original augmented max-min.

Related to coding the imprecise data involved in supplier selection problem, all models in literatures assumed such imprecision is tackled by assigning a given single estimated value. In this paper, a solution methodology for multi-objective supplier selection problem is developed in fuzzy environment in which the data imprecision regarding the selection criteria and related constraints, and vagueness in aspiration level of objectives are considered simultaneously as a source of fuzziness. Unlike the previous models, data imprecision is generated based on its possibility distribution in order to better capture the uncertainty. A fuzzy mathematical model is then developed by the aid of weighted additive aggregation function to derive a set of optimal solution.

2 Fuzzy Multi-objective Programming Methodology

2.1 Fuzzy Multi-objective Preliminary Formulation

A fuzzy formulation of the multi-objective linear programming (MOLP) with imprecise coefficient and fuzzy aspiration level of objectives can be stated as

$$\min Z_k = \sum_{i=1}^{n} \tilde{c}_{ki} x_i \leq \sim Z_k^0 , \quad k = 1,2,\dots,p \tag{1}$$

$$\max \tilde{Z}_l = \sum_{i=1}^{n} \tilde{c}_{li} x_i \geq \sim Z_l^0 , \quad l = p+1, p+2, \dots, q \tag{2}$$

subject to:

$$g_s = \sum_{i=1}^{n} a_{si} x_i \leq \tilde{b}_s , s = h+1, h+2, \dots, m \tag{3}$$

$$x_i \geq 0, \; i = 1,2,\dots,n \tag{4}$$

The symbol ≤~ and ≥~ denotes the fuzzified version of ≤ and ≥, respectively. The notation of $\tilde{c}_{ki}$ and $\tilde{c}_{li}$ are imprecise coefficients, and Z_k^0 and Z_l^0 are the aspiration levels that the DM wants to reach. The above fuzzy mathematical formulation is characterized by linear membership function whose value changes between 0 and 1. The linear membership function for fuzzy objectives are given as [12]:

$$\mu_{Zk} = \frac{Z_k^{max} - Z_k(x)}{Z_k^{max} - Z_k^{min}} \tag{5}$$

$$\mu_{Zl} = \frac{Z_l(x) - Z_l^{min}}{Z_l^{max} - Z_l^{min}} \tag{6}$$

Here Z_k^{max}, Z_l^{max}, Z_k^{min}, and Z_l^{min} means the maximum value and the minimum value of Z_k and Z_l, respectively. They are obtained by solving a single objective optimization problem respectively under each objective function.

2.2 Modeling Imprecise Parameter using Possibilistic Programming

In possibilistic programming, each imprecise data (ill-known parameter) has its possibility distribution which represents the possibility degree of occurrence of possible value for each imprecise parameter. A several number of distributions exist in literature such as triangular, trapezoidal and so on. Among them, triangular are the most commonly used distributions in solving possibilistic programming problems [2]. Using triangular distribution, a possibilistic programing with imprecise parameter $\sum_{i=1}^{n} \tilde{c}_i x_i$ is redefined as

$$\max/\min \sum_{i=1}^{n} \left(c_i^p, c_i^m, c_i^o\right) x_i \tag{7}$$

where c^p, c^m and c^o are the most pessimistic, the most likely and the most optimistic value of imprecise parameter, respectively. These values are usually estimated by the DMs based on available data as well as their knowledge.

Jimenez *et al.,* [13] proposed a method to define a single crisp representation of c^p, c^m and c^o based on the concept of expected interval and expected value of fuzzy numbers. It has been proven that this method is computationally efficient to solve such problems as it can preserve its linearity and do not increase the number of objective functions and inequality constraints [14].

The crisp representation of imprecise parameters of fuzzy MOLP problem in Eq. (1) - (4) can be formulated as follows [13]:

$$\tilde{Z}_k = \sum_{i=1}^{n} \left(\frac{c_{ki}^{pes} + 2c_{ki}^{mos} + c_{ki}^{opt}}{4} \right) x_i \leq \sim Z_k^0 \tag{8}$$

$$\tilde{Z}_l = \sum_{i=1}^{n} \left(\frac{c_{li}^{pes} + 2c_{li}^{mos} + c_{li}^{opt}}{4} \right) x_i \geq \sim Z_l^0 \tag{9}$$

subject to:

$$g_s = \sum_{i=1}^{n} a_{si} x_i \leq \left[\alpha \left(\frac{b_s^{pes} + b_s^{mos}}{2} \right) + (1 - \alpha) \left(\frac{b_s^{mos} + b_s^{opt}}{2} \right) \right] \tag{10}$$

$$x_i \geq 0, \; i = 1,2, \dots, n \tag{11}$$

where α is a minimum acceptable feasibility degree of decision vector which can be varied according to subjective preference of the DM.

2.3 Fuzzy Aggregation Function

A fuzzy aggregation function is typically used to solve fuzzy multi-objective programming problem by converting such problem into single objective formulation. Solving the aggregation function results in the efficient solution in terms of the satisfaction degree of each objective from which the DMs choose the final decision based on his/her preference (relative importance among objectives). Tiwari et al [15] proposed weighted additive aggregation function which had been widely used in vector-objective optimization problems. The function is stated as follow:

$$\text{Max} \sum_k \omega_k \lambda_k$$

subject to:

$$\lambda_k \leq \mu_{Zk} \tag{12}$$

$$\lambda_k, \; \mu_{Zk}, \omega_k \in [0,1]$$

$$\sum_k \omega_k = 1$$

where λ_k denote the satisfaction degree of k-th objective (individual satisfaction degree of each objective).

3 Fuzzy Multi-objective Supplier Selection Problem

3.1 Model Formulation

A typical linear model for multi-objective supplier selection problems is presented as follows [7]:

<u>*Index set*</u>
i index for suppliers, for all i = 1, 2, . . . , n

<u>*Decision variable*</u>
x_i The number of units purchased from the i-th supplier

<u>*Parameters*</u>
D Aggregate demand of the item over a fixed planning period.
n Number of suppliers competing for selection
p_i Unit net purchase cost from supplier i
f_i percentage of product quality of the supplier i
s_i Service performance of the supplier i
C_i Capacity of i-th supplier

Following the formulation of the fuzzy MOLP problem in Eqs. (1)-(4), the crisp representation of the above problem using Eqs. (8)-(11) can be stated as follows:

$$\text{Min } \tilde{Z}_1 = \sum_{i=1}^{n} \left(\frac{p_i^{pes}+2p_i^{mos}+p_i^{opt}}{4}\right) x_i \leq \sim Z_1^0 \tag{13}$$

$$\text{Max } \tilde{Z}_2 = \sum_{i=1}^{n} \left(\frac{f_i^{pes}+2f_i^{mos}+f_i^{opt}}{4}\right) x_i \geq \sim Z_2^0 \tag{14}$$

$$\text{Min } \tilde{Z}_3 = \sum_{i=1}^{n} \left(\frac{s_i^{pes}+2s_i^{mos}+s_i^{opt}}{4}\right) x_i \geq \sim Z_3^0 \tag{15}$$

subject to:

$$\sum_{i=1}^{n} x_i \geq \left[\alpha\left(\frac{D^{mos}+D^{opt}}{2}\right) + (1-\alpha)\left(\frac{D^{pes}+D^{mos}}{2}\right)\right] \tag{16}$$

$$x_i \leq \left[\alpha\left(\frac{C_i^{pes}+C_i^{most}}{2}\right) + (1-\alpha)\left(\frac{C_i^{most}+C_i^{opt}}{2}\right)\right] \tag{17}$$

$$x_i \geq 0 \tag{18}$$

Eq. (13) minimizes the net cost for ordering product to satisfy demand. Eq. (14) maximizes the quality requirement of each supplier. Eq. (15) maximized the service performance of each supplier. Eq. (16) ensures that order quantity assigned to suppliers must satisfy the total demand. Eq. (17) guarantees that the order quantity assigned to each supplier will not exceed supplier capacity limit. Eq. (18) is non-negativity constraint.

3.2 Step-by-step Solution Methodology

We propose solution methodology to facilitate the decision-making process in solving multi-objective supplier selection problem with imprecise parameters and fuzzy aspiration level of objectives. The steps are summarized as follows:

Step 1: Construct the fuzzy MOLP supplier selection problem with imprecise parameters and fuzzy aspiration level according to defined criteria and constraints.

Step 2: Transform the model into an equivalent crisp representation of multi-objective model by converting all the imprecise parameters (i.e., criteria data, aggregate demand and capacity of each supplier).

Step 3: Determine the minimum acceptable feasibility degree (α-level) and then construct membership function for each fuzzy objective function using lower and upper bounds of each objective for the desired α-level.

Step 4: Specify the weight of each objective and solve the model using weighted additive aggregation function.

Step 5: Present the optimal solution set according to predetermined α value. When the DM desires to change his/her preference in respond to uncertainty and/or the weight of each objective, change the corresponding values and repeat the procedure from step 3.

Table 1. Supplier quantitative information

Supplier n	Cost ($)	Quality (%)	Service (%)	Capacity (unit)
1	{11,13, 15.5}	{65,80,95}	{70,85,90}	{550,700,800}
2	{10,11.5, 13}	{60,70,80}	{60,75,85}	{400,600,700}
3	{13,15,16.5}	{70,80,99}	{70,80,95}	{300,500,650}

4 Numerical Example

The following example is based on Amid, Ghodsypour and O'Brien [7]' s study.

Consider one company which considers three candidates of supplier for ordering plan of one product. Management wants to improve the efficiency of the purchasing process by evaluating their suppliers using three criteria which are net price, quality and service. Based on this description the objectives are developed as minimizing net cost of purchasing a product to the suppliers, maximizing quality rate and maximizing service performance of suppliers.

To show the effectiveness of the proposed solution methodology, the original criteria data from Amid, Ghodsypour and O'Brien [7]' s study are presented as imprecise parameters, following the assumption that the data is imprecise. As a result, rather than estimates a single value for each of the data, the DM determines the estimation of its possibility distribution by deciding three prominent values (i.e., the most likely, the most pessimistic and the most optimistic values) based on their current available information and knowledge. The constraints regarding the total demand and the capacity of each supplier are also considered imprecise in nature. As a result, the estimated values of their cost, quality and delivery performance, and associated constraints of suppliers are presented in Table 1.

Several results with different α-level (i.e. α = 0.0, 0.2, 0.4, 0.6, 0.8, 1.0) are provided in performance testing and for each α-level alternative solution sets are generated by the aid of the weighted additive aggregation function. The weight of cost, quality and service are given as ω_1= 0.63, ω_1= 0.21 and ω_1= 0.16 [16]. Due to space limitation, the detail formulations according to the step-by-step procedures of methodology are not presented in the paper.

Table 2. Different sets of optimal solution

Item	Amid et al. (2011)	Proposed model			
		$\alpha = 0.0$	$\alpha = 0.2$	$\alpha = 0.4$	$\alpha = 0.6$
Z_1	12000	10756	11264	11773	12281
Z_2	740	655	686	717	748
Z_3	807	686	717	749	780
x_1,x_2,x_3	400,600,0	250,650,0	315,650,0	380,590,0	445,560,0
μ_{z1}	1.000	1.000	1.000	1.000	1.000
μ_{z2}	0.000	0.000	0.000	0.000	0.000
μ_{z3}	0.300	0.004	0.005	0.007	0.010

According to the result provided in Table 2 the value of all objective functions increases when the minimum acceptable feasibility degree ($\boldsymbol{\alpha}$-level) is increased. In other words, when the DM decided to response to uncertainty with a higher confidence level, all objective functions are also augmented. This could be due to the need to order more quantity of product (in total) in higher $\boldsymbol{\alpha}$-level.

It is also revealed that the second and third objective (quality and service) are critical objectives as the corresponding achievement level is always in the worst possible value in any $\boldsymbol{\alpha}$-levels. This implies that the model tends to sacrifice the performance of these objectives because it is at less of cost decreasing the performance of these objectives rather than decreasing the performance of the first objective (net price). This phenomenon is directly influenced by the fact that the first objectives is the most important ones whose assigned weight is the highest, according to the DM's preference ($\omega_1 >> \omega_2 > \omega_3$).

As it was mentioned in Section 3.2, the value of minimum acceptable feasibility degree ($\boldsymbol{\alpha}$-level) and the weight of the objectives can also be varied according to the DM preferences (other than illustrated above), yielding some alternative solution sets from which the DM select the most preferred solution. Hence, besides providing a broader decision spectrum, the proposed model is also more flexible and convenient than the previous models whose imprecise parameters are treated as a single estimated value.

5 Conclusion

In this paper, a solution methodology for multi-objective supplier selection problem is developed by simultaneously considering vagueness in aspiration level of objectives as well as the imprecision nature of to criteria data and related constraints. To better capture the uncertainty embedded in selection process, the model facilitates a judgment of the DM to estimate of the possibility distribution of each criterion and constraints by deciding three prominent values based on their current available information and knowledge.

According to the preliminary investigation, the main feature of the proposed model is the ability to yield different solution set with adjusted ordering decision based on a different minimum acceptable feasibility degree ($\boldsymbol{\alpha}$-level) in order to facilitate the DM to set his/her confident level in response to the uncertainty in imprecise criteria data and related constraint (i.e., demand and capacity) in supplier selection problem. Another interesting feature were also mentioned regarding the flexibility of the model compared to the recent models whose imprecise parameters are treated as a single estimated value.

Acknowledgments. This work has been funded by Directorate General of Higher Education, INDONESIA, under a program of Fundamental Research Grant 2015.

References

1. Dickson, G.W.: An analysis of vendor selection: system and decisions. Journal of Purchasing 1, 5–17 (1966)
2. Olson, D.L., Wu, D.: Simulation of fuzzy grey relationships. European Journal of Operational Research 175(1), 111–120 (2006)
3. Selim, H., Araz, C., Ozkarahan, I.: Collaborative production-distribution planning in supply chain: A fuzzy goal programming approach. Transportation Research Part E 44, 396–419 (2008)
4. Weber, C.A., Current, J.R., Benton, W.C.: Vendor selection criteria and methods. European Journal of Operation Research 50, 2–18 (1991)
5. Kumar, M., Vrat, P., Shankar, R.: A fuzzy programming approach for vendor selection problem in a supply chain. Int. J. Production Economics 101, 273–285 (2006)
6. Amid, A., Ghodsypour, S.H., O'Brien, C.: Fuzzy multiobjective linear model for supplier selection in a supply chain. Int. J. Production Economics 104, 394–407 (2006)
7. Amid, A., Ghodsypour, S.H., O'Brien, C.: A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain. Int. J. Production Economics 131, 139–145 (2011)
8. Yucel, A., Guneri, A.F.: A weighted additive fuzzy programming approach for multi-criteria supplier selection. Expert Systems with Applications 38, 6281–6286 (2011)
9. Arikan, F.: Fuzzy Solutio approach for fuzzy multi-objective supplier selection problem. Expert Systems with Applications 40, 947–952 (2013)
10. Lai, Y.J., Hwang, C.L.: Possibilistic linear programming for managing interest rate risk. Fuzzy Sets and Systems 49, 121–133 (1993)

11. Lai, Y.J., Hwang, C.L.: Fuzzy multiple objective decision making-methods and applications. Springer, Germany (1996)
12. Zimmermann, H.J.: Fuzzy programming and linear programming with several objective functions. Fuzzy sets and systems 1, 45–46 (1978)
13. Jimenez, M., Arenas, M., Bilbao, A., Rodriguez, M.V.: Linear programming with fuzzy parameters: An interactive method resolution. Eur. J. Oper. Res. 177, 1599–1609 (2007)
14. Pishvaee, S.M., Razmi, J.: Environmental supply chain network design using multi-objective fuzzy mathematical programming. Applied Mathematical Modelling 36, 3433–3446 (2012)
15. Tiwari, R.N., Dharmar, S., Rao, J.R.: Fuzzy goal programming an additive model. Fuzzy Sets and Systems 24, 27–34 (1987)
16. Ghodsypour, S.H., O'Brien, C.: A decision support system for supplier selection using an integrated analytical hierarchy process and linear programming. International Journal of Production Economics 56 57, 199–212 (1998)