Fuzzy MCDM Approach for Health-Care Performance Assessment in Istanbul

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ABSTRACT

Performance measurement in the health-care sector is a challenging task due to the wide variety in performance metrics and their interpretation. It is essential to develop a robust methodology to evaluate health-care performance since substantial and increasing amount of public resources are dedicated to health-care. With this goal in mind, this paper proposes a fuzzy decision making framework that enables to consider information imperfection such as imprecision and qualitative evaluations as well as crisp data for health-care performance assessment. Initially, a multi-criteria decision making (MCDM) approach based on fuzzy set theory and VIKOR method is employed for health-care performance evaluation of six regions in Istanbul, a metropolis with nearly 15 million inhabitants that is also among the world's most populated cities. Fuzzy TOPSIS is also used since a set of compromise solution obtained via fuzzy VIKOR does not enable a complete ranking of regions. A comparative analysis is presented to assess the health-care performance of six regions in Istanbul.

Keywords: Decision analysis, Multi-criteria decision making, Health-care, Performance evaluation, Fuzzy TOPSIS, Fuzzy VIKOR.

1. INTRODUCTION

Efficiency measurement represents a first step towards the evaluation of a coordinated health-care system, and constitutes one of the basic means of audit for the rational distribution of human and economic resources [1]. Turkey has been undergoing an important reform process called the Health Transformation Program since 2003, with the primary goal of achieving effectiveness, efficiency, and equity in organization, delivery, and financing of health-care services [2]. In order to satisfy the demands of both the public and the government to improve quality and efficiency of health-care services, various health-care performance measures have become essential.

The classical multi-criteria decision making (MCDM) methods that consider deterministic or random processes cannot effectively deal with decision making problems including imprecise and linguistic information. Many real-world problems incorporate information imperfection that can be better expressed using linguistic data such as poor, fair or good. Fuzzy sets appear as useful means to represent ambiguous, uncertain or imprecise information that cannot be properly expressed using crisp data [3]. Hence, fuzzy MCDM techniques have been used in tackling real-world decision making problems over the past two decades.

Even though the application of fuzzy decision making techniques is common in a wide variety of disciplines, there are only a few fuzzy MCDM studies published in the literature related to health-care performance assessment. Tsai et al. [4] developed fuzzy analytic hierarchy process (AHP) and fuzzy sensitive analysis-based approach to evaluate hospital organizational performance. Altuntas et al. [5] measured perceived hospital service quality using unweighted and weighted service quality (SERVQUAL) scales. AHP and analytic network process (ANP) were applied to determine a weight for each SERVQUAL dimension in their study. Buyukozkan and Cifci [6] combined fuzzy AHP and TOPSIS (technique for order preference by similarity to ideal solution) methodologies to evaluate web site alternatives of hospitals. Grigoroudis et al. [7] used balanced scorecard approach with UTASTAR method to monitor the health-care organization's overall performance. Kuo et al. [8] integrated fuzzy set theory and TOPSIS method in order to rank the failure risks in the health-care failure mode and effect analysis. Liu et al. [9] presented a VIKOR-based fuzzy MCDM method in order to evaluate health-care waste disposal alternatives for Shanghai.

The classical MCDM methods fall short of considering information imperfection due to imprecision and qualitative evaluations that are encountered in health-care performance assessment. The fuzzy modelling approach enables the decision-makers to deal quantitatively with the imprecision inherent in expressing the importance of each criterion and the preference regarding qualitative criteria by translating linguistic expressions to numerical values. Perceived service quality as a key quality performance measure of health outcome and the decision makers' importance assessment of evaluation criteria impose the need to incorporate linguistic data for conducting a comprehensive performance evaluation process. For this reason, this paper focuses on health-care performance evaluation of six regions in Istanbul using two pertinent fuzzy MCDM techniques, namely fuzzy VIKOR (multi-criteria optimization and compromise solution) and fuzzy TOPSIS. Fuzzy TOPSIS is particularly useful when a set of compromise solution obtained using fuzzy VIKOR does not result in a complete ranking of alternatives. The proposed methodologies are based on an aggregating function representing "closeness to the ideal", which originated in the compromise programming method [10]. These methods are apt to incorporate crisp and imprecise data as linguistic variables or fuzzy numbers in a decision making problem. They also possess advantages in that they are straightforward, logical and reliable distance-based methods. These properties facilitate the use of proposed approaches in health-care performance evaluation process.

The rest of the paper is structured as follows. The following section delineates the proposed fuzzy MCDM approaches. The application of the proposed decision making methodologies to evaluate health-care performance of six regions in Istanbul is presented in Section 3. Finally, concluding remarks are provided in the last section.

2. PROPOSED FUZZY MCDM METHODOLOGIES

Evaluating health-care performance requires considering multiple and conflicting criteria including both quantitative and qualitative data. Crisp data are inadequate to express perceived service quality information that is both subjective and imprecise. In order to incorporate vagueness, ambiguity and subjectivity of human judgment into the analysis, fuzzy set theory, which was introduced by Zadeh [11], has been employed.

In this section, two MCDM methods, namely VIKOR and TOPSIS, which are both based on an aggregating function representing "closeness to the ideal", are presented in a way that enables to account for imprecise data denoted using fuzzy sets.

2.1. Fuzzy VIKOR

The fuzzy VIKOR method has been developed to tackle fuzzy multi-criteria problems with conflicting and non-commensurable criteria [12]. The method focuses on ranking and selecting from a set of alternatives, and determines a compromise solution, providing a maximum group utility (majority rule) and the minimum individual regret of opponent.

The stepwise representation of the proposed fuzzy VIKOR-based MCDM algorithm is given below.

Step 1. Construct a fuzzy decision matrix. Identify the alternatives (A_1, A_2, …, A_m) and required selection criteria (C_1, C_2, …, C_n).

$$\tilde{\mathbf{D}} = \begin{matrix} & \begin{matrix} C_1 & C_2 & \cdots & C_n \end{matrix} \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{matrix} \quad i = 1, 2, ..., m;\ j = 1, 2, ..., n. \qquad (1)$$

Step 2. Construct a decision-makers' committee of Z decision-makers $(z = 1, 2, ..., Z)$. The importance weight of each criterion and the weight vector are computed using Eq. (2) and Eq. (3), respectively.

$$\tilde{w}_j = \frac{1}{Z}\left[\tilde{w}_j^1 \oplus \tilde{w}_j^2 \oplus \cdots \oplus \tilde{w}_j^Z\right] \qquad (2)$$

$$\tilde{\mathbf{w}} = \left[\tilde{w}_1, \tilde{w}_2, \cdots, \tilde{w}_n\right],\ j = 1, 2, \cdots, n. \qquad (3)$$

Step 3. Determine the fuzzy best ($\tilde{f}_j^*$) and fuzzy worst **(** $\tilde{f}_j^-$) values of all criterion functions, for $j = 1, 2, \cdots, n.$

$$\tilde{f}_j^* = \begin{cases} \max_i x_{ij},\ j \in B \\ \min_i x_{ij},\ j \in C \end{cases} \qquad (4)$$

$$\tilde{f}_j^- = \begin{cases} \min_i x_{ij},\ j \in B \\ \max_i x_{ij},\ j \in C \end{cases} \qquad (5)$$

where B and C denote benefit criteria and cost criteria, respectively.

Step 4. Compute the values $\tilde{S}_i$ and $\tilde{R}_i$, for $i = 1, 2, \cdots, m,$ by the relations

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{w}_j \left(\tilde{f}_j^* - \tilde{x}_{ij}\right) / \left(\tilde{f}_j^* - \tilde{f}_j^-\right), \qquad (6)$$

$$\tilde{R}_i = \max_j \left[\tilde{w}_j \left(\tilde{f}_j^* - \tilde{x}_{ij}\right) / \left(\tilde{f}_j^* - \tilde{f}_j^-\right)\right] \qquad (7)$$

where $\tilde{w}_j$ are the weights of criteria that express their relative importance.

Step 5. Compute the values $\tilde{Q}_i$, for $i = 1, 2, \cdots, m,$ as

$$\tilde{Q}_i = v \frac{\left(\tilde{S}_i - \tilde{S}^*\right)}{\left(\tilde{S}^- - \tilde{S}^*\right)} + (1 - v) \frac{\left(\tilde{R}_i - \tilde{R}^*\right)}{\left(\tilde{R}^- - \tilde{R}^*\right)} \qquad (8)$$

where

$\tilde{S}^* = \min_i \tilde{S}_i$, $\tilde{S}^- = \max_i \tilde{S}_i$,
$\tilde{R}^* = \min_i \tilde{R}_i$, $\tilde{R}^- = \max_i \tilde{R}_i$,

and v is defined as weight of the strategy of "majority of criteria" (or "the maximum group utility"), and $1-v$ is the weight of individual regret.

Step 6. Rank the alternatives, sorting by the values *S*, *R* and *Q*, in ascending order. The results are three ranking lists, with the best alternatives having the lowest value. Defuzzification of a triangular fuzzy number $\tilde{B}=(b_1,b_2,b_3)$ into a crisp value can be performed by the graded mean integration representation method as follows [13]:

$$P(\tilde{B})=\frac{(b_1+4b_2+b_3)}{6} \tag{9}$$

Step 7. Propose a compromise solution, the alternative $(A^{(1)})$ which is the best ranked by the measure Q (minimum) if the following two conditions are satisfied:

$C1$. "Acceptable advantage": $Q(A^{(2)})-Q(A^{(1)})\geq DQ$,

where $A^{(2)}$ is the alternative with second position in the ranking list by Q; $DQ=1/(m-1)$ where m is the number of alternatives.

$C2$. "Acceptable stability in decision making":
The alternative $A^{(1)}$ must also be the best ranked by S or/and R. This compromise solution is stable within a decision making process, which could be: "voting by majority rule" (when $v>0.5$ is needed), or "by consensus" $v\approx 0.5$, or "with veto" $(v<0.5)$.
If one of these conditions is not satisfied, then a set of compromise solutions is proposed, consisting of:

- Alternatives $A^{(1)}$ and $A^{(2)}$ if only condition $C2$ is not satisfied, or
- Alternatives $A^{(1)},A^{(2)},...A^{(M)}$ if the condition $C1$ is not satisfied; $A^{(M)}$ is determined by the relation $Q(A^{(M)})-Q(A^{(1)})<DQ$ for maximum M.

2.2. Fuzzy TOPSIS

TOPSIS is a widely accepted MCDM technique due to its sound logic, and simultaneous consideration of the ideal and the anti-ideal solutions. According to TOPSIS, the best alternative would be the one that that is closest to the ideal solution and farthest from the anti-ideal solution. The ideal solution is named as the one having the best criteria values attainable, and the anti-ideal solution is determined as the one possessing the worst criteria values attainable. The relative proximity of each alternative to the ideal solution is calculated based on its distances from both ideal and anti-ideal solutions simultaneously. The preference of the alternatives is determined by ranking the calculated proximity measures in a descending order. Since an alternative with the shortest distance from the ideal may not be the farthest from the anti-ideal, and vice versa, TOPSIS considers the distances from both ideal and anti-ideal solutions [14].

In here, fuzzy TOPSIS algorithm that is apt to handle fuzzy data as well as crisp data is presented. The steps of the fuzzy TOPSIS algorithm are as follows:

Step 1. Construct the decision matrix by identifying the criteria values for the considered alternatives. Assume that there are m alternatives and n selection criteria.

Step 2. Normalize the decision matrix so that criteria values are unit-free and comparable. If there exist crisp data x_{ij}, it can be represented as $\tilde{x}_{ij}=(x_{ij}^1,x_{ij}^2,x_{ij}^3)$ in triangular fuzzy number format, where $x_{ij}=x_{ij}^1=x_{ij}^2=x_{ij}^3$. The normalized values for the data regarding benefit-related ($j\in B$) as well as cost-related criteria ($j\in C$) are calculated via a linear scale transformation as

$$\tilde{r}_{ij}=\begin{cases}\left(\dfrac{x_{ij}^1-x_j^-}{x_j^*-x_j^-},\dfrac{x_{ij}^2-x_j^-}{x_j^*-x_j^-},\dfrac{x_{ij}^3-x_j^-}{x_j^*-x_j^-}\right), j\in B\\ \left(\dfrac{x_j^*-x_{ij}^3}{x_j^*-x_j^-},\dfrac{x_j^*-x_{ij}^2}{x_j^*-x_j^-},\dfrac{x_j^*-x_{ij}^1}{x_j^*-x_j^-}\right), j\in C\end{cases} \tag{10}$$

where $x_j^*=\max_i x_{ij}^3$ and $x_j^-=\min_i x_{ij}^1$.

Step 3. Determine the weight vector using Eq. (3). The weight vector represents the relative importance of the selection criteria.

Step 4. Calculate the weighted normalized fuzzy decision matrix. The weighted normalized values are calculated as follows:

$$\tilde{v}_{ij}=\tilde{w}_j\otimes\tilde{r}_{ij} \tag{11}$$

Step 5. Identify the fuzzy ideal solution $\tilde{A}^*$ and the fuzzy anti-ideal solution $\tilde{A}^-$ as follows:

$$\begin{aligned}\tilde{A}^*&=\{\tilde{v}_1^*,\tilde{v}_2^*,...,\tilde{v}_n^*\}\\&=\{\max_i v_{ij}\mid i=1,2,...,m;\ j=1,2,...,n\}\end{aligned} \tag{12}$$

$$\begin{aligned}\tilde{A}^-&=\{\tilde{v}_1^-,\tilde{v}_2^-,...,\tilde{v}_n^-\}\\&=\{\min_i v_{ij}\mid i=1,2,...,m;\ j=1,2,...,n\}\end{aligned} \tag{13}$$

Step 6. Calculate the distance from ideal solution and anti-ideal solution $\left(d_i^* \text{ and } d_i^-, \text{respectively}\right)$ for each alternative as

$$d_i^* = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right),\ i = 1, 2, ..., m \tag{14}$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right),\ i = 1, 2, ..., m \tag{15}$$

where distance between the triangular fuzzy numbers $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ can be calculated using the vertex method as follows [15]:

$$d_v\left(\tilde{A}, \tilde{B}\right) = \sqrt{\frac{1}{3}\left[\left(a_1 - b_1\right)^2 + \left(a_2 - b_2\right)^2 + \left(a_3 - b_3\right)^2\right]} \tag{16}$$

Step 7. Calculate the proximity of the alternatives to the ideal solution, P_i^*, by considering the distances from ideal and anti-ideal solutions as

$$P_i^* = \frac{d_i^-}{d_i^* + d_i^-}, i = 1, 2, ..., m. \tag{17}$$

Step 8. Rank the alternatives according to P_i^* in descending order. The alternative with the highest P_i^* value will be the best alternative.

3. HEALTH-CARE PERFORMANCE ASSESSMENT IN ISTANBUL

Health-care sector possesses too many dimensions to be fitted into a simple singular unit, and thus, assessing the performance of health-care services is a highly challenging task [16]. Moreover, there are no standard performance measures for the health-care sector since each provider, consumer and payer defines the performance of health-care based on his/her objectives, interests and interpretations.

Health Directorate of Istanbul defined six regions for health-care management purposes in Istanbul. These regions are as follows:

Region 1 $\left(R_1\right)$: North Anatolian

Region 2 $\left(R_2\right)$: South Anatolian

Region 3 $\left(R_3\right)$: Beyoglu

Region 4 $\left(R_4\right)$: Fatih

Region 5 $\left(R_5\right)$: Bakirkoy

Region 6 $\left(R_6\right)$: Cekmece

The criteria used for performance assessment of the regions and their explanations are given below.

Beds $\left(C_1\right)$: The total number of fully staffed hospital beds.

Clinical-staff $\left(C_2\right)$: The total number of specialists, general practitioners, nurses and midwifes.

Non-clinical staff $\left(C_3\right)$: The total number of administrative staff, technical staff and other supporting staff.

Operating expenses $\left(C_4\right)$: The amount of operating expenses measured in TL, excluding capital and depreciation.

Outpatients $\left(C_5\right)$: The total number of patients to outpatient departments and emergency rooms.

Discharged patients $\left(C_6\right)$: The total number of discharged patients.

Adjusted surgeries $\left(C_7\right)$: The total number of surgical interventions undertaken. Given that surgical interventions vary by the resources consumed, they are grouped as minor, medium and major surgeries based on the results of an earlier study conducted in Turkey [17]. Major, medium and minor surgeries are converted into a major surgery equivalent with the respective weights of 1, 1/3 and 1/7 [2].

Tangibility $\left(C_8\right)$: Health-care facility physical characteristics.

Responsiveness $\left(C_9\right)$: Staff responsiveness to patients' needs.

Empathy $\left(C_{10}\right)$: Individualized attention and caring provided to patients by hospital staff.

The data used in this study are obtained from Health Directorate of Istanbul for the year 2010 and the state hospitals operating in the predefined regions in Istanbul. Tangibility, responsiveness and empathy criteria are included as quality performance measures of health outcome in order to measure patient perceived service quality. Perceived service quality is measured considering these three dimensions via a survey study. A protocol is signed with Health Directorate of Istanbul to obtain the permission to apply the questionnaire in the state hospitals. This pilot study consists of 100 randomly chosen patients who receive treatment as inpatients or outpatients in the state hospitals in the respective regions.

Initially, fuzzy VIKOR is applied in order to evaluate the health-care performance of the regions.

In this study, decision-makers used the linguistic variables "very low (VL)", "low (L)", "moderate (M)", "high (H)" and "very high (VH)" to express their evaluations for tangibility, responsiveness and empathy criteria as well as to assess the importance degrees of criteria. The linguistic terms are defined as shown in Table 1.

Table 1. Linguistic term set

Very Low (VL)	(0, 0, 0.25)
Low (L)	(0, 0.25, 0.50)
Medium (M)	(0.25, 0.50, 0.75)
High (H)	(0.50, 0.75, 1.0)
Very High (VH)	(0.75, 1.0, 1.0)

The evaluation is conducted by a committee of five decision-makers, which consists of hospital managers and university professors. The five decision-makers used the linguistic variables denoted in Table 1 to assess the importance of the evaluation criteria as shown in Table 2.

Table 2. Importance weights of evaluation criteria

Criteria	DM_1	DM_2	DM_3	DM_4	DM_5
C_1	H	VH	M	M	M
C_2	M	M	H	M	H
C_3	L	M	L	L	M
C_4	M	VH	H	H	M
C_5	M	H	H	H	H
C_6	VH	VH	VH	H	H
C_7	M	H	H	M	H
C_8	H	M	M	L	H
C_9	H	VH	VH	H	VH
C_{10}	M	VH	H	M	VH

The fuzzy best and fuzzy worst values of all criteria are computed with respect to Eq. (4) and Eq. (5), respectively.

Next, the values for *S*, *R* and *Q* are calculated by Eqs. (6) - (8), respectively. In this study, the value of *v* is set to 0.5 in line with earlier research works [9]. The results are given in Table 3.

Table 3. The values of S, R and Q for $v = 0.5$

	Regions					
	R_1	R_2	R_3	R_4	R_5	R_6
S	4.259	3.582	2.956	3.031	4.180	2.225
R	0.688	0.692	0.552	0.470	0.875	0.875
Q	0.734	0.586	0.273	0.193	0.971	0.500

The performance ranking of the six regions summarized in Table 4 shows that R_4 is the highest ranked region according to *R* and *Q*. As condition *C*1 is not satisfied, a set of compromise solution is identified as R_4 and R_3 since $Q\left(A^{(4)}\right) - Q\left(A^{(3)}\right) = 0.080 < 0.200$.

Table 4. Rankings with respect to *S*, *R* and *Q*

By *S*	$R_6 \succ R_3 \succ R_4 \succ R_2 \succ R_5 \succ R_1$
By *R*	$R_4 \succ R_3 \succ R_1 \succ R_2 \succ R_5 \sim R_6$
By *Q*	$R_4 \succ R_3 \succ R_6 \succ R_2 \succ R_1 \succ R_5$

Since a set of compromise solution obtained using fuzzy VIKOR does not enable a complete ranking of regions, fuzzy TOPSIS is employed to check the validity of the results obtained via the proposed fuzzy VIKOR methodology and determine the best region with respect to health-care performance in Istanbul.

The weighted normalized fuzzy decision matrix is calculated by employing Eq. (11). Then, the ideal solution and the anti-ideal solution can be respectively determined using Eq. (12) and Eq. (13) as represented in Table 5.

Table 5. Ideal and anti-ideal solutions

Criteria	$\tilde{A}^*$	$\tilde{A}^-$
C_1	(0.400, 0.650, 0.850)	(0.000, 0.000, 0.000)
C_2	(0.350, 0.600, 0.850)	(0.000, 0.000, 0.000)
C_3	(0.100, 0.350, 0.600)	(0.000, 0.000, 0.000)
C_4	(0.450, 0.700, 0.900)	(0.000, 0.000, 0.000)
C_5	(0.450, 0.700, 0.950)	(0.000, 0.000, 0.000)
C_6	(0.650, 0.900, 1.000)	(0.000, 0.000, 0.000)
C_7	(0.400, 0.650, 0.900)	(0.000, 0.000, 0.000)
C_8	(0.155, 0.421, 0.754)	(0.115, 0.343, 0.661)
C_9	(0.297, 0.630, 0.903)	(0.183, 0.477, 0.780)
C_{10}	(0.291, 0.619, 0.868)	(0.230, 0.532, 0.786)

Finally, Table 6 provides both the distance from ideal and anti-ideal solutions for each region (d_i^* and d_i^-) and proximity of the regions to the ideal solution (P_i^*) that are computed as defined in Steps 6 and 7 of the fuzzy TOPSIS algorithm, respectively.

Table 6. Results obtained from fuzzy TOPSIS

Regions	d_i^*	d_i^-	P_i^*	Ranking
R_1	2.807	2.164	0.435	6
R_2	2.565	2.399	0.483	5
R_3	2.319	2.649	0.533	3
R_4	2.255	2.711	0.546	1
R_5	2.542	2.441	0.490	4
R_6	2.273	2.688	0.542	2

As it can be observed from Table 6, the rank-order of the regions is $R_4 \succ R_6 \succ R_3 \succ R_5 \succ R_2 \succ R_1$. Fatih ($R_4$) appears as the best performing region, followed by Cekmece (R_6) and Beyoglu (R_3). The results of both fuzzy MCDM algorithms reveal that Fatih $\left(R_4\right)$ ranks as the best region regarding health-care performance in Istanbul. Cekmece $\left(R_6\right)$ is ranked as second according to fuzzy TOPSIS and is also a high performer according to maximum group utility in fuzzy VIKOR since it yields the lowest values for cost-related criteria such as number of beds, number of clinical and non-clinical staff and operating expenses, and highest values for quality performance indicators (tangibility, responsiveness and empathy) among the six regions.

4. CONCLUSIONS

Performance measurement plays a crucial role for the management and improvement of health-care organizations. Thus, health-care performance assessment has become a major concern for health policy-makers and health-care managers. The use of MCDM in performance evaluation has the advantage of rendering subjective and implicit decision making more objective and transparent [18].

This paper presents fuzzy MCDM approaches that enable the consideration of both exact and linguistic data in order to obtain performance ranking of six regions defined for the health-care policy making in Istanbul. Tangibility, responsiveness, and empathy are selected as quality performance indicators that are represented via linguistic variables in order to quantify the inherent imprecision in patients' assessments. The health-care performance ranking of regions is determined by using fuzzy VIKOR and also verified by fuzzy TOPSIS method. The outcomes of the analysis will help health policy-makers to take strategic action involving resource planning, allocation and utilization decisions for low performing regions.

The proposed framework is a sound decision aid for providing a roadmap to enhance the performance of health-care services. Future research will focus on implementing the proposed methodology for assessing health-care performance over a nationwide scale.

5. REFERENCES

[1] L. O'Neill, M. Rauner, K. Heidenberger, M. Kraus, "A Cross-National Comparison and Taxonomy of DEA-Based Hospital Efficiency Studies", **Socio-Economic Planning Sciences**, Vol. 42, 2008, pp. 158-189.

[2] I. Sahin, Y.A. Ozcan, H. Ozgen, "Assessment of Hospital Efficiency Under Health Transformation Program in Turkey", **Central European Journal of Operations Research**, Vol.19, 2011, pp.19-37.

[3] A. Hatami-Marbini, S. Saati, M. Tavana, "An Ideal-seeking Fuzzy Data Envelopment Analysis Framework", **Applied Soft Computing**, Vol. 10, No. 4, 2010, pp. 1062-1070.

[4] H-Y. Tsai, C-H. Chang, H-L. Lin, "Fuzzy Hierarchy Sensitive with Delphi Method to Evaluate Hospital Organization Performance", **Expert Systems with Applications,** Vol. 37, 2010, pp. 5533-5541.

[5] S. Altuntas, T. Dereli, M.K. Yilmaz, "Multi-Criteria Decision Making Methods Based Weighted SERVQUAL Scales to Measure Perceived Service Quality in Hospitals: A Case Study from Turkey", **Total Quality Management & Business Excellence,** Vol. 23, 2012, pp. 1379-1395.

[6] G. Buyukozkan, G. Cifci, "A Combined Fuzzy AHP and Fuzzy TOPSIS Based Strategic Analysis of Electronic Service Quality in Healthcare Industry", **Expert Systems with Applications,** Vol. 39, 2012, pp. 2341-2354.

[7] E. Grigoroudis, E. Orfanoudaki, C. Zopounidis, "Strategic Performance Measurement in a Healthcare Organisation: A Multiple Criteria Approach Based On Balanced Scorecard", **Omega,** Vol. 40, 2012, pp. 104-119.

[8] R-J. Kuo, Y-H. Wu, T-S Hsu, Integration of Fuzzy Set Theory and TOPSIS into HFMEA to Improve Outpatient Service for Elderly Patients in Taiwan", **Journal of Chinese Medical Associations**, Vol. 75, 2012, pp. 341-348.

[9] H-C. Liu, J. Wu, P. Li, "Assessment of Health-Care Waste Disposal Methods Using a VIKOR-Based Fuzzy Multi-Criteria Decision Making Method", **Waste Management**, Vol.33, 2013, pp. 2744-2751.

[10] S. Opricovic, G-H. Tzeng, "Compromise Solution by MCDM Methods: A Comparative Analysis of VIKOR and TOPSIS", **Eur J Oper Res**, Vol. 156, 2004, pp. 445-455.

[11] L.A. Zadeh, "Fuzzy Sets", **Information and Control**, Vol. 8, No. 3, 1965, pp. 338-353.

[12] S. Opricovic, "Fuzzy VIKOR with An Application to Water Resource Planning", **Expert Systems with Applications,** Vol. 38, 2011, pp. 12983-12990.

[13] C. Chou, "The Canonical Representation of Multiplication Operation on Triangular Fuzzy Numbers", **Computers & Mathematics with Applications**, Vol. 45, 2003, pp. 1601-1610.

[14] E.E. Karsak, "Distance-Based Fuzzy MCDM Approach for Evaluating Flexible Manufacturing System Alternatives", **Int J Prod Res,** Vol. 40, 2002, pp. 3167-3181.

[15] C.T. Chen, "Extensions of the TOPSIS for Group Decision-Making Under Fuzzy Environment", **Fuzzy Sets and Systems**, Vol. 114, 2000, pp. 1-9.

[16] A. Emrouznejad, P.K. Dey, "Performance Measurement in the Health Sector: Uses of Frontier Efficiency Methodologies and Multi-Criteria Decision Making", **Journal of Medical Systems**, Vol. 35, 2011, pp. 977-979.

[17] http://www.istanbulsaglik.gov.tr/w/sb/imis/pdf/ek_8.pdf, [accessed in June 2013].

[18] S.S. Chung, C.S. Poon, "Evaluating Waste Management Alternatives by the Multiple Criteria Approach", **Resources, Conservation and Recycling**, Vol. 17, 1996, pp. 189-210.

ACKNOWLEDGEMENT

This research has been financially supported by Galatasaray University Research Fund under Grant 14.402.001.