USING MULTI-CRITERIA DECISION MAKING APPROACHES FOR EVALUATING HEALTH CARE PERFORMANCE OF DISTRICTS IN ISTANBUL

(İSTANBUL'DAKİ İLÇELERİN SAĞLIK HİZMETİ PERFORMANSLARININ ÇOK ÖLÇÜTLÜ KARAR VERME YAKLAŞIMLARI İLE DEĞERLENDİRİLMESİ)

by

Melis Almula KARADAYI, M.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

in

INDUSTRIAL ENGINEERING

in the

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

of

GALATASARAY UNIVERSITY

June 2017

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Date of Submission : May 8, 2017

Date of Defense Examination: June 9, 2017

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ACKNOWLEDGEMENTS

I owe my gratitude to many people who made this journey a pleasure for me.

I would like to express the deepest appreciation to my supervisor, Prof. Dr. E. Ertuğrul KARSAK for his guidance throughout my academic study and research. I consider myself amazingly fortunate to have him as an advisor.

I would like to express my thanks to committee members for their comments and words of encouragements.

Special acknowledgments and thanks to my friends Res. Asst. Duygun Fatih DEMİREL, Dr. Mine IŞIK, Tuğba HAŞİMZADE ÇİFCİ for their inputs, friendship, help and support.

My greatest gratitude goes to my lovely family; Suna and Hızır KARADAYI; to my dear uncle Halil KARADAYI and to my dear aunt Assoc. Prof. Dr. Funda TÜRKMEN; for their love and unconditional endless faith and confidence in me.

Finally, I would like to express my sincere gratitude to the TUBITAK (Scientific and Technological Research Council of Turkey) – BIDEB (Scientist Support Directorate) for their financial support.

Melis Almula KARADAYI
June, 2017

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LIST OF SYMBOLS

DEA	: Data Envelopment Analysis
FLP	: Fuzzy Linear Programming
HTP	: Health Transformation Programme
MCDM	: Multiple Criteria Decision Making
MoH	: Ministry of Health
OECD	: Organization for Economic Co-operation and Development
OR	: Operations Research
DMU	: Decision Making Unit
SFA	: Stochastic Frontier Analysis
VRS	: Variable Returns to Scale
CRS	: Constant Returns to Scale
CCR	: Charnes, Cooper, Rhodes
BCC	: Banker, Charnes, Cooper
WHO	: World Health Organization

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ABSTRACT

Over the past decade, health care sector has been one of the locomative sectors both in developed and developing countries. One of the main targets of most countries is to improve their health care system in terms of service quality and efficiency where Turkey is no exception. Since 2003, Turkey has been undergoing an important process of health reform called the “Health Transformation Programme” (HTP) in order to achieve efficiency and equity in health care institutions.

As government, insurance companies, communities and individual consumers have increased their pressures to improve health care quality with a lower cost, many health care performance measures have become critical. In this context, growing health expenditures and increased quality in the health sector put pressure on state hospitals to use their resources more efficiently. Health care institutions want to determine best performing managerial practice and their overall performance.

In this regard, objective of this thesis is to propose an imprecise data envelopment analysis (DEA) framework for evaluating the health care performance of 26 districts in Istanbul, the largest city of Turkey. The proposed approach takes into consideration quantitative and qualitative data represented as linguistic variables in order to evaluate health care performance. Patients perceived hospital service quality is included as quality performance measure of health outcome in the set of output variables which has been overlooked in previous studies.

This study also reckons that weight flexibility in DEA assessments can lead to unrealistic weighting schemes for some inputs and output variables, which are likely to result in overstated efficiency scores for a number of decision making units (DMUs).In order to overcome this problem, a weight restricted imprecise DEA model that constrains weight flexibility in DEA is suggested.

Furthermore, a DEA model for clustering and ranking in the presence of fuzzy data is also implemented to group districts operating under similar circumstances, and therefore, to gain insight on differentiating operational features. The proposed methodology determines subgroups of districts operating under similar circumstances, the best performing district, and also ranking of 26 districts in terms of health care in Istanbul as well.

The proposed imprecise DEA approach sets forth a more realistic decision methodology for evaluating the relative health care performance. According to the results of the proposed unrestricted fuzzy DEA model, 14 districts are determined as efficient according to the optimistic scenario, while the number of efficient districts reduces to 10 with respect to the pessimistic scenario. Including weight restrictions in the DEA models reduces the number of efficient districts from 14 to 6 in optimistic scenario, whereas from 10 to 1 in pessimistic scenario. Furthermore, the results reveal that a majority of state hospitals in Istanbul are run inefficiently. “Catalca” is the best performing district and “Bakirkoy” is the best performing region with respect to health care performance.

The second proposed methodology within the scope of this study provides a DEA-based approach for clustering and ranking of districts in Istanbul according to their health care performance. The results again reveal that 26 districts in Istanbul can be grouped into three clusters.“Catalca” is the best performing district with respect to health care performance, and it is followed by “Kagithane”, “Buyukcekmece”, “Tuzla” and “Sultangazi”, respectively.

Health care managers institutions and policy makers in the field could use the results of proposed procedures in this thesis to gain insight on differentiating operational features of 26 districts in Istanbul, and also to take strategic actions such as resource planning.

ÖZET

Son on yılda sağlık sektörü, gelişmiş ülkelerin yanı sıra ve gelişmekte olan ülkelerde de lokomotif sektörlerden birisi olmuştur. Birçok ülkenin temel hedeflerinden biri, sağlık sistemlerini hem hizmet kalitesi hem de etkinlik açısından iyileştirmektir. Türkiye de bu ülkeler arasında yer almaktadır. 2003 yılından bu yana, Türkiye sağlık kuruluşlarında etkinlik ve eşitliği sağlamak için “Sağlıkta Dönüşüm Programı" (SDP) adı verilen önemli bir reform sürecinden geçmektedir.

Devletin, sigorta şirketlerinin, sivil toplum kuruluşlarının ve bireysel tüketicilerin düşük maliyetle sağlık hizmetlerinin kalitesini iyileştirmek adına baskıları arttıkça, çeşitli performans ölçümleri kritik hale gelmiştir. Bu bağlamda, artan sağlık harcamaları, kalite beklentisi ve rekabet, hastaneleri kaynaklarını daha verimli kullanmaları üzerinde baskı yaratmaktadır. Sağlık kuruluşları, en iyi performans gösterdikleri yönetsel uygulamayı ve genel performanslarını belirlemek istemektedir.

Bu tez çalışmasında, Türkiye'nin en büyük şehri olan İstanbul'un 26 ilçesinin sağlık hizmeti etkinliğini değerlendirebilmek amacıyla bulanık veri zarflama analizi (BVZA) yaklaşımı önerilmektedir. Önerilen bu yaklaşım, performans değerlendirmesi yaparken nicel verilerin yanı sıra sözel verilerle ifade edilen nitel verileri de dikkate almaktadır. Daha önceki çalışmalarda gözardı edilen, algılanan hizmet kalitesi de performans ölçütü olarak çıktı değişkenleri kümesine dahil edilmiştir.

Bu çalışma ayrıca veri zarflama analizi (VZA) değerlendirmelerinde ağırlık esnekliğinin, bazı girdi ve çıktı değişkenleri için gerçekçi olmayan ağırlıklandırmalara yol açabileceğini ve bunun bir çok karar verme biriminin daha yüksek etkinlik değerine sahip olmasına neden olacağını göstermektedir. Bu sorunun üstesinden gelebilmek adına VZA’da ağırlık esnekliğini kısıtlayan, ağırlık kısıtlamalı, BVZA modeli önerilmektedir.

Ayrıca, benzer koşullar altında faaliyet gösteren ilçeleri gruplandırmak ve dolayısıyla operasyonel özelliklerin farklılaştırılması konusunda fikir sahibi olmak adına, bulanık verilerin varlığında kümeleme ve sıralama yapan VZA modeli uygulanmaktadır. Önerilen yöntem, benzer koşullar altında faaliyet gösteren ilçelerin alt gruplarını, en iyi performans gösteren ilçeyi ve İstanbul'daki sağlık hizmeti açısından 26 ilçenin performans sıralamasını belirlemektedir.

Önerilen BVZA yaklaşımı, göreceli sağlık hizmeti performans değerlendirmesi için daha gerçekçi bir karar yöntemi ortaya koymaktadır. Önerilen BVZA modelinin sonuçlarına göre, 14 ilçe iyimser senaryoya göre etkin olarak belirlenirken, etkin ilçelerin sayısı kötümser senaryoya göre 10'a düşmektedir. Ağırlık kısıtlamalı VZA modellerinde ise iyimser senaryoda etkin bölgeler sayısını 14'ten 6'ya inerken, kötümser senaryoya göre 10'dan 1'e düşmektedir. Ayrıca sonuçlar, İstanbul'daki devlet hastanelerinin çoğunun etkin olmadığını ortaya koymaktadır. Sağlık hizmeti açısından "Çatalca" en iyi performans gösteren ilçe ve "Bakırköy" en iyi performans gösteren bölge olarak belirlenmiştir.

Çalışma kapsamında önerilen ikinci yöntem ise İstanbul'un ilçe bazında sağlık hizmetlerinin etkinliğinin kümelenmesi ve sıralanması için VZA tabanlı bir yaklaşım sunmaktadır. Uygulanan yöntem, sağlık hizmeti etkinliğine göre ilçeleri üç kümede gruplandırmıştır. Sonuçlar, "Çatalca" nın sağlık performansı açısından en iyi performans gösteren ilçe olduğunu tekrar ortaya koymaktadır ve Çatalca'yı sırasıyla Kağıthane, Büyükçekmece, Tuzla ve Sultangazi ilçeleri takip etmektedir.

Sağlık alanındaki politika yapıcılar ve sağlık kuruluşları yöneticileri, bu tezde önerilen yaklaşımların sonuçlarını, değerlendirmeye konu olan İstanbul'daki 26 ilçenin operasyonel özelliklerini ayırt edebilmek amacıyla ve kaynak planlaması gibi sağlık sektörüne yönelik stratejik kararların alınmasında kullanabilirler.

1.INTRODUCTION

The health care sector is expanding across the world as a result of economic prosperity, evolving disease profile, increasing population, and last but not least the higher number of senior citizens, creating higher demand for health care services (Investment Support and Promotion Agency of Turkey, 2014). Turkey is no exception. Turkey initiated the Health Transformation Programme (HTP) in 2003 with the tag line “People First” and HTP brought about many significant improvements to the health care system. There were major improvements in capacity and service quality in health care. Hence, the health status of people has substantially improved in the country after the implementation of the transformation programme.

Providing high quality and efficient health care requires improved hospital management. Efficiency analysis of a health care system is crucial since it represents a first step and a basic means audit for the rational distribution of human and economic resources. A multifactorial analysis is required for the evaluation of health care delivery since the metrics are highly variable and difficult to be defined and measures accurately (O’Neill, 2008). Hence, performance analysis is quite difficult in health care sector than in other sectors.

This study aims to present an integrated framework using an imprecise data envelopment analysis (DEA) and clustering analysis for evaluating the health care performance of 26 districts in Istanbul. In this context, the objectives of this study include defining appropriate input and output variables and providing a robust performance evaluation methodology for health care organizations. The proposed approach sets for more realistic decision methodolology for evaluating the relative health care performance

The standard DEA approaches require precise evaluation of the input and the output variables. DEA generates the relative efficiencies of DMUs only by considering input and output data (Zhou et al., 2012). However, the observed values of inputs and outputs are sometimes imprecise or vague in real-world applications. Fuzzy logic and fuzzy sets can be used to represent ambiguous, uncertain or imprecise information (Hatami-Marbini, 2010). A variety of factors may cause imprecision such as unquantifiable, incomplete or unobtainable information along with partial ignorance (Tsai et al., 2010).

Evaluation of service quality in health care systems is as crucial as the service delivery system (Lee et al., 2000). Hence, fuzzy set theory is taken into consideration. Patients perceived hospital service quality is also added to output set as quality performance measures in the proposed evaluation model.

In addition, excessive weight flexibility can be regarded as a limitation of traditional DEA models via allowing a DMU to seek maximum efficiency by assigning a mix of weights that is either implausible because it neglects one or more input and/or output variables in the model, or provides inconsistent solutions with expert judgements (Estellita Lins et al.,2007). Hence, this thesis suggests a weight restricted DEA model to restrict weight flexibility in DEA for evaluating health care performance and also determine the best performing district in terms of health care performance in Istanbul.

A clustering analysis is also implemented to group districts operating under similar circumstances, and therefore, to gain insight on differentiating operational features. The proposed methodology determines subgroups of districts operating under similar circumstances as well as, the best performing district and ranking of 26 districts in terms of health care in Istanbul. It enables to handle crisp and fuzzy data expressed in linguistic terms or triangular fuzzy numbers.

To the best of our knowledge, a published work, which employs DEA methodology incorporating imprecise data and weight restrictions, does not exist in the health care performance evaluation literature. In addition, there is only one published paper (Flokou et al., 2011) that employed the concept of DEA and clustering in the health sector at hospital level. Thus, the proposed decision making framework is likely to make a novel contribution to health care performance evaluation since it evades unrealistic weight flexibility and includes service quality dimension in evaluation of health care performance. Furthermore, this study will be a useful decision aid for examining performance of hospitals and will be of interest to academics and health care managers and policy makers in the field.

The thesis is organized as follows: The following section outlines a review of the applications of DEA for evaluating health care performance. The basics of DEA are delineated in the third section. Section 4 outlines fuzzy DEA models. Section 5 presents the proposed imprecise DEA framework for evaluating the health care efficiency of 26 districts in Istanbul. Section 6 provides the DEA model for clustering and ranking in the presence of fuzzy data. The implementation of the proposed methodologies is presented in Section 7. Finally, conclusions and directions for future research are provided in Section 8.

2. LITERATURE REVIEW

More than thirty years after the publication of the seminal paper by Charnes, Cooper and Rhodes (Charnes et al., 1978), the development of DEA continues and DEA has been applied as a robust and valuable method for efficiency analysis (Wei et al., 2011).

More than 700 DEA papers were published in 2009. Up through the year 2009, there has been nearly 4500 studies in ISI Web of Science database (Liu et al., 2013). The value of DEA is as a result of its capability to compute the relative efficiency of a DMU in many application areas such as the banking industry, agriculture industry, transportation industry, health care industry, etc (Liu et al., 2013).

This section outlines a review of the many DEA applications in health care. There are various examples in which DEA has been employed for evaluating performance in health care field.

Since the early 1980s, efficiency analysis has been employed for analyzing health care performance (Hollingsworth, 2008). There are various studies applied in USA, Austria, Germany, Greece, Taiwan, Spain, Thailand, Norway, Ireland, Finland and most of other developed countries. *Number of beds, specialists, medical practitioners, medical staff, and managers* are seen to be most frequently considered inputs. In addition, *number of inpatients, outpatients, surgical operations, visitors,* and *patient days* are seen to be most frequently considered outputs in DEA models (Gok, 2012).

In the literature, there exist several types of DEA models. We classify DEA-based hospital efficiency studies into four groups depending on conditions of the problem at hand: (1) standard DEA models, (2) extended DEA models, (3) DEA models to improve discriminating power, and (4) integrated DEA models. Classification of DEA-based hospital efficiency studies are depicted in Figure 2.1.

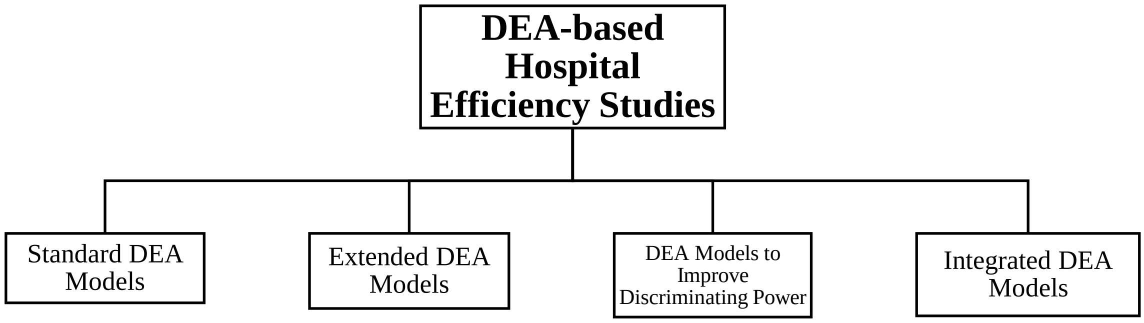

Figure 2.1: Classification of DEA-based hospital efficiency studies

First group of studies include standard DEA models. Grosskopf and Valdmanis (1987) presented a methodology for analyzing the realtive performance of hospitals in California. The inputs included number of physicians, non-physician staff, admission and net plant assets. The output variables were acute care, intensive care, surgeries, ambulatory and emergency care. Wang et al. (1999) measured hospital efficiency in United States using survey data for the period 1989-1993. The inputs used included service complexity, operational beds, labor and operating expenses, whilst the outputs included number of discharged patients and number of outpatients.

Chern and Wan (2000) analyzed the impact of prospective payment system implemantation using constant returns to scale (CRS), input-oriented DEA. The inputs utilized included capital assets, labor and operating expenses. The outputs were number of discharged patients and total outpatient visits. The Puig-Junoy (2000) evaluated cost, allocative, technical, pure technical, scale, and congestion efficiency of 94 Catalan acute care hospitals by DEA. Sahin and Ozcan (2000) employed input-oriented, variable returns to scale (VRS) type DEA model in order to analyze public health care performance in Turkey. The input variables were number of available beds for patients, number of specialists, general practitioners, nurses and other allied health care professionals and total revolving funds expenditure. On the output side, number of outpatients, number of discharged patients and also mortality rate as quality measure were considered in the study.

Bhat et al. (2001) employed CRS model to analyze hospital performance of district hospitals in Gujarat, state of India. Capital, labor and technological inputs were included in the stıdy. Output variables were selected due to provided services in hospitals such as outpatient services, inpatient services and laboratory services. Grosskopf et al. (2001) compared the health care performance of teaching and non-teaching hospitals in United States for the year 1994. Inputs were defined as the number of beds, the number of physicians, the number of medical interns and residents, the number of nurses and the number of other labors. The output variables included the number of inpatient, non-surgical patients treated, the number of surgeries, number of outpatients, and the total number of visits to emergency room.

Krigia et al. (2002) investigated hospital performance of public health centers in Kenya using CRS and VRS assumptions of DEA. Horfmarcher et al. (2002) used an input-oriented Farrell measure of efficiency. Cost efficiency of 70 Danish hospitals were evaluated in their study. The inputs used included medical staff, para-medical staff, administrative staff, beds and number of wards. The output variables were number of outpatients, patient days and case mix-adjusted discharges. Tsai and Molinero (2002) analzyed the performance of National Health Services in England. The input used was total operating expenditure. The outputs included medical specialties, surgical specialties, maternity specialties, psychiatric specialties, and other specialties.

Birman et al. (2003) applied DEA to 51 medical clinics in the United States. The input variables were number of treatment rooms, monthly technician cost, monthly registered nurse cost, monthly licensed practical nurse cost, and monthly medication costs. The output variables considered were monthly patients treated and monthly employees trained. Biørn et al. (2003) analyzed the impact of activity-based financing in Norway during the period 1992-2000 by DEA. Physicians, other labors, medical and total running expenses were considered as inputs. Inpatient care and outpatient care were considered as outputs. Field and Emrouznejad (2003) evaluated the health care performance of 22 neonatal care units in Scotland. The input variables were the number of medical staff, nurses per occupied cot-days, and the number of cots available. The output used was the number of successful treatments but ignored the cases terminated by death. Steianmann and Zweifel (2003) employed DEA in order to determine hospital efficiency of Swiss hospitals. The inputs included academic, nursing staff, administrative and nonlabour expenses. The outputs included number of discharged patients from pediatric, surgical, gynaecological and intensive care units.

Chang et al. (2004) analyzed the impact of Health Insurance Program on health care efficiency in Taiwan. The inputs included were number of patient beds, number of physicians and number of other medical supporting personnel. The output variables were number of patient days, number of outpatients and number of surgeries. Harrison et al. (2004) employed a VRS, input-oriented DEA model to measure hospital efficiency of federal hospitals in the United States. The inputs utilized included number of hospital beds, operating expenses and service complexity. On the output side, number of admissions and number of outpatient visits were used. Steinmann et al. (2004) used input-oriented CRS model to compare the efficiency of German and Swiss hospitals. Oseil et al. (2005) employed CRS and VRS to analyze the health care performance of public hospitals and medical centers in Ghana. The four inputs included number of health care officers, the number of technicians, the number of other staff, and the number of beds. The three outputs were the number of maternal and child care visits, the number of child deliveries, the number of fully-immunized children, and the number of discharged patients.

Ferrier et al. (2006) analyzed the effect of uncompensated care using output-oriented DEA model for Pennsylvania hospitals. The input variables included number of patient beds, registered nurses, licensed pratical nurses, residents and other labor, whilst the output variables included number of inpatient surgeries, outpatient surgeries, emergency service visits, outpatients, patient days and uncompensated care. Linna et al. (2006) conducted comparison for cost efficiency between Finnish and Norwegian hospitals. Input was measured by operating costs. The output data included number of admissions, outpatient visits, day care cases and inpatient days. Wang and Yu (2006) analyzed the efficiency of four hospital departments in Peking University Hospital. The CCR model was selected for the performance evaluation. Number of professors and physicians were considered as inputs. The outputs included turnover, number of patients, number of inpatients, operations done, national articles, international articles, numbers of candidate master and doctorate students. Zere et al. (2006) applied the CRS DEA to analyze the relative efficiency of hospitals in Namibia. Input variables included total recurrent expenditure, beds and nurses. Outpatients and inpatient days were defined as output variables in the study.

Dash et al. (2007) benchmarked the efficiency of hospitals in Tamil Nadu using input-oriented, VRS model of DEA. Number of beds, nurses, surgeons were used as inputs while the output variables included number of inpatients, outpatients, surgeries. Hajialiafzali et al. (2007) computed technical efficiency scores of hospitals in Iran. The inputs were the total number of doctors, nurses, other personnel and beds. Number of outpatient visits, emergency department visits, medical interventions and the ratio of major surgeries to total surgeries were considered as outputs. Masiye (2007) employed an input-oriented and VRS model of DEA in order to investigate health system performance in 30 Zambian hospitals. The inputs used included non-labour cost, doctors, nurses, and other clinical and nonclinical staff. Number of ambulatory visits, patient days, operations performed, deliveries under maternal and child health program were selected as outputs in the study.

Clement et al. (2008) focused on efficiency and quality of hospitals. The input variables specified were number of nurses, pratical nurses, other staff and beds. The output variables considered were number of births, surgeries, emergency department visits, outpatient visits and admissions. Nayar and Ozcan (2008) analyzed health care performance and quality of state hospitals in Virginia. Input-oriented CRS DEA model was selected for the evaluation. The input variables were hospital size, supply, total staff and assets. The output variables included number of discharged patients, outpatients and training full-time equivalents. The quality measures used as outputs were percentage of patients given initial antibiotic and percentage of patients given oxygenation assessment.

Ancarani et al. (2009) analyzed the efficiency of hospital wards in an Italian Hospital. The study used five inputs, i.e. number of staffed hospital beds, the shifts of surgery rooms utilisation, the number of physicians, the units of non-medical personel, and the maintenance costs of medical equipment. Whilst, the output variables were number of discharged patients, the number of cases treated under day-hospital and/or day surgery, the number of cases treated under ambulatory care. Kazley and Ozcan (2009) analyzed the effect of medical record use on hospital efficiency. The number of medical staff, beds, capital assets and operating expenses were considered as inputs. Output variables included number of admissions and outpatients. Mark et al. (2009) measured the technical efficiency of acute care nursing units using VRS model. The input factors for analysis were nurse hours, unlicensed hours of care, operating expenses, and number of hospital beds. Outputs were number of discharged patients, patient satisfaction, and medical error rates and patient falls.

Bayraktutan and Arslan (2010) employed DEA to measure comparative productivity of 21 different hospitals of chest illnesses. The inputs included number of specialists, beds, nurses, and total operating expenses. Total operating revenue, and total number of cases were considered as outputs. Caballer-Tarazona et al. (2010) analyzed the efficiency of general surgery, ophthalmology and traumatology-orthopaedic surgery departments of hospitals in Spain. The inputs were number of physicians and beds whereas the output variables were number of admissions, consultations, and surgeries. Dash et al. (2010) applied input-oriented DEA model under VRS assumption to analyze hospital performance of 29 district hospitals of Tamil Nadu state in India in 2004/2005. Number of hospital beds, nurses, assistant surgeons and civil surgeons were used as inputs in the study. The outputs used included number of outpatients, inpatients, surgeries, deliveries and emergency cases. Ozcan et al. (2010) employed the proposed model as VRS, input-oriented to analyze the hospital performance of university hospitals in Brazil.

Osman et al. (2011) evaluated performance of 32 nurses at critical care units in 2008. The inputs included job knowledge, work habits, teamwork and cooperation, interpersonal skills, using equipment skills and communication. The outputs employed included planning/organization, general performance, nursing performance, technical performance, patient education practice, emergency work follow-up, taking responsibility, quality/quantity of work, problem solving creativity. Ketabi (2011) used VRS model to evaluate the health care efficiency of cardiac care services. The inputs consisted of beds, health care equipment, staff and technological capabilities. The outputs included percent of bed occupancy, length of stay, percent of survival and performance ratio. Ng (2011) analyzed productive efficiency of Chinese hospitals after the health care reform in the country. The inputs utilized included number of doctors, nurses, pharmacists, and the other staff. Number of outpatient and inpatient cases were considered as outputs. Simões and Marques (2011) used input-oriented CRS and VRS DEA models to analyze the hospital performance in Portugal. The inputs employed included capital expenses, number of staff and operational expenses. As outputs, the study considered the number of patients treated, emergency department visits and outpatients.

Hu et al. (2012) analyzed health care performance of Chinese hospitals between 2002 and 2008. The total number of outpatients, inpatient days, emergency room visits, and patient mortality were used as outputs for the performance analysis. Whilst, the outputs included number of physicians, medical technicians, other personnel, hospital beds and fixed assets. Gok and Sezen (2012) employed DEA to analyze the capacity inefficiency causes of hospitals in Turkey. Gautam et al. (2013) estimated efficiency scores of hospitals in Missouri via VRS DEA.

Bilsel and Davutyan (2014) implemented CRS and VRS DEA models for 202 rural general hospitals in Turkey for the year 2006. As for the inputs, the study considered number of beds, specialists, general practitioners, nurses, other staff, operational expenses. The outputs utilized included outpatient discharges, inpatient visits, number of surgeries and death/ surgeries ratio. De Nicola et al. (2014) presented a DEA model to evaluate the efficiency of health care services in Italy. Recently, Prakash and Annapoorni (2015) analyzed the hospital efficiency of hospitals in Tamil Nadu using an output-oriented BCC model.

In the second group, extended DEA models were analyzed. Ersoy et al. (1997) utilized CCR input-oriented model to examine 573 acute hospitals in Turkey. The input variables were number of beds, specialists and physicians. The outputs included number of outpatients, inpatients, and surgeries. Parkin and Hollingsworth (1997) suggested a methodology for assessing validity in DEA. The study used six inputs, i.e. the number of beds, number of nurses, professional, technical, administrative and clerical personnel, non-nursing medical and dental staff, the cost of the drug supply for the hospital and the hospital’s capital charge; and six outputs, i.e. number of discharged patients, acute discharged patients, accident and emergency attendances, outpatient attendances, discharged patients from obstetrics and gynaecology departments, and other speciality discharges. O’Neill (1998) suggested multifactor efficiency calculations in DEA. As for the inputs, technological services, beds, full time employess, operational expenses were defined. The outputs employed included number of medical discharges, adjusted inpatient surgical discharges, adjusted outpatient visits and residents trained.

Olesen and Petersen (2002) offered a DEA model based on probabilistic assurance regions which incorporated the relative variation in treatment cost within different diagnosis related groups. Inputs were measured by observed cost for each hospital and outputs by the number of discharges in each group of discharges to be defined by some classification system. Oullette and Vierstraete (2004) proposed quasi-fixed inputs for efficiency calculations in DEA. Proposed methodology was applied to hospital emergency services in Montreal. Butler and Li (2005) analyzed the performance of Michigan rural hospitals and suggested a methodology for inefficient hospitals in order to evaluate returns to scale. The inputs used included total facility expenses minus payroll, beds, services and employees. The outputs were total facility inpatient days, total inpatient and outpatient surgeries, emergency department visits and total outpatient visits. O’Neill and Dexter (2005) worked on multifactor efficiency and non-radial super-efficiency techniques to evaluate performance of inpatient surgery departments of Iowa hospitals.

Jin (2009) performed a comparative study to analyze the health care performance of 31 regions in China via using comprehensive variable DEA approach and traditional DEA. The inputs utilized were number of beds, personnel, work day and total value of fixed assets. Number of discharged patients, outpatients and emergency units visits, hospitalized operation person-time and business income were defined as output variables. Weng et al. (2009) enhanced DEA using successive and overlapping windows/panels in order to assess the temporal behavior of the evaluated DMUs. The inputs were number of beds and personnel in the hospital. The outputs employed included acute care service speed, swing bed service speed and acute care patient admissions and swing bed patient adimissions. Du et al. (2014) suggested super-efficiency model under VRS assumption.

The suggested model was applied to evaluate performance of general acute hospitals in Pennsylvania. The inputs used included beds, doctors, nurses and total operating expenses. The output variables considered were total operating revenue, cases, and survival rate.

DEA models to improve discriminating power were employed in the third group. Chuang et al. (2011) introduced classification and regression tree efficiency model to improve resource allocation in health care institutions. The inputs included beds, physicians, other medical professionals and nurses. The outputs were inpatient days, outpatient/emergency visits, number of personnel using medical equipments, and survival rate in hospital. Wei et al. (2011) proposed an input oriented CCR model with and without weight restriction assumption and then compared the findings. The inputs utilized included beds and doctors. Output variables were the number of outpatients, inpatient days and medical interventions. Flokou et al. (2011) examined input-oriented CRS and VRS models. Cross-efficiency analysis and clustering were also employed to validate the obtained efficiency scores. The input items were number of beds, doctors and other health professionals. The outputs employed included number of hospitalized cases, case-mix adjusted cases, operations, outpatients.

In the fourth group, several studies used DEA in conjuction with other techniques such as stochastic frontier analysis (SFA), the Malmquist index, regression, and discrete event simulation. Chang (1998) combined DEA with regression analysis to analyze the hospital efficiency of in Taiwan. Inputs were defined as number of physicians, nurses, medical supporting staff and general and administration staff. The outputs were the number of total clinic visits, patient days and chronic care patient days. Maniadakis et al. (1999) employed DEA models and decomposed Malmquist indices of productivity and quality change. The proposed methodology was applied to Scottish acute hospitals. McCallion et al. (2000) presented information on determining the best practice frontier; measuring productive efficiency relative to the constructed frontier and decomposition of the input-based Malmquist productivity index in order to analyze Northern Ireland hospitals. Sommersguter-Reichmann (2000) calculated the input-based Malmquist productivity index to analyze Austrian hospitals' productivity. Jacobs (2001) focused on the consistency and robustness of efficiency scores across the DEA and SFA when applied to the same data set. Solà and Prior (2001) used Malmquist index to establish dynamic evolution of Catalan hospitals' productivity.

Hu and Huang (2004) employed Mann-Whitney test and Tobit regression to investigate the impact of environmental variables on efficiency after obtaining efficiency scores by DEA. Bates et al. (2006) applied DEA and multiple regression analysis to analyze the impact of many market structure elements on efficiency. The study used six inputs, i.e. number of beds, nurses, practical nurses, other salaried staff, expenditures on materials, supplies, and drugs, and number of active, nonfederal doctors. Output variables were defined as number of inpatient days, emergency unit visits, nonemergency-room visits, surgeries, and births.

Kirigia et al. (2008) measured productivity change utilizing DEA-based Malmquist total factor productivity index for 28 municipal hospitals in Angola. The input variables were number of doctors and nurses, expenditures on pharmaceutical and non-pharmaceutical supplies, and number of beds. The outputs were number of outpatient plus antenatal visits and admissions of inpatients in the study. O'Neill et al. (2008) conducted a review on hospital efficiency that used DEA, stochastic frontier analysis and the Malmquist index. Hospital input subcategories were capital investment, labor and other operating expenses. Four output subcategories were also identified, including medical visits, cases, patients, and surgeries, inpatient days, admissions, discharges, and services and atypical, teaching, and specific output categories. Tlotlego et al. (2010) used the DEA-based Malmquist productivity index with the aim of analyzing the health care performance of non-teaching hospitals in Botswana. The inputs were number of medical staff and beds. The outputs used were outpatient visits and inpatient days.

Androutsou et al. (2011) employed Malmquist productivity index in order to analyze technical efficiency and productivity change. The model was output-oriented and assumed VRS. The input factors consisted of total number of clinical and nursing staff and hospital beds. The outputs were number of inpatient discharges and inpatient days. Sahin et al. (2011) estimated relative efficiencies of 352 Ministry of Health hospitals in Turkey employing under VRS and CRS DEA models. The Malmquist index was adopted to investigate the operational performance of hospitals. The inputs used included number of beds, physicians, nurses, other personnel, and operational expenses. The output variables were number of outpatients, inpatients and surgeries in the model. Weng et al. (2011) combined discrete event simulation and DEA to evaluate operation efficiency of emergency departments in Taiwan hospitals.

Mitropoulos et al. (2013) combined DEA and location analysis with the aim of maximizing accessibility, utilization and mean efficiency of health centers. Audibert et al. (2013) combined DEA and Tobit regression analysis in order to analyze 24 randomly selected township hospitals in China from 2003 to 2008. Mitropoulos et al. (2015) combined DEA with Bayesian analysis in order to gather statistical properties of efficiency values of 117 Greek public hospitals. Lately, Chowdhury and Zelenyuk (2016) used DEA with bootstrapping and truncated regression in order to analyze performance of hospital services in Ontario for the years 2003 and 2006.

To sum up, literature review points out that DEA is a widely used, effective tool for evaluating the efficiency of health care facilities, using different input-output combinations. Eventually, it is obvious that the development of DEA methodologies and its applications in the health care field continue to flourish since DEA is a versatile technique for evaluating efficiency.

3. DATA ENVELOPMENT ANALYSIS

This thesis focuses on evaluating health care performance of districts in Istanbul using multiple criteria decision making (MCDM) approaches. MCDM is widely used in ranking alternatives with respect to multiple criteria. It provides a systematic approach that makes decision making more objective and transparent. Instead of cost-based considerations, there is a growing body of literature reporting on application of multiple criteria approaches. This trend may bring about better solutions since the proposed methods enable decision-makers to take account of a variety of other viewpoints apart from the costs involved (Hokkanen & Salminen, 1997). The decision process of performance evaluation has to take many factors into consideration. As the alternatives are evaluated, both qualitative and quantitative criteria may affect simultaneously which may cause the selection process to be complex and challenging.

Organizations focus on productivity improvement and efficiency measurement. Farrell (1957) stated the reasons for his focus as:

"The problem of measuring the productive efficiency of an industry is important to both economic theorist and the economic policy maker. If the theoretical arguments as to the relative efficiency of different economic systems are to be subjected empirical testing, it is essential to be able to make some actual measurements of efficiency. Equally, if economic planning is to concern itself with particular industries, it is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources."

In this thesis, DEA is used as a multiple criteria decision making approach for hospital efficiency measurement. Since 1978, there has been a continuous growth in theoretical developments and applications in many fields and practical situations. DEA offers many opportunities for its usage such as DEA provides collaboration between analysts and decision-makers (Cooper et al., 2000).

DEA provides an efficient frontier or envelope for all considered DMUs. In addition, DEA enables one to compute efficiency of non-frontier units, and to identify benchmarks against which such inefficient units can be compared (Cook & Seiford, 2009). In addition, DEA does not require any assumption on the shape of the frontier surface since it is a non-parametric approach (Hatami-Marbini et al., 2011).

DEA has been proven to be a versatile technique for evaluating health care performance and also adapted to many health care systems throughout the world (O'Neill, et al., 2008). It makes no assumptions about the form of the production function, enables the consideration of multiple inputs and outputs simultaneously. In addition, it is easy to use in computational sense.

DEA offers the following three possible orientations to efficiency analysis:
(1) Input-Oriented. With this orientation, input usage is minimized in order to produce given output for each DMU.
(2) Ouput-Oriented. With this orientation, output production is maximized with a given input for each DMU.
(3) Base-Oriented. With this orientation, optimal usage of inputs and optimal production of outputs are achieved simultaneously. Both inputs and outputs can be controlled in a Base-Oriented model (Lertworasirikul, 2002).

The first DEA model developed by Charnes, Cooper and Rhodes (1978), named the CCR model, was based on the assumption of constant returns to scale (CRS). Then, Banker, Charnes and Cooper (1984) enhanced the CCR model and developed the BCC model using the variable returns to scale (VRS). In DEA model based on the CRS assumption, efficiency frontier has constant slope and positioned through the DMUs with equally highest ratio of input and output variables. Conversely, VRS frontier consists of a series of segments displaying varying non-negative slopes positioned through the DMUs with the highest ratios of input and output variables given their scale of operations (Vitikainen et al.,2009).

There exist numerous DEA models in the published literature: the constant returns to scale (CRS or CCR "Charnes, Cooper and Rhodes") model, the variable returns to scale (VRS or BCC "Banker, Charnes, Cooper") model, the additive model, slacks-based measures and the Russell measure model.

3.1 CCR Model

DEA is a methodology for analyzing performance of DMUs which convert multiple inputs into multiple outputs (Cooper et al., 2011). It generalizes technical efficiency measure of Farrell (1957) to the multiple input and output case. DEA considers *n* DMUs to be evaluated, where each DMU consumes *m* different inputs to produce *s* different outputs. The relative efficiency of a DMU is calculated as a ratio of a weighted sum of outputs to a weighted sum of inputs. The mathematical programming model can be written as follows (Karsak, 2008):

$$\max E_{j_0} = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij_0}}$$

subject to (3.1)

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1, \quad j = 1, \ldots, n,$$

$$u_r, v_i \geq \varepsilon > 0, \quad r = 1, \ldots s; \; i = 1, \ldots, m.$$

where E_{jo} denotes the efficiency score for the target DMU (j_o), u_r is the weight of output r, v_i is the weight of input i, y_{rj} is the amount of output r produced by the jth DMU, x_{ij} is the amount of input i consumed by the jth DMU, and ε is an infinitesimal positive number. "Less-than-unity" constraints satisfy that the optimal weights for the DMU in the objective function do not imply an efficiency score greater than one either for itself or for the remaining DMUs. DEA assigns an efficiency score of one to a DMU only when comparisons with other relevant DMUs do not provide evidence of inefficiency in the use of any input or output.

The fractional program is not used for computation of the efficiency scores because of its non linear and nonconvex features (Charnes et al., 1978). DEA model can be easily converted into a linear programming model and solved by an LP solver. The fractional programming is converted into a linear program as follows:

$$\max E_{j_0} = \sum_r u_r y_{rj_0}$$

subject to (3.2)

$$\sum_i v_i x_{ij} = 1$$

$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \le 0, \ \text{j = 1,...,n}$$

$$u_r, v_i \ge \varepsilon > 0, \quad r = 1,...s; \ i = 1,..., m.$$

3.2 The BCC Model

The input-oriented BCC model calculate the efficiency of DMU_o $(o = 1,..., n)$ by employing the following LP model:

$$\min \ \theta_B$$

subject to

$$\theta_B x_o - X\lambda \ge 0$$

$$Y\lambda \ge y_o \qquad (3.3)$$

$$e\lambda = 1$$

$$\lambda \ge 0,$$

where $X = (x_j) \in R^{M \times n}$ and $Y = (y_j) \in R^{s \times n}$ are given data set of inputs and outputs, respectively. θ_B is a scalar, $\lambda \in \mathrm{R}^n$ and e is a row vector with all elements equal to 1. The difference between the BCC and CCR models is the condition that $e\lambda = \sum_{j=1}^{n} \lambda_j = 1.$ Together with the condition $\lambda_j \geq 0,$ for all $j,$ this imposes a convexity condition on allowable ways in which the n DMUs may be combined.

The dual form of model (3.3) is given as:

$$
\begin{aligned}
&\max\ z = uy_0 - u_0 \\
&\text{subject to} \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (3.4) \\
&vx_0 = 1 \\
&-vX + uY - u_0 e \leq 0 \\
&v \geq 0,\ \mathrm{u} \geq 0,\ u_0 \text{ free in sign,}
\end{aligned}
$$

where z and u_0 are scalars and since they are free in sign, they may be positive or negative or zero.

It is obvious that the difference between the CCR and BCC models is the free variable u_0, which is the dual variable associated with the constraint $e\lambda = 1$ that does not take place in the CCR model.

3.3 The Additive Model

When we combine input-oriented and output-oriented DEA models, it is called the additive DEA model. There are many types of the additive model, the most basic one is given in model (3.5) as follows:

$$P_o = \max \ \sum_i s_i^- + \sum_r s_r^+$$

subject to

$$\begin{aligned}
&\sum_j \lambda_j x_{ij} + s_i^- = x_{io}, \ i = 1,\ldots,m \\
&\sum_j \lambda_j y_{rj} - s_r^+ = y_{ro}, \ \mathrm{r} = 1,\ldots,s \\
&\sum_j \lambda_j = 1 \\
&\lambda_j, s_i^-, s_r^+ \geq 0, \ \forall j,i,r.
\end{aligned} \tag{3.5}$$

Various input and output variables in DEA models may be measured in non-commensurate units (Russell, 1988). It may not be practical to use the simple summation of slacks as the objective function in model (3.5). Thus, Charnes et al. (1985) suggested the use of Q_0 , where

$$Q_o = \delta\left(\sum_i s_i^- / x_{io} + \sum_r s_r^+ / y_{ro}\right)$$

subject to

$$\begin{aligned}
&\sum_j \lambda_j x_{ij} + s_i^- = x_{io}, \ i = 1,\ldots,m \\
&\sum_j \lambda_j y_{rj} - s_r^+ = y_{ro}, \ \mathrm{r} = 1,\ldots,s \\
&\sum_j \lambda_j = 1 \\
&\lambda_j, s_i^-, s_r^+ \geq 0, \ \forall j,i,r.
\end{aligned} \tag{3.6}$$

where δ is a scalar. A suggested value for δ was $1/(m+s)$. The division of the s_i^- and s_r^+ by x_{io} and y_{ro}, respectively is intended to render these slack units invariant, while multiplying by δ controls the overall scale.

Sueyoshi (1990) suggested $1-Q_o$ as a measure to provide consistency with the sense of efficiency in the CCR and BCC DEA models. But later Chang & Sueyoshi (1991) pointed out the problem that $0 \le 1-Q_o \le 1$ may not necessarily hold and it may also be negative.

3.4 Slacks-based Measures

To overcome the shortcomings in the additive model, Green et al. (1997) proposed a measure of efficiency:

$$R_o = \frac{1}{s+r}\left[\sum_i s_i^- \Big/ x_{io} + \sum_r s_r^+ \Big/ \left(y_{ro} + s_r^+\right)\right]$$

and suggest solving model (3.7):

$\max \; R_o$

subject to

$$\begin{aligned}
&\sum_j \lambda_j x_{ij} + s_i^- = x_{io}, \; i = 1, \dots, m \\
&\sum_j \lambda_j y_{rj} - s_r^+ = y_{ro}, \; \mathrm{r} = 1, \dots, s \\
&\sum_j \lambda_j = 1 \\
&\lambda_j, s_i^-, s_r^+ \ge 0, \; \forall j, i, r.
\end{aligned} \tag{3.7}$$

Tone (2001) suggested the slacks-based measure which is invariant to the units of measurement and is monotone increasing in each input and output slack. The slacks-based measure is determined from the solution of model (3.8) given below:

$$\min \; p = \frac{1 - \frac{1}{m}\sum_i s_i^- x_{io}}{1 + \frac{1}{s}\sum_r s_r^+ y_{ro}}$$

subject to

$$\sum_j \lambda_j x_{ij} + s_i^- = x_{io},\ i = 1,\ldots,m$$
$$\sum_j \lambda_j y_{rj} - s_r^+ = y_{ro},\ \mathrm{r} = 1,\ldots,s \tag{3.8}$$
$$\sum_j \lambda_j = 1$$
$$\lambda_j, s_i^-, s_r^+ \geq 0,\ \forall j,i,r.$$

3.5 The Russell Measure

The Russell measure model suggested by Färe & Lovell (1978) and revisited by Pastor et al. (1999) is given in model (3.9):

$$R_o = \min \left[\sum_i \theta_i / m \Big/ \sum_r \varphi_r / s \right]$$

subject to

$$\sum_j \lambda_j x_{ij} \leq \theta_i x_{io},\ i = 1,\ldots,m$$
$$\sum_j \lambda_j y_{rj} \geq \varphi_r y_{ro},\ \mathrm{r} = 1,\ldots,s \tag{3.9}$$
$$\sum_j \lambda_j = 1$$
$$\lambda_j \geq 0,\ \ 0 \leq \theta_i \leq 1,\ \varphi_r \geq 1,\ \text{all } i, j, r.$$

In model (3.9) above, the constraints $0 < \theta_i \leq 1$ and $\phi_r \geq 1$ are the requirements for dominance.

4. FUZZY DATA ENVELOPMENT ANALYSIS

This section presents a classification of fuzzy DEA models. Fuzzy DEA models can be categorized into four approaches, namely, the tolerance approach, the α-level based approach, the ranking approach and the possibility approach.

This section is organized according to these four procedures that have been suggested to solve the fuzzy DEA in the literature. A mathematical formulation of each approach is provided in this section.

4.1 The Tolerance Approach

Sengupta (1992) suggested the first approach to solve fuzzy DEA. Later, his study was improved by Kahraman and Tolga (1998). The proposed approach defines tolerance levels on constraint violations.

4.2 The α -Level Based Approach

In this approach, fuzzy DEA models are converted into a pair of parametric programming models to determine the lower and upper limits of the α-level of the efficiency score's membership functions. The most widely employed α-cut fuzzy DEA model is suggested by Kao and Liu (2000). They developed a pair of mathematical programming models to obtain the lower limit $\left(E_{j_0}\right)_\alpha^L$ and upper limit $\left(E_{j_0}\right)_\alpha^U$ of the fuzzy efficiency score for a given α -cut level as given in model (4.1a) and model (4.1b), respectively.

$$\left(E_{j_0}\right)_\alpha^L = \max \sum_{r=1}^{s} u_r \left(Y_{rj_0}\right)_\alpha^L$$

subject to

$$\sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^U = 1$$

$$\sum_{r=1}^{s} u_r \left(y_{rj_0}\right)_\alpha^L - \sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^U \le 0 \tag{4.1a}$$

$$\sum_{r=1}^{s} u_r \left(y_{rj}\right)_\alpha^U - \sum_{i=1}^{m} v_i \left(x_{ij}\right)_\alpha^L \le 0,\ j = 1, 2, \ldots, n;\ j \ne j_0$$

$$u_r,\ \mathrm{v}_i \ge \varepsilon > 0,\ r = 1, \ldots, s\ ;\ i = 1, \ldots, m.$$

$$\left(E_{j_0}\right)_\alpha^U = \max \sum_{r=1}^{s} u_r \left(Y_{rj_0}\right)_\alpha^U$$

subject to

$$\sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^L = 1$$

$$\sum_{r=1}^{s} u_r \left(y_{rj_0}\right)_\alpha^U - \sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^L \le 0 \tag{4.1b}$$

$$\sum_{r=1}^{s} u_r \left(y_{rj}\right)_\alpha^L - \sum_{i=1}^{m} v_i \left(x_{ij}\right)_\alpha^U \le 0,\ j = 1, 2, \ldots, n;\ j \ne j_0$$

$$u_r,\ \mathrm{v}_i \ge \varepsilon > 0,\ r = 1, \ldots, s\ ;\ i = 1, \ldots, m.$$

where E_{j_0} is the efficiency value of the target DMU $\left(j_0\right)$, u_r is the weight of output r, v_i weight of input i, y_{rj} represents the output r generated by the jth DMU, x_{ij} represents input i consumed by the jth DMU, and ε is an infinitesimal positive number.

Model (4.1a) provides the smallest efficiency value of a DMU since the largest possible input and the smallest possible output values are used for the evaluated DMU, while the smallest possible input and largest output values are utilized for all other DMUs. On the contrary, Model (4.2b) provides the highest relative efficiency value of a DMU, while the smallest possible input and largest output values are used for the evaluated DMU, whereas the largest possible input and smallest output values are utilized for all other remaining DMUs.

Lertworasirikul (2001) suggested best-best, worst-best, best-worst, and worst-worst case of α -level based approaches. The best-best scenario is employed for the decision maker who is optimistic about each DMU, while the worst-worst scenario is suitable for the decision maker who is pessimistic about each DMU. Under the worst-best scenario, the decision maker is pessimistic about the evaluated DMU and optimistic about the remaining DMUs. Conversely, under the best-worst scenario, the decision maker is optimistic about the evaluated DMU and pessimistic about the other DMUs (Lertworasirikul et al., 2003). Mathematical formulations for each of four cases are as follows:

Case 1: Best-Best

With this method, every DMU is evaluated in an optimistic way. The smallest input values and the largest output values are considered for every DMU at each α level.

$$\begin{aligned}
&\max \theta = v^T \left(\tilde{y}_0\right)_\alpha^U \\
&u^T \left(\tilde{x}_0\right)_\alpha^L = 1 \\
&-u^T \left(\tilde{x}_0\right)_\alpha^L + v^T \left(\tilde{y}_0\right)_\alpha^U \leq 0 \text{ for DMU}_0 \qquad (4.2) \\
&-u^T \left(\tilde{x}_i\right)_\alpha^L + v^T \left(\tilde{y}_i\right)_\alpha^U \leq 0,\ i = 1, \ldots, n \text{ and } i \neq o \\
&u \geq 0 \\
&v \geq 0,
\end{aligned}$$

where $(\tilde{\cdot})_\alpha^L$ is the column vector of the minimum values of the corresponding fuzzy sets obtained at the given α level, and $(\tilde{\cdot})_\alpha^U$ is the column vector of the maximum values of the corresponding fuzzy sets obtained at that α level.

Case 2: Worst-Worst

With this method, every DMU is evaluated in a pessimistic way. The largest input values and the smallest output values are considered for every DMU at each α level.

$$\begin{aligned}
&\max \theta = v^T \left(\tilde{y}_0\right)_\alpha^L \\
&u^T \left(\tilde{x}_0\right)_\alpha^U = 1 \\
&-u^T \left(\tilde{x}_0\right)_\alpha^U + v^T \left(\tilde{y}_0\right)_\alpha^L \le 0 \text{ for } \mathrm{DMU}_0 \\
&-u^T \left(\tilde{x}_i\right)_\alpha^U + v^T \left(\tilde{y}_i\right)_\alpha^L \le 0,\ i = 1, \dots, n \text{ and } i \ne o \\
&u \ge 0 \\
&v \ge 0.
\end{aligned} \tag{4.3}$$

Case 3: Best-Worst

With this method, DMU_0 is evaluated in an optimistic way but all remaining DMUs are evaluated in a pessimistic way. The smallest input values and the largest output values are considered for DMU_0, while the largest input values and smallest output values are considered for remaining DMUs.

$$\begin{aligned}
&\max \theta = v^T \left(\tilde{y}_0\right)_\alpha^U \\
&u^T \left(\tilde{x}_0\right)_\alpha^L = 1 \\
&-u^T \left(\tilde{x}_0\right)_\alpha^L + v^T \left(\tilde{y}_0\right)_\alpha^U \le 0 \text{ for } \mathrm{DMU}_0 \\
&-u^T \left(\tilde{x}_i\right)_\alpha^U + v^T \left(\tilde{y}_i\right)_\alpha^L \le 0,\ i = 1, \dots, n \text{ and } i \ne o \\
&u \ge 0 \\
&v \ge 0.
\end{aligned} \tag{4.4}$$

Case 4: Worst-Best

With this method, DMU_0 is evaluated in a pessimistic way but all remaining DMUs are evaluated in an optimistic way. The largest input values and the smallest output values are considered for DMU_0, while the smallest input values and largest output values are considered for remaining DMUs.

$$
\begin{aligned}
&\max \theta = v^T \left(\tilde{y}_0\right)_\alpha^L \\
&u^T \left(\tilde{x}_0\right)_\alpha^U = 1 \\
&-u^T \left(\tilde{x}_0\right)_\alpha^U + v^T \left(\tilde{y}_0\right)_\alpha^L \le 0 \text{ for } \mathrm{DMU}_0 \\
&-u^T \left(\tilde{x}_i\right)_\alpha^L + v^T \left(\tilde{y}_i\right)_\alpha^U \le 0,\ i = 1,\dots,n \text{ and } i \ne o \\
&u \ge 0 \\
&v \ge 0.
\end{aligned}
\tag{4.5}
$$

The other α-cut approach is suggested by (Saati et al.,2002). In their model fuzzy triangular numbers are transformed into crisp intervals and for each interval, the proposed methodology finds out a point that ensure the set of constraints and maximize the objective function value at the same time. Suppose that $\tilde{x}_{ij} = \left(x_{ij}^l, x_{ij}^m, x_{ij}^u\right)$ and $\tilde{y}_{rj} = \left(\tilde{y}_{rj}^l, \tilde{y}_{rj}^m, \tilde{y}_{rj}^u\right)$ Their model can be written as:

$$\left(E_{j_0}\right)_\alpha = \max \sum_{r=1}^{s} \bar{y}_{rj_0}$$

subject to (4.6)

$$\sum_{i=1}^{m} \bar{x}_{ij_0} = 1$$

$$\sum_{r=1}^{s} \bar{y}_{rj} - \sum_{i=1}^{m} \bar{x}_{ij} \le 0,\ \text{j=1,2,...,n.}$$

$$v_i\left[\alpha x_{ij}^M+(1-\alpha)x_{ij}^L\right]\le \bar{x}_{ij}\le v_i\left[\alpha x_{ij}^M+(1-\alpha)x_{ij}^U\right]$$

$$u_r\left[\alpha y_{rj}^M+(1-\alpha)y_{rj}^L\right]\le \bar{y}_{rj}\le u_r\left[\alpha y_{rj}^M+(1-\alpha)y_{rj}^U\right]$$

$$v_i,u_r\ge\varepsilon,\ r=1,2,\dots,s;\ i=1,2,\dots,m.$$

4.3 The Fuzzy Ranking Approach

The fuzzy ranking approach was initially developed by Guo and Tanaka (2001) for efficiency measurement. For model (4.7) below consider that there are n DMUs with m and s symmetrical triangular fuzzy input and output variables, respectively. Fuzzy output is represented by $\tilde{x}_{ij}=(x_{ij},w_{ij})$ and fuzzy input is represented by $\tilde{y}_{rj}=(y_{rj},q_{rj})$ Their LP model with two objective functions can be written as follows:

$$\left(E_{j_0}\right)_\alpha=\max\sum_{r=1}^{s}u_r\left[y_{rj_0}^M-(1-\alpha)q_{ij_0}\right]$$

subject to $\quad \max \sum_{i=1}^{m} v_i c_{ij_0}$ (4.7)

$$\begin{aligned}&\sum_{i=1}^{m}\left(v_i x_{ij_0}-(1-\alpha)v_i w_{ij_0}\right)=1-(1-\alpha)e,\\&\sum_{i=1}^{m}\left(v_i x_{ij_0}+(1-\alpha)v_i w_{ij_0}\right)\le 1+(1-\alpha)e,\\&v_i\ge 0,\ \forall i.\end{aligned}\qquad (4.7.1)$$

$$\sum_{r=1}^{s}\left(u_r y_{rj}+(1-\alpha)u_r q_{rj}\right)\ \le\ \sum_{i=1}^{m}\left(v_i x_{ij}+(1-\alpha)v_i w_{ij}\right),\forall j,$$

$$\sum_{r=1}^{s}\left(u_r y_{rj}-(1-\alpha)u_r q_{rj}\right)\ \le\ \sum_{i=1}^{m}\left(v_i x_{ij}-(1-\alpha)v_i w_{ij}\right),\forall j,$$

$$u_r\ge 0,\ \forall \text{r}.$$

where $\alpha \in [0,1]$ possibility level determined by decision-makers and a symmetrical triangular fuzzy number $1 = (1, e)$.

The fuzzy efficiency of each DMU with symmetrical triangular fuzzy inputs $\tilde{x}_{ij_0}$ and outputs $\tilde{y}_{rj_0}$ is computed for each α possibility level as a non-symmetrical triangular fuzzy number $\tilde{E}_{j_0} = \left(e^l_{j_0}, e^m_{j_0}, e^u_{j_0}\right)$ as follows:

$$e^m_{j_0} = \frac{u^*_r y_{rj_0}}{v^*_i x_{ij_0}}, \quad e^l_{j_0} = e^m_{j_0} - \frac{u^*_r \left(y_{rj_0} - q_{rj_0}(1-\alpha)\right)}{v^*_i \left(x_{ij_0} + w_{ij_0}(1-\alpha)\right)}, \quad e^u_{j_0} = \frac{u^*_r \left(y_{rj_0} + q_{rj_0}(1-\alpha)\right)}{v^*_i \left(x_{ij_0} - w_{ij_0}(1-\alpha)\right)} - e^m_{j_0} \qquad (4.8)$$

where values of u^*_r and v^*_i are determined from model (4.7.1) and $e^l_{j_0}$, $e^m_{j_0}$, $e^u_{j_0}$ are the left, right spreads and the center of $\left(E\, j_0\right)_\alpha$,respectively.

4.4 The Possibility Approach

Possibility theory was introduced by Zadeh (1978) in terms of fuzzy set theory. Zadeh suggested that "fuzzy variable which is associated with a possibility distribution in the same manner that a random variable is associated with a probability distribution". Each fuzzy coefficient can be assumed as a fuzzy variable and each constraint can be considered as a fuzzy event in fuzzy linear programming models. In this regard, utilizing possibility theory, possibilities of fuzzy constraints can be determined.

Lertworasirikul (2002) and Lertworasirikul et al. (2003a,b) suggested "possibility" and "credibility" approach. They developed the possibility approach from both pessimistic and optimistic viewpoints by incorporating uncertainty in fuzzy objective function and fuzzy constraints with possibility measures. The proposed possibility CCR model is given as model (4.9):

$$\max\ \mathrm{E}_{j_0} = \overline{f}$$

subject to

$$\left(\sum_{r=1}^{s} u_r \tilde{y}_{rj_0}\right)_{\beta}^{U} \geq \overline{f},$$

$$\left(\sum_{i=1}^{m} v_i \tilde{x}_{ij_0}\right)_{\alpha_0}^{U} \geq 1, \tag{4.9}$$

$$\left(\sum_{i=1}^{m} v_i \tilde{x}_{ij_0}\right)_{\alpha_0}^{L} \leq 1,$$

$$\left(\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij}\right)_{\alpha}^{L} \leq 0,\ \forall \mathrm{j},$$

$$u_r, v_i \geq 0,\ \forall \mathrm{r,i}.$$

where $\beta \in [0,1]$ $\alpha_0 \in [0,1]$ and $\alpha \in [0,1]$ are predetermined levels of possibility.

In addition, the proposed possibility BCC model is given in model (4.10):

$$\max\ \mathrm{E}_{j_0} = \left(\sum_{r=1}^{s} u_r \tilde{y}_{rp}\right)_{\beta}^{U} - u_0$$

subject to

$$\left(\sum_{i=1}^{m} v_i \tilde{x}_{ij_0}\right)_{\alpha_0}^{U} \geq 1,$$

$$\left(\sum_{i=1}^{m} v_i \tilde{x}_{ij_0}\right)_{\alpha_0}^{L} \leq 1, \tag{4.10}$$

$$\left(\sum_{r=1}^{s} u_r \tilde{y}_{rj} - \sum_{i=1}^{m} v_i \tilde{x}_{ij}\right)_{\alpha}^{L} - u_0 \leq 0,\ \forall \mathrm{j},$$

$$u_r, v_i \geq 0,\ \forall \mathrm{r,i}.$$

where $\beta \in [0,1]$ $\alpha_0 \in [0,1]$ and $\alpha \in [0,1]$ are predetermined levels of possibility.

The possibility approach can also be formulated from both optimistic and pessimistic viewpoints as:

4.4.1 Possibility Approach with an Optimistic Viewpoint

The optimistic possibility fuzzy CCR model is presented in model (4.11):

$$\max_{u,v,\bar{f}} \ \bar{f}$$

subject to

$$\begin{aligned}
&\pi\left(v^T \tilde{y}_0 \geq \bar{f}\right) \geq \beta \\
&\pi\left(u^T \tilde{x}_0 = 1\right) \geq \alpha_0 \\
&\pi\left(-u^T \tilde{X} + v^T \tilde{Y} \leq 0\right) \geq \alpha \\
&u \geq 0 \\
&v \geq 0
\end{aligned} \tag{4.11}$$

where $\beta \in [0,1]$ $\alpha_0 \in [0,1]$ and $\alpha \in [0,1]$ are predetermined levels of possibility.

4.4.2 Possibility Approach with a Pessimistic Viewpoint

The pessimistic possibility fuzzy CCR model is presented in model (4.12):

$$\max_{u,v} \ \min_{f \in R} \ f$$

subject to

$$\begin{aligned}
&\pi\left(v^T \tilde{y}_0 \leq \bar{f}\right) \geq \beta \\
&\pi\left(u^T \tilde{x}_0 = 1\right) \geq \alpha_0 \\
&\pi\left(-u^T \tilde{X} + v^T \tilde{Y} \leq 0\right) \geq \alpha \\
&u \geq 0 \\
&v \geq 0
\end{aligned} \tag{4.12}$$

where $\beta \in [0,1]$ $\alpha_0 \in [0,1]$ and $\alpha \in [0,1]$ are predetermined levels of possibility.

Lertworasirikul et al. (2003a,b) introduced "credibility approach" to solve fuzzy DEA models. In this approach, fuzzy DEA was transformed into a credibility programming model and fuzzy objectives and fuzzy constraints were replaced by their expected credits. Expected credits were calculated using credibility measures. "When the membership functions are symmetrical, the expected credits of normal, convex trapezoidal fuzzy numbers are located at the central point of their membership functions" (Lertworasirikul, 2002). The mathematical formulation of the credibility model is given in model (4.13):

$$\max_{u,v} \ \mathrm{E}\left(v^T \tilde{y}_0\right)$$

subject to

$$\mathrm{E}\left(u^T \tilde{x}_0\right) = 1 \tag{4.13}$$

$$\mathrm{E}\left(-u^T \tilde{X} + v^T \tilde{Y}\right) \leq 0$$

$$u \geq 0$$

$$v \geq 0.$$

The vectos u and v are selected to maximize the expected return of $\mathrm{E}\left(v^T \tilde{y}_0\right)$, while satisfying constraints on the expected credits of $u^T \tilde{x}_0$ and $-u^T \tilde{X} + v^T \tilde{Y}$. Consider that a trapezoidal fuzzy number $\tilde{r}_i = \left((\tilde{r}_i)_0^L, (\tilde{r}_i)_1^L, (\tilde{r}_i)_1^U, (\tilde{r}_i)_0^U\right)$. Then, when the membership functions are normal, convex trapezoidal the model (4.14) can be transformed into a LP model.

$$\max_{u,v} \ \frac{1}{4}\left[\left(v^T \tilde{y}_0\right)_1^U + \left(v^T \tilde{y}_0\right)_1^L + \left(v^T \tilde{y}_0\right)_0^U + \left(v^T \tilde{y}_0\right)_0^L\right]$$

subject to

$$\frac{1}{4}\left[\left(u^T \tilde{x}_0\right)_1^U + \left(u^T \tilde{x}_0\right)_1^L + \left(u^T \tilde{x}_0\right)_0^U + \left(u^T \tilde{x}_0\right)_0^L\right] \tag{4.14}$$

$$\frac{1}{4}\left[\left(-u^T \tilde{X} + -v^T \tilde{Y}\right)_1^U + \left(-u^T \tilde{X} + -v^T \tilde{Y}\right)_1^L + \left(-u^T \tilde{X} + -v^T \tilde{Y}\right)_0^U + \left(-u^T \tilde{X} + -v^T \tilde{Y}\right)_0^L\right] \leq 0$$

$$u \geq 0 \ ,$$

$$v \geq 0.$$

5. PROPOSED IMPRECISE DEA FRAMEWORK

Initially, unrestricted imprecise DEA models, and subsequently imprecise DEA models with weight restrictions are provided in this section.

5.1 Unrestricted Fuzzy DEA Model

The traditional DEA requires the evaluation of crisp input and the output variables. However, in real-world applications the values of input and output variables are sometimes in the form of qualitative and linguistic data. Evaluating health care service quality is as crucial as analyzing the service system for health system improvement (Lee et al., 2000). In this regard, the previous studies have been extended to handle the concept via using fuzzy set theory.

Karsak (2008) suggested DEA models that take into consideration exact and imprecise input and output variables at the same time to obtain relative efficiency of DMUs in the evaluation process. The preliminaries of proposed models based on Karsak's study (2008) are given as follows

Define $\tilde{x}_{ij} = \left(x_{ija}, x_{ijb}, x_{ijc}\right)$, for $0 \leq x_{ija} \leq x_{ijb} \leq x_{ijc}$ as the fuzzy input i consumed by the jth DMU, and $\tilde{y}_{rj} = \left(y_{rja}, y_{rjb}, y_{rjc}\right)$ as the fuzzy output r produced by the jth DMU, where $0 \leq y_{rja} \leq y_{rjb} \leq y_{rjc}$. Triangular fuzzy numbers are employed to define fuzzy input and output variables because of their intuitive appear and computational-efficient representation. Let $\left(x_{ij}\right)_{\alpha}^{L}$ and $\left(x_{ij}\right)_{\alpha}^{U}$ represent the lower and upper limits of the α-cut of the membership function of $\tilde{x}_{ij}$, and likewise, $\left(y_{rj}\right)_{\alpha}^{L}$ and $\left(y_{rj}\right)_{\alpha}^{U}$ represent the lower and upper limits of the α-cut of the membership function of $\tilde{y}_{rj}$, respectively. Let $\omega_i = v_i \cdot \alpha_i$, where $\alpha_i \in [0,1]$ and $0 \leq \omega_i \leq v_i$. Then, $\sum_i v_i \left(x_{ij} \right)_\alpha^L$ and $\sum_i v_i \left(x_{ij} \right)_\alpha^U$ can be written as

$$\sum_i v_i \left(xij \right)_\alpha^L = \sum_i v_i x_{ija} + \omega_i \left(x_{ijb} - x_{ija} \right),$$

$$\sum_i v_i \left(xij \right)_\alpha^U = \sum_i v_i x_{ijc} - \omega_i \left(x_{ijc} - x_{ijb} \right).$$

Similarly, define $\mu_r = u_r \cdot \alpha_r$, where $\alpha_r \in [0,1]$ and $0 \leq \mu_r \leq u_r$. Then, $\sum_r u_r \left(y_{rj} \right)_\alpha^L$ and $\sum_r u_r \left(y_{rj} \right)_\alpha^U$ can be written respectively as

$$\sum_r u_r \left(y_{rj} \right)_\alpha^L = \sum_r u_r y_{rja} + \mu_r \left(y_{rjb} - y_{rja} \right),$$

$$\sum_r u_r \left(y_{rj} \right)_\alpha^U = \sum_r u_r y_{rjc} - \mu_r \left(y_{rjc} - y_{rjb} \right).$$

Let $\left(E_{j_0} \right)^U$ and $\left(E_{j_0} \right)^L$ represent the upper and lower limits of the α-cut of the membership function of the efficiency score for the target DMU (j_0). Employing the substitutions given above, the optimistic scenario DEA model incorporating crisp input and output variables and fuzzy output variables is formulated as

$$\max \left(E_{j_0} \right)^U = \sum_{r \in C_R} u_r y_{rj_0} + \sum_{r \in F_R} u_r y_{rj_0c} - \mu_r \left(y_{rj_0c} - y_{rj_0b} \right)$$

subject to (5.1)

$$\sum_{i \in C_I} v_i x_{ij_0} = 1$$

$$\sum_{r\in C_R} u_r y_{rj_0} + \sum_{r\in F_R} u_r y_{rj_0c} - \mu_r\left(y_{rj_0c} - y_{rj_0b}\right) - \sum_{i\in C_I} v_i x_{ij_0} \le 0$$

$$\sum_{r\in C_R} u_r y_{rj} + \sum_{r\in F_R} u_r y_{rja} + \mu_r\left(y_{rjb} - y_{rja}\right) - \sum_{i\in C_I} v_i x_{ij} \le 0,\ j = 1,2,\ldots,n;\ j \ne j_0$$

$$\mu_r - u_r \le 0, \quad r \in F_R$$

$$\mu_r \ge 0, \quad r \in F_R$$

$$u_r \ge \varepsilon > 0, \quad r \in C_R, r \in F_R$$

$$v_i \ge \varepsilon > 0, \quad r \in C_I$$

In model (5.1), C_R and C_I represent the subset of crisp output variables and the subset of crisp input variables, respectively, whereas F_R denotes the subset of fuzzy output variables.

Model (5.1) provides an optimistic scenario since the input and the output variables of target DMU are adjusted at the lower limits and the upper limits of the membership functions, respectively, while the input and output variables are considered unfavorably for the remaining DMUs.

Conversely, under the pessimistic scenario the input and the output variables of the target DMU are taken respectively at the upper limits and the lower limits of the membership functions, and the input and output variables are considered favorably for the remaining DMUs .

Model (5.1) and Model (5.2) solved n times to evaluate the relative efficiency scores optimistic scenario and pessimistic scenario, respectively, of all DMUs.

The pessimistic scenario DEA model incorporating crisp inputs and outputs and fuzzy outputs is formulated as follows

$$\max\left(E_{j_0}\right)^L = \sum_{r\in C_R} u_r y_{rj_0} + \sum_{r\in F_R} u_r y_{rj_0 a} + \mu_r\left(y_{rj_0 b} - y_{rj_0 a}\right)$$

subject to (5.2)

$$\sum_{i\in C_I} v_i x_{ij_0} = 1$$

$$\sum_{r\in C_R} u_r y_{rj_0} + \sum_{r\in F_R} u_r y_{rj_0 a} + \mu_r\left(y_{rj_0 b} - y_{rj_0 a}\right) - \sum_{i\in C_I} v_i x_{ij_0} \le 0$$

$$\sum_{r\in C_R} u_r y_{rj} + \sum_{r\in F_R} u_r y_{rjc} - \mu_r\left(y_{rjc} - y_{rjb}\right) - \sum_{i\in C_I} v_i x_{ij} \le 0,\ j = 1, 2, ..., n;\ j \ne j_0$$

$$\mu_r - u_r \le 0, \quad r \in F_R$$

$$\mu_r \ge 0, \quad r \in F_R$$

$$u_r \ge \varepsilon > 0, \quad r \in C_R, r \in F_R$$

$$v_i \ge \varepsilon > 0, \quad r \in C_I$$

5.2 Weight Restricted Fuzzy DEA Model

The ratio model allows unrestricted weighting for inputs and outputs. "This may cause a DMU to achieve a high relative score by involving in unreasonable weighting scheme and heavily weigh few favorable measures and ignore the other input and output variables" (Talluri & Yoon, 2000). Therefore, the addition of weight restrictions has been recognized and several methods have been developed to resolve unrestricted weight flexibility in DEA (Lotfi et al., 2007).

There are many studies in the published literature concerned with restricting weight flexibility in DEA. Dyson and Thanassoulis (1988) applied regression analysis to define lower bounds for DEA weights in the single-input case using the data for rating departments. Charnes et al. (1989) developed cone ratio DEA via imposing limits on ratios of weights. Thompson et al. (1990) defined assurance region concept for efficiency analysis for Kansas farming. Wong and Beasley (1990) used proportions to restrict weight flexibility in DEA in multiple inputs and outputs case. Kornbluth (1991) applied cone restrictions in order to reduce weight flexibility in DEA analysis to evaluate firm’s performance. Pedraja-Chaparro et al. (1997) investigated how the introduction of sensible restrictions on the relative importance of each factor affects the results provided by DEA using simulated data from a well-known production process. Talluri and Yoon (2000) suggested a cone-ratio DEA to evaluate and select advanced manufacturing technology. Olesen and Petersen (2002) used DEA with probabilistic assurance regions to analyze the efficiency of Danish hospitals. Liu and Chuang (2009) presented a fuzzy DEA including the concept of assurance regions to evaluate the efficiency of university libraries in Taiwan. Wang et al. (2009) suggested a ranking methodology for DMUs that imposes an appropriate minimum weight restriction on the weights of input and output variables. Wei et al. (2011) explored of efficiency underestimation of CCR model with an application to medical centers in Taiwan. Zhou et al. (2012) developed fuzzy DEA model with assurance regions to analyze the performance of manufacturing enterprises. Dimitrov and Sutton (2013) proposed a generalized symmetric weight assignment method as a weight restriction method to include all managerial preferences.

However, it is worth noting that previously developed models in the literature just offer direct restrictions on the weights of some or all of input and output variables. Furthermore, they are not apt to constrain weight flexibility in DEA incorporating expert opinions when the evaluation model involves multiple inputs and outputs case.

In this study, a methodology that involves strategic thinking and expert opinions is employed to obtain the lower and upper limits for the inputs’ and output’s weight constraints. The weight restrictions are determined on the basis of the assurance region (AR) approach, initially suggested by Thompson et al. (1990). The stepwise representation of the proposed approach for determining the lower and upper limits for the weight constraints, which is based on Hamdan and Rogers (2008), is as follows

Step 1. Thirty experts (hospital managers, university professors) provided ratings for the input and output variables.

Step 2. A 3x30 matrix was constructed for the ratings of three input variables and a 5x30 matrix was constructed fort he ratings of five output variables.

Step 3. A 3x30 matrix was obtained for the pairwise comparisons of input variables and a 10x30 matrix was obtained for the pairwise comparisons of output variables.

Step 4. The minimum and maximum ratios of each row were calculated as the lower and upper bounds, respectively, for each comparison matrix (obtained in step 3)

Step 5. The minimum and maximum ratios are used to determine the lower and upper limits of the constraints to be added to unrestricted DEA model.

The additional weight constraints under this approach can be represented in the weight restricted DEA model:

$$c_1 \le \frac{v_i}{v_{i+1}} \le c_2$$

$$d_1 \le \frac{u_r}{u_{r+1}} \le d_2 \tag{5.3}$$

$$0 < c_1 < c_2, \text{ for } i = 1, 2, ..., m.$$

$$0 < d_1 < d_2, \text{ for r} = 1, 2, ..., s.$$

where v_i and u_r denote the weight of the *ith* input *and rth* output, respectively. In addition, c_1 and c_2 denote the lower and upper levels for the input variables. Likewise, d_1 and d_2 represent the lower and upper limits for the output variables. The schematic representation of the proposed performance evaluation methodologies are depicted in Figure 5.1.

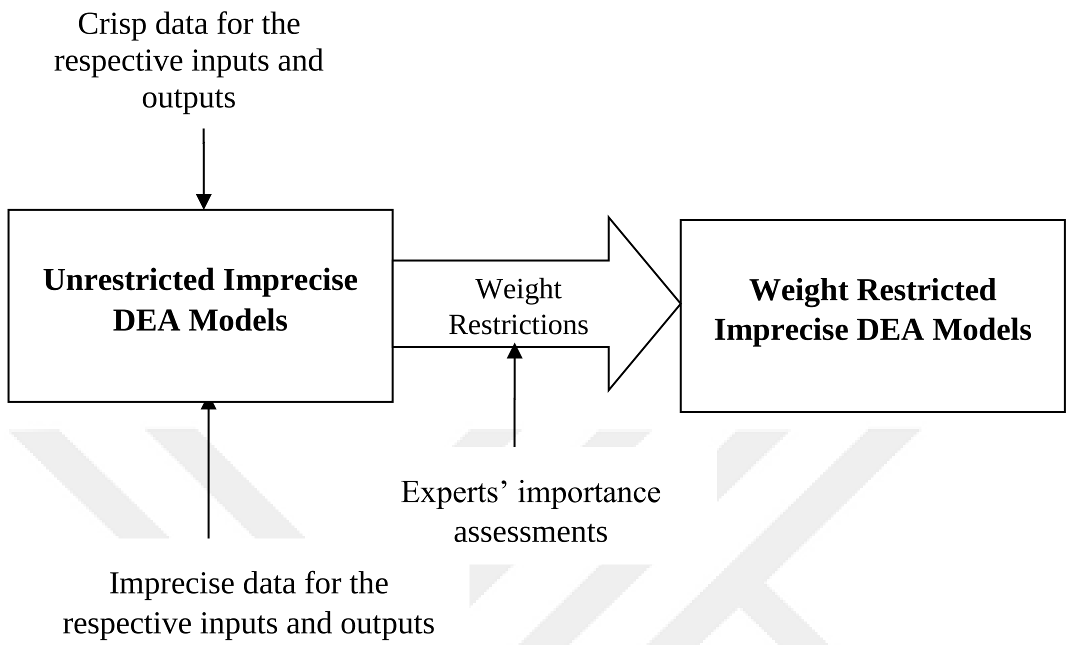

Figure 5.1: Schematic representation of the proposed methodology

6. DEA MODEL FOR CLUSTERING AND RANKING IN THE PRESENCE OF FUZZY DATA

Clustering is the task of grouping objects into set of clusters in such a way that the objects in the same cluster are more similar to each other, while the objects in different clusters are dissimilar (Zaït & Messatfa, 1997). It is a powerful technique for grouping data and showing the feature structure information of the given data set. It is a data-driven procedure for classifying data in a few classes via investigating its proximity and homogeneity in the feature space. Clustering approaches are divided into three broad categories: hierarchical clustering, learning network clustering, and distance-based clustering (Po et al., 2009). Classification of clustering approaches are depicted in Figure 6.1.

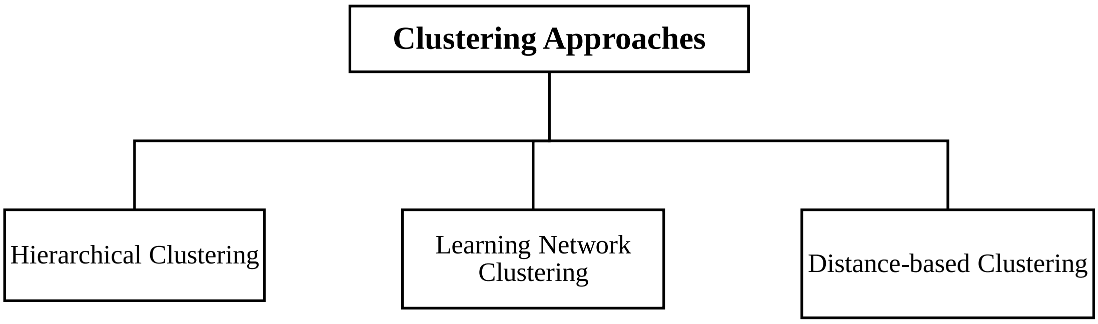

Figure 6.1: Classification of clustering approaches

Hierarchical clustering is a method of cluster analysis which seeks to build a hierarchy of clusters by generating a cluster tree or dendrogram. Sarkis and Talluri (2004) used a hierarchical clustering approach based on correlation coefficients of the columns in the cross-efficiency matrix for benchmarking of US airports. Cheng and Wu (2006) employed the Ward's method for hierarchical cluster approach to examine the Pearson correlation data of the twenty U.S. third-party logistic companies.

Flokou et al. (2011) suggested an iterative clustering approach based on correlation matrices. The suggested approach allowed to cluster all units in a hierarchical binary tree structure. Qiao et al. (2012) developed a hierarchical clustering method based on blockmodeling for web social networks. Rashedi and Mirzaei (2013) presented a hierarchical clusterer ensemble method called Bob-Hic based on the boosting theory. Nguyen et al. (2014) introduced a memory-efficient and fast hierarchical clustering approach named as SparseHC to group large data sets. Mall et al. (2015) suggested an approach to determine intervals for hierarchical clustering based on the Gershgorin circle theorem. The proposed method was implemented on real world data sets to prove its effectiveness. Learning network clustering maps high dimensional data into a discrete one or two dimensional space. It achieves clustering via a learning procedure.

Grossberg (1976) provided a classification of adult feature detector features in terms of functional properties. Lippmann (1987) analyzed six important neural network approaches that could be used for pattern recognition. Tsao et al. (1994) introduced a fuzzy Kohonen clustering network method. The proposed method was apt to combine the fuzzy c-means model into the learning rate and updating strategies of the Kohonen network. Kohonen (2000) studied self-organizing maps. Sharma and Yu (2009) used unsupervised clustering tool self-organizing map to overcome the problem that inefficient DMU and its benchmarks may not be inherently similar for benchmarking container terminals. Du (2010) made a complete overview of learning based clustering methods and then introduced a neural network based clustering method. Lei and Ghorbani (2012) introduced improved competitive learning network and supervised improved competitive learning network clustering algorithms in order to detect fraud and network intrusion. Mansur and Yusof (2013) applied significant learning attributes to the ontology clustering technique in order to classify students’ behavior.

Most distance-based clustering methods are mechanisms that minimize total dissimilarity or maximize total similarity by moving objects from one cluster to another. In the published literature, Groenen and Jajuga (2001) suggested a fuzzy clustering algorithm utilizing squared Minkowski distance which included squared and unsquared Euclidean distances and the L_1 distance. Wu and Yang (2002) suggested a new approach that changes Euclidean norm in c-means clustering algorithms and generated two new clustering methods called as the alternative hard c-means and alternative fuzzy c-means clustering techniques. Wallace et al. (2004) implemented k-means cluster analysis for understanding software project risk.

De A.T. de Carvalho et al. (2006) proposed fuzzy clustering approaches based on adaptive quadratic distances. Azadeh et al. (2007) employed fuzzy c-means method for increasing DMU's homogeneousness. Marroquin et al. (2008) compared the k-means and clustering artificial neural network techniques in a multiple criteria optimization problem. Samoilenko and Osei-Bryson (2008) implemented a two step procedure that involved application of k-means to determine groups of DMUs based on their structural similarity according to the levels of the input and output variables that DMUs produced. Chang et al. (2009) employed a new clustering procedure based on genetic algorithm using gene rearrangement.

Chitta and Murty (2010) proposed a variant of k-means method and proved that it was more efficient than standard k-means algorithms. Patra et al. (2011) introduced a distance-based clustering approach that is a hybrid scheme with a combination of leaders and single link techniques. Ji et al. [66] proposed a weighted image patch-based fuzzy c-means approach for image segmentation process. Taherdangkoo and Bagheri (2013) presented a hybrid clustering approach based on modified stem cells optimization algorithm and fuzzy c-means algorithm. More recently, Adhau et al. (2014) applied k-means clustering approach to examine the availability of micro hydro power in India.

In this study, a cluster analysis is employed to group districts into homogenous categories to detect subgroups of districts operating under similar operating circumstances. To rank DMUs inter-cluster and intra-cluster simultaneously, for each DMU the lower level of input variables and upper level of output variables are benchmarked via the inner part efficiency frontier. If the best part of DMU goes out of this part of frontier, then an efficiency score more than one will assign to it. In this study, DMUs are ranked based on the ranking approach suggested by Saati et al. (2002) in the imprecise environment as follows:

$$\min Z = \theta$$

subject to

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

$$\alpha y_{rp}^{m} + (1-\alpha)\, y_{rp}^{u} \leq \sum_{j=1}^{n} \lambda_j \left(\alpha y_{rj}^{m} + (1-\alpha)\, y_{rj}^{l}\right) \quad \forall r, \tag{6.1}$$

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

where n denotes number of DMUs. Each DMU consumes m different inputs to generate s different outputs. DMU_j consumes amounts x_{ij} $(i=1,...,m)$ amount of inputs and generates amounts y_{rj} $(r=1,...,s)$ amount of outputs. In the model, x_{ip} $(i=1,...,m)$ and y_{rp} $(r=1,...,s)$ represent the nonnegative crisp vectors of inputs and outputs for DMU_p, respectively.

The model ranks efficient DMUs in a fuzzy environment utilizing the concept of α-cut and provides a solution for different α-values. The α-cut approach is generally employed for incorporating the decision makers' confidence level. In addition, high α-value means lower degree of uncertainty, whereas low α-value means higher degree of uncertainty in decision making process (Saati et al., 2013).

After implementing model (6.1) in order to form clusters, DMUs whose efficiency scores greater than or equal to one are placed in the first cluster. In addition, the DMUs placed in the first cluster can be ranked within the cluster according to their θ values obtained from model (6.1). The DMU with the greater objective function value has priority over the remaining DMUs in the related cluster. Then, the DMUs that are assigned in the previous step are omitted and the model is resolved for the remaining DMUs. Consequently, the DMUs whose efficiency scores are greater than or equal to one are assigned to second cluster. In the same way, the assigned DMUs in the preceding step are omitted and the same procedure is employed until a single DMU remains. The representation of the DEA-based clustering approach is as follows (Saati et al., 2013).

Step 1. Consider a set of DMUs $\left(J = \{1, 2, ..., \text{n}\}\right)$,

Step 2. Set the cluster number as $k = 0$,

Step 3. Set $M = \emptyset$ as an index of clustered DMUs,

Step 4. Set $k = k + 1$,

Step 5. Use model (6.1) for the DMUs which consists of the J,

Step 6. Assign the DMUs to the k^{th} cluster (The DMUs whose objective function values (obtained in step 5) are greater than or equal to one),

Step 7. Rank the DMUs obtained from step 6 according to their objective function values,

Step 8. Add the index of the DMUs in the k^{th} cluster to the set of M,

Step 9. Set $J = J - M$,

Step 10. Stop the algorithm if $J = \emptyset$; otherwise, return to step 4.

The efficient DMUs will be ranked within and between clusters in the proposed model after conducting efficiency calculations and ranking of DMUs. We also find out the number of clusters required after applying the proposed DEA-based clustering approach.

In order to check its, robustness, the results of the applied methodology for efficiency analysis and ranking of DMUs are compared with the results obtained by Kao and Liu (2000).

Kao and Liu proposed an α–cut approach to convert a fuzzy DEA model to a number of crisp DEA models. In their proposed method, the efficiency scores of DMUs are defined by membership functions and efficiency values can be at different possibility levels.

By employing the α–cut technique, the range of a DMU's efficiency values at different possibility levels can be obtained. More information can be gathered as a result of using membership functions.

A fuzzy CCR model formulation of Kao and Liu's model is obtained as follows for lower and upper efficiency values for each α :

$$\left(E_{j_0}\right)_\alpha^L = \max \sum_{r=1}^{s} u_r \left(Y_{rj_0}\right)_\alpha^L$$

subject to

$$\sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^U = 1$$

$$\sum_{r=1}^{s} u_r \left(y_{rj_0}\right)_\alpha^L - \sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^U \leq 0$$

$$\sum_{r=1}^{s} u_r \left(y_{rj}\right)_\alpha^U - \sum_{i=1}^{m} v_i \left(x_{ij}\right)_\alpha^L \leq 0,\ j = 1, 2, \dots, n;\ j \neq j_0$$

$$u_r,\ \mathrm{v}_i \geq \varepsilon > 0,\ r = 1, \dots, s\ ;\ i = 1, \dots, m.$$

$$\left(E_{j_0}\right)_\alpha^U = \max \sum_{r=1}^{s} u_r \left(Y_{rj_0}\right)_\alpha^U$$

subject to

$$\sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^L = 1$$

$$\sum_{r=1}^{s} u_r \left(y_{rj_0}\right)_\alpha^U - \sum_{i=1}^{m} v_i \left(x_{ij_0}\right)_\alpha^L \leq 0$$

$$\sum_{r=1}^{s} u_r \left(y_{rj}\right)_\alpha^L - \sum_{i=1}^{m} v_i \left(x_{ij}\right)_\alpha^U \leq 0,\ j = 1, 2, ..., n;\ j \neq j_0$$

$$u_r,\ \mathrm{v}_i \geq \varepsilon > 0,\ r = 1, ..., s\ ;\ i = 1, ..., m.$$

where E_{j_0} denotes the efficiency value of the target DMU $\left(j_0\right)$, u_r is the weight of output r, v_i weight of input i, y_{rj} represents the output r produced by the jth DMU, x_{ij} represents input i consumed by the jth DMU, and ε is an infinitesimal positive number.

After obtaining lower and upper limits of the α–cuts of the efficiency measures of the weight restricted DEA model, the districts can be ranked by Chen and Klein's (1997) ranking procedure, which is given as follows:

Let $\tilde{X}_1, \tilde{X}_2, ..., \tilde{X}_i, ..., \tilde{X}_m$ be m arbitrary bounded fuzzy numbers, and h denotes the maximum height of $\mu_{\tilde{X}_i}$, i=1,2,...,m. Assume h is equally divided into s intervals such as $\alpha_p = ph / s, p = 0, 1, 2, ..., s.$ Chen and Klein (1997) formulated the following index in order to rank fuzzy numbers.

$$I_i = \sum_{p=0}^{s}\left(\left(X_i\right)_{\alpha p}^{U} - c\right) / \left(\sum_{p=0}^{s}\left(\left(X_i\right)_{\alpha p}^{U} - c\right) - \sum_{p=0}^{s}\left(\left(X_i\right)_{\alpha p}^{L} - d\right)\right), \ \mathrm{n} \to \infty \qquad (6.3)$$

where $c = \min_{p,i}\left\{\left(X_{ip}\right)_{\alpha p}^{L}\right\}$ and $d = \max_{p,i}\left\{\left(X_{ip}\right)_{\alpha p}^{U}\right\}$. The larger ranking index I_i means fuzzy number is more preferred.

7. CASE STUDY

“Efficiency analysis has never been a simple push-button technology. Within a performance assessment, various interactions can intricate the analysis. Indeed, changing the modelling techniques or the input or output variables might result in significantly different efficiency scores” (Emrouznejad & De Witte, 2010). In health care, performance indicators are progressively employed to analyze efficiency and quality (Van deer Geer et al., 2009). There are no standard measures for evaluating performance in health care field. Hence, each provider, should identify the performance of health care according to his/her aims, interests and interpretations (Li & Benton, 1996).

In this study, “number of beds”, “number of overall staff” and “operating expenses” are used as input variables whereas “number of outpatients”, “number of discharged patients”, “number of surgeries”, “tangibility” and “responsiveness” are used as output variables in order to evaluate relative efficiency of 26 districts in Istanbul. The output variables are almost entirely measures of patient care, that is, the numbers of outpatients, discharged patients and adjusted surgeries. There is no available diagnostic related groupings index in Turkey. Hence, output variables can not weighted on a diagnostic related grouping basis. Moreover, surgical interventions are categorized as “minor”, “medium” and “major” based on an earlier study since they consume different amounts of resources (Sağlık Kurumları Girişimsel İşlem Puan Listesi, 2013). The weights 1, 1/3 and 1/7 are employed, respectively, to covert major, medium and minor surgeries into a major surgery equivalent (Sahin et al., 2011). Detailed definition and explanation of study variables are presented in Table 7.1

Table 7.1: Definition and explanation of inputs and outputs

Variable	Description
Inputs	
Beds (v_1)	The total number of fully staffed hospital beds.
Overall staff (v_2)	The total number of clinical and non-clinical staff.
Operating expenses (v_3)	The amount of operational expenses measured in TL excluding capital and depreciation.
Outputs	
Outpatients (u_1)	The total number of visits to outpatient departments and emergency departments.
Discharged patients (u_2)	The total number of discharged patients within a year.
Surgeries (u_3)	The total number of adjusted surgical interventions undertaken.
Tangibility (u_4)	Health care facility physical characteristics.
Responsiveness (u_5)	Staff responsiveness to patients' needs

The data was gathered from Health Directorate of Istanbul for the year 2010. Descriptive statistics of hospital variables for each district for the year 2010 are given in Table 7.2.

Table 7.2: Descriptive statistics of inputs and outputs variables for each district (*N=26*)

Variables	**Mean**	**SD**	**Median**	**Min**	**Max**
Inputs					
Beds	550	684	302	39	2571
Overall staff	1363	1531	621	149	4667
Operating expenses	64585781	72849968	30189763	5137993	228401909
Outputs					
Outpatients	155693	1306699	1052498	292107	5075266
Discharged patients	27235	33023	12019	1859	127275
Adjusted surgeries	7545	9001	3745	459	32544

Patient expectations and satisfaction are so important since they can affect both patient health status and medical outcome (Ramsaran-Fowdar, 2008). Hence, it is crucial to understand inpatients' evaluations of their hospital service quality performance in order to enhance service quality in a hospital (Arasli et al., 2008).

In the literature, most widely used five service quality dimensions are, namely "tangibility", "reliability", "responsiveness", "assurance" and "empathy" (Parasuruman et al., 1988). Hence, in this study perceived service quality is measured due to physical characteristics of the hospital, reliability of the provided health care, staff responsiveness to patients' needs, patients' confidence in medical staffs' clinical competence, and medical staff empathy for patients (Bakar et al., 2008).

A questionnaire is prepared within the context of measuring perceived service quality in the hospital. A protocol is signed with Health Directorate of Istanbul for the purpose of having the permission to conduct the questionnaire. Sample 26 state hospitals from each district is selected. 100 randomly picked patients who receive treatment as inpatients or outpatients from each state hospital are used as participants.

Participants used the linguistic variables "very poor" (VP), "poor" (P), "moderate" (M), "good" (G) and "very good" (VG), which are depicted in Figure 7.1 to answer the respective questions. Prepared survey is presented in Appendix A and the averages for survey results are shown in Table 7.3.

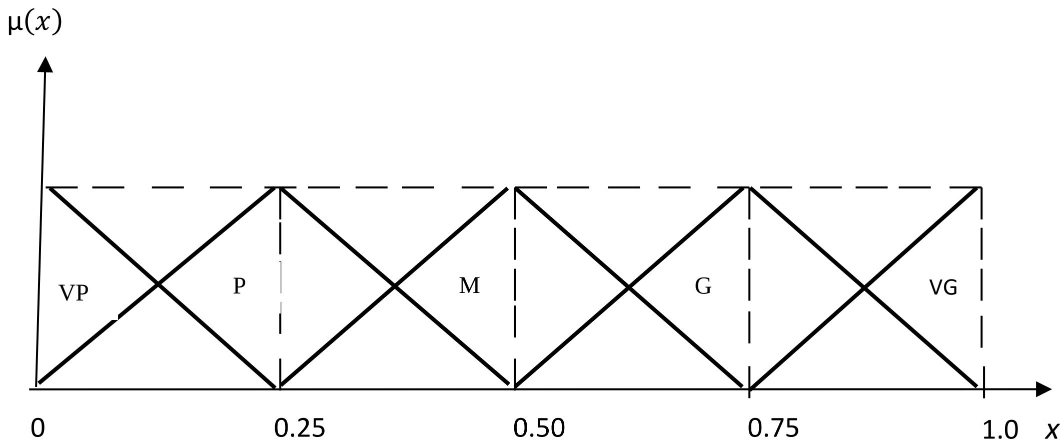

Figure 7.1: A linguistic term set where VP = (0, 0, 0.25), P = (0, 0.25, 0.5), M = (0.25, 0.5, 0.75), G = (0.5, 0.75, 1), VG = (0.75, 1, 1)

Table 7.3: Survey results

District	Tangibility	Reliability	Responsiveness	Assurance	Empathy
Atasehir	(0.356, 0.606, 0.851)	(0.417, 0.664, 0.886)	(0.263, 0.495, 0.735)	(0.379, 0.616, 0.848)	(0.379, 0.614,
Bagcilar	(0.404, 0.654, 0.904)	(0.477, 0.727, 0.962)	(0.283, 0.533, 0.783)	(0.460, 0.710, 0.942)	(0.419, 0.669,
Bakirkoy	(0.364, 0.614, 0.864)	(0.482, 0.732, 0.952)	(0.280, 0.528, 0.778)	(0.503, 0.753, 0.947)	(0.500, 0.750,
Basaksehir	(0.510, 0.758, 0.947)	(0.500, 0.747, 0.957)	(0.369, 0.614, 0.846)	(0.495, 0.740, 0.934)	(0.452, 0.689,
Bayrampasa	(0.412, 0.654, 0.871)	(0.460, 0.702, 0.911)	(0.409, 0.642, 0.858)	(0.477, 0.704, 0.910)	(0.444, 0.692,
Beyoglu	(0.379, 0.629, 0.879)	(0.503, 0.753, 0.972)	(0.343, 0.593, 0.843)	(0.505, 0.755, 0.957)	(0.503, 0.753,
Buyukcekmece	(0.513, 0.763, 0.942)	(0.566, 0.813, 0.965)	(0.462, 0.694, 0.908)	(0.578, 0.828, 0.977)	(0.598, 0.846,
Catalca	(0.364, 0.598, 0.841)	(0.487, 0.732, 0.939)	(0.348, 0.586, 0.826)	(0.525, 0.765, 0.942)	(0.520, 0.765,
Esenyurt	(0.515, 0.765, 0.949)	(0.563, 0.813, 0.967)	(0.487, 0.735, 0.919)	(0.631, 0.881, 0.992)	(0.646, 0.880,
Eyup	(0.601, 0.851, 0.982)	(0.598, 0.848, 0.995)	(0.548, 0.798, 0.985)	(0.611, 0.861, 0.985)	(0.652, 0.902,
Fatih	(0.424, 0.658, 0.908)	(0.515, 0.765, 0.977)	(0.293, 0.530, 0.780)	(0.520, 0.770, 0.965)	(0.500, 0.750,
Kadikoy	(0.326, 0.563, 0.801)	(0.394, 0.628, 0.867)	(0.255, 0.472, 0.722)	(0.346, 0.566, 0.801)	(0.351, 0.531,
Kagithane	(0.432, 0.682, 0.919)	(0.515, 0.765, 0.967)	(0.359, 0.609, 0.859)	(0.535, 0.785, 0.960)	(0.508, 0.758,
Kartal	(0.596, 0.846, 0.987)	(0.606, 0.856, 0.982)	(0.581, 0.828, 0.967)	(0.621, 0.871, 0.982)	(0.662, 0.909,
Kucukcekmece	(0.606, 0.856, 0.992)	(0.626, 0.876, 0.992)	(0.505, 0.755, 0.939)	(0.596, 0.846, 0.967)	(0.634, 0.884,
Maltepe	(0.422, 0.669, 0.874)	(0.583, 0.833, 0.992)	(0.535, 0.785, 0.960)	(0.621, 0.871, 0.985)	(0.631, 0.881,
Pendik	(0.376, 0.626, 0.869)	(0.500, 0.750, 0.957)	(0.354, 0.601, 0.841)	(0.503, 0.753, 0.942)	(0.495, 0.742,
Sariyer	(0.472, 0.722, 0.952)	(0.538, 0.788, 0.977)	(0.341, 0.588, 0.826)	(0.573, 0.823, 0.972)	(0.528, 0.773,
Silivri	(0.601, 0.851, 0.980)	(0.614, 0.864, 0.980)	(0.566, 0.816, 0.980)	(0.604, 0.848, 0.975)	(0.639, 0.889,
Sultanbeyli	(0.326, 0.576, 0.826)	(0.475, 0.725, 0.949)	(0.253, 0.500, 0.750)	(0.427, 0.677, 0.899)	(0.399, 0.646,
Sultangazi	(0.376, 0.626, 0.876)	(0.510, 0.760, 0.970)	(0.285, 0.535, 0.785)	(0.460, 0.710, 0.934)	(0.460, 0.710,
Sisli	(0.338, 0.578, 0.816)	(0.462, 0.712, 0.932)	(0.326, 0.553, 0.788)	(0.505, 0.753, 0.937)	(0.485, 0.735,
Tuzla	(0.530, 0.780, 0.975)	(0.578, 0.828, 0.995)	(0.457, 0.707, 0.907)	(0.566, 0.816, 0.987)	(0.553, 0.803,
Umraniye	(0.586, 0.831, 0.970)	(0.533, 0.783, 0.972)	(0.472, 0.717, 0.924)	(0.533, 0.783, 0.982)	(0.629, 0.879,
Uskudar	(0.263, 0.490, 0.735)	(0.452, 0.679, 0.888)	(0.263, 0.492, 0.722)	(0.432, 0.667, 0.861)	(0.434, 0.656,
Zeytinburnu	(0.462, 0.694, 0.871)	(0.654, 0.904, 0.987)	(0.551, 0.798, 0.960)	(0.576, 0.821, 0.960)	(0.669, 0.919,

Results of the survey are defuzzified employing Best Non-fuzzy Performance (BNP) method for practical use, and defuzzified values are used to rank the quality of service criteria. The BNP value of the triangular fuzzy number $\tilde{R}_j$ can be computed using Eq.(7.1):

$$BNP_j = \left[\left(UR_j - LR_j\right) + \left(MR_j - LR_j\right)\right] \big/ 3 + LR_j, \forall j \tag{7.1}$$

Aggregated values are provided in Table 7.4. Shannon's entropy method is employed (Shannon, 1948) to obtain the degree of importance of quality of service criteria. It is applied to evaluate the quantity of useful information provided by the survey data. In this manner, we determine the weight of each quality service criterion. After standardization of criteria, the standardized criterion matrix is $R' = \left[r_{ij} \right]_{m \times n}$ where m denotes the number of districts and n indicates the number of quality service criteria. The entropy of the jth criterion can be computed as

$$H_j = -\frac{\sum_{i=1}^{m} f_{ij} \ln f_{ij}}{\ln m}, \left(i = 1, \ldots, m;\ j = 1, \ldots, n \right) \tag{7.2}$$

where

$$f_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}, \left(i = 1, \ldots, m;\ j = 1, \ldots, n \right) \tag{7.3}$$

Entropy weight of the jth criterion is determined using Eq.(7.4):

$$w_j = \frac{1 - H_j}{n - \sum_{j=1}^{n} H_j}, \sum_{j=1}^{n} w_j = 1, \left(j = 1, \ldots, n \right) \tag{7.4}$$

The smaller the value of the entropy corresponds to a larger criterion weight. Criterion with larger entropy-based weight provides more information and becomes more important in the decision making process (Wu *et al.*, 2011).

Table 7.4: Aggregated triangular fuzzy numbers

District	Tangibility	Reliability	Responsiveness	Assurance	Empathy
Atasehir	0.604	0.656	0.497	0.614	0.609
Bagcilar	0.654	0.722	0.533	0.704	0.668
Bakirkoy	0.614	0.722	0.529	0.734	0.729
Basaksehir	0.738	0.735	0.609	0.723	0.675
Bayrampasa	0.646	0.691	0.636	0.697	0.671
Beyoglu	0.629	0.742	0.593	0.739	0.735
Buyukcekmece	0.739	0.781	0.688	0.795	0.807
Catalca	0.601	0.720	0.587	0.744	0.751
Esenyurt	0.743	0.781	0.714	0.835	0.837
Eyup	0.811	0.814	0.777	0.819	0.848
Fatih	0.664	0.753	0.535	0.752	0.734
Kadikoy	0.563	0.630	0.483	0.571	0.551
Kagithane	0.678	0.749	0.609	0.760	0.742
Kartal	0.810	0.815	0.792	0.825	0.852
Kucukcekmece	0.818	0.832	0.733	0.803	0.836
Maltepe	0.655	0.803	0.760	0.826	0.831
Pendik	0.624	0.736	0.598	0.732	0.725
Sariyer	0.715	0.768	0.585	0.790	0.752
Silivri	0.811	0.819	0.787	0.809	0.838
Sultanbeyli	0.576	0.716	0.501	0.668	0.642
Sultangazi	0.626	0.747	0.535	0.701	0.701
Sisli	0.577	0.702	0.556	0.731	0.717
Tuzla	0.762	0.801	0.690	0.790	0.777
Umraniye	0.795	0.763	0.705	0.766	0.832
Uskudar	0.496	0.673	0.492	0.653	0.642
Zeytinburnu	0.676	0.848	0.769	0.785	0.859

The criteria weights are 0.377 for responsiveness, 0.245 for tangibility, 0.184 for empathy, 0.117 for assurance and 0.077 for reliability. Results reveal that "Responsiveness" and "Tangibility" are the most distinguished dimensions for perceived service quality. Thus, they are considered as qualitative output variables in the proposed model due to their information content.

Generally, CRS model is employed in order to analyze hospital efficiencies. "The reason for applying the CRS model for examining the hospital efficiencies is to analyze the input-output correspondence in the absence of any scale or congestion effects" (Weng *et al*., 2009). Moreover, CRS model has greater discriminative power than VRS model since it can identify higher levels of inefficiency (Zelenyuk and Zelenyuk, 2015). Thus, CRS assumption is employed in this stuy.

The proposed DEA methodology presented in Section 5.1, which can handle qualitative and quantitative data, is employed. "The maximization of the discrimination among consecutive rank positions and the minimum importance attached to performance attributes can also be ensured by maximizing ε subject to the constraint set of the respective DEA formulation for j = 1, …, n, and after that by defining $\varepsilon_{\max} = \min_j \left(\varepsilon_j\right)$" (Sarkis & Talluri, 1999). The ε_{max} is the smallest feasible weight restriction value to ensure the best overall discrimination among the efficiency scores for all units. ε_{max} is computed as 0.0363 and 0.0242 for the optimistic scenario and pessimistic scenario, respectively.

Table 7.5 presents the efficiency scores for the optimistic and pessimistic scenarios, respectively. The results reveal that 14 districts are efficient according to the optimistic scenario and only 10 districts are efficient regarding to the pessimistic scenario. The discriminating power of DEA increases with the pessimistic scenario.

Table 7.5: Eficiency scores of districts-Unrestricted model

District	Optimistic Scenario Efficiency Score	Pessimistic Scenario Efficiency Score
Atasehir	1.000	0.903
Bagcilar	1.000	1.000
Bakirkoy	0.282	0.232
Basaksehir	1.000	1.000
Bayrampasa	1.000	1.000
Beyoglu	0.997	0.941
Buyukcekmece	1.000	1.000
Catalca	1.000	1.000
Esenyurt	1.000	0.889
Eyup	0.984	0.795
Fatih	0.606	0.598
Kadikoy	0.612	0.572
Kagithane	1.000	1.000
Kartal	0.209	0.116
Kucukcekmece	0.578	0.413
Maltepe	0.721	0.635
Pendik	1.000	1.000
Sarıyer	0.780	0.661
Silivri	1.000	0.812
Sultanbeyli	1.000	1.000
Sultangazi	1.000	0.996
Sisli	0.151	0.089
Tuzla	1.000	1.000
Umraniye	0.886	0.782
Uskudar	0.252	0.148
Zeytinburnu	1.000	1.000

Then, additional constraints for the weight restricted fuzzy DEA model were derived. A committee of thirty decision-makers, which consists of hospital managers and university professors provide their expert opinions for all input and output variables in the proposed model. Each expert rated each input and output using a scale from 1 to 9, with 1 being the least important and 9 being the most important. Prepared survey in order to collect data to determine the lower and upper limits for the constraints added to the unrestricted DEA model is given in Appendix B.

Table 7.6: Importance ratings of inputs and outputs

	Inputs			Outputs				
Decision Makers	v_1	v_2	v_3	u_1	u_2	u_3	u_4	u_5
1	4	6	8	8	7	7	7	8
2	4	7	8	6	6	6	7	8
3	5	6	7	5	5	5	6	7
4	5	6	7	8	7	7	7	8
5	4	5	6	8	7	7	7	8
6	4	5	5	8	7	8	8	9
7	5	7	8	6	5	6	8	9
8	5	6	7	5	5	6	7	8
9	4	5	6	6	6	6	6	7
10	4	5	5	5	5	6	7	8
11	6	7	9	8	7	7	7	8
12	4	6	7	7	7	5	7	8
13	7	5	6	5	6	7	6	9
14	4	6	8	5	5	7	9	7
15	5	7	9	5	3	9	7	9
16	5	6	7	5	5	5	6	7
17	5	7	8	8	7	8	8	9
18	5	6	7	9	7	5	8	9
19	6	5	7	3	5	5	5	7
20	4	5	6	7	9	7	6	9
21	7	6	6	7	8	8	7	8
22	5	7	9	6	4	6	6	8
23	5	6	7	8	7	7	7	8
24	4	5	7	6	6	6	7	8
25	4	6	8	5	5	7	8	9
26	5	7	9	8	6	6	8	9
27	5	6	7	8	7	7	7	8
28	6	5	7	7	7	6	8	9
29	7	7	9	7	6	7	7	8
30	7	6	7	6	6	6	7	8

Then, the following set of constraints (7.5)-(7.17) is added to the unrestricted DEA model using model (5.3):

$$0.571 \le \frac{v_1}{v_2} \le 1.400 \tag{7.5}$$

$$0.500 \le \frac{v_1}{v_3} \le 1.167 \tag{7.6}$$

$$0.714 \leq \frac{v_2}{v_3} \leq 1.000 \tag{7.7}$$

$$0.600 \leq \frac{u_1}{u_2} \leq 1.667 \tag{7.8}$$

$$0.556 \leq \frac{u_1}{u_3} \leq 1.800 \tag{7.9}$$

$$0.556 \leq \frac{u_1}{u_4} \leq 1.167 \tag{7.10}$$

$$0.429 \leq \frac{u_1}{u_5} \leq 1.000 \tag{7.11}$$

$$0.333 \leq \frac{u_2}{u_3} \leq 1.400 \tag{7.12}$$

$$0.429 \leq \frac{u_2}{u_4} \leq 1.500 \tag{7.13}$$

$$0.333 \leq \frac{u_2}{u_5} \leq 1.000 \tag{7.14}$$

$$0.625 \leq \frac{u_3}{u_4} \leq 1.286 \tag{7.15}$$

$$0.556 \leq \frac{u_3}{u_5} \leq 1.000 \tag{7.16}$$

$$0.667 \leq \frac{u_4}{u_5} \leq 1.286 \tag{7.17}$$

The weight restricted DEA model generates lower efficiency values and fewer number of efficient DMUs than the unrestricted DEA model. The optimistic and pessimistic scenario efficiency values of the restricted model for the performance evaluation of state hospitals of in 26 districts are presented in Table 7.7. It can be seen that 6 districts are efficient according to the optimistic scenario and only 1 district is efficient regarding to the pessimistic scenario. We aim to determine the best performing district in terms of health care performance. Thus, we use a weight restricted pessimistic scenario efficiency model. It can be seen that a weight restricted pessimistic scenario efficiency model increases the discriminating power of DEA and “Catalca” is determined as the best performing district in terms of health care performance in Istanbul.

Table 7.7: Efficiency scores of districts- Weight restricted model

District	Optimistic Scenario Efficiency Score	Pessimistic Scenario Efficiency Score
Atasehir	0.529	0.252
Bagcilar	0.362	0.188
Bakirkoy	0.141	0.078
Basaksehir	0.932	0.495
Bayrampasa	1.000	0.531
Beyoglu	0.336	0.177
Buyukcekmece	1.000	0.894
Catalca	1.000	1.000
Esenyurt	0.646	0.344
Eyup	0.820	0.459
Fatih	0.175	0.099
Kadikoy	0.188	0.096
Kagithane	1.000	0.855
Kartal	0.169	0.102
Kucukcekmece	0.506	0.266
Maltepe	0.272	0.140
Pendik	0.811	0.412
Sariyer	0.409	0.208
Silivri	0.816	0.443
Sultanbeyli	0.731	0.362
Sultangazi	1.000	0.802
Sisli	0.147	0.083
Tuzla	1.000	0.972
Umraniye	0.424	0.238
Uskudar	0.129	0.070
Zeytinburnu	0.405	0.218

Then, Li-test of Simar and Zelenyuk (2006) is employed in order to examine the discriminatory power of the proposed methodology in statistical sense. The distribution of unrestricted and weight restricted model efficiency scores which are given in Table 7.5 and Table 7.7, respectively, are compared. For the adapted Li-test, algorithm II of Simar and Zelenyuk (2006) is applied with 5000 bootstrap replications. Results are given in Table 7.8 where the test statistics are obtained using MATLAB code of Simar-Zelenyuk (2006).

Table 7.8: Simar-Zelenyuk adapted Li-test for equality of efficiency distributions*

H_0 (f is density)	Test Statistics	Bootstrap p-value
$f(\text{Eff}_{\text{unrestricted}})_{\text{opt}} = f(\text{Eff}_{\text{restricted}})_{\text{opt}}$	5.411	0.0048**
$f(\text{Eff}_{\text{unrestricted}})_{\text{pes}} = f(\text{Eff}_{\text{restricted}})_{\text{pes}}$	5.474	0.0072**

*We use the Gaussian density, and the bandwidth h used in the tests is computed according to Silverman (1986); B=5000.
**Statistically significant at 5% level.

It can be seen that efficiency scores obtained by unrestricted model and the proposed weight restricted model for both optimistic and pessimistic scenarios have statistically different distributions. The test yields estimated p-values of 0.0048 and 0.0072 for optimistic and pessimistic scenarios, respectively. Hence, we reject the null hypothesis of equality of the two distributions for both scenarios at the 0.05 significance level.

In addition, we compare our proposed approach with the possibility approach suggested by Lertworasirikul et al. (2003). They have suggested a possibility approach for solving fuzzy DEA models for different possibility levels. Their proposed approach has a low discriminating power due to its extremely permissive nature. It often results in many efficient DMUs at all possibility levels. Efficiency values of each district for five different possibility levels (0, 0.25, 0.5, 0.75, 1) are presented in Table 7.9.

Table 7.9: Efficiency scores of districts at 5 possibility levels by possibility approach

	Efficiency Score				
District	α=0	α=0.25	α=0.5	α=0.75	α=1
Atasehir	1.073	1.009	0.958	0.915	0.906
Bagcilar	1.060	1.038	1.022	1.010	1.000
Bakirkoy	0.987	0.987	0.987	0.987	0.987
Basaksehir	1.387	1.257	1.153	1.069	1.000
Bayrampasa	1.316	1.197	1.113	1.049	1.000
Beyoglu	1.018	0.985	0.976	0.976	0.976
Buyukcekmece	1.965	1.643	1.386	1.175	1.000
Catalca	2.370	1.878	1.511	1.227	1.000
Esenyurt	1.060	0.997	0.950	0.907	0.897
Eyup	0.990	0.898	0.827	0.808	0.808

Fatih	0.776	0.776	0.776	0.776	0.776
Kadikoy	0.628	0.628	0.628	0.628	0.628
Kagithane	2.040	1.684	1.406	1.183	1.000
Kartal	0.735	0.735	0.735	0.735	0.735
Kucukcekmece	0.583	0.522	0.479	0.444	0.416
Maltepe	0.733	0.701	0.676	0.657	0.640
Pendik	1.189	1.102	1.051	1.022	1.000
Sariyer	0.786	0.743	0.707	0.678	0.663
Silivri	1.067	0.971	0.899	0.846	0.813
Sultanbeyli	1.296	1.194	1.115	1.052	1.000
Sultangazi	1.894	1.529	1.270	1.110	0.997
Sisli	0.669	0.669	0.669	0.669	0.669
Tuzla	1.983	1.649	1.386	1.174	1.000
Umraniye	0.895	0.856	0.823	0.797	0.787
Uskudar	0.653	0.653	0.653	0.653	0.653
Zeytinburnu	1.122	1.079	1.047	1.021	1.000

As shown in Table 7.9, 10 districts, namely Bagcilar, Basaksehir, Bayrampasa, Buyukcekmece, Catalca, Kagıthane, Pendik, Sultanbeyli, Tuzla and Zeytinburnu are efficient at all possibility levels. It is clear that the proposed methodology improves discriminating power of DEA and it also enables an important saving in computations via reducing the number of linear programs to be solved.

Health Directorate of Istanbul defined five regions in order to accomplish health care management of Istanbul. The results of the weight restricted DEA model also provide useful information about relative health care performance of these regions. The average efficiency scores of optimistic and pessimistic scenarios for each region are computed by taking the average of related districts' efficiency scores.

Table 7.10: Average efficiency scores of regions.

Region	Districts	Optimistic Scenario Average Efficiency Score	Pessimistic Scenario Average Efficiency Score
North Anatolian	Atasehir Kadikoy Umraniye Uskudar	0.317	0.164
South Anatolian	Kartal Maltepe Pendik Sultanbeyli Tuzla	0.597	0.397
Beyoglu	Beyoglu Eyup Kagithane Sariyer Sisli	0.543	0.356
Fatih	Bayrampasa Fatih Sultangazi Zeytinburnu	0.645	0.412
Bakirkoy	Bagcilar Bakirkoy Basaksehir Buyukcekmece Catalca Esenyurt Kucukcekmece Silivri	0.675	0.464

The results that are provided in Table 7.10 reveal that "Bakirkoy" ranks as the best region in terms of health care performance in Istanbul. Regions' average efficiency scores are relatively close to each other for both scenarios except for the poorest performing North Anatolian region with the average efficiency scores of 0.317 and 0.164 for optimistic and pessimistic scenarios, respectively.

Then for the second part of the study, fuzzy DEA-based methodology given in Section 6, which enables ranking of DMUs between inter-clusters and intra-clusters is implemented. The ranks and obtained clusters are given in Table 7.11 and Table 7.12, respectively.

Table 7.11: The ranks by Saati et al.'s model

District	α=0	α=0.25	α=0.5	α=0.75	α=1
Atasehir	1.073	1.009	0.958	0.915	0.906
Bagcilar	1.060	1.038	1.022	1.010	1.000
Bakirkoy	0.987	0.987	0.987	0.987	0.987
Basaksehir	1.387	1.257	1.153	1.069	1.000
Bayrampasa	1.316	1.197	1.113	1.049	1.000
Beyoglu	1.018	0.985	0.976	0.976	0.976
Buyukcekmece	1.965	1.643	1.386	1.175	1.000
Catalca	2.370	1.878	1.511	1.227	1.000
Esenyurt	1.060	0.997	0.950	0.907	0.897
Eyup	0.990	0.898	0.827	0.808	0.808
Fatih	0.776	0.776	0.776	0.776	0.776
Kadikoy	0.628	0.628	0.628	0.628	0.628
Kagithane	2.040	1.684	1.406	1.183	1.000
Kartal	0.735	0.735	0.735	0.735	0.735
Kucukcekmece	0.583	0.526	0.479	0.444	0.416
Maltepe	0.733	0.701	0.676	0.657	0.640
Pendik	1.189	1.102	1.051	1.022	1.000
Sariyer	0.786	0.743	0.707	0.678	0.663
Silivri	1.067	0.971	0.899	0.846	0.813
Sultanbeyli	1.296	1.194	1.115	1.052	1.000
Sultangazi	1.894	1.529	1.270	1.110	0.997
Sisli	0.669	0.669	0.669	0.669	0.669
Tuzla	1.983	1.649	1.386	1.174	1.000
Umraniye	0.895	0.856	0.823	0.797	0.787
Uskudar	0.653	0.653	0.653	0.653	0.653
Zeytinburnu	1.122	1.079	1.047	1.021	1.000

Table 7.12: Clusters obtained for varying α values

α=0	α=0.25	α=0.5	α=0.75	α=1
Cluster 1	Cluster 1	Cluster 1	Cluster 1	Cluster 1
Catalca	Catalca	Catalca	Catalca	Bagcilar
Kagithane	Kagithane	Kagithane	Kagithane	Basaksehir
Tuzla	Tuzla	Tuzla	Buyukcekmece	Bayrampasa
Buyukcekmece	Buyukcekmece	Buyukcekmece	Tuzla	Buyukcemece
Sultangazi	Sultangazi	Sultangazi	Sultangazi	Catalca
Basaksehir	Basaksehir	Basaksehir	Basaksehir	Kagithane
Bayrampasa	Bayrampasa	Sultanbeyli	Sultanbeyli	Pendik
Sultanbeyli	Sultanbeyli	Bayrampasa	Bayrampasa	Sultanbeyli
Pendik	Pendik	Pendik	Pendik	Tuzla
Zeytinburnu	Zeytinburnu	Zeytinburnu	Zeytinburnu	Zeytinburnu
Atasehir	Bagcilar	Bagcilar	Bagcilar	Cluster 2
Silivri	Atasehir	Cluster 2	Cluster 2	Atasehir
Esenyurt	Cluster 2	Eyup	Eyup	Bakirkoy
Bagcilar	Eyup	Silivri	Silivri	Beyoglu
Beyoglu	Silivri	Atasehir	Atasehir	Esenyurt
Cluster 2	Esenyurt	Esenyurt	Esenyurt	Eyup
Eyup	Beyoglu	Beyoglu	Beyoglu	Silivri
Kucukcekmece	Umraniye	Umraniye	Umraniye	Sultangazi
Ümraniye	Sarıyer	Bakirkoy	Bakirkoy	Umraniye
Sarıyer	Bakirkoy	Cluster 3	Cluster 3	Cluster 3
Fatih	Kartal	Kucukcekmece	Kucukcekmece	Fatih
Bakirkoy	Cluster 3	Sarıyer	Sarıyer	Kadikoy
Maltepe	Kucukcekmece	Maltepe	Maltepe	Kartal
Kartal	Maltepe	Fatih	Fatih	Kucukcekmece
Cluster 3	Fatih	Kadikoy	Kadikoy	Maltepe
Kadikoy	Kadikoy	Uskudar	Uskudar	Sarıyer
Sisli	Uskudar	Kartal	Kartal	Sisli
Uskudar	Sisli	Sisli	Sisli	Uskudar

As shown in the Table 7.12 districts are grouped into three clusters with respect to $\alpha = \{0, 0.25, 0.5, 0.75, 1\}$. The priority of the districts within each cluster is also provided in the Table 7.12. Total number of clusters determined do not change with different α–cut values here. When we increase the α–cut from 0 to 1, the number of districts in the first cluster decreases from 15 to 10. The number of districts in the second cluster is almost the same and number of districts in the third cluster increases from 3 to 8. Moreover, the districts which are identified to be in the second and the third clusters when $\alpha = 0.5$ are also selected when $\alpha = 0.75$. Then, we rank the districts according to an average ranking score computed by taking the average of the five α–cut values to determine the best performing district in Istanbul. The lower average ranking scores point out better health care performance of districts. The obtained results are given in Table 7.13.

Table 7.13: The final ranking of districts

District	Sum of the ranking scores	Average ranking score	Final ranking
Atasehir	62	12.4	12
Bagcilar	48	9.6	10
Bakirkoy	88	17.6	18
Basaksehir	26	5.2	6
Bayrampasa	33	6.6	7
Beyoglu	76	15.2	16
Buyukcekmece	19	3.8	3
Catalca	9	1.8	1
Esenyurt	72	14.4	15
Eyup	68	13.6	13
Fatih	106	21.2	21
Kadikoy	114	22.8	23
Kagithane	14	2.8	2
Kartal	114	22.8	23
Kucukcekmece	98	19.6	19
Maltepe	109	21.8	22
Pendik	43	8.6	9
Sariyer	101	20.2	20
Silivri	68	13.6	14
Sultanbeyli	38	7.6	8
Sultangazi	25	5	5
Sisli	128	25.6	26
Tuzla	22	4.4	4
Umraniye	87	17.4	17
Uskudar	125	25	25
Zeytinburnu	50	10	11

The results reveal that “Catalca” is determined as the best performing district and it is followed by “Kagithane”, “Buyukcekmece”, “Tuzla” and “Sultangazi”, respectively.

In the next step, in order to test the robustness of the proposed methodology, the results of the proposed decision algorithm are compared with the results obtained by Kao and Liu (2000). The upper and lower efficiency scores of districts at five α values are given in Table 7.14 and Table 7.15 for unrestricted and weight restricted models, respectively.

Table 7.14: Upper and lower efficiency values of districts at five α values (unrestricted model)

District		α=0	α=0.25	α=0.5	α=0.75	α=1
Atasehir	E^L	0.886	0.887	0.892	0.898	0.906
	E^U	1.000	1.000	0.958	0.915	0.906
Bagcilar	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Bakirkoy	E^L	0.987	0.987	0.987	0.987	0.987
	E^U	0.987	0.987	0.987	0.987	0.987
Basaksehir	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Bayrampasa	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Beyoglu	E^L	0.976	0.976	0.976	0.976	0.976
	E^U	1.000	0.985	0.976	0.976	0.976
Buyukcekmece	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Catalca	E^L	0.840	0.973	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Esenyurt	E^L	0.897	0.897	0.897	0.897	0.897
	E^U	1.000	0.997	0.950	0.907	0.897
Eyup	E^L	0.808	0.808	0.808	0.808	0.808
	E^U	0.990	0.898	0.827	0.808	0.808
Fatih	E^L	0.776	0.776	0.776	0.776	0.776
	E^U	0.776	0.776	0.776	0.776	0.776
Kadikoy	E^L	0.628	0.628	0.628	0.628	0.628
	E^U	0.628	0.628	0.628	0.628	0.628

Kagithane	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Kartal	E^L	0.735	0.735	0.735	0.735	0.735
	E^U	0.735	0.735	0.735	0.735	0.735
Kucukcekmece	E^L	0.324	0.342	0.363	0.387	0.416
	E^U	0.583	0.522	0.479	0.444	0.416
Maltepe	E^L	0.621	0.621	0.621	0.626	0.640
	E^U	0.733	0.701	0.676	0.657	0.640
Pendik	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Sariyer	E^L	0.663	0.663	0.663	0.663	0.663
	E^U	0.786	0.743	0.707	0.678	0.663
Silivri	E^L	0.723	0.735	0.756	0.782	0.813
	E^U	1.000	0.971	0.899	0.846	0.813
Sultanbeyli	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Sultangazi	E^L	0.970	0.970	0.970	0.970	0.997
	E^U	1.000	1.000	1.000	1.000	0.997
Sisli	E^L	0.669	0.669	0.669	0.669	0.669
	E^U	0.669	0.669	0.669	0.669	0.669
Tuzla	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Umraniye	E^L	0.787	0.787	0.787	0.787	0.787
	E^U	0.895	0.856	0.823	0.797	0.787
Uskudar	E^L	0.653	0.653	0.653	0.653	0.653
	E^U	0.653	0.653	0.653	0.653	0.653
Zeytinburnu	E^L	1.000	1.000	1.000	1.000	1.000
	E^U	1.000	1.000	1.000	1.000	1.000

Table 7.15: Upper and lower efficiency values of districts at five α values (weight restricted model)

District		α=0	α=0.25	α=0.5	α=0.75	α=1
Atasehir	E^L	0.125	0.150	0.179	0.212	0.252
	E^U	0.529	0.433	0.359	0.300	0.252
Bagcilar	E^L	0.107	0.123	0.141	0.162	0.188
	E^U	0.362	0.302	0.255	0.218	0.188
Bakirkoy	E^L	0.049	0.055	0.062	0.069	0.078
	E^U	0.141	0.120	0.103	0.089	0.078
Basaksehir	E^L	0.260	0.305	0.358	0.421	0.495
	E^U	0.932	0.791	0.678	0.578	0.495
Bayrampasa	E^L	0.271	0.322	0.380	0.449	0.531
	E^U	1.000	0.884	0.739	0.624	0.531
Beyoglu	E^L	0.098	0.114	0.131	0.152	0.177
	E^U	0.336	0.285	0.243	0.207	0.177
Buyukcekmece	E^L	0.455	0.540	0.639	0.755	0.894
	E^U	1.000	1.000	1.000	1.000	0.894
Catalca	E^L	0.572	0.690	0.823	0.974	1.000
	E^U	1.000	1.000	1.000	1.000	1.000
Esenyurt	E^L	0.184	0.215	0.251	0.294	0.344
	E^U	0.646	0.543	0.463	0.398	0.344
Eyup	E^L	0.248	0.289	0.337	0.392	0.459
	E^U	0.820	0.702	0.608	0.526	0.459
Fatih	E^L	0.061	0.068	0.077	0.087	0.099
	E^U	0.175	0.150	0.131	0.113	0.099
Kadikoy	E^L	0.055	0.063	0.072	0.083	0.096
	E^U	0.188	0.156	0.131	0.112	0.096
Kagithane	E^L	0.413	0.499	0.599	0.716	0.855
	E^U	1.000	1.000	1.000	1.000	0.855
Kartal	E^L	0.065	0.073	0.081	0.090	0.102
	E^U	0.169	0.147	0.129	0.114	0.102
Kucukcekmece	E^L	0.138	0.163	0.192	0.225	0.266
	E^U	0.506	0.421	0.357	0.307	0.266
Maltepe	E^L	0.073	0.086	0.101	0.119	0.140
	E^U	0.272	0.226	0.191	0.163	0.140

Pendik	E^L	0.210	0.249	0.295	0.348	0.412
	E^U	0.811	0.683	0.577	0.487	0.412
Sariyer	E^L	0.110	0.129	0.151	0.177	0.208
	E^U	0.409	0.340	0.287	0.243	0.208
Silivri	E^L	0.239	0.279	0.325	0.379	0.443
	E^U	0.816	0.685	0.586	0.507	0.443
Sultanbeyli	E^L	0.179	0.215	0.256	0.304	0.362
	E^U	0.731	0.611	0.513	0.430	0.362
Sultangazi	E^L	0.356	0.442	0.543	0.661	0.802
	E^U	1.000	1.000	1.000	0.971	0.802
Sisli	E^L	0.053	0.059	0.065	0.073	0.083
	E^U	0.147	0.125	0.108	0.094	0.083
Tuzla	E^L	0.488	0.582	0.690	0.819	0.972
	E^U	1.000	1.000	1.000	1.000	0.973
Umraniye	E^L	0.136	0.156	0.179	0.206	0.238
	E^U	0.424	0.363	0.314	0.273	0.238
Uskudar	E^L	0.043	0.049	0.055	0.062	0.070
	E^U	0.129	0.109	0.093	0.081	0.070
Zeytinburnu	E^L	0.121	0.140	0.162	0.187	0.218
	E^U	0.405	0.340	0.290	0.250	0.218

Then, the ranking index for each district is calculated using Eq. (6.3). The ranking indices are presented in Table 7.16. The results reveal that "Catalca" ranks as the best district and "Uskudar" as the poorest performing district in terms of health care performance in Istanbul with the ranking indices scores of 0.836 and 0.053, respectively.

We observe that "Catalca" ranks as the first district. It is followed by "Tuzla", "Buyukcekmece", "Kagithane" and "Sultangazi". Thus, the results obtained from two applied methodology appear to be very close. Applying both methods, we obtain that "Catalca" is the best performing district in terms of health care performance in Istanbul.

Table 7.16: Ranking index values obtained using Chen and Klein's method

District	Ranking Indices
Atasehir	0.289
Bagcilar	0.206
Bakirkoy	0.063
Basaksehir	0.508
Bayrampasa	0.539
Beyoglu	0.193
Buyukcekmece	0.732
Catalca	0.836
Esenyurt	0.370
Eyup	0.469
Fatih	0.089
Kadikoy	0.092
Kagithane	0.707
Kartal	0.088
Kucukcekmece	0.290
Maltepe	0.147
Pendik	0.441
Sariyer	0.231
Silivri	0.458
Sultanbeyli	0.397
Sultangazi	0.675
Sisli	0.068
Tuzla	0.766
Umraniye	0.255
Uskudar	0.053
Zeytinburnu	0.236

Table 7.17: Comparative ranking of districts

District	Chen-Klein's Method	α=0	α=0.25	α=0.50	α=0.75
Atasehir	14	11	12	14	14
Bagcilar	18	14	11	11	11
Bakirkoy	25	21	19	18	18
Basaksehir	7	6	6	6	6
Bayrampasa	6	7	7	8	8
Beyoglu	19	15	16	16	16
Buyukcekmece	3	4	4	4	3
Catalca	1	1	1	2	1
Esenyurt	12	13	15	15	15
Eyup	8	16	13	12	12
Fatih	22	20	23	22	22
Kadikoy	21	24	24	23	23
Kagithane	4	2	2	1	2
Kartal	23	23	20	25	25
Kucukcekmece	13	17	21	19	19
Maltepe	20	22	22	21	21
Pendik	10	9	9	9	9
Sariyer	17	19	18	20	20
Silivri	9	12	14	13	13
Sultanbeyli	11	8	8	7	7
Sultangazi	5	5	5	5	5
Sisli	24	25	26	26	26
Tuzla	2	3	3	3	4
Umraniye	15	18	17	17	17
Uskudar	26	26	25	24	24
Zeytinburnu	16	10	10	10	10

Table 7.17 summarizes the comparative analysis of the results. In order to test the relationship between the rankings, Spearman's rank correlation coefficient is applied. Spearman's correlation coefficient, r_s , is computed as 0.921 at α =0, 0.895 at α =0.25, 0.903 at α =0.50 and 0.904 at α=0.75. H_0 , null hypothesis states that there is no correlation between the rankings obtained by the proposed methodology and the approach delineated in (Kao & Liu, 2000), is rejected if $r_s > r_{s,\alpha}$ where $r_{s,\alpha}$ is the benchmark value corresponding to the upper-tail area α and the number of DMUs n . For n =26 and α=0.01, the benchmark value is 0.501. As $r_s > r_{s,\alpha}$, H_0 is rejected and therefore both approaches give similar rankings.

8. CONCLUSION

Performance evaluation plays a crucial role for the management and improvement of health care organizations Thus, a methodology for measuring performance of health care organizations has become a major concern for health policy-makers and health care managers.

This paper suggests an imprecise DEA framework for evaluating and clustering 26 districts in Istanbul according to their health care performance based on data from state hospitals. The suggested methodology enables to incorporate the quality of health care, which has been omitted in similar studies, into the analysis using linguistic variables. In this study, quality performance indicators “tangibility” and “responsiveness” are employed as qualitative outputs, and they are represented via linguistic variables to quantify the inherent imprecision in patient’s assessments in a way to enhance health care quality.

Initially, unrestricted fuzzy DEA model is proposed for evaluating health care performance of 26 districts. The results show that 14 districts are relatively efficient according to the optimistic scenario, while the number of efficient districts reduces to 10 with respect to the pessimistic scenario. Identifying an inefficient district as efficient due to an improper analysis would cause serious problems for health care policy-makers and health care managers. Weight flexibility in DEA analysis can result in assigning extremely small weights to certain input and/or output variables as effectively to exclude them from the assessment of the target DMU. “The need to strike a balance between rigidity and excessive flexibility has led to the concept of weight restrictions in DEA models” (Estellita Lins et al., 2007). Therefore, weight restrictions are used in DEA models as a means to improve discriminating power. Weight restricted fuzzy DEA models are proposed in this study to avoid unrealistic weighting schemes, and thus, conduct robust evaluations of health care performance in Istanbul. Including weight restrictions in the DEA models reduces the number of efficient districts from 14 to 6 in optimistic scenario, whereas from 10 to 1 in pessimistic scenario. The results reveal that a majority of state hospitals in Istanbul are run inefficiently. “Catalca” is the best performing district and “Bakirkoy” is the best performing region with respect to health care performance.

In the second part of the study, an imprecise DEA-based approach for clustering and ranking of 26 districts in Istanbul is presented. The applied methodology groups districts operating under similar circumstances via performing clustering. Through cluster analysis, more realistic targets for improving poorly performing districts are identified. In addition, the best performing district as well as ranking of 26 districts in terms of health care in Istanbul is determined by considering the priority among clusters and the priority among DMUs in each cluster simultaneously. The proposed methodology also enables to incorporate imprecise data using linguistic variables, and thus, includes perceived service quality of patients to improve health care service quality in state hospitals. As a result, three clusters of districts are obtained with respect to their health care performance. The results also reveal that “Catalca” is the best performing district regarding health care performance.

The contribution of this thesis to the related literature is twofold. This paper evades unrealistic weight flexibility which may distort the relative evaluation of health care performance. Furthermore, it includes the service quality dimension, which has been overlooked in earlier studies, into the performance evaluation framework. Health care policy makers and managers of health care organizations can use the results of clustering and ranking procedure proposed in this study to gain insight on differentiating operational features of 26 districts in Istanbul and also to take strategic actions such as capacity and resource management decisions.

It is worth noting that identifying a set of inputs and outputs is a challenging task on its own, and the results may vary according to the inputs and outputs selected for use throughout the analysis. For future research, extensions of the proposed methodology may be developed by calculating examining other input-output combinations and all possible DEA specifications.

Moreover, in our case, the number of inputs and outputs are reasonable compared to the number of DMUs; however, if data were available for other potential inputs and outputs to be included into the analysis, a combination of principal component analysis (PCA) and DEA could be employed (Cinca & Molinero, 2004;Wu & Wu, 2010).

REFERENCES

Adhau, S.P., Moharil, R.M., Adhau, P.G. (2014). K-means clustering technique applied to availability of micro hydro power, *Sustainable Energy Technologies and Assessments* 8: 191-201.

Ahsan, M.K., Bartema, J. (2004). Monitoring healthcare performance by analtytic hierarchy process: a developing-country perspective, *International Transactions In Operational Research* 11: 465-478.

Ancarani, A., Di Mauro,C., Giammanco, M.D. (2009). The impact of managerial and organizational aspects on hospital wards' efficiency: Evidence from a case study, *European Journal of Operational Research* 194: 280–293.

Androutsou, L., Geitona, M., Yfantopoulos, J. (2011). Measuring efficiency and productivity across hospitals in the regional health authority of Thessaly, in Greece, *Journal of Health Management* 13(2): 121–140.

Arasli, H., Ekiz, E.H., Katircioglu, S.T. (2008). Gearing service quality into public and private hospitals in small islands, *International Journal of Health Care Qualiy Assurance* 21(1): 8-23.

Audibert,M., Mathonnat, J., Pelissier, A., Huang, X.X., Ma, A. (2013). Health insurance reform and efficiency of township hospitals in rural China: An analysis from survey data, *China Economic Review* 27: 326-338.

Azadeh, A., Ghaderi,S.F., Anvari, M., Saberi, M., Izadbakhsh, H. (2007). An integrated artificial neural network and fuzzy clustering algorithm for performance assessment of decision making units, Applied Mathematics and Computation 187: 584–599.

Bakar, C., Akgün, H.S., Assaf, A.F.A. (2008). The role of expectations in patients' hospital assessments, *International Journal of Health Care Quality Assurance* 21(5): 503-516.

Bates, L.J., College, B., Mukherjee, K., Santerre, R.E. (2006). Market structure and technical efficiency in the hospital services ındustry: A DEA approach, *Medical Care Research and Review* 63(4): 499-524.

Bayraktutan, Y., Arslan, I., Bal, V. (2010). The evaluation of the effects of health information systems to the performance of hospitals by data enveloping analysis: An application in the thoracic medicine hospitals, *Gaziantep Medical Journal* 16(3): 13-18.

Bhat, R., Verma, B.B., Reuben, E. (2001). Hospital efficiency. an empirical analysis of district hospital and Grant-in-aid hospitals in Gujarat, *Journal of Health Management* 3(2): 167-197.

Bilsel, M., Davutyan, N. (2014). Hospital efficiency with risk adjusted mortality as undesirable output: The Turkish case, *Annals of Operations Research* 221:73-88.

Biørn, E., Hagen, T.P., Iversen, T., Magnussen, J. (2003). The effect of activity-based financing on hospital efficiency: A panel data analysis of DEA efficiency scores 1992–2000, *Health Care Management Science* 6: 271–283.

Birman, S. V., Pirondi, P. E., Rodin, E. Y. (2003). Application of DEA to medical clinics, *Mathematical Computer Modelling* 37: 923-936.

Butler, T.W., Li, L. (2005). The utility of returns to scale in DEA programming: An analysis of Michigan rural hospitals, *European Journal of Operational Research* 161: 469–477.

Caballer-Tarazona, M., Moya -Clemente, I., Vivas-Consuelo,D., Barrachina-Martínez, D. (2010). A model to measure the efficiency of hospital performance, *Mathematical Computer Modelling* 52: 1095-1102.

Chang, D-X., Zhang, X-D., Zheng, C-W. (2009). A genetic algorithm with gene rearrangement for k-means clustering, *Pattern Recognition* 42: 1210-1222.

Chang, H., Chang, W-J., Das, S., Li, S-H. (2004). Health care regulation and the operating efficiency of hospitals: Evidence from Taiwan, *Journal of Accounting and Public Policy* 23: 483–510.

Chang, H-H. (1998). Determinants of hospital efficiency: The case of central government-owned hospitals in Taiwan, *International Journal of Management Science* 26(2): 307-317.

Chang, Y., Sueyoshi, T. 1991). An interactive application of DEA in microcomputers, *Computer Science in Economics and Management* 4 (1): 51–64

.

Charnes, A., Cooper, W.W, Rhodes, E. (1978) Measuring the efficiency of decision making units, *European Journal of Operational Research* 2: 429–444.

Charnes, A., Cooper, W.W., Golany, B., Seiford, L.M., Stutz, J. (1985). Foundations of data envelopment analysis and Pareto-Koopmans empirical production functions, *Journal of Econometrics* 30:91-107.

Charnes, A., Cooper, W.W., Wei, Q.L., Huang, Z.M. (1989). Cone ratio data envelopment analysis and multi-objective programming, *International Journal of Systems Science* 20: 1099-1118.

Chen,C.B., Klein, C.M. (1997). A simple approach to ranking a group of aggregated fuzzy utilities, *IEEE Transactions on Systems, Man, and Cybernetics Part B:Cybern* 27: 26-35.

Cheng, M-J.,Wu, Y-C.J. (2006). Key determinants of performance assessment for U.S. TPL: DEA and cluster analysis, *Service Operations and Logistics, and Informatics, SOLI '06. IEEE International Conference*: 370-375.

Chern, J-Y, Wan, T.T.H. (2000). The impact of the prospective payment system on the technical efficiency of hospitals, *Journal of Medical Systems* 24(3): 159-172.

Chitta, R., Murty, M.N. (2010). Two-level k-means clustering algorithm for k–τ relationship establishment and linear-time classification, *Pattern Recognition* 43: 796–804.

Chowdhury, H., Zelenyuk, V. (2016). Performance of hospital services in Ontario: DEA with truncated regression approach, *Omega* 63: 111-122.

Chuang, C-L.,Chang, P-C, Lin, R-H. (2011). An efficiency data envelopment analysis model reinforced by classification and regression tree for hospital performance evaluation, *Journal of Medical Systems* 35: 1075-1083.

Clement, J.P., Valdmanis, V.G., Bazzoli, G.J., Zhao, M., Chukmaitov, A. (2008). Is more better? An analysis of hospital outcomes and efficiency with a DEA model of output congestion, *Health Care Management Science* 11: 67-77.

Cook, W.D., Seiford, L.M. (2009). Data envelopment analysis (DEA)-Thirty years on, *European Journal of Operational Research*, 192 (1), p.1-17.

Cooper, W.W., Seiford, L.M., Tone, K. (2000). Data envelopment analysis. a comprehensive text with models, applications, references and DEA-solver software. Boston: Kluwer Academic Publishers.

Cooper, W.W., Seiford, L.M., Zhu, J. (2011). Data envelopment analysis, history, models and ınterpretations, *International Series in Operations Research & Management Science* 164: 1-39.

Dash, U., Vaishnavi, S.D., Muraleedharan, V.R. (2010). Technical efficiency and scale efficiency of district hospitals: a case study, *Journal of Health Management* 12: 231- 248.

Dash, U., Vaishnavi, S.D., Muraleedharan, V.R., Acharya, D. (2007). Benchmarking the performance of public hospitals in Tamil Nadu: An application of data envelopment analysis, *Journal of Health Management* 9: 59-74.

Datta, S. (1993). Applications of O.R. in health in developing countries: A review, *Social Science & Medicine* 37: 1441-1450.

De A.T. de Carvalho, F.,Tenório, C.P.,Calvanti Junior, N.L. (2006). Partitional fuzzy clustering methods based on adaptive quadratic distances, *Fuzzy Sets and Systems* 157: 2833 –2857.

De Nicola A, Gitto S, Mancuso P, Valdmanis V. (2014). Healthcare reform in Italy: An analysis of efficiency based on nonparametric methods, The *International Journal of Health Planning and Management* 29: 48-63.

Dimitrov, S., Sutton, W. (2013). Generalized symmetric weight assignment technique: Incorporating managerial preferences in data envelopment analysis using a penalty function, *Omega* 41: 48-54.

Du, J., Wang, J., Chen, Y., Chou, S.Y., Zhu, J. (2014). Incorporating health outcomes in Pennsylvania hospital efficiency: An additive super-efficiency DEA approach, *Annals of Operations Research* 221: 161-172.

Du, K-L. (2010). Clustering: A neural network approach, *Neural Networks* 23: 89-107.

Dyson, R.G., Thanassoulis, E. (1988). Reducing weight flexibility in data envelopment analysis, Journal of the Operational Research Society 39: 563-576.

Emrouznejad, A., De Witte, K. (2010). COOPER-framework: A unified process for non-parametric projects, *European Journal of Operational Research* 207: 1573-1586.

Ersoy, K., Kavuncubasi, S., Ozcan, Y.A., Harris J.M. (1997). Technical efficiencies of Turkish hospitals: DEA approach, *Journal of Medical Systems* 21(2): 67-74.

Estellita Lins, M.P., Moreira da Silva, A.C., Lovell, C.A.K. (2007). Avoiding ınfeasibility in DEA models with weight restrictions, *European Journal of Operational Research* 181: 956-966.

Fang, S.C. and Puthenpura, S.C. (1993). Linear Optimization and Extensions: Theory and Algorithms, Prentice Hall, Englewood Cliffs, NJ.

Färe, R.S., Lovell, C.A.K. (1978). Measuring the technical efficiency of production, *Journal of Economic Theory* 19: 150–162.

Farrell, M.J. (1957). The measurement of productive efficiency, *Journal of the Royal Statistical Society Series A* 120: 253-290.

Ferrier, G.D., Rosko, M.D., Valdmanis, V.G. (2006). Analysis of uncompensated hospital care using a DEA model of output congestion, *Health Care Management Science* 9: 181-188.

Field, K., Emrouznejad, A. (2003). Measuring the performance of neonatal care units in Scotland, *Journal of Medical Systems* 27(4): 315-324.

Flokou, A., Kontodimopoulos, N., Niakas, D. (2011). Employing post-DEA cross-evaluation and cluster analysis in a sample of Greek NHS hospitals, *Journal of Medical Systems* 35: 1001-1014.

Gautam S, Hicks L, Johnson T, Mishra B. (2013). Measuring the performance of critical access hospitals in Missouri using data envelopment analysis, *The Journal of Rural Health* 29: 150-158.

Gok, S.M. (2012). *Efficiency evaluation of Turkish hospitals by using data envelopment analysis*, Ph.D. Thesis, Gebze Institute of Technology Institute of Social Sciences, Gebze, Turkey.

Gok, S.M., Sezen, B. (2012). Capacity inefficiencies of teaching and non-teaching hospitals, *The Service Industries Journal* 32: 2307-2328.

Green, R.H., Cook, W.D., Doyle, J. (1997). A note on the additive data envelopment analysis model, *Journal of the Operational Research Society* 48(4): 446–448.

Groenen, P.J.F.,Jajuga, K. (2001). Fuzzy clustering with squared Minkowski distances, *Fuzzy Sets and Systems* 120: 227–237.

Grossberg, S. (1976). Adaptive pattern classification and universal recoding I. parallel development and coding of neural feature detectors, *Biological Cybernetics* 23: 121-134.

Grosskopf, S., Margaritis, D., Valdmanis, V. (2001). Comparing teaching and non-teaching hospitals: A frontier approach (teaching vs. non-teaching hospitals), *Health Care Management Science* 4: 83–90.

Grosskopf, S., Valdmanis, V. (1987). Measuring hospital performance: A non-parametric approach, *Journal of Health Economics* 6: 89-107.

Guo, P., Tanaka, H. (2001). Fuzzy DEA: A perceptual evaluation method, *Fuzzy Sets and Systems* 119: 149-160.

Hajialiafzali, H., Moss, J.R., Mahmood, M.A. (2007). Efficiency measurement for hospitals owned by the Iranian social security organisation, *Journal of Medical Systems* 31: 166–172.

Hamdan, A., Rogers, K.J. (2008). Evaluating the efficiency of 3PL logistics operations, *International Journal of Production Economics* 113: 235-244.

Harrison, J.P., Coppola, M.N., Wakefield, M. (2004). Efficiency of federal hospitals in the United States, *Journal of Medical Systems* 28(5): 411-422.

Hatami-Marbini, A., Emrouznejad, A., Tavana, M. (2011). A taxonomy and review of the fuzzy data envelopment analysis literature: Two decades in the making, *European Journal of Operational Research* 214: 457-472.

Hatami-Marbini, A., Saati, S., Tavana, M. (2010). An ideal-seeking fuzzy data envelopment analysis framework, *Applied Soft Computing* 10(4): 1062-1070.

Healthare industry in Turkey, invest.gov.tr, January 2014.Investment Support and Promotion Agency of Turkey.

Hokkanen, J., Salminen, P. (1997). Choosing a solid waste management system using a multicriteria decision analysis, *European Journal of Operational Research* 98: 19-36.

Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery, *Health Economics* 17: 1107-1128.

Horfmarcher, M., Paterson, I., Riedel, P. (2002). Measuring hospital efficiency in Austria – A DEA approach, *Health Care Management Science* 5: 7–14.

Hu, H-H., Qi, Q., Yang, C-H. (2012). Analysis of hospital technical efficiency in China: Effect of health ınsurance reform, *China Economic Review* 23(4): 865-877.

Hu, J-L., Huang, Y-F. (2004). Technical efficiencies in large hospitals: A managerial perspective, *International Journal of Management* 21(4): 506-513.

Jacobs, R. (2001). Alternative methods to examine hospital efficiency: Data envelopment analysis and stochastic frontier analysis, *Health Care Management Science* 4: 103–115.

Ji, Z., Xia, Y., Chen, Q., Sun, Q., Xia, D., Feng, D.D. (2012). Fuzzy C-means clustering with weighted image patch for image segmentation, *Applied Soft Computing* 12: 1659-1667.

Jin, Z. (2009). Comparative study on performance assessment of hospitals in various regions of China through comprehensive variable DEA and traditional DEA, *Computer Science and Information Technology, ICCSIT 2009*, pp. 423-427.

Kahraman, C., Tolga, E. (1998). Data envelopment analysis using fuzzy concept, *28th International Symposium on Multiple-Valued Logic*, pp.338-343.

Kao, C., Liu, S.T. (2000). Fuzzy efficiency measures in data envelopment analysis, *Fuzzy Sets and Systems* 113: 427-437.

Karsak, E.E. (2008). Using data envelopment analysis for evaluating flexible manufacturing systems in the presence of ımprecise data, *The International Journal of Advanced Manufacturing Technology* 35:867-874.

Kazley, A.S., Ozcan, Y.A. (2009). Electronic medical record use and efficiency: A DEA and windows analysis of hospitals, *Socio-Economic Planning Sciences* 43: 209-216.

Ketabi, S. (2011). Efficiency measurement of cardiac care units of Isfahan hospitals in Iran, *Journal of Medical Systems* 35: 143–150.

Kirigia, J.M., Emrounznejad, A., Sambo, L.G. (2002). Measurement of technical efficiency of public hospitals in Kenya: Using data envelopment analysis, *Journal of Medical Systems* 26(1): 39-45.

Kirigia, J.M., Emrouznejad, A.,Cassoma, B., Asbu, E.Z., Barry, S. (2008). A performance assessment method for hospitals: The case of municipal hospitals in Angola, *Journal of Medical Systems* 32: 509-519.

Kohonen, T. (2000). Self-Organizing Maps. third ed. Berlin: Springer-Verlag.

Kornbluth, J.S.H. (1991). Analysing policy effectiveness using cone restricted data envelopment analysis, *Journal of the Operational Research Society* 42: 1097-1104.

Lee, H., Delene, L.M., Bunda, M.A., Kim, C. (2000). Methods of measuring health-care service quality, *Journal of Business Research* 48: 233-246.

Lei, J.Z., Ghorbani, A.A. (2012). Improved competitive learning neural networks for network intrusion and fraud detection, *Neurocomputing* 75: 135-145.

Lertworasirikul, S. (2001). *Fuzzy data envelopment analysis for Supply Chain Modeling and Analysis*, Dissertation Proposal in Industrial Engineering, North North Carolina State University, Raleigh.

Lertworasirikul, S. (2002). *Fuzzy data envelopment analysis*, Ph.D. Thesis. North Carolina State University, Raleigh.

Lertworasirikul, S., Fang, S-C., Joines, J.A. and Nuttle, H.L.W. (2003a). Fuzzy data envelopment analysis (DEA): A possibility approach, *Fuzzy Sets and Systems*, 139: 379-394.

Lertworasirikul, S., Fang, S-C., Nuttle, H.L.W. and Joines, J.A. (2003b). Fuzzy BCC model for Data Envelopment Analysis, *Fuzzy Optimization and Decision Making*, 2: 337-358.

Li, L.X., Benton, W.C. (1996). Performance measurement in health care organizations: Review and future research directions, *European Journal of Operational Research* 93: 449-468.

Linna, M., Häkkinen, U., Magnussen, J. (2006). Comparing hospital cost efficiency between Norway and Finland, *Health Policy* 77: 268–278.

Lippmann, R.P. (1987). An introduction to computing with neural nets. *IEEE Transactions on Acoustics, Speech Signal Processing:* 4-22.

Liu, J.S., Lu, L.Y.Y., Lin, B.J.Y. (2013). A survey of DEA applications, *Omega-The International Journal of Management Science* 41: 893-902.

Liu, J.S., Lu, L.Y.Y., Lu, W-M., Lin, B.J.Y. (2013). Data envelopment analysis 1978-2010 a cititation-based literature survey, *Omega-The International Journal of Management Science* 41: 3-15.

Liu, S-T., Chuang, M. (2009). Fuzzy efficiency measures in fuzzy DEA/AR with an application to university libraries, *Expert Systems with Applications* 36: 1105-1113.

Lotfi, F.H., Jahanshahloo, G.R., Esmaeili, M. (2007). An alternative approach in the estimation of returns to scale under weight restrictions, *Applied Mathematics and Computation* 189: 719-724.

Mall, R., Mehrkanoon, A., Suykens, J.A.K. (2015). Identifying intervals for Hierarchical Clustering Using The Gershgorin Circle Theorem, *Pattern Recognition* 55: 1-7.

Maniadakis, N., Hollingsworth, B., Thanassoulis, E. (1999). The impact of the internal market on hospital efficiency, productivity and service quality, *Health Care Management Science* 2: 75–85.

Mansur, A.B.F., Yusof, N. (2013). Social learning network analysis model to identify learning patterns using ontology clustering techniques and meaningful learning, *Computers & Education 63:* 73-86.

Mark, B.A., Jones, C.B., Lindley, L., Ozcan, Y.A. (2009). An examination of technical efficiency, quality, and patient safety in acute care nursing units, *Policy, Politics, & Nursing Practice* 10(3): 80– 186.

Marroquin, M., Pena, M., Castro, C., Castro, J., Cabrera-Rios, M. (2008). Use of data envelopment analysis and clustering in multiple criteria, *Optimization. Intelligent Data Analysis* 12: 89-101.

Masiye, F. (2007). Investigating health system performance: An application of data envelopment analysis to Zambian Hospitals, *BMC Health Services Research* 7: 58-69.

McCallion, G., Glass, J.C., Jackson, R., Kerr, C.A., McKillop, D.G. (2000). Investigating productivity change and hospital size: A nonparametric frontier approach, *Applied Economics* 32: 161-174.

Mitropoulos P., Mitropoulosi I., Giannikos, I. (2013). Combining DEA with location analysis for the effective consolidation of services in the health sector, *Computers & Operations Research* 40(9): 2241-2250.

Mitropoulos, P., Talias, M.A., Mitropoulos, I. (2015). Combining stochastic DEA with bayesian analysis to obtain statistical properties of the efficiency scores: An Application to Greek public hospitals, *European Journal of Operational Research* 243: 302-311.

Nayar, P., Ozcan, Y.A. (2008). Data envelopment analysis comparison of hospital efficiency and quality, *Journal of Medical Systems* 32: 193-199.

Ng, Y.C. (2011). The productive efficiency of Chinese hospitals, *China Economic Review* 22: 428–439.

Nguyen, T-D., Schmidt, B., Kwoh, C-K. (2014). SparseHC: A memory-efficient online hierarchical clustering algorithm, *Procedia Computer Science* 29: 8-19.

O'Neill, L. (1998). Multifactor efficiency in data envelopment analysis with an application to urban hospitals, *Health Care Management Science* 1: 19–27.

O'Neill, L., Dexter, F. (2005). Methods for understanding super efficient data envelopment analysis results with an application to hospital inpatient surgery, *Health Care Management Science* 8: 291–298.

O'Neill,L., Rauner,M., Heidenberger, K., Kraus, M. (2008). A cross-national comparison and taxonomy of dea-based hospital efficiency studies, *Socio-Economic Planning Sciences* 42: 158–189.

Olesen, O.B., Petersen, N.C. (2002). The use of data envelopment analysis with probabilistic assurance regions for measuring hospital efficiency, *Journal of Productivity Analysis* 17: 83–109.

Osei1,D., d'Almeida, S., George, M.O, Kirigia, J.M., Mensah, A.O., Kainyu, L.H. (2005). Technical efficiency of public district hospitals and health centres in Ghana: A pilot study, *Cost Effectiveness and Resource Allocation* 3: 9-22.

Osman, I.H., Berbary, L.N., Sidani, Y., Al-Ayoubi, B., Emrouznejad, A. (2011). Data envelopment analysis model for the appraisal and relative performance evaluation of nurses at an intensive care unit, *Journal of Medical Systems* 35: 1039-1062.

Oullette, P., Vierstraete, V. (2004). Technological change and efficiency in the presence of quasi-fixed inputs: A DEA application to the hospital sector, *European Journal of Operational Research* 154: 755–763.

Ozcan, Y.A., Lins, M.E., Stella, M., Lobo, C., Da Silva, A.C.M., Fiszman, R., Pereira, B.B. (2010). Evaluating the performance of Brazilian university hospitals, *Annals of Operations Research* 178: 247-261.

Parasuruman, A., Zeithaml, V.A., Berry, L.L. (1988). SERVQUAL: a multiple-item scale for measuring consumer perception of service quality. *Journal of Retailing* 64(1): 12-40.

Parkin, D., Hollingsworth, B. (1997). Measuring production efficiency of acute hospitals in Scotland, 1991- 94: Validity ıssues in data envelopment analysis, Applied Economics 29: 1425-1433.

Pastor, J.T., Ruiz, J.L., Sirvent, I. (1999). An enhanced DEA Russell graph efficiency measure, *European Journal of Operational Research* 115: 596–607.

Patra, B.K., Nandi, S., Viswanath, P. (2011). A distance based clustering method for arbitrary shaped clusters in large datasets, *Pattern Recognition*, 44: 2862-2870.

Pedraja-Chaparro, F., Salinas-Jimenez, J., Smith, P. (1997). On the role of weight restrictions in data envelopment analysis, *Journal of Productivity Analysis* 8: 215-230.

Po, R-W., Guh, Y-Y., Yang, M-S. (2009). A new clustering approach using data envelopment analysis, *European Journal Of Operational Research* 199: 276-284.

Prakash, V., Annapoorni, D. (2015). Performance evaluation of public hospitals in Tamil Nadu: DEA Approach, *Journal of Health Management* 17(4): 417-424.

Puig-Junoy, J. (2000). Partitioning input cost efficiency into its allocative and technical components: An empirical DEA application to hospitals, *Socio-Economic Planning Sciences* 34: 199-218.

Qiao, S., Li, T., Li, H., Peng, J., Chen, H. (2012). A new blockmodeling based hierarchical clustering algorithm for web social networks, *Engineering Applications of Artificial Intelligence* 25: 640-647.

Ramsaran-Fowdar, R.R. (2008). The relative ımportance of service dimensions in a healthcare setting, *International Journal of Health Care Quality Assurance* 21(1): 104-124.

Rashedi, E., Mirzaei, A. (2013). A hierarchical clusterer ensemble method based on boosting theory, *Knowledge-Based Systems* 45: 83-93.

Russell, R.R. (1988). Measures of technical efficiency, Journal of Economic Theory 35: 109-126.

Saati, M. S., Memariani, A., Jahanshahloo, G.R. (2002). Efficiency analysis and ranking of DMUs with fuzzy data, *Fuzzy Optimization and Decision Making* 1: 255-267.

Saati, S., Hatami-Marbini, A., Tavana, M., Agrell, P.J. (2013). A fuzzy data envelopment analysis for clustering operating units with imprecise data, International *Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 21(1): 29-54.

Sağlık Kurumları Girişimsel İşlem Puan Listesi (2013).

Sahin, I., Ozcan, Y.A., Ozgen, H. (2011). Assessment of hospital efficiency under health transformation program in Turkey, *Central European Journal of Operations Research* 19: 19-37.

Sahin, I., Ozcan, Y.A., Ozgen, H. (2011). Assessment of hospital efficiency under health transformation program in Turkey, *Central European Journal of Operations Research* 19: 19-37.

Sahin, I.,Ozcan, Y.A. (2000). Public sector hospital efficiency for provincial markets in Turkey, *Journal of Medical Systems*, 24(6): 307-320.

Samoilenko, S., Osei-Bryson, K-M. (2008). Increasing the discriminatory power of DEA in the presence of the sample heterogeneity with cluster analysis, *Expert Systems with Applications* 34: 1568-1581.

Sarkis, J., Talluri, S. (1999). A decision model for the evaluation of flexible manufacturing systems in the presence of both cardinal and ordinal factors, *International Journal of Production Research* 37(13): 2927-2938.

Sarkis, J.,Talluri, S. (2004). Performance based clustering for benchmarking of US airports, *Transportation Research Part A* 38: 329–346.

Serrano-Cinca, C. and Mar-Molinero, C. (2004). Selecting DEA specifications and ranking units via PCA, *Journal of the Operational Research Society* 55: 521-528.

Shannon Claude, E. (1948). A mathematical theory of communication, *Bell System Technical Journal* 27(3): 379-423.

Sharma, M.J., Yu, S.J. (2009). Performance based stratification and clustering for benchmarking of container terminals, *Expert Systems with Applications* 36 (3): 5016-5022.

Silverman, B. W. (1986). Density estimation for statistics and data analysis. Chapman and Hall, London, UK.

Simar, L. and Zelenyuk, V. (2006). On testing equality of distributions of technical efficiency scores, *Econometric Reviews* 25(4): 497-522.

Simões, P., Marques, R.C. (2011). Performance and congestion analysis of the Portuguese hospital services, *Central European Journal of Operations Research* 19: 39-63.

Sinuay-Stern, Z., Mehrez, A., Hadad, Y. (2000). An AHP/DEA methodology for ranking decision making units, *International Transactions in Operational Research* 7: 109-124.

Solà, M., Prior, D. (2001). Measuring productivity and quality changes using data envelopment analysis: an application to Catalan hospitals, *Financial Accountability & Management* 17(3): 219-245.

Sommersguter-Reichmann, M. (2000). The impact of the Austrian hospital financing reform on hospital productivity: empirical evidence on efficiency and technology changes using a non-parametric ınput-based Malmquist approach, *Health Care Management Science* 3: 309–321.

Steianmann, L., Zweifel, P. (2003). On the (in)efficiency of Swiss hospitals, *Applied Economics* 35: 361-370.

Steinmann, L., Dittrich, G., Karmann, A., Zweifel, P. (2004). Measuring and comparing the (in)efficiency of German and Swiss Hospitals, *European Journal of Health Economics* 5: 216-226.

Sueyoshi, T. (1990). A special algorithm for the additive model in DEA, *Journal of the Operational Research Society* 41 (3): 249–257.

Sulku, S.N. (2011). The health sector reforms and the efficiency of public hospitals in Turkey: provincial markets, *European Journal of Public Health* 22(5): 634-638.

Taherdangkoo, M., Bagheri, M.H. (2013). A powerful hybrid clustering method based on modified stem cells and fuzzy C-means algorithms, *Engineering Applications of Artificial Intelligence* 26: 1493-1502.

Talluri, S., Yoon, P.K. (2000). A cone-ratio DEA approach for AMT justification, *International Journal of Production Economics* 66: 119-129.

Thompson, R.G., Langemeier, L.N., Lee, C-T., Lee, E, Thrall, R.M. (1990). The role of multiplier bounds in efficiency analysis with application to Kansas farming, *Journal of Econometrics* 46: 93-108.

Tlotlego, N., Nonvignon, J., Sambo, L.G., Asbu, E.Z., Kirigia, J.M. (2010). Assessment of productivity of hospitals in Botswana: A DEA application, *International Archives of Medicine* 3: 27-42.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis, *European Journal of Operational Research* 130: 498–509.

Tsai, H.Y., Chang, C.W., Lin, H.L. (2010). Fuzzy hierarchy sensitive with delphi method to evaluate hospital organization performance, *Expert Systems with Applications* 37: 5533–5541.

Tsai, P.F., Molinero, C.M. (2002). A variable returns to scale data envelopment analysis model for the joint determination of efficiencies with an example of the UK health service, *European Journal of Operational Research* 141: 21-38.

Tsao, E.C.K., Bezdek, J.C., Pal, N.R. (1994). Fuzzy Kohonen clustering networks, *Pattern Recognition* 27: 757-764.

URL: http://www.istanbulsaglik.gov.tr/w/sb/imis/pdf/ek_8.pdf

URL:http://www.who.int/countryfocus/cooperation_strategy/ccsbrief_tur_en.pdf

Van der Geer,E., Van Tuijl, F.J.M.H.,Rutte, C.G. (2009). Performance management in healthcare: Performance indicator development, task uncertainty, and types of performance indicators, *Social Science & Medicine* 69: 1523–1530.

Vitikainen K, Street A, and Linna M. (2009). Estimation of hospital efficiency-Do different definitions and casemix measures for hospital output affect the results?, *Health Policy*, 89: 149-159.

Wallace, L., Keil, M., Rai, A. (2004). Understanding software project risk: A cluster analysis, *Information and Management* 42: 115-125.

Wang, B.B., Ozcan, Y.A., Wan,T.T.H.,Harrison, J. (1999). Trends in hospital efficiency among metropolitan markets, *Journal of Medical Systems* 23(2): 83-97.

Wang, R., Yu, M. (2006). Evaluating the efficiency of hospital 's departments using DEA. Service Operations and Logistics, and Informatics, SOLI '06. IEEE International Conference.

Wang, Y-M., Luo, Y., Liang, L. (2009). Ranking decision making units by imposing a minimum weight restriction in the data envelopment analysis, *Journal of Computational and Applied Mathematics* 223: 469-484.

Wei C-K, Chen L-C, Li R-K, Tsai C-H (2011). Using the DEA-R model in the hospital industry to study the pseudo-ınefficiency problem, *Expert Systems with Applications* 38: 2172-2176.

Wei, C-K., Chen, L-C., Li, R-K., Tsai C-H. (2011). Exploration of efficiency underestimation CCR model: Based on medical sectors with DEA-R model. *Expert Systems with Applications* 38: 3155-3160.

Wei, C-K., Chen, L-C., Li, R-K., Tsai, C-H. (2011). Using the DEA-R model in the hospital ındustry to study the pseudo-inefficiency problem, *Expert Systems with Applications* 38: 2172–2176.

Weng, S-J., Wu, T., Blackhurst, J.,Mackulak, G. (2009). An extended DEA model for hospital performance evaluation and improvement, *Health Services Outcomes Research Methodology* 9: 39-53.

Weng, S.J.,Wang,L.M., Tsai, B.S., Chang, C.Y., Gotcher, D. (2011). Using simulation and data envelopment analysis in optimal healthcare efficiency allocations, *Proceedings of the 2011 Winter Simulation Conference*: 1295-1305.

White, L., Smith, H., Currie, C. (2011). OR in developing countries: A review, *European Journal of Operational Research* 208: 1-11.

Wong, B.,Y.-H., Beasley, J.E. (1990). Restricting weight flexibility in data envelopment analysis, *Journal of the Operational Research Society* 41: 829-835.

Wu, D. and Wu, D.D. (2010). Performance evaluation and risk analysis of online banking service, *Kybernetes* 39(5): 723-734.

Wu, J., Sun, J., Liang, L., Zha, Y. (2011). Determination of weights for ultimate cross efficiency using Shannon entropy, *Expert Systems with Applications* 38: 5162-5165.

Wu, K-L.,Yang, M-S. (2002). Alternative C-means clustering algorithms, *Pattern Recognition* 35: 2267 – 2278.

Zadeh, L.A. (1978). Fuzzy sets as a basis for a theory of possibility, *Fuzzy Sets and Systems* 1: 3-28.

Zaït, M., Messatfa, H.A. (1997). Comparative study of clustering methods, *Future Generation Computer Systems* 13: 149-159.

Zelenyuk, N., and V. Zelenyuk. (2015). Drivers of efficiency in banking: Importance of model specifications, Centre for Efficiency and Productivity Analysis (CEPA) Working Paper Series, WP08/2015.

Zere,E., Mbeeli, T., Shangula, K., Mandlhate,C., Mutirua, K.,Tjivambi, B., Kapenambili, W. (2006). Technical efficiency of district hospitals: Evidence from Namibia using data envelopment analysis, *Cost Effectiveness and Resource Allocation* 4: 5-14.

Zhou, Z., Zhao, L., Lui, S., Ma, C. (2012). A generalized fuzzy DEA/AR performance assessment model, *Mathematical and Computer Modelling* 55: 2117-2128.

APPENDICES

APPENDIX A.

This questionnaire is constituted for my Ph.D. thesis entitled “Using Multi-Criteria Decison Making Approaches for Evaluating Health Care Performance of Districts in Istanbul” for measuring perceived service quality for state hospitals. Please mark the suitable answer for you. Thanks for your contribution.

Best Regards,
Melis Almula KARADAYI
Ph.D. Candidate
Galatasaray University
Graduate School of Science and Engineering
Industrial Engineering Program

Hospital:

District:

Gender: Female ☐ Male ☐

Age: ………

Education

1- Illiterate ☐
2- Literate ☐
3- Primary school ☐
4- Secondary school ☐
5- High school ☐
6- Vocational school ☐
7- Undergraduate ☐
8- Graduate ☐

1) How would you rate the general appearance, cleanliness, illumination, sign boards, ventilation of the hospital?

5- Very good ☐

4- Good ☐

3- Moderate ☐

2- Poor ☐

1- Very poor ☐

2) How would you confide the accuracy of examination and treatment provided at the hospital?

5-Very confident ☐

4- Confident ☐

3-Moderately confident ☐

2- Insufficiently confident ☐

1- Not confident ☐

3) How would you rate the waiting time for provision of health services?

5-Very good ☐

4- Good ☐

3- Moderate ☐

2- Poor ☐

1- Very poor ☐

4) How would you rate the information about treatment, examination, medications and diagnosis given by the doctors?

5- Very good ☐

4- Good ☐

3- Moderate ☐

2- Poor ☐

1- Very poor ☐

5) How would you rate the caring and individualised attention of medical staff (doctor, nurses, technician, government official) to you?

5- Very good ☐

4- Good ☐

3- Moderate ☐

2- Poor ☐

1- Very poor ☐

APPENDIX B.

This questionnaire is constituted for my Ph.D. thesis entitled “Using Multi-Criteria Decision Making Approaches for Evaluating Health Care Performance of Districts in Istanbul”. Please assign your scores for each given input and output in the following tables. Thanks for your contribution.

Sincerely,
Melis Almula KARADAYI
Ph.D. Candidate
Galatasaray University
Graduate School of Science and Engineering
Industrial Engineering Program

In the following table, I listed the most significant inputs and outputs for evaluating health care performance with their related definitions.

Table A.1 Explanation of inputs and outputs

Inputs	**Definition and explanation**
Beds	The total number of hospital beds.
Overall staff	The total number of clinical and non-clinical staff
Operating expenses	The amount of operational expenses measured in TL excluding capital and depreciation.
Outputs	**Definition and explanation**
Outpatients	The total number of patients to outpatient departments and emergency rooms.
Discharged patients	The total number of discharged patients.
Surgeries	The total number of adjusted surgical interventions undertaken.
Tangibility	Physical characteristics of health care facility
Responsiveness	Staff prompt responsiveness to patients’ needs.

Please assign your scores for inputs in the following table:

Table A.2 Scores for inputs

Inputs	**Rating (1 to 9)**
Beds	
Overall-staff	
Operating Expenses	

Please assign your scores for outputs in the following table:

Table A.3 Scores for outputs

Outputs	**Rating (1 to 9)**
Outpatients	
Discharged patients	
Surgeries	
Tangibility	
Responsiveness	

End of the Survey

Thank you.

BIOGRAPHICAL SKETCH

Melis Almula KARADAYI was born in Istanbul on February 28, 1985. In 2007, she received the B.S. degree in Industrial Engineering from Dogus University as a first ranking graduate. She received an M.S. degree in Industrial Engineering from Galatasaray University in 2009. She worked as a research assistant in Industrial and Systems Engineering Department of Yeditepe University between 2008 and 2015. She has been working as a research assistant in Industrial Engineering Department of İstanbul Bilgi University since September 2015. Her areas of interest include health care management, waste management, multiple criteria decision making, data envelopment analysis, fuzzy optimization, and applications of mathematical programming and fuzzy set theory.

PUBLICATIONS

Journal Articles

Karsak, E. E., Karadayi, M.A., “Imprecise DEA Framework for Evaluating Health-Care Performance of Districts”, Kybernetes, Vol. 46(4), 706-727, (2017). [SCI-Expanded]

Dursun, M., Karsak, E. E., Karadayi, M.A., “Assessment of Health-Care Waste Treatment Alternatives Using Fuzzy Multi-Criteria Decision Making Approaches”, Resources Conservation and Recycling, Vol. 57, 98-107, (2011). [SCI-Expanded]

Dursun, M., Karsak, E. E., Karadayi, M.A., “A Fuzzy Multi-Criteria Group DecisionMaking Framework for Evaluating Health-Care Waste Disposal Alternatives”, Expert Systems with Applications, Vol. 38(9), 11453-11462, (2011). [SCI-Expanded]

Dursun, M., Karsak, E.E., Karadayi, M.A., “Fuzzy Group Decision Making for Health-Care Waste Management”, The Journal of Management & Engineering Integration, Vol. 3(2), 54-62, (2010).

Conference Papers

Karadayi, M.A., Karsak, E.E., “İstanbul’da İlçe Bazında Sağlık Hizmetlerinin Etkinliğinin Kümeleme ve Sıralama Analizi ile Değerlendirilmesi”, Yöneylem Araştırması ve Endüstri Mühendisliği 35.Ulusal Kongresi, (2015).

Karadayi, M.A., Karsak, E.E., “İstanbul’un İlçelerindeki Sağlık Hizmetlerinin Etkinliğinin Bulanık Veri Zarflama Analizi ile Değerlendirilmesi”, Yöneylem Araştırması ve Endüstri Mühendisliği 34.Ulusal Kongresi, (2014).

Karadayi, M.A., Karsak, E.E., “Imprecise DEA Framework for Evaluating the Efficiency of State Hospitals in Istanbul”, Proceedings of the World Congress on Engineering (WCE 2014), London, UK, Vol. II, (2014).[Certificate of Merit Award]

Karadayi, M.A., Karsak, E.E., “Fuzzy MCDM Approach for Health-Care Performance Assessment in Istanbul”, Proceedings of The 18th World Multi-Conference on Systemics, Cybernetics and Informatics (WMSCI 2014), Orlando, Florida, USA, Vol. II, 228-233, (2014).

Dursun, M., Karsak, E.E., Karadayi, M.A., “Fuzzy Group Decision Making for Health-Care Waste Management”, Proceedings of the World Academy of Science, Engineering and Technology, Paris, Issue 66, 1270-1275, (2010).