Indian Journal of Economics & Business, Vol. 13, No. 2, (2014) : 207-217

ASSESSING HEALTHCARE SURGICAL PERFORMANCE USING DATA ENVELOPMENT ANALYSIS APPROACH

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Abstract

Clinicians and hospital administrators rely on information models for healthcare management and decision-making. However, healthcare surgical performance measurements include both qualitative and quantitative data, often with conflicting and interdependent variables. As a result many statistical modeling approaches can break down with healthcare data. Other more resilient algorithms, such as Data Envelopment Analysis (DEA) and Fuzzy Composite Programming (FCP) hold promise to address these issues. This paper applies DEA to comprehensively assess the surgical performance. The results of the DEA model are compared to the results obtained from a prior fuzzy composite programming (FCP) analysis to establish additional validity.

Keywords: *Healthcare Ddisease Management, Multiple Criteria Decision Making (MCDM), Data Envelopment Analysis (DEA)*

I. INTRODUCTION

The use of information systems (IS) in healthcare organizations is on the rise. Such applications include knowledge management systems, decision support systems and reporting systems based on patient record management systems. Among the reasons for this trend are pressures to reduce costs, which have been growing at an unsustainable rate and to improve the quality of healthcare. Also these systems can help healthcare professionals to cope with information overload and to learn about and utilize current research developments into their practice. Reports indicate that several healthcare organizations are proceeding to introduce evidence-based medicine and disease management practices by implementing information systems based on this clinical information (McGrath, *et al.*, 2008). The recent increase in the use of Electronic Health Record (EHR) systems in health care facilities has resulted in a huge amount of clinical data being collected and available online. Such data is presenting opportunities for creating information systems for various

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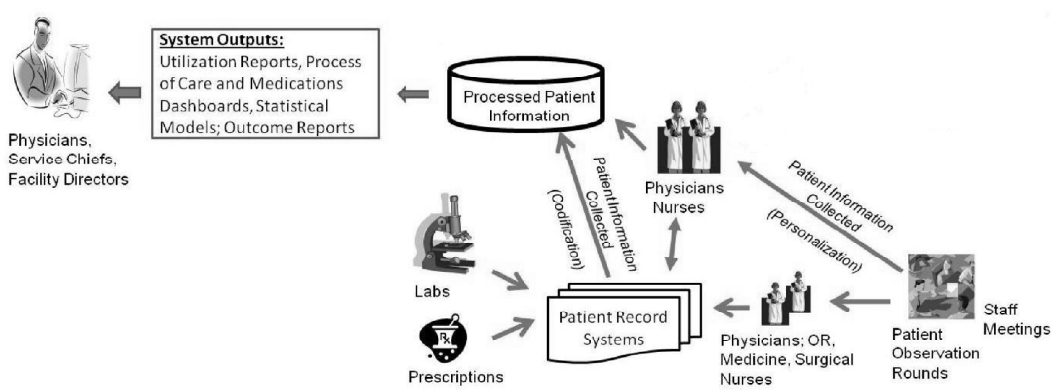
healthcare organizational management and decision making purposes (Figure 1). Personnel at multiple levels in a healthcare organization can rely on such information systems to create and deploy analytical models that facilitate decision-making. For example, medical chiefs and hospital directors need to track resource utilization and outcomes of selected treatment and procedures and plan unit based resource allocation and standardized procedures (Epstein, 2006). Healthcare system policy makers also need information from across a healthcare network to make strategic decisions on standardization of treatment protocols and procedures. Clinicians need historical patient outcome information to facilitate decisions on elective treatment (e.g. elective surgeries) and judge the suitability of treatment options and medical procedures for a presenting patient.

Figure 1: Patient Data Collection, Aggregation and Processing in the Health Information System



A classification of information systems that facilitate the processes of decision making in an organization are referred to as Decision Support Systems (DSS). Most DSS offer managers functionality intended to support all phases of decision making – intelligence, design, choice and implementation. DSS technologies support- (1) the general goals of reducing the uncertainty in the decision making process, such as framing the right questions and problem(s) to solve, (2) building a model to evaluate choices and estimating the impact of the choices on one or more objectives and (3) the capability to evaluate changes in assumptions, model inputs and parameter values on a chosen decision. All activities involve the efficient and accurate collection, management, processing and application of data/information to the decision making process steps.

Data Envelopment Analysis (DEA) is a useful modeling platform for complex decision making scenarios, as it allows for use of different types of data which have large variability in the data set. Real life situations such as in healthcare organizations are often different because the actual values of the selected measurement criteria may exhibit variability as well have imprecision in the way they are collected. Statistical data analysis techniques are able to account for variability but may not work well with imprecision, as well as criteria that are not statistically independent (e.g. surgical wait time and complications). By using DEA, an area/volume is used to represent each scenario, instead of a single point (statistical approach) to get a more complete classification of each scenario under variability. This leads to better decision making in these domains, such as healthcare.

The goals of this research are as below:

1. Use Data Envelopment Analysis (DEA) to evaluate the performance of surgical Units in 6 different hospitals.
2. Compare the results of DEA analysis with analysis done with Fuzzy Composite Programming (FCP)
3. Demonstrate how DEA analysis can help identify the factors that can be worked on by the lower performing units to improve their performance.

II. MEASURING HEALTH CARE QUALITY

Healthcare organizations can vary greatly by size, scope, geographic dispersion, patient mix, treatment policies for medications and patient procedures. However, the end result, in effect of the success or failure of a healthcare organization is the outcome of the diagnosis and treatment of the patients' condition. Outcomes can be influenced by other patient factors such as age, sex, severity of the disease, lifestyle, body weight, blood pressure, etc. For example patient death could be an inevitable outcome in many situations and cannot always be used as an indicator of the failure of a care process (Lezzoni, 1994). These factors determine a risk factor, which is different for each patient, patient group and patient load at a given facility. Hence in decision support systems for comparing healthcare organizations, risk adjusted outcome measures are needed. Therefore the success of a health care system should be measured by patient outcomes, such as treatment compliance, patient satisfaction and risk adjusted complication rates.

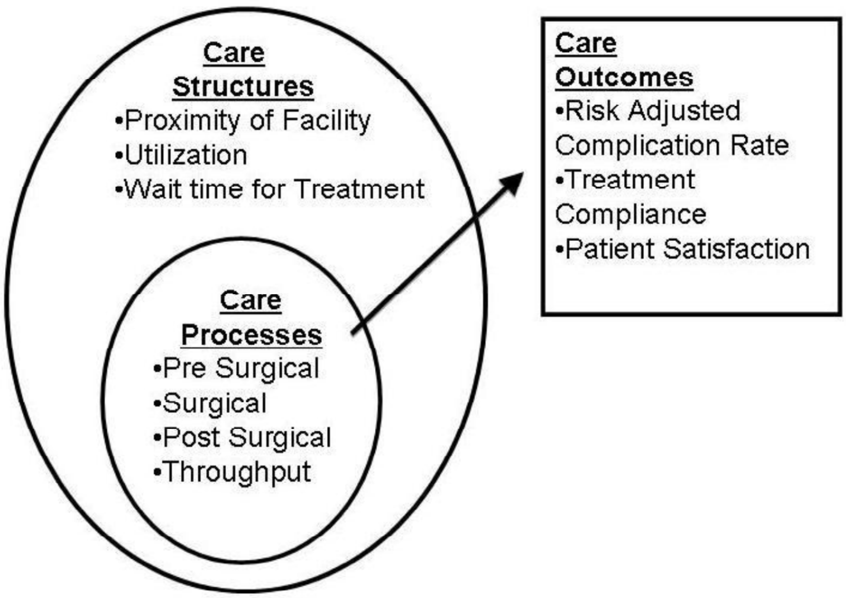
There are important limitations on the sole of use of patient outcomes as indicators of the process of care (Donabedian, 1976). The overall classification measures must also include the pathways of medical care – programs and structures, which are important for the delivery of the care and should be part of any measured of success or failure of the healthcare institution. Process measures can be collected for resource planning and utilization tracking needs as the delivery of patient care is through these clinical processes (Donabedian, 1976). A care process is a workflow or a set of activities around the delivery of patient care. Care processes are delivered by different units in a hospital, such as ICU and pre and post surgical medical units. Institutional measures must include measures of these hospital units.

Finally these care processes are highly dependent on the structure or settings in which care takes place and the instrumentalities of which it is a product of.

These structures include the administrative and related infrastructure that support and direct the provision of care, the utilization of the facilities and equipment, the nature of the medical staff, the timely access of the facilities to the patient (Donabedian, 1968).

These three dimensions of medical care measurement (Donabedian, 1966) – structures, processes and outcomes- are illustrated in Figure 2.

Figure 2: Evaluating Medical Care



III. DATA ENVELOPMENT ANALYSIS MODEL

DEA assess the relative efficiency of performance units by obtaining the maximum of a ratio of weighted outputs to weighted inputs (Charnes, et.al., 1978; Charnes and Cooper, 1985; Moreno and Lall, 1999). The fundamental formulation for the relative efficiency of a performance unit is as follows:

$$\max\ h_0 = \frac{\sum_{r=1}^{s} u_r\, y_{ro}}{\sum_{i=l}^{m} v_i\, x_{lo}}$$

$$\textit{subject to}: \frac{\sum_{r=1}^{3} u_r\, y_{ij}}{\sum_{i=1}^{m} v_i\, x_{ij}} \leq 1;\ j = 1,\ldots,n \quad u_r, v_t > 0; \quad r = 1,\ldots,s;\ i = 1,\ldots,m.$$

where, s indicates the number of outputs, m the number of inputs, n the number of performance units, yrj the value of the r-th output of the j-th performance unit, xij the value of the i-th input of the j-th performance unit and ur and vi the variable weights to be determined by the solution. Notice that the formulation allows for multiple output (s) and multiple input (m) measures, extending the traditional single-input, single-output efficiency ratio analysis to multi-output, multi-input situations. In the DEA model, in general terms, the larger value of an output variable the better, while smaller the value of an input variable the better. However, the efficiency ratio for a performance unit is the ratio of inputs and outputs. For output variables in the DEA model, if lower values are considered better, or for input variables if higher values are considered better, then the inverse value of that variable is used in the DEA efficiency calculation formula. The maximum efficiency value of 1 for each performance unit is limited in value to 1 by the n constraints. A relative efficiency value of 1 for a given performance unit would indicate that there is no other performance unit capable of producing better outputs with the same amounts of inputs. In this study, a hospital Unit showing a relative efficiency value of 1 would imply that for the Unit's level of inputs, no better output would be produced by any of the other hospital Units under evaluation (Moreno and Lall, 1999).

IV. FUZZY COMPOSITE PROGRAMMING MODEL

FCP is one of MCDM techniques, which can handle mixed indicator data (quantitative and qualitative), and also work with conflicting, uncertain and hierarchical criteria. FCP methodology was developed by Bardossy and Duckstein (1992). There have been a lot of successful applications of FCP in the DSS literature (Lee, *et al.*, 1992; Hagemeister, *et al.*, 1996; Ghosh, 2008; Sadip and Veitch, 2002; Prodanovic and Simonovic, 2002).

The normalization is done by using the best and worst basic indicator values that are described by the following equation (Lee, *et al.*, 1992):

$$\beta_{ij} = \frac{f_{ij} - f_{ij}^{-}}{f_{ij}^{+} - f_{ij}^{-}} \text{ (When } f_{ij}^{+} \text{ is best)}$$

Or

$$\beta_{ij} = \frac{f_{ij}^{+} - f_{ij}}{f_{ij}^{+} - f_{ij}^{-}} \text{ (When } f_{ij}^{-} \text{ is best)}$$

FCP is based on a Fuzzy Composite Index (FCI). The equation is:

$$L_j = \{\sum_{i=1}^{n_j} w_{ij}\beta_{ij}^{p_j}\}^{1/p_j}$$

Where, Lj is Fuzzy Composite Index for the B+1 level group j of B level indicators;

wij is weight of B level indicators in group j;

pj is balancing factors among indicators for group j;

fij+ is the best value of ith fuzzy indicators for group j;

fij- is the worst value of ith fuzzy indicators for group j;

fij is the value of ith fuzzy indicators for group j.

The final fuzzy composite index, which is used for ranking, is obtained by calculating the FCI from basic level to top level. The weight parameters for indicators at different levels (wij) are established based on the degree of importance that decision makers feel each indicator has relative to other indicators of the same group (Bardossy and Duckstein, 1992).

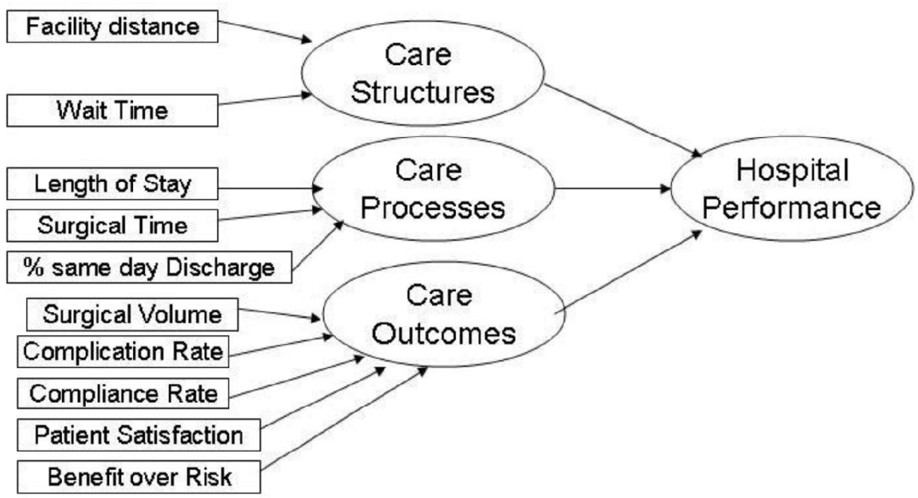
The balancing factors (p_j) reflect the importance of maximal deviations between indicators in the same group, and determine the degree of substitution between indicators of the same group. Low balancing factors (equal to 1) are used for a high level of allowable substitution. High balancing factors (equal to 3) are used for minimal substitution (Bardossy and Duckstein, 1992). The best value (f_{ij+}) stands for the maximum possible value of the indicator, and the worst value (f_{ij-}) stands for the minimum possible value of indicator.

V. RESEARCH MODEL

The research model is shown in Figure 3. The focus of this research is on the development of a fuzzy decision making model to rank several hospitals in their surgical performance. As described in section 2, the hierarchical model contains three first level indicators of (1) care structures, (2) care processes and (3) care outcomes. Prior healthcare measurement research has proposed varied indicators for each of the above three measures (Dlugacz, 2006). Items that measure care structure could include indicators such as accessibility, utilization and the training and experience of hospital staff. In our research model, care structure is measured using 2 quantitative indicators – distance in miles of the patient's reported residence to the hospital and the average wait time for a procedure in weeks. The indicators to measure process of care typically include the patient turnaround time in various departments and activities – length of stay in various Units, operating room turnaround time, patient throughput using admit and discharge times, etc. In this model, indicators for the process of care measurement include measures of average overall length of stay in days, the average duration of surgery in hours and percentage of surgeries involving same day discharge.

The indicators in the measurement of outcomes were based on using a combination of quantitative and qualitative survey data from discharged patients. The quantitative measures include the surgical volume of the hospital in number of cases handled per month, the risk adjusted complication rate for a monthly period and the percentage of patients in compliance with post discharge prescribed medication for the monthly period. The qualitative measure include data from a patient survey for two questions (using a Liekert scale of 1-7) – (1) Level of

Figure 3: Research Model



satisfaction with the treatment provided and the (2) whether the patient felt that the perceived benefits of their treatment outweighed the risks involved.

VI. RESULTS

The research methodology consists of measurement of each of the indicators over the patient mix in 15 units for 6 hospitals. Each hospital unit provided a complete data set.

Table 1
DEA Assessment Results – Efficiency Ratios

HOSPITAL	*1*	*2*	*3*	*4*	*5*	*6*
Unit # 1	1	0.8451	0.7628	0.9244	1	1
Unit # 2	0.7762	1	1	1	1	1
Unit # 3	0.9022	0.7579	0.7926	0.7111	1	1
Unit # 4	0.8909	0.7750	0.7684	1	0.9907	0.8487
Unit # 5	0.9447	0.5605	0.7527	0.8832	0.9921	1
Unit # 6	0.9448	0.9932	0.8967	0.7614	1	0.8100
Unit # 7	1	0.9643	0.8877	0.8213	1	1
Unit # 8	0.9082	0.7971	1	1	1	0.5649
Unit # 9	0.8252	0.6285	0.7901	0.6910	1	1
Unit # 10	1	0.7940	1	0.7720	1	0.7611
Unit # 11	1	0.8828	0.6337	1	0.9822	0.8589
Unit # 12	1	0.6170	0.7118	1	1	1
Unit # 13	1	0.7950	1	1	0.9732	0.9819
Unit # 14	0.9419	1	0.6852	0.7620	0.7047	1
Unit # 15	1	0.9958	0.7372	0.9946	1	1
Number of Perfect Efficiency Scores (1)	7	2	4	6	10	9
Performance Rank	3th	6th	5th	4th	1st	2nd

The DEA results from Table 1, suggest that Hospital 5 has the best performing Units and hospital 2 has the worst performance. Hospital 6 is a close second best performance. Hospitals 1, 3 and 4 are middle performers.

Table 2
DEA Assessment Results – Unit #5 in Hospital #2

Variable	*Hospital 2, Unit # 5 VALUE*	*DEA Algorithm Reference Set*			
		Hospital 1 Unit 7	*Hospital 5 Unit 6*	*Hospital 6 Unit 3*	*Hospital6 Unit 9*
Input Variables (Lower the better)					
Same Day	0	0	92.5	0	81.13
Length of Stay	8	5	4	7	5
Surgical Time	5.167	3.25	2.72	0	3.33
Distance	11.75	5.88	10.94	41.67	3.17
Wait	6.06	6.23	1.92	2.73	1.78
Output Variables (Higher the better)					
Complication Rate	5.035	5.15	1.70	2.64	2.41
Comply	88.46	95.18	81.93	91	99.02
Volume	50	58	57	58	111
PS	1	6	5	7	4
PSBR	4	7	4	7	4

The lowest efficiency ratio (0.5605) is exhibited by Unit #5 in Hospital 2. This Unit's data is analyzed further in Table 2 to ascertain factors that help to improve its efficiency ratio. The DEA algorithm establishes a reference set of performance units with perfect efficiency scores and then compares the unit under calculation against that reference set. Table 2 lists the values of the input and output variables of Unit 5 of hospital 2 and the values of those variables for its reference set of Units (Unit 7 in hospital 1, Unit 6 in hospital 6 and Units 3 and 9 in hospital 6). The comparison indicates that Unit 5 in hospital 2 is deficient in surgical time and wait time areas along with surgical volume and patient satisfaction scores.

(A) FCP Results at Hospital Level

The ranking of the hospitals and the final FCI values are shown in Table 3 (Ghosh, 2008). From Table 3, we can see the comprehensive assessment results of organization effectiveness for the six hospitals. Among these six hospitals, 5 has the best performance, while 2 has the worst performance (Ghosh, 2008).

Table 3
FCP Assessment Results (Ghosh, 2008)

HOSPITAL	**1**	**2**
FCP Index	0.532	0.513
Rank	5th	6th
HOSPITAL	**3**	**4**
FCP Index	0.541	0.535
Rank	3rd	4th
HOSPITAL	**5**	**6**
FCP Index	0.585	0.578
Rank	1st	2nd

The final ranking based on Hospital performance is close to that based on structures of care (Ghosh, 2008). For example, for units E and F are ranked as first and second, respectively by both the overall FCI score and the structure score. The overall score and the structure score also correspond on the least effective hospitals, A and B. The above congruence in the scores for the top two and bottom two performing hospitals indicate that structures of care plays the most important role on assessing hospital performance in the fuzzy model.

Table 4
Second Level Indicators (Ghosh, 2008)

No	*Structure*		*Process*		*Outcome*		*Final*
	FCI	*#*	*FCI*	*#*	*FCI*	*#*	*Rank*
5	0.635	1	0.521	1	0.645	1	1
6	0.630	2	0.509	2	0.629	2	2
3	0.609	4	0.424	5	0.622	4	3
4	0.611	3	0.440	3	0.602	5	4
1	0.604	5	0.411	6	0.627	3	5
2	0.503	6	0.438	4	0.593	6	6

Other second level indicators (processes of care and outcomes of care) have less impact on measuring the hospital performance in the fuzzy model. For each of those dimensions, there were at least 3 mismatches with the overall ranking (Table 4). Under structures of care, the ranking based on wait time is the closest to that based on the structure indicator and the final ranking (Table 5). So, wait time plays the most important role in assessing structures of care and hospital performance in the fuzzy model.

Table 5
Third Level Indicators for Structure (Ghosh, 2008)

No	*Volume*	*Distance*	*Wait Time*	*Final Rank*
5	3	4	1	1
6	2	6	2	2
3	1	3	3	3
4	5	1	5	4
1	4	2	4	5
2	6	5	5	6

VII. CONCLUSIONS

This study aimed to build a multi-criteria decision making model using data envelopment analysis and fuzzy composite programming to compare the surgical performance of several Units in six hospitals. By drawing on past epidemiological research, criteria was selected for measuring structures, processes and outcomes of care to build the final DEA and FCP models. Both quantitative data and qualitative data were used in the hierarchical model. As seen from this research, both data envelopment analysis (DEA) and Fuzzy Composite Programming (FCP) are appropriate decision making model to work with mixed indicator data (quantitative and qualitative), as well as with conflicting, uncertain and hierarchical criteria. There was agreement among the results obtained from DEA and FCP. Both algorithms, FCP and DEA ranked hospital 5 as the best performing hospital, followed by Hospital 6. Both algorithms ranked hospital 2 as the worst performing hospital.

DEA allows for finding the variables in which a Unit is performing poorly, while FCP allows for pin pointing the most important factors that play a role in hospital performance. By analyzing the second and third level rankings in FCP, structures of care played the most important role in assessing hospital performance. Other second level indicators (processes of care and outcomes of care) had less effect on the measurement of hospital performance. Inside structures of care, wait time had the most impact on hospital performance.

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