Reliability Evaluation of Healthcare Services by Assessing the Technical Efficiency

Abstract

Classical reliability analysis techniques of manufacturing and defense industries are not perfect fit for the assessment of reliability of services. This is partly due to the lack of proper and valid reliability testing procedures in service systems and complications faced in identifying critical service parameters. Since the most prominent performance indicators of a system can be associated with the maximum overall reliability it achieves, then factors that degrade the reliability can be identified with respect to its superior peers. This study utilizes the data envelopment analysis for the evaluation of reliability in service systems with focus on healthcare. Our approach comparably evaluates the performance of a service provider over a period of time by means of failure rates and identifies the factors affecting unreliable time phases. Application of the proposed method is illustrated on a private Turkish hospital along with an example of FMEA for inpatient treatment.

Key words: data envelopment analysis; service reliability; healthcare; failure mode effect analysis

Introduction

Many of the developed countries shifted large portion of their economical activities and future investment initiatives from industrialized based to service based in the last 20 years. This strategy has been an inevitable act since the competitive effect of globalization opened new markets in service sectors while closing some traditional ones, which once these giant economies dominated. Growing importance of service systems also attract the interest of academicians for development of new procedures in order to improve the quality of the services provided. Healthcare services offered within this domain account for the largest market share by means of revenues generated and costs incurred from operational errors.

Consequently, there are serious risks associated with the service quality. According to reports from Institute of Medicine of US, errors occurring from health services cause more than 100,000 deaths annually just in United States alone. The same report states that medical errors are just behind heart disease and cancer as the third leading cause of death. Another study, based on Medicare records, found that such errors cost United States almost $20 billion between 2000 and 2002. Collier (2004) quotes that "There is little evidence that patient safety has improved in the last five years. The equivalent of 390 jumbo jets full of people are dying each year due to likely preventable, in hospital medical errors, making this one of the leading killers in the U.S." highlighting the importance of healthcare reliability compared to aviation industry in which the reliability is the leading quality dimension.

These and many other studies concur that health services are simply not as safe and reliable as they should be. Governments and other local agencies are taking actions for improving the reliabilities of these crucial set of activities by developing new procedures such as periodical mandatory reporting of incidents and classification of these in a more scientific manner. But still, a widely recognized quantitative analysis system doesn't exist in the literature. The implementation of such a system can be achieved with the help of tools already proven itself by successful evaluation of quality and productivity of other service systems. Inoue and Koizumi (2004) utilize human reliability analysis to identify nursing errors in hospitals. They also identified critical practices such as medication, working shift, threat type, etc. by developing a classification and coding module in a failure mode and effect analysis (FMEA) manner. In a similar fashion, Gordon (1998) highlights the importance of technical, human, social, organizational, managerial, and environmental factors in the performance of complex systems in which the failure of one of these factors may cause large scale safety issues. Spyrou et al. (2008) introduce a stochastic reliability model for a health care domain in the early design of regional health network by using customer behavior model and activity diagrams to monitor state transitions. Human reliability analysis for various nursing errors such as patient monitoring, infection, injection, etc. are performed by Inoue and Koizumi (2004) to detect organizational factors influencing medical errors occurring in a hospital.

Use of failure rate analysis is advocated by Gunes and Deveci (2002) for the evaluation of a single stage service system; the student office of a university college and by Gunawardene (2004) in the multistage manner with the application on a healthcare management company. Dai et al. (2003) investigates the service reliability of distributed systems by evaluating certain performance characteristics such as the availability of the system and mean time to repair. Hospital operations are also an example of a distributed system and can be characterized by certain performance characteristics. However, these characteristics cannot be analyzed by using parametric methods because of the uncertain behavior of the healthcare service system structure.

We employ a nonparametric approach to analyze the reliability of healthcare organizations from a performance evaluation perspective by identifying critical operational indicators and resulting failure rates. Data Envelopment Analysis (DEA) has long been used as a popular technique to evaluate the relative efficiency of entities having identical performance attributes. These entities are often referred as Decision Making Units (DMUs) and the attributes are referred as inputs and outputs of these DMUs. Our proposed methodology assumes that the efficiency of a DMU can be best described by analyzing the failures as the output and the influencing effects (causes) as the input of the system.

Rest of the paper is organized as following. The paper briefly introduces the DEA methodology and then presents a comparable reliability analysis procedure by the help of DEA. Application of the proposed methodology is illustrated on a data set from Turkish healthcare system.

Data Envelopment Analysis

DEA has been introduced by Charnes et al. (1978) as generalization of the ideas initially presented by Farrell (1957). It is an optimization technique for evaluating the relative efficiency of homogenous decision making units, those utilizing inputs and transforming them into outputs. The term relative is used because the evaluation is carried out by a comparison. This comparison is performed by finding the efficiency of each DMU with respect to other DMUs, to those setting a benchmark for most efficient. Interesting service applications of DEA for performance evaluation can be found in Min et al. (2009) for hotel industry and Chilingerian (1995), Athanassopoulos and Gounaris (2001), Su et al. (2009) for healthcare industry.

The simplest form of efficiency is the ratio of one output to one input. In most real world applications, however, problem with hundreds of inputs and outputs may be faced, and weighted efficiency approaches are not always realistic. Methods that require the practitioner to prespecify the weights for each input and output without having detailed information may lead to biased results. So when we move to more realistic contexts that involve multiple output/input, the need for a modelling approach to measure the performance becomes inevitable. Unlike other methods, DEA does not enforce the practitioner to specify these numerical weights (can be relaxed if required) thus avoids subjective insights. Sarkis (2000) discusses several applications of DEA incorporating decision maker specified weights and no weights at all. While the former approach provides comparable results to those found by alternative multi criteria decision making methods, later approach proved to be more effective in cases where less information is available about the nature of the decision making process and sensitivity analysis of the output/input domain is important.

There exist several DEA models each inspired and derived from the original version given as

$$
\begin{aligned}
& Min \quad \theta \\
& subject\ to \\
& \theta x_{ij_o} - \sum_{i=1}^{n} \lambda_j x_{ij} \geq 0 \\
& \sum_{r=1}^{n} \lambda_j y_{rj} \geq y_{rj_0} \\
& \lambda_j \geq 0 \\
& r = 1,2,\ldots,s\,,\ \ j = 1,\ldots,j_0,\ldots,n\,,\ \ i = 1,2,\ldots,m\,.
\end{aligned}
$$

This model, known as the CCR model, characterizes the transformation of inputs to outputs by constant returns to scale. Under this assumption, if the input levels of a feasible output/input correspondence are scaled up or down then another feasible output/input correspondence is obtained in which the output levels are scaled by the same factor as the input levels. The other slightly different one, the BCC model developed by Banker et al. (1984), assumes variable returns to scale meaning that the scale efficiency necessity is relaxed. DEA model evaluates the efficiency score, θ, of DMU j_0 with respect to all other n - 1 DMUs where x_{ij} and y_{rj} are the associated input and output levels of the DMU under evaluation from the data matrix. We have an output/input matrix with a size of n (# of DMUs) by $s + m$ (# of inputs + # of outputs). Efficiency scores and ranking of DMUs based on these efficiency scores is achieved by solving this model for each DMU separately. Note that λ_j's are the weights assigned to each DMU's output/input set existing in the associated row of the data matrix. These weights are decision variables of the model and are not predetermined.

The efficiency also depends on the orientation of the model. By definition, a model can be formed either input oriented or output oriented. This is best described in Thanassoulis (2001) as "Measures of efficiency are based on estimates of the degree to which the DMU of interest could have secured more output for its input levels, or the degree to which it could have used less input for its output levels, implying that the DMUs evaluated may have more discretion over their input or output levels". So when the model is output oriented, it would not be possible to raise any one of its outputs without lowering at least another one of its outputs, or without increasing at least one of its inputs. And vice versa holds for input oriented models as it would not be possible to lower any one of its inputs without increasing at least another one of its inputs, or without lowering at least one of its outputs. Note that, all the measures are in relative terms, so every efficiency rating is dependent on the efficiency of one or multiple other DMU(s).

Reliability Evaluation via DEA

Classical definition of reliability can be given as the probability of non-failure for a given period of time. This definition has to be translated into a more specific domain when speaking of healthcare by accepting reliability as the level of service performance over time. Performance of the services provided may be related to several objectives simultaneously, particularly diagnosis and effectiveness of the treatment, facility restrictions, and patient expectations. This domain should clearly indicate all possible failure causes and mechanisms in order to identify the factors effecting service performance. Only by doing so, one can construct the necessary output/input matrix of DEA formulation.

Failure mode and effect analysis (FMEA) is a vigorous method in the evaluation of the service systems for failure causes and for selecting critical performance indicators. Nolan et al. (2004) provides a detailed example of a FMEA process used to evaluate and improve the reliability of a chemotherapy service. In this study, each failure mode is associated with a risk priority number with respect to its severity and proposals are made to minimize the sum of risk priority number from whole chemotherapy process. FMEA also gives the practitioner a chance to initiate an in depth sensitivity analysis once the reliability of the system is evaluated and the failure based efficiency ratings are obtained. Several objectives of the FMEA proposed by IEEE Standard 352 (1987) are a perfect match to the problem of identifying failure mechanisms in healthcare systems. These can be listed as;

- Determination of all reasons how a system may fail and what the effect of the failure in question on the system.
- Listing potential failures and identifying each one's impact on the system.
- Collection and classification of the data necessary for risk, reliability and availability analysis.
- Compilation of historical information for future reference to aid the efforts in analyzing and improving system design.
- Establishing procedures for sensitivity and trade-off analysis.
- Evaluation of system requirements such as redundancy, test frequency, fail-safe characteristics and establishing corrective action priorities.

As mentioned previously, DEA measures the efficiency by relative terms in a nonparametric manner. This bold nature of DEA brings in both an advantage and a disadvantage for the application to reliability problems. It is an advantage since there is no need for a prior distributional knowledge or assumption regarding the failure mechanism of the system. But on the other hand, efficient frontier has to be built from an observed reference set where all the indicators are present. In other words, entity in question has to be compared to a so-called best performer(s); to which underperformers desire to attain. This becomes a problematic feature when speaking of reliability analysis since we are mostly measuring the reliability performance of a unique entity and no comparable reference set is usually present. So our solution procedure is going to include a single system with multiple snapshots of the performance of the system overtime. Each snapshot will play the role of different decision making units of the respective DEA model. Typical example of a DEA application to such time based problems can be found in Parkan (1999) in which the performance of a government department that provides services to public facilities is measured over a period of 16 months. On the other hand, snapshot approach eliminates the need for scale efficiency analysis because of the uniqueness of the entity under investigation. Since all DMUs represent the same healthcare service at different time frames, scale efficiency will be secured automatically.

Another issue that may arise in the application of DEA to reliability evaluation problems is the size and the character of output/input matrix. In DEA, the inputs represent the resources consumed by the operation in question while the outputs are the level of achievement of this operation on which the assessment of the efficiency is based on. For reliability analysis purpose, we consider a single output model with multiple inputs. Since technical efficiency depends on operations without failure, reliability rate is chosen as the single outcome of DEA transformation process. Unfortunately, there is no clear cut definition of "failure free" for healthcare services. The ideal way is to cross check all services offered to each patient against the FMEA and try to determine if the service is affected from any one of the failure modes displayed there. Then the reliability rate can be calculated by taking the ratio of the patients that are totally failure free to the all patients serviced.

On the other hand, selection of inputs is more versatile. This selection should be based on how well the inputs represent the related failure modes of services provided, since the resources consumed for failures are originating from these failure modes. While including as much information (as many inputs) as possible is important, DEA methodology restricts this to a certain level. Drake and Howcroft (1994) shows that DEA operates more effectively when the number of DMUs exceeds total number of the inputs and outputs by at least twice. Input selection is also important as the orientation of the chosen model plays an important role in the solution procedure of DEA. Efficiency scores of output and input oriented constant returns to scale models are to be exactly same with the difference occurring in the projected levels of output/input values for inefficient DMUs (time frames). In this case, output oriented model is not preferable since the single output of the model, reliability rate, is not directly controllable for to be maximized by keeping the input levels steady. Instead, input orientation is utilized by aiming to reduce the input levels as much as possible to attain at worst the current reliability rating.

DEA's nonparametric nature makes it immune to the challenges that may arise due to correlation between outputs and inputs or the interaction of several input variables. Selection of these variables should still be done discreetly with respect to their impact on the efficient frontier but statistical nature does not parametrically affect the DEA results. These characteristics become an important obstacle in carrying out DEA when there is missing data in the output/input matrix. Aksezer and Benneyan (2010) discuss several methods of handling missing data in DEA for different type and size of problems faced in the literature.

Reliability Assessment: Application on a Turkish Hospital

This case study considers a private hospital funded by a non-profit foundation located in a metropolitan area of Turkey. Selection of a private hospital is entirely based on practical reasons since the management already established the infrastructure necessary for collection and storage of the data related to reliability and performance analysis. Although the facility provides services both for inpatients and outpatients, our focus is on the reliability of services tendered to inpatients visiting the surgery room for a diagnosed and operable sickness. FMEA process is applied to understand failure causes affecting the system and to record the number of failures occurred. Table 1 provides the output of the FMEA performed on this specific service during a period of 24 months. Note that there is no risk priority number assigned to any of the 6 failure modes (inputs) in question. This is especially important in justifying the use of DEA without weight restrictions. The input variables are;

- Waiting time for admission: This is the length of time elapsed from the decision of surgery until the surgery taking place. Private hospitals tend to initiate operations in a timely manner because of the almost unrestricted scheduling of staff, personnel and facilities. This performance indicator is more crucial when speaking of public hospitals since they usually have scarce resources and a delay in treatment widely occurs. This indicator is especially included to have a contrast of pre and post operation failure domain.
- Post operation stay: This is the length of time that a patient spends in hospital after the surgery. Many complications may arise in the post operation time domain while the patient is still under the control of medical personnel and within immediate reach of medical facilities. Time spend and complication occurred in the intensive care unit is not included here.
- Short term fatalities: This performance indicator consists the number of fatalities occurred during or within 7 days of the surgery or the ones occurred with a longer stay in intensive care unit. Measure of the performance is related with failures occurring from short term complications as direct result of misconduct during operation.
- Medication: Prescribed medicine is a basic resource consumed in every kind of healthcare operation and effect of drug related failure modes on reliability can be measured by the number of medicines prescribed by a specialist.

- Complaints: Failures occurred from improper execution of procedures may lead to non-severe failures such as dissatisfaction of the patient and cost increasing repetitive administrations
- Legal actions: Complaints of patients that are taken to courts or penalties incurred by the lawmaker lead to financial losses. Other costs such as public relations, social responsibility etc. may also be faced in order to amend the reputation lost. (Note that compensations for damages are not included since actions that caused these damages occurred before the time domain of interest)

Table 1

Table 2

In order to achieve a balance between the failure modes, they are selected from a collection of similar severities. One can also argue the generality of the failure modes selected. From theoretical point of view, it is surely better to explore the details of each failure mode separately. For example; failures occurred from wrong medication can be specified as distinct modes such as pharmacist error; wrong drug mix, side effects, etc. However, the number of inputs are limited at 6 (that covers almost all failures in general perspectives) to prevent the DEA methodology from producing ineffective results because of a large output/input matrix. Lastly, reliability rate of each month is gathered to process as the output column of the DEA data matrix by identifying failure free patients against total number operated during that specific month. (Table 2)

CCR model is run on Saitech DEA-Solver Pro (version 3.0) and the results for scores, ranks and reference set for each month are illustrated in Table 3. CCR model assigns an efficiency score between 0 and 1 to each DMU with efficient months getting the score of 1 and relatively inefficient ones, getting less than 1. During the years 2007-2008, 6-months are found to be efficient (score = 1) with 18-months being inefficient (score < 1). From the reliability point of view, relatively inefficient means that during the given month the inpatient service can obtain the same reliability rate by using way less resources. For example; December of 2007 has the poorest efficiency score, which is 0.61. This means that services provided during that month should produce exactly the same reliability rate of 0.71 by just using the 61% of the resources it already consumed.

Table 3

Another useful result of the DEA model is the identification of reference (peer) sets that are used in the calculation of inefficiencies. It is already mentioned that DEA gives a comparable measure of efficiency. This comparison is done through the calculation of excess resources used by inefficient DMUs with respect to some of the most efficient superiors. Table 3 presents the reference set for inefficient months and the weight of each efficient month in calculating the projected values of inputs consumed during the given month if it is to be efficient. December of 2007 is to be efficient when it consumes as much as the weighted average of January07, September07, June08 by factors of 0.006, 0.248 and 0.564 respectively. Projections of excess inputs are also illustrated here. These projections imply the possible reductions that can be achieved in the consumption of the inputs.

Conclusions

Reliability analysis of services provided in medical facilities is a challenging task for healthcare professionals since most of the existing models are mathematically rigorous and involves rigid assumptions. This paper presents the use of DEA, a popular linear programming based efficiency evaluation technique, towards the analysis of factors influencing failures and resulting reliability rates.

FMEA is already a proven method in the identification of failure mechanisms and effected components of the system that is under evaluation. These mechanisms are the critical reliability performance indicators of the system and can be evaluated by DEA. The efficiency measure based on reliability should reflect the difference between actual reliability performance and potential performance of the entity being evaluated. Application of DEA on reliability problems proves to have several flexibilities. Firstly, DEA practitioner has no need for predetermined weights that associate each input with a risk factor. This eliminates the subjective nature of the solution procedure. Secondly, if the evaluated service is one of a kind, then technical efficiency should be enough for analysing the reliability performance during a given period of time. This also eliminates the questions regarding the scale efficiency of the unit under investigation.

Application of the proposed procedure to a Turkish hospital showed that the reliability performance of the inpatient treatment service is underperforming during most of the months in a 2-year period. As a potential managerial decision making and supporting tool, DEA solution produces many useful statistics. In an input oriented model as applied here, underperforming months are probed to identify the causes of inefficiencies by examining the excessive resources they consumed. These statistics are particularly appropriate for suggesting where underperformers should reside in performance domain in order to be at acceptable levels. More over, a virtual best performer can be created to be included in the DEA. This is the ideal DMU that don't exist in reality but assumed to be the target of efficiency. In this way, comparative nature of DEA should be manipulated in any direction the practitioner wishes. On the other hand, a sensitivity analysis with respect to the chosen performance indicators and time phase would be highly beneficial for validating the results obtained and (or) for observing effects of uncontrollable factors such as seasonality, new management practices, and mono-method bias.

Another efficient frontier estimation technique, stochastic frontier analysis, can be applied to such problems as a future research topic when the underlying distribution of the failures of the system is known or approximated. This may be interesting in displaying the advantages and disadvantages of parametric and nonparametric approaches in a comparable environment.

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Table 1. FMEA for Inpatient Treatment

Mode Number	Failure Mode	Possible Causes	Effect on System/Patient	Detection Method	Related DEA Input
1	Delay of the treatment	Scarce resources such as medical personnel, facility, medicine	Longer recovery time; Deterioration in patient's condition; Death	Outpatient visits; Medical records	Length of inpatient waiting time for admission
2	Long term surgical complications	Environmental factors; Procedural misconducts	Deterioration in patient's condition; Facility shutdown	Post-op diagnosis; Patient complaints	Length of post operation stay
3	Short term surgical complications	Surgeon error;	Severe deterioration in patient condition; Death	Monitoring vital signs; Observations for other surgeons and medical personnel	Number of fatalities within 7 days of surgery
4	Wrong medication	Problem with the dose; Medicine administered inappropriately; Wrong drug	Increase in length of stay; Deterioration in patient condition; Death	Post-op diagnosis;	Number of drugs prescribed
5	Non-fatal clinical negligence	Medical staff error; Laboratory staff error	Deterioration in patient condition; Inefficiency of the system by duplicate procedures	Pre-op diagnosis; Patient complaints	Number of complaints filed
6	Failure to comply with the rules and regulations	Violation of standard procedures; Actions not taken on time to correct other failure modes	Increase in operational costs; Patient Dissatisfaction; Loss of reputation	Independent audits; Exit surveys	Costs incurred for legal expenses, settled damages, and other penalties

Table 2. Inpatient Data for DEA

Month	Inputs						Output
	Admission Waiting Time	Post-op Time	Fatalities	Drugs	Complaints	Cost	Free-Failure Rate
January07	2.40	2.70	4	2590	31	25634	0.82
February07	3.91	5.39	3	2393	27	28774	0.76
March07	5.08	4.49	7	2869	54	49527	0.64
April07	2.75	4.08	3	2236	25	18987	0.86
May07	3.22	4.79	5	2521	30	32405	0.84
June07	4.14	9.59	4	2224	12	22546	0.82
July07	7.56	5.32	1	2171	23	24876	0.80
August07	5.45	4.24	5	2177	23	22365	0.90
September07	6.67	3.36	2	1881	17	23967	0.88
October07	4.81	3.35	4	2337	27	24765	0.82
November07	5.86	4.88	5	4816	32	56734	0.83
December07	5.41	5.01	6	2478	65	23387	0.71
January08	3.43	7.20	2	1894	17	17116	0.89
February08	3.90	3.26	3	2628	32	29369	0.80
March08	3.35	5.23	2	1947	19	17452	0.79
April08	4.48	5.22	1	2425	27	27293	0.83
May08	5.40	5.21	1	1523	10	8911	0.86
June08	2.81	3.93	2	1832	16	14543	0.87
July08	5.11	7.68	2	1637	12	11236	0.84
August08	7.28	3.97	4	2145	28	22784	0.83
September08	6.02	6.76	2	1578	17	15485	0.89
October08	3.19	6.11	3	2758	37	32678	0.81
November08	5.83	5.86	4	2556	34	30462	0.79
December08	4.93	4.68	2	2062	21	19316	0.82

Table 3. DEA Solution

Month	Score	Rank	Reference set {(DMU):(weight)}	Excess Inputs					
				Adm.Time	Post-op Time	Fatalities	Drugs	Complaints	Cost
January07	1	1	-	-	-	-	-	-	-
February07	0.67	20	{(May08 - June08):(0.052 - 0.828)}	0	0.07	0.29	0	4.25	6694.84
March07	0.56	24	{(January07 - September07 - June08):(0.273 - 0.214 - 0.266)}	0	0	1.85	0	13.71	11583.33
April07	0.98	8	{(January07 - June08):(0.350 - 0.656)}	0	0.45	0.21	71.46	3.04	0
May07	0.82	18	{(January07 - June08):(0.337 - 0.650)}	0	0.46	1.44	0	3.71	8433.18
June07	0.99	7	{(May08 - June08):(0.553 - 0.397)}	0	5.06	2.61	632.54	0	11623.36
July07	0.93	11	{(May08):(0.931)}	2.01	0.10	0	603.75	12.11	14874.85
August07	0.88	14	{(January07 - September07 - June08):(0.017 - 0.486 - 0.524)}	0.05	0.00	2.32	0	3.09	0
September07	1	1	-	-	-	-	-	-	-
October07	0.91	13	{(January07 - September07 - June08):(0.440 - 0.377 - 0.149)}	0.38	0	0.82	0	2.08	0
November07	0.66	21	{(January07 - September07 - June08):(0.345 - 0.328 - 0.300)}	0	0	0.66	1113.22	0	16318.19
December07	0.61	23	{(January07 - September07 - June08):(0.006 - 0.248 - 0.564)}	0.06	0	2.03	0	26.38	0
January08	0.97	9	{(May08 - June08):(0.164 - 0.861)}	0	2.71	0.04	0	0.98	2531.06
February08	0.92	12	{(January07 - September07 - June08):(0.437 - 0.289 - 0.215)}	0	0	0	345.45	7.51	5731.71
March08	0.85	15	{(April08 - May08 - June08):(0.027 - 0.094 - 0.794)}	0	0.72	0	0	1.86	1790.37
April08	1	1	-	-	-	-	-	-	-
May08	1	1	-	-	-	-	-	-	-
June08	1	1	-	-	-	-	-	-	-
July08	0.95	10	{(May08 - June08):(0.804 - 0.180)}	0	2.40	0.74	0	0.47	887.05
August08	0.85	16	{(January07 - September07 - June08):(0.068 - 0.501 - 0.380)}	1.59	0.00	1.35	0	6.99	0
September08	1	1	-	-	-	-	-	-	-
October08	0.81	19	{(January07 - June08):(0.256 - 0.700)}	0	1.49	0	283.24	10.76	9661.65
November08	0.63	22	{(September07 - May08 - June08):(0.171 - 0.183 - 0.556)}	0	0	0.90	0	7.92	5488.94
December08	0.84	17	{(September07 - May08 - June08):(0.219 - 0.231 - 0.500)}	0	0	0	40.71	3.49	1543.30