Chapter 8
Hospital Applications

8.1 Introduction

In health care, the first application of DEA is dated to 1983 by the study of Nunamaker, measuring routine nursing service efficiency. Since then, DEA analysis is used widely in the assessment of hospital technical efficiency in the United States as well as around the world at different levels of decision making units.

Earlier DEA studies were aimed at specific characteristics or types of hospitals, such as teaching and non-teaching hospitals, studied by O'Neill (1998), Grosskopf et al. (2001, 2004). Harrison et al. (2004) evaluated the technical efficiency of 280 U.S. federal hospitals in 1998 and 245 U.S. federal hospitals in 2001 using DEA methodology. The study found that overall efficiency in federal hospitals improved from 68% in 1998 to 79% in 2001, while at the same time there was a potential for savings of $2.0 billion annually through more efficient management of resources. Harrison and Sexton (2006) evaluated the efficiency of religious not-for-profit hospitals using DEA and found that overall efficiency in religious hospitals improved from 72% in 1998 to 74% in 2001. Wang et al. (1999) evaluated trends in efficiency among 314 metropolitan American hospital markets with 6,010 hospitals. Results suggested that larger hospital size was associated with higher inefficiency. Ozcan (1995) studied the hospital industry's technical efficiency in 319 U.S. metropolitan areas and found that at least 3% of health care costs in the gross domestic product (GDP) are due to inefficiencies created by the excessive buildup of providers.

Changes in hospitals' technical efficiency resulting from impact of policy, technology and environment issues also were studied in literature. One of the areas of application of DEA to the hospital industry was an assessment of hospital mergers (Harris et al. 2000; Ferrier and Valdmanis, 2004). Lee and Wan (2004) used DEA in the study of relationship between information system (IS) integration and efficiency of 349 urban hospitals, measured in 1997 and 1998. Chu et al. (2004) examined effect of capitated contracting on hospital efficiency in California and found that less efficient hospitals are more likely to participate in capitated contracting and that hospital efficiency generally increases with respect to the degree of capitation involvement. Mobley and Magnussen (2002) assessed the impact of managed care penetration and hospital quality on efficiency in hospital staffing in California using DEA production function model, including ancillary care among the inputs and outputs. The study found that market share and market concentration were the major determinants of excess staffing and poor quality was associated with less efficient staffing. Chirikos and Sear (1994) studied technical efficiency and the competitive behavior of 189 acute Florida hospitals and found that inefficiency ratings were systematically linked to the competitive conditions of local health care markets. A study by Brown (2002) used the HCUP sample of hospitals for 1992–1996 for estimation of hospital technical efficiency and found that increased managed care insurance is associated with higher technical efficiency.

Different studies used different levels of DMUs (Ozcan and McCue, 1996; Ozcan et al. 1996a, b). While most of researchers used hospital level, there are also applications of DEA at managerial level. O'Neill (2005) compared multifactor efficiency (MFE) and non-radial super-efficiency (NRSE) for operating room managers at an Iowa hospital. These techniques lead to equivalent results for unique optimal solutions and a single output. MFE incorporates the slack values from multiple output variables and can be easier for managers because it does not require additional steps beyond the DEA. O'Neill and Dexter (2004) developed and validated a method to measure "market capture" of inpatient elective surgery using DEA for Perioperative Services at 53 non-metropolitan Pennsylvania hospitals, demonstrating DEA's potential as a valuable tool for managers' decision-making.

Data envelopment analysis for estimation of different aspects of health care services and hospitals' technical efficiency was used in Spain (Pina and Torres, 1996; Sola and Prior, 2001; Dalmau-Atarrodona and Puig-Ju, 1998), Taiwan (Chang, 1998), Thailand (Valdmanis et al. 2004), Turkey (Ersoy et al. 1997; Sahin and Ozcan, 2000), Greece (Giokas, 2001; Athanassopoulos and Gounaris, 2001), Germany (Helmig and Lapsley, 2001), Canada (Ouellette and Vierstraete, 2004), United Kingdom (Field and Emrouznejad, 2003; McCallion et al. 2000), Belgium (Creteur et al. 2003), Kenya (Kirigia et al. 2004), Botswana (Ramanathan et al. 2003), and Sweden (Gerdtham et al. 1999). Biorn et al. (2003) studied the effect of activity-based financing on hospital efficiency in Norway. DEA also was used for international comparison (Mobley and Magnussen, 1998; Steinmann et al., 2003). For more in-depth evaluation and a summary of health and hospital applications of DEA, the reader is referred to papers by Hollingsworth (2003) as well as O'Neill et al. (2007).

8.2 Defining Service Production Process in Hospital Sector

The various studies mentioned above defined hospital service production in varying models. Sherman and Zhu (2006) identified the variations in hospital production models and suggested that it is hard to compare outcome of efficiency studies due to a lack of standard conceptualization of inputs and outputs in this process. O'Neil et al. (2007), in a recent taxonomy of DEA hospital studies, illustrated various inputs and outputs used by different researchers in service production process.

Ozcan et al. (1992), Ozcan (1993), Ozcan and Luke (1993) and later studies by Ozcan identified three major categories of inputs as capital investment, labor and other operating costs. Similarly, O'Neill et al. (2007) taxonomy provide categories of inputs and outputs and identify three broad categories of inputs; namely capital investment, labor and other operating expenses. These categories of inputs through the research over the years emerged as the standard for hospital service production. On the output side, Ozcan and associates (in early 1990s) introduced the following output measurements: case-mix adjusted discharges for inpatient side, outpatient visits for ambulatory activities, and teaching for those hospitals engaged in medical education. O'Neill and associates taxonomy also includes outpatient visits, admissions or discharges, and teaching. Although inpatient days are also identified as another output category in this taxonomy, O'Neil and associates also provide trends that shape the usage of inputs and outputs in hospital studies. More specifically, they show that the use of "inpatient days" measuring inpatient activities is replaced by adjusted admissions or discharges as DRG-based reimbursement took place both in the USA and some European countries.

While conceptualization of service production using these input and output categories is very important for robust DEA modeling, it is equally important to operationalize these variables with available measurements from the field via existing data bases.

American Hospital Association (AHA) data, http://www.aha.org, is the main source for operationalization of the DEA input and output variables in the United States. However, the AHA database alone cannot provide all the necessary components for a robust model. Thus, other databases such as the Centers for Medicare and Medicaid Services (CMS), http://www.cms.hhs.gov, are necessary to identify the nature of the outputs, especially for inpatients through determination of case-mix for the hospitals. It should be also noted that, data elements collected by AHA changes overtime. For example, until the 1990s financial data that could determine the operational costs were reported. However, in later years, researchers could only obtain such data from the CMS database. Furthermore, reporting of some variables was also substituted with their variants, as is the case with the AHA, which no longer reports discharges but reports admissions.

These idiosyncrasies challenge practicing administrators and researchers to operationalize the inputs and outputs for a robust DEA model of hospital service production. However, culmination of the research to date demonstrates that most commonly agreed to and available variables from the mentioned databases are used to evaluate general hospital efficiency throughout the United States. Non-US examples appear to follow similar steps.

Based on this discussion, it is possible to create a nomenclature for performance evaluation and a robust DEA model that is operationalized for hospital sector in general.

8.3 Inputs and Outputs for General Hospitals

As it is briefly introduced in previous section, inputs of hospitals can be categorized in three major areas as: capital investments, labor, and operating expenses. Outputs, on the other hand, should reflect both inpatient and outpatient activity. Those hospitals which provide teaching function would be considered as extension to this model.

8.3.1 Hospital Inputs

Operationalization of three broad categories of inputs using AHA and CMS databases requires construction of variables and proxies. For example, the capital investment is a variable that not directly available from these data bases. State wide databases or hospitals in their accounting books may report this variable as "assets," however, value of assets depends on their recorded or acquisition time and their depreciation. Thus, using the book values of such investments do not reflect what is on the ground as a health service plant.

8.3.1.1 Capital Investments

Ozcan and Luke (1993) showed that one can estimate capital investments in a hospital using two indicators: (1) plant size, measured by number of operational beds, and (2) plant complexity, measured using number of diagnostic and special services provided exclusively by the hospital. These two proxy variables were tested using Virginia data to assess their approximation to actual assets of the hospitals in the state. Their assessment found significant association between the two proxies and hospital assets, thus validating these measures for capital investment. Although we will use same variables in defining our model, we will choose more commonly used names that correspond to current literature. For example, plant complexity will be referred as service-mix.

Beds. AHA database routinely provides operational beds in their annual survey reports, thus the measurement of this variable is readily available.

Service–mix. AHA database currently identifies up to 80 services that are offered by a hospital and provides coding that indicates whether these services are offered by the hospital or through the hospital by others. The key to the coding is whether the services are offered by the hospital, thus appropriate investment is in place. If the service is not offered or offered by others for this hospital, then it can be coded as zero (0), otherwise code would be one (1) indicating the service offering. By adding the number of services offered by the hospital, service-mix variable is created. The value of this variable technically can change from 0 to 80, however, 2004 AHA survey report we calculated the median number of service-mix for small, medium, and large hospitals as 9, 14, and 18, respectively.

8.3.1.2 Labor

Labor is the second major category for hospital inputs. Operationalization of this variable would be different in USA and other countries, especially in those where socialized medicine is practiced and physicians are the part of the labor force for the hospitals. In the USA, however, physicians generally are not hospital employees with an exception of chiefs and department heads. Thus, in evaluating the performance, it is prudent to attribute the labor as non-MD labor or their full time equivalents (FTEs). The number of non-physician FTEs employed by a hospital would cover all nursing, diagnostic, therapy, clerks and technical personnel. It is also prudent to remind the reader that some of the DEA studies used labor costs to measure this variable. Depending upon the location of the hospital and the availability of skill-mix, labor salaries may not accurately reflect this input variable. Thus, the labor costs would require regional or even state or city based adjustments. However, using FTEs overcomes this weakness.

FTEs. AHA database provides the total FTEs as well for various categories. Part time labor is converted to FTE by multiplying ½ of their numbers.

8.3.1.3 Operating Expenses

Operating expenses for hospitals can be obtained from CMS data base, however, to eliminate double counting, labor expenses and expenses related to capital investments such as depreciation should be subtracted from this amount. Ozcan and Luke (1993) labeled this variable as supplies indicating all necessary non-labor resources in provision of patient care. We label this variable as other operational expenses.

Other operational expenses. This variable provides the account for medical supplies, utilities, etc. to provide the services to patients.

8.3.2 Hospital Outputs

Inpatient and outpatient services constitute the majority of outputs for general hospitals that do not provide teaching function. Thus, each type of service needs to be accounted for in the hospital service production with appropriate measurements.

8.3.2.1 Inpatient

Inpatient services are easy to account for through admissions or discharges. However, not all patients arriving at the hospital require same level of attention and service. Some come for a day for a minor ailment, yet others go through major medical or surgical procedures. In order to account for this diversity in health service demand or its provision, we must account for severity for the admissions. CMS publishes case-mix index for hospitals each year. The case-mix indexed is calculated based on patient diagnostic related groups (DRGs) providing relative weight for acuity of the services provided by a hospital. For instance, if case-mix for a hospital is equivalent to 1.2, this means the hospital served 20% more acute patients than a standard hospital (compared to hospital with case-mix index value of 1). This measure is calculated based on Medicare and Medicaid patients, and since a good portion of the hospital revenues come from this source, we could extrapolate the case-mix index for the other patients of the hospital.

Case-mix adjusted admissions. This variable is created using admissions from AHA data base and multiplying them by CMS case-mix index. This way a hospital with 10,000 admissions a year and case-mix index of 1.2 would be reflected as 12,000 adjusted admissions. Similarly, a hospital with case-mix index of 0.9 and 10,000 admissions would be reflected as 9,000 adjusted admissions.

8.3.2.2 Outpatient

Outpatient visits are a readily available variable from AHA data base. Unfortunately it does not have case-mix adjustments as in inpatient, since the payment systems are not in a similar vein. Here, health care managers and researchers have options to differentiate the visits, indicating whether these are day surgery, emergency or routine visits. Unfortunately, most general databases do not differentiate the visits.

Outpatient visits. This variable is available from AHA data base as described. The ongoing identification of input and output variables for a robust hospital sector service production via DEA model is summarized in Fig. 8.1. This model includes two outputs and four inputs and encompasses the majority of the hospital service production processes.

In this model, hospital managers are in control of the assets of the hospital, its labor, medical supplies and associated operational expenses. Admitted patients and visits to clinics (outpatient) constitute its final outputs. Of course, in order to produce these outputs given inputs, many intermediate processes are to occur, and these processes involve clinical decisions largely controlled by physicians or other clinicians. The aim of the proposed model is to capture the managerial performance (although often affected by clinical decisions) that can be attributed to hospital management.

Using the model and its variants described in this section, various studies were conducted to date. Most of these studies were applied to acute and general hospitals while others targeted federal government run institutions such as veterans administration (VA) hospitals as well as department of defense (DoD) hospitals. Furthermore, hospitals with a teaching mission or Academic Medical Centers were also considered in various studies where outputs or inputs of the model adjusted accordingly. Ensuing sections of the chapter provide brief discussions of these studies, starting with acute general hospitals (8.4), government hospitals (8.6), and Academic Medical Centers (8.7).

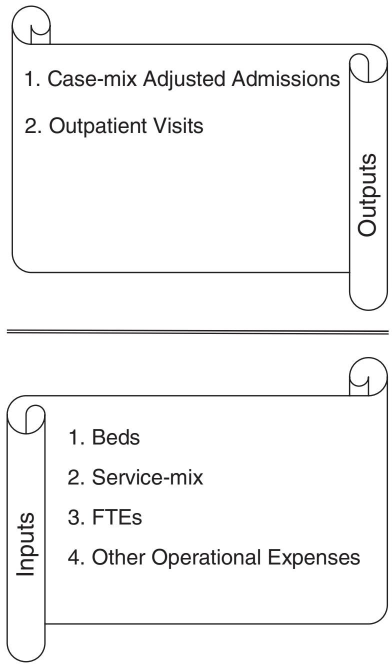


Fig. 8.1 Outputs and inputs for a robust hospital DEA model

8.4 Acute and General Hospital Applications

Acute and general hospital applications are the most frequently reported application area in health institution performance measurement. These studies can be grouped by their profit and non-profit, public comparisons as well as religious affiliations.

Grosskopf and Valdmanis (1987) conducted the first study comparing 82 public and not-for profit hospitals. This study showed that public hospitals were slightly more efficient (96%) than non-profit counterparts (94%). The results of Valdmanis (1990) study with 41 hospitals showed 98% efficiency for public hospitals compared to 88% for not-for-profit hospitals. Similarly, using 1989 AHA data base, Ozcan et al. (1992) and Ozcan and Luke (1993) found public hospitals were more efficient (91%) than church (87%), not-for-profit (88%), and for-profit (83%) hospitals.

These studies also intrigued further investigation of religious affiliation, and White and Ozcan (1996) examined the non-profit hospitals further by examining ownership by church and secular dimensions. This study examined 170 California hospitals using the variant of the robust model described above, and found that church based hospitals were more efficient (81%) than secular (76%) hospitals.

Using the DEA techniques learned in earlier chapters, and the robust hospital performance model presented in this chapter, we will show a hospital application example.

8.5 Large Size General Hospital Performance Evaluation

It is prudent to illustrate the robust model with recent data. This example follows the model presented in Sect. 9.3 for large acute and general hospitals in US. The data is drawn from 2004 AHA and CMS data bases. Few hospitals were deleted from consideration because of important missing information. This yielded 131 hospitals with 600 or more beds for evaluation of their efficiency. Table 8.1 summarizes the descriptive statistics for this group of hospitals.

Large US hospitals considered in this example have an average 805 beds and average 20 different services offered. They employ equivalent of 4,786 full time employees and spend over 311 million on their operational expenses not including labor. On output side, on average 61,767 adjusted (due to high severity) inpatient admissions and over one half million outpatient visits occurred to each hospital.

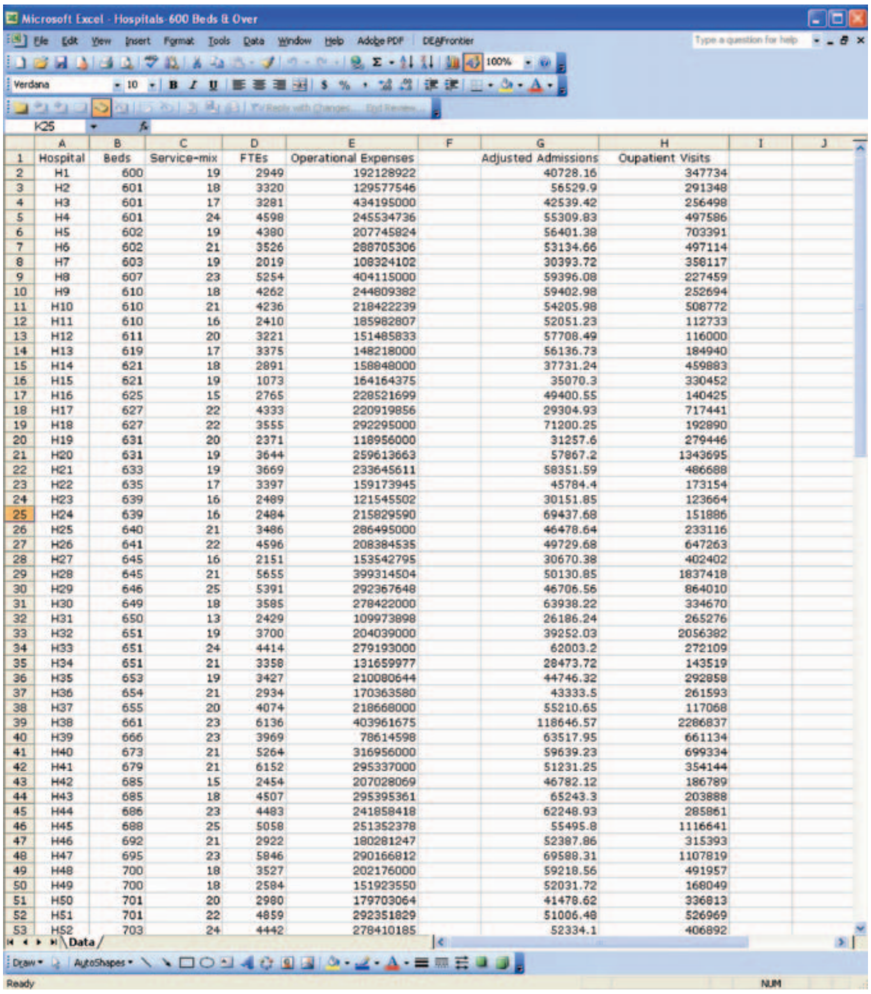
Although these 131 large hospitals account for about 2.6% of the non-federal hospitals, the total number of beds in these hospitals represents approximately 13.2% of all US non-federal hospital beds. Similarly, outputs of these 131 large hospitals constitute approximately 23% of all inpatient admissions and 12.6% of all outpatient visits in the US. Thus, evaluation of performance for large hospitals is important and may shed some light on health care performance, as well as identify excessive resources spent in this country.

Figure 8.2 displays a partial view of data input and set up for 131 hospitals with 600 or more beds for DEAFrontier software. Figure 8.3 provides also a partial view of the results of the efficiency evaluations for these hospitals. The reader can note that four inputs and two outputs are shown at the top of the results spreadsheet in this figure. The results are summarized in Table 8.2. Large hospitals' average efficiency scores were about 0.685, indicating on average 31.5% overall inefficiency. One hospital reported 66%, the worst inefficiency. Further description of efficiency is displayed in Table 2.4, where range of efficiency, number of hospitals and percentage of hospitals are reported. Only ten hospitals (7.6% of large hospitals) achieved a perfect efficiency score of one among their peers. Another five hospitals achieved

Table 8.1 Descriptive statistics for US hospitals with 600 or more beds (n = 131)

Statistics	Inputs				Outputs	
	Beds	Service-mix	FTEs	Operational expenses (in million $)	Adjusted admissions	Outpatient visits
Mean	805.2	20	4,786	311	61,767	556,350
St. Dev.	239.6	3	2,362	171	22,866	448,902
Min	600	13	1,073	5	15,268	101,581
Max	2,095	25	15,570	1,021	171,563	2,875,388
Total	105,476	2,628	626,924	39,542	8,091,472	72,881,823
US total[1]	800,000		4,000,000		575,000,000	35,000,000

[1]Approximate values based on AHA 2004 data.



	Hospital	Beds	Service-mix	FTEs	Operational Expenses	Adjusted Admissions	Oupatient Visits
2	H1	600	19	2949	192128922	40728.16	347734
3	H2	601	18	3320	129577546	56529.9	291348
4	H3	601	17	3281	434195000	42539.42	256498
5	H4	601	24	4598	245534736	55309.83	497586
6	H5	602	19	4380	207745824	56401.38	703391
7	H6	602	21	3526	288705306	53134.66	497114
8	H7	603	19	2019	108324102	30393.72	358117
9	H8	607	23	5254	404115000	59396.08	227459
10	H9	610	18	4262	244809382	59402.98	252694
11	H10	610	21	4236	218422239	54205.98	508772
12	H11	610	16	2410	185982807	52051.23	112733
13	H12	611	20	3221	151485833	57708.49	116000
14	H13	619	17	3375	148218000	56136.73	184940
15	H14	621	18	2891	158848000	37731.24	459883
16	H15	621	19	1073	164164375	35070.3	330452
17	H16	625	15	2765	228521699	49400.55	140425
18	H17	627	22	4333	220919856	29304.93	717441
19	H18	627	22	3555	292295000	71200.25	192890
20	H19	631	20	2371	118956000	31257.6	279446
21	H20	631	19	3644	259613663	57867.2	1343695
22	H21	633	19	3669	233645611	58351.59	486688
23	H22	635	17	3397	159173945	45784.4	173154
24	H23	639	16	2489	121545502	30151.85	123664
25	H24	639	16	2484	215829590	69437.68	151886
26	H25	640	21	3486	286495000	46478.64	233116
27	H26	641	22	4596	208384535	49729.68	647263
28	H27	645	16	2151	153542795	30670.38	402402
29	H28	645	21	5655	399314504	50130.85	1837418
30	H29	646	25	5391	292367648	46706.56	864010
31	H30	649	18	3585	278422000	63938.22	334670
32	H31	650	13	2429	109973898	26186.24	265276
33	H32	651	19	3700	204039000	39252.03	2056382
34	H33	651	24	4414	279193000	62003.2	272109
35	H34	651	21	3358	131659977	28473.72	143519
36	H35	653	19	3427	210080644	44746.32	292858
37	H36	654	21	2934	170363580	43333.5	261593
38	H37	655	20	4074	218668000	55210.65	117068
39	H38	661	23	6136	403961675	118646.57	2286837
40	H39	666	23	3969	78614598	63517.95	661134
41	H40	673	21	5264	316956000	59639.23	699334
42	H41	679	21	6152	295337000	51231.25	354144
43	H42	685	15	2454	207028069	46782.12	186789
44	H43	685	18	4507	295395361	65243.3	203888
45	H44	686	23	4483	241858418	62248.93	285861
46	H45	688	25	5058	251352378	55495.8	1116641
47	H46	692	21	2922	180281247	52387.86	315393
48	H47	695	23	5846	290166812	69588.31	1107819
49	H48	700	18	3527	202176000	59218.56	491957
50	H49	700	18	2584	151923550	52031.72	168049
51	H50	701	20	2980	179703064	41478.62	336813
52	H51	701	22	4859	292351829	51006.48	526969
53	H52	703	24	4442	278410185	52334.1	406892

Fig. 8.2 Data input and setup for hospitals with 600 and more beds for DEAFrontier

less than perfect efficiency, with an efficiency score above 0.9 but less than 1.00 (Table 8.3).

Figure 8.4 displays the efficient targets for the input-oriented CRS model. As the reader can observe, the target values for efficient hospitals are equivalent to their original input and output values (see hospitals H15, H32, H38, and H39 from the figures). Calculation of targets is the same as in the CRS model and they can be found in Chap. 2. For detailed formulation of these calculations, the reader is referred to Appendix B, Part 3.

One of the aims of DEA evaluation of performance is to find out how much unnecessary resources are used by each hospital and how much they lack in attracting patients to their facilities. Elimination of the excessive resource use and production

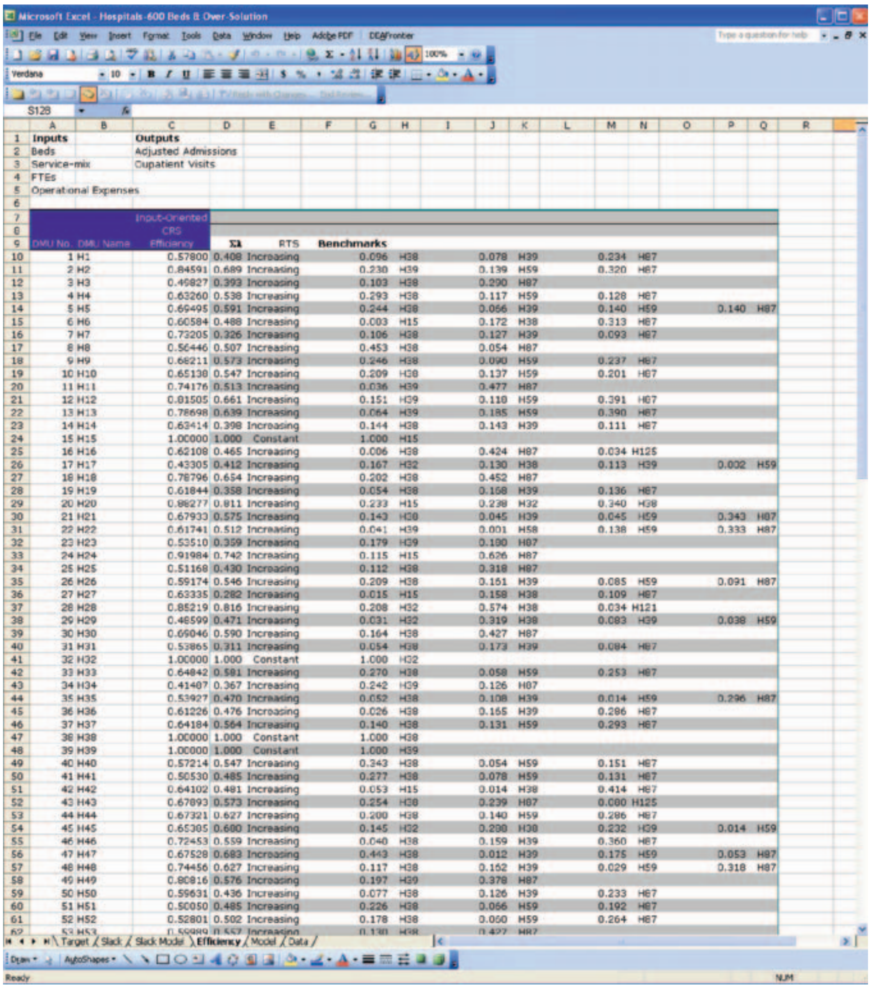


Fig. 8.3 Efficiency results for hospitals with 600 and more beds using DEAFrontier

Table 8.2 Summary of efficiency results

Statistic	Efficiency
Mean	0.685
St. Dev.	0.145
Min	0.340
Max	1.0

of more health services with given resources will improve efficiency of each hospital. In order to find the exact amount of the excess resource (input) use and lack of outputs, we can subtract the target values of each input and output variable presented

Table 8.3 Magnitude of efficiency

Efficiency level	Hospitals	Percent
1.0	10	7.6
$\geq 0.9- < 1.0$	5	3.8
$\geq 0.8- < 0.9$	9	6.9
$\geq 0.7- < 0.8$	22	16.8
$\geq 0.6- < 0.7$	48	36.6
$\geq 0.5- < 0.6$	29	22.1
$\geq 0.4- < 0.5$	7	5.3
< 0.4	1	0.8
Total	131	100

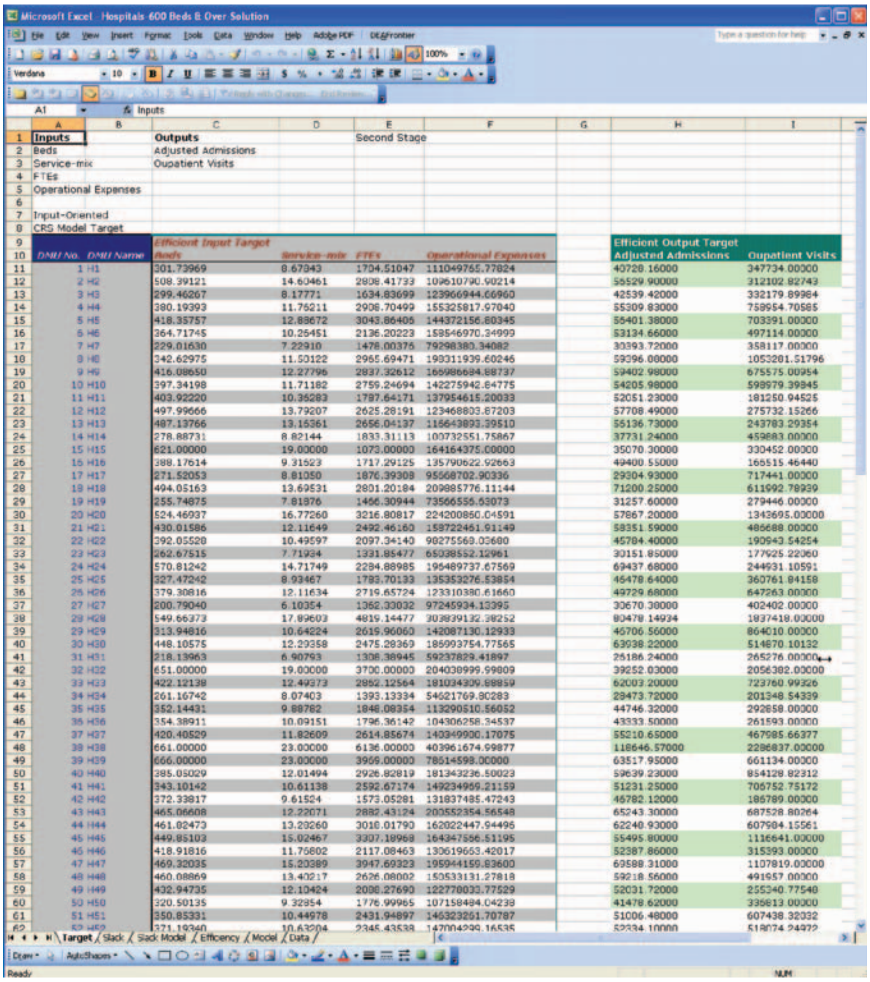


Fig. 8.4 Efficient targets for hospitals with 600 and more beds using DEAFrontier

				Inefficiencies		
		Excessive Inputs			Shortage of Outputs	
Hospital	Beds	Service-mix	FTEs	Operational Expenses	Adjusted Admissions	Oupatient Visits
H1	-298.3	-10.3	-1244.5	-81079156.2	0.0	0.0
H2	-92.6	-3.4	-511.6	-19966755.1	0.0	20754.8
H3	-301.5	-8.8	-1646.2	-310228055.3	0.0	75681.9
H4	-220.8	-12.2	-1689.3	-90208918.0	0.0	261368.7
H5	-183.6	-6.1	-1336.1	-63373667.2	0.0	0.0
H6	-237.3	-10.7	-1389.8	-130158335.7	0.0	0.0
H7	-374.0	-11.8	-541.0	-29025721.7	0.0	0.0
H8	-264.4	-11.5	-2288.3	-205803060.4	0.0	825822.5
H9	-193.9	-5.7	-1424.7	-77822697.1	0.0	422881.0
H10	-212.7	-9.3	-1476.8	-76146296.2	0.0	90207.4
H11	-206.1	-5.6	-622.4	-48028191.8	0.0	68517.9
H12	-113.0	-6.2	-595.7	-28017029.1	0.0	159732.2
H13	-131.9	-3.8	-719.0	-31574106.6	0.0	58843.3
H14	-342.1	-9.2	-1057.7	-58115448.2	0.0	0.0
H15	0.0	0.0	0.0	0.0	0.0	0.0
H16	-236.8	-5.7	-1047.7	-92731076.1	0.0	26090.5
H17	-355.5	-13.2	-2456.6	-125251153.1	0.0	0.0
H18	-132.9	-8.3	-753.8	-82409223.9	0.0	419102.8
H19	-375.3	-12.2	-904.7	-45389443.4	0.0	0.0
H20	-106.5	-2.2	-427.2	-35412803.0	0.0	0.0
H21	-203.0	-6.9	-1176.5	-74923149.1	0.0	0.0
H22	-242.9	-6.5	-1299.7	-60898377.0	0.0	17789.5
H23	-376.3	-8.3	-1157.1	-56506949.9	0.0	54261.2
H24	-68.2	-1.3	-199.1	-19339852.3	0.0	93045.1
H25	-312.5	-12.1	-1702.3	-151141723.5	0.0	127645.8
H26	-261.7	-9.9	-1876.3	-85074154.4	0.0	0.0
H27	-444.2	-9.9	-788.7	-56296860.9	0.0	0.0
H28	-95.3	-3.1	-835.9	-95475371.6	0.0	0.0
H29	-332.1	-14.4	-2771.0	-150280517.9	0.0	0.0
H30	-200.9	-5.7	-1109.7	-91428245.2	0.0	180200.1
H31	-431.9	-6.1	-1120.6	-50736068.6	0.0	0.0
H32	0.0	0.0	0.0	0.0	0.0	0.0
H33	-228.9	-11.5	-1551.9	-98158690.1	0.0	451652.0
H34	-389.8	-12.9	-1964.9	-77038207.2	0.0	57829.5
H35	-300.9	-9.1	-1578.9	-96790133.4	0.0	0.0
H36	-299.6	-10.9	-1137.6	-66057321.7	0.0	0.0
H37	-234.6	-8.2	-1459.1	-78318099.8	0.0	350917.7
H38	0.0	0.0	0.0	0.0	0.0	0.0
H39	0.0	0.0	0.0	0.0	0.0	0.0
H40	-287.9	-9.0	-2337.2	-135612763.5	0.0	154794.8
H41	-335.9	-10.4	-3559.3	-146102030.8	0.0	352608.8
H42	-312.7	-5.4	-880.9	-75190583.5	0.0	0.0
H43	-219.9	-5.8	-1624.6	-94843006.4	0.0	483640.8
H44	-224.2	-9.7	-1465.0	-79035970.1	0.0	322123.2
H45	-238.1	-10.0	-1750.8	-87004811.5	0.0	0.0
H46	-273.1	-9.2	-804.9	-49661583.6	0.0	0.0
H47	-225.7	-7.8	-1898.3	-94222652.2	0.0	0.0
H48	-239.9	-4.6	-900.9	-51642868.7	0.0	0.0
H49	-267.1	-5.9	-495.7	-29145516.2	0.0	87291.8
H50	-380.5	-10.7	-1203.0	-72544580.0	0.0	0.0
H51	-350.1	-11.6	-2427.1	-146028567.3	0.0	80469.3

Fig. 8.5 Calculation of inefficiencies

in Fig. 8.4 from the original data of input and outputs shown in Fig. 8.2. Figure 8.5 displays partial view of results for the inefficiencies. As the reader can note, the negative values in inputs indicates that they must be reduced by that amount. Shortage of outputs, on the other hand, requires augmentation of the outputs by the indicated amount.

Although Fig. 8.5 provides an excellent prescription for individual hospitals for their course of action towards efficiency, we can also study the impact of these efficiencies for a larger economy. As indicated before, these 131 large hospitals account for approximately 13.2% of all US non-federal hospital beds, 23% of all inpatient admissions and 12.6% of all outpatient visits in the US. Thus, improvement of overall inefficiency for the large hospitals in the health care industry would contribute

Table 8.4 Excessive inputs and shortage of outputs for US hospitals with 600 or more beds

Statistics	Excessive inputs				Shortage of outputs	
	Beds	Service mix	FTEs	Operational expenses (in million $)	Adjusted admissions	Outpatient visits
Mean	304	7	1630	111	0	103,712
St. Dev.	183	4	1217	104	0	191,205
Total	39, 867	931	213,516	14,566	0	13,515,586

significantly to this sector. To view this from a macro perspective, we can summarize the values obtained from Fig. 8.5.

A summary of excessive inputs and lack of outputs for all 131 large hospitals is shown in Table 8.4. As the reader can note, a total value on the last row indicates the total excessive input or total shortage by all 131 hospitals. Results show that collectively large hospitals can reduce beds by 39,867 from 105,476 existing beds shown in Table 8.1. Additionally, 931 services can be curtailed while FTEs can be reduced from 626,924 by 213,516 (a 34% reduction). Furthermore, large hospitals must reduce non-labor operational expenses by 14.5 billion dollars. These findings are similar to Ozcan (1995), who determined that at least 3% of health care costs in the GDP are due to inefficiencies created by the excessive buildup of providers.

Although there is no shortage of inpatient admissions, to achieve efficiency the large hospitals must attract 13.5 million more outpatient visits (augmentation of output). This way outpatient visits should increase from current 72.9 million visits to 86.4 million visits. This means more care should shift to outpatient by some hospitals (see H2, H3, H5 and so on in Fig. 8.5).

8.6 Federal Government Hospitals (VA and DoD)

A study by Burgess and Wilson (1993) evaluated 32 veterans administration (VA) hospitals and compared them to non-federal hospitals (n = 1445). Ozcan and Bannick (1994) compared VA hospitals to DoD hospitals (n = 284). A Burges and Wilson study showed that VA hospitals were more efficient (91.8%) than their non-government counterparts (84.9–88.0%). On the other hand, Bannick and Ozcan (1995) showed that defense hospitals (n = 126) were generally more efficient (87%) than VA (n = 158) hospitals (78%). Due to different size and comparison groups, it is hard to generalize the results on a comparison of government to non-government hospitals. Even within a government hospital framework, there might be idiosyncrasies that should be accounted for in the comparisons. Bannick and Ozcan (1995) provide useful discussion on the homogeneity and heterogeneity of DoD vs. VA hospitals. Nevertheless, due to funding and administration differences, comparison of non-government hospitals to non-governmental acute care hospitals may produce misleading results. Thus, the VA or DoD hospitals should be only compared among themselves.

Ozcan and Bannick (1994) in an earlier study used DEA to evaluate trends in DoD hospital efficiency from 1998 to 1999 using 124 military hospitals, with data from the American Hospital Association Annual Survey. This study used the model described earlier, and included army, air force and navy hospitals in the comparison. They found that average efficiency ranged from 91 to 96% among these three services.

Coppola (2003) conducted a DEA study of military hospitals using 1998–2002 data. In his study, he selected the following input variables: costs, number of beds in the military facility, FTEs, and number of services offered. For output variables, he included surgical visits, ambulatory patient visits (APVs), emergency visits, case mix adjusted discharges (CMAD), and live births. Data was obtained from the US DoD and 390 facilities were included in the study. Cappola's study found that 119 (31%) of the hospitals were efficient. Air Force hospitals were leading with 92% efficiency while Navy hospitals were recorded at 87%. Average efficiency gradually declined from 91% in 1998 to 89% in 2002.

Up to this point, the studies were conducted at the strategic level under a different operational paradigm prior to the large-scale adoption of managed care. In the most recent work in the area of MTF, Fulton (2005) analyzed the performance of 17 U.S. Army Community Hospitals and seven Army Medical Centers over a 3-year period, 2001–2003. Fulton's model, however, uses different approach than Coppola's and evaluates from the managed care perspective by including quality, patient satisfaction, readiness measure, relative value units (RVUs) and relative weighted product (RWP), and GME training as outputs. His inputs include cost and enrollment/population measures as a non-discretionary input. The VRS input-oriented model yielded 97.6% efficiency while an output-oriented VRS model showed 98.9% efficiency. According to Fulton, the results suggest that about $10 million reduction in cost could have been achieved in 2001.

Depending upon the purpose of the efficiency evaluation, models deployed by various researchers utilized the variants of the essential inputs and outputs presented in the robust model shown in Fig. 8.1.

8.7 Academic Medical Center Applications

Academic Medical Center application of DEA is another variant of the model presented above. The only difference in this model is capturing the training or teaching output (Morey et al. 1995). This particular variable can be captured in terms of resident MD and dentist FTEs from AHA data base. This begs the question, then, of if this variable should be considered just as output (teaching function of the Academic Medical Centers)? Others may also argue that these FTEs provide an immense resource for the hospitals, thus they can also be considered as input. To test these assertions, in separate studies Ozcan (1992) and Valdmanis (1992) performed sensitivity analysis to test the impact of using teaching variable (FTEs) as input, output or

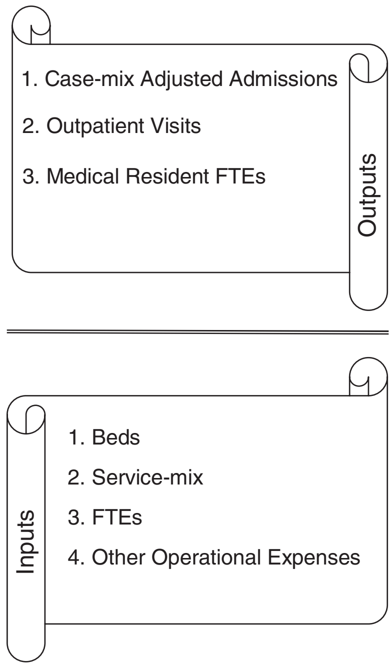


Fig. 8.6 DEA model for Academic Medical Centers

both. Both studies showed that using input, output, or both did not affect efficiency scores dramatically, other than having the effect of the additional variable. Thus, not to over inflate efficiency scores, a more prudent approach would be including the variable only one time. Since the teaching is an important output for Academic Medical Centers, using the variable as output seems a more reasonable approach. Hence, we can identify medical resident FTEs as teaching output for Academic Medical Centers as shown in Fig. 8.6.

8.8 Summary

This chapter provided general guidance for a robust hospital performance model and its operationalization using generally available data basis. Furthermore, development of these models is connected to research conducted during the past several decades. Using the robust model presented, efficiency of large size US hospitals is also examined. Variation of the models for federal government hospitals and Academic Medical Centers are also discussed.